ESSAYS IN FINANCIAL INTERMEDIATION

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To my parents,

Jaya Rao and Narsing Rao,

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SUMMARY

This thesis uncovers the behavior of market participants in reponse to regulatory changes in the financial intermediation sector. The first essay, "Repo Regret?", I find that Independent Mortgage Companies (IMCs), which accounted for a third of all mortgage originations in the U.S., experienced an exogenous increase in their funding after the passage of the 2005 bankruptcy reform act. The act increased creditor protection by including mortgage related collateral to bankruptcy safe harbored repos, thereby expanding IMCs funding opportunities. Using multiple identification strategies based on funding constraints, discontinuity in securitization propensity, and geographic discontinuity in anti-predatory lending laws, I find that IMCs responded to this funding shock by increasing the issuance of risky home loans which culminated in higher ex-post defaults. Areas exposed to significant IMC lending also experienced a greater house price growth. My results highlight the unintended role of regulation in aiding the U.S. housing market boom and bust by safe harboring mortgage related repo collateral.

In the second essay, "Are credit ratings still relevant?", we show that firms' stock prices react significantly less to credit rating downgrade announcements when they have Credit Default Swap (CDS) contracts trading on their debts. We find that CDS spreads predict firms' future rating downgrades and defaults, and document a significant information flow from the CDS to equity and bond markets before firms are downgraded. Further, the CDS term structure can be used to construct a more reliable measure of default risk premium for firms undergoing rating revisions. While the CDS market is not a perfect substitute for credit ratings, our results suggest that credit rating revisions have become less informative to equity investors in the presence

of the CDS market.

In the third essay, “Credit Default Swaps and Moral Hazard in Bank Lending”, we analyze whether introducing Credit Default Swaps (CDSs) on a borrower’s debt leads to lender moral hazard around covenant violations, wherein lending banks can terminate or accelerate the loan. Using a regression discontinuity design, we show that CDS firms, including those with agency problems, do not decrease their investment after covenant violations, pay a higher loan spread, and perform poorly, but do not go bankrupt at a higher rate when compared with non-CDS firms that violate covenants. These results are magnified when lenders have weaker incentives to monitor and suggest that introducing CDSs misaligns incentives between lenders and borrowers.

In the fourth essay, “Do Bond Investors Price Tail Risk Exposures of Financial Institutions?”, we analyze whether bond investors price tail risk exposures of financial institutions using a comprehensive sample of bond issuances by U.S. financial institutions. Although primary bond yield spreads increase with an institutions’ own tail risk (expected shortfall), systematic tail risk (marginal expected shortfall) of the institution doesn’t affect its yields. The relationship between yield spreads and tail risk is significantly weaker for depository institutions, large institutions, government-sponsored entities, politically-connected institutions, and in periods following large-scale bailouts of financial institutions. Overall, our results suggest that implicit bailout guarantees of financial institutions can exacerbate moral hazard in bond markets and weaken market discipline.

CHAPTER I

REPO REGRET?

1.1 Introduction

The early 2000s saw an exponential growth in mortgage debt which rose to $14.6 trillion by 2008 before the collapse of the U.S. housing market.[1] Since then, there has been a concerted effort to understand the origins of the expansion in mortgage credit and its consequences (see [105, 106, 107, 6, 7, 8, 45]). Central to our understanding of the recent mortgage credit growth is the regulatory environment and incentives under which the mortgage industry operated. This study contributes to the literature focusing on the recent mortgage credit expansion by analyzing a class of mortgage originators known as independent mortgage companies – which accounted for about 34% of all mortgage origination in the mid-2000s [2] – and the inadvertent role regulation played in subsidizing their issuance of risky mortgage credit by safe harboring derivative contracts.

An important regulatory change in the treatment of certain derivative contracts in the event of bankruptcy occurred in April 2005 when Congress expanded the range of safe harbored repos or repurchase agreements with the passage of the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 (BAPCPA).[3] The act expanded the range of bankruptcy safe harbored repos by amending the definition of the

[1] Mortgage debt rose by 106% from $6.9 trillion in 2000 to $14.6 trillion in 2008. Sources: `http://www.federalreserve.gov/econresdata/releases/mortoutstand/mortoutstand20090331.htm` ; `http://www.federalreserve.gov/Pubs/supplement/2004/01/table1_54.htm`

[2] Source: Home Mortgage Disclosure Act (HMDA) data

[3] See *Bankruptcy Abuse Prevention and Consumer Protection Act*, 2005, Pub. L. No. 109-8; `http://www.gpo.gov/fdsys/granule/STATUTE-119/STATUTE-119-Pg23/content-detail.html`

"*repurchase agreement*" to include mortgage loans, mortgage related securities, interests in mortgage related securities or mortgage loans, and qualified foreign government securities. The rationale behind this specific provision was to prevent systemic risk by granting derivative counterparties an exemption to the bankruptcy automatic stay rule, thereby allowing them to close out their positions (See [100], [111], and [134]). Instead, I document that this change to the bankruptcy code expanded the funding opportunities of Independent Mortgage Companies (IMCs), which in turn led to an expansion in the supply of risk mortgage credit. Specifically, IMCs increased the issuance of risky home loans such as Subprime, Alt-A, Low-documentation and Complex mortgages by about 10% per quarter due to the passage of BAPCPA. This culminated in an increase in ex-post default rate by about 2.24% relative to a control group.

IMCs operate using an originate-to-distribute (OTD) model of lending wherein they originate mortgages and sell them off for securitization (see [55]). Unlike banks, IMCs do not take deposits and thus fund their mortgage origination business by relying on short-term revolving lines of credit called warehouse loans and repurchase agreements (repos). After BAPCPA, repos with mortgage related collateral were made exempt from the bankruptcy automatic stay rule. This exemption allows repo lenders immediate rights to their collateral if a borrowing IMC defaults. However, lenders extending warehouse loans to an IMC have to wait in line for an orderly liquidation process and the bankruptcy court's approval. By parsing 8-K filings and collecting excerpts from 10-K filings of IMCs, I first document that the financing documentation significantly shifts towards the use of repurchase agreements. This is expected given that a secured loan and a repo are economically equivalent, but a repo lender has greater protection in the event of a bankruptcy.

There are two potential reasons why BAPCPA affected IMCs' funding. First, to the extent that increased creditor protection lowers a lender's loss given default and reduces the risk-premium demanded, a competitive lending market will drive down funding costs for repos. Second, by expanding the eligibility of the safe harbored repo collateral to include mortgage related securities, IMCs could borrow greater amounts via repos by using mortgages in their pipeline as repo collateral.[4] Using a merged database of BlackBox Logic (BBx Logic) data and Home Mortgage Disclosure Act (HMDA) data, I first show that the proposed funding shock due to BAPCPA in turn translated to an increase in supply of mortgage credit by IMCs. Subsequently, I study the consequences of this mortgage credit expansion on loan performance and house prices.

The major impediments to identifying the effect of BAPCPA on IMCs are concerns regarding the exogeneity of BAPCPA, choice of a good control group for the IMCs, and the fact that BAPCPA was a singular as opposed to a staggered shock. The exogeneity of BAPCPA with respect to IMC's funding mechanisms derives from the fact that the safe harbor rules were instituted to prevent systemic risk arising from the inability to close out derivative positions due to the bankruptcy automatic stay rule [5] (See [100], [111], and [134]). Moreover, the fact that a reduction in funding costs and an increase in funding amount can only take place once the BAPCPA law is in effect, gives rise to a causal interpretation of BAPCPA on IMC funding and the growth in mortgage issuance. For the second and third concerns, I employ multiple identification strategies based on funding constraints, discontinuity in securitization propensity, and geographic discontinuity in anti-predatory lending laws. In each case there is a different set of treated and control groups, and additionally I also include $County \times Quarter$ fixed effects in the bulk of my analysis. The former allows the results to be independent of the choice of control groups and alleviates the concern

[4] Before BAPCPA, safe harbored repo collateral included only U.S. Treasuries and Agency debt.

[5] This especially seemed to be a growing concern after the LTCM (Long-Term Capital Management) crisis which allegedly provided an example of how derivatives and systemic risk might be associated

that the results are being driven due to a particular control group. The later controls for any time-varying common shocks influencing the treatment and control groups that might affect the results.

My first identification strategy is based on exploiting the funding constraints of IMCs compared to affiliated mortgage companies (AMCs) to test for the growth in IMC mortgage credit due to BAPCPA. AMCs' funding needs are mostly met via their affiliated sister depository institutions or parent Bank Holding Company (BHC).[6] Thus arguably, AMCs are less financially constrained when compared with IMCs. Therefore, the proposed BAPCPA-related funding shock should affect IMCs more than AMCs. Furthermore, as Section 1.2 discusses in detail, IMCs and AMCs were similar on other important dimensions such as their primary line of business (OTD), and the lack of regulatory oversight ([44]). I also show that the difference in quarterly growth rates of the volume of mortgage credit originated between IMCs and AMCs did not significantly differ from each other in the pre-BAPCPA period (see Figure 2). This establishes *parallel trends* between the treated (IMCs) and control (AMCs) groups prior to the law change. However, in the post-BAPCPA period, the growth rate of IMCs is significantly greater than that of AMCs and has an overall increasing trend over time.

In a more formal regression setup, I confirm that IMCs have a higher growth in mortgage origination in the post BAPCPA period – both in terms of the number and volume of loans. Consistent with the hypothesis of an increase in supply of credit, controlling for the loan's risk characteristics, there is a reduction in the average mortgage interest rate, as well as an increase in the size of the mortgage loan

[6]For instance Citigroup in its 2006 10-K filing states that the primary source of funding for Citigroup and its subsidiaries comes from diverse types such as deposits, collateralized financing transactions, senior and subordinated debt, issuance of commercial paper, proceeds from issuance of trust preferred securities, purchased/wholesale funds, and securitization of financial assets.
Source: `https://www.sec.gov/Archives/edgar/data/831001/000104746906002377/a2167745z10-k.htm`

for a given borrower income level. These results are robust to including both *Firm* and *County*$\times$*Quarter* fixed effects, which control for any time-invariant unobserved heterogeneity at the firm-level and any common time-varying factors at the county-level. To the extent that a borrower's access to credit is rationed in equilibrium, a positive shock to the supply of credit translates into a higher growth in mortgage originations, especially for the lower credit quality borrowers ([142]). Using subsamples of low, medium and high FICO score samples, I find that the growth in mortgage credit and reduction in interest rates monotonically decrease with FICO scores. In other words, the low credit quality borrowers experience the highest growth rate in mortgages and the highest reduction in interest rates when IMCs lend to them.

If IMCs and AMCs are inherently different kinds of firms, one concern with the above tests is that they could differ on certain time-varying unobserved characteristics (such as differences in regulatory treatment). To address this concern, I compare mortgage credit growth among small and large IMC originators. In general, as firms of the same kind are more similar on broader dimensions, a "within-IMC" comparison potentially alleviates the aforementioned concern. I find that small IMC originators have a larger growth in mortgage issuance compared with large IMC originators. This is consistent with the relaxation of funding constraints due to a positive funding supply shock as smaller firms in general tend to be more constrained than larger firms ([151]).

Although comparing small and large IMC originators relieves the concern of time-varying heterogeneity among treated and controls to a certain extent, it does not entirely eliminate it. To further address this concern, I test within IMCs by relying on a discontinuity in mortgage origination documented by [94]. This discontinuity exists due to the ease of securitization beyond certain FICO scores, particularly 620 for low-documentation loans, and 580 for full-documentation loans.[7] As the number

[7]Consistent with [75], I find a discontinuity in loan originations at FICO scores of 620 and 580

of potential borrowers at each FICO score is continuous, the demand for mortgages is continuous. Thus, a discontinuity in mortgage origination at any FICO score implies a discontinuity in the supply of credit at that FICO score. As mentioned previously, IMCs rely on the OTD business model by securitizing their originated mortgages. Therefore, as the propensity to securitize just above the FICO threshold is higher, a positive shock to the supply of credit should result in a higher growth in loan originations for borrowers with FICO scores just above the threshold compared to borrowers just below the threshold. Using a regression discontinuity design (RDD), I report a discontinuity in the growth of the number and volume of low-documentation loans, and find weak evidence for a discontinuity in the case of full-documentation loans. Overall, this test also provides support for the BAPCPA-led mortgage credit growth. Moreover, it suggests a robust mortgage credit growth for the low-documentation loans which tend to be riskier than full-documentation loans.

Arguably the discontinuity in the propensity to securitize provides a cleaner setting to test for a change in the supply of credit. However, a potential drawback is that it can be applied only locally around the FICO thresholds to test for the BAPCPA-related mortgage credit growth. To overcome this shortcoming, I exploit another source of variation in state anti-predatory lending (APL) laws to capture the effect of BAPCPA on mortgage credit growth. I specifically consider APL laws which make the securitization trusts and the investors who acquire loans liable for statutory violations committed by the original lender. Focusing on counties bordering states with weak and strong APL laws, I find that counties with weaker APL laws indeed experienced a higher growth in mortgage credit in the post-BAPCPA period. This approach mitigates any potential unobserved differences across counties as economic forces tend to be quite similar across neighboring geographic areas.

While the above results are suggestive of an increase in credit supply, there could

unlike [94] who find it at 620 and 600 for full-doc and low-doc loans respectively.

be alternate explanations for the observed results such as a shock to the expected income growth or the house price growth. The demand for housing may increase if borrowers expect a future growth in income. On the other hand, lenders might be more willing to lend more if they expect a growth in houses prices which in turn would reduce their loss given default. I find an expansion in mortgage credit even in counties with a negative real income growth which is evidence against the income-growth hypothesis. Similarly, areas with a high housing supply elasticity should experience only a minimal to moderate appreciation in house prices as any demand for housing can be met with new construction of houses ([68]). I find that even in such areas there is a substantial increase in mortgage credit, thus contradicting the house price appreciation hypothesis.

Next, I document the consequences of the expansion of mortgage credit. Section 1.2 details the life-cycle of a loan originated by mortgage companies and the incentives of the various intermediaries involved to issue risky mortgages.[8] As warehouse lenders are unsure about the loan quality, they typically mitigate the originators' risk-taking incentives by applying haircuts to the collateral, and by the spreads charged on the warehouse loan. However, the exemption from the automatic stay rule of bankruptcy increased the seniority of warehouse lenders' as they could readily liquidate the pledged mortgage collateral without requiring the bankruptcy court approval. This seniority claim results in avoiding potential bankruptcy costs and thereby increases the warehouse lender's recovery rate.[9] Further, theory suggests an inverse relationship between seniority of debt claims and lender's incentive to monitor ([125]). Without adequate due diligence by the warehouse lender, originators can have the incentive to significantly misrepresent loan applications ([89, 75, 121]).

[8] [105, 94, 124] show evidence for the deteriorating lending standards for mortgage loans sold for securitization

[9] Estimated costs of financial distress in the existing literature vary from a 3% ([149]) to as high as 20% ([10]).

Therefore, I argue that BAPCPA lowered creditor monitoring[10] which helped fund riskier mortgage loans via repos as long as they could be readily securitized.[11]

Consistent with this notion, I find that the increase in credit supply by IMCs mainly funded riskier types of loans in the post-BAPCPA period compared to the pre-BAPCPA period. This result is corroborated by the evidence of higher default rates of the loans originated in the post- versus pre-BAPCPA period. I also observe that the default rates increase over time and peak between two and three after the loan origination. This is consistent with the typical period after which the initial lower fixed rates on complex adjustable rate mortgages (ARM) expire, following which there is a substantial increase in the monthly repayments for the borrowers. Interestingly, subsample analysis also conveys a higher default rate in the medium and high quality borrowers, and counties with higher income growth and higher competition compared to the AMC control group. This indicates risk-shifting within good quality borrowers by the mortgage companies in addition to supplying credit to lower quality borrowers due to lower credit rationing. Lastly, I examine the relationship between credit growth and house prices and find that counties experiencing a higher growth in IMC lending are also associated with a higher growth in house prices. Again, consistent with the default results, I find the highest house price growth for the medium and high house price indexes.

Overall, the results in this paper show the unanticipated adverse consequences of BAPCPA which assisted the growth of risky mortgage credit via IMCs.[12] My study contributes to the literature focusing on explaining the expansion of risky credit in

[10]See the Taylor, Bean & Whitaker Mortgage Corporation (TBW) and Colonial Bank's case of fraud as a result of pending repurchase obligations. The case highlights the failure of counterparty monitoring in the mortgage market. Sources: `http://www.fhfaoig.gov/Content/Files/SIR_TBW_Colonial%20Investigation%20Lessons%20Learned%20August%202014.pdf`; `https://www.sec.gov/litigation/complaints/2011/comp-pr2011-68.pdf`

[11]The growth in subprime mortgage credit from 12% in 2000 to 36% of all mortgages in 2006 in part was due to the ease of subprime securitzation ([105]).

[12]The adverse consequences in the form of externalities on the economy due to higher house price growth and higher default rates have been documented in the recent literature ([107, 108])

the mortgage market specifically through mortgage companies which were largely overlooked despite their significant share in the mortgage market. The results also add to the literature exploring regulatory design by documenting the unintended consequences of a regulatory change to the bankruptcy code in the mortgage market. Specifically for BAPCPA, there still exists a debate on the costs and benefits of privileged status of derivatives in bankruptcy (See [52], [99], [50], and [23]). The results in this paper enrich that debate by furnishing new evidence on the real costs of BAPCPA related to the safe harbor exemptions for repos which led to the expansions of risky mortgage credit. This paper also contributes to the literature exploring the role repo market played in the 2008 financial crisis ([71]).

The remaining paper is organized as the following: Section 1.2 elaborates on the structure of U.S. mortgage market with information relevant to the study in this paper. Section 1.3 gives details and provides evidence on effect of BAPCPA on IMC funding. Section 1.4 describes the data used in the empirical analysis. Section 1.5 details the empirical setup and presents results testing the positive "credit supply shock" hypothesis due to BAPCPA. Section 1.6 studies the consequences of the BAPCPA-led increase in mortgage credit and finally Section 1.7 concludes.

1.2 The mortgage market

In this section, I briefly describe the mortgage market in the context of this study. There are different types of mortgage lenders in the U.S., and they can be broadly divided into two main categories – depository institutions and mortgage companies. Depository institutions take deposits and can be primarily categorized into banks, thrifts and credit unions. Mortgage companies do not take deposits and can exist either as independent mortgage companies (IMCs) or can be owned by or affiliated with banks, thrifts and holding companies (AMCs). These different types of mortgage originating institutions differ in the extent to which they may participate in the mortgage market. In general, mortgages account for only a portion of a bank's overall business, which also includes other consumer loans, business loans and credit extensions through other instruments; whereas mortgage companies typically focus on originating mortgages. Based on the Home Mortgage Disclosure Act (HMDA) data from the period of 2004 to 2006, mortgage companies companies together accounted for about 54% all mortgage originations.

The various types of mortgage lenders in the U.S. also differed significantly in regulation. Bank holding companies (BHCs) and state member banks are regulated by the Federal Reserve System (FRS), national banks are regulated by the Office of the Comptroller of the Currency (OCC), and thrifts are regulated by the Office of Thrift Supervision (OTS). Mortgage companies that are subsidiaries are regulated by their parent's regulator, while independent mortgage companies are regulated by the state and the federal trade commission to the extent that they engaged in any unfair or deceptive practice in violation of the Federal Trade Commission Act (see [55]). [44] point out that the mortgage companies were relatively free of regulatory oversight due to the fragmented U.S. regulatory system, despite having a market share of about 50% in the mortgage origination market since the 1990s.[13] They argue that mortgage companies do not hold deposits and hence do not require a charter from an institutional regulator such as the FRS, OCC, OTS or FDIC; and that their activities did not fall under the purview of functional regulators such the SEC, CFTC or state insurance regulators. The Gramm-Leach-Bliley (GLB) Act of 1999 also stated that the non-bank subsidiaries of BHCs could only be examined by the FRS if their activities were deemed to have adverse material impact on the safety and soundness of their sister affiliate banks. [14] This meant that regulating mortgage companies was

[13]For instance consider a BHC that has two subsidiaries - a mortgage company and a national bank. If the national bank has another mortgage company as a subsidiary, then the national bank and its mortgage company subsidiary would be regulated by OCC while the BHC and its mortgage company subsidiary would be regulated by the FRS.

[14]See *Gramm-Leach-Bliley Act*, 1999, Pub. L. No. 106-102

a matter of discretion rather than a decree of the law. In fact [44] show that mortgage company subsidiaries of BHCs (AMCs) originated riskier mortgages and had higher default rates when compared to the BHC bank subsidiaries.

Borrowers in the 2000s could get mortgage loans from three main channels, namely the (i) retail channel, (ii) wholesale channel and (iii) correspondent channel. Retail lenders work directly with the homeowner to originate the mortgage loan without any middlemen or brokers. These loans are generally made in person, over the Internet or via call centers and are processed by in-house loan officers as opposed to outside brokers. Wholesale lenders work with independent mortgage brokers who generate loan applications for them by working on the retail end with the borrowers. Once the mortgage deal is secured, the brokers send it to the wholesale lenders who underwrite the loan and fund it. Correspondent lenders are institutions that make loans through retail operations at their end, but according to underwriting standards set by a wholesale lender who in turn commits in advance to buy the loans from the correspondent lender at a set price. Although lenders might use multiple channels to originate mortgages, mortgage companies typically originate through wholesale and/or correspondent channels ([129]). [15]. For instance an IMC usually originates a mortgage loan to a borrower by drawing down on their lines of credit in order to fund the mortgage.

Typically, these lines of credit are secured by the originated mortgages. However, within a short period of time, which usually ranges from 30-45 days, the mortgage is sold to a third-party, often for the purpose of securitization, and the warehouse line of credit is then paid down. The bulk of IMCs' income is usually earned through originating fees and selling the originated loans for a higher value than when they were made. Meanwhile, the warehouse lenders earn interest on their lines of credit

[15]The liabilities structure of American Home Mortgage Company, which is a large IMC, is shown in Table A.1 Although they use multiple sources of financing, warehouse line of credit and repurchase agreements remain their largest sources.

when a draw-down occurs. In a typical case when the IMCs exhaust their credit lines, they will need to securitize or sell the originated loans in their pipeline before they can replenish their credit lines and further draw-down on them.

Mortgage brokers are generally independent agents who serve as a contact between the borrowers and lenders. Brokers allow wholesale lenders to lend in markets where they have no physical presence. Brokers earn commissions on every loan they arrange. Each day the lenders provide brokers with "rate sheets" which have information on the various types of mortgages the lender would underwrite along with the minimum price they would accept for a loan for a given credit score. In the 2000s, the commissions were higher if the brokers could get the borrower on a higher interest rate mortgage with prepayment penalties ([55]). Brokers also earned higher commissions on low-documentation (low-doc) and no-documentation (no-doc) loans.[16]. For instance [55] note that the fees on a $300,000 low-doc was $15,000 whereas a comparable full-doc loan would yielded less than $5,000 in fees Moreover, borrowers opted for the low-doc loans as it entailed less paperwork and less processing time, or due to the concern that the mortgages rates and house prices might rise. Borrowers who did not qualify for conventional fixed-rate mortgages, were offered complex products such as ARMs, option ARMs and hybrid ARMs which tended to have lower initial payments compared to fixed-rate until the rates are reset to a higher number after a specified term. In these cases, the borrowers were assured that they could refinance their mortgages when the rates went up (see [55]).

1.3 Effect of BAPCPA on IMC Funding

This section describes the effect of BAPCPA on the funding opportunities of IMCs in further detail. As discussed previously, unlike depositories, IMCs do not take

[16] The Wall Street journal article *Subprime Debacle Traps Even Very Credit-Worthy, Dec 2007* by Brooks and Simon reports that 55% of all subprime loans in 2005 went to borrowers with credit scores high enough to qualify for prime loans

deposits and rely on funding their mortgage originations through external credit facilities such as lines of credit provided by warehouse lenders. Warehouse lenders are typically banks which allow collateralized short-term borrowings that are secured by the originated mortgages.[17] A principal concern of the warehouse lender is the potential default of the mortgage company to which it lends. As a result, bankruptcy law has been a predominant factor in driving the type and cost of funding. Arguably, IMCs' cost of funding was significantly lower after the passage of the BAPCPA act which subsidized the latter of the two major types of funding agreements used by warehouse lenders and mortgage companies which are the "Master Loan and Security Agreement" and the "Master Repurchase Agreement" (MRA). In the event of a default or bankruptcy, under the *loan and securities agreement*, the warehouse lender would not have the unfettered right to take over the ownership of the pledged mortgage loans. They would be halted by the "automatic stay" feature of the bankruptcy code. On the other hand, under the *repurchase agreement*, the warehouse lender would have the right to liquidate the pledged mortgage loans without having to obtain the bankruptcy court approval and recover the related advances.[18]

After BAPCPA expanded the "safe harbored" securities to include mortgage loans, the financing documentation for IMCs significantly shifted towards the use of repurchase agreements. Figure 1 shows the result of parsing 8-K filings for IMCs for the number of occurrences of *repurchase* and *loan* agreements. The number of repurchase agreements used have evidently increased after the BAPCPA took effect in 2005-Q4, while the number of loan agreements have decreased over the same period.

To supplement this evidence, A.2 provides excerpts from the 10-K filings of IMCs

[17] A relatively large IMC – American Home Mortgage Company's 2004 10-K filing states their warehouse lenders were: UBS ($1.2 Bil), Bank of America ($600 Mil), CDC Mortgage Capital ($450 Mil), Morgan Stanley ($350), Lehman Brothers ($250 Mil), Bear Stearns ($500 Mil), and Caylon Americas ($250 Mil). Source: `https://www.sec.gov/Archives/edgar/data/1256536/000091412105000607/am031605-10k.txt`

[18] Table A.1 reports that the cost of warehouse repos is indeed lower than warehouse lines of credit based on the 10-K filings of a large IMC.

and the industry responses to the U.S. Housing and Urban Development's (HUD) solicitation on the changes of funding mechanisms in the mortgage industry. These excerpts clearly state a preference for repurchase agreements as a means for funding IMC operations. Moreover they affirm an increase in the size of warehouse lines of credit under these repurchase agreements as well as a change in the eligibility of the collateral backing them.[19]

There are two potential reasons why BAPCPA reduced the funding costs and increased the line of available credit to IMCs. First, the exemption from the bankruptcy automatic stay allowed repurchase lenders immediate rights to their collateral if a borrowing IMC defaulted. This results in increasing the warehouse lender's recovery rate by avoiding potential bankruptcy costs. [10] estimate that bankruptcy costs can be as high as 20%. Second, as a repurchase agreement involved a "true sale" of the collateral unlike a loan agreement, this allowed warehouse lenders to account for these warehouse facilities as "loans held for sale" instead of a financing transaction.

There are benefits to accounting for repurchase agreements in this manner. The risk-weights assigned to purchased qualifying mortgages is 50% (20% for FHA and VA loans) whereas a traditional warehouse line of credit is recognized with a 100% risk-weight ([141]).[20] This also allows warehouse lenders (especially the smaller banks) to extend bigger lines of credit without violating the "loans-to-one-borrower" restriction.[21] Together, these advantages of repurchase agreements can incentivize more banks to enter the warehouse lending business, and also enable them to commit higher amounts towards credit lines written through MRAs.

[19]Prior to the BAPCPA, since the early 1980s, safe harbored repos included only U.S. Treasury and Agency securities backed by the government's full faith and credit, certificates of deposits, and bankers acceptances.

[20]The OCC in its 2012 memorandum has reiterated that warehouse repurchase agreements should receive a 100% risk weight. Despite that, lenders still continue to account for them as "loans held for sale". See Texas Capital Bancshares Inc's (a warehouse lender's) 2012 10-K filing: `https://www.sec.gov/Archives/edgar/data/1077428/000119312513068855/d468799d10k.htm`

[21]See Section 32.3 on Lending Limits at `https://www.fdic.gov/regulations/laws/rules/8000-7400.html`

1.4 Data and descriptive statistics

The two main datasets used in this study are BlackBox Logic (BBx Logic) and Home Mortgage Disclosure Act (HMDA). BBx data covers about 90% of the U.S. residential mortgage-backed securities (RMBS) non-agency market while HMDA covers the loan originations by 99% of depository and non-depository financial institutions. BBx data is mainly gathered from securitization trustees and contains information on borrower credit scores, as well as loan characteristics such as the loan-to-value (LTV) ratio, loan principal, maturity and variety of indicators identifying the purpose, occupancy status, documentation type. It also maintains a time-varying record of the history of the loan payoff status such as delinquency, modification, prepayment, loss from liquidation etc. at a monthly frequency for each loan. However, the identity of the loan originator – whether a loan has been originated by an independent or affiliated mortgage company, or a depository – is recorded in the HMDA dataset.[22] Thus the BBx data is a richer dataset compared to HMDA.

Arguably a positive shock to credit supply in the mortgage industry leads to the expansion of mortgage credit to borrowers with lower credit quality who were previously rationed out ([142]).Furthermore, the incentive structures in the mortgage market as discussed in Section 1.2 encourages the underwriting of complex and riskier mortgages. Therefore the effect of an increase in mortgage credit due to the BAPCPA act is conceivably more apparent in the non-agency market. Hence this also motivates the use of the BBx dataset.

The matching of loans between BBx and HMDA databases is carried out based on loan characteristics and the geography of the underlying mortgage property. BBx reports data by zip-code while HMDA reports data by census-tract. Census-tract

[22] Although BBx data has a raw data field for the name of loan originator, it is missing for about 90% of the loans. As a result, BBx does not provide a cleaned and standardized version of this data field.

and zip-codes are not uniquely identified and intersect each other. Census-tract classification can change when every decennial census is conducted whereas zip-codes are relatively stable. To merge BBx and HMDA based on geographic information, I use the zip-code to census-tract crosswalk files. The variable used for determining the portion of a census-tract region that overlaps with a given zip-code region is the number of housing units (according to the 1990 or 2000 census [23]). This is an intuitive weight especially when one is trying to gauge the probability of a mortgage origination in a given census-tract to be in a particular zip-code [24]. Loans BBx and HMDA are matched exactly on four loan characteristics loan amount, loan purpose, occupancy type and lien type, but coarsely on the geography of the property. Details of the matching algorithm are provided in A.3.

The HMDA dataset is augmented to the "HMDA Lender File" compiled by Robert Avery from the Board of Governors of the Federal Reserve System which provides information used to identify the type of originator/lender. Originators are broadly classified into (i)independent depository institutions which include commercial banks, savings banks and credit unions; (ii) affiliated depository institutions which are typically subsidiaries thrift or bank holding companies; (iii) independent mortgage companies (IMCs); and (iv) affiliated mortgage companies which are typically subsidiaries or affiliates of holding companies or depository institutions.

Table 1 provides the summary statistics of the matched BBx-HMDA datasets in the pre- and post-BAPCPA periods. On an average IMC issue mortgage loans with a smaller loan amount compared with AMCs in both periods. This is consistent with IMCs being more financially constrained compared to AMCs. Panel A shows that the number and dollar volume of loans for both IMCs and AMCs increased in the post-BAPCPA period. The table also shows that the initial interest rates at

[23] Census-tract definition in HMDA changed in 2003 to make use of the 2000 census classification. Prior to 2003, the 1990 census classification was used.

[24] Census-tract (∼73,000 areas) has more granularity compared with zip-codes (∼43,000 areas).

origination have increased in the post-BAPCPA period. Although this is inconsistent with a reduction in mortgage origination costs vis-á-vis increased repo financing after BAPCPA, it is likely that the increase is due to originating riskier mortgages to low credit-quality borrowers. Support for this is noted in Panel B which shows that the fraction of low-documentation loans, Alt-A, and Subprime loans increased in the post-BAPCPA period. However, these are univariate statistics and one needs to control for county-level factors and time-varying risk factors to draw any useful conclusions on the effect of the passage of BAPCPA on the expansion of mortgage credit.

1.5 Results: Mortgage credit growth via IMCs

This section tests the hypothesis that the 2005 BAPCPA act led to an expansion of mortgage credit for the IMCs. As BAPCPA was a singular shock as opposed to a series of staggered stocks, I use four sets of treated and control groups for my identification strategy. This alleviates concerns that the results may be driven by the choice of the control group rather than the treated group in the post-BAPCPA period. Additionally, I also control for any time-varying common shocks influencing the treatment and control groups by including $County \times Quarter$ fixed effects. While the first set of treated and control groups in my identification strategy compares IMCs with AMCs, the next three are comparisons within IMCs. Comparisons within IMCs mitigate the concern that IMCs and AMCs might differ on certain unobservable characteristics that might drive the results. Arguably, firms of the same kind are more aligned on broader dimensions. The later subsections test alternate explanations and carry out a host of robustness checks for the BAPCPA-led mortgage credit expansion.

1.5.1 Exploiting funding constraints: IMCs vs AMCs

In the first identification test, I use IMCs as the treated group and AMCs as the control group. This choice of treated and control groups exploits the setting that IMCs are more financially constrained compared to AMCs while being similar on other dimensions such as their core line of business and lack of regulatory oversight as discussed in Section 1.2

To test for the growth in mortgage credit after the passage of the 2005 BAPCPA act, I estimate the following difference-in-difference identification model on quarterly data at the firm-county-quarter observation level:

$$Y_{ict} = \alpha + \beta_1 dPostBAPCPA_t \times dIMC_i + \beta_2 dIMC_i + \beta_3 dPostBAPCPA_t + \theta X_{c,t} + \lambda_i + \delta_{ct} + \varepsilon_{ict} \quad (1)$$

where the subscripts i, c and t stand for firm, county and quarter respectively. *dPost-BAPCPA* is a dummy variable equal to 1 for all quarters on or after the fourth quarter of 2005 during which the provisions of the 2005 BAPCPA act started to apply, and 0 prior to that. *dIMC* is dummy variable equal to 1 if the mortgage company is an independent mortgage company (IMC), whereas it is 0 if it a subsidiary or an affiliate of a bank or a holding company and will be thereafter referred to as an affiliated mortgage company (AMC) for the sake of convenience. Y_{ict} stands for one of the five observed firm-county level activities in the mortgage market, namely the log-growth rate in the number and volume of loans issued, the average FICO score, interest rate and loan-to-income (LTI) ratio. X_{ict} are the firm-specific controls I can explicitly measure. As I only have information on the loan-mix at origination for each firm and no other firm-level information, X_{ict} mainly reflect the loan-mix of each firm and are included in the interest rate and LTI regressions only.

Equation (1) also includes firm fixed effects (λ_i) to control for any time-invariant unobserved heterogeneity across firms and *County*$\times$*Quarter* fixed effects (δ_{ct}) to control for time-varying factors at the county-level that might drive credit expansion. The coefficient on the interaction term *dPostBAPCPA*$\times$*dIMC* is the difference-in-difference (DID) estimator, and it is the key variable of interest while the base coefficients *dPostBAPCPA* and *dIMC* are absorbed in the fixed effects. The coefficient on the term $dPostBAPCPA \times dIMC$ captures the change in the dependent variable of interest between the IMCs (treated group) and the AMCs (control group).

Table 2 shows the results for the regression specification in Equation (1) wherein I restrict the sample period to six quarters before and after the 2005 BAPCPA act.[25] The positive and significant coefficient on $dPostBAPCPA \times dIMC$ in columns (1) and (2) indicates that the growth rates in the total number and total volume of loans increases when compared with AMCs. The median IMC firm during the sample period from 2004-2006 issues close to $500 million in loan volume per county in a given quarter. An 11% increase in growth rate amounts to a growth of $55 million in loan volume per county over a given quarter.

The evidence presented in A.2 and Table A.1 suggests that the 2005 BAPCPA act resulted in a positive supply shock by lowering the cost of funding a mortgage loan as well as increasing the capacity of the warehouse line of credit to IMCs. Consistent with that notion, columns (3) and (4) show that the growth rate in the number and volume of jumbo loans[26] increases for IMCs after the 2005 BAPCPA act when compared to AMCs. Column (5) shows that IMCs also originated mortgages with lower interest rates controlling for the types of mortgage issuance by each firm. In line with expectations, column (5) shows that higher loan-to-value ratios, higher percentage of Alt-A, subprime and low-doc loans, and loans to lower quality borrowers increase the average issuing mortgage interest rate by a firm. Similarly column (6) shows that a higher mortgage loan was made for a given income level of the borrower by IMCs in the post BAPCPA period when compared to AMCs.

[25] I drop singleton groups in regression. Singleton groups are groups which have only one observation and hence will not contribute to any "within-group" variation when fixed effects are included. However, adding singleton groups to the total observations may lower the standard errors and bias the t-statistics upwards.

[26] The jumbo loan limits form 2004, 2005 and 2006 were 333700, 359650 and 417000 respectively.

1.5.1.1 *Variation across borrower quality*

Next I examine the variation of mortgage credit growth across borrower quality. If lower credit quality borrowers are typically rationed out ([142]) when credit supply is tight, then one expects to see larger growth for them with the loosening of credit supply. Furthermore, as discussed in Section 1.2, the saturation of the prime market and broker incentives in the form of higher commissions for non-prime loans leads to the effect of a positive credit supply shock to manifest in the lower credit quality borrower category.

Following [120] I divide the mortgage origination sample into three groups based on borrower credit quality measured using FICO scores: low quality (FICO $\leq$ 620), medium quality (620 $\leq$ FICO $\leq$ 680), and high quality (FICO $\geq$ 680). To test the above hypothesis, I run the baseline regression model in equation 1 for the above three groups defined based on FICO scores. In line with expectations, columns (1) and (2) in Panels A, B, and C in Table 3 show that the mortgage credit growth is higher for the low FICO category along with a larger reduction (11 basis points) in the average interest rate of an originated mortgage loan. The growth in mortgage credit and the reduction of mortgage rates show a monotonic decreasing relationship with FICO scores consistent with an increase in credit supply relieving the constraints of lower credit quality borrowers.

1.5.2 Exploiting funding constraints: Small vs large IMCs

In the second identification test, I exploit that notion that small IMCs are more financially constrained compared to large IMCs ([151]). To classify IMCs as small and large, I divide the sample of IMC issuers based on total mortgage issuance volume from 2001 to 2003 (prior to the sample period of my analysis). A dummy variable *dSmallIMC* is created to be equal to 1 if the total issuance volume is below the median (small IMCs), and equal to 0 if it above the median (large IMCs). Arguably, IMCs that are more financially constrained have lower mortgage issuance volumes. They are likely to rely on traditional sources of financing such as lines of credit from warehouse lenders as opposed to other sophisticated means. Therefore, a positive shock to the funding structure of IMCs should affect the small IMCs more than the large IMCs.

I run the baseline specifications in Table 2 for IMCs to test the above hypothesis in Table 4. The positive and significant coefficient on the DID estimator *dPost-BAPCPA*$\times$*dSmallIMC* for all columns (1)–(4) confirms that the positive supply shock to funding leads to a higher growth in loan volume, loan number, and jumbo loans for small IMCs compared to the large IMCs. In line with positive funding supply shock hypothesis, column (5) shows that the reduction in the average interest rate of the originated loans by small IMCs is also greater compared to large IMCs. Furthermore, comparing small and large IMCs as opposed to IMCs and AMCs is advantageous as it rules out any plausible unobservable differences (such as implementation of regulatory oversight) between IMCs and AMCs that might be driving the results.

1.5.3 Exploiting securitization propensity

In the third identification test, I exploit a specific rule of thumb in the lending market that generates an exogenous variation in the ease of securitizing mortgages around certain FICO scores. This was first documented by [94] (henceforth KMSV) who show that although the distribution of the population of potential borrowers with respect to FICO scores is continuous, there is a discontinuity in the number of originated mortgages at the FICO score of 620 (600) for low-doc (full-doc) loans.[27]

Following KMSV, I plot the number and volume of loans originated by IMCs

[27]Generally homeowners are required to provide information on their assets, liabilities, income, credit history, employment history and personal information. Low documentation loans are loans where borrowers with acceptable payment histories are not required to provide any information regarding income. Thus such loans potentially rely significantly on soft information as noted in KMSV.

at each FICO score for low-doc loans and full-doc loans for the periods before and after the BAPCPA. First, Figure 3 plotted for low-doc loans confirms the results in KMSV, showing that there is indeed a discontinuous increase in the number and volume of originated loans around the 620 FICO score. Given that IMCs rely on securitizing their originated mortgages, as long as the propensity to securitize around the FICO threshold remains constant, a positive shock to the supply of credit should result in a higher growth in loan volume for borrowers with FICO score just above the threshold compared to the borrowers just below the threshold. Sub-figures 3a and 3b compare the number of mortgage originations six quarters before and after the BAPCPA respectively. As it can be seen, the discontinuity in the number of originations is higher in the post-BAPCPA period compared to the pre-BAPCPA period. Moreover, the total originations at each FICO score in the post-BAPCPA period is higher than the pre-BAPCPA period, consistent with the increase in the supply of mortgage credit. One can note a similar pattern for the volume of mortgage originations in Sub-figures 3c and 3d. Figure A.4 plots the same graphs for full-doc loans with a discontinuity at the FICO score of 580.[28] The plots for the full-doc loans also indicate an increase in the number and volume of loans at the 580 FICO score after the BAPCPA.

However, the increase in the discontinuity in the post-BAPCPA period could be due to a secular increase in supply or demand of credit at each FICO score.[29] In order to control for this, I compute the growth in mortgage credit at each FICO score from the pre- to post-BAPCPA period and test whether or not there is a discontinuity at 620 and 580 for low-doc and full-doc loans respectively. In similar spirit to KMSV's

[28]While KMSV find a discontinuity at the FICO score of 600 for full-doc loans, I find the discontinuity threshold to be at 580 similar to [75].

[29]In other words, even if there is a $K\%$ increase in the number/volume of loans at each FICO score, then the discontinuity in the post-BAPCPA period will be greater than the pre-BAPCPA period. In the absence of any other supply shock, such as BAPCPA, which has heterogeneous effects around the FICO threshold, a plot of the growth of loans against the FICO score will be a constant $K\%$ without a discontinuity at the threshold.

empirical setup, I collapse the data on each FICO score and estimate the following regression:

$$Y_i = \alpha + \beta dThreshold + \theta f(FICO(i)) + \delta dThreshold \times f(FICO(i)) + \varepsilon_i \qquad (2)$$

where Y_i is the *growth* in number or volume of loans at the FICO score i from the pre- to post-BAPCPA period, *dThreshold* is a dummy variable that is equal to 1 if the FICO score is greater than 620 (580) for low-doc (full-doc) loans, and 0 otherwise. f(FICO(i)) is a flexible fifth-order distance polynomial for a smooth fit estimated on the left side of the threshold, and while *dThreshold*$\times$ *f(FICO(i))* is estimated on the right side of the threshold. The main coefficient of interest is the term *dThreshold*, which is the average treatment effect (ATE) for the growth of loans around the discontinuity.

Table 5 Panel A reports the results of the regressions using Equation 2. The ATE (coefficient on *dThreshold*) is estimated to be about 21% in mortgage credit growth at the threshold in six quarters after BAPCPA for low-doc loans, but is insignificant for full-doc loans. The increase in growth of only low-doc loans is in line with the documented incentives which reward mortgage brokers with higher commissions for low-documentation risky loans as discussed in Section 1.2. I also fit a non-parametric local linear polynomial around an optimal bandwidth computed using the method in [28].[30] Table 5 Panel B reports these results and shows that there is an estimated 11% (13%) increase in mortgage credit growth at the threshold in six quarters after BAPCPA for low-doc (full-doc) loans. As this estimation method is typically sensitive to the choice of bandwidth, in Table A.10 I also report the results for half and twice the optimal bandwidth. Additionally, I plot the results for the local linear polynomial fit around the discontinuity thresholds in Figure 4. In all these scenarios, ATE for low-doc loans is robust and significant compared with full-doc loans. Overall, these

[30][76] emphasize using non-parametric local polynomial regressions as opposed to global flexible polynomials for regression discontinuity designs.

results provide support for the BAPCPA-led mortgage credit growth. Moreover, these results also show that the growth in mortgage credit was higher for risky loans such as low-documentation loans compared to the relatively safer full-documentation loans.

1.5.4 Exploiting variation in anti-predatory lending laws

In the final identification test, I consider a subsample of only IMC loans which were originated in counties along a state border such that one of the bordering states has a stronger anti-predatory lending (APL) laws compared to the other. This approach alleviates any potential unobserved heterogeneity across counties as economic forces tend to be quite similar across such neighboring geographic areas. Thus the bordering counties enable the effect of BAPCPA resulting from the differences in the legal framework across these geographic areas to be captured.

APL laws vary considerably across states in terms of their coverage, restriction and enforcement. The coverage category includes regulation on the type of loans, APR triggers on first and higher lien loans, and points and fees on loans. The restriction category entails prohibitions and limits on prepayment penalties and balloon payments during specific periods after mortgage origination, credit counseling requirements and restrictions of mandatory arbitration. The enforcement category mainly covers the strength of assignee liability and enforcement against creditors (see [81, 25]). These different categories of APL laws have been shown to have different effects in the mortgage market. On one hand these laws can alleviate borrower concerns about fraudulent lenders and increase demand for mortgage credit, while on the other hand these laws can ration credit to the lower credit quality borrowers. For instance, [81, 25] find that a broader coverage category is associated with an increase in mortgage origination, while a stringent restriction category is associated with a decrease in mortgage credit.

In this paper however, I mainly focus on the enforcement category for the following reason - the assignee liability clause makes securitization trusts and investors who acquire loans, liable for statutory violations committed by the original lender. The liability in such cases may result in the imposition of monetary fines. For this reason, Moodys' analysis of residential mortgage backed securities (RMBS) takes into account the likelihood that a lender may have violated anti-predatory lending laws, which may lower the proceeds available to repay securitization investors ([45]). Thus the presence and the strength of assignee laws is expected to be critical for IMCs given that their primary business model is to originate mortgages and sell them off for securitization. Therefore a funding shock to IMCs such as BAPCPA, will lead them to expand mortgage credit in areas with weaker APL laws concerning assignee liabilities and enforcement against creditors.

To test the above hypothesis, I gather data on anti-predatory laws from [25] for all the states in the U.S. with APL laws in effect until 2005. This data is presented in Table A.5. I further sort states based on the strength of the enforcement of APL laws and classify the states in the top half as weak-APL states and the bottom half strong-APL states. I then define "neighboring counties" across weak and strong APL state borders to be within 30 miles of each other.[31] This yields a sample of 195 counties in weak-APL states (treated) and 207 counties in strong-APL states (controls). To test for the BAPCPA-led increase in mortgage credit supply, I run the following difference-in-difference identification model on IMCs' quarterly origination data at the firm-county-quarter observation level:

$$\begin{aligned} Y_{ict} = \alpha + \beta_1 dPostBAPCPA_t \times dWeakAPLCounty_c + \beta_2 dWeakAPLCounty_c \\ + \beta_3 dPostBAPCPA_t + \theta X_{c,t} + \lambda_i + \delta_c + \tau_t + \varepsilon_{ict} \quad (3) \end{aligned}$$

where all the variables are the same as in the baseline specification in Equation 1

[31] While smaller distances ensure greater similarity in economic forces governing areas across state borders, they also reduce the sample size and power of the tests considerably – thus a trade-off exists. However I find that the results are qualitatively robust to using a cut-off of 50 and 100 miles and cross-sectionally across entire states as well.

except for two changes – $dWeakAPLCounty$ is a dummy variable that takes the value of 1 if counties belong to weak-APL states and 0 otherwise. I also use *County* and *Quarter* fixed effects as opposed to $County \times Quarter$ fixed effects in order to identify the coefficient on $dPostBAPCPA \times dWeakAPLCounty$ which is at the county-quarter level. $dPostBAPCPA \times dWeakAPLCounty$ is the difference-in-difference (DID) estimator and it is the key variable of interest.

Table 6 presents the results for the regression specification in Equation 3, which shows that counties with weaker APL enforcement laws indeed experienced a higher growth in mortgage credit in the post-BAPCPA period. Consistent with the supply hypothesis, the results also show that there was a decrease in the average mortgage interest rate and the loan-to-income ratio after controlling for the risk of the originated loans. As robustness, I conduct these tests by defining neighboring counties to be within a distance of 50 miles, 100 miles, and cross-sectionally across states by including all the counties. These results which are presented in Table A.11 are qualitatively similar, but get weaker as distance increases. This is likely due to the increasing time-varying heterogeneity among counties that are geographically farther apart.

Overall the results documented in Section 1.5 indicate an increase in supply of mortgage credit after BAPCPA went into effect.

1.5.5 Testing alternate hypotheses

In this section, I test two potential alternate hypothesis which might drive the results so far. The first alternate hypothesis is the *income-based demand* hypothesis which argues that the increase in mortgage credit is due to the growth in incomes of the borrowers who respond by increasing their demand for mortgages ([65]). To test this hypothesis, I gather the publicly available county-level income data from the U.S. Census Bureau. Using this data, I compute the growth in per-capita income and median income for each county from 2004-2006 as this period covers most of event window around the BAPCPA. The counties are then divided into four quartiles based on the computed growth rates. The lowest and the highest quartile counties based on the growth rate of per-capita income (median income) have average annual growth rates of 1.4% (1.8%) and 10.1% (7.7%) respectively. The average inflation rate during this period was 3.3%, which implies that the average real growth in wages for the counties in the lowest quartile was -1.9% (-1.5%). If the results in this study are driven by income growth, then the counties in the lowest income growth quartiles, which have a negative real growth in wages, should be less likely to experience a growth in mortgage credit.

I test the above *income-based demand* hypothesis in Table 7 Panel A. Columns (1), (2) and (4), (5) run the baseline specification in Equation 1 for the counties in the lowest quartiles of per-capita and median income growth rates respectively. The results show that there is an expansion of mortgage credit even in these counties which experienced negative real growth rates in wages. Furthermore, I classify borrowers in my dataset as low-income borrowers if their income is lower than 80% of the median income in their counties. The results for this subset which are provided in specifications (3) and (6) also show a growth in mortgage credit. The magnitude of the coefficient of $dPostBAPCPA \times dIMC$ in all the specifications are similar to those in the full sample regressions in Table 2. Overall, the results in Table 7 Panel A suggest evidence against the *income-based demand* hypothesis.

The second alternate hypothesis for the expansion in mortgages credit could be due to an expectation of the increase in future house prices. As [105] note, higher house prices lower the estimated loss given default, and hence the lenders would be more willing to lend to lower quality borrowers. [68] note that house price run-ups occur mainly in areas with an inelastic housing supply. Whereas in areas where housing supply is elastic, any pressure on house prices will lead to increased construction thereby keeping the house prices in check.[32] If the increase in mortgage credit, especially to the low quality borrowers, is due to the *increasing house price expectation* hypothesis, then areas with a higher housing supply elasticity should not see a growth in mortgage credit.

To test the above hypothesis, I gather data on housing supply elasticity from [131] at the MSA level. This measure of elasticity is based on the percentage of land which cannot be developed for housing, either due to the presence of water bodies or uneven terrain. Finally, this elasticity measure takes into account both the physical and regulatory land constraints.[33] [131] computes and ranks the measure of supply elasticities for 95 MSAs. I classify the counties overlapping with the MSAs into two samples: (i) very high housing supply elasticity areas (where the rank of supply elasticity lies between 72 and 95) and (ii) high housing supply elasticity areas (where the rank of supply elasticity lies between 48 and 95). Table 7 Panel B provides results for these subsamples after running the baseline regression in Equation 1. The results show an expansion in mortgage credit of the same order as the full sample results in Table 2 for the two subsamples of high land supply elasticity. Thus, overall these tests also suggest evidence against the *increasing house price expectation* hypothesis.

1.5.6 Robustness

I use growth rates in equation 1 to test for the increase in mortgage credit (volume and number of mortgages) as opposed to levels for two main reasons. First, the levels in mortgage credit and county-level variables may exhibit heterogeneous trends. Taking the first difference cancels out any time-invariant trend at the firm-county level for the mortgage credit variables. Thus, any type of county fixed effects would be guaranteed to capture county-specific trends (see [116] and [59]). Second, a law change such as the

[32]See [105] who demonstrate this fact by comparing the house price growth in elastic and non-elastic housing supply MSAs

[33]See [131] for more details on the construction of this measure

2005 BAPCPA act can be argued to be a permanent shock as opposed to a temporary shock to credit supply. Permanent shocks are commonly modeled as shocks to the first-difference in the level rather than the level itself (temporary shocks).

Regardless, in Table A.9 Panel A, I test for an alternate specification using levels instead of first differences. Specifically, I regress the logarithm of the number and volume of loans and control for any auto-dependence in the levels by including the lagged dependent variable in the regressions as well. Columns (1) and (2) show that there was a 3% and 4% overall growth in loan origination volume and number respectively for IMCs over AMCs in the six quarters after the BAPCPA act compared to the six quarters before. As an additional check, in Panel B, columns (1)–(4), I test using different time-periods before and after the BAPCPA law change and find that the results are qualitatively the same for an event window of four and eight quarters. However, I stick to the event window of six quarters for the rest of the paper as the window is long enough to capture the effect of the law, and the post-event window ends in 2007-Q1 which is just before the period when the financial crisis began to materialize.[34] I also test using a placebo law change date 12 quarters before the implementation of BAPCPA in 2005-Q4 so that the event window is non-overlapping with the event window around the actual law change date. In this case, I do not find any significant difference between the loan volume and loan number growth rates of IMCs and AMCs.

Overall, the results thus far support the hypothesis that the 2005 BAPCPA act resulted in a positive supply shock to the funding of the IMCs, which in turn resulted in the expansion of mortgage credit. In the next section, I focus on the consequences of this credit expansion and test for the types of originated mortgages and their ex-post delinquency rate.

[34][124] documents a disruption to the securitization market after 2007-Q1 which would have affected the mortgage companies as they primarily rely on securitizing their originated mortgages.

1.6 Results: Consequences of IMC mortgage credit growth

1.6.1 Types of mortgage issuance

I use the information in the BBx dataset to classify loans as Alt-A, Subprime, Complex and Low-doc loans. Alt-A, which stands for Alternative-A, are loans which are typically originated to moderate and good credit quality borrowers, who would otherwise qualify for a prime loan (see [136]), with an aggressive underwriting compared to conforming or jumbo classes. These loans typically have no income documentation and/or have higher loan-to-value ratios due to which they do not qualify as conforming mortgages. Subprime loans are loans mainly made to lower credit quality borrowers (see [13]) who have impaired or incomplete credit histories. I classify complex mortgages to be either Interest Only, Hybrid ARM, Pay-option ARM, and Negative Amortizing mortgages.

Since the early 2000s, there has been a rapid growth in these non-traditional mortgages. For instance, IOs and Pay-option ARMs represented only 3% of the total non-prime mortgage originations in 2002, but rose to more than 50% at the end of 2005 ([11]). Hybrid ARMs, which were the most common non-traditional mortgages, represented about 75% of the loans in subprime securitizations from 2004 to 2006 ([55]). Hybrid ARMs were a combination of fixed and adjustable rate mortgages that had a fixed interest rate in the initial period followed by an adjustable rate period.[35] Pay-option ARMs allowed investors to choose among 3 payment options each month: (i) paying the monthly principal and interest according to the amortization schedule, (ii) paying the interest only (IOs), or (iii) paying a minimum amount that is less than the interest owed (Negative Amortization). Borrowers found Pay-option ARMs and Hybrid ARMs attractive as a result of the teaser rates that were offered in the form of

[35] A 2/28 hybrid ARM meant that it has 2 years of a fixed rate and 28 years of adjustable rates typically adjusting every six months.

minimum initial payments. However, at the end of the initial period for these ARMs, the mortgage payments went up substantially after accounting for any missed and lower interest payments.[36] Furthermore, with the advent of automated underwriting, Subprime and Alt-A loans with low- or no-documentation rose significantly from 11% in 2003 to about 33% of all mortgage originations in 2005 ([11]).

The effect of a positive funding shock to IMCs can manifest itself in the form of origination of riskier mortgage types. As Section 1.2 discuses, this is especially likely in the presence of a saturated prime mortgage market and the broker incentives in the form of higher commissions for non-prime loans and low-doc loans. Moreover, the increased protection and seniority for warehouse lenders in the post-BAPCPA period likely reduced their due diligence for mortgage collateral placed under repo financing agreements. Without adequate due diligence, originators (possibly in collusion with the borrowers) can have significant incentives to misreport information on the loan applications. For instance [89] showed that the income in low-documentation loans had been overstated by 20% to 25%. [121], and [75] document misreporting of mortgage characteristics for loans in the non-agency market. These misreported loans eventually had over a 50% higher likelihood of defaulting compared to the loans without any misreporting.

I test whether the positive funding shock to IMCs resulted in the origination of risky mortgage types in Table 8. I run the baseline regression specification in Equation 1 with the dependent variables as the growth in the number and volume of different types of mortgages loans. Panel A shows the results for the full sample, which indicates that the growth of Alt-A, Subprime, Complex and Low-doc mortgages rose significantly after BAPCPA for the IMCs compared to the AMCs. Moreover, the growth in Alt-A, Low-doc, and Complex loans is larger than the growth in overall

[36] Borrowers were also assured that they could refinance the loan with a new teaser rate when their monthly payments went up. However, a major assumption was that the house price would be higher for the refinance.

loans reported in Table 2.

1.6.2 Mortgage defaults

I now compare the performance of the loans originated by IMC before and after the BAPCPA. As argued in the previous section, if the funding shock to IMCs led to the origination of riskier mortgages, then loans in the post-BAPCPA period should underperform loans in the pre-BAPCPA period. Following KMSV I define a default to occur if any of the following three conditions are true: (i) The loans are 60^+ days delinquent as defined by the Office of Thrift Supervision (OTS),[37] (ii) the loan is in foreclosure, or (iii) the loan is real estate owned (REO). I compute the frequency of defaulted loans that were originated every quarter around the BAPCPA and regress it on $dPostBAPCPA \times dIMC$ after controlling for the difference in loan-mix of each institution that might drive defaults ([102]). Additionally, I compute the frequency of defaults over multiple horizons, namely early defaults (loans that became delinquent within 6 months of the first payment date), 15 months, 18 months, 2 years, 3 years after origination and until the end of 2010.

The plot of the fraction of loan defaults within 2 years after origination between IMCs and AMCs is presented in Figure 5. The default rates of IMCs and AMCs in the pre-BAPCPA period do not differ significantly from each other, thus establishing *parallel trends* between the treated (IMCs) and control (AMCs) groups prior to the law change. This is also indicates that IMCs and AMCs did not differ in the riskiness of their mortgage issuances prior to the passage of BAPCPA. However in the post-BAPCPA period, the default rate of IMCs is significantly greater than that of AMCs and trends upward over time.

[37] As KMSV point out, there are two different definitions of default used in the industry – the OTS definition and the Mortgage Bankers Association (MBA) definition. The OTS starts counting the days of delinquency one month after the missed payment whereas MBA starts counting it from the day after the payment is missed. Thus, OTS's delinquency definition is more stringent compared to MBA's.

Next, I analyze the time variation of defaults in Table 9. The dependent variable for these specifications are early default rates (default rates within 6 months of the first payment date), and defaults within 15 months, 18 months, 2 years, 3 years and until the end of 2010. The rate of defaults increases over time for IMCs compared to AMCs in the post- vs pre-default period. This is consistent with the origination of complex mortgages such as Interest Only, Hybrid ARM, Pay-option ARM, and Negative Amortizing mortgages. These mortgages tend to have lower payments in the initial periods before the monthly payments spike up. The typical reset period for such loans is around two years. That is arguably why default rates peak after two years (2.24%) for the IMCs in the post BAPCPA period, as seen by the magnitude of the coefficient on $dPostBAPCPA \times dIMC$ in Column (4).

In Table 10, I run the default regressions with the percentage of defaults in 2 years as the dependent for subsamples of borrower credit quality based on FICO scores as defined in Section 1.5.1.1. The results show that the frequency of defaults was the highest for medium credit quality borrower (3.69%) followed by the high credit quality borrower (3.01%). This is likely to be a result of the ease of securitization and issuance of Alt-A loans in the medium and good credit quality categories. Moreover, it indicates risk-shifting by originators within these better quality borrowers which is consistent with the notion of lower due diligence after BAPCPA. Finally, in Table 11 I analyze the default frequency subsamples based on high and low income, growth in per-capita income, and competition. Columns (3) and (4) show that the default frequency is higher for individuals with a higher income (3.31%) and for those counties with a higher growth in per-capita income (3.36%) just as the results in Table 10.

To classify counties as high and low competition counties, I construct a Herfindahl index (HHI) of loan origination concentration at the county-level using the entire HMDA dataset by aggregating the loans by each originator in a given county. Counties with HHI below (above) the median county HHI are then classified as high (low) competition counties. Column (6) in Table 8 shows that the default frequency in counties with greater competition is 2.11% higher in the post-BAPCPA period compared to the pre-BAPCPA period. However, the default frequencies for the low competition counties are not significantly different between the pre- and post BAPCPA period as shown in column (5). This suggests that the expansion of risky mortgage credit took place in counties with higher competition.

Overall, the performance of loans originated by IMCs after BAPCPA is lower compared to the loans originated before the BAPCPA. The subsample analyses are in line with the origination of riskier mortgages due to the incentives of the mortgage brokers in the form of higher commissions for riskier loans.

1.6.3 Effect on house prices

Recent literature has focused on the effect of credit supply on house prices. For instance, [59] use the passage of the Interstate Banking and Branching Efficiency Act (IBBEA) of 1994 to show the casual effect of an increase in credit availability on house prices; [6] use the exogenous changes in the conforming loan limit on house prices; while [45] exploit OCC's federal preemption for national banks from predatory lending on house price growth. In similar spirit, I test the effect of an increase in credit availability after the BAPCPA on house prices. However, for this study I now limit my sample to counties with a significant presence of IMCs and AMCs lending and aggregate the originations of IMC and AMC firms at the quarter level. Specifically, I use a subsample of counties in which IMCs and AMCs together originate more than 50% of all the mortgages in the event window around BAPCPA. Further, I classify these counties every quarter by creating a dummy variable *dHighIMC*, which takes the value 1 if the growth in the volume of mortgage loans issued is higher for IMCs than AMCs in a given county and quarter. House prices at the county-quarter level are gathered from zillow.com. I collect the median estimated house price for single family homes, median estimated house prices for the bottom, middle and top tier homes in each county. Tiers in zillow are defined by dividing the house prices in a region into terciles.

To test for the growth in house prices after the passage of the 2005 BAPCPA act, I estimate the following model on quarterly data at the county-quarter observation level:

$$gH_{c,t} = \alpha + \beta_1 dPostBAPCPA \times dHighIMC_{c,t} + \beta_2 dHighIMC_{c,t} + \beta_3 dPostBAPCPA \\ + \theta gX_{c,t-1} + \lambda_c + \delta_t + \varepsilon_{ct} \quad (4)$$

where gH_{ct} is the log growth rate in house prices in county c and quarter t in annual terms, and $gX_{c,t-1}$ are the current and lagged control variables which include county c's growth rates in population, per-capita income and competition in mortgage origination. $dHighIMC_{c,t}$ is a dummy variable that takes the value of 1 if the growth rate of the aggregated IMC loans in county c and quarter t is greater than the growth rate of the aggregated AMC loans, and 0 otherwise. Additionally, I also include county and quarter fixed-effects in all the regressions. The assignment of $dHighIMC_{c,t}$ to counties cannot be argued to be completely exogenous, hence the following results indicate the association of credit growth due to BAPCPA and house prices rather than a causal interpretation.[38]

Table 12 presents the regression results and the coefficient on *dPostBAPCPA*$\times$ *dHighIMC* determines the consequence of credit expansion on house price growth. Column (1) indicates that the median house price growth for single family homes was higher by 1.97% per year in counties which had a higher growth in mortgage originations due to IMCs in the post BAPCPA period. Columns (2)-(4) indicate that the house price appreciation is higher for the middle (2.44%) and top (2.97%) tercile

[38]For example, if IMCs have a greater propensity to expand in counties with rising house prices compared to AMCs, then this omitted variable can introduce a positive bias while estimating coefficients involving $dHighIMC_{c,t}$.

of house prices. This is in line with the higher default rates observed for the medium and good quality borrowers in Table 10, which are likely explained by the boom and the subsequent bust of house prices in these counties.

As robustness, I also test within the subsample of counties with high and low housing supply elasticities[39] in Table 13 as the effect of credit supply on house prices are expected to be more pronounced in the areas with a low housing supply elasticity. Consistent with expectation, the growth in house prices in the post BAPCPA period in the high-IMC mortgage origination counties with low housing supply elasticities is more than twice as high when compared to Table 12 and is significant for all specifications. The house price growth per year are 6.33% for the median single family homes and 4.82%, 6.73% and 5.57% for median house prices in the bottom, middle and top tiers respectively. On the other hand, high-IMC mortgage origination counties with high housing supply elasticities do not experience any significant growth in house prices post-BAPCPA compared with pre-BAPCPA.

1.7 Conclusion

The past decade saw an unprecedented growth in mortgage credit which eventually led to the 2008 housing crisis and the recent economic downturn. Since then there has been a push to understand the role of the mortgage industry and its interplay with regulation in leading to the 2008 financial crisis. This paper provides evidence for one such channel that induced credit expansion in the recent decade. Specifically, this paper documents an increase in risky mortgage credit due to the unintended consequences of the 2005 *Bankruptcy Abuse Prevention and Consumer Protection Act* (BAPCPA) which expanded the safe harbored repos to include mortgage related securities.

BAPCPA effectively increased repo creditors' protection thereby subsidized repo

[39] I define low supply elasticity counties as ranks 1 to 47 and high supply elasticity counties as 48 to 95 from [131]

financing, and triggered the use of repurchase agreements by Independent Mortgage Companies (IMCs) to finance their mortgage originations. Using BAPCPA as an exogenous shock to IMCs' funding, and multiple identification strategies based on funding constraints, discontinuity in securitization propensity, and geographic discontinuity in anti-predatory lending laws, I document an increase in the growth of mortgage credit in the post-BAPCPA period compared with the pre-BAPCPA period. Consistent with a supply shock that reduces credit rationing, I find that the growth in mortgage credit is not uniform across all borrowers, but is higher among borrowers with lower credit quality. In line with a reduction in mortgage financing costs, I also find that IMCs charged lower interest rates on their originated mortgages after controlling for the risk of mortgage loans.

Further analysis of the types of mortgages originated in the post-BAPCPA by IMCs reveals a higher degree of growth in risky mortgage types which culminated in higher ex-post defaults rates. Interestingly, the default rates, when compared to those of a control group, are higher for medium and high quality borrowers. This suggests risk-shifting by IMCs within good quality borrowers, potentially due to greater creditor protection in the post-BAPCPA period which disincentivized warehouse lenders' due diligence. Furthermore, in line with the recent literature showing a causal link between credit growth and asset prices, I find that counties experiencing a higher growth in mortgage credit through IMCs also experienced a higher growth in house prices. The growth in house prices also has a similar pattern as defaults, wherein it is higher for medium and higher house price indexes.

The early 2000s saw an exponential growth in technology (automated underwriting) and financial engineering (option ARMs, IOs, MBS, CDOs etc). We also witnessed public policy promoting homeownership and the eventual saturation of the prime market. In the midst of this environment, I document the unintended and unanticipated consequences of a financial regulation namely BAPCPA. Although

BAPCPA was intended to reduce systemic risk, it ironically increased the U.S. household leverage by encouraging the underwriting of riskier mortgages enabled by the incentive structure of certain mortgage lenders. This conceivably, at least in part, enabled the boom and eventual bust of the U.S. mortgage market. Specifically for BAPCPA, there still exists a debate on the costs and benefits of privileged status of derivatives in bankruptcy. The results in this paper enrich that debate by furnishing new evidence on the real costs of BAPCPA related to the safe harbor exemptions for repos. Thus, the results of this paper also contribute to the literature exploring regulatory design by documenting the unanticipated real costs of BAPCPA.

Figure 1: 8-K Filings Parsing

The figure presents the number of occurrences of master repurchase and master loan agreements in the 8-K filings for firms belonging to the SIC codes 6162 (Mortgage Bankers and Loan Correspondents), 6163 (Loan Brokers), 6798 (Real Estate Investment Trusts) from 2004 to 2007. These SIC codes are assigned to most Independent Mortgage Companies (IMCs). The dashed vertical line indicates the passage of BAPCPA while the solid vertical line indicates the quarter since BAPCPA went into effect.

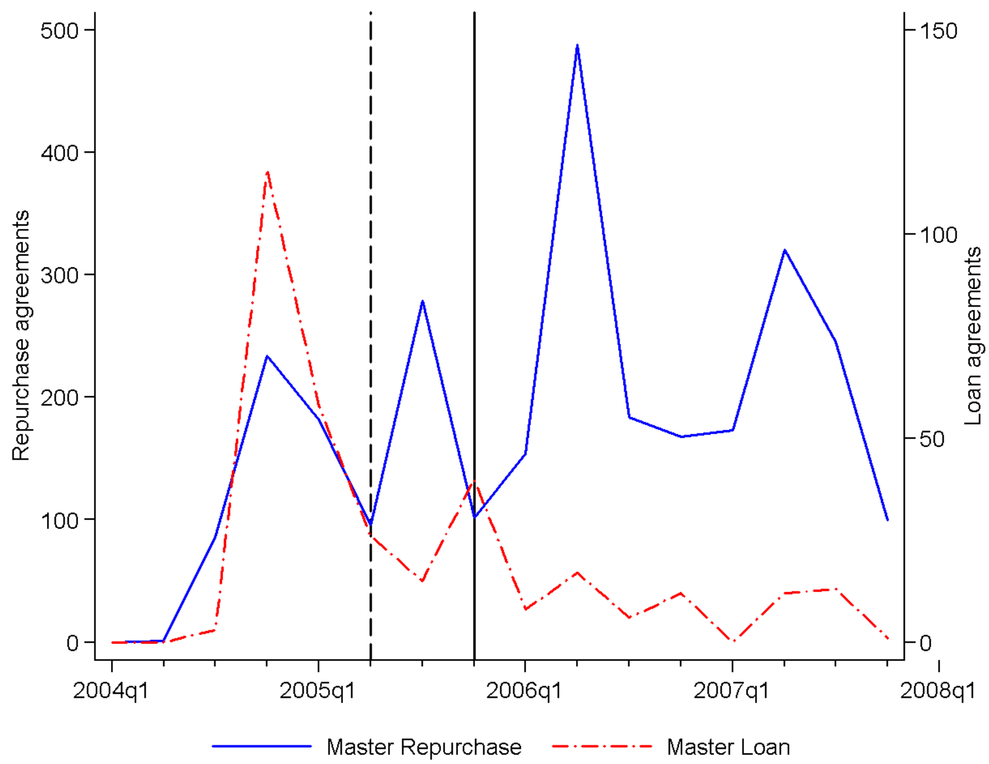


Figure 2: IMC vs AMC Quarterly Growth Rates Trend

The figure presents the quarterly growth rates for IMCs compared with AMCs before and after the 2005 BAPCPA. The figure plots the point estimates for the leading and lagging indicators over 2 years before and after BAPCPA using the following specification: $Y_{ict} = \alpha + \beta_{-3}dIMCQtr_{i,-3} + \beta_{-2}dIMCQtr_{i,-2} + \beta_0 dIMCQtr_{i,0} + \cdots + \beta_7 dIMCQtr_{i,7} + \lambda_i + \delta_{ct} + \varepsilon_{ict}$. Y_{ict} is the log growth rate in the volume of loans issued by firm i, in county c and quarter t. $dIMCQtr_{i,t}$ $\forall t \in \{-2, 0, 1, \ldots, 7\}$ is a dummy variable set to 1 if firm i is an IMC and t is the number of quarters before/after the quarter in which BAPCPA takes effect, and 0 otherwise. $dIMCQtr_{i,-3}$ is a dummy variable set to 1 from the eighth quarter up to and including the third quarter prior to the quarter in which BAPCPA takes effect. λ_i and δ_{ct} are *firm* and *county×quarter* fixed effects respectively. The vertical bars correspond to the 95% confidence intervals of the point estimates. The solid black vertical line at 0 represents 2005-Q4 which is when the BAPCPA regulation took effect. The dot-dashed red line is the best fit line in the pre- and post-BAPCPA period indicating the trend of growth rates over time. Standard errors are clustered at the county-level.

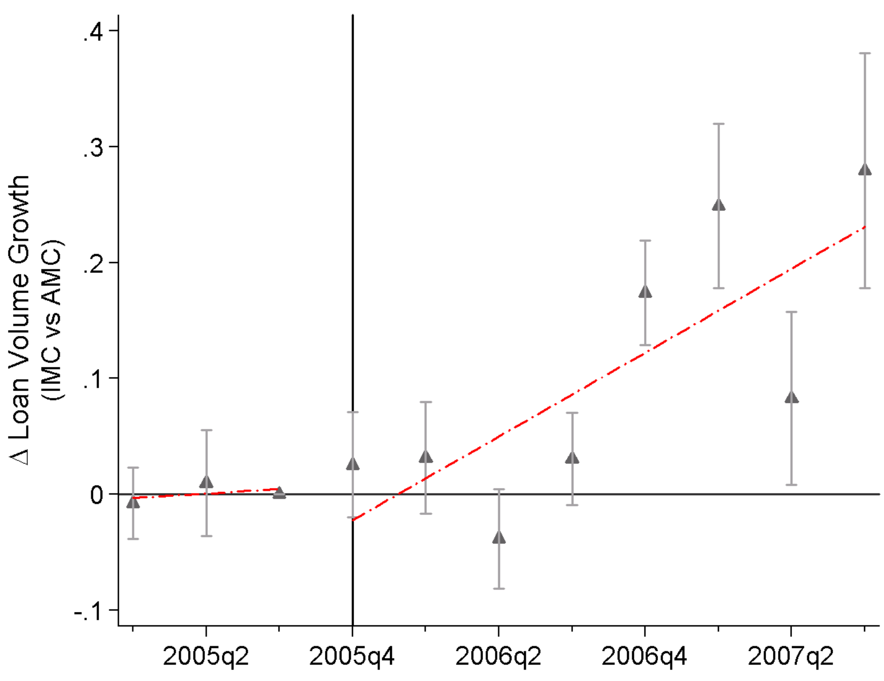
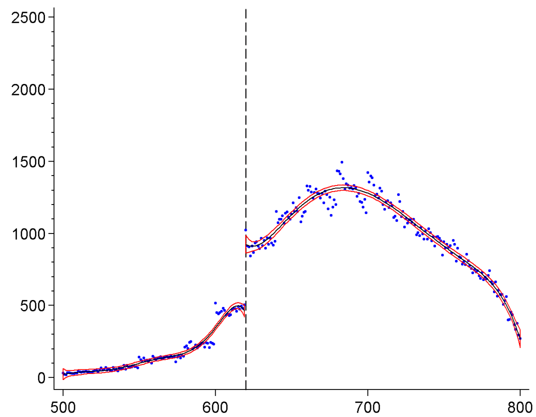
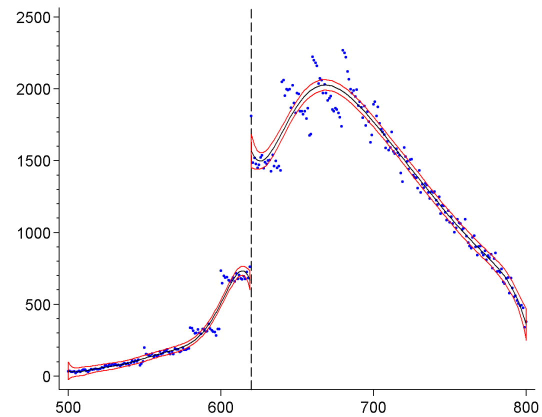


Figure 3: Discontinuity in Low-Doc Loan Issuance : Around 620 FICO Threshold

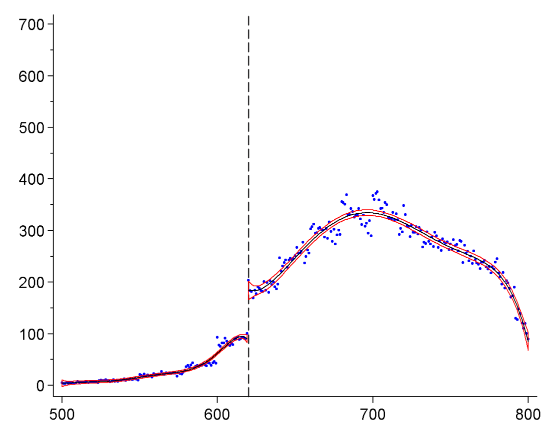
The figure shows the number and volume of low-documentation mortgages issued at each FICO score in blue dots. The black solid line fits a flexible seventh-order polynomial as in Equation 2 on either side of the cut-off FICO score of 620. The red lines are the 95% confidence intervals. The black dashed line passes through the 620 FICO score point.



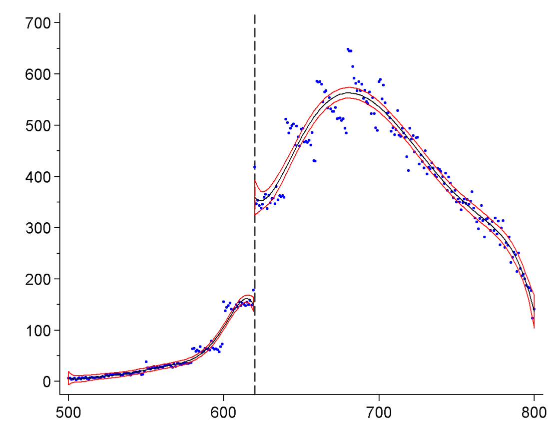
(a) ***Pre-Bankruptcy Act: Number of Loans***



(b) ***Post-Bankruptcy Act: Number of Loans***



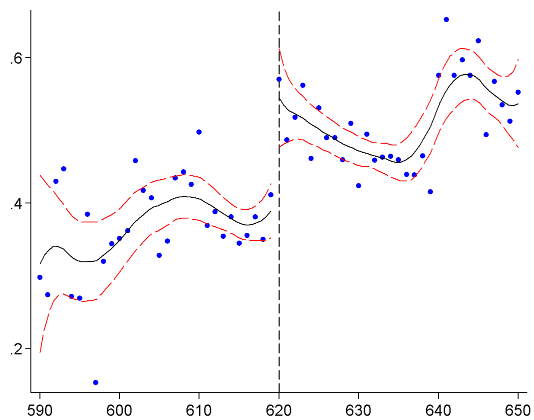
(c) ***Pre-Bankruptcy Act: Volume of Loans***



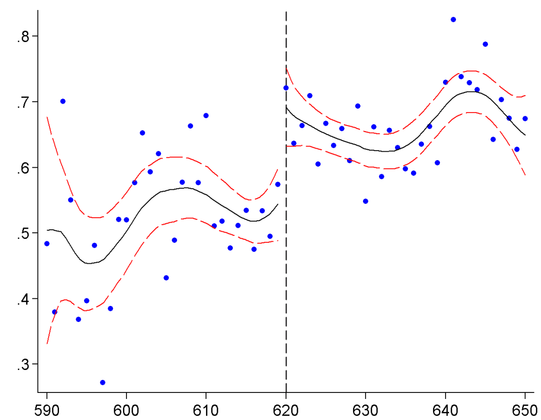
(d) ***Post-Bankruptcy Act: Volume of Loans***

Figure 4: Discontinuity in Loan Growth

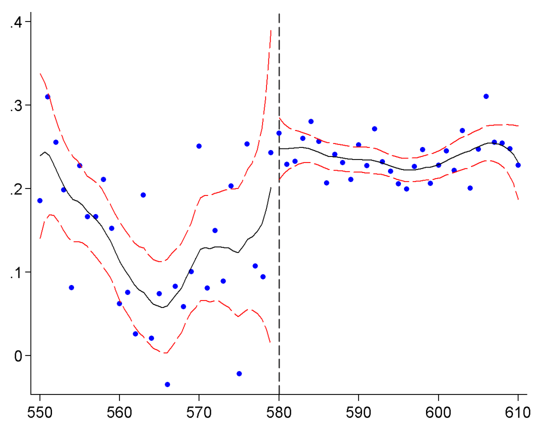
The figure shows the growth in the number and volume of low- and full-documentation mortgages issued at each FICO score in blue dots. The threshold for low-documentation loans is 620 and for full documentation loans is 580. The black solid line fits a non-parametric local linear polynomial using a triangular kernel within a bandwidth of 30 around the threshold. The red long-dashed lines are the 95% confidence intervals. The black dashed line passes through the threshold FICO score point.



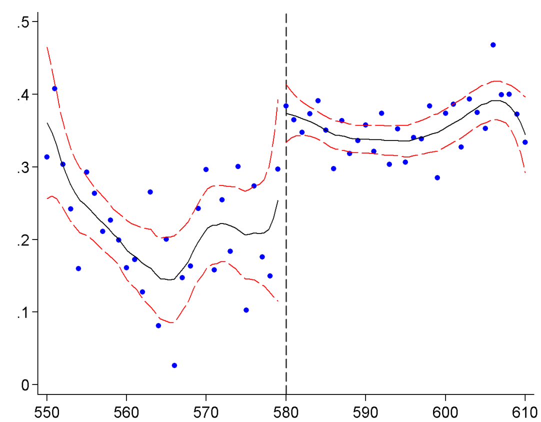
(a) ***Growth in Number of Low-doc Loans***



(b) ***Growth in Volume of Low-doc Loans***



(c) ***Growth in Number of Full-doc Loans***



(d) ***Growth in Volume of Full-doc Loans***

Figure 5: IMC vs AMC Quarterly Default Rates Trend

The figure presents the quarterly default rates for IMCs compared with AMCs before and after the 2005 BAPCPA. The figure plots the point estimates for the leading and lagging indicators before and after BAPCPA using the following specification: $D_{ict} = \alpha + \beta_{-3} dIMCQtr_{i,-3} + \beta_{-2} dIMCQtr_{i,-2} + \beta_0 dIMCQtr_{i,0} + \cdots + \beta_5 dIMCQtr_{i,5} + \lambda_i + \gamma_c + \delta_t + X_{ict} + \varepsilon_{ict}$. D_{ict} is the percentage of defaulted loans issued by firm i, in county c and quarter t. $dIMCQtr_{i,t}$ $\forall t \in \{-2, 0, 1, \ldots, 5\}$ is a dummy variable set to 1 if firm i is an IMC and t is the number of quarters before/after the quarter in which BAPCPA takes effect, and 0 otherwise. $dIMCQtr_{i,-3}$ is a dummy variable set to 1 from the eighth quarter up to and including the third quarter prior to the quarter in which BAPCPA takes effect. X_{ict} are a set of controls including the perentage of ARM and Low-Doc loans, loans with a prepayment penalty, and average borrower FICO, loan amount, LTV ratio and interest rate computed for issuances by firm i, in county c and quarter t. λ_i and δ_{ct} are *firm* and *county×quarter* fixed effects respectively. The vertical bars correspond to the 95% confidence intervals of the point estimates. The solid black vertical line at 0 represents 2005-Q4 which is when the BAPCPA regulation took effect. The dot-dashed red line is the best fit line in the pre- and post-BAPCPA period indicating the trend of growth rates over time. Standard errors are clustered at the county-level.

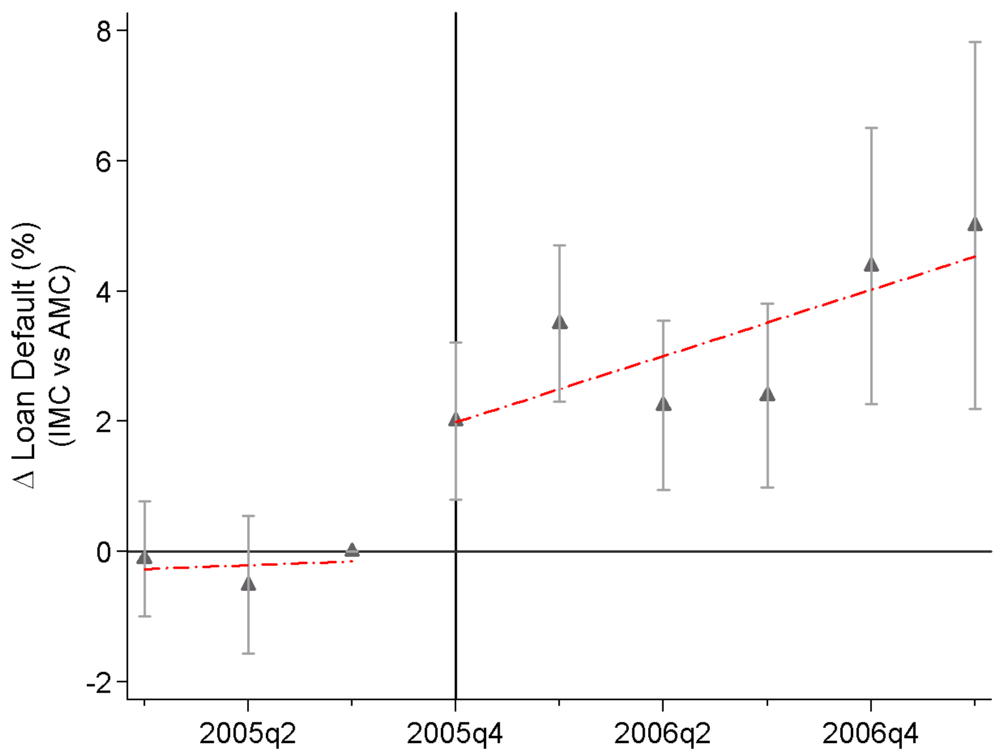


Table 1: Summary Statistics

This table presents the changes in the broad measures of loan origination before and after the 2005 *Bankruptcy Abuse Prevention and Consumer Protection Act* (BAPCPA) for IMCs (independent mortgage companies) and AMCs (affiliated mortgage companies). The BAPCPA was signed into law on April 14th 2005 and took effect in October 2005. The *Pre-BAPCPA* period refers to six quarters from 2004Q2 to 2005Q3, and the *Post-BAPCPA* period refers to six quarters from 2005Q4 to 2007Q1. Loan-types are defined in A.1.

Panel A:*Main Loan Variables*

	Pre-BAPCPA		*Post-BAPCPA*	
	IMC	AMC	IMC	AMC
Total Number of Loans (1000s)	385.82	144.27	469.20	199.98
Total Loan Dollar Volume ($ Billions)	86.31	37.20	118.41	54.81
Average Loan Amount (1000s)	223.70	257.84	252.37	274.06
Average Loan-to-Income Ratio	2.75	2.75	2.74	2.64
Average Loan-to-Value Ratio	82.36	81.95	81.84	81.43
Average FICO Score	671.45	679.74	665.93	671.99
Average Borrower Income (1000s)	84.74	98.44	96.54	109.47
Average Initial Interest Rate (%)	6.67	6.45	7.61	7.41

Panel B:*Loan Types*

	Pre-BAPCPA		*Post-BAPCPA*	
	IMC	AMC	IMC	AMC
Low Documentation Loans (%)	52.77	56.30	61.40	62.57
Alt-A Loans (%)	19.60	17.58	19.95	19.13
Subprime Loans (%)	26.13	22.90	32.92	27.57
ARM Loans (%)	80.08	76.58	77.41	71.48
Loans with Pre-payment Penalty (%)	53.38	46.04	53.12	49.74
Complex Loans (%)	43.13	48.61	41.51	53.24
Jumbo Loans (%)	17.58	25.17	16.52	22.87

Table 2: Mortgage Credit Growth: Exploiting Funding Constraints – IMCs vs AMCs

This table examines the changes in the broad measures of loan origination before and after the 2005 BAPCPA between IMCs and AMCs. The dataset is at the mortgage originating firm-county-quarter level. The dependent variables in columns (1)–(4) are quarterly growth rates in total volume of loans (*g_LoanVol*), total number of loans (*g_LoanNum*), total volume of jumbo loans (*g_JumboVol*), total number of jumbo loans (*g_JumboNum*) made by a mortgage originating firm in a given county and quarter. The dependent variables in columns (5) & (6) are the average initial interest rate (*AvgIntRate*) in percentage terms, and the average loan-to-income ratio (*AvgIntRate*). The Indicator variable *dPostBAPCPA* takes the value 1 for six quarters from 2005Q4 to 2007Q1 and 0 for six quarters from 2004Q2 to 2005Q3. The Indicator variable *dIMC* is equal to 1 if the mortgage originating firm is an IMC, and 0 otherwise. Other regression *loan-mix* controls are defined in A.1. All regressions include *Firm FE* and *County*×*Quarter FE*. *T*-statistics displayed in parentheses are robust and clustered at the *County* level. *, **, and *** indicate significance greater than 10%, 5%, and 1% respectively.

Depvar:	g_LoanVol (1)	g_LoanNum (2)	g_JumboVol (3)	g_JumboNum (4)	AvgIntRate (5)	AvgLTI (6)
dPostBAPCPA×dIMC	0.11***	0.11***	0.06***	0.06***	-0.08***	0.04***
	(11.57)	(13.18)	(2.95)	(3.09)	(-8.89)	(6.17)
Avg FICO					-0.01***	0.00
					(-55.35)	(1.04)
Avg LTV					0.04***	
					(64.83)	
ARM Loans(%)					0.01	0.07***
					(0.53)	(11.35)
Alt-A Loans(%)					0.33***	-0.02**
					(24.80)	(-2.50)
Subprime Loans(%)					0.86***	-0.04***
					(51.68)	(-4.06)
LowDoc Loans(%)					0.23***	-0.06***
					(25.58)	(-12.97)
Firm FE	✓	✓	✓	✓	✓	✓
County×*Quarter FE*	✓	✓	✓	✓	✓	✓
N	295932	295932	53194	53194	267885	264277
Adj. R^2	0.051	0.053	0.054	0.060	0.603	0.369

Table 3: Mortgage Credit Growth: Variation Across Borrower Quality

This table examines the changes in the broad measures of loan origination before and after the 2005 BAPCPA between IMCs and AMCs across subsamples of *low* (FICO $\leq$ 620), *medium* (620 $\leq$ FICO $\leq$ 680), and *high* (FICO $\geq$ 680) quality borrowers. The dataset is at the mortgage originating firm-county-quarter level. The dependent and independent variables are the same as in Table 2. All regressions include *Firm FE* and *County*$\times$*Quarter FE*. T-statistics displayed in parentheses are robust and clustered at the *County* level. *, **, and *** indicate significance greater than 10%, 5%, and 1% respectively.

Panel A: *Low Borrower Quality – FICO Category 500–619*

Depvar:	g_LoanVol (1)	g_LoanNum (2)	AvgIntRate (3)	AvgLTI (4)
dPostBAPCPA$\times$dIMC	0.17***	0.16***	-0.11***	0.02*
	(9.91)	(10.17)	(-5.99)	(1.65)
Loan-mix Controls			✓	✓
Firm FE	✓	✓	✓	✓
County$\times$*Quarter FE*	✓	✓	✓	✓
N	121216	121216	114141	112937
Adj. R^2	0.028	0.026	0.392	0.298

Panel B: *Medium Borrower Quality – FICO Category 620–680*

Depvar:	g_LoanVol (1)	g_LoanNum (2)	AvgIntRate (3)	AvgLTI (4)
dPostBAPCPA$\times$dIMC	0.13***	0.14***	-0.04**	0.06***
	(8.97)	(9.71)	(-2.38)	(6.54)
Loan-mix Controls			✓	✓
Firm FE	✓	✓	✓	✓
County$\times$*Quarter FE*	✓	✓	✓	✓
N	143013	143013	134569	132634
Adj. R^2	0.036	0.035	0.379	0.312

Panel C: *High Borrower Quality – FICO Category 681–800*

Depvar:	g_LoanVol (1)	g_LoanNum (2)	AvgIntRate (3)	AvgLTI (4)
dPostBAPCPA$\times$dIMC	0.12***	0.12***	-0.02	0.05***
	(7.82)	(8.69)	(-1.22)	(5.30)
Loan-mix Controls			✓	✓
Firm FE	✓	✓	✓	✓
County$\times$*Quarter FE*	✓	✓	✓	✓
N	152638	152638	142277	140433
Adj. R^2	0.047	0.048	0.325	0.338

Table 4: Mortgage Credit Growth: Exploiting Funding Constraints within IMCs

This table examines the changes in the broad measures of loan origination before and after the 2005 BAPCPA between small and large IMCs. *Large IMCs* (*Small IMCs*) are defined as IMCs which are above (below) the median in terms of the aggregate volume of mortgage origination between 2001–2003. The Indicator variable *dPostBAPCPA* takes the value 1 for six quarters from 2005Q4 to 2007Q1 and 0 for six quarters from 2004Q2 to 2005Q3. The Indicator variable *dSmallIMC* is equal to 1 if the mortgage originating IMC is a small IMC, and 0 otherwise. The dependent and rest of the control variables are the same as in Table 2. All regressions include *Firm FE* and *County*×*Quarter FE*. *T*-statistics displayed in parentheses are robust and clustered at the *County* level. *, **, and *** indicate significance greater than 10%, 5%, and 1% respectively.

Depvar:	g_LoanVol (1)	g_LoanNum (2)	g_JumboVol (3)	g_JumboNum (4)	AvgIntRate (5)	AvgLTI (6)
dPostBAPCPA×dSmallIMC	0.06*** (6.62)	0.05*** (6.56)	0.06*** (3.42)	0.05*** (3.08)	-0.04*** (-4.81)	0.01 (1.63)
Avg FICO					-0.01*** (-51.23)	0.00 (1.26)
Avg LTV					0.04*** (57.59)	
ARM Loans(%)					-0.00 (-0.07)	0.06*** (8.88)
Alt-A Loans(%)					0.33*** (22.13)	-0.02** (-2.02)
Subprime Loans(%)					0.86*** (48.57)	-0.03*** (-3.10)
LowDoc Loans(%)					0.23*** (22.22)	-0.06*** (-10.02)
Firm FE	✓	✓	✓	✓	✓	✓
County×*Quarter FE*	✓	✓	✓	✓	✓	✓
N	205458	205458	36240	36240	184967	182617
Adj. R^2	0.053	0.056	0.056	0.062	0.601	0.364

Table 5: Mortgage Credit Growth: Exploiting Securitization Propensity

Panel A of this table presents the estimates in the regression specification Equation 2 in which a fifth degree distance polynomial is fitted on either side of the threshold value. Panel B fits a non-parametric local linear polynomial using a triangular kernel within an optimal bandwidth proposed by [28]. The dependent variable in both panels is either the growth in *number* or *volume* of mortgage originations at each FICO score from the pre- to post-BAPCPA period covering 2004Q2 to 2007Q1. The Indicator variable *dThreshold* is equal to 1 if the FICO score is greater than 620 (580) for low (full) documentation loans, and 0 otherwise. T-statistics displayed in parentheses. *, **, and *** indicate significance greater than 10%, 5%, and 1% respectively.

Panel A: ***Flexible fifth degree polynomial fit***

	Low-Doc Loans (FICO Threshold=620)		*Full-Doc Loans (FICO Threshold=580)*	
Depvar:	g_LoanVol (1)	g_LoanNum (2)	g_LoanVol (3)	g_LoanNum (4)
dThreshold	0.21*** (2.82)	0.22** (2.52)	0.02 (0.39)	0.03 (0.50)
N	301	301	301	301
Adj. R^2	0.597	0.562	0.939	0.900

Panel B: ***Local linear polynomial fit within optimal bandwidth***

	Low Doc Loans (FICO Threshold=620)		*Full Doc Loans (FICO Threshold=580)*	
Depvar:	g_LoanVol (1)	g_LoanNum (2)	g_LoanVol (3)	g_LoanNum (4)
d_Threshold	0.11*** (4.30)	0.11*** (5.68)	0.13*** (3.45)	0.08* (1.83)
N	57	57	41	41

Table 6: Mortgage Credit Growth: Exploiting APL Laws Across State Borders

This table examines the changes in the broad measures of IMC loan origination before and after the 2005 BAPCPA between counties bordering states with weak and strong anti-predatory lending (APL) laws. The dataset is at the mortgage originating firm-county-quarter level. States are sorted in ascending order based on the strength of the enforcement of APL laws presented in Table A.5. States in the top and bottom half are classified as weak-APL states and strong-APL states respectively. Neighboring counties are defined as counties within 30 miles across borders of states with weak and strong APL laws. The dummy variable *dWeakAPLCounty* is equal to 1 if a county belongs to a weak-APL state and is 0 otherwise. The dependent variable and rest of the control variables are the same as in Table 2. All regressions include *Firm FE*, *County*, and *Quarter FE*. *T*-statistics displayed in parentheses are robust and clustered at the *County* level. *, **, and *** indicate significance greater than 10%, 5%, and 1% respectively.

Depvar:	g_LoanVol (1)	g_LoanNum (2)	AvgIntRate (3)	AvgLTI (4)
dPostBAPCPA×dWeakAPLCounty	0.07*** (2.96)	0.06*** (2.96)	-0.06* (-1.66)	0.04** (2.32)
Avg FICO			-0.01*** (-23.17)	-0.00 (-0.09)
Avg LTV			0.04*** (24.80)	
ARM Loans (%)			0.10*** (3.28)	0.04** (2.50)
Alt-A Loans (%)			0.27*** (7.28)	-0.04* (-1.82)
Subprime Loans (%)			0.75*** (20.39)	-0.03 (-1.13)
LowDoc Loans (%)			0.28*** (12.96)	-0.05*** (-3.63)
Firm FE	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
N	31786	31786	28387	28069
Adj. R^2	0.033	0.034	0.562	0.353

Table 7: Mortgage Credit Growth: Testing Alternate Hypotheses

This table examines the changes in the broad measures of loan origination before and after the 2005 BAPCPA between IMCs and AMCs across different subsamples to test the *borrower demand hypothesis* and the *house-price appreciation hypothesis*. The dataset is at the mortgage originating firm-county-quarter level. The subsamples in Panel A columns (1), (4) and (2), (5) are counties with the lowest per-capita income growth (*LowPCI_g*) and lowest median income growth (*LowMedInc_g*). The lowest group in each case is defined as the 1^{st} quartile of growth rates computed over the 2004–2006 period for each county and then ordered from the smallest to the largest value. The *LowIncome* subsample in Panel A column (3), (6) consists of borrowers whose income is below 0.8×*their median county income*. The *VHighSupElas* and *HighSupElas* subsamples in Panel B are defined as counties that overlap with MSAs (metro statistical areas) ranked based on land supply elasticities between 72–95 and 48–95 respectively from Table VI in [131]. The dependent variable in Panel A columns (1)–(3) and Panel B columns (1)–(2) is the quarterly growth rate in total volume of loans (*g_LoanVol*). The dependent variable in Panel A columns (4)–(6) and Panel B columns (3)–(4) is the quarterly growth rate in total number of loans (*g_LoanNum*). The Indicator variable *dPostBAPCPA* takes the value 1 for six quarters from 2005Q4 to 2007Q1 and 0 for six quarters from 2004Q2 to 2005Q3. The Indicator variable *dIMC* is equal to 1 if the mortgage originating firm is an IMC, and 0 otherwise. All regressions include *Firm FE* and *County*×*Quarter FE*. *T*-statistics displayed in parentheses are robust and clustered at the *County* level. *, **, and *** indicate significance greater than 10%, 5%, and 1% respectively.

Panel A: ***Testing the Demand Hypothesis***

Depvar:	g_LoanVol			g_LoanNum		
Subsample:	LowPCI_g (1)	LowMedInc_g (2)	LowIncome (3)	LowPCI_g (4)	LowMedInc_g (5)	LowIncome (6)
dPostBAPCPA×dIMC	0.07** (2.49)	0.06*** (3.20)	0.12*** (7.13)	0.06** (2.12)	0.05** (2.38)	0.13*** (7.18)
Firm FE	✓	✓	✓	✓	✓	✓
County×Quarter FE	✓	✓	✓	✓	✓	✓
N	31329	63354	85537	31329	63354	85537
Adj. R^2	0.032	0.044	0.070	0.033	0.041	0.091

Panel B: ***Testing the House Price Appreciation Hpothesis***

Depvar:	g_LoanVol		g_LoanNum	
Subsample:	VHighSupElas (1)	HighSupElas (2)	VHighSupElas (3)	HighSupElas (4)
dPostBAPCPA×dIMC	0.05* (1.97)	0.08*** (4.71)	0.04 (1.63)	0.07*** (3.90)
Firm FE	✓	✓	✓	✓
County×Quarter FE	✓	✓	✓	✓
N	40162	75530	40162	75530
Adj. R^2	0.037	0.044	0.034	0.040

Table 8: Mortgage Credit Growth: Loan Types at Issuance

This table examines the changes in the broad measures of loan origination before and after the 2005 BAPCPA using different types of loans. The main headers for the specifications namely *g_LoanVol* and *g_LoanNum*, indicate the measure of loan origination used as the dependent variable. Whereas the sub-headers for the specifications namely *Alt-A*, *Subprime*, *LowDoc* and *Complex*, indicate the type of mortgage loan used to compute the measure. For instance, the dependent variable in Panel A column (1) is the quarterly growth rate in the volume of Alt-A mortgages made by a mortgage originating firm in a given county, quarter. The Indicator variable *dPostBAPCPA* takes the value 1 for six quarters from 2005Q4 to 2007Q1 and 0 for six quarters from 2004Q2 to 2005Q3. The Indicator variable *dIMC* is equal to 1 if the mortgage originating firm is an IMC, and 0 otherwise. All regressions include *Firm FE* and *County×Quarter FE*. *T*-statistics displayed in parentheses are robust and clustered at the *County* level. *, **, and *** indicate significance greater than 10%, 5%, and 1% respectively.

Full Sample

Depvar:	g_LoanVol				g_LoanNum			
Loan-type:	Alt-A (1)	Subprime (2)	LowDoc (3)	Complex (4)	Alt-A (5)	Subprime (6)	LowDoc (7)	Complex (8)
dPostBAPCPA×dIMC	0.14***	0.04***	0.14***	0.11***	0.13***	0.05***	0.14***	0.11***
	(8.06)	(3.29)	(10.37)	(7.17)	(8.56)	(3.75)	(11.18)	(7.92)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
County×Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
N	121241	176380	172513	155680	121241	176380	172513	155680
Adj. R^2	0.029	0.031	0.043	0.050	0.028	0.029	0.042	0.052

Table 9: Consequences of Mortgage Credit Growth: Loan Defaults – Time Variation

This table examines the percentage of defaulted loans among the loans that were originated around the 2005 BAPCPA period over different time horizons. The dependent variable for each column is the percentage of defaulted loans within a given time-period after origination as specified by the header of the column. A loan is classified as under default if any of the conditions are true: (a) payments on the loan are 60^{+} days late as defined by the Office of Thrift Supervision; (b) the loan is in foreclosure; or (c) the loan is real estate owned (REO), that is, the bank has retaken possession of the home. Early default (*Early*) is defined as the loan which defaults within six months from the first payment date. The Indicator variable *dPostBAPCPA* takes the value 1 for six quarters from 2005Q4 to 2007Q1 and 0 for six quarters from 2004Q2 to 2005Q3. The Indicator variable *dIMC* is equal to 1 if the mortgage originating firm is an IMC, and 0 otherwise. Rest of the control variables are defined in A.1. All regressions include *Firm FE* and *County FE* and *Loan Origination Quarter FE*. *T*-statistics displayed in parentheses are robust and clustered at the *County* level. *, **, and *** indicate significance greater than 10%, 5%, and 1% respectively.

Depvar: Default Percentage	Early	15 Mons	18 Mons	2 Yrs	3 Yrs	Until 2010
	(1)	(2)	(3)	(4)	(5)	(6)
dPostBAPCPA×dIMC	0.11	0.57**	0.96***	2.24***	1.67***	1.03**
	(0.92)	(2.28)	(3.17)	(5.53)	(3.20)	(2.08)
ARM Loans(%)	0.85***	2.97***	4.00***	6.09***	10.69***	8.47***
	(7.53)	(14.53)	(16.89)	(20.87)	(29.72)	(21.86)
Low-Doc Loans(%)	1.10***	2.68***	3.36***	4.56***	6.50***	8.97***
	(9.86)	(13.65)	(15.79)	(17.33)	(20.51)	(28.23)
PPt-Penalty Loans (%)	0.66***	0.96***	1.56***	2.80***	4.23***	5.12***
	(5.92)	(3.62)	(5.50)	(8.57)	(10.39)	(10.99)
Avg FICO (log)	-17.51***	-54.90***	-67.87***	-88.98***	-112.30***	-120.95***
	(-25.57)	(-46.19)	(-52.46)	(-58.75)	(-60.96)	(-57.40)
Avg LoanAmt (log)	0.88***	2.30***	2.67***	3.49***	3.97***	3.09***
	(6.83)	(9.78)	(9.83)	(11.01)	(10.64)	(7.23)
Avg LTV	0.03***	0.04***	0.05***	0.08***	0.17***	0.24***
	(5.21)	(4.45)	(4.89)	(5.77)	(9.81)	(12.56)
Avg IntRate(%)	0.33***	1.24***	1.43***	1.77***	1.94***	1.48***
	(11.05)	(21.56)	(21.98)	(24.73)	(21.97)	(15.48)
Firm FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
Origination-quarter FE	✓	✓	✓	✓	✓	✓
N	276568	276568	276568	276568	276568	276568
Adj. R^2	0.051	0.112	0.133	0.174	0.240	0.225

Table 10: Consequences of Mortgage Credit Growth: Loan Defaults Across Borrower Quality

This table examines the percentage of defaulted loans among the loans that were originated around the 2005 BAPCPA period over subsamples of different borrower quality. The dependent variable in each column is the percentage of defaulted loans within *two years* after origination. A loan is classified as under default if any of the conditions are true: (a) payments on the loan are 60^{+} days late as defined by the Office of Thrift Supervision; (b) the loan is in foreclosure; or (c) the loan is real estate owned (REO), that is, the bank has retaken possession of the home. Loans are classified based on borrower credit quality namely: *low* (FICO $\leq$ 620), *medium* (620 $\leq$ FICO $\leq$ 680), and *high* (FICO $\geq$ 680) quality. The Indicator variable *dPostBAPCPA* takes the value 1 for six quarters from 2005Q4 to 2007Q1 and 0 for six quarters from 2004Q2 to 2005Q3. The Indicator variable *dIMC* is equal to 1 if the mortgage originating firm is an IMC, and 0 otherwise. Rest of the control variables are defined in A.1. All regressions include *Firm FE* and *County FE* and *Loan Origination Quarter FE*. *T*-statistics displayed in parentheses are robust and clustered at the *County* level. *, **, and *** indicate significance greater than 10%, 5%, and 1% respectively.

		Borrower Quality		
Depvar: Default Percentage	FullSample (1)	Low (2)	Medium (3)	High (4)
dPostBAPCPA×dIMC	2.24***	1.22**	3.69***	3.01***
	(5.53)	(2.17)	(6.60)	(7.61)
ARM Loans(%)	6.09***	3.00***	6.37***	6.66***
	(20.87)	(5.90)	(16.28)	(19.74)
Low-Doc Loans(%)	4.56***	4.96***	5.97***	5.59***
	(17.33)	(10.34)	(16.73)	(20.29)
PPt-Penalty Loans (%)	2.80***	1.58**	2.96***	1.04***
	(8.57)	(2.19)	(5.43)	(3.33)
Avg FICO (log)	-88.98***	-12.57***	-16.38***	-13.50***
	(-58.75)	(-5.05)	(-7.22)	(-7.40)
Avg LoanAmt (log)	3.49***	2.18***	4.50***	2.69***
	(11.01)	(4.51)	(10.51)	(7.59)
Avg LTV	0.08***	0.10***	0.06***	0.11***
	(5.77)	(4.34)	(3.00)	(7.88)
Avg IntRate(%)	1.77***	1.29***	1.63***	1.23***
	(24.73)	(9.16)	(15.20)	(14.86)
Firm FE	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Origination-quarter FE	✓	✓	✓	✓
N	276568	176714	188738	168855
Adj. R^2	0.174	0.083	0.146	0.157

Table 11: Consequences of Mortgage Credit Growth: Loan Defaults in Subsamples

This table examines the percentage of defaulted loans among the loans that were originated around the 2005 BAPCPA period over various subsamples. The dependent variable in each column is the percentage of defaulted loans within *two years* after origination. A loan is classified as under default if any of the conditions are true: (a) payments on the loan are 60^{+} days late as defined by the Office of Thrift Supervision; (b) the loan is in foreclosure; or (c) the loan is real estate owned (REO), that is, the bank has retaken possession of the home. The header for each column indicates the subsample of loans. The *LowIncome* (*HighIncome*) subsample consists of loans made to borrowers whose income is below (above) 0.8×*their median county income* (1.2×*their median county income*) . The *g_LowPCI* (*g_HighPCI*) subsample consists of loans made in counties with the lowest per-capita income growth. The lowest (highest) group in each case is defined as the 1^{st} (4^{th}) quartile of growth rates computed over the 2004–2006 period for each county and then ordered from the smallest to the largest value. The *HighComp* (*LowComp*) subsample consists of loans made to borrowers in counties with lending competition above (below) the median lending competition. Lending competition in a county is computed using the entire HMDA dataset from 2004–2006. It is defined as the Herfindahl index of loan originations by firms in a county. The Indicator variable *dPostBAPCPA* takes the value 1 for six quarters from 2005Q4 to 2007Q1 and 0 for six quarters from 2004Q2 to 2005Q3. The Indicator variable *dIMC* is equal to 1 if the mortgage originating firm is an IMC, and 0 otherwise. Rest of the control variables are defined in A.1. All regressions include *Firm FE* and *County FE* and *Loan Origination Quarter FE*. *T*-statistics displayed in parentheses are robust and clustered at the *County* level. *, **, and *** indicate significance greater than 10%, 5%, and 1% respectively.

Depvar: Default Percentage	LowIncome (1)	g_LowPCI (2)	HighIncome (3)	g_HighPCI (4)	LowComp (5)	HighComp (6)
dPostBAPCPA×dIMC	-0.58	-0.24	3.31***	3.36***	-1.65	2.11***
	(-1.10)	(-0.26)	(7.16)	(5.64)	(-1.28)	(5.27)
ARM Loans(%)	2.51***	5.79***	6.73***	6.38***	3.90***	6.14***
	(4.44)	(6.73)	(20.40)	(13.43)	(4.08)	(20.32)
Low-Doc Loans(%)	2.83***	4.63***	4.96***	4.53***	0.99	4.54***
	(5.48)	(5.31)	(15.88)	(10.39)	(1.00)	(16.65)
PPt-Penalty Loans (%)	0.77	4.78***	2.19***	3.06***	3.63*	2.64***
	(1.04)	(4.60)	(5.47)	(5.93)	(1.90)	(8.09)
Avg FICO (log)	-83.35***	-95.30***	-81.47***	-84.10***	-88.10***	-87.91***
	(-26.85)	(-21.32)	(-46.06)	(-32.96)	(-15.26)	(-55.76)
Avg LoanAmt (log)	4.09***	3.16***	2.90***	3.61***	1.21	3.59***
	(7.69)	(3.29)	(7.79)	(6.83)	(1.10)	(10.83)
Avg LTV	0.03	0.04	0.09***	0.09***	-0.02	0.08***
	(1.17)	(0.93)	(5.48)	(4.04)	(-0.32)	(5.63)
Avg IntRate(%)	1.62***	1.86***	1.75***	1.72***	1.82***	1.79***
	(9.37)	(7.63)	(20.50)	(14.71)	(6.00)	(24.12)
Firm FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
Origination-quarter FE	✓	✓	✓	✓	✓	✓
N	90157	31864	196810	95279	15985	250266
Adj. R^2	0.108	0.153	0.164	0.199	0.106	0.176

Table 12: Consequences of Mortgage Credit Growth: House Price Growth

This table examines the changes in house price growth before and after the 2005 BAPCPA between IMCs and AMCs. The dataset is at the county-quarter level. Median house prices at the county-quarter level are gathered from zillow.com. The dependent variables in the regression are the quarterly growth rates in house prices (*g_HP*) in every county. *SFH* stands for the median single family house price in a given county, quarter. While *Bottom*, *Mid* and *Top* are the median estimated house price for the bottom, middle and top tier homes in each county, quarter respectively. Tiers in zillow are defined by dividing the house prices in a region into terciles. The sample in this table is limited to counties in which IMCs and AMCs together originate more than 50% of all the mortgages issued in a county over the event window around BAPCPA. These counties are then classified every quarter by comparing the growth rate in the volume of loans issued by IMCs with that of AMCs. *dHighIMC* is an indicator variable that takes the value 1 if the growth in the volume of mortgage loans issued is higher for IMCs than AMCs in a given county and quarter. The Indicator variable *dPostBAPCPA* takes the value 1 for six quarters from 2005Q4 to 2007Q1 and 0 for six quarters from 2004Q2 to 2005Q3. Lagged values of county population growth and county per-capita income (PCI) are included as controls in all specifications. All regressions include *County FE*, and *Quarter FE*. *T*-statistics displayed in parentheses are robust and clustered at the County level. *, **, and *** indicate significance greater than 10%, 5%, and 1% respectively.

Depvar:	g_HP(SFH) (1)	g_HP(Bottom) (2)	g_HP(Mid) (3)	g_HP(Top) (4)
dPostBAPCPA×dHighIMC	1.88**	0.97	2.30**	2.82***
	(2.00)	(0.94)	(2.46)	(3.67)
dHighIMC	-1.16*	-0.35	-1.34*	-1.90***
	(-1.69)	(-0.44)	(-1.92)	(-3.30)
Pop. growth(%)	2.24***	2.56***	2.52***	2.35***
	(6.67)	(7.40)	(8.26)	(8.50)
PCI growth(%)	0.32***	0.35***	0.42***	0.25***
	(3.62)	(3.50)	(5.28)	(3.25)
HHI growth(%)	-3.90***	-3.80***	-3.35***	-2.35***
	(-4.01)	(-3.27)	(-3.61)	(-2.62)
Lagged Pop growth(%)	1.51***	1.47***	1.27***	1.05***
	(3.39)	(3.91)	(2.88)	(3.43)
Lagged PCI growth(%)	0.38***	0.38***	0.41***	0.36***
	(3.61)	(3.05)	(4.10)	(3.96)
Lagged HHI growth(%)	1.07	0.38	0.03	-0.51
	(1.00)	(0.30)	(0.03)	(-0.57)
County FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
N	9656	8526	9128	9829
Adj. R^2	0.381	0.395	0.419	0.370

Table 13: Consequences of Mortgage Credit Growth: House Price Growth in Subsamples

This table examines the changes in house price growth before and after the 2005 BAPCPA between IMCs and AMCs in subsamples of high and low housing supply elasticities. The *Low Housing Supply Elasticity* (Panel A) and *High Housing Supply Elasticity* (Panel B) subsamples are defined as counties that overlap with MSAs (metro statistical areas) ranked based on land supply elasticities between 1–47 and 48–95 respectively from Table VI in [131]. The dependent and independent variables are the same as in Table 12. All regressions include *County FE*, and *Quarter FE*. T-statistics displayed in parentheses are robust and clustered at the County level. *, **, and *** indicate significance greater than 10%, 5%, and 1% respectively.

Panel A: ***Low Housing Supply Elasticity***

Depvar:	g_HP(SFH) (1)	g_HP(Bottom) (2)	g_HP(Mid) (3)	g_HP(Top) (4)
dPostBAPCPA×dHighIMC	5.51**	4.04**	5.92***	4.79***
	(2.54)	(1.98)	(3.05)	(2.97)
dHighIMC	-3.30*	-0.89	-3.05*	-2.55*
	(-1.75)	(-0.48)	(-1.72)	(-1.74)
Pop. growth(%)	4.12***	3.16***	4.11***	3.21***
	(5.80)	(5.37)	(6.89)	(4.91)
PCI growth(%)	0.94***	0.81***	0.96***	0.76***
	(5.87)	(4.76)	(7.29)	(5.43)
HHI growth(%)	-5.80**	-6.99***	-3.26	-6.31***
	(-2.34)	(-2.61)	(-1.62)	(-2.93)
Lagged County controls	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
N	2001	1967	1981	1994
Adj. R^2	0.623	0.653	0.658	0.621

Panel B: ***High Housing Supply Elasticity***

Depvar:	g_HP(SFH) (1)	g_HP(Bottom) (2)	g_HP(Mid) (3)	g_HP(Top) (4)
dPostBAPCPA*dHighIMC	-0.74	-2.66	-0.15	1.01
	(-0.49)	(-1.33)	(-0.09)	(0.82)
dHighIMC	0.60	1.69	0.09	-0.40
	(0.47)	(1.00)	(0.06)	(-0.38)
Pop growth(%)	1.96***	1.76**	1.91***	1.03**
	(3.38)	(2.26)	(3.48)	(2.16)
PCI growth(%)	-0.07	0.06	0.05	-0.01
	(-0.41)	(0.31)	(0.40)	(-0.08)
HHI growth(%)	1.13	-1.60	1.04	0.01
	(0.69)	(-0.72)	(0.56)	(0.01)
Lagged County controls	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
N	2228	2026	2256	2297
Adj. R^2	0.316	0.262	0.309	0.294

CHAPTER II

ARE CREDIT RATINGS STILL RELEVANT?

2.1 Introduction

Credit rating agencies that specialize in assessing the credit worthiness of bond issuers are an integral component of the financial landscape. Investors, regulators, and managers have historically relied on credit ratings, yet they are also frequently criticized for their slow response in predicting corporate defaults (e.g., Enron, Worldcom), accuracy of their ratings, and the conflicts of interest inherent in the agencies' business model (see [150]). As a consequence of these criticisms, regulators have initiated proposals in the Dodd-Frank Act to reduce regulatory and supervisory reliance on credit rating agencies.

A firm's credit rating is the opinion of a particular credit rating agency about the firm's credit worthiness, and it reflects the agency's view on the firm's physical default probability $PD^{\mathbb{P}}$. The prevailing consensus is that such opinion by a rating agency is relevant as documented by negative stock market reactions to rating downgrade announcements (see for examples [77]; [47]; [90]). In contrast, CDS contracts are a market-based measure of a firm's default risk, and provide an estimate of the firm's risk-neutral default probability $PD^{\mathbb{Q}}$ (see [98]). Although credit ratings and CDS spreads provide an assessment of the firm's default risk under two different probability measures ($\mathbb{P}$ versus $\mathbb{Q}$), insights based on Merton's (1974) structural model suggest they share common information about the firm's fundamentals. If CDS spreads provide information about the underlying firm, in lieu of, or in addition to that conveyed by credit ratings, rating change announcements should become less pricing relevant to equity investors. In this paper, we analyze whether the stock market still reacts to credit rating agencies' downgrade announcements after CDS trades on their underlying firm's debt.

We use a comprehensive sample of credit rating change announcements from three major credit rating agencies — Standard and Poor's, Moody's, and Fitch, and find that, consistent with the prior literature, stock and bond markets react significantly negatively to credit rating downgrades. However, when CDS contracts are introduced on the firm's debt, the stock market reaction to credit rating downgrades is muted compared with the period before CDS contracts start trading on a firm's debt. Also, stock and bond prices of firms with traded CDS contracts react significantly less to rating downgrades relative to those of firms without traded CDS contracts. These results are robust to a number of tests such as instrumental variable regressions and propensity score matching analysis, which were used to mitigate endogeneity concerns.

In order to understand the information content of CDS contracts relative to credit ratings, we first construct CDS-implied credit ratings non-parametrically following the approach in [26] and [97] and find that they start deteriorating 180 days prior to a downgrade. Second, using a semi-parametric hazard model (See [139] and [32]), we find that CDS spreads contain information that significantly predict the likelihood of rating downgrade announcements. In the same vein, we show that information in CDS spreads complements credit ratings by enhancing corporate default prediction models.

Bond yields also reflect the market's assessment of a firm's default risk. However, CDS contracts are standardized credit derivative contracts that generally trade more liquidly than bonds and allow investors to more easily short or hedge credit risk. Further, [98] and [56] show that CDS spreads are a "more pure" measure of a firm's default risk than corporate bond spreads (also see [147] and [144]). Using the Hasbrouck's (1995) information share measure, we show the CDS market, on average, dominates the bond market in credit price discovery (see also, [21]). However, before rating downgrades, the CDS market's information share increases substantially to about 90% relative to the bond market. Thus, the CDS market is a leading venue for credit price discovery before rating downgrade announcements.

The presence of the CDS market also helps improve equity valuation. Examining the information flow between the CDS and stock markets, we find that unanticipated changes in CDS spreads lead stock returns, predominantly before firms are downgraded. In support of our main conclusion, we find evidence suggesting that stock prices react less to rating change announcements because a bulk of their price adjustment occurred in the pre-announcement period.

An important channel through which the CDS market improves equity pricing is by providing investors with information that can be used to better estimate the default risk premium. In particular, [15] find that the distress risk puzzle, i.e., lower rated firms earn lower returns, is most pronounced around rating downgrades.[1] We test this implication by examining the value of the CDS market in explaining the cross-section of stock returns for firms that are about to be re-rated. We follow the method developed in [62]. Their general idea is that the firm's equity risk premium can be extracted using the term structure of CDS spreads over time. Our results, based on portfolio sorting, show a strong, positively monotonic relationship between CDS-implied equity risk premia and average one-year equity returns. Importantly, this finding holds when we focus our samples on firms that are about to be downgraded. However, we observe the opposite pattern — i.e., firms with higher default risk have lower returns, when sorting firms based on credit rating levels.

Our paper contributes to two strands of literature. The first is the literature documenting abnormal stock and bond market returns to credit rating downgrades,

[1] For the review of literature, see [29] and [34].

but not for upgrades.[2] [90] argue that the Regulation Fair Disclosure (Reg FD) might have bestowed upon the credit rating agencies an informational advantage because the rating agencies were exempted from the regulation.[3] Our results show that even after Reg FD, the onset of CDS trading significantly reduces the importance of these rating change announcements.

The second strand of literature to which we contribute is related to studies that examine whether the CDS market helps in price discovery. For example, [85], and [114] show that CDS spreads anticipate credit rating downgrades, and some evidence exists that CDS spreads lead the stock ([4]) and bond market ([21]) in price discovery. Motivated by these studies, we examine whether stock and bond markets perceive credit rating announcements to be less pricing relevant when the underlying firm has a CDS contract traded on its debt.

Any market based benchmark of default risk, such as CDS, provides a risk-neutral assessment of default risk. However, credit ratings which convey the agency's objective view of a firm's default risk are built "through the cycle" and may be more suitable from a corporate policy or a risk-management perspective. So, without making additional assumptions, CDS contracts and credit ratings are not completely equivalent and hence not a perfect substitute. Similar to credit ratings, CDS can convey many false positives. Furthermore, as with any market-based measures, changes in CDS spreads can be volatile, which may make them less suitable for use as a benchmark in financial contracts such has bond covenants or rating triggers. Credit rating agencies can still play an important role in financial markets, but the increased competition from the CDS market and the availability of a market-based benchmark for default risk can potentially improve the performance of rating agencies.

The rest of this paper is organized as follows. Section 2.2 develops hypotheses

[2] For examples, see [83], [77], [69], and [47].

[3] We confirm the finding in [90] on the effect of Reg FD introduced in August 2000.

that motivate empirical tests in this paper. Section 2.3 describes the data. Section 2.4 presents the main empirical tests of stock price reactions to rating revisions. Sections 2.5 and 2.6 examine why stock prices react significantly less to credit rating downgrades in the presence of CDS contracts. Section 2.7 examines the value of CDS contracts for explaining the cross-section of stock returns in relation to default risk premia. Finally, Section 2.8 concludes.

2.2 Hypotheses development

In this section, we develop hypotheses that motivate subsequent empirical tests using insights based on the Merton's (1974) structural model, which assumes the firm value V follows a geometric Brownian motion with drift μ and volatility σ. The model values equity E as a call option on the firm value with the strike price equal to the face value D of a non-coupon paying bond with maturity T. The firm can default only at the maturity T of its debt. It can be shown that the expected excess equity return over the risk-free rate $\mu_E - r$ (i.e. equity risk premium), and the equity volatility σ_E are given by

$$\mu_E - r = (\mu - r)\left(\frac{V}{E}E_V\right) \tag{5}$$

$$\sigma_E = \sigma\left(\frac{V}{E}E_V\right), \tag{6}$$

where E_V denotes the partial derivative of E with respect to V. Using standard call option pricing notation for E, and noting that E_V is the call option delta, we can rewrite equation (5) as

$$\mu_E - r = \frac{\mu - r}{1 - Le^{-rT}\left[\frac{\Phi(d_2)}{\Phi(d_1)}\right]}, \tag{7}$$

where $L = \dfrac{D}{V}$ is the firm's leverage, and Φ denotes the cumulative distribution function of the standard normal random variable.[4] Equation (7) shows that the firm's

[4] In the standard Black-Scholes option pricing formula, $d_1 = \frac{log(V/D)+(r+\frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}}$, and $d_2 = d_1 - \sigma\sqrt{T}$

equity risk premium (ERP) is a function of its asset return, asset return volatility, and leverage. For instance, ceteris paribus, a shock to the firm's asset return μ is amplified when translated to a change in the firm's equity return due to the leverage effect.

The default probabilities under the physical measure ($PD^{\mathbb{P}}$) and the risk-neutral measure ($PD^{\mathbb{Q}}$) are respectively given by

$$PD^{\mathbb{P}} = \Phi\left(-\frac{log(1/L) + (\mu - \frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}}\right) \tag{8}$$

$$PD^{\mathbb{Q}} = \Phi\left(-\frac{log(1/L) + (r - \frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}}\right). \tag{9}$$

Combining equations (8) and (9) and using the relationships shown in equations (5) and (6), we can write the equity risk premium as

$$\mu_E - r = \left(\Phi^{-1}(PD_t^{\mathbb{Q}}) - \Phi^{-1}(PD_t^{\mathbb{P}})\right)\frac{\sigma_E}{\sqrt{T}}. \tag{10}$$

Equation (10) shows that changes to $PD^{\mathbb{P}}$ and $PD^{\mathbb{Q}}$ can affect the equity risk premium thereby resulting in the stock price reaction. Therefore, we expect the stock price to react to new information about the firm's physical and risk-neutral default probabilities.

A credit rating, by definition, conveys the rating agency's opinion about the firm's ability to meet its financial obligations on time.[5] Therefore, a rating change reflects the change of an agency's view on the firm's physical default probability $PD^{\mathbb{P}}$. A related question is, what new information about the firm's fundamentals does it contain? Equations (7) and (8) provide some insights. For instance, a rating downgrade, which corresponds to an increasing $PD^{\mathbb{P}}$ can be due to a deterioration in the firm's performance (decreasing μ, $\frac{\partial PD^{\mathbb{P}}}{\partial \mu} < 0$) or uncertainty of its cash flows (increasing σ, $\frac{\partial PD^{\mathbb{P}}}{\partial \sigma} > 0$), or both. As a result, stock prices react negatively to unanticipated bad

[5]For instance, Standard & Poor's website states that credit ratings express the agency's opinion about the ability and willingness of an issuer, such as a corporation or state or city government, to meet its financial obligations in full and on time.

news about μ and σ because $\frac{\partial ERP}{\partial \mu} > 0$, and $\frac{\partial ERP}{\partial \sigma} < 0$. An increase in $PD^{\mathbb{P}}$ can also arise due to the change in firm leverage L as seen from $\frac{\partial PD^{\mathbb{P}}}{\partial L} > 0$. Distinguishing between which information change conveyed by rating agencies is more relevant to equity investors can be difficult.[6] As we do not observe the exact reason in terms of the change in fundamentals that drives the rating change event, we include all the rating change announcements in our analysis.

Our first hypothesis relates to the information relevance of credit rating agencies. If credit ratings provide equity investor with pricing-relevant information about that firm's physical default probability, then rating change events should elicit stock market reactions.

Hypothesis 1 *The stock market reacts to a firm's credit rating change announcement as the news reveals changes in the firms physical default probability.*

The simple structural model offers us insights into how the presence of the CDS market may affect the value of credit rating changes. CDS spreads embody a risk-neutral assessment of the firm's default probability $PD^{\mathbb{Q}}$. Taking partial derivatives of $PD^{\mathbb{P}}$ and $PD^{\mathbb{Q}}$ (see equations (8) and (9)) with respect to σ, L, and μ, respectively, shows that (1) $\frac{\partial PD^{\mathbb{Q}}}{\partial \sigma} > 0, \frac{\partial PD^{\mathbb{P}}}{\partial \sigma} > 0$; (2) $\frac{\partial PD^{\mathbb{Q}}}{\partial L} > 0$, $\frac{\partial PD^{\mathbb{P}}}{\partial L} > 0$; and (3) $\frac{\partial PD^{\mathbb{Q}}}{\partial \mu} = 0$, $\frac{\partial PD^{\mathbb{P}}}{\partial \mu} > 0$. These relationships suggest that the risk-neutral default probability $PD^{\mathbb{Q}}$ and the physical default probability $PD^{\mathbb{P}}$ contain correlated information about the firm's fundamentals (i.e., regarding σ and L). Therefore, if the CDS market provides information about the underlying firm's fundamentals, in lieu of, or in addition to that conveyed by credit ratings (through $PD^{\mathbb{P}}$), then rating change announcements should become less pricing relevant to equity investors.

[6] [69] documented that rating changes – specifically downgrades – due to a deterioration in firm's financial prospects are informative and produce a negative abnormal stock return while those due to an increase in leverage are uninformative.

Hypothesis 2 *Stock market reactions to a firm's rating change events are attenuated if CDS contracts trade on the underlying firm's debt.*

The hypothesis above tests for the effect of CDS trading on the information value of rating changes, which is the main conclusion of this paper. In the remaining hypotheses, we focus on how and why the CDS market may affect the magnitude of stock market reactions to credit rating changes.

As discussed previously, static analyses of the structural model show that CDS spreads and credit ratings convey common information about the firm's fundamentals. If CDS spreads contain information about the firm that anticipates changes in $PD^{\mathbb{P}}$ associated with rating revisions, then rating change announcements should become less informative about the firm's equity risk premium. This, in turn, implies a smaller stock market reaction to rating change announcements.

Hypothesis 3 *CDS spreads contain information that predict credit rating revisions.*

We test the above hypothesis by examining whether CDS spreads predict credit rating changes on a firm, and whether they improve the model for predicting defaults.

The presence of the CDS market can improve equity valuation, if it contains new information about the firm's risk-neutral default probabilities (see equation (10)). Although CDS and corporate bond spreads provide a risk-neutral assessment of their underlying firm's default risk, existing evidence suggests that the CDS market leads the bond market in credit price discovery (see [21]). CDS contracts also provide a feasible way to short credit risk, thereby helping complete the credit risk market.[7] Until then, shorting corporate bonds was limited to the repo market which typically has a very short maturity. Whereas, CDS contracts are standardized and can be used for shorting credit risk for longer periods ranging from one to ten years. Further, the CDS market generally trades more frequently relative to the corporate bond market.

[7] See [60] for supporting arguments.

This enables market participants to construct high frequency estimates of risk-neutral default probability.

Equity prices also contain information about the firm's credit risk. However, [4] find that changes in CDS spreads lead stock returns especially around negative credit events. They argue that unlike the stock market, trading in the CDS market is dominated by large institutions, mostly banks, which explains why the information revelation may occur in the CDS market before the equity market. In relation to credit rating changes, if the CDS market provides new information about the firm's credit risk before rating change announcements, we expect unanticipated changes in CDS spreads to lead stock and bond returns during this period. As a result, stock prices react less to rating change announcements because a bulk of their price adjustment occurred in the pre-announcement period.

Hypothesis 4 *CDS spreads lead other market measures that embody risk-neutral default probabilities before rating change announcements.*

We test the hypothesis above by examining whether the CDS market contributes to price discovery in the stock and bond markets before rating change announcements.

Arguments in Hypotheses 2–4 posit that the presence of CDS market improves equity valuation by providing investors with new (or more reliable) information about the firm's credit risk. This statement has an important implication in light of the well documented distress risk puzzle, i.e., lower rated firms earn lower returns, because the structural model shows that risk premia in equity and credit markets are related (see equation (10)). In particular, [15] find that the puzzle is most pronounced around rating downgrades. Therefore, if the CDS market provides information that improves equity valuation, we expect equity risk premia estimated using CDS information to relate better to firms' default risks than credit ratings, particularly for firms that are about to be re-rated. We test this important implication in the next hypothesis.

Hypothesis 5 *The CDS market provides investors with a more reliable measure of default risk premium than credit ratings for firms undergoing rating revisions.*

To test the hypothesis above, we examine whether the equity risk premia extracted from CDS data can explain the cross-section of stock returns of firms that are undergoing rating revisions.

2.3 Data and descriptive statistics

We use a CDS database that is widely used among financial market participants (CMA Datavision database (CMA)) to identify all firms for which we observe CDS quotes on their debt. CMA contains consensus data sourced from 30 buy-side firms, including major global investment banks, hedge funds, and asset managers which is disseminated through Bloomberg since October 2006.[8] We further ensure the accuracy in the coverage of CDS quotes by augmenting the CMA database with CDS data obtained from Bloomberg. The earliest quotes were then taken as the first sign of active CDS trading on a firm's debt.

Data on bond ratings were gathered from the Mergent Fixed Income Securities Database (FISD). FISD provides comprehensive data on issue-level details on over 140,000 corporations, U.S. agencies, and U.S. Treasury debt securities. The data contains detailed information for each issue, including the issuer name, rating date, rating level, agency that rated the issue, and credit watch status, etc. We include only those ratings issued by the top three NRSROs – S&P, Moody's, and Fitch. We restrict our sample to U.S. domestic corporate debentures, and exclude yankee bonds, and bonds issued via private placements, preferred stocks, mortgage-backed, trust preferred capital, convertible bonds and bonds with credit enhancements. We also consider only the issuers whose stocks are traded on either the NYSE, AMEX,

[8][103] compare the data qualities of the six most widely used databases – GFI, Fenics, Reuters, EOD, CMA, Markit and JP Morgan – and find that the CMA database quotes lead the price discovery process.

or NASDAQ. Approximately 18% of the ratings are from Fitch, and the remaining ratings are split evenly between S&P and Moody's.

We consider a rating change for an issuer as one observation. When there are rating changes on multiple bond issues for an issuer on the same day, we use the issue with the greatest absolute rating scale change because such changes are likely to create the strongest impact on bond and stock prices. We consider only the rating announcements that are associated with either "DNG" (downgrade) or "UPG" (upgrade), which constitute about 90% of the total rating events.[9] The main sample is from January 1996 to December 2010 and consists of 4665 downgrades and 2171 upgrades; we refer to it as the "Full sample" for the remainder of this paper. The Full sample consists of 1142 unique firms, of which 390 have CDS trading at some point during the sample period. There are about 2.1 downgrades for every upgrade, which is line with the findings in [47]. More details on the sample are provided in the internet appendix.

Many of the firms in our sample never experienced CDS trading over the 1996-2010 period. In order to control for the differences between firms with and without CDS contracts traded on their debt, we consider a subsample of firms for which CDS starts trading at some point during our sample period. We refer to this sample as the "Traded-CDS". We use firms' rating changes in this subsample to compare their stock reactions to rating change announcements made between their pre-CDS and post-CDS trading periods. The average size of rating change for this sample is 1.45 before CDS trading starts and 1.49 after CDS trading starts. The distribution of the rating changes are provided in the internet appendix.

We obtain corporate bond price data from TRACE, which contains individual bond transactions starting on July 1, 2002. Corporate bond data prior to July 2002

[9] The FISD ratings database reports the reason for the rating change on an issue. About 4.8% of the total rating change reasons are "IR" (Internal Review), while about 2% are "AFRM" (Affirmed).

is obtained from Mergent FISD historical NAICS database. We apply a number of standard filters to the data set. Following [17], we eliminate trades that have been canceled or corrected, trades that have commissions, and non-institutional trades because they show that they help increase the power of the test for detecting abnormal performance. Therefore, consistent with [51], we remove observations in which the par value of the transaction is less than or equal to $\$100,000$ as smaller trades tend to be non-institutional trades.[10]

2.4 Stock price reaction to rating changes

This section tests Hypotheses 1 and 2 of the paper. First we provide univariate evidence that the stock market reacts to rating downgrades, but the magnitude significantly decreases when CDS contracts trade on the firm's debt. We then confirm our results using multivariate regressions. Subsequently, we address endogeneity concerns regarding the timing of the CDS introduction.

2.4.1 Abnormal stock returns

We study changes in daily abnormal stock returns on the date of rating change announcements for CDS and non-CDS firms. We carry out the analysis separately for upgrades and downgrades. We define the daily abnormal stock return of firm i on day t, AR_{it}, as the residual estimated from the market model:

$$AR_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt}),$$

where R_{it} is the raw return for firm i on day t, and R_{mt} is the value-weighted NYSE/AMEX/NASDAQ index return. We examine whether the mean cumulative abnormal return (CAR) around the event period is significantly different from zero.

[10]The prices reported in the TRACE bond database are the "clean" prices. They do not include the accrued coupon payment. We add the accrued coupon payment to the clean prices by merging in variables from the Mergent FISD database. The final bond prices that we use are therefore settlement prices.

Following [83], we compute CAR using the three-day window centered on the announcement date. That is, $CAR_i(-1,1) = \sum_{t=-1}^{+1} AR_{it}$. [96] show that short–horizon event studies such as ours are not highly sensitive to the assumption of cross-sectional or time-series dependence of abnormal returns, as well as the benchmark model used for computing abnormal returns.[11]

2.4.2 Univariate analysis

Table 14 presents the mean of cumulative adjusted return (CAR) for the pre- and post-CDS trading periods. The results in Panel A are based on the "Full-sample" which consists of traded-CDS and non-traded-CDS firms. The results in Panel B are based on the "Traded-CDS–sample". Traded-CDS firms are those that have CDS traded at some point during our sample period. However, non-traded-CDS firms are those that do not have CDS trading in our sample period, which is from 1996 to 2010. Results obtained using the "Traded-CDS–sample" can be usefully thought of as fixed-effects tests because only firms that experience CDS trading are considered. Consistent with previous studies, Panel A shows that overall, stock price reacts significantly to downgrades (-4.31%) but only weakly to upgrades (0.14%).[12] This finding supports of Hypothesis H1.

The results in Panel A show the mean CARs over the three-day window around rating downgrades is negative and significant at the 1% level for the pre- and post-CDS periods. However, the magnitude is significantly weaker for the post-CDS period. The mean CAR in the post-CDS period is -2.51%, compared to -5.10% in the pre-CDS period. The difference in CAR between these two groups is 2.58% and is statistically significant at the 1% level. On the other hand, we do not find that stock prices react

[11] We estimate $\hat{\alpha}_i$ and $\hat{\beta}_i$ using a rolling window over a period of 255 days from -91 to -345 relative to the event date. Using a shorter estimation window and a different factor model do not affect our conclusions. Table I.A1 in the Internet Appendix shows that we obtain similar findings when using the Fama-French 3-factor model to calculate abnormal return.

[12] The magnitude of CAR to rating downgrades is in line with existing studies that examine announcement returns to rating changes using the more recent sample, e.g. [90].

significantly differently to rating upgrades in the post-CDS period. The difference in CAR to credit rating upgrades do not differ significantly between the pre- and post-CDS periods.

In Panel B of Table 14, we report univariate results for firms that eventually have CDS contracts traded on its debt. Restricting our analysis to the Traded-CDS sample mitigates the concern that traded-CDS firms are inherently different from non-traded-CDS firms. We find that stock price reaction to credit rating downgrades is significantly weaker in the post-CDS period. The difference in the mean CAR values is 0.95% between the post-CDS and pre-CDS periods, and is statistically significant.[13]

2.4.3 Regression analysis

We employ multivariate regressions to control for factors that could affect stock price reactions to rating changes. Following previous studies (e.g., [83]), we run the regressions separately for upgrades and downgrades. The results are reported in Table 15. The regression model that we estimate is

$$\begin{aligned} CAR_i = &\beta_0 + \beta_1 dCDS_i + \sum \gamma_i \textit{Rating-level characteristic}_{it} + \\ &\sum \delta_i \textit{Firm-level characteristic}_{it} + \sum \phi_i \textit{CDS-trading control}_{it} + \varepsilon_i \end{aligned} \tag{11}$$

where for bond issue i, CAR is the 3-day cumulative abnormal return centered on the date of rating change announcements – i.e., event window (-1,1). The main variable of interest is $dCDS$, an indicator variable equal to one if the rating change takes place when CDS trades on the underlying firm and 0 otherwise. Panel A of Table 15 reports results for rating downgrades, while Panel B reports results for rating upgrades. Each panel reports results for three regression specifications. Regression models (I) and (II) are run on the full sample, while regression model (III) is estimated

[13] [90] find that stock price reactions to rating downgrades is significantly stronger after Regulation Fair Disclosure (Reg FD) was implemented in Oct 2000 because rating agencies are exempt from Reg FD and could still access private information on the rated firms. For a robustness check, we eliminate rating changes prior to the year 2001 (before Reg FD was put in place) and find that our conclusions remain unchanged.

using the traded-CDS sample. All variables are defined in Appendix B.[14]

If rating changes are less informative in the presence of CDS trading, we would expect the coefficient of $dCDS$ in equation (11) to be positive for downgrades and negative for upgrades. Panel A of Table 15 shows the coefficients on $dCDS$ are positive and statistically significant across the three regression specifications. Controlling for industry- and year-fixed effects in specification (II), we find the difference in CARs between firms that have and do not have CDS trading is 1.70%. Looking only at the traded-CDS sample, (i.e. model (III)), we find the evidence is stronger. Stock prices react significantly less to credit rating downgrades by an average of 2.59% in the traded-CDS sample. The results in Panel B, however, show that all three coefficients on $dCDS$ are not significantly different from zero. Overall, our regression results in Table 15 confirm our univariate results (see Table 14) that stock price reaction is significantly weaker to credit rating downgrades, and not upgrades, when CDS contracts trade on the firms' debt.

The coefficients on the control variables are in line with the results documented in the literature (see [77], and [90]). Table 15 shows the coefficients on *Previous Rating* and *AbsRating Change* are negative and highly significant, suggesting that ratings downgrades on lower-rated firms, as well as downgrades across multiple cardinal scales, lead to larger stock price reactions. The time since the previous credit rating does not seem to impact how the new rating change influences stock response. However, rating downgrades accompanied by firms' earnings announcements elicit a larger stock price reaction. Among the firm-level characteristics, we find that firms'

[14] All regression models include three sets of control variables to account for potential factors affecting the magnitude of stock price reactions. The first set of control variables are rating-level characteristics: previous rating level, the size of rating change, how long has the previous rating been outstanding for, and whether rating change occurs in relation with the company's earnings announcement. The second set of control variables includes various firm-level characteristics. The third set of control variables account for characteristics that may be related to the propensity that firms that have CDS trading. All variables are defined in Appendix B. All firm-level characteristics and CDS-trading controls are lagged by one period, i.e. a month or a quarter, depending on the frequency of data sources.

recent return performance, (i.e. *Avg Return*), robustly predict the magnitude of stock price reactions to rating downgrades. *Leverage,* as well as *Avg Trading Volume* appear to be negatively related to CAR for downgrades, though, their statistical significance disappears when we restrict our regressions to traded-CDS firms.

We confirm that our regression results are robust to a series of robustness checks, which are reported in the Internet Appendix. Table B.6 Panel A reports regression results showing that our main conclusion holds when we allow for Industry$\times$Year fixed effects, which helps controlling for time-varying industry risk factors. Table B.6 Panel B shows our regression results hold when using a subsample of only non-financial firms. We find that the coefficients on *dCDS* are slightly larger in magnitude for downgrades when we focus our analysis only non-financial firms. Further, to ensure that our results are unaffected by the financial crisis, we focus on rating changes prior to 2008 and find that our conclusions remain intact. Table B.7 Panel A replicates the results in Table 15 using the Fama-French 3-factor model to compute CARs and Table B.7 Panel B conducts a pooled analysis on downgrades and upgrades together. In both cases we verify that our results are robust.

2.4.4 Instrumental variable analysis

A potential concern with any study on the impact of the CDS market is that the timing of CDS introduction is not exogenous. CDS contracts may have been introduced during a period when the firm's credit quality improves, thereby affecting how its stock price reacts to rating changes. In this section, we address the concern that the emergence of the CDS market is not exogenous using the instrumental variable method.

We follow [132] to find an instrument that correlates with the firm's likelihood of having CDS contracts traded on its debt, while being directly unrelated to how the firm reacts to its credit rating changes. [132] use the foreign exchange derivatives traded for hedging purposes by banks that have a lending relationship with a given firm as the instrument for CDS market introduction. The choice of this instrument is motivated by [110] who show that banks that use interest rate, foreign exchange, equity, and commodity derivatives are more likely to be net buyers of CDS, and hence are related to the emergence of the CDS market. Among banks' various derivatives activities, their foreign exchange position is arguably least likely to directly influence the credit risk of firms with which they conduct business. Importantly, the amount of foreign exchange derivatives used by banks reflect their hedging need for macro risk, and hence should not affect the credit risk of domestic firms (i.e., U.S. entities) in our sample. We further exclude non-financial firms from the instrumental variable regression results for two reasons. First, financial firms are more likely to act as borrowers and lenders amongst themselves and with several banks simultaneously, which makes their nature and the extent of relationship difficult to identify. Second, we want to maintain consistency with [132] who motivated the use of the instrumental variable.

Our instrumental variable, *Forex Derivative Hedging*, is defined as the average foreign exchange derivatives amount used for hedging (i.e., non-trading purposes) relative to total assets by the lead syndicate banks and bond underwriters that the firm has conducted business with over the past five years. We use the Dealscan syndicated loan database to identify firms' lenders (i.e., lead syndicates), and Mergent FISD database to identify firms' bond underwriters. Banks' derivatives usage data is obtained from the Bank Holding Company (BHC) Y9-C filings. We lag *Forex Derivative Hedging* by one quarter when including it in the instrumental variable (IV) estimation. The average *Forex Derivative Hedging* at the firm-level in our full sample is 1.98% of the total assets with a standard deviation of 1.54%. These values are in line with [132].

In order to address concerns that CDS introduction is endogenous, we re-estimate the main regression results using *Foreign Derivative Hedging* to instrument for *dCDS*. We follow [152] and apply the fitted variable from a probit model for *dCDS* to the regression model in equation (11); see also [18] and [132] for similar applications. We include firm-level characteristics and CDS-trading controls in the probit model. The instrument that we use is available quarterly and therefore the model is estimated at the firm-quarter level. Table B.2 in the Appendix reports the probit model from the IV estimation. After accounting for various firm-level characteristics and variables that may influence CDS trading, we find that the amount of foreign exchange derivatives usage significantly predicts the likelihood that a firm will have CDS trading on its debt (t-statistic of 4.84).[15]

Table 16 reports the regression results using the fitted instrumental variable, *dCDS IV* for 1966 downgrades and 886 upgrades belonging to 609 unique firms. The number of observations are lower compared to Table 15 because we restrict our sample to non-financial firms with lending or underwriting relationships with banks that are active in the *forex derivatives* market. Further, bank *forex derivatives* activities are reported in the BHC Y-9C filings and call reports are from 2001 onwards.

Table 16 shows the coefficients on *dCDS IV* are positive and statistically significant for downgrades, but not for upgrades, which is consistent with our previous findings. A one-standard deviation change in the *dCDS IV* is related to a 2.26 and 2.01 percent attenuation in CAR response to credit rating downgrades for the regressions specifications with industry-fixed effects (I) and year and industry-fixed effects (II), respectively. Overall, we conclude that our main results hold when using *Foreign Derivative Hedging* as an instrument to address the potential bias associated with the endogeneity of CDS market introduction.

[15] The incremental psuedo-R^2 of the instrument is about 1.1%. The economic impact of foreign exchange derivatives usage on the probability of CDS trading is reasonably large. We find that a one-standard deviation increase in *Forex Derivative Hedging* increases the likelihood that a firm has CDS traded on its debt by 4.2. Overall, consistent with [132], we find that the instrument is not weak.

2.4.5 Matched sample analysis

In addition to the instrumental variable regression, we carry out a matched-sample analysis to mitigate concerns that traded-CDS and non-traded-CDS firms are different on some observable dimensions. A traded-CDS firm is matched with a firm that does not have a CDS traded on its debt at any point in our sample period (i.e., a non-traded-CDS firm). We use a propensity score matching method that can incorporate a large number of matching dimensions ([130]). The matching is carried out in the month when CDS starts trading on a traded-CDS firm based on 14 observable characteristics. These matching characteristics are motivated by [12], [132], and include other factors that might affect the introduction of CDS trading.

We estimate firms' propensity of having CDS trading using a probit model. The dependent variable in the model, *dCDS*, is an indicator variable equal to one starting on the month when CDS begins trading on the firm, and zero otherwise. All explanatory variables in the probit model are lagged by one period and defined in Appendix B. We require that firms entering the matching sample have complete time-series information on their observable variables from 2001 onwards, which is when we first observe CDS trading in our sample. This requirement leaves us with 382 traded-CDS firms and 492 non-traded-CDS firms for estimating the propensity score model, which we refer to as the *before-matching* sample. In the Appendix, Table B.3 reports diagnostics of the propensity score matched sample. In Panel A, the column labeled "Before matching" reports results for the probit model estimated at the firm-month level using the before-matching sample. Most of the estimated coefficients are significant with the magnitude roughly in line with the probit model estimated using firm-quarter observations for the instrumental variable estimator (see Table B.2). The fitted probability from the probit model is then used as the propensity score to match traded-CDS firms to non-traded-CDS firms.

For each traded-CDS firm, we use its propensity score in the month that CDS starts trading to identify a non-traded-CDS firm with the closest propensity score in the same month. We require that the propensity score of the matched non-traded-CDS firms be within ±2% of the propensity score of the traded-CDS firm. The matching technique used for this is the nearest-neighborhood caliper method of [37]. We match one traded-CDS (treated) firm with five non-traded-CDS firms (control), i.e., one-to-five matching, in order to increase our sample of matched pairs (see [42], and [140]). The matching is carried out with replacement.[16] This exercise leaves us with 286 unique traded-CDS firms each matched to five eligible control firms.

We report various diagnostics of the matched sample in Table B.3 in the Appendix. The column labeled "After matching" in Panel A reports results derived from estimating the probit model using the matched observations. Overall, the explanatory power of the probit model decreases significantly with the pseudo R^2 of 9% relative to 49% observed in the "Before matching" sample. We find that some observable characteristics remain statistically significant in the probit model for the matched sample. Given the large observable dimensions used for matching, we do not expect to find a perfect match. Nevertheless, Panel A shows that all the probit coefficients in the after-matching sample either lost statistical significance or have become substantially less significant relative to the before-matching sample. We further report the quality of our matched sample in Panels B and C in the Appendix Table B.3. In Panel B, we report univariate means of the 14 observable dimensions for the before-matching and after-matching samples. The findings echo the results reported in Panel A, which show that the propensity-score matching significantly reduces observable differences between the traded-CDS firms (treatment group) and the non-traded-CDS firms (control group). Nevertheless, traded-CDS firms in the matched sample still tend to be

[16]We also verify that our results are similar when using one-to-one matching without replacement. In this case, we have 162 uniquely matched pairs. Table B.8 in the Internet Appendix reports difference-in-difference regression results verifying our main finding using the one-to-one matched sample too.

larger, better rated, and have greater bond debt outstanding. In order to control for remaining differences in these observable dimensions, we include all matching characteristics as control variables in the matched sample regression. Additionally, in Panel C we report the industry distribution of firms in the treatment and control samples. Overall, we find that industry distributions of the two samples do not differ greatly.

Using the matched sample, we estimate the following difference-in-difference regression

$$
\begin{aligned}
CAR_i = \beta_0 + \beta_1 dCDS_i + \beta_2 dTreatment_i + \beta_3\ dTreatment_i \times dCDS_i \\
+ \sum \gamma_i \textit{Rating-level characteristic}_{it} + \sum \delta_i \textit{Firm-level characteristic}_{it} \\
+ \sum \phi_i \textit{CDS-trading control}_{it} + \varepsilon_i,
\end{aligned} \tag{12}
$$

where the dependent variable CAR_i is the cumulative abnormal stock return of firm i to a credit rating downgrade. Table 17 reports the results. To save space, we do not report results for credit rating upgrades as our previous evidence suggests that CAR to credit rating upgrades are, on average, not significant. The above regression model in (12) is similar to the baseline regression model in (11), with the additions of two new variables. The first is $dTreatment_i$, which is an indicator variable equal to one if the firm corresponding to the observation is from the treatment group, i.e. a traded-CDS firm in the matched sample, and zero otherwise. The second variable we introduce is $dTreatment_i \times dCDS_i$, which is the difference-in-difference (DID) estimator and is our key variable of interest. It is an interaction term of the $dTreatment_i$ with the indicator variable for CDS trading, $dCDS_i$. For firms in the treatment group, $dCDS_i$ simply takes the value of 1 when CDS starts trading on the firm's debt, and zero otherwise. Control-group firms are assigned counterfactual $dCDS_i$ variables that are identical to their matched traded-CDS firms. The coefficient on the DID estimator therefore captures the difference in CARs to credit rating downgrades between the traded-CDS firms and their matched non-traded-CDS firms over the two periods: before and after CDS introduction.

Panel A of Table 17 reports difference-in-difference regression results using the matched sample. Industry-fixed effects are included in the first regression specification (I), while both industry- and year-fixed effects are included in the second regression specification (II). In both cases, we find the coefficient on the DID estimator is positive and highly significant. Looking at a more conservative regression specification (II), the coefficient on DID estimator is 2.16. This finding suggests that stock prices of firms with CDS trading react less to credit rating downgrades by about 2.16% relative to firms sharing similar observable characteristics, but without CDS trading. Overall, the results suggest that the information content in rating announcements has decreased for downgrades after the onset of CDS trading.

In Panel B of Table 17, we run regression diagnostics based on equation (12) for four different subsamples. The regression model (III) reports results for firms that are in the treatment group ($dTreatment = 1$), while regression model (IV) reports results for firms that are in the control ($dTreatment = 0$). Because the regressions are estimated separately for the treatment and control groups, the variable $dTreatment$ is dropped from the regressions as it is not identified. In these two subsamples, the variable of interest is $dCDS$, which examines the impact of the $dCDS$ variable on CAR to bond downgrades for treatment-group firms and control-group firms, respectively. We expect coefficients on $dCDS$ to be positive and significant for the treatment group because this dummy variable indicates when the firms have CDS trading. In fact, the regression model (I) is similar to the regression model (III) for the traded-CDS sample in Table 15. However, we do not expect $dCDS$ to be significant for the subsample consisting only of control-group firms because they do not actually have CDS trading. The coefficients on $dCDS$ in the regression models (III) and (IV) confirm our expectation. We do not find that firms in the control sample, which have similar characteristics as traded-CDS firms, experience weaker stock price reactions to credit rating downgrades.

The regression models (V) and (VI) in Table 17 report results for firms in both the treatment and control groups estimated using two different subsample periods. The regression model (V) uses only firms that are in the post-CDS period ($dCDS = 1$), while the regression model (VI) uses firms in the pre-CDS period ($dCDS = 0$). In these two regression models, the variable $dCDS$ is excluded because it is not identified. The main variable of interest is $dTreatment$ which tests for the difference in CAR values between treatment-group firms and control-group firms in the post-CDS period (V) and pre-CDS period (VI). We expect the coefficient on $dTreatment$ to be positive and significant for the post-CDS period, if CAR to rating downgrades is weaker for firms that have CDS trading relative to control-group firms. Recall that control-group firms do not actually have a traded CDS but are assigned to the post-CDS period because their observable characteristics resemble those of traded-CDS firms. The positive coefficient on $dTreatment$ in the regression model (V) is 2.27 and statistically significant, which confirms our expectation. However, the statistically insignificant coefficient on $dTreatment$ in the regression model (VI) shows that firms in the treatment and control groups do not react differently to rating downgrades, and thus suggest *parallel trends* in the pre-CDS period and also shows the efficacy of our matching procedure. Overall, results in the regression models (VI) suggest that firms the in the treatment and control groups are well matched in how they respond to rating changes in the pre-CDS period, while results in (V) suggest the difference in post-CDS CARs between the treatment and control groups is due to the introduction of CDS contracts in the treatment-group firms.

2.5 Information in CDS spreads about credit ratings

This section tests Hypothesis 3 of the paper. Insights from the simple structural model show that CDS spreads and credit ratings convey common information about the firm's fundamentals. If CDS spreads contain information that anticipates changes in the physical default probability $PD^{\mathbb{P}}$ associated with rating revisions, then rating change events should become less informative. We provide three sets of empirical results to support Hypothesis 3. First, we back out CDS-implied ratings using a non-parametric method and show that they significantly lead rating downgrades issued by credit rating agencies. Second, we show the predictive power of CDS spreads on credit rating downgrades in a multivariate framework using a hazard model. Third, we show that information in CDS spreads improve the model for predicting historical defaults.

2.5.1 CDS-implied ratings

One reason why CDS spreads appear more information-relevant than credit ratings is their timely response to changes in the underlying firm's credit condition. [4] find that information discovery occurs in the CDS market prior to negative credit news. In this subsection, we back out the rating levels implicit in CDS spreads (CDS-implied ratings) and compare them with those issued by rating agencies. Our objective is to examine the dynamics of CDS-implied ratings around rating downgrades. If trading in the CDS market reveals information about changes in a firm's default risk, we expect CDS-implied ratings to significantly change prior to a downgrade issued by credit rating agencies.

We calculate CDS-implied ratings following the approach in [26] and [97]. The basic idea is to estimate the CDS boundaries separating two adjacent rating classes in a non-parametric manner. Once the boundaries are determined, we assign each firm to a rating class corresponding to its CDS spread level. We estimate CDS boundaries by minimizing the penalty function with the objective of reducing the number of misclassifications, which we define as the discrepancy between the firm's CDS spread level and its rating class. For instance, missclassification occurs when the CDS spread of a higher-rated firm is greater than the spread of a lower-rated firm. Following this intuition, the penalty function for estimating the boundary between the A and BBB ratings classes, b_{A-BBB}, is

$$F(b_{A-BBB}) = \frac{1}{m}\sum_{i=1}^{m}[\max(s_{i,A}-b_{A-BBB},0)]^2+\frac{1}{n}\sum_{j=1}^{n}[\max(b_{A-BBB}-s_{j,BBB},0)]^2, \quad (13)$$

where $s_{i,A}$ is the CDS spread of A-rated firm i, and $s_{j,BBB}$ is the CDS spread of BBB-rated firm j. When the spread of A-rated firm is higher than the boundary b_{A-BBB}, the firm's CDS spread is considered misclassified with the error equal to their difference. Similarly, when the spread of BBB-rated firm is lower than the boundary b_{A-BBB}, the firm's CDS is considered misclassified. The objective is then to minimize the error from misclassifications by minimizing the penalty function described in equation (13). The numbers of firms in the A and BBB rating classes are denoted as m and n, respectively, and the penalty function for estimating boundaries between other adjacent rating classes are defined similarly. We estimate CDS spread boundaries for all adjacent rating classes.[17] The estimation uses all CDS spreads on firms that have CDS spreads traded on each day.

Figure 6 plots average CDS-implied ratings over the interval [-360,180] days centered on the rating change events. The solid line plots the official ratings issued by credit rating agencies and the dotted line plots average CDS-implied ratings. The rating levels are plotted on the rating class scale. A higher rating class corresponds to a higher credit risk. To save space, we plot the results for three adjacent rating classes that have the most rating change events: A-BBB, BBB-BB, and BB-B. Figure 6 shows that CDS-implied ratings started increasing at least 180 days prior to a downgrade announcement. This finding suggests that the CDS market responds to the firm's deteriorating credit quality significantly faster than credit rating agencies.

[17] The mapping between rating codes and rating classes is shown in the Appendix Table B.1. Due to the large number of daily observations required to precisely estimate the boundary, we do not consider adjacent rating levels that are in the same rating classes. For instance, AA+, AA, AA- are considered to be rated AA. Fitch estimates CDS-implied ratings based on a method similar to ours but with a slightly different penalty function. As a robustness check, we implement Fitch's penalty function and obtain roughly the same boundaries.

However, Figure 6 shows that CDS-implied ratings do not change significantly prior to an upgrade announcement. In fact, CDS-implied ratings were already at the level that represents the future rating class of the soon-to-be upgraded firm. This finding is consistent with the prevailing consensus, as well as our previous results that rating upgrades have little pricing relevance.

2.5.2 Predictability of credit rating changes

So far, we have visually shown in Section 2.5.1 that credit ratings backed out from CDS spreads anticipate rating downgrades issued by credit rating agencies. An important question is whether CDS spreads provide additional predictability of rating downgrades after controlling for variables such as accounting measures and bond spreads that have been shown to anticipate credit rating changes. We test the hypothesis that information derived from the CDS market can predict future downgrades using a hazard model.[18]

We estimate the extended Cox model commonly used for survival analysis in epidemiological studies (e.g. Platt et al. (2004)). The survival time in our analysis is the number of months from current time to the next rating change event. Let t be the current time period, and $T \geq t$ be when rating change occurs, the hazard rate associated with future rating changes is given by

$$h(t) = \lim_{y \to 0} \frac{\mathbb{P}(t \leq T < t + y | T \geq t)}{y}.$$

In our analysis, the hazard function is represented by

$$h(t, \mathbf{x}, \mathbf{z}(t)) = h_q(t) \exp\left(\sum_{i=1}^{p_1} \beta_i x_i + \sum_{j=1}^{p_2} \delta_j z_j(t) \right), \tag{14}$$

where $\mathbf{x} = (x_1, x_{2,} \ldots, x_{p_1})'$ is a time-independent vector of variables, i.e., industry,

[18]Our approach is similar to [85] who use a logistic model to show that changes in CDS spreads increase the likelihood of future rating events. However, our analysis differs from theirs as we use a much longer and more extensive set of firms in our sample, and control for a number of variables that can potentially predict future rating changes.

rating agency, and year-fixed effects, and $\mathbf{z}(t) = (z_1(t), z_2(t), \ldots, z_{p_2}(t))'$ is a time-dependent vector of covariates affecting the hazard rate of having rating changes (i.e., CDS spreads, bond spreads, and accounting variables). When $\delta_j = 0$ for all j's, the above equation (14) is known as the Cox proportional hazard (Cox PH) model, where $h_q(t)$ is the baseline hazard function. The baseline function is semi–parametric and hence we do not need to define the functional form for $h_q(t)$. We further allow $h_q(t)$ to be different for different rating levels, i.e. strata. Arguably, a one unit rating change for a lower-rated firm and a higher-rated firm may be perceived differently by investors. This intuition is supported by our results in Table 15, which shows that *Previous Rating* robustly explains the difference in firms' stock price reactions to credit rating downgrades. Therefore, credit rating agencies may use a different model to decide when to revise their ratings on a lower-rated firm relative to a higher-rated firm. The use of stratification controls for a predictor that does not satisfy the proportional hazard assumption.[19] In our estimation, we allow firms in different rating levels to have different baseline hazard functions $h_q(t)$, while sharing the same coefficients β_i and δ_j. The model is estimated using maximum likelihood at the issue-month level.

Table 18 presents the results from estimating the hazard model in equation (14) separately for downgrades (Panel A) and upgrades (Panel B). All explanatory variables are described in Appendix B and are lagged by one period. We also control for credit watch announcements in all regression models using the indicator variable *Credit watch dummy*, which indicates whether the firm (or bond issue) is put on credit watch prior to a credit rating change.[20]

[19] We confirm the importance of using rating scale as the strata by testing whether the proportional hazard (PH) assumption holds. Following the test of [74], we reject the PH assumption when using rating scale as a predictor for downgrades at the 5% level.

[20] This monthly indicator variable is equal to one from the month of the watch announcement to the month of the rating change event, or until "Off Watch" or "Not On Watch" is announced. For downgrades, only negative watches are considered while for upgrades, only positive watches are considered. Credit watch announced 180 days or more prior to when a firm is re-rated is not

The variables of interest in Table 18 are average CDS spreads, bond yields and their changes. Bond yields are calculated as the trade-weighted average monthly bond yield at the issue level. We require that firms in the estimation sample have CDS spreads currently traded on their debt. We use 5-year to maturity CDS spreads as they are the most liquid. Our primary CDS data are from CMA Datavision. We also supplement CMA data with CDS quotes from Markit. We obtain corporate bond data from TRACE, which contains individual bond transactions starting from July 1, 2002. Corporate bond data prior to July 2002 is obtained from Mergent FISD historical NAICS database. We also include industry, year and rating agency-fixed effects in all hazard model regression specifications.

In Table 18 regression model (I), we test whether recent changes in CDS spreads and bond yields are informative about future rating changes. We find a positive and significant coefficient on *CDS Spread Change*, suggesting that an increase in CDS spreads in the prior month increases the likelihood that the firm will be downgraded. The coefficient on *CDS Spread Change* is negative, but not statistically significant for upgrades. Our findings that CDS spread changes are predictive of rating downgrades, but not upgrades, are consistent with prior results shown in Figure 6. Interestingly, we find that the coefficient on *Bond Yield Change* is negative and weakly significant for downgrades, which is counter-intuitive from the credit risk perspective. A possible explanation could be the relatively low liquidity and high trading costs in the corporate bond market, which might cause the prices between these two instruments to diverge. Because of the relative liquidity advantage, the CDS market is likely the more attractive trading venue for hedgers, speculators, and short-term investors as opposed to long-term investors in the bond market (see [115]). The heterogeneous investor base in these two markets and their different trading frequencies in response

considered to be related to the rating change event. Credit watch data is obtained from Mergent FISD and Moody's Default Risk Database (MDRS).

to information-related events could further render bond yields stale.

Regression model (II) in Table 18 compares the predictive power of CDS spreads versus bond yields on rating downgrades and upgrades. We again find that the coefficient on *CDS spread* is positive and significant only for downgrades, but not upgrades. This suggests that a higher CDS spread level in the current month increases the likelihood that the firm will be downgraded in the following month. However, the coefficient on *CDS spread* is negative for predicting rating upgrades, which is consistent with the general observations that higher rated firms have lower CDS spreads, though it is not statistically significant. The sign on the coefficient for *Bond Yield*, for both upgrades and downgrades, is somewhat unexpected. As discussed previously, this could be due to the low bond market liquidity. The regression model (III) includes both CDS spreads, bond yields and their changes. Overall, the results remain qualitatively similar for this specification too. We conclude that the level of CDS spread and the change in CDS spreads have incremental predictive power for future rating downgrades, after controlling for credit watch events and other standard accounting variables.

2.5.3 Predicting default

We examine whether the information embedded in CDS spreads can improve the estimation of default risk under the physical measure using a hazard model. We follow the approach similar to the hazard model for predicting rating changes described in Section 2.5.2, however, the event of interest here is the firm's actual default date. Data on firms' default history is obtained from Moody's Ultimate Recovery Database (Moody's URD), which contains information on all bonds rated by Moody's during our sample period 1996–2010. Moody's URD has information on default history of the bonds and recovery rates in the event of default ([49], and [36]). We restrict our attention to firms that are in the intersection of Moody's URD, CRSP, COMPUSTAT, and the CDS databases during 1996-2010. We use Moody's definition of default in our analysis. The sample includes 616 firms of which about 6 percent of them experienced default.

We estimate the extended Cox model similar to equation (14) at the firm-month level. Because the number of defaults observed is small, we do not allow for stratification. Table 19 reports the results. All regression models include accounting variables that have been shown to predict default. The first regression model (I) shows that credit rating levels, defined as the average ratings of the three agencies, significantly predict future default. The pseudo R^2 is about 69% suggesting that credit ratings along with standard accounting variables can explain a significant variation of default risks across firms.

In the regression models (II)–(IV), we test whether the level of CDS spread, and the change in CDS spread can improve default risk estimation. Based on the R^2, we find that each of these two pieces of information extracted from CDS spreads do not improve default risk modeling relative to the model that relies on credit ratings (model (I)). The coefficients *CDS Spread* and *CDS Spread Change* are positive and significant, which is consistent with the prediction of the structural model that the risk-neutral and physical default probabilities are positively correlated (see equations (8) and (9)).

The regression model (V) in Table 19 reports estimation results of the hazard rate model when both credit ratings and CDS-related variables are included. We find a substantial increase in pseudo R^2 from 69% to about 78%. Importantly, we find the coefficients on credit ratings, as well as on the two CDS variables are mostly significant with their signs consistent with the prediction of the structural model. Overall, the results in Table 19 show that both credit ratings and CDS spreads carry important information for modeling default probability. In other words, information extracted from CDS spreads substantially improves the default prediction model when used jointly with credit ratings.

2.6 *Price discovery before rating change announcements*

This section tests Hypothesis 4 of the paper. We examine whether the CDS market leads other market measures embodying risk-neutral default probabilities, e.g., stock and bond prices. We first show that the CDS market's information share of credit price discovery relative to the bond market increases substantially before credit rating downgrades. After, we show that unanticipated changes in CDS spreads lead stock returns particularly before rating downgrade announcements.

2.6.1 Credit price discovery in the CDS and bond markets

We examine how much the CDS market contributes to credit price discovery particularly in the period prior to credit rating downgrades. We follow the method in [21] and study lead-lag dynamics of CDS and bond spreads using the Vector Error Correction Model (VECM). We choose the VECM approach because the approach conveniently allows us to examine which of the two markets is more important for credit price discovery using the Hasbrouck's (1995) "information share" measure. Further, the theoretical equivalence between CDS and corporate bond spreads suggests that the two time-series are cointegrated through a long-run relationship. The VECM is therefore a suitable technique because it adjusts for their long-run changes, as well as deviations from equilibrium.

We estimate the VECM in two steps. First, we estimate the following first-stage regression model for each firm individually using all daily oberservations:

$$CDS_{i,t} = \alpha_{0i} + \alpha_{1i} CS_{i,t} + E_{i,t}, \tag{15}$$

where $CDS_{i,t}$ and $CS_{i,t}$ are CDS and corporate bond spreads of firm i with the same maturity observed on day t. The residual term, $E_{i,t}$, represents daily deviation from the long-run relationship between CDS and corporate bond spreads. It is also referred to as the error correction term. Next, we apply residuals from the first-stage regression in equation (15) to estimate the following panel regression specification:

$$\Delta CDS_{i,t} = \lambda_1 E_{i,t-1} + \sum\nolimits_{j=1}^{5} \beta_{1j} \Delta CDS_{i,t-j} + \sum\nolimits_{j=1}^{5} \gamma_{1j} \Delta CS_{i,t-j} + \varepsilon_{1i,t} \tag{16}$$

$$\Delta CS_{i,t} = \lambda_2 E_{i,t-1} + \sum\nolimits_{j=1}^{5} \beta_{2j} \Delta CDS_{i,t-j} + \sum\nolimits_{j=1}^{5} \gamma_{2j} \Delta CS_{i,t-j} + \varepsilon_{2i,t}, \tag{17}$$

where $\Delta CDS_{i,t}$ and $\Delta CS_{i,t}$ are diferences in $CDS_{i,t}$ and $CS_{i,t}$ spreads for firm i between days t and $t-1$, respectively.

In equations (16) and (17), we are interested in the estimated coefficients λ_1 and λ_2, which show how CDS and bond spreads adjust after a deviation to their long-run relationship. When $E_{i,t-1}$ is positive, equation (15) suggests the CDS spread is too high relative to the bond spread and their long-run relationship predicts that the CDS spread will decrease ($\lambda_1 < 0$), while the corporate bond spread will increase ($\lambda_2 > 0$). A similar logic holds when $E_{i,t-1}$ is negative. The sign and magnitude of coefficients λ_1 and λ_2 are used to infer the information-flow direction and the adjustment speeds of the two securities. If both coefficients are significant with correct signs, i.e. $\lambda_1 < 0$ and $\lambda_2 > 0$, then both markets contribute to price discovery. However, when only λ_2 is positive and significant, the CDS market is the main contributor to price discovery because it suggests that corporate bond spreads adjust to reconcile their deviation from CDS spreads. Analogously, when only λ_1 is negative and significant, the bond market leads in the credit risk's price discovery.

We estimate the VECM system using daily CDS and bond spreads with constant 5-year maturity. We use CDS contracts that are written on senior debt and with no restructing clause. Unlike CDS contracts, corporate bonds do not trade at standardized maturities. Therefore, we need 5-year bond yields to match the constant 5-year CDS spreads. We follow the procedure similar to [21]. On each day and for each reference entity, we search for a bond with maturities between three and five years, and another bond with maturity of 6.5 years of more. We then linearly interploate between these yields to estimate a 5-year yield to maturity bond. Bond spread is calculated by subtracting bond yield with the constant 5-year Treasury rate.

In order for firms to enter our sample, we require that they have CDS and bond data traded simultaneously and continuously for at least two calendar years. This filter ensures that we can precisely estimate the first-stage regression in (15). This requirement leaves us with 305 firms. In order to use VECM analysis, we apply the Johansen trace test for cointegration between CDS and bond spreads. We find for 210 reference entities, their CDS and bond spreads are cointegrated with order one, i.e., $I(1)$. Our empirical analysis in this section is therefore based on 210 reference entities.

Table 20 reports results from the second-stage panel regression model in equations (16)–(17). We report results estimated from three estimation samples.[21] The first estimation sample uses all $249,306$ daily observations. The second estimation sample uses only daily observations that fall in the window [-90,-2] days relative to firms' rating downgrade announcements. This estimation period is used to examine credit price discovery prior to rating downgrade announcements. Finally, the third estimation sample uses only daily observations that fall in the window [-90,-2] days relative to firms' rating upgrade announcements.

Using all observations, we find the coefficient estimates of λ_1 and λ_2 are -0.017 and 0.033, respectively, and are statistically significant. This finding suggests that, on average, CDS and corporate bond spreads adjust toward their long-run relationship consistent with [21] who apply the VECM approach to 33 investment-grade firms. Using the VECM estimates in Table 20, we calculate the lower and upper bounds of Hasbrouck's (1995) measure of the CDS market contribution to price discovery.

[21]The first-stage regression (see equation (15)) is estimated for each firm individually using all available observations. To save space, we do not report their estimates.

Their expressions are given by

$$\mathrm{HAS}_1 = \frac{\lambda_2^2\left(\sigma_1^2 - \frac{\sigma_{12}^2}{\sigma_2^2}\right)}{\lambda_2^2\sigma_1^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2\sigma_2^2}, \quad \mathrm{HAS}_2 = \frac{\left(\lambda_2\sigma_1 - \frac{\sigma_{12}}{\sigma_2}\right)^2}{\lambda_2^2\sigma_1^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2\sigma_2^2}, \tag{18}$$

where HAS_1 and HAS_2 are the two bounds of Hasbrouck's measures. The remaining variables σ_1^2, σ_2^2, and σ_{12} in (18) are the covariance matrix terms between $\varepsilon_{1i,t}$ and $\varepsilon_{2i,t}$ in equations (16)–(17).

Table 20 shows that for the first estimation sample, the CDS market's contribution to price discovery of credit risk is between 81 and 85 percent, which is roughly in line with [21]. However, prior to rating downgrades, the contribution from the CDS market increases to between 90 and 91 percent. We also find that the coefficient $\lambda_2 = 0.037$ is positive and significant, while the λ_1 is no longer significant. This finding suggests that prior to rating downgrades, bond spreads always adjust toward CDS spreads in order to maintain their equilibrium relationship. In other words, the CDS market is the leading venue for credit price dicovery prior to rating downgrades. Given our finding that bond prices adjust following CDS spreads before credit rating downgrades, we expect firms with CDS trading to experience a weaker bond price reaction to rating downgrade announcements. We test this conjecture in the Internet B.1.8 section. Using the event-study method similar to our analysis for stock price reactions, we find that bond price reacts less to credit rating downgrades for firms with CDS trading.

We next turn to the VECM results for the period prior to rating upgrades. Table 20 shows the contribution of the CDS market to credit price discovery falls substantially, ranging between 51 and 56 percent. We also find the coefficient $\lambda_1 = -0.024$ is significant and negative, while λ_2 is not significant. This finding suggests that the bond market leads the CDS market in credit price discovery prior to rating upgrades.

Overall, the lead-lag analyses using the VECM show that on a day-to-day basis, both the CDS and corporate bond markets contribute to price discovery of their firm's credit risk. The contribution of the CDS market however, significantly increases over the quarter-period prior to rating downgrades where CDS spreads lead bond spreads in their daily changes. Whereas, in the quarter-period prior to rating upgrades, we find the opposite relation holds. Collectively, our results in Table 20 strongly support the main conclusion of this paper that the CDS market provides important information to equity and bond investors prior to rating downgrades, which explains why stock and bond prices react less to rating downgrades for firms with CDS trading on their debts.

2.6.2 Does information flow from the CDS to equity markets?

Following the empirical framework in [4], we study how the information flows between the CDS and equity markets by looking at the lead-lag relationship between CDS and stock returns. The objective is to test whether there is any incremental information in the CDS market that is not already contained in the equity market. An important concern with the lead-lag study between the credit and equity markets is that the two markets could be highly dependent. It is therefore important to remove components in CDS changes that are predictable using lagged CDS returns, contempraneous stock return, and lagged stock returns.

We regress daily CDS returns (i.e., percentage changes) for each firm i using past information up to five lags as follows:

$$\text{CDS return}_{i,t} = \alpha_i + \sum_{k=0}^{5} \beta_{i,t-k}\text{Stock return}_{i,t-k} + \sum_{k=0}^{5} \gamma_{i,t-k}\left(\frac{\text{Stock return}_{i,t-k}}{\text{CDS level}_{i,t}}\right) + \sum_{k=1}^{5} \delta_{i,t-k}\text{CDS return}_{i,t-k} + u_{i,t} \quad (19)$$

Besides lagged CDS, lagged stock returns, and contemporaneous stock returns, we include the ratio of past stock return to the current CDS spread in equation (19) to capture the nonlinear elasticity between CDS spread and equity value. The above regression is estimated for each firm separately. The residuals $u_{i,t}$ from the regression represent the unexpected change in CDS spreads that is unanticipated by both the equity and CDS markets. We refer to $u_{i,t}$ as CDS innovation, which is used in the second-stage regression for studying the information flow from the CDS market to the stock market. Consistent with [4], we find that R^2 from the unreported first-stage regressions are mostly in the single digits.

Next, we test whether the unanticipated component in CDS spread changes can predict future stock returns. We estimate the following panel regression specification:

$$\begin{aligned}\text{Stock return}_t &= a + \sum_{k=1}^{5} \left(b_k + b_k^d \text{ Rating-downgrade}_t + b_k^u \text{ Rating-upgrade}_t\right) \times u_{i,t-k} \\ &+ \sum_{k=1}^{5} \left(c_k + c_k^d \text{ Rating-downgrade}_t + c_k^u \text{ Rating-upgrade}_t\right) \times \text{Stock return}_{t-k} + \varepsilon_t\end{aligned} \tag{20}$$

where $u_{i,t-k}$ is the CDS innovation on day $t-k$ estimated from equation (19). We also include lagged stock returns in the above equation to ensure that any relationships between past CDS innovations and future stock returns are not artifacts of stock return autocorrelations. We introduce two new variables in the above regression specification. *Rating-downgrade*$_t$ is an indicator variable equal to one on day t if it is within [-90,-2] days of credit rating downgrades, and zero otherwise. This variable is designed to capture information flow from the CDS to equity markets that occurs before rating downgrade announcements. Similarly, *Rating-upgrade*$_t$ is an indicator variable equal to one on day t if it is within [-90,-2] days of credit rating upgrades, and zero otherwise.[22] For our analysis, we use CDS spreads with the constant 5-year maturity because they are the most liquid. We also consider only CDS spreads that are written on senior debt and those without a restructuring clause. Table 21 reports results based on the regression model in equation (20).

[22]We obtain similar conclusions when replicating the results with rating condition dummies defined over the following event windows [-60,-2], [-60,+30], and [-30,+30] relative to rating change events.

The regression model (I) in Table 21 reports results based on equation (20) without *Rating-downgrade*$_t$ and *Rating-upgrade*$_t$. In this case, the coefficient $\sum_{k=1}^{5} b_k$ quantifies the amount of information discovered through the CDS market that is informative of future stock prices on the day-to-day basis. Table 21 shows that $\sum_{k=1}^{5} b_k$ $= -0.0074$, which is negative and significant at the 10 percent confidence level. The negative sign on the sum of coefficients is consistent with [104], which shows that as default risk increases equity price falls. However, the magnitude of 0.74% is economically trivial, suggesting that the CDS market, on average, is not substantially informative of the equity price. On the other hand, we find that past stock returns significantly predict future stock returns with the coefficient of -7.23%. This strong negative auto-correlation that we observe is consistent with the well-established mean-reversion characteristic of stock returns.

The regression model (II) in Table 21 reports results without *Rating-upgrade*$_t$. In this case, $\sum_{k=1}^{5} b_k$ and $\sum_{k=1}^{5} b_k^d$ quantify information flow from the CDS to equity markets in the periods that are outside and during rating-downgrades, respectively. We find that the flow measure during the rating-downgrade period $\left(\sum_{k=1}^{5} b_k^d\right)$ is negative and statistically significant, indicating an approximate 4.3% transmission of information from CDS innovation to future stock returns. We find the information flow measure outside the rating-downgrade period $\left(\sum_{k=1}^{5} b_k\right)$ is no longer significant, suggesting that the CDS market is not very informative of future stock returns outside the rating-downgrade period. Interestingly, estimates from regression model (II) show that past stock returns do not significantly predict future stock returns during the rating-downgrade period. This can be seen by the statistically insignificant estimates on $\sum_{k=1}^{5} c_k^d$.

Lastly, the regression model (III) reports results based on the model in equation (20) without *Rating-downgrade*$_t$. In this case, $\sum_{k=1}^{5} b_k^u$ captures the information flow from the CDS to equity markets during the rating-upgrade period. We do not find that the CDS market provides new information to the equity market during the period around credit rating upgrades. However, it is interesting to point out that stock returns are quite persistent when the firm experiences rating upgrades, which is observed through the positive and significant coefficients on $\sum_{k=1}^{5} c_k^u = 20.7\%$.

Overall, the results in Table 21 show that there exists significant information flow from the CDS to equity markets before the firm is being downgraded. We conclude that the CDS market is an important venue for equity price discovery prior to credit rating downgrades, providing support to explain why stock prices of firms with CDS trading react significantly less to credit rating downgrades. These results are consistent with [4] who document insider trading by privately informed parties in the CDS markets around negative events.[23]

2.7 CDS spreads and the cross-section of stock returns

The distress risk puzzle, i.e., lower-rated firms earn lower returns, has been documented by a number of empirical studies. In particular, [15] find that the puzzle is most pronounced around rating downgrades. In this section, we test Hypothesis 5 by examining the value of the CDS market in explaining the cross-section of stock returns for firms that are about to be re-rated.

We are motivated by [62] who estimate the equity risk premia from CDS spreads and show that they positively correlate with firms' stock returns. Their general idea is that the firm's equity risk premium is related their CDS spread dynamics under the risk-neutral ($\mathbb{Q}$) and physical ($\mathbb{P}$) measures, which can be extracted using the term structure of CDS spreads over time, i.e., panel CDS data. Building on the insight of the Merton's structural model, the equity risk premium, $\mu_E - r$, is related to the

[23]For instance, these informed parties could be banks that have relationships with firms and simultaneously act as intermediaries in the CDS market.

CDS excess return by

$$\mu_E - r = \frac{-\left(\mu_s^{\mathbb{P}} - \mu_s^{\mathbb{Q}}\right)}{\sigma_S}\sigma_E, \tag{21}$$

where $\mu_s^{\mathbb{P}} - \mu_s^{\mathbb{Q}}$ is the CDS spread excess return defined as the difference between the drifts under the physical and risk-neutral probability measures.[24] Equity volatility and CDS spread volatility are denoted by σ_E and σ_S, respectively. [62] suggest that equation (21), can be inferred from the CDS spread dynamics with constant maturity T as follows

$$ERP_{t+\tau}^{T} \equiv -\left(\frac{\log E_t^{\mathbb{P}}\left[S_{t+\tau}^{T}\right] - \log E_t^{\mathbb{Q}}\left[S_{t+\tau}^{T}\right]}{\sqrt{\int_t^{t+\tau}\sigma_{S,u}^2 du}}\right)\cdot\sqrt{\int_t^{t+\tau}\sigma_{E,u}^2 du}, \tag{22}$$

where $E_t^{\mathbb{Q}}\left[S_{t+\tau}^{T}\right]$ and $E_t^{\mathbb{P}}\left[S_{t+\tau}^{T}\right]$ denote the conditional time-t expectation of CDS spread at the future time $t+\tau$ under the $\mathbb{Q}$ and $\mathbb{P}$-measure, respectively. The denominator in the above equation (22) refers to the volatility of CDS spreads across the interval $[t, t+\tau]$, and $\int_t^{t+\tau}\sigma_{E,u}^2 du$ is the equity variance calculated over the same period. The term in brackets on the right-hand side of equation (22) can be usefully thought of as the Sharpe ratio of CDS spreads with constant maturity T.

We estimate equation (22) using the term structure of CDS spreads at various points in time. The method is based on the well-established approach of [38] in the fixed income literature. To save space, we describe the procedure in Internet B.1.10. We estimate one-year CDS-implied equity risk premium on a daily basis for each firm in the sample, i.e., $\tau = 1$ in equation (22). We refer to the estimate as ERP. In order for firms to be eligible for the equity risk premia estimation, they must have sufficient CDS quotes traded at maturities 1, 3, 5, 7, and 10 years. In Table B.12, we report portfolio characteristics sorted based on ERP, credit ratings, and CDS spreads. The sorting is done at the beginning of each month. We find that ERP positively and monotonically increases with average portfolio returns. This positively

[24]The risk-neutral drift of the CDS spread $\mu_s^{\mathbb{Q}}$ does not need to be equal to the risk-free rate as the CDS spread is not a traded asset, only the CDS contract is.

monotonic relationship, however, does not hold for portfolios sorted by either credit ratings or CDS spreads, confirming the findings in [62].

We next examine whether CDS implied ERP can explain the cross-section of equity returns of firms that are about to be downgraded. Panel A of Table 22 reports average one-year portfolio returns of firms before credit rating downgrades quintile–sorted based on ERP, credit ratings, and CDS spreads. Only firms that will be downgraded by one of the three rating agencies within the next 30 calendar days are kept in the sample. The average one-year returns of all portfolios in Panel A are negative, which is consistent with [47] who documented negative stock returns persisting for a year after downgrades. However, importantly for this sample, we find that ERP monotonically increases with average one-year equity returns. The difference in average one-year returns between the highest and lowest ERP-sorted portfolio is 29.2% and statistically significant at the one percent level. On the other hand, we do not find that sorting firms prior to rating downgrades based on their rating scales result in a cross–sectional difference in one-year equity returns. The relationship between credit ratings and one-year equity returns is not monotonic, and the difference in equity returns between the worst-rated group and the best-rated group is not statistically significant.

Similar to sorting based on credit ratings, we do not find that CDS spreads alone can explain the cross-section of equity returns before rating downgrade announcements. Interestingly, sorting portfolios based on credit ratings and CDS spreads produces results that are synonymous with the distressed puzzle, i.e., firms with higher CDS spreads (worse credit ratings) have lower expected equity returns.

We replicate the results in Panel A using firms that will be upgraded in the next 30 days, i.e. prior to rating upgrade announcements. The results are reported in Panel B of Table 22. Sorting based on either ERP, credit ratings or CDS spreads, we do not observe a strictly monotonic relationship in returns unlike in the case of downgrades. Overall, the results in this section show that the ERP estimated from CDS spreads perform better than credit ratings in explaining equity returns, especially before rating downgrade announcements.

2.8 Conclusion

We present evidence that firms' stock prices react significantly less to credit rating downgrades when they have CDS contracts trading on their debt. Our results are robust to different model specifications such as the instrumental variable regression and the propensity-score-matched difference-in-difference analysis. Drawing insights from the simple structural model, we examine various economic channels that can potentially explain our results. We show that CDS spreads contain information that anticipates credit rating downgrades as far as 180 days ahead of the revision date. Using a hazard model for default, we find that CDS spreads provide information that significantly helps improve historical default prediction. Further, the CDS market significantly contributes to price discovery in the stock and bond markets before rating change announcements, and CDS term structures contain information that allow equity investors to construct a more reliable measure of default risk premium than credit ratings.

Overall, our findings suggest that the CDS market leads, and provides new and complementary information to that already conveyed by credit rating agencies. Therefore, it may also be beneficial for regulators to design policies that can enhance the transparency and liquidity in the CDS market instead of focusing solely on regulating the credit rating agencies.

Figure 6: CDS-implied credit ratings

We plot daily averaged CDS-implied ratings over the interval [-360,180] days centered on the rating change events. The left (right) panels plot results for downgrades (upgrades) for three adjacent rating classes: A-BBB, BBB-BB, and BB-B. On each day, we classify firms according to their CDS spread into six rating classes; see Table B.1 in the appendix for the mapping. The CDS spread boundaries used to classify firms into rating classes are estimated non-parametrically following the method in [26] and [97]. The plotted CDS-implied ratings are daily averaged values across rating–change events. The y-axis in each panel indicates the credit rating classes. Higher credit rating classes imply higher default probability. The x-axis indicates event days relative to the rating change date. In each panel, the solid line plots the official ratings, in rating class scale, issued by credit agencies, while the dotted line plots average CDS-implied ratings.

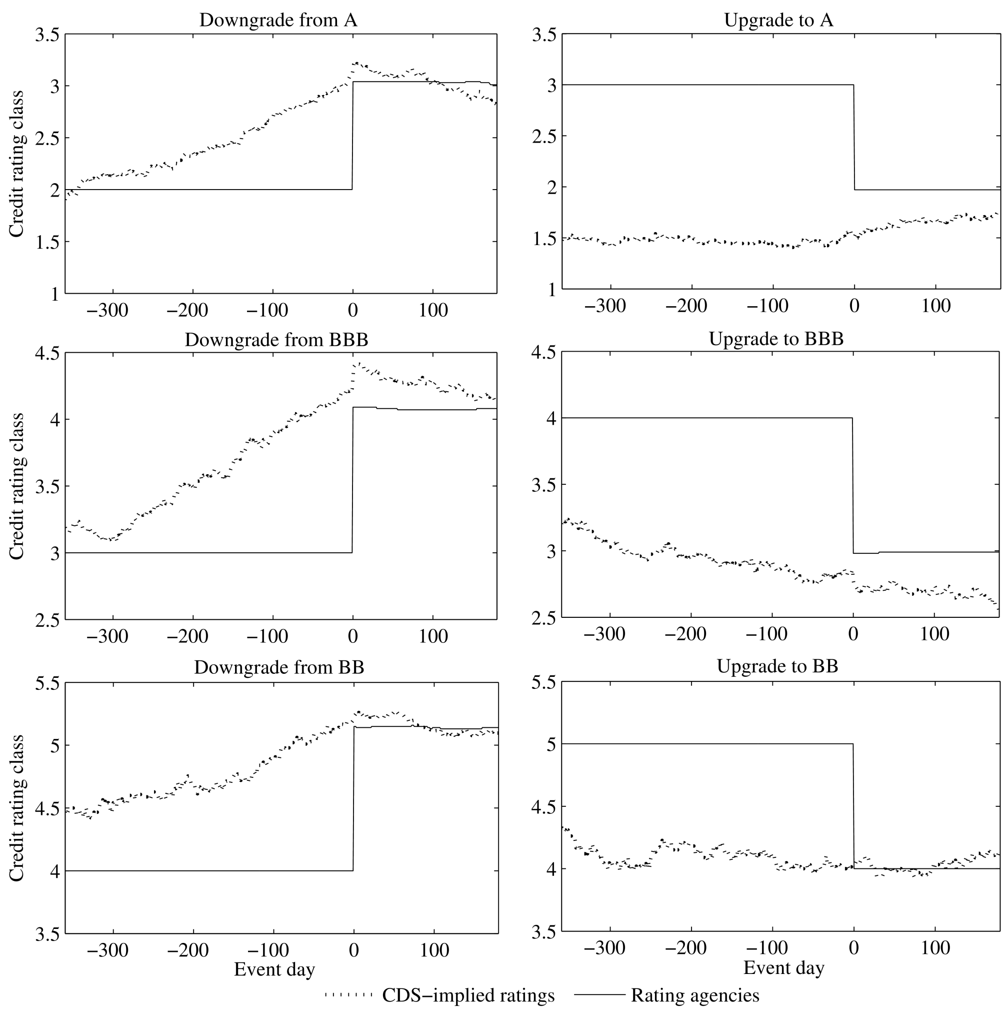


Table 14: Stock price reactions to rating changes

This table reports stock price reactions to bond downgrades and upgrades. The sample consists of credit rating downgrades and upgrades on taxable corporate bonds issued by U.S. firms from January 1996 to December 2010. Panel A reports results for the full sample, while Panel B reports results for the traded-CDS sample. The full sample consists of 4,665 credit rating downgrades and 2,171 credit rating upgrades. The traded-CDS sample (Panel B) consists only of firms that have CDS trading at any point in our sample period, i.e from 1996 to 2010. In each panel, we report cumulative abnormal returns (CAR) calculated over the 3-day event window (-1,+1), where day 0 represents the rating change event day. CAR is calculated using the market model. *Count* reports the number of rating change observations used in each CAR calculation. We report averaged CAR values separately for the Pre-CDS period and the Post-CDS period. Rating changes that occur in the presence of CDS trading are considered to be in the post-CDS period, while rating changes that occur in the absence of CDS trading are considered to be in the pre-CDS period. *Difference* reports the difference in averaged CAR values between the Pre-CDS period and the Post-CDS period. T-statistics are reported in brackets below each estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

Panel A: Full sample

	Downgrades		Upgrades	
	Mean CAR(%)	Count	Mean CAR(%)	Count
Pre-CDS	-5.10***	3249	0.16*	1482
	(-19.72)		(1.60)	
Post-CDS	-2.51***	1416	0.09	689
	(-6.42)		(0.61)	
Difference (Post−Pre)	2.58***		-0.07	
	(5.51)		(-0.39)	
Total	-4.31***	4665	0.14*	2171
	(-19.93)		(1.67)	

Panel B: Traded-CDS sample

	Downgrades		Upgrades	
	Mean CAR(%)	Count	Mean CAR(%)	Count
Pre-CDS	-2.87***	803	0.18	300
	(-7.23)		(0.85)	
Post-CDS	-1.92***	1029	0.06	574
	(-5.48)		(0.39)	
Difference (Post−Pre)	0.95*		-0.12	
	(1.79)		(-0.46)	
Total	-2.34***	1832	0.10	874
	(-8.89)		(0.82)	

Table 15: Regression analysis of stock price reactions to rating changes

This table reports regression results of stock price reactions to bond rating changes. The dependent variable is CAR (-1,+1) calculated over the 3-day event window around a rating change event using the market model. All the variables are defined in B.1. Robust t-statistics are clustered at the firm-level and reported in bracket. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

	Panel A: Downgrades			***Panel B: Upgrades***		
	Full sample		**Traded-CDS**	**Full sample**		**Traded-CDS**
	(I)	(II)	(III)	(I)	(II)	(III)
dCDS	2.08***	1.70**	2.59***	-0.14	0.03	0.08
	(3.38)	(2.39)	(3.73)	(-0.65)	(0.11)	(0.19)
Rating-level controls						
Prev Rating (log)	-3.04***	-3.19***	-3.48***	-0.16	0.02	-0.41
	(-3.42)	(-3.45)	(-2.99)	(-0.40)	(0.05)	(-0.69)
Abs Rating Change	-2.24***	-2.27***	-1.87**	0.03	0.01	0.04
	(-5.03)	(-5.08)	(-2.22)	(0.33)	(0.16)	(0.20)
Days Since Last Rating (log)	0.13	0.12	-0.02	0.09	0.10	0.18
	(0.54)	(0.50)	(-0.09)	(0.74)	(0.84)	(1.10)
Earnings Ann Related	-2.09**	-2.15**	-1.44	0.78	0.80	0.12
	(-2.20)	(-2.25)	(-1.20)	(1.34)	(1.36)	(0.13)
Firm-level controls						
Sales (log)	0.62	0.66	-0.27	-0.14	-0.17	-0.27
	(1.55)	(1.61)	(-0.63)	(-1.11)	(-1.30)	(-1.55)
Profitability	0.44	0.38	-0.59	0.85	0.79	0.66
	(0.32)	(0.28)	(-0.39)	(1.08)	(1.00)	(0.59)
Leverage	-3.38	-3.73*	2.18	0.20	0.11	0.59
	(-1.58)	(-1.71)	(0.75)	(0.32)	(0.18)	(0.59)
Mkt-to-Book	0.19*	0.20**	0.10	-0.02	-0.02	-0.00
	(1.96)	(2.07)	(0.85)	(-0.94)	(-1.00)	(-0.08)
Avg Volatility (log)	-0.78	-0.68	-0.33	0.19	-0.04	0.53
	(-1.52)	(-1.01)	(-0.43)	(0.83)	(-0.19)	(1.53)
Avg Trading Volume (log)	-0.81***	-0.86**	-0.52	0.15	0.18	0.01
	(-2.64)	(-2.51)	(-1.06)	(0.94)	(1.09)	(0.03)
Avg Return	7.16***	6.71***	8.02***	-1.38	-1.20	-1.98
	(4.33)	(4.11)	(2.71)	(-1.25)	(-1.05)	(-1.29)
CDS-trading controls						
Analyst Coverage (log)	0.12	0.22	-0.19	-0.06	-0.06	0.08
	(0.28)	(0.51)	(-0.26)	(-0.44)	(-0.38)	(0.43)
Analyst Dispersion	0.00	0.00	0.00	-0.00	-0.00	-0.01*
	(1.20)	(1.28)	(0.47)	(-0.42)	(-0.49)	(-1.80)
Institutional Ownership	1.32**	1.31**	-1.12*	-0.22*	-0.19	-0.10
	(1.99)	(1.98)	(-1.77)	(-1.75)	(-1.41)	(-0.43)
Stock Illiquidity	1.33	1.51	-3.39	0.87	0.94	10.25
	(0.56)	(0.64)	(-0.21)	(0.23)	(0.25)	(1.10)
Bond Illiquidity	-0.28	-0.23	-0.39	0.11	0.11	0.32**
	(-0.68)	(-0.57)	(-0.85)	(1.01)	(0.96)	(1.99)
Debt Outstanding (log)	-0.44	-0.44	-0.14	0.05	0.06	0.31
	(-1.17)	(-1.16)	(-0.28)	(0.42)	(0.45)	(1.65)
Fixed effects	Ind	Ind & Year	Ind	Ind	Ind & Year	Ind
Observations	4176	4176	1775	1972	1972	834
Adjusted R^2	0.123	0.124	0.091	-0.000	-0.004	0.000

Table 16: Instrumental variable regression of stock price response to rating changes

This table reports instrumental variable regression results of stock price reactions to bond rating changes. The dependent variable is CAR (-1,+1) calculated over the 3-day event window around a rating change event using the market model. All the variables are defined in B.1. Robust t-statistics are clustered at the firm-level and reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

	Panel A: Downgrades		*Panel B: Upgrades*	
	(I)	(II)	(I)	(II)
dCDS IV	6.10***	5.44*	0.13	1.44
	(4.44)	(1.76)	(0.17)	(1.23)
Rating-level controls				
Prev Rating (log)	-2.91**	-2.96**	-1.07	-0.76
	(-2.36)	(-2.35)	(-1.50)	(-0.99)
Abs Rating Change	-1.06*	-1.10*	0.20	0.23
	(-1.87)	(-1.94)	(1.35)	(1.57)
Days Since Last Rating (log)	0.21	0.19	0.22	0.27
	(0.75)	(0.71)	(1.13)	(1.30)
Earnings Ann Related	-1.25	-1.32	0.72	0.65
	(-1.01)	(-1.07)	(0.87)	(0.77)
Firm-level controls				
Sales (log)	0.15	0.11	-0.22	-0.38*
	(0.29)	(0.18)	(-1.02)	(-1.67)
Profitability	6.49*	6.52**	-0.03	-0.33
	(1.96)	(2.00)	(-0.02)	(-0.21)
Leverage	-0.01	-0.53	-0.14	-0.40
	(-0.00)	(-0.21)	(-0.16)	(-0.42)
Market-to-Book	0.03	0.03	0.03	0.04
	(0.29)	(0.33)	(1.16)	(1.34)
Avg Volatility (log)	-0.31	-0.35	0.96**	0.72*
	(-0.45)	(-0.44)	(2.39)	(1.83)
Avg Trading Volume (log)	-1.02**	-0.93**	-0.04	-0.02
	(-2.25)	(-1.99)	(-0.19)	(-0.09)
Avg Return	8.71***	8.15***	-0.97	-0.66
	(3.89)	(3.56)	(-0.63)	(-0.42)
CDS-trading controls				
Analyst Coverage (log)	0.40	0.45	-0.04	-0.02
	(0.74)	(0.83)	(-0.18)	(-0.06)
Analyst Dispersion	0.00	0.00	-0.00	-0.00
	(1.10)	(1.19)	(-0.90)	(-0.91)
Institutional Ownership	-0.02	0.08	-0.84***	-0.75***
	(-0.03)	(0.12)	(-3.22)	(-2.66)
Stock Illiquidity	-3.22	-2.70	-8.28	-8.03
	(-0.76)	(-0.63)	(-1.08)	(-0.95)
Bond Illiquidity	-0.77	-0.71	0.13	-0.02
	(-1.47)	(-1.14)	(0.67)	(-0.09)
Debt Outstanding (log)	-1.04**	-0.96	0.21	0.11
	(-2.04)	(-1.61)	(0.93)	(0.45)
Fixed effects	Ind	Ind & Year	Ind	Ind & Year
Observations	1966	1966	886	886
Adjusted R^2	0.128	0.133	0.014	-0.017

Table 17: Diff-in-diff regression of stock price reactions to downgrades

This table reports difference-in-difference regression analysis of stock price response to bond downgrades for the 1:5 propensity-score matched sample with replacement. The dependent variable is CAR (-1,+1) calculated over the 3-day event window around a rating change event using the market model. All the variables are defined in B.1. Robust t-statistics are clustered at the firm-level and reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

	Panel A: Matched sample		***Panel B: Subsamples (diagnostics)***			
			Treatment	Control	Post-CDS	Pre-CDS
	(I)	(II)	(III)	(IV)	(V)	(VI)
Diff-in-diff variables						
dTreatment×dCDS	2.58***	2.16**				
	(2.77)	(2.40)				
dCDS	0.00	-0.93	2.50***	0.10		
	(0.00)	(-1.06)	(3.22)	(0.12)		
dTreatment	-0.17	-0.27			2.27***	0.04
	(-0.25)	(-0.40)			(2.97)	(0.05)
Rating-level controls						
Prev Rating (log)	-3.72**	-3.76**	-2.69***	-3.69	-4.89*	-2.88***
	(-2.32)	(-2.32)	(-2.75)	(-1.41)	(-1.89)	(-2.59)
Abs Rating Change	-1.26***	-1.19***	-1.45**	-1.11***	-1.10*	-1.60***
	(-3.80)	(-3.46)	(-2.30)	(-2.91)	(-1.89)	(-6.25)
Days Since Last Rating (log)	0.45	0.33	-0.08	0.72	1.36**	-0.63
	(1.20)	(0.93)	(-0.29)	(1.31)	(2.55)	(-1.49)
Earnings Ann Related	-4.42***	-4.26***	-2.29	-5.59**	-5.05**	-2.61**
	(-2.87)	(-2.87)	(-1.51)	(-2.49)	(-2.29)	(-2.07)
Firm-level controls						
Sales (log)	-0.41	-0.37	0.22	-0.52	-0.64	-0.09
	(-0.72)	(-0.69)	(0.48)	(-0.62)	(-0.75)	(-0.16)
Profitability	-4.17**	-4.55***	-5.95***	-2.50	-5.10**	-2.65
	(-2.52)	(-2.80)	(-3.31)	(-1.01)	(-2.31)	(-1.26)
Leverage	0.40	0.85	1.90	-0.85	0.30	-1.26
	(0.17)	(0.38)	(0.59)	(-0.27)	(0.11)	(-0.40)
Mkt-to-Book	0.14	0.12	0.15	0.17	0.11	0.22
	(1.48)	(1.16)	(1.41)	(1.22)	(0.72)	(1.28)
Avg Volatility (log)	-0.71	-0.23	-0.89	-0.49	-2.00**	2.00*
	(-1.13)	(-0.28)	(-1.24)	(-0.51)	(-2.45)	(1.70)
Avg Trading Volume (log)	-0.39	-0.62	-0.30	-0.39	0.56	-1.67***
	(-1.06)	(-1.56)	(-0.64)	(-0.68)	(1.00)	(-3.06)
Avg Return	8.19***	8.58***	3.62	10.60***	9.19***	7.10***
	(3.62)	(3.90)	(1.38)	(3.49)	(3.12)	(3.13)
CDS-trading controls						
Analyst Coverage (log)	0.06	0.36	-0.09	-0.03	-0.23	-0.13
	(0.13)	(0.77)	(-0.12)	(-0.05)	(-0.32)	(-0.23)
Analyst Dispersion	0.01**	0.01**	0.01	0.01**	0.01	0.01**
	(2.52)	(2.54)	(1.40)	(2.04)	(1.43)	(2.17)
Institutional Ownership	0.44	0.07	-0.55	1.24	0.68	-0.02
	(0.82)	(0.13)	(-0.85)	(1.38)	(0.89)	(-0.03)
Stock Illiquidity	8.05	6.83	8.98	11.13	32.06*	-17.87
	(0.80)	(0.67)	(0.48)	(0.82)	(1.73)	(-1.35)
Bond Illiquidity	-0.42	-0.35	-0.92**	-0.10	-0.93	0.14
	(-1.04)	(-0.86)	(-2.18)	(-0.16)	(-1.37)	(0.34)
Debt Outstanding (log)	-0.77	-0.67	-0.12	-1.14	-0.81	-0.56
	(-1.36)	(-1.11)	(-0.23)	(-1.36)	(-0.96)	(-1.16)
Fixed effects	Ind	Ind & Year	Ind	Ind	Ind	Ind
Observations	4899	4899	1518	3381	2585	2314
Adjusted R^2	0.153	0.162	0.079	0.194	0.161	0.181

Table 18: CDS, and the predictability of rating changes

This table reports results from estimating the extended Cox model for predicting bonds' credit rating change events. The sample consists of corporate bonds issued by U.S. firms that have CDS contracts trading on its debt. We estimate the hazard rate function (see equation (14)) for the time-to-rating change events (in months) at the bond-issuance level. We allow the baseline hazard functions to differ between different credit rating levels, i.e. strata. Panel A reports results for downgrades, while Panel B reports results for upgrades. *Observations* and *Nob. events* indicate the number of issuance-month observations and the number of rating change events used in the estimation, respectively. *CDS spread* is the average 5-year CDS spread in the prior month (in %). *Bond Yield* is the trade-weighted average bond yield in the prior month (in %). *CDS Spread Change* is the log difference in 5-year CDS spreads at the start and end of the previous month. *Bond Yield change* is the log difference in trade-weighted average bond yields at the start and end of the previous month. *Credit Watch dummy* is an indicator variable equal to one if the firm has been put on the credit watch list. We obtain credit watch announcements data from FISD, as well as from Moody's Default Risk Database (MDRS). We only consider negative watches for downgrades, and positive watches for upgrades. All remaining explanatory variables are described in B.1 and are lagged by one month. All regressions include *industry*, *rating agency* and *year* fixed-effects. We report robust t-statistics clustered at the firm level in brackets below each estimate.

	Hazard rate of future rating change event					
	Panel A: Downgrades			***Panel B: Upgrades***		
	(I)	(II)	(III)	(I)	(II)	(III)
CDS Spread Change	0.42**		0.38**	-0.24		-0.23
	(2.56)		(2.36)	(-0.73)		(-0.68)
Bond Yield Change	-0.14*		-0.14*	0.11		0.05
	(-1.75)		(-1.75)	(0.50)		(0.23)
CDS Spread		0.01*	0.01*		-0.02	-0.02
		(1.95)	(1.70)		(-0.74)	(-0.76)
Bond Yield		-0.00	-0.00		0.01***	0.01***
		(-0.59)	(-0.44)		(4.19)	(4.74)
Credit watch dummy	1.69***	1.71***	1.70***	1.90***	1.89***	1.90***
	(19.65)	(20.11)	(19.83)	(11.44)	(11.53)	(11.43)
Market Cap (log)	-0.56***	-0.55***	-0.54***	0.37***	0.38***	0.38***
	(-6.30)	(-6.48)	(-6.21)	(2.75)	(2.83)	(2.78)
Profitability	-0.09	-0.08	-0.09	0.29	0.31	0.30
	(-1.56)	(-1.47)	(-1.54)	(1.47)	(1.56)	(1.48)
Long Term Debt-to-Assets	-0.02	-0.10	-0.10	-0.67	-0.63	-0.65
	(-0.04)	(-0.19)	(-0.18)	(-0.71)	(-0.66)	(-0.68)
Leverage	0.01***	0.01**	0.01***	0.03*	0.03**	0.03*
	(2.76)	(2.53)	(2.70)	(1.80)	(1.99)	(1.79)
Avg Trading Volume (log)	0.82***	0.80***	0.80***	0.23*	0.22*	0.23*
	(10.08)	(10.23)	(10.08)	(1.88)	(1.79)	(1.84)
Avg Volatility (log)	0.24**	0.21*	0.22*	-0.38	-0.37	-0.37
	(2.05)	(1.83)	(1.92)	(-1.62)	(-1.62)	(-1.62)
Avg Return	0.09	-0.13	0.08	-1.11*	-1.03	-1.12*
	(0.27)	(-0.38)	(0.24)	(-1.75)	(-1.59)	(-1.76)
Observations	206338	211259	206338	113639	115610	113639
Nob. events	7541	7640	7541	2251	2273	2251
Pseudo R-sq	0.088	0.087	0.089	0.057	0.057	0.058

Table 19: CDS and the predictability of defaults

This table reports results from estimating the extended Cox model for predicting default. We estimate the hazard rate function (see equation (14)) for the time-to-default events (in months) at the firm level. We obtain default and bankruptcy filing data from Moody's Ultimate Recovery Database (Moody's URD), FISD and Bankrupcy.com. The sample consists of U.S. firms that have CDS contracts trading on their debt at some point between January 1996 and December 2010 (i.e. traded-CDS firms). A firm is considered to be in default in the month that it misses a disbursement of interest and/or principal, as well as when it files for bankruptcy. *Observations* and *Nob. events* indicate the number of firm-month observations and default events used in the estimations. *Credit Rating* is the credit rating level, in cardinal scale, of the firm in the prior month averaged across the three rating agencies. *CDS spread* is the firm's average 5-year CDS spread in the prior month (in %). *CDS Spread Change* is the log difference in 5-year CDS spreads at the start and end of the previous month. All remaining explanatory variables are described in Appendix B and are lagged by one period. All regressions include *industry* and *year* fixed-effects. We report robust t-statistics clustered at the firm level in brackets below each estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

	Probability of default				
	(I)	(II)	(III)	(IV)	(V)
Credit Rating (Avg of 3 CRAs)	0.52***				0.61***
	(3.61)				(3.57)
CDS Spread Level (5yr)		0.16**		0.17***	0.12*
		(2.12)		(2.73)	(1.65)
CDS Spread Change (5yr)			2.85**	3.23**	3.83**
			(2.27)	(2.13)	(2.18)
Net Income-to-Assets	-5.16	-8.08	-9.68*	-12.64**	-14.22
	(-0.77)	(-1.08)	(-1.69)	(-2.09)	(-1.35)
Total Liabilities-to-Assets	3.52**	1.64	2.37	1.58	1.83
	(2.24)	(1.02)	(1.54)	(0.97)	(0.85)
Relative Size	0.34	-0.14	-0.42*	-0.21	0.24
	(1.47)	(-0.44)	(-1.87)	(-0.72)	(0.50)
Excess Return	-3.68***	-2.06	-1.52	-1.77	-4.13*
	(-3.02)	(-1.27)	(-1.02)	(-1.02)	(-1.87)
Market-to-Book	-0.15***	-0.39**	-0.47***	-0.42***	-0.37***
	(-2.79)	(-2.54)	(-2.87)	(-2.67)	(-3.28)
Avg Volatility (log)	2.58***	1.55***	2.08***	1.31**	1.40*
	(5.39)	(2.79)	(3.96)	(2.35)	(1.93)
Observations	54215	46470	45897	45897	45203
Nob. events	37	33	33	33	32
Pseudo R-sq	0.690	0.661	0.646	0.675	0.775

Table 20: CDS contribution to credit price discovery

We report coefficient estimates from the Vector Error Correction Model (VECM), and Hasbrouck measures of CDS spreads' contribution to the credit price discovery process. The sample consists of 210 reference entities for which the Johansen trace test statistics conclude that their daily secondary bond yields and CDS spreads are cointegrated $I(1)$ variables. Secondary bond yields data are obtained from TRACE, which starts in July 2001. Our sample period ends in December 2010. We use daily CDS spreads with a 5-year. We follow the method in [21] and estimate the constant 5-year maturity bond yield by interploating the daily bond yields curve. Corporate bond spread is the difference between the 5-year interpolated bond yield and the 5-year treasury yield. The coefficients λ_1 and λ_2 are estimates from the following second-stage panel regression

$$\begin{aligned}\Delta CDS_{i,t} =& \lambda_1 E_{i,t-1} + \sum\nolimits_{j=1}^{5} \beta_{1j}\Delta CDS_{i,t-j} + \sum\nolimits_{j=1}^{5} \gamma_{1j}\Delta CS_{i,t-j} + \varepsilon_{1i,t} \\ \Delta CS_{i,t} =& \lambda_2 E_{i,t-1} + \sum\nolimits_{j=1}^{5} \beta_{2j}\Delta CDS_{i,t-j} + \sum\nolimits_{j=1}^{5} \gamma_{2j}\Delta CS_{i,t-j} + \varepsilon_{2i,t},\end{aligned}$$

where $\Delta CDS_{i,t}$, and $\Delta CS_{i,t}$ are daily diferences in CDS and corporate bond spreads for firm i between days t and $t-1$. The error correction term, $E_{i,t-1}$, is obtained from the following first-stage regression estimated firm-by-firm using all daily oberservations:

$$CDS_{i,t} = \alpha_{0i} + \alpha_{1i}CS_{i,t} + E_{i,t}.$$

The residual term, $E_{i,t}$, represents daily deviation to the long-run relationship between CDS and corporate bond spreads. This table reports from the second-stage panel regression for the three estimation samples. The first estimation sample uses all daily observations available. The second estimation sample uses daily observations over a quarter-period prior to the firm's credit rating downgrades, i.e. [-90,-2] days relative to the event date. Similarly, the third estimation sample uses daily observations over [-90,-2] days prior to the firm's credit rating upgrades. Hasbrouck's measure provides upper and lower bounds to the price discovery contribution made in the CDS market; see equation (18). The coefficients λ_1 and λ_2 measure the relationship between changes in CDS and corporate bond spreads in relation to their cointegrated relationship. Robust t-statistics are clustered at the firm level and reported in brackets beneath the λ_1 and λ_2 estimates. Superscripts ***, **, * indicate significance at the 1, 5, and 10 percent levels, respectively.

Estimation sample	Observations	Vector Error Correction Model (VECM)				
		Coefficient estimates		Hasbrouck share of CDS market		
		λ_1	λ_2	Lower	Mid	Upper
(1) All observations	249306	-0.017**	0.033***	0.8143	0.8327	0.8511
		(-2.24)	(3.85)			
(2) Prior to downgrades	22529	-0.011	0.037***	0.9001	0.9073	0.9145
		(-1.20)	(2.90)			
(3) Prior to upgrades	12449	-0.024*	0.094	0.5074	0.5324	0.5574
		(-1.90)	(1.46)			

Table 21: Lead-lag analysis of CDS and stock returns

This table reports results from the panel regression of daily stock returns on lagged CDS innovations, and lagged stock returns under different credit-rating conditions. We estimate the following panel regression model:

$$\begin{aligned}\text{Stock return}_t =& a + \sum_{k=1}^{5} \left(b_k + b_k^d \text{ Rating-downgrade}_t + b_k^u \text{ Rating-upgrade}_t\right) \times \text{CDS innovation}_{t-k} \\ &+ \sum_{k=1}^{5} \left(c_k + c_k^d \text{ Rating-downgrade}_t + c_k^u \text{ Rating-upgrade}_t\right) \times \text{Stock return}_{t-k} + \varepsilon_t.\end{aligned}$$

We surpress firm-level notation above for brevity. Stock return at time t is calculated as the daily difference between the log of stock prices. *CDS innovation*$_t$ represents daily changes to CDS returns due to shock in the credit markets that is not anticipated by stock markets at time t. We estimate *CDS innovation*$_t$ using the residual from the first-stage regression according to equation (19). We interact lagged CDS innovations and stock returns with dummy variables indicating when the firm is under different credit-rating conditions. Regression model (I) reports results for the baseline regression without a rating-condition dummy. For the regression model (II), *Rating-downgrade*$_t$ is equal to one on days [-90,-2] relative to when the firm's credit rating is downgraded, and zero otherwise. For the regression model (III), *Rating-upgrade*$_t$ is equal to one on days [-90,-2] relative to when the firm's credit rating is upgraded, and zero otherwise. We report robust t-statistics clustered at the firm level in brackets beneath each estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

Dependent variable: Stock return$_t$			
	(I) None	(II) Downgrade	(III) Upgrade
Intercept	0.0004***	0.0004***	0.0004***
	(8.58)	(8.72)	(8.38)
$\sum_{k=1}^{5}$ CDS innovation$_{t-k}$	-0.0074*	-0.0038	-0.0054
	(-1.76)	(-0.97)	(-1.39)
$\sum_{k=1}^{5}$ Stock return$_{t-k}$	-0.0723***	-0.0672***	-0.0796***
	(-4.41)	(-4.65)	(-4.83)
$\sum_{k=1}^{5}$ Rating-downgrade$_t$ $\times$ CDS innovation$_{t-k}$		-0.0428**	
		(-2.12)	
$\sum_{k=1}^{5}$ Rating-downgrade$_t$ $\times$ Stock return$_{t-k}$		-0.0306	
		(-0.48)	
$\sum_{k=1}^{5}$ Rating-upgrade$_t$ $\times$ CDS innovation$_{t-k}$			-0.0513
			(-0.93)
$\sum_{k=1}^{5}$ Rating-upgrade$_t$ $\times$ Stock return$_{t-k}$			0.2074***
			(3.30)
Observations	286777	286777	286777
No. of clusters	345	345	345
Adj. R^2	0.17%	0.31%	0.20%

Table 22: CDS-implied equity risk premia and the cross-section of stock returns: Before rating change announcements

This table reports means of one-year portfolio returns based on quintile monthly portfolio sorts. The sample consists of U.S. firms that have CDS contracts traded with maturity of 1, 3, 5, 7, and 10 years. The portfolios are formed at the beginning of each month based on three dimensions: CDS-implied equity risk premia (ERP), credit ratings, and CDS spreads. We calculate CDS-implied ERP for each reference entity using its CDS term structures following the method in [62] (see Section 2.7 & B.1.10 for details). Average credit rating levels of the three rating agencies are used for portfolio sorting based on credit ratings. The level of 5-year CDS spreads are used for portfolio sorting based on CDS spreads. Panel A reports average one-year returns calculated using firms that are about to be downgraded. In Panel B, average one-year returns are calculated using firms that are about to be upgraded. Newey-West t-statistics adjusted for 11 lags are reported in brackets below the average portfolio returns. *, **, and *** indicate significance greater than 10%, 5%, and 1%, respectively.

Panel A: Portfolio-sorted average one-year returns before rating downgrades

	Average one-year return		
	Sorted by ERP	Sorted by Credit ratings	Sorted by CDS spreads
1 (lowest)	-0.456***	-0.386***	-0.139***
	(-17.95)	(-11.47)	(-4.84)
2	-0.333***	-0.250***	-0.169***
	(-8.94)	(-8.16)	(-5.55)
3	-0.326***	-0.366***	-0.320***
	(-8.33)	(-10.33)	(-9.30)
4	-0.302***	-0.290***	-0.405***
	(-8.53)	(-7.98)	(-12.19)
5 (highest)	-0.164***	-0.454***	-0.492***
	(-3.59)	(-12.21)	(-15.73)
5−1	0.292***	-0.068	-0.353***
	(5.59)	(-1.36)	(-8.32)

Panel B: Portfolio-sorted average one-year returns before rating upgrades

	Average one-year return		
	Sorted by ERP	Sorted by Credit ratings	Sorted by CDS spreads
1 (lowest)	-0.027	-0.021	0.103***
	(-0.61)	(-0.30)	(3.85)
2	0.083**	0.103***	0.110***
	(2.21)	(2.81)	(3.74)
3	0.160***	0.114***	0.088***
	(4.97)	(3.91)	(2.58)
4	0.117***	0.054**	0.102***
	(4.57)	(1.82)	(3.11)
5 (highest)	0.254***	0.241***	0.220***
	(9.07)	(10.06)	(7.10)
5−1	0.281***	0.262***	0.118***
	(5.39)	(3.53)	(2.87)

CHAPTER III

CREDIT DEFAULT SWAPS AND MORAL HAZARD IN BANK LENDING

3.1 Introduction

Credit Default Swaps (CDSs) are a relatively new financial instrument that allow lenders to reduce exposure to the credit risk of their borrowers. Credit risk transfer, through a CDS, can be used to hedge on-balance sheet asset credit risk. Commercial banks and other lenders are natural buyers of CDS protection to mitigate credit risk which helps free up regulatory capital,[1] diversify risk, and potentially increase credit supply to firms ([73, 119, 22, 133]). On the flip side, credit risk transfer through a CDS can reduce the incentives of banks to screen and monitor their borrowers, even though they still retain control rights[2] ([43, 117]). This separation of cash flow exposure and control rights could potentially give rise to an even stronger form of incentive misalignment, the *empty creditor problem* ([84, 22, 145]).

In this paper, we focus on the private debt market to study whether the initiation of CDS trading on borrowers' debt misaligns incentives between lenders and borrowers. Covenant violations and the consequent renegotiation between banks and borrowers provide an ideal setting to understand whether lender moral hazard exists when lenders can easily engage in credit risk transfer. Covenant violations give creditors contractual rights similar to those in the case of payment defaults – rights

[1]For instance, the Basel II regulation permits using a CDS as a hedge against loan credit risk if the CDS reference obligation (typically a bond) is junior to the loan being hedged

[2]Banks may now originate a loan, hold the loan on their balance sheet, and continue to service the loan without being exposed to the borrowing firm's prospects. Servicing includes monitoring the borrower and enforcing the covenants, even though economic exposure to credit risk is passed on to the credit default swap insurance provider.

include requesting immediate repayment of the principal and termination of further lending commitments – enhancing the bargaining power of lenders vis-á-vis the borrowers ([35, 112]). If the lenders are indeed empty creditors and intend to impose harsher renegotiated loan terms to extract rents or if they intend to push borrowers into bankruptcy, borrowers' covenant violations give lenders an ideal opportunity to do so. Covenant violations also allow us to employ a regression discontinuity design to help with identification.

There are potential countervailing forces against moral hazard in the private debt market that may not be as relevant for public bond holders. First, banks, in contrast to public bond holders, may face reputation costs if they push borrowers into inefficient bankruptcy or liquidation. These reputation costs are two-fold and are not directly modeled in the one period setup of [22]. One cost that lead-lenders face is the damage to their reputation in the loan syndication market in the event that the borrower files for bankruptcy ([70]). In addition, in a competitive lending market, a lender with a reputation of being an empty creditor, who imposes harsh renegotiated loan terms or pushes borrowers into bankruptcy, would be at a disadvantage. Moreover, lenders risk losing all the relationship-specific information and future profits in the case of borrower bankruptcy. These reputation costs may be large enough to discourage banks from engaging in the aforementioned exploitative behavior in a multi-period setting. Thus, whether or not lender moral hazard exists in the private debt market, is ultimately an empirical question that we address in this paper.

In order to answer this question, we first analyze changes in corporate policies of borrowers conditional on covenant violations in a regression discontinuity framework. [35] and [112] document that lenders in the private debt market use their bargaining power to influence borrowers' corporate policies after a covenant violation, and this type of creditor governance improves firm value ([113]). On the other hand, banks that hedge borrower exposure with CDSs, may be prone to moral hazard and not expend costly effort in negotiating and influencing firm policies. We find that borrowers with CDS trading on their debt do not reduce their investment after their covenant violations. This is in contrast to firms without CDSs which experience a significant reduction in firm investment. These results are broadly supportive of lender moral hazard and suggest that lenders do not expend much effort on influencing investment policies of borrowers after covenant violations when borrowers have CDS trading on their debt.

In the absence of availability of data on the exact net credit risk exposure of the lender to the borrower, we use other measures of lenders' propensity to engage in credit risk transfer and consequent lender moral hazard. We consider three proxies: banks' purchase of credit derivatives, their securitization activity, and their reliance on non-interest income. Consistent with our hypotheses, when lenders are more likely to lay off credit risk and exhibit moral hazard (i.e., banks that engage in credit risk transfer through credit derivatives or securitization, or rely more on non-interest income), we find that covenant violations do not have a material impact on a firm's investment policies.

A potential alternative explanation for our results could be that investment projects of firms with CDSs are more valuable and, hence, investment is not cut even after covenant violations. [35] show that there is a significantly larger decrease in firm investment post covenant violation when borrowers have information asymmetry or agency conflicts (as proxied by cash holdings and the length of the relationship with the lender), highlighting that inefficient investment is reduced. In contrast, we find that when lenders can purchase CDSs on borrowers, there is no significant drop in investment even when borrowers are more exposed to information asymmetry and agency problems. These results provide further support to credit risk transfer through CDS causing lender moral hazard.

We next consider the result of debt renegotiations after a borrower violates a covenant and when the borrower has a CDS trading on its debt. As discussed before, after the covenant violations, creditors can request immediate repayment of the principal and terminate further lending commitments. Alternatively, creditors can use their additional bargaining power and extract higher spreads on loans extended consequent to the covenant violation. Consistent with the argument that the availability of credit derivatives on the borrower's debt increases the lender's outside options ([22]) and, hence, their bargaining power vis-á-vis the borrower, we find that lenders extract rents after covenant violations by imposing higher spreads on renegotiated loans of borrowers with a traded CDS. These results suggest that the availability of CDS on borrowers induces lender moral hazard, where lenders do not expend costly effort to influence firm policies that increase firm value, but extract rents using their stronger bargaining power.

We next examine the effect of lender intervention on the stock returns of the borrowing firm after covenant violation in the presence of a traded CDS on the firm's debt. For non-CDS firms, we find that after a covenant violation, the actions taken by creditors to influence borrowers' policies increase the value of the firm ([113]). However, for firms with traded CDSs, the post covenant violation cumulative abnormal returns are not significantly different from zero and are negative in the long-run, indicating deteriorating firm performance. Consistent with this evidence, we find that firms with traded CDSs on their debt are more likely to experience a credit rating downgrade consequent to a covenant violation. Overall, these results again support the existence of lender moral hazard wherein the lender doesn't expend costly effort to influence firm policies to improve firm value. Instead, lenders renegotiate higher loan spreads post-covenent violation using their enhanced bargaining power. Consequently, firm performance deteriorates as evidenced by credit rating downgrades and lower stock returns.

One implication of severe moral hazard problems is that CDS trading may lead to higher borrower bankruptcies (see [22, 145]). Our results from a Cox proportional hazards model of the survival time of the firm after covenant violation suggests that CDS firms are neither more nor less likely to make a distressed exit or go bankrupt after a covenant violation than firms without CDS.[3] These results indicate that banks may not be actively causing firm bankruptcies due to overinsurance (empty creditor problem). Rules regarding risk-weighting of bank assets, such as those prescribed by Basel Accords, suggest why banks may not overinsure against borrowing firms. The risk weights, determined based on the credit rating of a borrower, can be substituted by those of the CDS protection seller when the CDS is used to hedge credit exposure from the borrower. Typically, as the CDS protection/insurance seller is better rated than the borrower, it leads to lower risk weights on the credit exposure. However, if CDS purchases lead to overinsurance, they are deemed speculative assets and receive higher risk weights. Thus, overinsurance can be quite costly for banks. Banks that do not overinsure are less likely to be empty creditors. Another potential reason could be the inability of banks, which are arguably more informed, to overinsure (as opposed to partially insure) against the borrower due to increased adverse selection problems making any marginal credit protection expensive, especially after a covenant violation.

Finally, we explore whether these ex-post lender moral hazard problems in the presence of CDS trading on borrowers are consistent with ex-ante loan announcement returns. Theoretically, [46] suggests that bank monitoring improves firm value. Empirical evidence that bank credit line announcements indeed generate positive abnormal borrower returns is presented in [109], [86], [101], and [20] among others. If capital markets anticipate lender moral hazard in the presence of CDS trading and, consequently, lower lender monitoring (see [43, 117]), then loan announcement returns

[3] Following [66] and [67], firms are identified as distressed if they are in the bottom 5% of the universe of firms in the Center for Research in Security Prices (CRSP) on the basis of the past three-year cumulative return.

for a firm with CDSs, should be relatively lower than returns for firms without CDSs. In the absence of any agency problems between banks and firms, the loan announcement returns of firms with CDSs should be statistically indistinguishable from firms without CDSs. We find that loan announcement returns for CDS firms are muted and not statistically different from zero. However, the loan announcement returns for non-CDS firms are positive and significant, which is in line with the previous studies.

Overall, our results complement and enrich our understanding of the impact of CDSs on the credit risk of the borrowers. [145] show that CDS introduction leads to a higher incidence of bankruptcy and credit rating downgrades for firms. However, they do not distinguish between public and private debt. In a related paper, [41] analyzes out-of-court restructurings of public debt and shows that firms with CDSs face difficulties with reducing debt out-of-court, thus increasing the likelihood of future bankruptcy. The dramatically different results that we document in the context of bankruptcy incidents after covenant violations on bank loans suggest that lenders in the private market behave very differently from public bond holders. In contrast to public debt holders, reputational concerns, future lending and non-lending business from established relationships, and lower debt renegotiation frictions due to concentrated ownerships are a few of the factors that can mitigate such severe moral hazard concerns in the private debt market.

Our work is also related to the contemporaneous paper by [137] who find that debt covenants are less strict if CDS contracts exist on the borrowing firm's debt at the time of loan initiation. Interestingly, we find that, even ex-post, lenders do not influence CDS firms to reduce their investment after covenant violations.

Our paper is related to work that examines the impact of credit transfer mechanisms on lenders.[4] However, CDSs are not the only mechanism that lenders have to

[4]The CDS market has grown quickly to an outstanding notional value as high as 5 Trillion U.S. dollars, or approximately 15% of the total over the counter derivative markets in the 2007–2008 period.

reduce their exposure to the borrowers. Some other possibilities are loan syndication, loan sales, and loan securitization. In the context of loan sales, [40] empirically show that firms whose loans are sold by their banks suffer negative stock returns, and suggest that a loan sale conveys the selling bank's private negative information on the borrower to the market. As [118] discuss, the broad difference between loan sales and a CDS purchase on a loan is that in the former cash flows are bundled with control rights, while in the latter they are not.

[148] show that banks impose less restrictive covenants in anticipation of securitization. However, [48] show that sold loans have significantly more covenants than loans that are not sold, reducing the financial flexibility of the borrowers. Securitization and hedging borrower exposure with a CDS have very different economic implications for lenders.[5] Our results contribute to this literature and highlight lender moral hazard when banks maintain control rights (but not economic exposure).

Our work also relates to the literature on the special nature of banks as information producers and monitors.[6] We show that the market reaction to a loan announcement is insignificant when there is a potential for lender moral hazard in the presence of CDS trading on the borrower's debt. However, the loan announcement returns for non-CDS firms are positive and significant, consistent with the previous studies.

The remaining sections are organized as follows. Section 3.2 discusses sources of data and summary statistics. Section 3.3 discusses our empirical specifications and results. Section 3.4 concludes.

[5] Also, as [148], among others, point out, generally loans of borrowing firms with high leverage, non-investment grade rating, and severe information problems are securitized. On the other hand, as [133] and our paper among others find, firms with CDSs traded against them are in similar, if not in better, financial health than other firms.

[6] [101] focus on the status of the lending relationship and find that new bank loans generate zero average abnormal returns, while loan renewals have a positive effect. The type of lender also matters. [86] finds that loans placed with banks have a higher announcement effect compared to loans placed through private placements. In contrast, [123] find a smaller return for bank loans. The findings of [20] suggest that the quality of the lender affects the market's perception of firm value.

3.2 Data

3.2.1 Data sources and sample selection

We utilize five main datasets for our analysis: (i) Loan Pricing Corporation (LPC) Dealscan database; (ii) Credit Market Analysis (CMA) Datavision dataset; (iii) Bloomberg; (iv) Markit; (v) Consolidated Financial Statements for Bank Holding Companies (FR Y-9C) and Bank Call Report data. We obtain firm-quarter level financial data from COMPUSTAT and equity return-related information from the CRSP.

Loan information is extracted from the Dealscan database. The basic unit of loans reported in Dealscan is a loan facility. Loan facilities are grouped into packages. Packages may contain various types of loan facilities for the borrower. Loan information such as loan amount, maturity, type of loan, and other information, is reported at the facility level. The database consists of private loans made by bank and non-bank lenders to U.S. corporations. The Dealscan database contains the majority of all commercial loans issued in the U.S. We construct our covenant violation sample following [35] for the period between 1994 and 2012[7]. We focus on loans of non-financial firms with covenants written on current ratio, net worth, or tangible net worth, as these covenants are more frequent and the accounting measures used for these covenants are unambiguous, standardized and less susceptible to manipulation.

The data on the timing of CDS introduction is obtained from three separate sources: Markit, CMA Datavision, and Bloomberg. The CMA Datavision database collects data from 30 buy-side firms which consist of major investment banks, hedge funds, and asset managers. [103] compare multiple CDS databases, namely GFI, Fenics, Reuters, EOD, CMA, Markit, and JP Morgan, and find that the CDS quotes in the CMA database lead the price discovery process. The CMA database is widely

[7] The covenant sample begins in 1994 as the information on covenants is limited before that period in the Dealscan database

used among financial market participants. We use the CMA database to identify all firms for which we observe CDS quotes on their debt. To further ensure the accuracy of CDS initiation dates on a firm, we augment the CMA database with the CDS data from Bloomberg and Markit. We take the earliest quote date from those three databases as the first sign of active CDS trading on a firm's debt.

As discussed later, our primary variables of interest in the combined dataset are (i) an indicator that shows if the firm violates a financial covenant, and (ii) an indicator that shows if the firm has outstanding CDS trades in the corresponding quarter. We do not have access to data regarding the exact firms against which lending banks protect themselves using CDSs. However, since CDS protection can only be obtained for firms with traded CDS, we divide firms based on traded CDS. We use the lead bank's Y9C and call report data to identify which lenders are active in the credit derivatives market. Arguably, most stock market participants and investors also may not have access to information on which specific bank loans are protected with a CDS. Hence, we believe that our analysis based on the credit derivative exposure of the bank and CDS trading for a firm is justified from a market investor's point of view. This is especially true when we try to assess the stock market reaction to loan announcements and covenant violations.

3.2.2 Descriptive statistics

Table 23 summarizes the statistics for the loan announcement sample. Loan agreements are significant external financing events: the median loan or commitment size is 31% of the firm's total assets, which also implies that the median loan announcer is not a very large firm. The median maturity of a loan is approximately four years. Panel B of Table 23 summarizes the number of loan announcements along with the mean size of the loan each year. There are about 1,200 loan announcements per year, which is consistent with previous studies. We observe that the number of loans issued increased from 1990 to 1997, before declining and plateauing thereafter. Since the recent financial crisis, the number of loans issued per year has almost halved. The increasing trend in the earlier part of the sample may be due to Dealscan's increasing coverage of issued loans over time. Panel B of Table 23 also shows that the average size of loan announcements has also increased over the years. There are 3,074 loan announcements for 507 unique firms where the borrowing firms have traded CDS contracts. On the other hand, there are 24,375 loan announcements for 5,962 unique firms when the borrowing firms have not traded CDS contracts. Table 23 also shows that the median loan size for firms that have CDS contracts traded is larger than the average loan size for firms that do not have CDS contracts traded. This difference in loan size leads us to specifically control for loan size in the latter part of the analysis.

Table 24, Panel A summarizes the statistics for the current ratio and net worth covenant samples from 1994 to 2012. The current ratio and net worth samples consist of all firm-quarter observations of non-financial firms in the COMPUSTAT database. These two samples are further divided based on whether a firm-quarter observation is determined to be in covenant violation (denoted by "Bind") or not in covenant violation (denoted by "Slack") for the corresponding covenant. Panel B displays the same set of firm-quarter observations split by firms with CDSs and without CDSs issued against them. The outcome variables and control variables used in the analysis for changes in firm characteristics when a covenant violation occurs are defined in the Appendix section. The distributions of the covenant violations and the control variables are in line with data used in previous studies (see [35] and [113]).

3.3 Empirical results

This section provides evidence regarding the existence of lender moral hazard in the presence of CDS trading on a borrowing firm's debt. It also tests if an empty creditor problem exists, and whether markets anticipate lender moral hazard. Sections 3.3.1, 3.3.2, and 3.3.3 test for moral hazard based on (i) lender intervention in the firm's operations, (ii) loan renegotiations after covenant violation, and (iii) the realized stock market returns in the post covenant violation period respectively. Section 3.3.4 tests for the presence of an empty creditor problem where banks can overinsure and cause a higher rate of firm bankruptcies by studying firm exit hazard rates post covenant violation. Finally, Section 3.3.5 tests whether capital markets anticipate and discount for the potential agency problems by comparing the stock market returns to the loan announcement conditional on whether or not CDS trades against a firm's debt.

3.3.1 CDS and Capital Expenditure After Covenant Violations

Financial covenant violations provide an ideal setting for studying agency problems that banks face in the presence of CDSs. Covenant violations give creditors contractual rights similar to those in the event of payment defaults, such as the right to request immediate repayment of the principal and terminating further lending commitments. Such rights provide creditors with a sudden increase in bargaining position post-violation. Hence, if agency problems between lenders and borrowers exist, they should manifest after covenant violation.

Granting waivers for a violation to a borrowing firm requires banks to investigate the firm's current condition, and its future prospects, and then handle each waiver on a case-by-case basis. This requires the lending bank to exert effort at a significant cost. Hence, if a bank hedges or reduces its exposure to a firm through CDS trading, and the firm violates a covenant, the bank may not have economic incentives to take corrective actions. To test for such lender moral hazard in the presence of CDS trading, we follow the regression discontinuity approach in [35].

The identification is based on comparing firms just around the contractually written covenant violation threshold. We compare the average treatment effects (ATE) of firms that violate a covenant and have a traded CDS, with firms that violate a covenant and do not have a traded CDS. [35] have shown that after covenant violation, creditors intervene and firm investment is reduced significantly. [112] show that such intervention helps the firm regain financial strength over time, helping equity holders as well. If banks with CDS protection intervene less in firm policy, then we should see smaller corrective changes, resulting in smaller drops in investment, for firms with CDSs traded against their debt than for firms without.

The empirical specification is as follows, where i is the subscript to denote a specific firm, and subscript t represents time quarter:

$$\begin{aligned} Investment_{it} = \alpha + &\beta_1 d\_Bind_{it-1} \times d\_CDS_{it-1} + \beta_2 d\_Bind_{it-1} \\ &+ \beta_3 d\_CDS_{it-1} + \beta_4 X_{it-1} + \eta_i + \delta_t + \varepsilon_{it}, \end{aligned} \tag{23}$$

where $Investment_{it}$ is the ratio of the capital expenditures to the capital in the beginning of the period. Our main variables of interest is the interaction term $d\_Bind_{it-1} \times d\_CDS_{it-1}$. d_Bind_{it-1} is an indicator variable equal to one if a firm i in quarter $t-1$ is in covenant violation and zero otherwise. Similarly, d_CDS_{it-1} is an indicator variable equal to one if there is a traded CDS contract for a firm i in quarter $t-1$. The coefficient β_1 captures the average difference in investment between a firm with a traded CDS and a firm without a traded CDS, after covenant violation. Coefficient β_2 captures the ATE of covenant violation for the firms that do not have a traded CDS. X_{it-1} is a vector of control variables to control for potential differences in dynamic firm characteristics that affect firm investment. η_i denotes firm fixed effects and δ_t estimates year-quarter fixed effects to control for unobserved heterogeneity across firms and time. Detailed variable definitions of the dependent variable and all the firm controls included in the regression specifications are provided in the Appendix.

Table 25, Panel A reports the results. The first three columns utilize the full dataset and the last three columns conduct the analysis using the regression discontinuity sample. The regression discontinuity sample limits the sample of observations to 30% of the relative distance around the covenant violation boundary. Columns (2), (3), (5), and (6) include firm level characteristics, and Columns (3) and (6) also include the distance from covenant violation threshold as additional controls.

The negative and statistically significant coefficients that we find on the *d_Bind* indicator variable confirm the findings of [35], who show that firms face a significant reduction in investment after a covenant violation due to creditor intervention. The positive coefficient on the interaction term $d\_Bind \times d\_CDS$ shows that firms which violate a covenant and have a CDS traded do not have as large a decrease in investment. In fact, adding the coefficients on *d_Bind* and $d\_Bind \times d\_CDS$, we note that the net effect of violating a covenant on firm investment is statistically indistinguishable from zero for firms with traded CDSs. The results hold through all six specifications. This supports the hypothesis that in the presence of CDS trading, which allows lending banks to reduce credit exposure to borrowing firms, banks do not intervene in changing firm investment policy after gaining control post covenant violation.

For a visual representation, Figure 7 plots firm investment with respect to the distance of the firm from the covenant violation threshold [8]. We consider two types of covenants, net worth and current ratio, and use the tighter of the two covenants when both are present to calculate the distance to covenant violation. The top panel reports the relationship between firm investment and the distance to covenant violation for firms which do not have CDSs traded against them. The bottom panel is for firms with traded CDSs. In the case of firms without CDSs, we note a significant decline in investments once a covenant is violated. However, in the bottom panel we do not see any marked change in firm investment for firms with a traded CDS.

[8] We also plot the polynomial fit for firm investment versus firm distance to covenant violation in the appendix section in Figure C.1

3.3.1.1 CDS and Borrower CapEx After Violations: Lender Heterogeneity

In this section, we delve deeper into the hypothesis that bank moral hazard is causing the muted reduction in firm investment after covenant violation. We investigate if lender characteristics that affect bank moral hazard have predictable effects on firm investment post covenant violation.

We match lenders from Dealscan to their parent bank holding companies (BHCs). Using the parent BHC's FR Y-9C reports, we gather data on their activities in the credit derivatives market, loan sales, and securitization market and the total amount of non-core banking activities. We are able to find matches for lenders for about 70% of the packages in our sample. Data for credit derivatives and securitization & loan sales are available from 1997 Q1 and 2001 Q2 onwards, respectively, while data on non-interest income is available for the entire sample period from 1994-2012. Detailed definitions for these lender variables are in the Appendix.

High (*Low*) lender activity for a specific lender variable is defined as the variable being above (below) its computed median value using the entire sample period over which data for it is available. Similar to specifications in Table 25, the dependent variable is *Investment* and the main independent variables of interest are *d_Bind*$\times$*d_CDS* and *d_Bind*. As before, along with firm level controls such as *Macro q*, *Cash Flow*, and *Assets (log)*, we also include the initial distance to the covenant violation threshold. The distance to threshold helps control for the probability of covenant violation (and ensuing conflicts of interest with the borrower) that the lender expects while setting the initial covenant tightness.

We find that banks that actively reduce their credit exposure – by either buying protection in the credit derivatives market or removing loans from their balance sheets by securitizing them and/or selling them in the secondary loan market – intervene less in borrowing firms' investment policies after covenant violation. Table 26, Panels A and B report these results for the full sample and the regression discontinuity sample, respectively. By noting the positive and significant coefficient of the interaction variable $d\_Bind \times d\_CDS$ in Column (2) compared to the statistically and economically insignificant coefficient in Column (1), we note that banks that have higher amounts of CDS protection bought, intervene less. This holds true for Columns (3) and (4) where banks with higher amounts of loans securitized, intervene less post covenant violation. Finally, Columns (5) and (6) show that banks that have higher amounts of non-interest income, i.e. banks with more non-core banking activities such as proprietary trading and investment banking activities, intervene less as well. Overall, banks that are more likely to hedge credit risk exposure intervene less in firms' investment policies post-violation. These results are consistent with a bank moral hazard argument.

3.3.1.2 CDS and Borrower CapEx After Violations: Borrower Heterogeneity

Table 27, Panels A and B conduct a test similar to the one above, where we investigate whether borrowing firm characteristics that increase intervention costs for the lender affect moral hazard. We examine two sets of problems that can increase the costs of monitoring for the lender: (i) agency problems, such as free cash flow problems, are exacerbated for firms that have a higher fraction of assets held as cash ([88]); and (ii) information asymmetry and related monitoring costs should be higher when firms have a shorter relationship history with the lending bank. Banks that are exposed to such agency and information problems have even higher incentives to intervene in firm policies after a credit event than in the case of firms in general. However, a creditor hedged with a CDS has less incentive to intervene after a credit event, even for firms with higher agency and information problems.

To conduct the test, we first divide our sample based on cash holdings and lending relationship length. These borrower characteristics, as we argued above, should affect the level of intervention post covenant violation, based on our hypothesis. Borrowing firms' cash holdings data is from COMPUSTAT and lending relationship length is obtained from Dealscan. *High* (*Low*) *Cash* is defined as cash being above (below) its computed median value using the entire sample period over which data is available. Lending relationship is computed at the firm level when a loan is made by summing up the lending relationships of all lenders in the syndicate. A *High* lending relationship sample corresponds to loans in which 30% or greater of the borrower's past loans have been made by the lending syndicate. A *Low* lending relationship sample corresponds to loans in which a borrower has no historical relationship with the lenders in the syndicate. As before, detailed definitions of these variables are in the Appendix.

Our dependent variable remains *Investment* and the main independent variables of interest remain the interaction term $d\_Bind \times d\_CDS$ and also d_Bind. Along with firm-level controls, we again include the initial distance to the covenant threshold to take into account potential future problems, such as covenant violation, that the lenders might anticipate.

Comparing Columns (2) and (1) for both panels, we first note that the coefficient of d_Bind is twice as large and negative for firms with higher cash holdings when compared to firms with low cash holdings. This result suggests that lenders recognize possible free cash flow problems and reduce investment in firms with more cash. Next, we note the positive and significant coefficient for the interaction term $d\_Bind \times d\_CDS$ for firms with a greater fraction of cash holdings. Thus, even though possible free cash flow problems are large, the net effect of the presence of a CDS is that there is effectively no reduction in firm investment after covenant violation. The same phenomenon holds true when we compare the coefficient of interaction terms in Columns (3) and (4) in either panel. Firms with shorter relationship history, which implies higher information asymmetry and higher costs of due diligence by banks, face less intervention in the presence of CDS trading.

A potential concern is that CDS traded firms tend to be large and if covenant violations are less constraining for larger firms then our results may possibly be driven by size [9]. In order to examine this we analyze the subsample of non-CDS firms by dividing it into small and large firms. Large firms are defined as firms with an asset value greater than \$1 billion (which is close to the median asset value of CDS firms). We follow the regression discontinuity setup as in column (4) of Table 25 and substitute d_CDS with the large-firm dummy d_Large instead. We find that the $d\_Bind \times d\_Large$ coefficient is indeed positive but statistically insignificant from zero with a t-statistic of 1.23 and a coefficient value of 0.006 which is half the magnitude of the comparable $d\_Bind \times d\_CDS$ coefficient in column (4) of Table 25.

Overall, these results further bolster the hypothesis that banks suffer from moral hazard in the presence of CDS trading, which results in muted or no corrective action after a credit event.

3.3.2 Debt renegotiation after covenant violation

As discussed before, intervention, renegotiation, and monitoring are costly to banks. If a lending bank has hedged or reduced its credit exposure to a borrowing firm by purchasing a CDS, then the lender may not have incentives to intervene and help improve the firm's future prospects. At the same time, the lending bank still has control rights over the firm, which allows it to renegotiate loans and grant waivers after covenant violation. Thus, in the presence of a CDS against the firm, a hedged lending bank may minimize the costly monitoring efforts post covenant violation.

If lending banks can overinsure themselves, through CDS, then arguably they will have a higher incentive to accelerate the loan payment by not granting a waiver and push the borrowing firm into bankruptcy (empty creditor problem). However, there are many reasons why banks cannot get overinsured against their borrowers:

[9] We control for firm-size and include firm fixed-effects in our covenant violation regression which should arguably address this issue to some extent. In unreported specifications, we also control for non-linear terms of firm-size and find that our results are qualitatively unaltered.

(a) regulatory reasons,[10] (b) adverse selection,[11] and (c) reputation concerns.[12] In such cases however, banks could grant waivers to borrowing firms and extract rents via the renegotiated loan terms due to their increased bargaining power vis-á-vis the borrower. This can be achieved, for instance, by imposing higher spreads or fees on renegotiated loans of borrowing firms that have violated a covenant.

Table 28 investigates changes in the major loan contract terms post covenant violation. We focus on loans initiated and amended by the same borrower-lead lender pair before and after covenant violation [13] . The loan issuance date post covenant violation is restricted to before the maturity of the loan facility which was affected by the violation, or within one year of the covenant violation, whichever is the shorter period. In addition to new issuances, we also gather data from the Dealscan facility amendment datafile on the covenant violating loan facilities. Again, we require that the amendment date be within one year of the covenant violation date.

Loan spread is the main dependent variable in our regression analysis. The main independent variable of interest is the interaction term $d\_AfterCovViol \times d\_CDS$. $d\_AfterCovViol$ is an indicator variable set equal to one for loan facilities initiated

[10] The rules regarding risk-weighting of bank assets, such as those prescribed by Basel Accords, may also suggest why banks do not overinsure against borrowing firms. A CDS purchased to hedge credit exposure receives a lower weight in terms of the risk based on the credit rating of the CDS seller according to the Basel credit risk methodology. However, purchases that lead to overinsurance are deemed speculative assets and receive higher risk weights as they are evaluated under the Basel market risk methodology. Thus, overinsurance can be costly for banks.

[11] One can purchase CDS protection only if there is a counterparty willing to sell it. Given that a lending bank is in an informationally advantageous position regarding a borrowing firm's health, it may be harder to find protection sellers to lay off credit risk at an attractive price, especially during or after a credit event like a covenant violation.

[12] The concern of losing future loan origination business or syndicate ties might deter lending banks from getting overinsured and pushing firms into bankruptcy after a credit event like a covenant violation. However, given that large banks with diversified businesses are more active in the credit derivatives market, reputation may be a weak disciplining mechanism for such lending banks (See [70]).

[13] When there is a unanimous decision among the lenders to restructure or refinance a given loan then the loan is entered as a new loan as opposed to an amended loan in Dealscan. Some of these loans are marked as refinanced loans but many are not. Whereas the facility amendment dataset in Dealscan mainly consists of amendments which requires a majority (51%) of lenders to agree to the amendment (See [128])

or amended after the covenant violation date and is set to zero otherwise. *d_CDS* is an indicator variable equal to one if the loan facility announcement occurs when CDS is traded on the underlying firm's debt, and zero otherwise. *d_TradedCDS* is an indicator variable equal to one if the firm in our sample has CDS traded on the debt at any point during our sample period, and zero otherwise.

By noting the coefficient of *d_AfterCovViol* in Column (1) of Table 28, we find that after covenant violation, the spread of the renegotiated loan increases, which is in line with the results in [113].[14] The coefficient in Column (1) of our variable of interest $d\_AfterCovViol \times d\_CDS$ suggests that firms that have CDS traded against them, experience an increase in spread of approximately 51%, or about 90 bps on average compared to firms that do not have a traded CDS. The summation of coefficients in Column (1) shows that post covenant violation, firms with a CDS experience a 65% increase in loan spread (by approximately 120 bps). The main observed change in loan terms post-violation is in the loan spread, through which the lending banks can extract additional rents.[15] Thus, renegotiation in the presence of CDS seems to only benefit the lending bank and not the borrowing firm.

The remaining columns investigate if extraction of rents is higher in cases where banks have a higher probability of hedging their economic exposure to borrowing firms. Columns (2)–(9) in Table 28 report the results for changes in loan spreads by dividing the sample by credit derivative market activity, securitization activity, proportion of non-interest income, and syndicate size, respectively. A larger syndicate size can imply a greater coordination failure among lenders upon a credit event incentivizing lenders to hedge themselves in the CDS market ([22]). Therefore using these subsamples we test the hypothesis that lenders who actively reduce their

[14]We also find that the maturity decreases and the syndicate size is also significantly reduced.

[15]In unreported tests, we also check non-price loan terms such as whether the loan is secured, or has performance pricing terms, sweep provisions. Although we note that CDS firms are significantly less likely to have secured loans and sweep provisions, we do not see a significant change in the non-price terms for CDS firms compared with non-CDS firms post covenant violation.

credit exposure extract more surplus from borrowing firms as a result of the higher bargaining power vis-á-vis the borrower.

The coefficients of interaction variable $d\_AfterCovViol \times d\_CDS$ in Columns (3), (5), (7), and (9) are all positive and statistically significant. This suggest that banks that have high credit derivative market activity, high securitization activity, a high proportion of non-interest income, and banks that have large syndicates, and are thus more likely to hedge credit risk of their borrowers, extract surplus by charging a statistically significant higher loan spread in the case that CDS trades on borrower debt. Overall, this evidence supports the hypothesis that banks attempt to extract additional surplus from firms where they have higher bargaining resulting from a lower credit exposure.

3.3.3 Equity return after violation

In this section, we examine the effect of lender intervention on the stock returns of the borrowing firm after covenant violation where there is a traded CDS on the firm's debt. [113] find that after a covenant violation, the actions taken by creditors to change the firm policy increase the value of the firm. On average, if creditor intervention improves firm quality, then the equity markets should respond with higher cumulative abnormal returns in the long run.

However, as discussed above, as a result of moral hazard stemming from the ability to buy CDS protection, creditors may not take corrective action post covenant violation. Creditors may not expend costly effort to reign in inefficient firm investment, and instead may extract higher surplus from firms. In such a case, firms should experience lower cumulative abnormal returns after a covenant violation. Therefore, in the long run, firms with a traded CDS should have lower cumulative abnormal returns after a covenant violation compared with firms that do not have a traded CDS.

We compare the stock return post-violation for firms with an outstanding CDS with firms without an outstanding CDS for the full sample as well as the regression discontinuity sample. As before, the regression discontinuity sample limits the observations in the sample to 30% of the relative distance around the covenant violation boundary. Following the regression framework developed in [146] and [135] and implemented in [113], we compute monthly abnormal returns using a four-factor model (three Fama-French factors and the momentum factor). We also account for delisting returns which are calculated from the CRSP delisting file. We then use the estimated model to calculate cumulative abnormal returns of each firm over various horizons after covenant violation. For our analysis, as in [113], we define a "new covenant violation" for a firm as a violation where the firm has not violated another covenant in the previous four quarters.

Figure 8 plots event-time abnormal returns after a new covenant violation, and compares the returns of firms with CDSs with those of firms without CDSs. The figure shows that in the post-violation period, firms without a traded CDS show substantially higher positive abnormal returns than firms with a traded CDS. The equity price of violating firms with a traded CDS also increases in the early part of the post-violation period, but then remains flat after about a year.

Table 29, Panel A reports the results of the monthly CAR regressions post covenant violation for the full sample of firms. Panel B reports the results for the regression discontinuity sample. The dependent variable is the monthly cumulative abnormal return *CAR* computed at various horizons. For instance, for every firm i and quarter q, *CAR(1,m)* is computed by summing up the monthly abnormal returns of firm i from the first month following quarter q until the m^{th} month. The main independent variables of interest remain *d_Bind* and *d_Bind*$\times$*d_CDS*. The control variables included in the regressions are *assets (log)*, *tangible assets*, *operating cash flow*, *book leverage*, *interest expense*, and *market-to-book*. All control variables are lagged by one quarter and their definitions are provided in the Appendix. All columns include firm level accounting variables as controls along with firm fixed effects and year quarter fixed effects.

Consistent with Figure 8 and the findings of [113], we note that the coefficient estimates of the *d_Bind* indicator variable suggest that on average violating firms experience positive stock returns after covenant violation. This can be attributed to a reduction in inefficient investment and an improvement of management discipline in general by lending banks that gain control rights. The coefficient estimates of the *d_CDS* indicator variable are not significant, suggesting that just the presence of CDS trading does not lead to a different stock market performance. The variable of interest is, as before, the estimated coefficient of the interaction between the *d_Bind* and *d_CDS* indicator variables. We note that over time, the coefficient of the interaction variable is statistically and economically significant and negative. The net effect on firms with a CDS traded against them post covenant violation is statistically indistinguishable from zero, as observed by the sum of the *d_Bind* and $d\_Bind \times d\_CDS$ coefficients.

We next carry out similar CAR regressions for our regression discontinuity sample. In support of our results from the full sample, we again find that violating firms with a CDS have much lower abnormal stock returns than firms without a CDS. The coefficient of the interaction variable, over 24 months, i.e., two years post covenant violation is -17% and is statistically and economically significant. The same remains true 30 months and three years out.

Overall, these results suggest the absence of lender intervention in the borrowing firm's interest when the firm has a traded CDS, which potentially allows creditors to hedge their credit risk.

3.3.4 Firm survival after covenant violation

If banks face an empty creditor problem, then firms should default more often in the presence of CDS trading. This is because in this extreme case of moral hazard, overinsured banks benefit from firm bankruptcy. As banks gain control rights after covenant violation, they should use these control rights to push firms into bankruptcy. To test this hypothesis, we conduct a survival analysis for firms after a covenant violation.

We first examine the frequency of firm exit from our sample. We identify firm exits from the CRSP delisting codes[16] and Moody's Ultimate Recovery Database (Moody's URD) which contains information on all bonds rated by Moody's.[17] Firms which do not have delisting codes in the CRSP dataset are classified as dropped due to financial distress, in case we also fail to find firm data on total assets, total sales, common shares outstanding, and the closing share price in COMPUSTAT.

Overall, we find that the frequency of firm exit within four quarters after covenant violation is 7.82% in our sample compared to a firm exit rate of 3.30% when there is no covenant violation. Distress related exits within the four quarters after covenant violations are 4.5% while non-distress related exits (mergers, going private) over the same period after covenant violation is 3.32%. We also note that only 5% of all the exits over fours quarters after covenant violations are CDS firms, whereas this number is 2% for our entire sample period.

We run a Cox proportional hazards model on loan-quarter observations, where the hazard rate is the likelihood of a firm exit after a covenant violation. The survival time

[16]Financial failure is defined as liquidation (400 – 490), bankruptcy (574). Other forms of firm exit include mergers (200 – 290), or going private (573). Active firms have codes ranging from (100 – 170).

[17]Moody's defines default as an event when one or more of the following occurs: (a) there is a missed or delayed disbursement of interest and/or principal, including delayed payments made within a grace period; (b) the company files for bankruptcy, administration, legal receivership, or other legal blocks to the timely payment of interest or principal; and (c) a distressed exchange takes place.

is measured in quarters from the firm's covenant violation until its exit. Specifically, we estimate the hazard rate $h(t)$ which is the conditional probability that a firm will exit between t and $t+\delta t$ conditional on surviving until time t. Formally, let T be the time when the firm exits. Then $h(t)$ is defined as:

$$h(t) = \lim_{\delta t \to 0} \frac{\mathbb{P}(t \le T < t + \delta t | T \ge t)}{y}.$$

In our hazard regression model, the hazard function is then represented by:

$$h(t, \mathbf{x}, \mathbf{z}(t)) = h(t) \exp\left(\sum_{i=1}^{k_1} \beta_i x_i + \sum_{j=1}^{k_2} \gamma_j z_{j,t-1} \right) \tag{24}$$

In the above equation, $\mathbf{x} = (x_1, x_{2,}, \ldots, x_{k_1})'$ is a time-independent vector of variables which consists of the initial covenant tightness, industry fixed effects and year fixed effects. $\mathbf{z}_{t-1} = (z_{1,t-1}, z_{2,t-1}, \ldots, z_{k_2,t-1})'$ is a time-dependent vector of lagged firm characteristics affecting the hazard rate of firm exit.

Table 30 reports the results. Specification (1) examines all firm exits, while specifications (2) and (3) examine distress related exits and non-distress related exits, respectively. An insignificant coefficient for the d_CDS indicator variable, which is our main variable of interest, suggests that CDS firms are neither more nor less likely to exit the sample after covenant violation. This result is evidence against the presence of a severe empty creditor problem where an over-hedged creditor has an incentive to push the firm into bankruptcy.

Next, we measure firm distress in an alternative manner. We define distress and outperformance based on [66] and [67], among others, to be the firms in the bottom and top 5% of the entire universe of firms in the CRSP dataset based on the past three-year cumulative return. The reason we focus on distress is because distressed firms are generally more likely to be bankrupt. The insignificant coefficient estimates on the d_CDS indicator variable for the distress regression in specification (4) based on cumulative equity return confirms our previous result that CDS firms are not more likely to be distressed when compared with non-CDS firms. As a comparison, we also investigate the probability of firms outperforming the universe of CRSP firms in Column (5). Interestingly, the negative and significant result on the d_CDS indicator variable suggests that firms with a CDS traded against them have a significantly lower likelihood of outperforming the universe of firms. These results suggest that creditors do not cause the CDS firm to be distressed or push them into bankruptcy after covenant violation as suggested by the severe empty creditor problem where lenders are over-hedged. However, if the creditors are at least partially hedged, they do not exert effort to improve firm performance either.

A concern may be that firms with a CDS traded against them are inherently different or distressed to begin with. To address such potential selection concerns regarding the presence of CDS trading, we employ an instrumental variables approach. Following [133], we instrument the presence of CDS trading by the average amount of forex derivatives used for hedging purposes relative to total assets of the lead syndicate banks and bond underwriters with which the borrowing firm has conducted business in the past five years. Data on bond underwriters is obtained from Mergent Fixed Income Securities Database (FISD). Following the methodology in [152], we use the fitted value from a probit model for *d_CDS* as shown in the appendix Table C.2 as an instrumental variable for *d_CDS*. We estimate the model for the determinants of CDS trading on firm-quarter observations for the full sample including additional controls that might affect the propensity of CDS trading on a firm. We then run a 2SLS regression using a linear probability model with the fitted CDS probability as an instrument. Table C.1 in the Appendix reports the results. As in Table 30, the negative coefficient in Column (1) for all exits, and the insignificant coefficients for the d_CDS indicator variable in Columns (2)-(4) suggests that CDS firms are not more likely to exit the sample after covenant violation. As before, Column (5) suggests that firms that have CDS traded against them have a lower likelihood of outperformance.

While exits and stock performance provide corroboration of our hypothesis of bank moral hazard in the presence of CDSs (but not the extreme case of an empty creditor problem), another firm event that can shed light on bank behavior before firm exit is a debt rating change. Hence, we examine the frequency of a rating downgrade or upgrade conditional on covenant violation. We gather rating change events from FISD and construct loan-quarter level observations post covenant violation. If a firm in a given quarter post covenant violation is downgraded (upgraded) by any of the three rating agencies – namely S&P, Moody's or Fitch – then an indicator varible d_DNG (d_UPG) is set to one; otherwise it is set to zero. We then run a hazard model similar to the firm exit regressions. However, in this case, the sample is limited to loan-quarter observations of rated firms.

Table 31 reports the results for the ratings change using a Cox proportional hazards model. Specifications (1) and (2) show that traded CDS firms are more likely to get downgraded, and not upgraded after a covenant violation compared with non-traded CDS firms. Columns (3) and (4) show that these results are robust to using the instrument variables approach for CDS trading as well.

Overall, the evidence above suggests that the lender moral hazard in the presence of CDS trading leads to under-performance of firms, but does not increase the likelihood of distress or default.

3.3.5 Loan announcement results

Do capital markets anticipate lender moral hazard in presence of CDS trading, and the resulting under-performance of firms due to lax monitoring? To answer this question, we focus on loan announcement results. The literature has shown that bank loan announcements lead to positive abnormal returns for stocks (see [109, 86, 101, 20] among others). The theoretical argument hinges on the special role of banks: bank monitoring increases firm value and loan issuance signals positive private information regarding the firm (see [46]). However, if the purchase of CDS protection by banks creates moral hazard, then equity holders who anticipate such agency problems should discount the significance of bank loan announcements. This, in turn, should lead to lower loan announcement abnormal returns for CDS firms when compared with non-CDS firms.

To test this, we conduct an event study on the abnormal return of firms' stocks around the loan announcement date (using the deal active date of a loan in Dealscan). We compare the loan announcement effect in a five-day window (-2,+2) for firms with CDS against their debt with those firms without. The null hypothesis is that there is no difference in the loan announcement return between firms with CDS and those without, and hence, the estimate of interest is the average effect of the presence of CDS trading on loan announcement returns.

We first compare the loan announcement effect for the full sample. The full sample includes both firms that never had CDS traded against their debt and firms that have had CDS traded at some point in the sample period. Table 32 reports the results. Consistent with previous studies, we find a significantly positive stock price reaction at the time of the loan announcement for the full sample. The average five-day abnormal return is 0.39%, significant at 1% level. These results are similar in magnitude to findings in the literature that suggests that bank loans are special in terms of providing monitoring benefits to the firm. However, we find that for loan announcements of firms with CDS, the stock abnormal return is close to zero (mean five-day CAR of 0.10%, which is statistically insignificant).

A potential concern is that the firms with CDS are inherently different from firms that have never had CDS traded. The right-hand side of the table reports the results only for firms that had CDS traded against their debt at some point in time, compared to the same firms when they did not have CDS traded against their debt. Even within this set of firms that have traded CDSs, the average five-day loan announcement abnormal return is 0.31%, significant at the 1% level, before the introduction of CDS trading, and in the period after the introduction of CDS trading, the five-day abnormal return drops to 0.08%, which is not statistically significant.

The univariate comparison of loan announcement returns described above suggests a possible decline in the traditional value that the market places on a bank's role after the introduction of CDS trading. We next conduct a multivariate regression analysis to examine whether this conclusion changes when we control for other determinants of borrower loan announcement abnormal returns identified in the literature.

The dependent variable for the multivariate analysis is the five-day (-2,+2) stock cumulative abnormal return (CAR) of the borrowing firm, where day 0 refers to the loan announcement day. The main variable of interest is, as before, the CDS indicator variable d_CDS, that takes a value of 1 if a firm has CDS trading on its debt at the time of the loan announcement and 0 otherwise.[18] If CDS trading leads to bank moral hazard that the market anticipates ex-ante, then we should expect the coefficient on the CDS indicator variable to be negative and statistically significant.

We employ four sets of controls to capture additional determinants of loan announcement returns: (i) loan-level characteristics; (ii) pre-announcement stock performance controls; (iii) firm level accounting variables as controls; and (iv) controls that may determine the presence of CDS trading. Loan-level characteristics include variables such as the interest rate spread at which the loan was obtained, the size of the loan, the horizon of the loan, and the number of lenders in the syndicate. All these characteristics contain potential information about the firm's future plans

[18] As discussed before, we do not have access to data regarding which bank obtains protection using a CDS against which firm. We divide firms based on traded CDSs. We think this approach is reasonable since stock market participants also may not have access to bank data regarding which bank loans are protected with a CDS. Hence, stock market participants also respond to loan announcements based on a similar information set, i.e., expected CDS exposure of the bank with respect to a firm.

and how banks perceive them. [95] show that firms tend to sell new equity claims following a run-up. If the issuance of bank loans are related to similar trends, then pre-announcement stock performance such as *Runup* and *Beta* of the firm's stock may be related to the abnormal return around loan announcement. We also include idiosyncratic volatility as an independent variable since shareholders in a risky firm might react more positively to the initiation of a loan and accompanied monitoring, than shareholders of a less risky firm (see [20]). [19] show that large firms are able to obtain large loans at lower interest rates. Hence, firm level accounting variables such as size of the firm and leverage may be relevant to firm performance around loan announcement. A loan announcement event for a profitable company or a firm with a high current ratio could convey a different signal to the market than an unprofitable firm or a firm with a low current ratio, which may require more monitoring. Consequently, we expect a relationship between variables such as profitability and current ratio and the abnormal stock return on the day of loan announcement. Firms with high market-to-book ratios tend to have more growth options, and hence, we expect alleviation of financial constraints to be especially important for such firms (see [63]). Since we are interested in the impact of CDS trading on bank behavior, we also included controls that may determine which firms have CDS traded against their debt.

Table 33 reports the loan announcement regression results for the full sample of firms. To address any industry level announcement effects, the specifications include industry fixed effects. The columns also include an indicator variable *d_TradedCDS* to control for firms that have ever had a CDS traded against them. This control helps address concerns about selection bias due to the inherent heterogeneity of firms that ever had a CDS traded against their debt. We also control for the purpose of the deal and time fixed effects.

All specifications (1)-(4) show that the coefficient of the CDS indicator variable

(d_CDS) is indeed negative and statistically significant in each case. As shown in specification (4), which is the most exhaustive, firms with traded CDS conservatively have approximately a 0.5% lower abnormal loan announcement return.

These results are consistent with the hypothesis that suggests that capital markets anticipate bank moral hazard ex-ante when firms with CDSs obtain loans.

3.3.6 Evidence against adverse selection

In this section, we further investigate whether selection in terms of the quality of firms that have traded CDS can explain the muted loan announcement response. The muted loan announcement returns could be because the quality of firms that have CDS traded against them is worse at the time of loan announcement. In other words, the presence of a CDS market allows lower quality firms to obtain loans, and hence, markets discount the loan announcements since the markets believe banks are not screening firms with CDSs carefully.

Table C.3 in the Appendix investigates this concern by considering various measures of firm health such as Altman Z-score, proportion of intangible assets, interest coverage, and cash flow volatility. Controls include firm level characteristics such as whether the firm has a rating, which may indicate different access to credit markets, firm size, leverage, market-to-book, profitability, and current ratio, and other characteristics that may affect the probability of CDS trading.

In Column (1), we note that the indicator variable CDS loads positively on the Altman Z-score, suggesting that firms with traded CDS are, in fact, in relatively better health statistically, and not worse health. A higher proportion of intangible assets at the firm may suggest higher information asymmetry and riskier loans. The insignificant coefficient of d_CDS in Column (2) shows this not to be the case. Firms with low interest coverage may be risky as they are closer to potential technical default. Column (3) shows that firms with traded CDSs do not have statistically different interest coverage than firms without. Cash flow volatility can also indicate firm level risk. Column (4) again shows that firms with traded CDSs are similar in this dimension as well to firms without traded CDSs. These results suggest that firms with traded CDSs are not in relatively worse financial health at the time of loan announcement. This evidence suggests that the quality of firms at the time of loan announcement cannot explain the muted response of the markets.

Another possible explanation for the muted loan announcement returns could be that the lenders lending to CDS and non-CDS firms are different. In that case, the loan announcement result between CDS and non-CDS firms may be driven by some unobserved heterogeneity among different lender-types. Table C.4 investigates this concern by including Lender fixed-effects in the loan announcement CAR regressions in specifications (1) & (2). Specifications (3) & (4) are more exhaustive and include both Lender and Firm fixed-effects. In all of the columns (1) – (4), the negative and statistically significant coefficients on *d_CDS* show that the even after controlling for lender heterogeneity, loan announcement returns for CDS traded firms are muted.

3.4 Conclusion

The growth of CDSs have allowed banks to now originate a loan and continue to service the loan without being exposed to the borrowing firm's prospects. This paper empirically investigates agency problems that banks may suffer in the presence of CDS trading. By analyzing changes in firm policy in case of covenant violations, we provide evidence consistent with the presence of bank moral hazard in the presence of CDS contracts. CDS firms do not decrease their investment after a covenant violation, even those that are more prone to agency issues. Moreover, consistent with the increased bargaining power of the lenders, CDS firms pay a significantly higher spread on loans issued after covenant violations than non-CDS firms that violate covenants. These results are magnified when lenders have weaker incentives to monitor (higher purchase of credit derivatives, higher amount of securitization, and higher non-interest income).

However, we do not find evidence in support of a more severe empty creditor problem, where banks overinsure themselves and cause firms to go bankrupt more often. Our loan announcement return results are also more consistent with lender moral hazard but not the empty creditor problem. The capital markets seem to anticipate this lender moral hazard, leading to insignificant loan announcement return, for firms with CDSs, as compared to positive returns for non-CDS firms. It seems, in contrast to public debt investors, the reputation of the lenders or regulatory capital requirements constrain private lenders to not overinsure themselves with CDSs, and push firms into inefficient bankruptcy or liquidation.

Figure 7: Investment vs distance to violation: CDS vs non-CDS firms

This figure plots investment vs distance to covenant violation. Distance to covenant violation is defined as the negative of the relative covenant distance for every firm-quarter observation ($-\frac{Ratio - CovenantThresholdRatio}{CovenantThresholdRatio}$). In case both, net worth and current ratio covenants are present, the tighter of the two is chosen to compute the distance to covenant violation. The plot displays the mean investment for 60 bins defined along the distance to covenant violation on each side with 95% confidence bands.

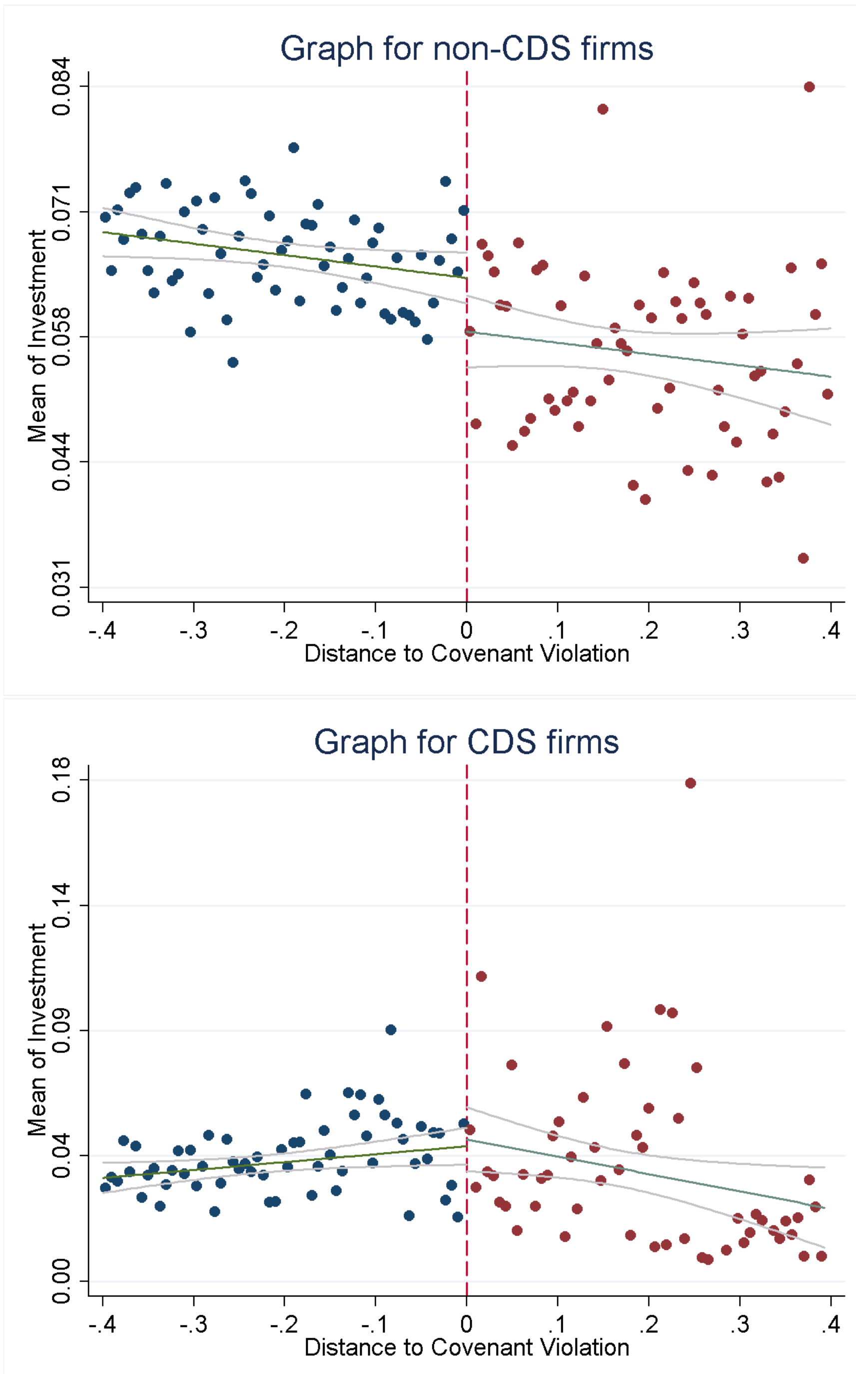


Figure 8: Financial covenant violations and stock price performance

This figure plots event-time abnormal returns post covenant violation for firms in the presence and absence of CDS on its underlying debt. Following the regression framework developed in [146] and [135] and implemented in [113], monthly abnormal returns are computed using a four-factor model (three Fama-French factors and the momentum factor) over the entire sample period by including dummy variables for the covenant violation event month and for months prior and post the event month for which we need to compute the monthly abnormal returns. We also account for delisting returns computed from the CRSP delisting file. The estimated model is then used to compute the monthly abnormal return for each firm and the cumulative abnormal returns. Data for the three monthly Fama-French factors and the momentum factor are gathered from Kenneth French's web data library.

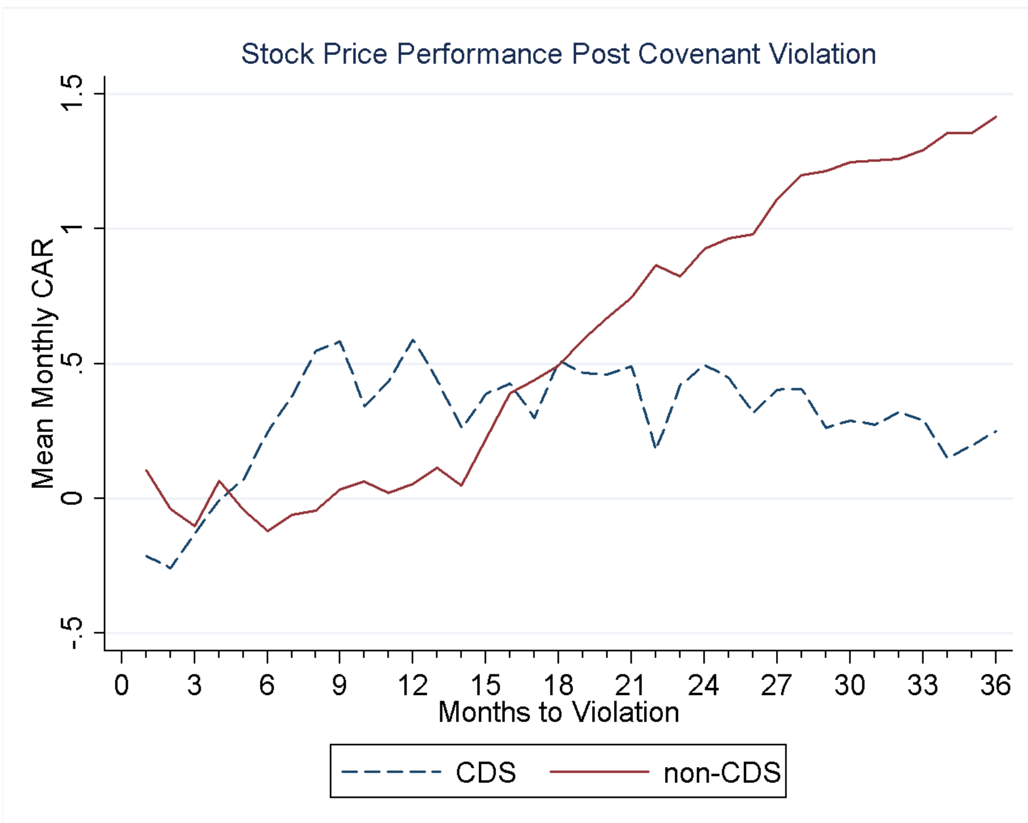


Table 23: Loan sample summary statistics

This table presents summary statistics (mean, median, standard deviation, and the 10^{th} and 90^{th} percentile) for the loan characteristics for all loans made to non-financial firms found in the Dealscan database during the period of 1990–2012. The sample consists of 5,951 firms and 27,450 packages and the following loan characteristics are at the package level. A package is a collection of loans made under a common agreement or a deal. Variable definitions for the loan and firm cahracteristics are provided in the Appendix section.

Panel A : Summary statistics of loan sample

	Mean	**Median**	10^{th}	90^{th}	**Std. Dev**	**N**
Loan Size (Mil)	352.030	127.000	10.500	1000.000	580.861	27449
Relative Loan Size	0.308	0.192	0.036	0.658	0.620	27449
Maturity (Months)	48.582	48.700	12.133	85.233	28.264	25946
Assets (log)	6.529	6.449	4.021	9.274	1.922	27450
Book Leverage	0.297	0.286	0.026	0.564	0.199	27120
Market-To-Book	1.658	1.352	0.898	2.815	0.933	26400

Panel B : Summary statistics by year

Year	**CDS=0**		**CDS=1**	
	Count (#)	**Loan Size (Median)**	**Count (#)**	**Loan Size (Median)**
1990	588	30.00		
1991	802	35.00		
1992	1019	40.00		
1993	1141	55.00		
1994	1436	75.00		
1995	1442	100.00		
1996	1806	77.00		
1997	2324	100.00		
1998	1840	100.00		
1999	1619	135.00		
2000	1502	150.00		
2001	1261	100.00	197	650.00
2002	1103	85.40	263	600.00
2003	971	100.00	308	500.00
2004	948	133.50	383	680.00
2005	847	165.00	399	750.00
2006	796	175.00	334	950.00
2007	711	225.00	338	1000.00
2008	485	150.00	136	750.00
2009	345	100.00	130	600.00
2010	484	200.00	178	917.50
2011	666	300.00	303	1000.00
2012	239	300.00	105	1250.00
Total	24375	100.00	3074	750.00

Table 24: Summary statistics of the covenant violation sample

This table provides the summary statistics for the covenant violation sample which was constructed based on [35]. The covenant sample begins in 1994 as the information on covenants is limited before that period. There are two main covenant samples included in the analysis - the current ratio covenant sample and the net worth covenant sample. The median and standard error are provided in square brackets and round brackets respectively.

Panel A provides summary statistics for the current ratio and net worth covenant samples from 1994 to 2012. The current ratio and net worth sample consists of all firm-quarter observations of non-financial firms in the COMPUSTAT database. The current ratio (net worth) sample consists of firms whose private loans have a current ratio (net worth and/or tangible net worth) covenant as per the Dealscan database between 1994 to 2012. These two samples are further divided based on whether a firm-quarter observation is determined to be in covenant violation (denoted by "*Bind*") or not in covenant violation (denoted by "*Slack*") for the corresponding covenant.

Panel B displays the same firm-quarter observations for CDS and non-CDS firms. The data on the timing of CDS introduction is obtained from three separate sources: Markit, CMA Datavision (CMA), and Bloomberg. Firm-quarter observations are classified as "CDS" observations if there are CDS contracts trading on the firm's debt in that quarter. The sample is further divided on whether the observation is determined to be in covenant violation for either the current ratio, net worth covenant, or both. Variable definitions of all the firm characteristics in the table are provided in the Appendix section.

Panel A: Current ratio vs net worth. Mean, Median, and Standard error

	Current Ratio				**Net Worth**			
	Bind		**Slack**		**Bind**		**Slack**	
Assets(log)	5.335	(0.034)	5.191	(0.013)	5.277	(0.034)	5.882	(0.011)
	[5.243]		[5.190]		[4.945]		[5.803]	
Market-to-Book	1.453	(0.022)	1.745	(0.014)	1.439	(0.022)	1.753	(0.014)
	[1.215]		[1.339]		[1.138]		[1.292]	
Macro q	4.991	(0.221)	9.733	(0.161)	6.847	(0.237)	10.370	(0.121)
	[1.974]		[3.713]		[2.375]		[3.739]	
ROA	0.016	(0.002)	0.034	(0.000)	0.005	(0.001)	0.035	(0.003)
	[0.026]		[0.034]		[0.018]		[0.033]	
Tangible Capital	0.506	(0.007)	0.334	(0.002)	0.298	(0.004)	0.316	(0.002)
	[0.477]		[0.259]		[0.231]		[0.241]	
Investment	0.066	(0.005)	0.099	(0.007)	0.050	(0.004)	0.086	(0.002)
	[0.043]		[0.055]		[0.025]		[0.048]	
Cash Flow	-0.051	(0.008)	0.100	(0.003)	-0.099	(0.008)	0.099	(0.002)
	[0.028]		[0.076]		[0.020]		[0.076]	
Book Leverage	0.433	(0.006)	0.258	(0.002)	0.401	(0.006)	0.244	(0.001)
	[0.384]		[0.232]		[0.358]		[0.235]	
Firm-Qtr Obs.	2353		11104		3388		23797	
Firms	395		901		541		1817	

Table 24 (continued)

Panel B: CDS vs non-CDS firms. Mean, Median, and Standard error

	CDS				Non-CDS			
	Bind		**Slack**		**Bind**		**Slack**	
Assets(log)	9.291	(0.040)	8.769	(0.022)	5.106	(0.023)	5.600	(0.010)
	[9.887]		[8.738]		[5.010]		[5.585]	
Market-to-Book	1.187	(0.016)	1.443	(0.018)	1.460	(0.017)	1.773	(0.012)
	[1.159]		[1.276]		[1.161]		[1.313]	
Macro q	6.468	(0.748)	7.568	(0.344)	6.055	(0.178)	10.419	(0.109)
	[2.478]		[3.512]		[2.119]		[3.801]	
ROA	0.027	(0.001)	0.032	(0.001)	0.009	(0.001)	0.035	(0.002)
	[0.025]		[0.032]		[0.020]		[0.033]	
Tangible Capital	0.368	(0.015)	0.340	(0.006)	0.389	(0.004)	0.320	(0.001)
	[0.347]		[0.270]		[0.300]		[0.244]	
Investment	0.041	(0.003)	0.047	(0.002)	0.059	(0.003)	0.093	(0.003)
	[0.024]		[0.038]		[0.032]		[0.051]	
Cash Flow	0.066	(0.016)	0.122	(0.009)	-0.085	(0.006)	0.100	(0.002)
	[0.051]		[0.075]		[0.022]		[0.077]	
Book Leverage	0.316	(0.008)	0.291	(0.003)	0.412	(0.004)	0.248	(0.001)
	[0.298]		[0.285]		[0.372]		[0.232]	
Firm-Qtr Obs.	330		1601		5172		28360	
Firms	42		110		814		2228	

Table 25: Investment response to covenant violations: Regression discontinuity

This table follows the regression discontinuity (RD) approach for investment in [35]. The sample consists of firm-quarter observations for non-financial firms merged with COMPUSTAT. Panels A and B present results for the full sample and the RD sample, respectively. The RD sample in Panel B is defined as those firm-quarter observations that have a relative distance (absolute value) of less than 0.3 around the covenant violation boundary. The dependent variable is *Investment* and the main independent variables of interest are *d_Bind* and *d_Bind*×*d_CDS*, where *d_Bind* is an indicator variable equal to one if a firm-quarter observation is determined to be in covenant violation and zero otherwise; and *d_CDS* is an indicator variable equal to one if there is a traded CDS contract for that firm-quarter observation. All control variables are lagged by one quarter. Variable definitions of all the firm characteristics in the table are provided in the Appendix section. All t-statistics displayed in parantheses are robust to within-firm correlation and heteroscedasticity. *, **, and *** indicate significance greater than 10%, 5%, and 1% , respectively.

	Panel A: Full sample			**Panel B: RD sample**		
	(1)	(2)	(3)	(4)	(5)	(6)
d_Bind	-0.015***	-0.014***	-0.011***	-0.009***	-0.008***	-0.005*
	(-8.13)	(-8.29)	(-5.68)	(-4.91)	(-4.06)	(-1.87)
d_Bind×d_CDS	0.010***	0.010**	0.008*	0.014***	0.013**	0.012**
	(2.77)	(2.56)	(1.88)	(3.08)	(2.32)	(2.06)
d_CDS	0.007**	0.011***	0.011***	0.000	0.008	0.008
	(2.09)	(3.35)	(3.43)	(0.03)	(1.39)	(1.46)
Macro q		0.002***	0.002***		0.002***	0.002***
		(16.81)	(16.76)		(6.90)	(6.91)
Cash Flow		0.011***	0.011***		0.015***	0.015***
		(4.71)	(4.65)		(3.73)	(3.63)
Assets(log)		-0.011***	-0.011***		-0.013***	-0.012***
		(-5.51)	(-5.37)		(-3.21)	(-3.14)
NW Distance			0.000***			0.015
			(15.14)			(1.60)
CR Distance			0.028***			0.037**
			(3.54)			(2.44)
ΣCoeff	-0.005	-0.004	-0.003	0.004	0.005	0.007
T-stat	(-1.38)	(-0.92)	(-0.72)	(1.02)	(0.94)	(1.31)
N	33439	28584	28584	11054	9532	9532
Adj. R^2	0.385	0.434	0.434	0.418	0.455	0.456
Firm FE	✓	✓	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓	✓	✓

Table 26: Investment response to covenant violations : Lender characteristics

Panels A and B divide our main sample based on lender characteristics that may affect the level of intervention post covenant violation. The observations in the sample are at lender-firm-quarter level. *High* (*Low*) lender activity in a given lender variable is defined as the variable being above (below) its computed median value using the entire sample period over which data for it is available. Panels A and B present results for the full sample and the RD sample respectively. The RD sample in Panels B1 and B2 is defined as those firm-quarter observations that have a relative distance (absolute value) of less than 0.3 around the covenant violation boundary. The dependent variable is *Investment* and the main independent variables of interest are *d_Bind* and *d_Bind*×*d_CDS*, where *d_Bind* is an indicator variable equal to one if a firm-quarter observation is determined to be in covenant violation and zero otherwise; and *d_CDS* is an indicator variable equal to one if there is a traded CDS contract for that firm-quarter observation. All control variables are lagged by one quarter. Firm-level controls included in the regressions are *Macro q*, *Cash Flow*, *Assets (log)*, and the initial distance to the covenant threshold. Variable definitions of all the firm and lender characteristics in the table are provided in the Appendix section. All t-statistics displayed in parentheses are robust to within-firm correlation and heteroscedasticity. *, **, and *** indicate significance greater than 10%, 5%, and 1%, respectively.

Panel A: Lender characteristics – Full sample

	CD bought		Loans securitized		Non-interest income	
	Low	*High*	*Low*	*High*	*Low*	*High*
	(1)	(2)	(3)	(4)	(5)	(6)
d_Bind	-0.015***	-0.010***	-0.013***	-0.011***	-0.017***	-0.010***
	(-6.19)	(-4.12)	(-4.18)	(-3.59)	(-6.96)	(-4.53)
d_Bind×d_CDS	0.004	0.010**	0.009	0.010*	0.006	0.010*
	(0.51)	(2.01)	(0.99)	(1.82)	(1.09)	(1.89)
d_CDS	0.015**	0.007**	0.012*	0.002	0.017***	0.007**
	(2.51)	(2.37)	(1.82)	(0.49)	(3.12)	(2.26)
ΣCoeff	-0.011	0.000	-0.004	-0.001	-0.011**	-0.001
	(-1.57)	(-0.11)	(-0.45)	(-0.31)	(-2.22)	(-0.14)
N	15185	14674	8834	8889	15770	16379
Adj. R^2	0.447	0.462	0.450	0.458	0.449	0.448
Firm Controls	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓	✓	✓

Table 26 (continued)

Panel B: Lender characteristics – RD sample

	CD Bought		Loans Securitized		Non-Interest Income	
	Low	*High*	*Low*	*High*	*Low*	*High*
	(1)	(2)	(3)	(4)	(5)	(6)
d_Bind	-0.011***	-0.006*	-0.011***	-0.011***	-0.011***	-0.006**
	(-3.70)	(-1.90)	(-3.06)	(-2.65)	(-3.71)	(-2.14)
d_Bind×d_CDS	0.002	0.014**	0.010	0.020**	0.008	0.014**
	(0.27)	(2.12)	(1.52)	(2.49)	(1.33)	(2.06)
d_CDS	0.005	0.009	0.009	0.007	0.005	0.011
	(0.84)	(1.31)	(1.49)	(0.56)	(0.93)	(1.48)
ΣCoeff	-0.008	0.008	-0.001	0.009	-0.003	0.008
	(-1.11)	(1.33)	(-0.16)	(1.37)	(-0.56)	(1.27)
N	5201	4945	2839	2826	5460	5619
Adj. R^2	0.480	0.480	0.499	0.484	0.481	0.484
Firm Controls	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓	✓	✓

Table 27: Investment response to covenant violations: Borrower characteristics

Panels A and B divide our main sample based on borrower characteristics that may affect the level of intervention post covenant violation. The observations in the sample are at the firm-quarter level. We compute the cash from COMPUSTAT and lending relationship using Dealscan. *High* (*Low*) cash is defined as cash being above (below) its computed median value using the entire sample period over which data for it is available. Lending relationship is computed at the firm level when a loan is made by summing up the lending relationships of all lenders in the syndicate. A *High* lending relationship sample corresponds to loans in which 30% or greater of the borrower's past loans have been made by the lending syndicate. A *Low* lending relationship sample corresponds to loans in which the borrower has no historical relationship with the lenders in the syndicate.

Panel A and B present results for the full sample and the RD sample, respectively. The RD sample in Panel B1 and B2 is defined as those firm-quarter observations that have a relative distance (absolute value) of less than 0.3 around the covenant violation boundary. The dependent variable is *Investment* and the main independent variables of interest are *d_Bind* and *d_Bind*×*d_CDS*, where *d_Bind* is an indicator variable equal to one if a firm-quarter observation is determined to be in covenant violation and zero otherwise; and *d_CDS* is an indicator variable equal to one if there is a traded CDS contract for that firm-quarter observation. All control variables are lagged by one quarter. Firm-level controls included in the regressions are *Macro q*, *Cash Flow*, *Assets (log)*, and the initial distance to the covenant threshold. Variable definitions of all the firm characteristics in the table are provided in the Appendix section. All t-statistics displayed in parentheses are robust to within-firm correlation and heteroscedasticity. *, **, and *** indicate significance greater than 10%, 5%, and 1%, respectively.

Panel A: Firm Characteristics – Full Sample

	Cash		Lending Relationship	
	Low	*High*	*Low*	*High*
	(1)	(2)	(3)	(4)
d_Bind	-0.009***	-0.019***	-0.016***	-0.011***
	(-4.09)	(-6.15)	(-7.01)	(-3.56)
d_Bind×d_CDS	0.004	0.017***	0.013	0.011
	(0.58)	(3.12)	(1.53)	(1.57)
d_CDS	0.006*	0.014**	0.013**	0.008**
	(1.72)	(2.45)	(2.37)	(2.04)
ΣCoeff	-0.005	-0.002	-0.003	0.000
	(-0.64)	(-0.34)	(-0.33)	(-0.03)
N	13335	14275	17995	8705
Adj. R^2	0.400	0.437	0.428	0.448
Firm Controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓

Table 27 (continued)

Panel B: Firm Characteristics – RD Sample

	Cash		Lending Relationship	
	Low	*High*	*Low*	*High*
	(1)	(2)	(3)	(4)
d_Bind	-0.008***	-0.007*	-0.008***	-0.010***
	(-2.95)	(-1.68)	(-3.13)	(-2.79)
d_Bind×d_CDS	0.005	0.020**	0.022*	0.017*
	(0.57)	(2.17)	(1.71)	(1.81)
d_CDS	0.007	0.002	-0.006	0.018*
	(0.78)	(0.16)	(-0.59)	(1.93)
ΣCoeff	-0.003	0.013	0.014	0.007
	(-0.32)	(1.55)	(1.11)	(0.78)
N	5352	4009	5922	3097
Adj. R^2	0.426	0.491	0.467	0.436
Firm Controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓

Table 28: Renegotiated loan spread

This table examines the loan spreads that were renegotiated/amended post covenant violation in the presence and absence of a traded CDS on the covenant violating a firm's debt. The sample of renegotiated/amended loans are initiated by the same borrower-lender pair before and after covenant violation. *Loan spread* (LoanSpread) is the main dependent variable in the regression analysis. The main independent variable of interest is the interaction term *d_AfterCovViol*×*d_CDS*. *d_AfterCovViol* is an indicator variable set equal to one for loan facilities initiated or amended after the covenant violation date and is set to zero otherwise. *d_CDS* is an indicator variable equal to one if the loan facility announcement occurs when CDS is traded on the underlying firm's debt, and zero otherwise. *d_TradedCDS* is an indicator variable equal to one if the firm in our sample has CDS traded on the debt at any point during our sample period, and zero otherwise.

Data for column (1) results are for the full sample of renegotiated/amended loans and is at the loan facility level. Data in columns (2)-(9) are further divided based on the lender activity in the credit derivatives market. The observations in this sample are at the lender-facility level. Detailed definitions for the lender variables are provided in the Appendix. t-statistics displayed in parentheses are robust to within-firm correlation and heteroscedasticity. *, **, and *** indicate significance greater than 10%, 5%, and 1%, respectively.

	Firm-level	**CD Bought**		**Loans Securitized**		**Non-Interest Income**		**Syndicate Size**	
	Full	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
d_AfterCovViol×d_CDS	0.51**	0.58	0.52**	0.50	0.60**	0.77**	0.54**	-0.51*	0.77***
	(2.12)	(1.64)	(2.11)	(1.37)	(2.33)	(2.06)	(2.32)	(-1.75)	(3.21)
d_AfterCovViol	0.14***	0.14**	0.20***	0.24***	0.12	0.10	0.18***	0.25***	0.06
	(2.93)	(2.04)	(2.88)	(3.46)	(1.48)	(1.38)	(2.71)	(4.59)	(0.69)
d_CDS	-0.85***	-0.97***	-0.96***	-0.99***	-1.27***	-0.98***	-0.99***	-0.57*	-1.09***
	(-4.16)	(-2.82)	(-3.86)	(-2.64)	(-5.55)	(-2.93)	(-4.37)	(-1.88)	(-5.11)
d_TradedCDS	-0.57***	-0.28	-0.46**	-0.15	-0.26	-0.26	-0.51***	-0.77**	-0.35**
	(-4.30)	(-1.28)	(-2.27)	(-0.54)	(-1.31)	(-1.18)	(-2.69)	(-2.57)	(-2.32)
ΣCoeff	0.65***	0.73**	0.72***	0.74**	0.73***	0.87**	0.72***	-0.26	0.82***
	(2.76)	(2.08)	(3.07)	(2.04)	(3.01)	(2.36)	(3.28)	(-0.90)	(3.70)
N	849	463	399	347	289	454	463	464	453
Adj. R^2	0.383	0.337	0.479	0.383	0.565	0.310	0.471	0.306	0.422
Loan type FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 29: Regression discontinuity: Stock performance

This table compares the stock return of firms post covenant violation in the presence and absence of a traded CDS on the firm's underlying debt. Following the regression framework developed in [146] and [135] and implemented in [113], monthly abnormal returns are computed using a four-factor model (three Fama-French factors and the momentum factor) over the entire sample period by including dummy variables for the covenant violation event month and for months prior and post the event month for which we need to compute the monthly abnormal returns.

Panels A and B present results for the full sample and the RD sample, respectively. The RD sample in Panel B is defined as those firm-quarter observations that have a relative distance (absolute value) of less than 0.3 around the covenant violation boundary. The dependent variable is the monthly cumulative abnormal return (*CAR*) computed at various horizons at each firm-quarter observation. For instance, for every firm i and quarter q, *CAR(1,m)* is computed by summing up the monthly abnormal returns of firm i from the first month following quarter q until the m^{th} month. The main independent variables of interest are *d_Bind* and *d_Bind*×*d_CDS*, where *d_Bind* is an indicator variable equal to one if a firm-quarter observation is determined to be in covenant violation and zero otherwise; and *d_CDS* is an indicator variable equal to one if there is a traded CDS contract for that firm-quarter observation. The control variables included in the regressions are *assets (log)*, *tangible assets*, *operating cash flow*, *book leverage*, *interest expense* and *market-to-book*. All control variables are lagged by one quarter and their definitions are provided in the Appendix. All t-statistics displayed in parentheses are robust to within-firm correlation and heteroscedasticity. *, **, and *** indicate significance greater than 10%, 5%, and 1%, respectively.

Table 29 (continued)

Panel A – Full sample: Monthly CAR regressions post covenant violation

	CAR(1,3)	**CAR(1,6)**	**CAR(1,9)**	**CAR(1,12)**	**CAR(1,18)**	**CAR(1,24)**	**CAR(1,30)**	**CAR(1,36)**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
d_Bind	0.020	0.051**	0.083**	0.110***	0.124***	0.150***	0.144***	0.142***
	(1.55)	(2.24)	(2.41)	(2.73)	(2.70)	(2.85)	(2.75)	(2.70)
d_Bind×d_CDS	0.003	0.018	0.000	-0.029	-0.080	-0.176*	-0.208*	-0.221*
	(0.14)	(0.45)	(0.00)	(-0.45)	(-0.95)	(-1.69)	(-1.81)	(-1.81)
d_CDS	-0.017	-0.038	-0.022	-0.010	0.018	0.056	0.074	0.081
	(-0.78)	(-0.97)	(-0.50)	(-0.19)	(0.27)	(0.70)	(0.80)	(0.75)
ΣCoeff	0.023	0.069**	0.083*	0.082	0.044	-0.026	-0.064	-0.080
	(1.18)	(2.11)	(1.91)	(1.58)	(0.61)	(-0.28)	(-0.61)	(-0.70)
N	11787	11787	11787	11787	11787	11787	11787	11787
Adj. R^2	0.222	0.465	0.670	0.724	0.734	0.756	0.755	0.762
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓

Panel B – RD sample: Monthly CAR regressions post covenant violation

	CAR(1,3)	**CAR(1,6)**	**CAR(1,9)**	**CAR(1,12)**	**CAR(1,18)**	**CAR(1,24)**	**CAR(1,30)**	**CAR(1,36)**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
d_Bind	0.037**	0.065**	0.078***	0.086***	0.088**	0.081*	0.057	0.056
	(2.25)	(2.43)	(2.86)	(2.61)	(2.21)	(1.87)	(1.34)	(1.36)
d_Bind×d_CDS	-0.015	-0.008	0.002	-0.003	-0.070	-0.168**	-0.180**	-0.190**
	(-0.35)	(-0.14)	(0.03)	(-0.05)	(-0.95)	(-2.32)	(-2.18)	(-2.13)
d_CDS	0.009	-0.014	-0.025	-0.036	-0.009	-0.019	-0.062	-0.077
	(0.23)	(-0.25)	(-0.36)	(-0.39)	(-0.08)	(-0.18)	(-0.52)	(-0.63)
ΣCoeff	0.021	0.057	0.079	0.083	0.018	-0.087	-0.123	-0.134
	(0.53)	(1.08)	(1.29)	(1.20)	(0.27)	(-1.31)	(-1.59)	(-1.58)
N	5812	5812	5812	5812	5812	5812	5812	5812
Adj. R^2	0.373	0.643	0.801	0.775	0.731	0.764	0.775	0.785
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓

Table 30: Cox hazard regressions: Distress and outperformance

This table conducts a survival analysis for firms after a covenant violation in the presence and absence of traded CDS on its underlying debt. Firm exits in our sample are classified based on the CRSP delisting codes and Moody's URD database. Financial failure from the CRSP codes is defined as liquidation (400 – 490), bankruptcy (574). Failure in URD is defined as missed/delayed interest/principal payments, bankruptcy, or distressed exchange. Other forms of firm exit include mergers (200 – 290) or going private (573). Distress and outperformance is defined based on [66] and [67] as the firms in the bottom and top 5% of the entire universe of firms in the CRSP based on the past three-year cumulative return.

The data is constructed at the firm-quarter level. The main independent variable of interest is *d_CDS*, which is an indicator variable equal to one if a CDS is traded on the underlying firm's debt for that firm-quarter observation, and zero otherwise. t-statistics displayed in parentheses are robust to within-firm correlation and heteroscedasticity. *, **, and *** indicate significance greater than 10%, 5%, and 1%, respectively.

	All exits	**Distress related**	**Non-distress related**	**Equity distress**	**Equity outperformance**
	(1)	(2)	(3)	(4)	(5)
d_CDS	0.09	0.24	0.03	0.45	-1.62***
	(0.17)	(0.40)	(0.05)	(1.24)	(-2.82)
d_Rated	0.29	0.55*	0.15	-0.23	-0.11
	(1.50)	(1.69)	(0.63)	(-1.35)	(-0.53)
Assets(log)	-0.19***	-0.25**	-0.16**	-0.05	0.11*
	(-3.02)	(-2.55)	(-2.15)	(-0.79)	(1.65)
Profitability	-2.39***	-6.45***	-0.88	-4.14***	0.64
	(-4.50)	(-6.77)	(-1.52)	(-8.69)	(1.24)
Book Leverage	-0.54	0.05	-0.63	2.24***	-0.14
	(-1.19)	(0.07)	(-1.21)	(5.95)	(-0.23)
Interest Expense/Assets	9.83***	24.19***	1.76	5.93**	-0.23
	(2.60)	(3.68)	(0.37)	(1.99)	(-0.04)
Market-to-Book	-0.14	-0.50**	-0.10	-1.63***	0.54***
	(-1.62)	(-2.41)	(-1.02)	(-8.95)	(6.13)
Initial Covenant Tightness	-0.03	-0.13	-0.01	0.06	0.01
	(-0.56)	(-1.33)	(-0.07)	(0.87)	(0.19)
N	29077	29077	29077	29077	29077
Nob. events	1478	432	1046	2059	1561
Pseudo. R^2	0.03	0.11	0.03	0.06	0.06
Industry FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Table 31: Ratings change Cox proportional hazard rate model

This table conducts rating change hazard regression using Cox hazard regressions and a 2SLS IV regression using a linear probability model for firms after a covenant violation in the presence and absence of traded CDS on its underlying debt. Downgrade and upgrade rating change event data are gathered from FISD. The instrument used for CDS trading is the average amount of forex derivatives used for hedging purposes relative to total assets of the lead syndicate banks and bond underwriters with which the firms have conducted business in the past five years.

The data is constructed at the firm-quarter level. The main independent variable of interest is *d_CDS*, which is an indicator variable equal to one if a CDS is traded on the underlying firm's debt for that firm-quarter observation, and zero otherwise. t-statistics displayed in parentheses are robust to within-firm correlation and heteroscedasticity. *, **, and *** indicate significance greater than 10%, 5%, and 1%, respectively.

	Cox hazard		**2SLS IV**	
	DNG	UPG	DNG	UPG
	(1)	(2)	(3)	(4)
d_CDS	1.43***	1.56		
	(3.07)	(1.61)		
CDS IV			0.18**	0.05
			(2.00)	(1.33)
Assets(log)	0.04	0.04	-0.01	-0.01
	(0.33)	(0.17)	(-0.59)	(-0.85)
Profitability	-5.67***	3.65**	-0.56***	0.03
	(-5.08)	(2.16)	(-3.13)	(0.65)
Book Leverage	-0.05	0.72	0.10	0.04
	(-0.04)	(0.26)	(0.95)	(0.68)
Interest Expense/Assets	13.04	-25.97	-0.03	-0.72
	(1.11)	(-0.91)	(-0.03)	(-1.11)
Market-to-Book	0.05	1.16**	-0.01	0.03
	(0.14)	(2.32)	(-0.20)	(1.58)
Initial Covenant Tightness	0.20	-0.11	0.00	-0.01
	(1.20)	(-0.69)	(0.10)	(-0.87)
Observations	11228	11228	7805	7805
Nob. events	652	208		
Pseudo. R^2	0.07	0.15		
Adj. R^2			0.15	0.03
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Table 32: Loan announcement univariate results

This table reports stock price reactions to firm loan announcements. The sample consists of loan announcements from 1990 to 2012. The full sample consists of all the loan announcements in the period 1990-2012. The traded-CDS sample consists only of firms that have a CDS traded on their underlying debt at any point in our sample period, i.e., from 1990 to 2012. In each panel, we report cumulative abnormal returns (CAR) calculated over the 5-day event window (-2,+2), where day zero represents the loan announcement event day. CAR is calculated using the market model. *Count* reports the number of loan announcements used in each CAR calculation. We report averaged CAR values separately for the "CDS=0" period and the "CDS=1" period. Loan announcements that occur in the presence of CDS trading are considered to be in the "CDS=1" period, while loan announcements that occur in the absence of CDS trading are considered to be in the "CDS=0" period. *Difference* reports the difference in averaged CAR values between the "CDS=1" period and the "CDS=0" period. t-statistics displayed in parentheses are robust to within-firm correlation and heteroscedasticity. *, **, and *** indicate significance greater than 10%, 5%, and 1%, respectively

	Full Sample		**Traded-CDS Sample**	
	Mean CAR (%)	Count	Mean CAR (%)	Count
CDS=0	0.39***	24376	0.31***	3713
	(9.61)		(4.08)	
CDS=1	0.10	3074	0.08	2959
	(0.90)		(0.95)	
Difference	-0.29**		-0.23**	
	(-2.37)		(-2.01)	
Total	0.36***	27450	0.21***	6672
	(9.36)		(3.67)	

Table 33: Loan announcement CAR regression

The specifications in Panel A report regression results of stock price reactions to firm loan announcements. The dependent variable is the cumulative abnormal return (CAR) calculated over the five-day event window (-2,+2), where day zero represents the loan announcement event day. CAR is calculated using the market model. Our main variable of interest is *d_CDS*, which is an indicator variable equal to one if the loan announcement occurs when CDS is traded on the underlying firm's debt, and zero otherwise. *d_TradedCDS* is an idicator variable equal to one if the firm in our sample has CDS traded on the debt at any point during our sample period, and zero otherwise. We control for *loan-level* characteristics, *pre-announcement* characteristics, *firm-level* characteristics, and *CDS-trading* characteristics which are defined in detail in the Appendix.

Loan announcement CAR (-2,+2) regression

	(1)	(2)	(3)	(4)
d_CDS	-0.51***	-0.59***	-0.71***	-0.55***
	(-3.10)	(-3.42)	(-2.84)	(-3.14)
d_TradedCDS	0.28**	0.26*		0.25*
	(2.07)	(1.83)		(1.75)
Loan-level controls				
Loan Spread	0.00	0.00	0.00	0.00
	(0.04)	(0.09)	(0.15)	(0.20)
Loan Size (log)	0.13**	0.07	0.05	0.08
	(2.07)	(1.09)	(0.57)	(1.20)
Maturity (Months)	-0.00	-0.00	-0.00	-0.00
	(-0.81)	(-1.28)	(-0.12)	(-1.04)
Syndicate Size	-0.01	-0.00	-0.00	-0.00
	(-1.01)	(-0.39)	(-0.21)	(-0.56)
Pre-announcement controls				
Beta	-0.25**	-0.11	0.07	-0.15
	(-2.18)	(-0.81)	(0.31)	(-0.99)
Idiosyncratic Volatility	20.70***	7.20	3.51	6.37
	(3.76)	(0.86)	(0.27)	(0.76)
Runup	-2.03***	-1.97***	-2.08***	-1.98***
	(-15.07)	(-12.03)	(-8.95)	(-11.84)

Table 33 (continued)

Firm-level controls				
d_Rated	-0.20	-0.24*	-0.34	-0.24*
	(-1.54)	(-1.72)	(-1.23)	(-1.70)
Assets (log)	-0.07	0.04	-0.39**	0.03
	(-1.15)	(0.49)	(-2.10)	(0.41)
Book Leverage	0.71**	0.48	1.23	0.47
	(2.26)	(1.35)	(1.60)	(1.30)
Market-to-Book	-0.15**	-0.11	-0.24	-0.11
	(-2.39)	(-1.46)	(-1.56)	(-1.51)
Profitability	1.10**	0.44	-0.19	0.66
	(1.97)	(0.66)	(-0.16)	(0.97)
Current Ratio	-0.03	-0.01	-0.11	-0.01
	(-0.69)	(-0.22)	(-1.01)	(-0.11)
CDS-trading controls				
Analyst Coverage (log)		-0.06	-0.03	-0.06
		(-0.76)	(-0.24)	(-0.77)
Institutional Ownership		0.15	0.01	0.15
		(1.58)	(0.04)	(1.64)
Stock Illiquidity		0.50	1.68**	0.46
		(1.24)	(2.34)	(1.14)
Analyst Dispersion		-0.08	-0.17*	-0.08
		(-1.40)	(-1.93)	(-1.31)
N	20683	15436	15436	15436
Adj. R^2	0.024	0.024	0.123	0.026
Deal Purpose FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✗
Industry FE	✓	✓	✗	✗
Firm FE	✗	✗	✓	✗
Industry×Year FE	✗	✗	✗	✓

CHAPTER IV

DO BOND INVESTORS PRICE TAIL RISK EXPOSURES OF FINANCIAL INSTITUTIONS?

4.1 Introduction

The experience of the recent financial crisis highlights two aspects of risk-taking by financial institutions that reinforced each other in the run-up to the crisis and contributed to an increase in systemic risk.[1] First, executives at financial institutions have incentives to take on *tail risks*, that is, risks that generate severe adverse consequences with small probability but, in return, offer generous returns the rest of the time ([126], [92], [82] and [143]). Second, institutions have incentives to herd with other institutions in investment choices, thus increasing their exposure to systemically important sectors, such as housing, because they expect to be bailed out in the event of a systemic crisis ([58]).

Given the importance of the financial sector and the negative externality on the real economy from a widespread failure of financial institutions, there is an increased focus on how to contain tail risk exposures of financial institutions. One recurring idea in financial-sector regulation is that regulators increase their reliance on "market discipline" in controlling institutions' risk exposures. The idea is that a financial institution will be more restrained in its risk-taking behavior if its cost of capital increases with its risk exposure. However, market discipline can only be effective if investors price the risk exposure of financial institutions. In this paper, we examine whether bond market investors price the tail risk exposure of financial institutions in

[1]Systemic risk is the risk of widespread failure of financial institutions or the freezing up of capital markets (see [5] and [79] for a more detailed discussion).

which they invest.

We focus on tail risk because financial institutions are highly-levered entities, whose equity capital may not be adequate to absorb the large losses that materialize when a tail event occurs. Given that bondholders hold uninsured liabilities that do not share in the upside from tail risk but may have to absorb losses when the tail risk materializes, it is rational to expect that they will demand higher yield spreads from institutions with higher tail risk exposures. This should be particularly true for investors in subordinated bonds, whose claims are junior to those of senior bondholders. In fact, Pillar III of the New Basel Capital Accord places special emphasis on market discipline through subordinated bonds, which are meant to act as loss-absorbing instruments.

On the other hand, there are two reasons why bondholders may not price tail risk exposures. First, implicit bailout guarantees may engender moral hazard problems among bond market investors. Bondholders of systemically important financial institutions (SIFIs) may rationally anticipate a taxpayer-funded bailout of their institution in the event of a systemic crisis, and thus, may not price the institution's exposure to tail risk, especially systematic tail risk. Even bondholders of smaller institutions may be subject to moral hazard, because they may rationally anticipate indirect benefits from bailouts of SIFIs with which their institution has counterparty links in the derivatives and wholesale funding markets. The experience of the recent financial crisis, during which bondholders of many distressed institutions were able to avoid losses thanks to government bailouts, lends credence to the moral hazard argument.[2] Second, it may be that, investors did not really expect a large tail event

[2]For instance, the government-assisted buyout of Bear Stearns by J.P. Morgan lifted the rating on Bear Stearn's bonds from junk status to investment-grade status, and ensured that senior bondholders of Bear Stearns did not have to suffer any losses. Similarly, the government bailout of A.I.G. ensured that none of its counterparties had to take any haircuts on their claims. In the 2010 bailout of Irish banks, unsecured senior bondholders were paid in full even though the bonds did not carry any explicit government guarantees. The only two U.S. institutions where senior bondholders had to take significant haircuts were Lehman Brothers and Washington Mutual. The benefits to

like the financial crisis to materialize, and hence, ignored tail risk as a low-probability nonsalient risk before the crisis ([24] and [64]).[3]

We test these hypotheses using a large sample of primary bond issuances by U.S. financial institutions during the 1990 to 2010 period. We focus on the primary bond market because it directly affects the cost of institutions' debt capital. As is standard in the literature, we proxy for institutions' *expected* tail risk using *realized* measures of tail risk computed using the recent history of stock returns.[4] We measure an institution's own tail risk using expected shortfall (*ES*), which measures its expected loss conditional on returns being less than some α-quintile. Specifically, *ES* is defined as the negative of the average return on the institution's stock over the 5% worst return days for the institution over the year; i.e., *ES* measures the institution's loss in its own left tail. We capture the tail dependence between the institution and the stock market using the marginal expected shortfall (*MES*), which measures the institution's expected loss when the stock market is in its left tail (see [5], [27]). Specifically, *MES* is defined as the negative of the average return on the institution's stock over the 5% worst return days for the S&P 500 index over the year. Clearly, both *ES* and *MES* are realized measures of risk. [5] show that *MES* is an important determinant of a financial institution's overall contribution to systemic risk, and that institutions with high *MES* before the onset of the financial crisis had worse stock returns during the crisis years, all else equal. Henceforth, we will refer to *MES* as the institution's systematic tail risk, to distinguish it from *ES*, which may also be driven by risk factors that are idiosyncratic to the institution.

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bondholders from bailouts can be gauged from the fact that senior bondholders in Lehman were only able to recover 21 cents on the dollar, whereas holders of Lehman's commercial paper were only to recover around 48–56 cents on the dollar.

[3]This view is supported by [87] and [39] who show that, before the financial crisis, the sensitivities of structured products like CDOs to home prices were not taken into account by rating agencies and investors alike.

[4]It is possible to obtain forward-looking measures of tail risk derived from equity options, but that would significantly reduce the size of our sample, because only 30% of the institutions have options traded.

We first examine whether the yield spreads on new bond offerings at issuance (*Yield Spread*) vary with the tail risk exposure of the financial institution issuing the bonds. To test this, we estimate regressions similar to that in [30], where we include the tail risk measures one at a time as the main independent variable of interest.[5] As expected, we find a robust positive relationship between *Yield Spread* and *ES*, which indicates that the cost of debt capital is higher for institutions with a higher total tail risk. Interestingly, however, we fail to detect any significant relationship between *Yield Spread* and *MES*; that is, bond market investors seem to ignore an institution's systematic tail risk. To alleviate the concern that the effect of systematic tail risk may be subsumed by a bond's credit rating or an institution's size and leverage, we estimate our regression after omitting these important controls, and obtain qualitatively similar results. To test the robustness of this result that systematic risk is not priced whereas total risk is priced, we regress *Yield Spread* against equity volatility (e.g., standard deviation of the institution's stock return) and *Beta*, and arrive at a similar conclusion: *Yield Spread* increases with equity volatility but does not respond to systematic risk (*Beta*).

We next explore how the relationship between yield spreads and tail risk varies with different bond characteristics that can affect an institution's default risk and the loss given default. When we distinguish between senior and subordinate bonds, we find that, as expected, the positive relationship between yield spreads and *ES* is significantly stronger for subordinated bonds. However, the pricing of systematic tail risk *MES* does not vary between senior and subordinated bonds. In fact, a more striking result is that the institutions' *MES* is not priced even in the case of subordinated bonds. We also find that, as expected, the positive relationship between

[5] As expected, *ES* and *MES* are highly correlated with each other, and with other risk measures, such as equity volatility and *Beta*. Hence, we cannot include all risk measures simultaneously. We focus on the pricing of tail risk because, given the high leverage of financial institutions, tail risk should be a first-order concern for bondholders.

yield spreads and tail risk is stronger for bonds with poorer credit ratings.

Next, we examine how the pricing of tail risk varies with firm characteristics that may affect bailout expectations. As [143] highlights, if investors place a positive probability that creditors would be protected in the event of failure, the prices of financial instruments would be distorted - the greater the probability, the greater the distortion. Consistent with the existence of too-big-to-fail (TBTF) subsidies for large financial institutions (e.g., see [3]), we find that the relationship between yield spreads and total tail risk *ES* is weaker for large financial institutions, although *ES* is priced even in case of large financial institutions. However, there is no such variation in terms of the pricing of *MES*, which is not priced regardless of the institution's size. An interesting class of institutions in our sample are the government-sponsored entities (GSEs) such as Fannie Mae and Freddie Mac. Although bonds issued by GSEs carry no explicit government guarantee of creditworthiness, there is a perception of an implicit guarantee because it is widely believed that the government will not allow such important institutions to fail or default on their debt ([143]). Consistent with the existence of such an implicit guarantee, we find that the relationship between yield spreads and tail risk measures is significantly weaker for GSEs.

We conduct several additional tests to further distinguish between the moral hazard hypothesis and the nonsalient-risks hypothesis. First, we estimate our regressions separately for the following four categories of institutions: depository institutions, broker-dealers, insurance companies, and other financial institutions. Institutions across these categories vary not only in terms of their risk exposures and balance-sheet composition, but also in terms of implicit bailout guarantees from the government. For instance, ever since the bailout of the Continental Illinois National Bank in 1984, the FDIC and other regulatory agencies have repeatedly indicated that they consider large banks too-big-to-fail (TBTF) because their closure might destabilize the financial system and impose a negative externality on the real economy. On the other hand, there are no implicit guarantees for debt issued by insurance companies as these are less likely to be considered systemically important. Thus, as per the moral hazard hypothesis, the relationship between bond yield spreads and tail risk should be weaker for depository institutions compared with other types of financial institutions.

Consistent with this argument, we uncover striking differences in the pricing of tail risk between depository institutions and other types of financial institutions. We find that neither the total tail risk *ES* nor the systematic tail risk *MES* is priced in the case of bonds issued by depository institutions, whereas both *ES* and *MES* are priced in the case of bonds issued by broker-dealers and insurance companies. More strikingly, we find that *ES* and *MES* are not priced even in the case of subordinated bonds issued by depository institutions. These results cast serious doubt on the idea that market discipline can be used to control the tail risk exposure of depository institutions.

Second, we examine how the relationship between yield spreads and tail risk varies based on the political connectedness of financial institutions. The idea is to exploit political connectedness as a source of cross-sectional variation in bailout expectations, because politically connected institutions are more likely to receive government bailouts ([57]). To test this idea, we hand-collect information on corporate lobbying expenditures by financial institutions from the Center for Responsive Politics (CRP). Consistent with the moral hazard hypothesis, we find that the relationship between yield spreads and tail risk is significantly weaker for politically-connected institutions compared with non-connected institutions, suggesting the existence of a bailout subsidy for the debt of politically-connected institutions. If such a subsidy exists, a natural question that arises is whether politically-connected institutions exploit the subsidy to issue more debt. To investigate this question, we examine how the debt issuance of institutions varies with their political connectedness. Although we do not find evidence that politically-connected institutions issue more debt on average, our analysis shows that large and politically-connected institutions undertake more bond issues and issue larger amounts, all else equal.

Third, we examine how the relationship between yield spreads and tail risk varies in the immediate aftermath of crisis events, such as the Long Term Capital Management (LTCM) crisis and the recent financial crisis. The idea underlying this test is to exploit the time-series variation in bailout expectations following the large-scale bailouts of troubled institutions during these crises. Not surprisingly, we find an across-the-board increase in the cost of debt for all financial institutions following a crisis event. However, consistent with the moral hazard hypothesis, the relationship between yield spreads and tail risk is significantly weaker in the immediate aftermath of the LTCM crisis and the recent financial crisis. In sharp contrast, we do not find any such patterns surrounding the dotcom crisis of 2001. This is interesting because the dotcom crisis was confined to the technology sector and did not lead to bailouts of financial institutions. This differential impact of the dotcom crash compared with the other two crisis events suggests that our results are more likely driven by expectations of future bailouts rather than a general neglect of nonsalient risks.

Our paper is closely related to and complements the results in a contemporaneous paper by [3] that finds that secondary bond yield spreads of large financial institutions are lower compared with other financial institutions even after controlling for their risk exposures. They attribute this phenomenon to investor expectations of implicit state guarantees for large institutions. Our paper differs from theirs in the following respects: First, we focus on primary bond yield spreads that directly reflect the institutions' cost of debt capital. Second, our analysis is focused on the pricing of tail risk measures that are of particular concern to bondholders, especially investors in subordinated bonds. Finally, we provide further support for the moral hazard hypothesis by showing that the pricing of tail risk is significantly weaker for politically-connected institutions compared with non-connected institutions. Overall, our evidence points to moral hazard in the primary debt markets for financial institutions and complements the secondary debt market evidence in [3].

Our paper is related to prior studies of bank market discipline that focus on whether uninsured bank liabilities such as certificates of deposit (CDs) and subordinated notes and debentures (SNDs) contain appropriate risk premia. The literature generally concludes that CD rates paid by large money-center banks include significant default risk premia (e.g., see [54], [78], and [31]). On the other hand, the literature is divided with respect to the pricing of SNDs. Using a sample from 1983 and 1984, [14] and [72] fail to detect any relationship between SND pricing and balance sheet measures of bank risk. However, examining a longer sample period, [61] conclude that SND prices become more sensitive to risk measurements as expectations of government-sponsored bailouts decrease. The main difference between our study and this literature is that we focus exclusively on the pricing of tail risk exposures of financial institutions. Similar to [14] and [72], we fail to find any evidence that subordinated bondholders of depository institutions care more about tail risk than senior bondholders. Also, similar to [61], we find that the pricing of tail risk changes with expectations of government bailouts.

Past research has highlighted the perverse impact of implicit bailout guarantees on risk-taking behavior of financial institutions. This literature argues that expectations of future systemic bailouts causes banks to correlate their risk exposure and take on high leverage ([58]), incentivizes small banks to herd together with large banks and increases the risk that many banks fail together ([2]), and generally exacerbates the moral hazard of banks and bank managers ([16] and [127]). We contribute to this literature by highlighting how implicit bailout guarantees also exacerbate the moral hazard of bond investors, thus undermining bank market discipline. Our finding is also in line with a recent study by [93] that shows that a large amount of aggregate tail risk is missing from the price of financial sector crash insurance (i.e., price of puts on the financial sector index) during the recent financial crisis, which suggests that investors in the options market are pricing in a collective government guarantee for the financial sector.

Our study has potential regulatory implications in favor of internal restructuring/bail-in provisions, which lower the expectations of future government bailouts. In particular, it is important that bondholders are made to share in any loss arising from the institution's failure. This is essential in restoring market discipline and ensuring that prices of uninsured liabilities of financial institutions are in line with their risk exposures. [6]

The remainder of the paper is organized as follows. We describe our data sources and construction of variables in Section 4.2, and provide descriptive statistics and preliminary results in Section 4.3. We present our main empirical results in Section 4.4. We do additional tests in Section 4.5 to distinguish between our competing hypotheses. Section 4.6 concludes the paper.

4.2 Data, Sample Construction, and Key Variables

Given the focus of our paper, our sample comprises only bonds issued by U.S. financial institutions over the 1990 to 2010 period. Following Acharya et al. (2010), we classify U.S. financial institutions into the following four groups based on SIC codes: depositories, which have a 2-digit SIC code of 60 (e.g., Bank of America, JP Morgan, Citigroup, etc.); broker-dealers, which have a 4-digit SIC code of 6211 (e.g., Goldman Sachs, Morgan Stanley, etc.); insurance companies, which have a 2-digit SIC code of either 63 or 64 (e.g., AIG, Metlife, Prudential, etc.); and other financial institutions,

[6] Possibly recognizing these issues, Mario Draghi, President of the European Central Bank (ECB), recently advocated that even senior bondholders must share in the losses at the worst-hit savings banks in Spain. This was in sharp contrast to the bailout of Irish banks in late 2010 in which unsecured senior bondholders were paid in full using taxpayer money even though they had absolutely no form of government guarantee.

which have a 2-digit SIC code of 61, 62, 65 or 67, and consist of nonbank finance companies (e.g., American Express), real estate companies (e.g., CIT Group), and GSEs (e.g., FNMA and FHLM), etc. We include all financial institutions in our sample regardless of their size. We have verified that our results are qualitatively similar even if we confine our analysis to large institutions, defined as those with market capitalization in excess of $5 billion dollars over the entire sample period. The names of these large U.S. financial institutions are listed in Table D.1.

We obtain primary bond market data from Mergent's Fixed Investment Securities Database (FISD). FISD is a comprehensive database that provides issue details for over 140,000 corporations, U.S. agencies, and U.S. Treasury debt securities.[7] We restrict our sample to U.S. domestic bonds and exclude yankee bonds, bonds issued via private placements, and issues that are asset-backed or have credit-enhancement features. We also exclude preferred stocks, mortgage-backed securities, trust-preferred capital, and convertible bonds.[8] We include only ratings issued by the top three NRSROs – Standard and Poor (S&P), Moody's, and Fitch. Our sample consists of both senior and subordinated bonds.[9] We obtain firm-level control variables from COMPUSTAT's quarterly firm fundamentals file and merge this information with the primary market data.

Our main dependent variable of interest is *Yield Spread*, which is the yield to maturity (YTM) on the bond at issuance minus the YTM on a Treasury security with comparable maturity. Another variable of interest is *Rating*, which measures

[7]FISD contains detailed information for each issue such as the issuer name, bond yields, bond yield spreads over the closest benchmark treasury, maturity date, offering amount, bond types, optionality features, rating date, rating level, and the agency that rated the issue, etc. See [33] for more details of the FISD database.

[8]Lehman Brothers and Morgan Stanley issued large number of equity-linked bonds in 2007 and 2008. Such issues were dropped after a search based on the issue description field.

[9]FISD usually provides information regarding the seniority of the bond issue. In cases where the information is not provided, we obtain the missing seniority information by matching the issue in FISD using its complete CUSIP with the corresponding issue in Moody's Default Risk Database (DRS) and S&P's CUSIP master file. Additionally, we also classify issues as senior or subordinated based on the issue description for bonds.

the bond's credit rating at issuance. To obtain *Rating*, we first convert the credit ratings provided by S&P (Moody's) into an ordinal scale starting with 1 as AAA (Aaa), 2 as AA+ (Aa1), 3 as AA (Aa2), and so on until 22, which denotes the default category. As Fitch provides three ratings for default, we follow the existing literature and chose 23 instead of 22 for the default category, which is the average of the three default ratings; i.e., DD. Because each bond issue may be rated by multiple agencies, we compute *Rating* as the simple average of the ordinal rating assigned by each rating agency. Note that by construction, a lower value for *Rating* denotes a better credit quality at issuance.

We obtain stock price data from CRSP and use it to compute our risk measures. We measure tail risk using expected shortfall (*ES*), which is widely used within financial firms to measure expected loss conditional on returns being less than some α-quintile. Its computation involves identifying the 5% worst return days during the year for the firm's stock (i.e., days on which the return was lower than its fifth-percentile cutoff), and then computing the negative of the average of the firm's daily returns on these days. We measure systematic tail risk using marginal expected shortfall (*MES*), which measures the firm's expected loss when the market is in its left tail (see Acharya et al. (2010)). Specifically, *MES* is defined as the negative of the average return on the firm's stock over the 5% worst return days for the S&P500 index over the year. As we show below, there is a high correlation between *ES* and *MES* in our sample, which is not surprising: given the systemic importance of the financial sector, financial institutions are more likely to experience a tail event when the market as a whole experiences a tail event.

Apart from the tail risk measures, we also compute two commonly used measures of risk: *Volatility*, which is a measure of the total firm-specific risk and defined as the standard deviation of the firm's daily return over the year; and *Beta*, which is a measure of systematic risk, and is obtained by estimating the market model

$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it}$ using daily returns over the year. We use a rolling yearly window to compute the risk measures, so that for each quarter, risk measures are computed using the information from the preceding four quarters. For example, the risk measures pertaining to quarter from April 2007 to June 2007 are computed using the stock and S&P returns over the one-year period from April 2006 to March 2007.

4.3 Descriptive Statistics and Preliminary Results

4.3.1 Summary Statistics

We provide a year-wise summary of bond offerings by financial institutions during the 1990 to 2010 period in Table 34. As can be seen, there is a great deal of variation in total annual bond issuances by number over our sample period, with the 1992–1995 period being the most active in terms of number of bonds issued. However, although there were fewer issues in the latter half of the sample period, the median offering amount in the second half of the sample period is significantly higher than in the first half. Therefore, examining the total dollar amount issued each year, we find that the later half of the sample period has a larger dollar amount of bonds issued even though there are a fewer number of total issues in this period. The majority of the sample consists of senior bonds, with subordinated bonds making up only 18% of total issuances by number. A little more than half of the bonds in our sample have a maturity of less than 10 years and about half have a redeemable feature.

We provide the mean and median values (in parentheses) of the key variables by institution type in Panel B of Table I. Examining firm characteristics, we see that broker-dealers have the highest leverage, whereas insurance companies have the lowest leverage. On average, depository and broker-dealer institutions are also larger (higher $log(assets)$) and better rated (lower *Rating*) than insurance firms. Consistent with Acharya et al. (2010), depository institutions have lower aggregate risk and lower tail risk (both *ES* and *MES*), whereas broker-dealers have the highest level of systematic risk (*Beta*), tail risk (*ES*), and systematic tail risk (*MES*) mainly due to the nature of their business. Other financial institutions account for half of the total bond issuances in our sample; out of these, GSEs account for about 40%. Depository institutions account for about a quarter of the total bond issuances by number, whereas broker-dealers and insurance firms together account for another quarter. However, as can be seen from the mean and median offering sizes, the bond offerings by broker-dealers and depository institutions are much larger in size compared with those of insurance companies and other financial institutions. Depository institutions are the main issuers of subordinated debt, which accounts for around 40% of their bond offerings. This is mainly due to regulatory reasons. As per the Basel Capital Accord, subordinated debt is among the three types of eligible loss-absorbing instruments that banks are required to issue at regular intervals in order to facilitate market discipline.

4.3.2 Correlations

We provide univariate correlations between our key variables in Table 35. Not surprisingly, total tail risk (*ES*) and systematic tail risk (*MES*) are highly correlated. This suggests that, given the systemic importance of the financial sector, financial institutions are more likely to experience a tail event when the market as a whole experiences a tail event. Therefore, in our subsequent multivariate analysis, we are careful to only include either *ES* or *MES* as an independent variable. We also note the high correlation between *ES* and *Aggregate Risk*, which suggests that riskier institutions also have higher tail risk. Similarly, the high correlation between *Beta* and *MES* suggests that institutions with high overall systematic risk also have higher systematic tail risk.

We find that *Yield Spread* is positively correlated with the tail risk measures (*ES, MES*) and *Aggregate Risk*. We must, however, interpret this with caution because these are univariate correlations that do not control for other important institutional characteristics. In particular, *Yield Spread* is negatively correlated with *Size* and *Leverage*, which are two important characteristics that are positively correlated with tail risk. In the case of rating assignments, we find that *Rating* is positively correlated with *ES* and *Aggregate Risk*, suggesting that institutions with higher tail risk and higher total risk are assigned worse ratings. On the other hand, *Rating* is uncorrelated with *MES*. As with the yield spreads, we find that *Rating* is highly negatively correlated with *Size* and *Leverage*, suggesting that large and highly levered financial institutions are assigned better ratings.

We now proceed to multivariate analysis in which we examine the relationship between *Yield Spread* and tail risk after controlling for differences in size, leverage, and other risk characteristics across institutions.

4.4 Empirical Results

4.4.1 Bond Yield Spreads and Tail Risk

We begin our empirical analysis by examining whether investors in the primary bond markets price the tail risk exposures of the financial institution issuing the bonds. To test this, we estimate the following OLS regression model:

$$\text{Yield Spread}_{ift} = \alpha + \beta * \text{Tail Risk}_{f,t} + \gamma * X_{f,t-1} + \rho * X_i + YearFE + InstTypeFE.$$

In the above equation, we use subscript 'i' to denote the bond, subscript 'f' to denote the issuer firm, and subscript 't' to denote the quarter of issuance. Each observation in the regression sample corresponds to a primary bond issue. The main dependent variable of interest is the bond's *Yield Spread* at issuance. The main independent variable of interest is *Tail Risk*, which we measure using either *ES* or *MES*. We control the regression for important firm characteristics (X_f), issue characteristics (X_i), and macroeconomic variables that may affect *Yield Spread*. All the variables are defined in the Appendix. The firm characteristics that we control for are *Size*, *Profitability*, market leverage (*Leverage*), and book leverage (*LongTermDebt_Assets*). The issue characteristics that we control for are the bond's *Rating*, issue size, maturity, and indicator variables to identify subordinated debt, callable bonds, and agency debt. We also include year fixed effects in all specifications, and control for *Term Spread*, which is defined as the yield spread between 10-year and 1-year Treasury bonds.

We begin by estimating regression (4.4.1) on all financial institutions in our sample pooled together, but include institution-type fixed effects to control for differences between depository institutions, broker-dealers, insurance companies, and other financial institutions. The results of our estimation are presented in Table 36. The standard errors reported in parentheses are robust to heteroskedasticity, and are clustered at the level of the institution.

The main independent variable of interest is *ES* in column (1) and *MES* in column (2). As we mentioned previously, we do not include *ES* and *MES* simultaneously to avoid multicollinearity. The positive and significant coefficient on *ES* in column (1) indicates that yield spreads at issuance are higher for bonds issued by institutions with high tail risk. A one standard deviation increase in *ES* increases the primary bond issuance yield by 18 basis points. However, the coefficient on *MES* in column (2) is statistically insignificant, and is also much smaller in magnitude than the coefficient on *ES* in column (1). Thus, it appears from the results in column (1) and (2) that primary bond market investors care about the institution's total tail risk, but not its systematic component of tail risk.

The coefficients on the control variables in columns (1) and (2) are broadly as expected. The positive coefficients on *Rating* and *Maturity* indicate that yield spreads are higher for lower rated bonds and longer maturity bonds, whereas the negative coefficient on *Log(Issue Size)* indicates that yield spreads are lower for larger issues. Examining firm characteristics, we find that yield spreads are higher for institutions with higher leverage. However, controlling for issue size, the size of the institution has no effect on yield spreads.

One possible reason for the lack of a significant association between *Yield Spread* and *MES* is that we may be over-controlling our regressions. That is, it is possible that the impact of the tail risk measures is being subsumed by *Size*, *Leverage*, *Rating*, and other firm-level factors, which we showed to be significantly correlated with the risk measures. To alleviate this concern, we repeat our tests from (1) and (2) after omitting all firm-level controls and the bond's credit rating. The results are reported in columns (3) and (4). As can be seen by comparing columns (1) and (3), the coefficient on *ES* does become stronger after we omit firm-level controls and rating from the regression specification, suggesting that the omitted controls are somewhat subsuming the effect of *ES*. However, the coefficient on *MES* continues to be insignificant and actually decreases in magnitude after omission of the controls.

To summarize, the results in Table III suggest that primary bond market investors care about the institution's total tail risk, but not its systematic component of tail risk.

4.4.2 Bond Yield Spreads and Other Risk Measures

We did not control the regressions in Table 36 for well-known risk measures, such as *Volatility* and *Beta*, because these are highly correlated with *ES* and *MES*, respectively. Thus, including *Volatility* along with *ES*, or *Beta* along with *MES*, may give rise to multicollinearity. For the same reason, we did not include *ES* and *MES* together in the same regression. In this section, for robustness, we examine how primary bond yield spreads vary with *Volatility* and *Beta*. The results of our estimation are presented in Table IV. Apart from the fact that we employ different risk measures, the empirical specification and control variables in columns (1) through (3) are exactly the same as that of column (1) of Table 36; i.e., we control for the full set of firm-level and issue characteristics, and include year fixed effects and institution-type fixed effects. However, to conserve space, we do not report the coefficients on the control variables.

The risk measures of interest in columns (1) and (2) are *Volatility* and *Beta*, respectively. Recall that *Volatility* is a measure of the institution's aggregate risk, whereas *Beta* is widely used as a measure of systematic risk. Consistent with our results in Table III, we find that primary bond market investors price the institution's aggregate risk (positive and significant coefficient on *Volatility*) but do not price its systematic risk (insignificant coefficient on *Beta*).

As we noted in Table II, *ES* and *MES* are highly correlated. To isolate the idiosyncratic component of tail risk, we construct a new risk measure, ES_{idio}, by orthogonalizing *ES* with respect to *MES*.[10] We then estimate regression (4.4.1) after including both ES_{idio} and *MES* as independent variables. As can be seen from column (3), the coefficient on ES_{idio} is positive and significant whereas the coefficient on *MES* is insignificant. Moreover, the coefficient on ES_{idio} appears to be larger than the coefficient on *ES* in column (1) of Table III. Thus, it appears that primary bond market investors only price the idiosyncratic component of the institution's tail risk.

As in Table III, we repeat the estimations in columns (1) through (3) after omitting firm-level characteristics and credit rating as control variables, just to make sure that these control variables are not subsuming the effect of the risk variables. As can be seen from columns (4) through (6), our qualitative results hold even after we omit these control variables. Moreover, consistent with our findings in Table III, the coefficients on *Volatility* and ES_{idio} become stronger after the omission of the control variables, whereas the coefficient on *Beta* becomes significantly weaker.

Note that the results in Tables III and IV are more consistent with the moral hazard hypothesis than the nonsalient-risks hypothesis. As per the nonsalient-risks

[10]Formally, we obtain ES_{idio} by adding the constant and the residual from the regression of *ES* on *MES*. We conduct the orthogonalization separately for each institution type because the sensitivity of *ES* to *MES* can vary across depositories, broker-dealers, insurance companies, and other financial institutions.

hypothesis, yield spreads should not respond to either the idiosyncratic or the systematic component of tail risk. However, we find that although bond yield spreads do not respond to the systematic component of tail risk (*MES*), they do increase with the total tail risk (*ES*) and the idiosyncratic component of tail risk (ES_{idio}). On the other hand, given that bailouts are more likely in the event of a systemic failure, the fact that investors only ignore *MES* is consistent with the moral hazard hypothesis.

4.4.3 Variation of Results with Bond Characteristics

In this section, we examine how our baseline results on the association between *Yield Spread* and risk measures vary with key bond characteristics, such as seniority, maturity, and rating. The results of our analysis are in Table 38.

In columns (1) and (2) of Table 38, we examine how the pricing of tail risk varies between senior and subordinated bonds. Absent government bailout, the loss given default should be significantly higher for subordinated bonds. Hence, it is logical to expect that the positive association between *Yield Spread* and tail risk measures should be stronger for subordinated bonds. To test this, we define the dummy variable *d_Sub* to identify subordinated bonds, and estimate regression (4.4.1) after including *d_Sub* and its interaction with the tail risk measures as additional regressors. The empirical specification and control variables are exactly the same as in columns (1) and (2) of Table 36, although we suppress the coefficients on the control variables in order to conserve space. The positive and significant coefficient on $d\_Sub \times ES$ in column (1) indicates that the association between tail risk and yield spreads is indeed stronger for subordinated bonds. However, the insignificant coefficient on $d\_Sub \times MES$ indicates that there is no incremental effect of *MES* on yield spreads for subordinated bonds over senior bonds. A more striking finding is that the sum of the coefficients on *MES* and $d\_Sub \times MES$ is also statistically insignificant, which suggests that *MES* is not priced even in the case of subordinated bonds issued by financial institutions.

In columns (3) and (4), we examine how our baseline results vary with the bond's credit quality at issuance. Intuitively, we expect our results to be stronger for bonds with lower credit ratings. To test this, we define the dummy variable *d_LowGrade* to identify bonds with an S&P credit rating of "A" or worse at issuance (i.e., $Rating \geq 5$), and interact this with the tail risk measures.[11] The positive coefficients on the interaction terms *d_LowGrade*×*ES* and *d_LowGrade*×*MES* indicate that the effect of tail risk on yield spreads is indeed stronger for low grade bonds. These results are inconsistent with the nonsalient-risks hypothesis as yield spreads respond to both the idiosyncratic and systematic component of tail risk.

In columns (5) and (6), we examine whether the effect of tail risk on yield spreads is stronger for longer maturity bonds. There are two reasons to expect that the effect should be stronger for longer maturity bonds. First, there is more uncertainty in the long run than in the short run. Second, given that financial institutions rely heavily on short-term debt, long-term bondholders are also exposed to the risk that the institution may not be able to rollover or refinance its short-term debt ("rollover risk"). To test this, we define the dummy variable *d_LongMat* to identify bonds with stated maturity of 10 years or more. We then estimate our baseline regressions after including *d_LongMat* and its interaction with the tail risk measures as additional regressors. As can be seen from the insignificant coefficients on *d_LongMat*×*ES* and *d_LongMat*×*MES*, we fail to detect any incremental effect of tail risk on primary yield spreads for longer maturity bonds. Moreover, the sum of the coefficients on *MES* and *d_LongMat*×*MES* in column (4) is also statistically insignificant, which suggests that *MES* is not priced for long maturity bonds.

[11] High-grade bonds (defined as those with credit rating of AAA or AA) constitute roughly 33% of our sample, medium-grade bonds (defined as those with credit rating between A and BBB) constitute 63% of our sample, and speculative-grade bonds (i.e., credit rating worse than BBB) constitute the remaining 4%.

4.4.4 Variation of Results with Firm Characteristics

Next, we examine how our baseline results on the association between *Yield Spread* and tail risk measures vary with important firm characteristics, such as size, leverage, and implicit bailout expectations. The results of our analysis are in Table 39.

We begin with the effect of firm size. As per the moral hazard hypothesis, the relationship between *Yield Spread* and tail risk should be weaker for large institutions, which are more likely to be considered systemically important and qualify for implicit too-big-to-fail guarantees. To test this, we define the dummy variable *d_Large* to identify firms that are larger than the median size by the book value of assets in the universe of all the financial firms in COMPUSTAT.[12] We then estimate our baseline regressions after including *d_Large* and its interactions with tail risk measures as additional regressors. The negative and significant coefficient on *d_Large*$\times$*ES* in column (1) indicates that the incremental effect of *ES* on *Yield Spread* is significantly weaker for large institutions. However, the sum of coefficients on *ES* and *d_Large*$\times$*ES* is still positive and significant, which suggests that yield spreads increase with total tail risk even for large financial institutions. On the other hand, the coefficients on *MES* and *d_Large*$\times$*MES* in column (2), as well as the sum of these coefficients are all statistically insignificant. This indicates that yield spreads do not vary with *MES* regardless of the institution's size.

In columns (3) and (4), we examine if our results vary with the level of the institution's leverage. As with size, we define the dummy variable *d_HighLeverage* to identify institutions whose market leverage exceeds the median leverage in the universe of all the financial firms in COMPUSTAT. As expected, the positive and significant coefficient on *d_Leverage* signifies that firms with higher leverage have higher bond yield spreads, all else equal. However, we fail to find any incremental

[12]This classification yields 144 small firms and 160 large firms. However, the large firms contribute to more than three-quarters of the issuance sample while the remainder comes from the smaller firms.

effect of tail risk on yield spreads for institutions with high leverage.

An interesting class of institutions in our sample are the GSEs such as Fannie Mae and Freddie Mac. Although bonds issued by GSEs carry no explicit government guarantee of creditworthiness, there is a perception of an implicit guarantee because it is widely believed that the government will not allow such important institutions to fail or default on their debt.[13] Hence, as per the moral hazard hypothesis, we should also expect the relationship between *Yield Spread* and tail risk measures to be weaker for GSEs. We examine this in columns (5) and (6) where we interact the tail risk measures with *d_Agency*, a dummy variable that identifies GSEs. The strong negative and significant coefficients on *d_Agency*×*ES* and *d_Agency*×*MES* indicate that the effect of tail risk exposure on yield spreads is indeed much weaker for bonds issued by GSEs.

As a further robustness check, in unreported results, we also compare financial firms and industrial firms by employing the nearest-neighborhood (NN) matching technique (see [1]) to match debt issued by financial firms to debt issued by non-financials (industrial firms). We conduct an exact matching on the subordination status, callability feature, and year of origination, and then use the NN matching on the remaining controls in the bond yield spread regression model, namely, *Rating*, *LogAssets*, *Profitability*, *LongTermDebt_Assets*, *Leverage*, *LogIssueSize*, and *Maturity*.[14] To ensure that our results are not sensitive to the sample of matched counterfactuals, we match each bond offering by a financial institution (treated sample) with three bond offerings by non-financial firms (control sample). We then estimate OLS regressions to examine how the yield spread on bonds issued by financial institutions varies with their tail risk exposure, *after controlling for the yield spread on the matched*

[13] According to estimates by the Congressional Budget Office and the Treasury Department in 1997, GSEs saved about $2 billion per year in funding costs because of this implicit guarantee.

[14] Optimal matching resulted in 100% matching on the subordinated and callable dummy, and 91% on offering year of the bond. As the optimal matching on offering year is not exact, we include year fixed effects in our regressions.

counterfactuals. Consistent with earlier results and the moral hazard hypothesis, we find that investors do not price the systematic tail risk exposure (MES) for either senior or subordinated debt issuances of financial institutions, and do not price tail risk (ES) for bonds issued by GSEs.

4.5 Why Don't Primary Bond Market Investors Price Tail Risk Exposures of Financial Institutions ?

As we noted in the introduction, there are two potential reasons why primary bond market investors may not price an institution's tail risk. It may be that bond market investors are subject to moral hazard because, given the systemic importance of the financial sector, they rationally anticipate taxpayer-funded bailouts in the event of large losses. Alternatively, it may be that investors neglect low-probability nonsalient risks, in general, and are caught unaware when the debt that they had considered safe turns out to be risky ([64]). In this section, we conduct additional tests aimed at distinguishing between these competing hypotheses.

4.5.1 Variation of Results Across Institution Types

One way to distinguish between the moral hazard hypothesis and the nonsalient-risk hypothesis is to examine how the pricing of tail risk varies across different types of financial institutions. Certain types of financial institutions, such as depositories and GSEs, are more likely to be considered systemically important because the failure of such institutions imposes a large negative externality on the real economy. Such institutions are also more likely to receive government bailouts if a negative event materializes. Thus, as per the moral hazard hypothesis, the relationship between bond yield spreads and tail risk should be weaker for depository institutions compared with other types of financial institutions.

To test this idea, we now estimate regression (4.4.1) separately for bonds issued by each institution type. The results of our estimation are presented in Panel A of Table VII. We estimate the regressions separately on the subsamples of bonds issued by depository institutions (columns (1) and (2)), broker-dealers (columns (3) and (4)), insurance companies (columns (5) and (6)), and other financial institutions (columns (7) and (8)). We control these regressions for the full set of firm and bond characteristics as in Table III, and also include year fixed effects. However, to conserve space, we do not report the coefficients on the control variables.

As can be seen, the results in Panel A highlight a striking difference in the pricing of tail risk between bonds issued by depository institutions and bonds issued by all other types of financial institutions. The insignificant coefficients on *ES* and *MES* in columns (1) and (2) indicate that the cost of debt for depository institutions does not vary with their exposure to tail risk. On the other hand, we find a positive and significant association between *Yield Spread* and tail risk measures for all other institution types, except for the category of other financial institutions for which the coefficient on *MES* is positive but statistically insignificant. The lack of significance on *MES* in column (8) may be driven by bonds issued by GSEs, which are included in the category of other financial institutions. As we showed in Panel B of Table VI, the relationship between bond yield spreads and tail risk is significantly weaker in case of bonds issued by GSEs.

Our results in Panel A cast doubt on the idea that primary bond markets can provide effective market discipline to depository institutions. One particular category of bonds that bank regulators and supervisors rely on to enhance market discipline are subordinated bonds, which are meant to act as loss-bearing instruments and are thus treated as part of regulatory capital. As we noted in the discussion following Table I, depository institutions are by far the largest issuers of subordinated bonds. In Panel B of Table VII, we separately examine whether the pricing of tail risk varies between subordinated and senior bonds for depository institutions (in columns (1) and (2)) and for all other types of financial institutions (in columns (3) and (4)).

The positive and significant coefficient on *d_Sub*$\times$*ES* in column (1) indicates that in the case of bonds issued by depository institutions, the relationship between *Yield Spread* and *ES* is indeed stronger for subordinated bonds. However, the coefficient on *ES* is itself negative, although not statistically significant. Moreover, the sum of coefficients on *ES* and *d_Sub*$\times$*ES* is insignificant, which indicates that tail risk is not priced even in the case of subordinated bonds issued by depository institutions. In column (2), we find that the coefficients on *MES* and *d_Sub*$\times$*MES*, as well as the sum of these coefficients, are all statistically insignificant. That is, systematic tail risk *MES* is not priced either for senior or subordinated bonds issued by depository institutions.

Turning to the non-depository institutions, we can see that the coefficients on *d_Sub*$\times$*ES* in column (3) and *d_Sub*$\times$*MES* in column (4) are both positive but are not statistically significant at the conventional 10% level (the $t-$statistics of 1.61 and 1.49, respectively, are lower than the cutoff value of 1.652). However, the coefficient on *ES* as well as the sum of coefficients on *ES* and *d_Sub*$\times$*ES* in column (3) are both statistically significant, which indicates that total tail risk is priced for both senior and subordinated bonds issued by non-depository institutions. The same is true for systematic tail risk *MES* in column (4).

Overall, the results in Table VII indicate that the pricing of tail risk in the primary bond market varies between depository institutions and non-depository institutions. The result that neither *ES* nor *MES* is priced for bonds issued by depository institutions is consistent with the moral hazard hypothesis, because depository institutions are more likely to be considered systemically important and benefit from implicit government guarantees. In unreported tests, we verify that the qualitative results in Table VII are robust to the exclusion of firm-level characteristics and credit rating as control variables; that is, we verify that the effect of tail risk is not being subsumed by *Size*, *Leverage*, and *Rating* of depository institutions.

4.5.2 Political Connectedness and the Pricing of Tail Risk

In this section, we focus on cross-sectional variation in bailout expectations across financial institutions. One such source of cross-sectional variation is the political connectedness of financial institutions. If politically connected institutions are more likely to receive government bailouts, then we expect the relationship between bond yield spreads and tail risk measures to be weaker for better connected institutions.

We measure political connectedness using information on lobbying expenditures by financial institutions obtained from the Center for Responsive Politics (CRP), which compiles data from lobbying disclosure reports filed with the Secretary of the Senate's Office of Public Records (SOPR).[15] This data is available from 1998 through the most recent quarter. We hand-match lobbying records with our data set by firm name and broad industry classification. We measure political connectedness using two variables: a dummy variable *d_PoliticalConnection*, which identifies financial institutions that have ever lobbied the government; and *Log(Lobby Expenditure)*, which is the natural logarithm of the amount of total lobbying expenditure by the institution since the data became available in 1998.

As per our definition of *d_PoliticalConnection*, 53% of the institutions in our sample are politically connected, and include large institutions that were bailed out during the recent financial crisis; e.g., Bear Stearns, AIG, Citigroup, Merrill Lynch, Bank of America, JP Morgan, CIT Group, Freddie Mac, and Fannie Mae among others. The average lobbying amount per year for our sample of firms is close to $1.8 million. Depositories on average have the highest lobbying amount per year, as well as the highest percentage of politically connected firms, followed by broker-dealers.

[15]This data is also publicly available for download on SOPR's website. As per the lobbying disclosure act of 1995, firms that hire lobbyists are required to provide a good-faith estimate rounded to the nearest $20,000 of all lobbying-related expenditures in each six-month period. An organization that spends less than $10,000 in any six-month period does not have to state its expenditures. In those cases, the Center treats the figure as zero.

In general, there seems to be a positive correlation between our measures of political connectedness and bailout probability ([57]). A simple correlation analysis shows that our measures of political connectedness are positively correlated with firm assets and leverage, which implies that larger institutions lobby the government more. Similarly, the correlation between *Yield Spread* and our political connections measures are negatively correlated, which indicates that politically connected firms seem to enjoy a lower cost of capital.

To test whether the pricing of tail risk varies with the institutions' political connectedness, we estimate regression (4.4.1) after including our measures of political connectedness and their interactions with the tail risk measures as additional regressors. We can estimate this regression only for the 1998 to 2010 period as the data on lobbying expenditures is available only after 1998. The results of our analysis are presented in Table 41. The empirical specification and control variables are exactly the same as in Table III although we suppress the coefficients on control variables in order to conserve space.

The negative and significant coefficients on *d_PoliticalConnection*$\times$*ES* and *Log(Lobby Expenditure)*$\times$*ES* in columns (1) and (3), respectively, indicate that the relationship between *Yield Spread* and tail risk is indeed weaker for politically connected institutions. On the other hand, although the coefficients on *d_PoliticalConnection*$\times$*MES* and *Log(Lobby Expenditure)*$\times$*MES* in columns (2) and (4), respectively, are negative, they are not statistically significant. Hence, we cannot conclude that the pricing of systematic tail risk varies between politically-connected and non-connected financial institutions. However, the sum of coefficients on *MES* and *d_PoliticalConnection*$\times$*MES* in column (3) is statistically insignificant, which indicates that the yield spreads of bonds issued by politically-connected institutions does not vary with their *MES*.

Note that the regression sample in columns (1) through (4) includes both crisis periods and noncrisis periods. It is possible that political connections matter less in the midst of a systemic crises, when the government is focussed on bailing out the entire financial sector. For example, the massive liquidity infusions into the interbank market in the immediate aftermath of Lehman's bankruptcy were not aimed at any specific institution, but were rather meant to prevent a complete breakdown of money markets. Hence, a better test of the impact of political connectedness is to examine bond issuances during noncrisis periods. We do this in columns (5) through (8), where we estimate the regressions on a subsample spanning the crisis-free period from 2001:Q2 to 2008:Q2 (i.e., the period from immediately after the LTCM and dotcom crises to immediately before the recent financial crisis). As can be seen, all the interaction terms between measures of political-connectedness and tail risk in columns (5) through (8) are negative and statistically significant: that is, consistent with the moral hazard hypothesis, we find that the relationship between yield spreads and tail risk is significantly weaker for politically-connected institutions compared with non-connected institutions, suggesting the existence of a bailout subsidy for the debt of politically-connected institutions.

If indeed politically-connected financial institutions benefit from an implicit bailout subsidy in bond markets, then a natural question that arises is whether politically-connected institutions exploit the implicit subsidy to undertake more and larger bond issuances. To investigate this question, we aggregate all bond issuances for each financial institution in each calendar quarter during our sample period, and create an institution-quarter bond issuance panel dataset. We then examine how bond issuances vary with the institutions' political connectedness, after controlling for all possible institution- and market-level characteristics that may affect bond issuances. The main dependent variables of interest are: (a) *d_Issue*, which is a dummy variable that identifies whether the institution issued any bonds during that calendar quarter; (b) *Total Issue Amount*, which is the total issuance amount across all the bond issuances by the institution during the quarter; and (c) *Number of issues* which is the total number of issues undertaken by the institution during the quarter. We control for both lagged institution-level determinants (assets, book leverage, market leverage, market-to-book, asset growth) and include year-quarter fixed effects to control for market-level conditions of bond issuance activity. The results of our estimation are in Table 42.

In column (1), we report the results of a Probit regression with *d_Issue* as the dependent variable. The insignificant coefficient on *d_PoliticalConnection* indicates that politically-connected institutions are no more likely to issue bonds in any given quarter than non-connected institutions. However, the positive coefficient on *d_Political-Connection*×*Lag1Q-Assets(log)* in column (1) indicates that among large institutions, politically-connected institutions are more likely to undertake bond issuances than non-connected institutions. We arrive at very similar conclusions when we examine total issuance amounts (in column (3)) and the number of bond issuances (in column (5)). In columns (2), (4), and (6), we verify that these results are also robust to using *Total Lobby Amount* as the measure of political connectedness.

Overall, the results in Table 41 and Table 42 provide more evidence in support of the moral hazard hypothesis by highlighting that primary bond market investors are less likely to price the tail risk exposures of politically-connected institutions, and that large, politically-connected institutions exploit this implicit bailout subsidy by issuing more debt in the bond markets.

4.5.3 Pricing of Tail Risk Around Crisis Periods

In the previous section, we used political connectedness to identify the cross-sectional variation in bailout expectations across firms. Another way to distinguish between the moral hazard hypothesis and the nonsalient-risks hypothesis is to examine how the association between *Yield Spread* and the tail risk measures varies around crisis periods. In general, a crisis can affect the pricing of tail risk in two ways. In the absence of bailout expectations, a crisis may serve as a reminder of the existence of tail risks, and thus strengthen the relationship between *Yield Spread* and the tail risk. However, if the crisis triggers large-scale bailouts of troubled institutions, that may weaken the relationship between *Yield Spread* and the tail risk.

To better understand these effects, we focus on three crisis events that occurred during our sample period: the failure and bailout of LTCM in August 1998, the dot-com crash of March 2000, and the recent financial crisis in March 2008. Note that unlike the dotcom crash, which was largely confined to the technology sector, the LTCM crisis and the recent financial crisis adversely affected the financial sector and triggered government bailouts of troubled institutions. We exploit this key difference to understand the extent to which our results are being driven by changes in expectations of future bailouts. For each of these crisis events, we construct a sample of bond issuances by all financial institutions that occurred in a two-year (i.e., eight calendar quarters) window around the crisis event, and divide this into pre-crisis and post-crisis windows of four calendars quarters each.[16] We then compare how the pricing of tail risk varies between the pre-crisis and post-crisis samples.

The results of our analysis are summarized in Table 43. In columns (1) and (2), we examine the effect of the LTCM crisis that occurred during August and September of 1998. The LTCM bailout was announced on September 23, 1998 when 14 financial institutions agreed to a $3.6 billion recapitalization under the supervision of the Federal Reserve. Accordingly, we use the sample of bonds issued during the two-year period from 1997:Q4 to 1999:Q3 surrounding this crisis event; the sample consists of 154 bond offerings. In this sample, we define the dummy variable *d_LTCM*

[16]Choosing a two-year window around the crisis provides a reasonable sample size for our analysis without introducing other confounding events, thus allowing for cleaner interpretation of results. We must note that it is not feasible to conduct these tests separately for each institution type as the sample size for each institution type would be very small. Hence, we conduct these tests for all financial institutions pooled together, but include institution-type fixed effects in the regression specification.

to identify bonds issued between 1998:Q4 and 1999:Q3, that is, after the LTCM bailout was announced. We then estimate regression (4.4.1) after including *d_LTCM* and its interactions with the tail risk variables as additional regressors. The empirical specification and control variables are otherwise the same as in Table III, but with one important difference: we exclude the year dummies, and instead use the specific crisis dummy to understand how the pricing of tail risk changed pre- and post-crisis. We suppress the coefficients on the control variables in order to conserve space.

The positive and significant coefficients on *d_LTCM* in columns (1) and (2) indicate that primary bond yield spreads of financial firms increased significantly in the immediate aftermath of the LTCM crisis. However, the negative and significant coefficients on $d\_LTCM \times ES$ and $d\_LTCM \times MES$ in columns (1) and (2), respectively, indicate that the relationship between *Yield Spread* and tail risk was significantly weaker in the immediate aftermath of the LTCM crisis. Moreover, the sum of the coefficients on *ES* and $d\_LTCM \times ES$ in column (1) is insignificant, and so is the sum of the coefficients on *MES* and $d\_LTCM \times MES$ in column (2). These indicate that tail risk was not priced at all in the immediate aftermath of the LTCM crisis.

We examine the effect of the recent financial crisis in columns (3) and (4). The main events of the financial crisis occurred during mid-September to early October of 2008.[17] Accordingly, to understand the impact of the financial crisis, we use the sample of bonds issued during the two-year period from 2007:Q4 to 2009:Q3. In this sample, we use the dummy variable *d_FinCrisis* to identify bonds issued between 2008:4Q and 2009:Q3, which denotes the post-crisis period. As can be seen from columns (3) and (4), the impact of the financial crisis was very similar to that of the LTCM crisis: although there was an across-the-board increase in primary bond

[17] The collapse of Lehman Brothers and the collapse and bailout of AIG occurred on September 15 and 16, 2008, triggering widespread panic and a liquidity crisis that required the intervention of the U.S. government and the Federal Reserve. In the next few weeks, other financial institutions including Merrill Lynch, Fannie Mae, Freddie Mac, Washington Mutual, Wachovia, and Citigroup were either acquired under duress, or were subject to government takeover.

yield spreads for all financial institutions following the crisis (positive coefficient on *d_FinCrisis*), the relationship between yield spreads and tail risk was also significantly weaker after the crisis as evidenced by the negative and significant coefficients on $d\_FinCrisis \times ES$ and $d\_FinCrisis \times MES$.

Finally, in columns (5) and (6), we study the effect of the dotcom crisis, which was triggered by the collapse of the NASDAQ-100 Index on March 10, 2000. Accordingly, we use the sample of bonds issued in the two-year period from 1999:Q2 to 2001:Q1. In this sample, the dummy variable *d_Dotcom* identifies bonds issued between the period 2000:Q2 and 2001:Q1, the period right after the dotcom bubble burst on March 10, 2000. As with the LTCM crisis and the financial crisis of 2008, we find that there was an across-the-board increase in primary bond yield spreads of financial institutions in the immediate aftermath of the dotcom crisis (positive and significant coefficient on *d_DotCom*). However, in stark contrast to the other two crises, the coefficients on $d\_DotCom \times ES$ and $d\_DotCom \times MES$ are statistically insignificant, which suggests that there was no difference in the pricing of tail risk in the primary bond markets in the immediate aftermath of the dotcom crisis. This could be due to the fact that the dotcom crash did not change bond market investors' expectations of future bailouts of financial institutions.

Overall, the evidence in Table 43 lends more support to the moral hazard hypothesis over the nonsalient-risks hypothesis.

4.5.4 Do Rating Agencies Account for Tail Risk Exposures?

Investors may rely on rating agencies to price tail risk, as rating agencies specialize in determining creditworthiness of firms. For example, a rating agency may be better positioned to judge the quality of loans and other non-traded assets on a bank's balance sheet. Rating agencies also have access to a firm's private information as they were exempt from the Fair Disclosure Regulation (Reg FD) during our sample period. If rating agencies are also subject to the aforementioned bailout moral hazard problem then they may not price tail risk. Bond investors, who may rely on rating agencies to price tail risks, will consequently not price it too. On the other hand rating agencies may price tail risk and investors might rationally choose to ignore them. To investigate this issue we run an ordered probit model with *Rating* as the dependent variable, and *ES* and *MES* as the key independent variables of interest. We include all the control variables in equation (4.4.1) except of course *Rating* itself. The results of our estimation are presented in Panel A of Table 44.

In columns (1) and (2), we estimate the regression separately on the subsample of bonds issued by depository institutions. Although we find a positive association between *Rating* and total tail risk (*ES*), we fail to find any association between *Rating* and systematic tail risk (*MES*). Interestingly, while rating agencies appear to price *ES*, investors seem to ignore it as shown in Table 40. In columns (3) and (4), we estimate the regression separately on the subsample of bonds issued by broker-dealers. In this subsample, we fail to find any significant association between *Rating* and either tail risk or systematic tail risk. In contrast, even though rating agencies seem to ignore the tail risk exposures of broker-dealers, primary bond market investors as shown in Table 40 seem well aware of these risks and do price them. When we estimate the regression on bonds issued by insurance companies (columns (5) and (6)) and other financial institutions (columns (7) and (8)), we find a positive association between *Rating* and both tail risk measures, which is particularly strong for bonds issued by insurance companies.

Next, we examine how the association between *Rating* and the tail risk measures varies with bonds' seniority status. As in the previous section, we repeat our regression in Panel A after including the interaction terms $d\_Sub \times ES$ and $d\_Sub \times MES$, where d_Sub is an indicator variable that identifies subordinated bonds. The results of the estimation are presented in Panel B. The positive and significant coefficient on d_Sub indicates that subordinated bonds are assigned lower ratings, all else equal, which is to be expected because the loss given default should be higher for these bonds. However, surprisingly, there is no adverse incremental effect of tail risk on the credit ratings of subordinated bonds. As can be seen, the coefficients on $d\_Sub \times ES$ and $d\_Sub \times MES$ are mostly insignificant; in fact, we find a negative and significant coefficient on $d\_Sub \times ES$ in column (1). In a separate row, we also report the statistical significance on the sum of coefficients on the tail risk measure and its interaction term with the d_Sub dummy. Overall, these coefficients are positive and significant for depositories whereas they are insignificant for the rest of the financial firms suggesting that rating agencies account for tail risk for subordinated debt issued by depositories although not incrementally over senior bonds.

To summarize, the results in Table 44 highlight interesting differences in how credit rating agencies rate new bond issuances by different types of financial institutions compared with investors. In particular, rating agencies do not seem to account for tail risk exposures of broker-dealers and the systematic tail risk exposure of depository institutions. More strikingly, although subordinated bonds are assigned lower credit ratings, there is no additional adverse impact of the institution's tail risk on the credit ratings assigned to subordinated bonds. Again, to ensure we are not over-controlling our regressions, we repeat all of our tests from Panels A and B after omitting these firm-level factors as controls. The results of these robustness tests are however not reported and our qualitative results from Panels A and B are unchanged when we omit these additional controls. The only noticeable difference is that the coefficient on MES is significantly lower for these repeat tests of Panels A and B and all of the sum of coefficients on the tail risk measure and its interaction term with the d_Sub dummy are small and statistically insignificant. Overall, the ordered probit rating regression results indicate that it is not the investors' reliance on rating agencies that leads to the mispricing of tail risk.

4.6 Conclusion

In the aftermath of the recent financial crisis, there is an increased focus on containing tail risk and systematic risk exposure of financial institutions. One recurring idea in financial sector regulation is for regulators to increase their reliance on "market discipline" in controlling institutions' risk exposure. However, market discipline is effective only if investors price the risk exposure of financial institutions. In the recent U.S. subprime financial crisis, large-scale government interventions were enacted, which included bailouts designed to prevent the financial industry from a potential system-wide breakdown. However, a consequence of implied government guarantees and bailouts for financial institutions is a weakening of market discipline. Investors can be subject to moral hazard and may not rationally price an institution's exposure to tail risks.

In this paper, we use a large sample of bond issuances by U.S. financial institutions during the 1990 to 2010 period to examine whether bond market investors price the tail risk exposure of financial institutions. We find that primary bond yield spreads increase with institutions' own tail risk (expected shortfall) but do not respond to their systematic tail risk (marginal expected shortfall), even in the case of subordinated bonds. When we distinguish between different types of financial institutions, we find a striking result that primary bond yield spreads of depository institutions do not respond to tail risk for either senior bonds or subordinated bonds. On the other hand, primary bond yield spreads of broker-dealers and insurance companies respond to both total tail risk and systematic tail risk.

There are two potential explanations for why bond market investors may neglect tail risk exposure of financial institutions. It may be that bond market investors are subject to moral hazard because they rationally expect to be bailed out by the government if a negative tail event materializes. Alternatively, it may be that investors neglect low-probability non-salient risks are are caught unaware when the assets that they had considered to be safe turn out to be risky. Consistent with the moral hazard hypothesis, we find that systematic tail risk is not priced in situations where ex-ante bailout expectations are higher: that is, for depositories and government-sponsored entities (GSEs), large institutions, and politically connected firms. Moreover, bond investors' concern for tail risk seems to have weakened in the immediate aftermath of financial crises (such as LTCM and the recent financial crisis) that involved government bailouts of financial institutions.

Overall, our results point to moral hazard in the primary bond markets due to implicit bailout guarantees and cast doubt on the idea that market discipline can be sufficient in controlling the tail risk exposures of depository institutions.

Table 34: Summary statistics of bond sample.

The table displays the summary statistics of the sample of senior and subordinated corporate bonds issued by U.S. financial firms (1-digit SIC code=6) during the period from 1990 to 2010. We restrict our sample to U.S. domestic bonds and exclude yankee bonds, bonds issued via private placements, issues which are asset-backed or have credit-enhancement features. In addition we exclude preferred stocks, mortgage backed securities, trust preferred capital and convertible bonds. Panel A displays the summary statistics year-wise. The numbers for Subordinated, Maturity, and Callable feature are expressed as a percentage of the total sample. In addition, Panel B displays the summary statistics by firm-type for our risk measures, bond-level variables and firm-level variables. Our *tail risk* measures are defined as: **ES**: the negative of the average of the firm's daily returns on 5% worst return days during the calendar year for the firm; **MES**: the negative of the average firm's daily return on 5% worst return days of the market (S&P 500 instead of for the firm) during the calendar year; $\mathbf{ES}_{idio}$: is the residual plus constant upon regressing *ES* on *MES* separately for each firm-type. *Other risk* measures are **Volatility**: is the standard deviation of daily firm equity return over the calendar year; **Beta**: is the estimate of the coefficient upon regressing the firm's daily return on market's daily return (S&P 500); *Volatility, ES, MES,* ES_{idio} are expressed in percentage terms. Other variables are defined as: *Yield Spread* is the bond yield minus closest benchmark treasury yield expressed in basis points. *Rating* is generated by converting the bond ratings to a cardinal scale measured on a 23 point scale for ratings issued by S&P, Moody's and Fitch and then taking their average for a given firm, *Leverage* is the ratio of market value of assets and market value of equity; *Assets (log)* is the log of total assets. The firms are categorized into 4 groups (firm-types): Depositories (2-digit SIC code=60); Broker-Dealers (4-digit SIC code=6211); Insurance (2-digit SIC code=60 & 64); Other (2-digit SIC code=61, 62(except 6211), 65, 67)

Table 34 (continued)

Panel A : Summary Statistics by Year

Year	**Count**	**Subordinated**	**Maturity(%)**			**Callable**	**Offering Amount**	
		Yes(%)	< 10 Yrs	10-20 Yrs	> 20 Yrs	Yes(%)	Median($Mil)	Total($Bil)
1990	33	15.15	75.76	24.24	0.00	30.30	150	7.90
1991	56	14.29	82.14	14.29	3.57	21.43	175	13.70
1992	101	27.72	61.39	34.65	3.96	34.65	150	22.21
1993	178	20.79	55.62	42.70	1.69	44.38	150	36.91
1994	146	19.18	39.04	57.53	3.42	67.12	100	19.12
1995	202	22.77	55.94	38.12	5.94	50.99	75	21.35
1996	84	40.48	39.29	45.24	15.48	21.43	200	17.94
1997	76	27.63	40.79	44.74	14.47	39.47	150	15.82
1998	88	18.18	44.32	35.23	20.45	36.36	250	24.41
1999	60	13.33	66.67	31.67	1.67	33.33	425	33.48
2000	72	15.28	65.28	31.94	2.78	37.50	465	43.43
2001	59	8.47	62.71	32.20	5.08	49.15	500	51.78
2002	86	13.95	56.98	40.70	2.33	51.16	312	51.06
2003	105	11.43	58.10	41.90	0.00	44.76	350	64.24
2004	81	12.35	67.90	30.86	1.23	39.51	500	57.06
2005	84	5.95	52.38	47.62	0.00	61.90	400	48.86
2006	90	16.67	51.11	30.00	18.89	57.78	500	57.89
2007	91	25.27	31.87	45.05	23.08	64.84	500	81.23
2008	40	17.50	37.50	37.50	25.00	77.50	900	54.16
2009	58	8.62	51.72	39.66	8.62	77.59	400	39.17
2010	83	2.41	46.99	43.37	9.64	74.70	400	52.36
Total	1873	18.05	53.23	39.40	7.37	48.96	250	814.06

Table 34 (continued)

	Panel B : Summary Statistics by Firm Type				
	BrokerDeal	**Depository**	**Insurance**	**Other**	**Total**
Bond Vars					
Number of Issues	228	470	269	906	1873
Subordinated	6.1%	39.6%	9.7%	12.4%	18.0%
Offering Amount ($mil)	711.85	694.40	397.32	241.19	434.63
	(400.00)	(386.79)	(300.00)	(150.00)	(250.00)
Rating Scale	5.57	5.55	7.26	5.04	5.55
	(5.00)	(6.00)	(7.00)	(5.00)	(6.00)
Yield Spread (bps)	140	127	189	110	129
	(101)	(92)	(160)	(83)	(95)
Tail Risk Vars					
ES	4.54	3.84	4.47	3.82	4.01
	(3.97)	(3.41)	(4.12)	(3.31)	(3.45)
MES	3.01	2.22	2.35	1.91	2.19
	(2.70)	(1.89)	(1.69)	(1.79)	(1.88)
ES_{idio}	1.44	1.88	2.41	2.18	2.05
	(1.34)	(1.54)	(2.08)	(1.81)	(1.75)
Other Risk Vars					
Volatility	2.28	1.89	2.20	1.86	1.97
	(2.00)	(1.62)	(1.92)	(1.63)	(1.67)
Beta	1.53	1.10	1.00	1.10	1.14
	(1.56)	(1.09)	(0.89)	(1.19)	(1.14)
Firm Vars					
Assets (log)	11.98	12.14	10.44	9.94	10.81
	(12.13)	(12.28)	(10.57)	(10.69)	(11.18)
Market Leverage	17.66	9.24	8.62	10.20	10.64
	(16.52)	(7.42)	(5.06)	(7.84)	(7.87)
Book Debt/Equity	24.80	12.18	8.06	12.92	13.48
	(26.78)	(12.02)	(6.09)	(14.99)	(12.69)

Table 35: Correlations

The following table displays the correlations of our main dependent variables (*Yield Spread* and *Rating*), firm risk measures and other firm characteristics by firm-type during the period from 1990 to 2010. Our *tail risk* measures are defined as: **ES**: the negative of the average of the firm's daily returns on 5% worst return days during the calendar year for the firm; **MES**: the negative of the average firm's daily return on 5% worst return days of the market (S&P 500 instead of for the firm) during the calendar year; **ES**$_{idio}$: is the residual plus constant upon regressing *ES* on *MES* separately for each firm-type. *Other risk* measures are **Volatility**: is the standard deviation of daily firm equity return over the calendar year; **Beta**: is the estimate of the coefficient upon regressing the firm's daily return on market's daily return (S&P 500); *Volatility, ES, MES,* ES_{idio} are expressed in percentage terms. Other variables are defined as: *Yield Spread* is the bond yield minus closest benchmark treasury yield expressed in basis points. *Rating* is generated by converting the bond ratings to a cardinal scale measured on a 23 point scale for ratings issued by S&P, Moody's and Fitch and then taking their average for a given firm, *Leverage* is the ratio of market value of assets and market value of equity; *Assets (log)* is the log of total assets; *MktToBk* is the ratio of market value of equity and book value of equity; The firms are categorized into 4 groups (firm-types): Depositories (2-digit SIC code=60); Broker-Dealers (4-digit SIC code=6211); Insurance (2-digit SIC code=60 & 64); Other (2-digit SIC code=61, 62(except 6211), 65, 67). *, ** and *** indicate significance greater than 10%, 5% and 1%, respectively.

	Yield Spread	Rating	ES	MES	Volatility	Beta	Leverage	Assets (log)
Main Dep Vars								
Yield Spread	1.00							
Rating Scale	0.48***	1.00						
Tail Risk Vars								
ES	0.45***	0.17***	1.00					
MES	0.36***	-0.04	0.75***	1.00				
Other Risk Vars								
Volatility	0.46***	0.18***	0.96***	0.74***	1.00			
Beta	0.00	-0.36***	0.44***	0.72***	0.47***	1.00		
Firm Vars								
Market Leverage	-0.06**	-0.22***	0.21***	0.16***	0.18***	0.18***	1.00	
Assets (log)	-0.15***	-0.54***	0.05**	0.35***	0.06***	0.53***	0.24***	1.00

Table 36: Bond Yield Spreads and Tail Risk

The following table displays the primary bond yield regressions with dependent variable as bond yield minus the closest benchmark treasury yield expressed in basis points on firm tail-risk measures and other firm and bond characteristics during the period from 1990 to 2010. Our *tail risk* measures are defined as: **ES**: the negative of the average of the firm's daily returns on 5% worst return days during the calendar year for the firm; **MES**: the negative of the average firm's daily return on 5% worst return days of the market (S&P 500 instead of for the firm) during the calendar year; *ES, MES* are expressed in percentage terms. *Rating* is generated by converting the bond ratings to a cardinal scale measured on a 23 point scale for ratings issued by S&P, Moody's and Fitch and then taking their average for a given firm. The firms are categorized into 4 firm-types: Depositories (2-digit SIC code=60); Broker-Dealers (4-digit SIC code=6211); Insurance (2-digit SIC code=60 & 64); Other (2-digit SIC code=61, 62(except 6211), 65, 67). Standard bond yield regression controls which are defined in Appendix D.1 and included in the regression specification are: *log assets, profitability, long-term debt to assets, leverage, term spread, log issue size, years to maturity*. Firm-type fixed effects (FE) are included by defining a dummy variable *d_Firm-Type* for each firm-type that is set to 1 if a firm belongs to that firm-type or else it is set to 0. Bond-type fixed effects are controlled by including *d_Agency*, *d_Sub* and *d_Callable* which are dummy variables set to 1 if the type of bond is an agency debt, subordinated or callable respectively or else they are set to 0. Year fixed effects are included in the regressions. All standard errors are clustered at firm level to correct for correlation across observations of a given firm. All t-statistics are displayed in brackets. *, ** and *** indicate significance greater than 10%, 5% and 1%, respectively.

Table 36 (continued)

	All Controls		No Firm Controls	
	(1)	(2)	(3)	(4)
Tail Risk Vars				
ES	10.25***		14.80***	
	(3.12)		(4.09)	
MES		3.47		2.97
		(1.09)		(0.84)
Firm Vars				
Market Leverage	0.63**	0.79***		
	(2.42)	(2.64)		
LongTermDebt_Assets	50.35***	51.26***		
	(2.68)	(2.63)		
Assets (log)	1.43	2.27		
	(0.44)	(0.68)		
Profitability	-2.83	-5.90		
	(-0.16)	(-0.33)		
Bond Vars				
d_Agency	-5.85	-3.99	-65.06***	-69.98***
	(-0.34)	(-0.22)	(-7.59)	(-7.52)
Rating Scale	12.81***	14.22***		
	(5.10)	(5.60)		
Maturity (yrs)	1.11***	1.01***	0.76***	0.55*
	(4.56)	(4.04)	(2.70)	(1.84)
IssueSize (log)	-16.31***	-16.98***	-22.32***	-22.96***
	(-3.39)	(-3.56)	(-4.99)	(-4.93)
Macro Vars				
10yr-1yr Treasury Spread	-8.48*	-5.15	-14.39**	-9.08
	(-1.68)	(-1.06)	(-2.46)	(-1.62)
N	1873	1873	1873	1873
Adj. R^2	0.577	0.569	0.536	0.518
Year FE	✓	✓	✓	✓
FirmType FE	✓	✓	✓	✓
BondType FE	✓	✓	✓	✓

Table 37: Bond Yield Spreads and Other Risk Measures

The following table displays the pricing effect of other risk measures, which are closely related to tail risk, on bond yield issuance in the primary market controlling for bond and firm characteristics during the period from 1990 to 2010. Our risk measures are defined as the following: **ES**$_{idio}$: is the residual plus constant upon regressing *ES* on *MES* separately for each firm-type; **Volatility**: is the standard deviation of daily firm equity return over the calendar year; **Beta**: is the estimate of the coefficient upon regressing the firm's daily return on market's daily return (S&P 500). *Volatility, MES,* ES_{idio} are expressed in percentage terms. Other variables are defined as: *Yield Spread* is the bond yield minus closest benchmark treasury yield expressed in basis points. The firms are categorized into 4 firm-types: Depositories (2-digit SIC code=60); Broker-Dealers (4-digit SIC code=6211); Insurance (2-digit SIC code=60 & 64); Other (2-digit SIC code=61, 62(except 6211), 65, 67). $d\_firm-type$ is defined as a dummy variable that is set to 1 if a firm belongs to that firm-type or else it is set to 0. *d_Agency*, *d_Sub* and *d_Callable* are dummy variables set to 1 if the type of bond is an agency debt, subordinated or callable respectively or else they are set to 0. Standard bond yield regression controls which are defined in Appendix D.1 and included in the regression specification are: *log assets, profitability, long-term debt to assets, leverage, term spread, log issue size, years to maturity and rating scale* Year fixed effects are included in the regressions. All standard errors are clustered at firm level to correct for correlation across observations of a given firm. All t-statistics are displayed in brackets. *, ** and *** indicate significance greater than 10%, 5% and 1%, respectively.

	All Controls			**No Firm Controls**		
	(1)	(2)	(3)	(4)	(5)	(6)
Volatility	18.65***			27.76***		
	(3.00)			(4.16)		
Beta		3.95			0.54	
		(0.47)			(0.06)	
ES$_{idio}$			13.26***			20.45***
			(3.09)			(4.63)
MES			5.07			5.67
			(1.54)			(1.55)
N	1873	1873	1873	1873	1873	1873
adj. R^2	0.579	0.568	0.578	0.547	0.517	0.542
Year FE	✓	✓	✓	✓	✓	✓
FirmType FE	✓	✓	✓	✓	✓	✓
BondType FE	✓	✓	✓	✓	✓	✓
Firm-level Vars	✓	✓	✓	✗	✗	✗
OtherControls	✓	✓	✓	✓	✓	✓

Table 38: Bond Characteristics and Pricing of Tail Risk

The following table displays the primary bond yield regressions with dependent variable as bond yield minus closest benchmark treasury yield expressed in basis points on firm tail-risk measures and other bond characteristics during the period from 1990 to 2010. The analysis consists of the interaction results of tail-risk measures with bond features which are defined in the following manner: Dummy variable *d_Sub* is set to 1 if the bond is subordinated else it is set to 0. Dummy variables *d_LowGrade* is set to 1 if it's rating scale $\geq$ 5 (A or lower for S&P, Fitch and Moodys') implying they are medium-grade bonds else it is set 0 implying they are high-grade bonds (AAA or AA - High-grade AAA and AA bonds constitute about 33% of the sample; Medium grade A to BBB constitute 63% and the rest 4% are speculative grade bonds). Similarly $d\_LongMat$ is set to 1 if the years to maturity of the bond is $\geq$ 10 (the mean and median maturity in the sample is close to 10 years) else it is set to 0. Our *tail risk* measures are defined as: **ES**: the negative of the average of the firm's daily returns on 5% worst return days during the calendar year for the firm; **MES**: the negative of the average firm's daily return on 5% worst return days of the market (S&P 500 instead of for the firm) during the calendar year; *ES, MES* are expressed in percentage terms. *Rating* is generated by converting the bond ratings to a cardinal scale measured on a 23 point scale for ratings issued by S&P, Moody's and Fitch and then taking their average for a given firm. The firms are categorized into 4 firm-types: Depositories (2-digit SIC code=60); Broker-Dealers (4-digit SIC code=6211); Insurance (2-digit SIC code=60 & 64); Other (2-digit SIC code=61, 62(except 6211), 65, 67). Standard bond yield regression controls which are defined in Appendix D.1 and included in the regression specification are: *log assets, profitability, long-term debt to assets, leverage, term spread, log issue size, years to maturity*. Firm-type fixed effects (FE) are included by defining a dummy variable *d_Firm-Type* for each firm-type that is set to 1 if a firm belongs to that firm-type or else it is set to 0. Bond-type fixed effects are controlled by including dummy variables d_Agency, *d_Sub* and $d\_Callable$. Year fixed effects are included in the regressions. All standard errors are clustered at firm level to correct for correlation across observations of a given firm. All t-statistics are displayed in brackets. *, ** and *** indicate significance greater than 10%, 5% and 1%, respectively.

Table 38 (continued)

	Subordinated		Low Grade		Bond Maturity	
	(1)	(2)	(3)	(4)	(5)	(6)
ES	7.50**		-0.38		11.36***	
	(2.18)		(-0.09)		(2.98)	
MES		3.15		-4.34		3.92
		(0.96)		(-0.92)		(1.06)
d_Sub×ES	11.72**					
	(2.10)					
d_Sub×MES		2.27				
		(0.31)				
d_LowGrade×ES			18.36***			
			(4.72)			
d_LowGrade×MES				14.65***		
				(3.09)		
d_LongMat×ES					-3.63	
					(-1.08)	
d_LongMat×MES						-1.13
						(-0.31)
d_Sub	2.42	1.61	13.85*	13.38	4.32	4.66
	(0.29)	(0.18)	(1.74)	(1.61)	(0.48)	(0.51)
d_LowGrade			5.64	2.61		
			(0.74)	(0.34)		
d_LongMat					8.41*	6.32
					(1.86)	(1.27)
ΣCoeff	19.22***	5.42	17.98***	10.31***	7.73**	2.80
	(3.37)	(0.74)	(5.05)	(2.81)	(2.34)	(0.79)
N	1873	1873	1873	1873	1873	1873
adj. R^2	0.580	0.569	0.563	0.542	0.574	0.565
Year FE	✓	✓	✓	✓	✓	✓
FirmType FE	✓	✓	✓	✓	✓	✓
BondType FE	✓	✓	✓	✓	✓	✓
Rating	✓	✓	✗	✗	✓	✓
Maturity	✓	✓	✓	✓	✗	✗
OtherControls	✓	✓	✓	✓	✓	✓

Table 39: Firm Characteristics and Pricing of Tail Risk

The following table displays the primary bond yield regressions with dependent variable as bond yield minus closest benchmark treasury yield expressed in basis points on firm tail-risk measures and other firm characteristics during the period from 1990 to 2010. The analysis consists of the interaction results of tail-risk measures with firm features which are defined in the following manner: *d_Large* is a dummy variable set to 1 if the log of firm assets is greater than the median in the universe of financial firms in COMPUSTAT, else it is set to 0. *d_HighLeverage* is a dummy variable set to 1 if the firm leverage is greater than the median in the universe of financial firms in COMPUSTAT, else it is set to 0. *d_Agency* is set to 1 if the bond is an agency bond else it is set to 0. Our *tail risk* measures are defined as: **ES**: the negative of the average of the firm's daily returns on 5% worst return days during the calendar year for the firm; **MES**: the negative of the average firm's daily return on 5% worst return days of the market (S&P 500 instead of for the firm) during the calendar year; *ES, MES* are expressed in percentage terms. *Rating* is generated by converting the bond ratings to a cardinal scale measured on a 23 point scale for ratings issued by S&P, Moody's and Fitch and then taking their average for a given firm. The firms are categorized into 4 firm-types: Depositories (2-digit SIC code=60); Broker-Dealers (4-digit SIC code=6211); Insurance (2-digit SIC code=60 & 64); Other (2-digit SIC code=61, 62(except 6211), 65, 67). Standard bond yield regression controls which are defined in Appendix D.1 and included in the regression specification are: *log assets, profitability, long-term debt to assets, leverage, term spread, log issue size, years to maturity.* Firm-type fixed effects (FE) are included by defining a dummy variable *d_Firm-Type* for each firm-type that is set to 1 if a firm belongs to that firm-type or else it is set to 0. Bond-type fixed effects are controlled by including dummy variables *d_Agency*, *d_Sub* and *d_Callable*. Year fixed effects are included in the regressions. All standard errors are clustered at firm level to correct for correlation across observations of a given firm. All t-statistics are displayed in brackets. *, ** and *** indicate significance greater than 10%, 5% and 1%, respectively.

Table 39 (continued)

	Assets		Leverage		Agency Debt	
	(1)	(2)	(3)	(4)	(5)	(6)
ES	17.97***		10.82**		11.62***	
	(3.33)		(2.44)		(3.43)	
MES		10.30		2.26		4.99
		(1.51)		(0.50)		(1.55)
d_Large×ES	-10.14*					
	(-1.72)					
d_Large×MES		-5.98				
		(-0.86)				
d_Leverage×ES			-0.77			
			(-0.16)			
d_Leverage×MES				0.66		
				(0.13)		
d_Agency×ES					-29.98***	
					(-5.35)	
d_Agency×MES						-32.84***
						(-4.40)
d_Large	-16.45	-18.26				
	(-1.58)	(-1.49)				
d_Leverage			13.43	19.31*		
			(1.33)	(1.90)		
d_Agency	-3.03	-1.15	12.35	14.57	-12.98	-5.67
	(-0.18)	(-0.07)	(0.78)	(0.90)	(-0.74)	(-0.31)
ΣCoeff	7.83**	4.32	10.05***	2.92	-18.36***	-27.85***
	(2.31)	(1.32)	(2.74)	(0.79)	(-3.37)	(-3.95)
N	1873	1873	1873	1873	1873	1873
adj. R^2	0.581	0.570	0.573	0.565	0.581	0.571
Year FE	✓	✓	✓	✓	✓	✓
FirmType FE	✓	✓	✓	✓	✓	✓
BondType FE	✓	✓	✓	✓	✓	✓
LogAssets	✗	✗	✓	✓	✓	✓
Leverage	✓	✓	✗	✗	✓	✓
RatingScale	✓	✓	✓	✓	✓	✓
OtherControls	✓	✓	✓	✓	✓	✓

Table 40: Pricing of Tail Risk for Different Institution Types

The following table displays the primary bond yield regressions with dependent variable as bond yield minus closest benchmark treasury yield expressed in basis points on firm tail-risk measures and other firm and bond characteristics during the period from 1990 to 2010 separately for each firm type. Our *tail risk* measures are defined as: **ES**: the negative of the average of the firm's daily returns on 5% worst return days during the calendar year for the firm; **MES**: the negative of the average firm's daily return on 5% worst return days of the market (S&P 500 instead of for the firm) during the calendar year; *ES, MES* are expressed in percentage terms. *Rating* is generated by converting the bond ratings to a cardinal scale measured on a 23 point scale for ratings issued by S&P, Moody's and Fitch and then taking their average for a given firm. The firms are categorized into 4 firm-types: Depositories (2-digit SIC code=60); Broker-Dealers (4-digit SIC code=6211); Insurance (2-digit SIC code=60 & 64); Other (2-digit SIC code=61, 62(except 6211), 65, 67). Standard bond yield regression controls which are defined in Appendix D.1 and included in the regression specification are: *log assets, profitability, long-term debt to assets, leverage, term spread, log issue size, years to maturity.* Firm-type fixed effects (FE) are included by defining a dummy variable *d_Firm-Type* for each firm-type that is set to 1 if a firm belongs to that firm-type or else it is set to 0. Bond-type fixed effects are controlled by including *d_Agency*, *d_Sub* and *d_Callable* which are dummy variables set to 1 if the type of bond is an agency debt, subordinated or callable respectively or else they are set to 0. Year fixed effects are included in the regressions. All standard errors are clustered at firm level to correct for correlation across observations of a given firm. All t-statistics are displayed in brackets. *, ** and *** indicate significance greater than 10%, 5% and 1%, respectively.

Panel A analyzes the effect of tail-risk on bond issuance yields controlling for all our bond-level, firm-level and macroeconomic variables. Panel B analyzes the incremental effect of tail-risk on subordinated bond issuance yields controlling for all our bond-level, firm-level and macroeconomic variables.

Table 40 (continued)

Panel A: Only Tail Risk

	Depository		Broker-Dealer		Insurance		Other	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ES	-1.45		37.92***		11.85*		15.56***	
	(-0.22)		(3.34)		(1.68)		(3.57)	
MES		-8.57		35.68***		16.28**		5.23
		(-0.98)		(3.59)		(2.44)		(1.10)
N	470	470	228	228	269	269	906	906
adj. R^2	0.476	0.478	0.494	0.483	0.552	0.558	0.656	0.635
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
BondType FE	✓	✓	✓	✓	✓	✓	✓	✓
OtherControls	✓	✓	✓	✓	✓	✓	✓	✓

Panel B: Tail Risk×Subordinated

	Depository		Rest	
	(1)	(2)	(3)	(4)
ES	-7.23		10.85***	
	(-0.89)		(2.88)	
d_Sub×ES	14.91***		13.56	
	(2.85)		(1.60)	
MES		-8.80		7.78**
		(-0.81)		(2.12)
d_Sub×MES		0.61		14.69
		(0.06)		(1.49)
d_Sub	4.08	5.00	11.85	21.73
	(0.42)	(0.43)	(0.92)	(1.51)
ΣCoeff	7.68	-8.19	24.41***	22.47**
	(1.20)	(-1.00)	(3.10)	(2.22)
N	470	470	1403	1403
adj. R^2	0.484	0.477	0.616	0.604
Year FE	✓	✓	✓	✓
FirmType FE	✗	✗	✓	✓
BondType FE	✓	✓	✓	✓
OtherControls	✓	✓	✓	✓

Table 41: Political Connectedness and Pricing of Tail Risk

The following table displays the primary bond yield regressions with dependent variable as bond yield minus closest benchmark treasury yield expressed in basis points on firm tail-risk measures and other firm and bond characteristics during the period from 1998 to 2010. Our *tail risk* measures are defined as: **ES**: the negative of the average of the firm's daily returns on 5% worst return days during the calendar year for the firm; **MES**: the negative of the average firm's daily return on 5% worst return days of the market (S&P 500 instead of for the firm) during the calendar year; *ES, MES* are expressed in percentage terms. *Rating* is generated by converting the bond ratings to a cardinal scale measured on a 23 point scale for ratings issued by S&P, Moody's and Fitch and then taking their average for a given firm. The firms are categorized into 4 firm-types: Depositories (2-digit SIC code=60); Broker-Dealers (4-digit SIC code=6211); Insurance (2-digit SIC code=60 & 64); Other (2-digit SIC code=61, 62(except 6211), 65, 67). Standard bond yield regression controls which are defined in Appendix D.1 and included in the regression specification are: *log assets, profitability, long-term debt to assets, leverage, term spread, log issue size, years to maturity.* Firm-type fixed effects (FE) are included by defining a dummy variable *d_Firm-Type* for each firm-type that is set to 1 if a firm belongs to that firm-type or else it is set to 0. Bond-type fixed effects are controlled by including *d_Agency*, *d_Sub* and *d_Callable* which are dummy variables set to 1 if the type of bond is an agency debt, subordinated or callable respectively or else they are set to 0. All standard errors are clustered at firm level to correct for correlation across observations of a given firm. All t-statistics are displayed in brackets. *, ** and *** indicate significance greater than 10%, 5% and 1%, respectively.

To study the impact of political connectedness, we use lobbing expenditure data from the Center for Responsive Politics (CRP) which compiles data from lobbying disclosure reports filed with Secretary of the Senate's Office of Public Records (SOPR). The data covers lobbying activity that took place from 1998 to 2010. Lobbying records are matched with our dataset on the name and the broad industry classification of the firm. Political connectedness is defined in two ways - a dummy variable *d_PoliticalConnection* equal to 1 if the financial firm has ever lobbied the government and 0 otherwise; and *Total Lobby Amount(log)* as the natural logarithm of the amount of total lobbying expenditure since the year of data availability in 1998.

Table 41 (continued)

	Full period: 1998-2010				Non-Crisis Period: 2001Q2-2008Q2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ES	19.99***		11.63***		37.74***		15.83***	
	(4.04)		(3.05)		(5.07)		(2.92)	
MES		10.27*		4.34		26.64**		7.63
		(1.72)		(1.15)		(2.06)		(1.08)
d_PoliticalConnection×ES	-12.30**				-32.78***			
	(-2.41)				(-3.91)			
d_PoliticalConnection×MES		-8.28				-28.13**		
		(-1.34)				(-1.99)		
Total Lobby Amount(log)×ES			-0.85**				-2.31***	
			(-2.34)				(-3.81)	
Total Lobby Amount(log)×MES				-0.52				-1.82*
				(-1.17)				(-1.83)
d_PoliticalConnection	-3.79	-6.32			-29.17*	-31.34		
	(-0.34)	(-0.54)			(-1.66)	(-1.40)		
Total Lobby Amount(log)			0.28	0.14			-1.67	-1.59
			(0.31)	(0.15)			(-1.17)	(-0.95)
ΣCoeff	7.69*	1.99			4.96	-1.49		
	(1.81)	(0.50)			(0.80)	(-0.20)		
N	997	997	997	997	614	614	614	614
adj. R^2	0.479	0.462	0.478	0.462	0.348	0.302	0.348	0.301
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
FirmType FE	✓	✓	✓	✓	✓	✓	✓	✓
BondType FE	✓	✓	✓	✓	✓	✓	✓	✓
OtherControls	✓	✓	✓	✓	✓	✓	✓	✓

Table 42: Political Connectedness and Debt Issuance

The following table displays the regression results of measures of bond issuance on political connectedness and other firm characteristics during the period from 1998 to 2010 on a firm-quarter panel dataset. The dependent variables are d_Issue: a dummy variable set to 1 for a firm-quarter observation if the firm issues a bond in the given quarter, and 0 otherwise; Total Issue Amount: is the total bond issue amount for a given firm in a given quarter in log terms; Number Of Issues: is the total number of bond issues for a given firm in a given quarter. Control variables, defined in Appendix D.1 and included in the regression specification are 1 quarter lagged values of: *log assets, profitability, long-term debt to assets, market leverage, market-to-book, asset growth.* Firm-type fixed effects (FE) are included by defining a dummy variable *d_Firm-Type* for each firm-type that is set to 1 if a firm belongs to that firm-type or else it is set to 0. All standard errors are clustered at firm level to correct for correlation across observations of a given firm. All t-statistics are displayed in brackets. *, ** and *** indicate significance greater than 10%, 5% and 1%, respectively.
To study the impact of political connectedness, we use lobbing expenditure data from the Center for Responsive Politics (CRP) which compiles data from lobbying disclosure reports filed with Secretary of the Senate's Office of Public Records (SOPR). The data covers lobbying activity that took place from 1998 to 2010. Lobbying records are matched with our dataset on the name and the broad industry classification of the firm. Political connectedness is defined in two ways - a dummy variable *d_PoliticalConnection* equal to 1 if the financial firm has ever lobbied the government and 0 otherwise; and *Total Lobby Amount(log)* as the natural logarithm of the amount of total lobbying expenditure since the year of data availability in 1998.

	Pr(Issue)		**Tot. Issue Amount**		**Num. Of Issues**	
	(1)	(2)	(3)	(4)	(5)	(6)
d_PoliticalConnection	-0.10		-0.16		-0.02	
	(-1.36)		(-0.76)		(-0.25)	
d_PoliticalConnection×Lag1Q-Assets(log)	0.12**		0.70***		0.33***	
	(2.51)		(4.11)		(3.53)	
Total Lobby Amount(log)		-0.01		-0.01		-0.00
		(-1.52)		(-0.74)		(-0.18)
Total Lobby Amount(log)×Lag1Q-Assets(log)		0.01***		0.06***		0.03***
		(2.58)		(4.27)		(3.41)
Lag Assets(log)	0.26***	0.30***	0.54***	0.79***	0.06**	0.17***
	(7.45)	(11.11)	(6.23)	(9.47)	(2.18)	(5.21)
ΣCoeff	0.37***		1.24***		0.38***	
	(9.95)		(7.72)		(4.40)	
N	8366	8366	8366	8366	8366	8366
pseudo. R^2	0.164	0.164				
adj. R^2			0.152	0.156	0.103	0.108
Year-Quarter FE	✓	✓	✓	✓	✓	✓
FirmType FE	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓

Table 43: Pricing of Tail Risk Around Crisis Periods

The following table displays the primary bond yield regressions with dependent variable as bond yield minus closest benchmark treasury yield expressed in basis points on firm tail-risk measures and other firm and bond characteristics during the crisis periods from 1990 to 2010. Our *tail risk* measures are defined as: **ES**: the negative of the average of the firm's daily returns on 5% worst return days during the calendar year for the firm; **MES**: the negative of the average firm's daily return on 5% worst return days of the market (S&P 500 instead of for the firm) during the calendar year; *ES, MES* are expressed in percentage terms. *Rating* is generated by converting the bond ratings to a cardinal scale measured on a 23 point scale for ratings issued by S&P, Moody's and Fitch and then taking their average for a given firm. The firms are categorized into 4 firm-types: Depositories (2-digit SIC code=60); Broker-Dealers (4-digit SIC code=6211); Insurance (2-digit SIC code=60 & 64); Other (2-digit SIC code=61, 62(except 6211), 65, 67). Standard bond yield regression controls which are defined in Appendix D.1 and included in the regression specification are: *log assets, profitability, long-term debt to assets, leverage, term spread, log issue size, years to maturity.* Firm-type fixed effects (FE) are included by defining a dummy variable *d_Firm-Type* for each firm-type that is set to 1 if a firm belongs to that firm-type or else it is set to 0. Bond-type fixed effects are controlled by including *d_Agency*, *d_Sub* and *d_Callable* which are dummy variables set to 1 if the type of bond is an agency debt, subordinated or callable respectively or else they are set to 0. All standard errors are clustered at firm level to correct for correlation across observations of a given firm. All t-statistics are displayed in brackets. *, ** and *** indicate significance greater than 10%, 5% and 1%, respectively.

To study the impact of crisis periods, we construct bond issuance samples of all the financial firms in a 2-year window around the crisis-period and divide the period into equal pre- and post- crisis periods of four quarters each. Post-crisis dummies are defined in the following manner: For bonds issued between the period 1997:Q4 and 1999:Q3, *d_LTCM* takes the value 1 for all bonds issued between the 1998:Q4 and 1999:Q3, and 0 otherwise. For bonds issued between the period 1999:Q2 and 2001:Q1 , *d_Dotcom* takes the value 1 for all bonds issued between 2000:Q2 and 2001:Q1, and 0 otherwise. For bonds issued between the period 2007:Q4 and 2009:Q3, *d_FinCrisis* takes the value 1 for all bonds issued between 2008:4Q and 2009:Q3, and 0 otherwise.

Table 43 (continued)

	LTCM		Dotcom		Financial Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)
ES	27.57**		2.24		43.41***	
	(2.09)		(0.31)		(3.53)	
MES		9.57		-7.04		18.76
		(1.10)		(-1.10)		(1.09)
d_LTCM×ES	-33.16***					
	(-2.92)					
d_LTCM×MES		-16.55**				
		(-2.03)				
d_DotCom×ES			9.65			
			(1.24)			
d_DotCom×MES				-17.10		
				(-1.36)		
d_FinCrisis×ES					-61.22**	
					(-2.51)	
d_FinCrisis×MES						-74.70***
						(-3.41)
d_LTCM	70.28***	86.66***				
	(2.77)	(4.08)				
d_DotCom			47.77***	40.31***		
			(3.81)	(2.80)		
d_FinCrisis					175.59***	230.37***
					(2.80)	(5.11)
ΣCoeff	-5.59	-6.98	11.89	-24.13*	-17.82	-55.95***
	(-0.88)	(-1.25)	(1.17)	(-1.69)	(-0.71)	(-2.86)
N	154	154	126	126	100	100
adj. R^2	0.656	0.602	0.364	0.374	0.605	0.626
Year FE	✗	✗	✗	✗	✗	✗
FirmType FE	✓	✓	✓	✓	✓	✓
BondType FE	✓	✓	✓	✓	✓	✓
OtherControls	✓	✓	✓	✓	✓	✓

Table 44: Credit Ratings and Tail Risk

The following table displays the ordered probit regressions with dependent variable as rating scale on tail risk and other firm characteristics during the period from 1990 to 2010 separately for each firm-type. Credit ratings are converted into a cardinal scale starting with 1 as AAA(Aaa), 2 as AA+(Aa1), 3 as AA(Aa2), and so on. Our *tail risk* measures are defined as: **ES**: the negative of the average of the firm's daily returns on 5% worst return days during the calendar year for the firm; **MES**: the negative of the average firm's daily return on 5% worst return days of the market (S&P 500 instead of for the firm) during the calendar year; *ES, MES* are expressed in percentage terms. The firms are categorized into 4 firm-types: Depositories (2-digit SIC code=60); Broker-Dealers (4-digit SIC code=6211); Insurance (2-digit SIC code=60 & 64); Other (2-digit SIC code=61, 62(except 6211), 65, 67). Standard bond yield regression controls which are defined in Appendix D.1 and included in the regression specification are: *log assets, profitability, long-term debt to assets, leverage, term spread, log issue size, years to maturity.* Firm-type fixed effects (FE) are included by defining a dummy variable *d_Firm-Type* for each firm-type that is set to 1 if a firm belongs to that firm-type or else it is set to 0. Bond-type fixed effects are controlled by including *d_Agency*, *d_Sub* and *d_Callable* which are dummy variables set to 1 if the type of bond is an agency debt, subordinated or callable respectively or else they are set to 0. Year fixed effects are included in the regressions. All standard errors are clustered at firm level to correct for correlation across observations of a given firm. All t-statistics are displayed in brackets. *, ** and *** indicate significance greater than 10%, 5% and 1%, respectively.

Panel A analyzes the effect of tail-risk on bond rating assignment by credit rating agencies controlling for all our bond-level, firm-level and macroeconomic variables. Panel B analyzes the incremental effect of tail-risk on subordinated bond rating assignment controlling for all our bond-level, firm-level and macroeconomic variables.

Table 44 (continued)

Panel A: Only Tail Risk

	Depository		Broker-Dealer		Insurance		Other	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ES	0.27***		0.08		0.43***		0.15***	
	(3.68)		(0.37)		(4.19)		(2.93)	
MES		0.21		-0.30		0.38***		0.16**
		(1.46)		(-1.17)		(3.31)		(2.34)
N	470	470	228	228	269	269	906	906
Pseudo-R^2	0.298	0.290	0.368	0.375	0.189	0.175	0.436	0.433
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
BondType FE	✓	✓	✓	✓	✓	✓	✓	✓
OtherControls	✓	✓	✓	✓	✓	✓	✓	✓

Panel B: Tail Risk×Subordinated

	Depository		Rest	
	(1)	(2)	(3)	(4)
ES	0.33***		0.18***	
	(3.77)		(3.92)	
d_Sub×ES	-0.17*		-0.14	
	(-1.79)		(-1.36)	
MES		0.17		0.11*
		(1.12)		(1.67)
d_Sub×MES		0.09		0.09
		(0.78)		(0.78)
d_Sub	1.10***	1.05***	0.30	0.39**
	(7.89)	(8.18)	(1.49)	(1.98)
ΣCoeff	0.16*	0.26*	0.04	0.20
	(1.94)	(1.82)	(0.37)	(1.54)
N	470	470	1403	1403
Pseudo-R^2	0.301	0.290	0.376	0.371
Year FE	✓	✓	✓	✓
FirmType FE	✗	✗	✓	✓
BondType FE	✓	✓	✓	✓
FirmControls	✓	✓	✓	✓

APPENDIX A

MISCELLANEOUS SECTION FOR CHAPTER 1

A.1 Variable Definitions

This section provides the definitions of variables used in the paper's analysis. The mortgage loans used in this paper are all *owner occupied, first lien, single family homes* from HMDA and BBx databases. County-level income and population data is from the publicly available U.S. Census Bureau data. House prices are gathered from Zillow.com.

The Loans in BBx and HMDA are matched exactly on four loan characteristics, namely loan amount, loan purpose, occupancy type and lien type. Additionally loans are matched on the geographic location of the property as shown in Figure A.1 .

- *Number of Loans* is computed as $\sum_i^N p_i$ where p_i is the probability of a matched loan-pair from BBx and HMDA. N is the number of matched loan pairs in the aggregation set (ex: firm-county-quarter level set). The definition of N and p remain the same when defining the rest of the variables below.

- *Volume of Loans* is computed as $\sum_i^N p_i \times A_i$ where. A_i is the mortgage loan amount of the matched pair (matching is exact on this dimension).

- *Average Loan Amount* is computed as the $\left(\sum_{i=1}^N p_i \times A_i\right) \div \sum_{i=1}^N p_i$.

- *Average Loan-to-Income Ratio* is computed as the $\left(\sum_{i=1}^N p_i \times LTI_i\right) \div \sum_{i=1}^N p_i$ where LTI_i is the loan-to-income ratio of the matched loan pair i available in the HMDA dataset.

- *Average Loan-to-Value Ratio* is computed as the $\left(\sum_{i=1}^N p_i \times LTV_i\right) \div \sum_{i=1}^N p_i$

where LTV_i is the loan-to-value ratio of the matched loan pair i available in the BBx dataset.

- *Average Borrower Income* is computed as the $\left(\sum_{i=1}^{N} p_i \times Income_i\right) \div \sum_{i=1}^{N} p_i$ where $Income_i$ is the mortgage borrower's Income corresponding to the matched loan pair i available in the HMDA dataset.

- *Average FICO Score* is computed as the $\left(\sum_{i=1}^{N} p_i \times FICO_i\right) \div \sum_{i=1}^{N} p_i$ where $FICO_i$ is the mortgage borrower's FICO credit score corresponding to the matched loan pair i available in the BBx dataset.

- *Average Interest Rate* is computed as the $\left(\sum_{i=1}^{N} p_i \times Rate_i\right) \div \sum_{i=1}^{N} p_i$ where $Rate_i$ is the is the initial interest rate in percentage terms of the matched loan pair i available in the BBx dataset.

- *ARM Loans* are adjustable rate mortgages.

- *Complex Loans* are defined as either Interest Only (IO), Hybrid ARM (HARM), Pay-option ARM, or Negative Amortizing mortgages.

- *Jumbo Loans* are mortgages with loan amount greater than a particular loan limit. The loan limits for 2004, 2005 and 2006 were \$333,700, \$359,650 and \$417,000 respectively.

- *Loan-type* are low-documentation loans, Alt-A loans, Subprime loans, ARM loans, loans with pre-payment penalty, complex loans and jumbo loans. Loans are classified based on BBx data.

- *Loan-type (%)* is computed as $\left(\sum_{i=1}^{N} p_i \times \mathbb{I}_{loan-type}\right) \div \sum_{i=1}^{N} p_i$ in percentage terms where $\mathbb{I}_{loan-type}$ is an indicator function taking the value of 1 if the loan is of *type=loan-type* and 0 otherwise. For instance, the fraction of *Alt-A* loans is

$\left(\sum_{i=1}^{N} p_i \times \mathbb{I}_{Alt-A}\right) \div \sum_{i=1}^{N} p_i$ where $\mathbb{I}_{Alt-A}$ is an indicator function taking the value of 1 if the loan is an Alt-A mortgage and 0 otherwise.

- *Loan default* is defined if any of the following conditions are true: (a) payments on the loan are 60^+ days late as defined by the Office of Thrift Supervision (OTS); (b) the loan is in foreclosure; or (c) the loan is real estate owned (REO), that is, the lending bank has retaken possession of the home.
- *Default Percentage$_T$* is computed as $\left(\sum_{i=1}^{N} p_i \times \mathbb{I}_{Def,T}\right) \div \sum_{i=1}^{N} p_i$ in percentage terms where $\mathbb{I}_{Def,T}$ is an indicator function taking the value of 1 if the loan has defaulted within T periods after origination and 0 otherwise.

A.2 Supplemental Notes on Repo Financing and Bankruptcy Code

1. "The Amended Repurchase Agreements increased the capacity of the Mortgage Repurchase Facility from \$500 million to \$750 million, expanded the eligibility of underlying mortgage loan collateral and modified certain other covenants and terms. In addition, the Mortgage Repurchase Facility has been modified to conform to the revised bankruptcy remoteness rules with regard to repurchase facilities adopted by the IRS in October 2005." – *PHH Corporation 10-K filings.*

   Source: `https://www.sec.gov/Archives/edgar/data/77776/000095012306014446/y26027e10vk.htm`

2. "Our use of repurchase agreements to borrow money may give our lenders greater rights in the event of bankruptcy." – *American Mortgage Acceptance Company 10-K filings.*

   Source: `https://www.sec.gov/Archives/edgar/data/878774/000132404207000007/f10k_dec2006-amac.txt`

3. “Our borrowings under repurchase agreements may qualify for special treatment under the bankruptcy code, giving our lenders the ability to avoid the automatic stay provisions of the bankruptcy code and to take possession of and liquidate our collateral under the repurchase agreements without delay in the event that we file for bankruptcy.” – *American Home Mortgage Investment Corp 10-K filings.*

   Source: `https://www.sec.gov/Archives/edgar/data/1256536/000119312507044477/d10k.htm`

4. “Our repurchase facilities are dependent on our counterparties ability to resell our obligations to third-party purchasers. There have been in the past, and in the future there may be, disruptions in the repurchase market. If there is a disruption of the repurchase market generally, or if one of our counterparties is itself unable to access the repurchase market, our access to this source of liquidity could be adversely affected.” – *American Home Mortgage Investment Corp 10-K filings.*

   Source: `https://www.sec.gov/Archives/edgar/data/1256536/000119312507044477/d10k.htm`

5. “Repurchase agreements are used instead of warehouse loans in part to qualify for an exemption from the automatic stay provisions under Section 362(a) of the federal Bankruptcy Code” – *Wells Fargo* responding as a *Warehouse Lender* to a HUD solicitation of “Information on Changes in Warehouse Lending and Other Loan Funding Mechanisms”.

   Source: `http://www.regulations.gov/#!documentDetail;D=HUD-2010-0121-0008`

6. “Since the adoption of the 2005-06 Bankruptcy Amendments, the Financing

Documentation has significantly shifted towards the use of Repurchase Agreements" – *American Securitization Forum* responding to a HUD solicitation of "Information on Changes in Warehouse Lending and Other Loan Funding Mechanisms".

Source: `http://www.regulations.gov/#!documentDetail;D=HUD-2010-0121-0005`

A.3 BBx and HMDA Matching Algorithm

The HMDA dataset contains information on whether a loan was sold to a secondary market entity within the same calendar year as the origination year. This field allows for breaking down the mortgages sold to GSE and non-GSE financial institutions. The mortgages sold to non-GSE financial institutions are classified as (i) mortgages sold for private securitization, (ii) mortgages sold to non-bank institutions such as insurance companies, credit unions, mortgage banks or other finance companies, (iii) mortgages sold to banking institutions which include commercial and savings banks and (iv) mortgages sold to originating institution affiliates [1]. Following [105]'s classification and [13] who show that ten of the largest issuers of MBS from securitization belong to category (ii), categories (i) and (ii) are classified as mortgages most likely sold for the purpose of securitization. Summary statistics for the filtered HMDA dataset are shown in Table A.2 Panel A. Using the zip-code and census-tract crosswalk file, this dataset is then matched to the BBx data based on four loan characteristics: loan amount, loan purpose, occupancy type and lien type and the geography of the property[2]. While the matching can be carried out exactly on the four loan characteristics, matching on geography yields a probability related to the overlap of

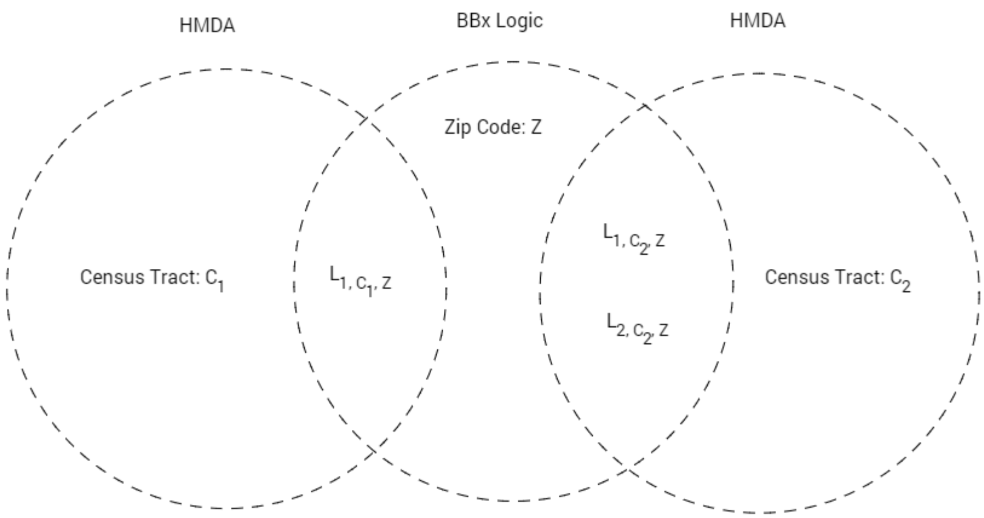
[1] The HMDA reporting format and thereby the classification codes for mortgages sold changes in 2004. Different codes are used for pre- and post-2004 periods.

[2] The HMDA loan amount is rounded to the nearest thousand, but BBx contains the exact loan amount. This leads to a coarse match on the loan amount. Moreover, while the data on the identity of the loan originator is complete in the HMDA dataset, it is missing for about 90% of the BBx data. This does not allow for matching on the loan originator.

a HMDA census-tract region with the BBx zip-code region. Specifically, within the subset of HMDA and BBx loans that have matched on the four loan characteristics, let there be N census-tracts which overlap with the zip-code z of a matched BBx loan. Let $K_{c,z}$ be the number of matched loans in census-tract c which overlaps with the zip-code z of a matched BBx loan, where $c \in \{1, 2, 3 \ldots N\}$. The conditional probability[3] of any one loan $L_{i,c,z}$ in census-tract c to be a match for the given HMDA loan in zip-code z is computed as $\mathbb{P}(L_{i,c,z}) = \dfrac{\mathbb{P}(A_{c,z})/K_{c,z}}{\sum_{j=1}^{N} \mathbb{P}(A_{j,z})}$ where $\mathbb{P}(A_{c,z})$ is the proportion of a census-tract region c that overlaps with a given zip-code region z based on the number of housing units. Refer to Figure A.1 for a simple pictorial depiction of the above matching algorithm. Summary statistics for the matched BBx-HMDA data is shown in Table A.2 Panel B. The matching quality of both databases is compared by plotting the Epanechnikov kernel densities in Figure A.2 and Figure A.3 across various loan characteristics.

[3] I.e. conditional on matching exactly on the four loan-characteristics.

Figure A.1: Databases Matching Exercise



In the above Figure, the matching probability for each loan is given by:

$$\mathbb{P}(L_{1,C_1,Z}) = \frac{\mathbb{P}(A_{C_1,Z})}{\mathbb{P}(A_{C_1,Z}) + \mathbb{P}(A_{C_2,Z})}$$

$$\mathbb{P}(L_{1,C_2,Z}) = \mathbb{P}(L_{2,C_2,Z}) = \frac{\mathbb{P}(A_{C_2,Z})/2}{\mathbb{P}(A_{C_1,Z}) + \mathbb{P}(A_{C_2,Z})}$$

Where $\mathbb{P}(A_{C,Z})$ is the proportion of a census-tract region C that overlaps with a given zip-code region Z based on the percentage of common housing units.

Figure A.2: BBx Matching Quality: Epanechnikov Kernel Densities

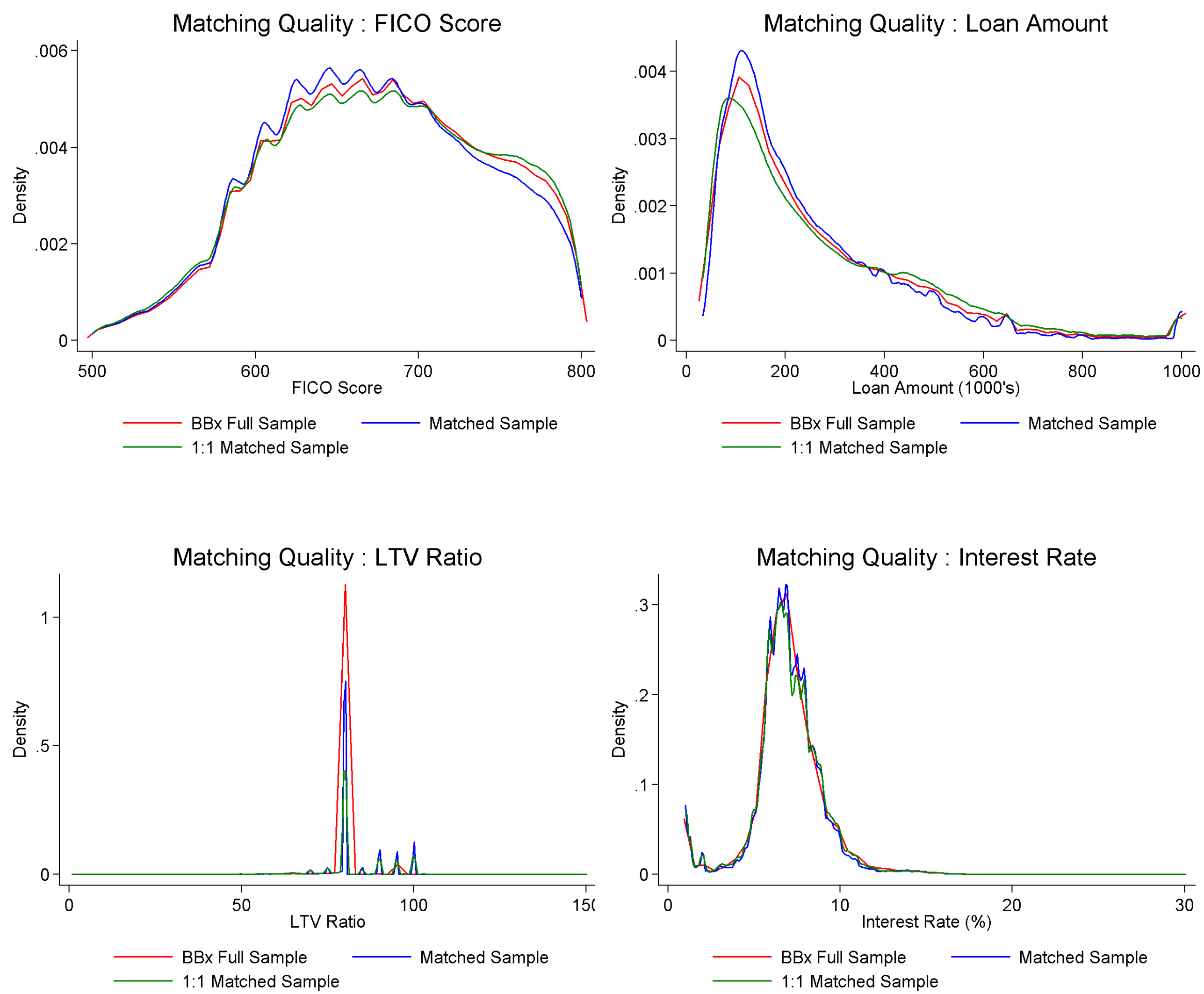


Figure A.3: HMDA Matching Quality: Epanechnikov Kernel Densities

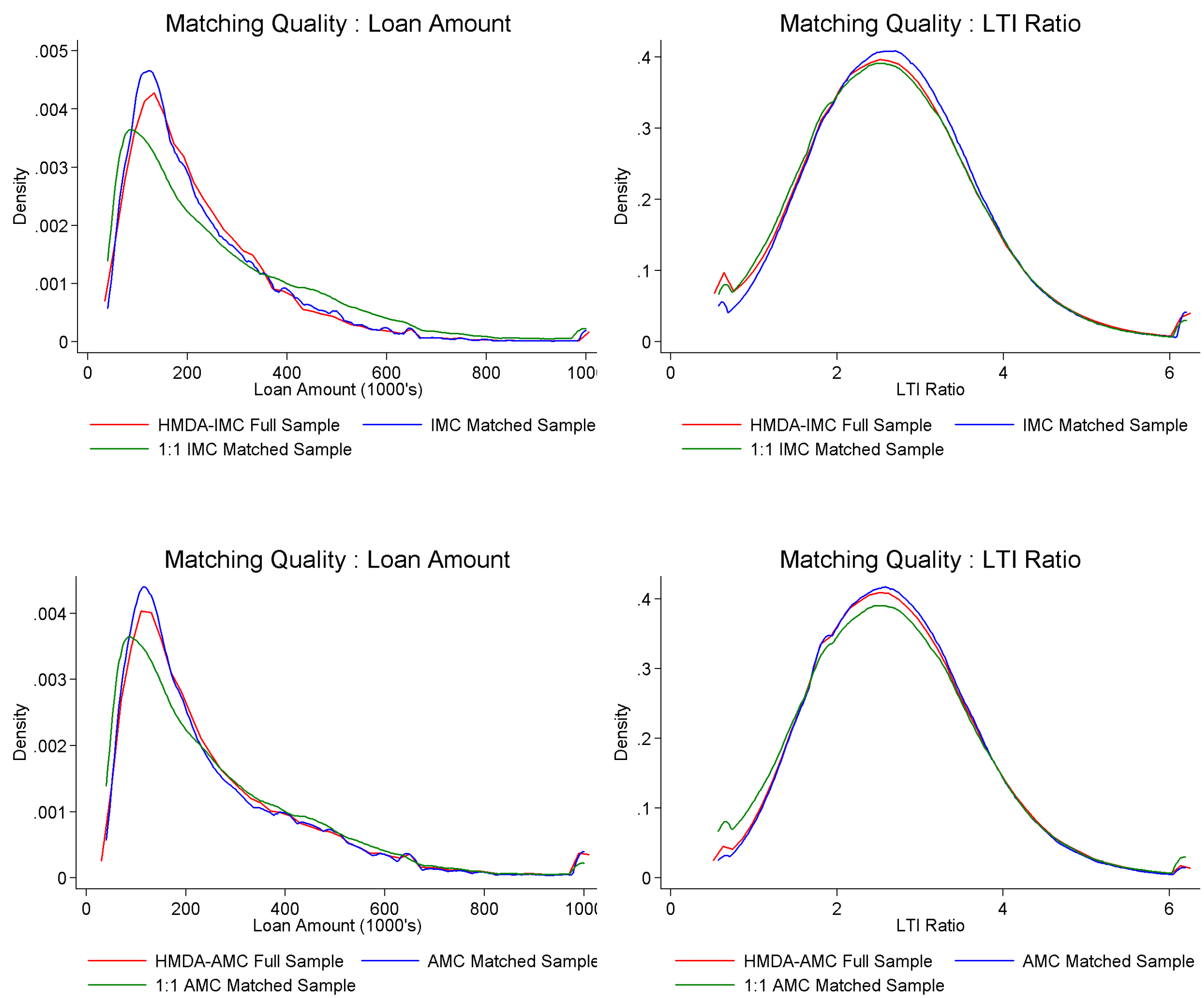
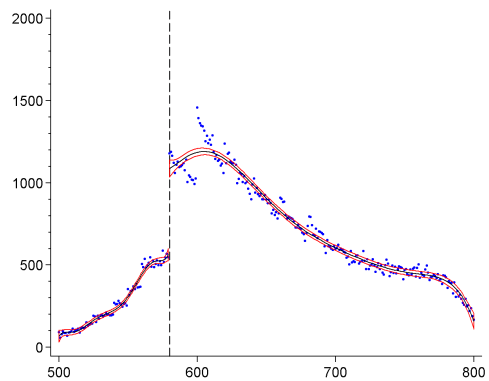
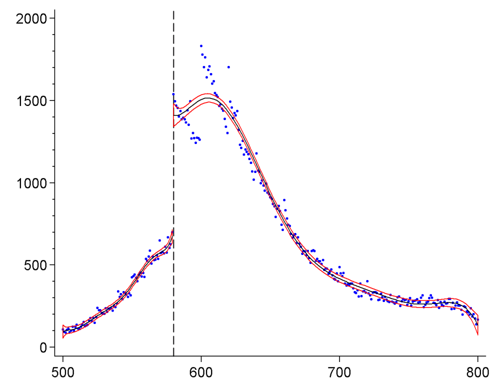


Figure A.4: Discontinuity in Full-Doc Loan Issuance : Around 580 FICO Threshold

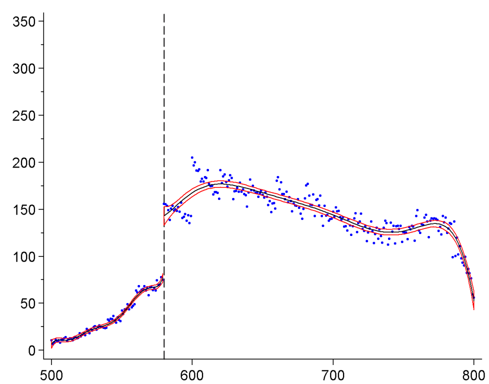
The figure shows the number and volume of full-documentation mortgages issued at each FICO score in blue dots. The black solid line fits a flexible seventh-order polynomial as in Equation 2 on either side of the cut-off FICO score of 580. The red lines are the 95% confidence intervals. The black dashed line passes through the 580 FICO score point.



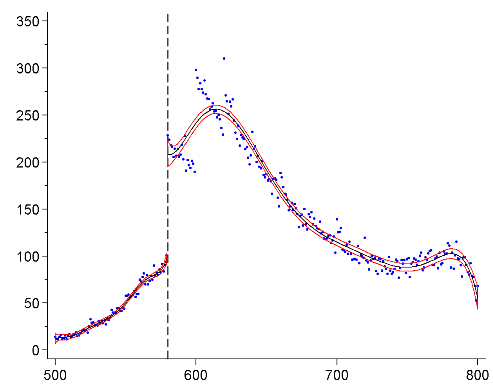
(a) ***Pre-Bankruptcy Act: Number of Loans***



(b) ***Post-Bankruptcy Act: Number of Loans***



(c) ***Pre-Bankruptcy Act: Volume of Loans***



(d) ***Post-Bankruptcy Act: Volume of Loans***

Table A.1: Operating Data & Liabilities: American Home Mortgage

This table presents the operating data and liabilities of American Home Mortgage Company which is an independent mortgage company (IMC). The data has been gathered from the firm's SEC 10-K filings. The CIK identifier for the firm is 0001256536. *Retail loans* are made by directly working with the homeowner without any middlemen or brokers. *Wholesale loans* are made by independent mortgage brokers (middlemen) who generate loan applications for a firm by working on the retail end with the borrowers. *Correspondent loans* are made on behalf of a wholesale lender by another institution – these loans are made through the institution's retail operations but according to the underwriting standards set by the wholesale lender. *Warehouse LOC* stands for warehouse line of credit. *Repo* stands for repurchase agreements. *CDO* stands for Collateralized Debt Obligations.

Panel A: *Operating Data*

Year:	**2004**	**2005**	**2006**
Loan originations	23,069,085	45,298,006	58,899,354
Retail	11,238,235	20,362,095	20,802,657
Wholesale	11,830,850	24,298,621	32,227,235
Correspondent	0	637,290	5,869,462
Loans sold to third parties	13,685,246	28,465,935	55,974,228
Loan servicing portfolioloans sold or securitized	11,955,608	25,044,676	38,480,246
Loans securitized and held	1,847,987	4,498,672	0

Panel B: *Liabilities*

Year:	**2004**			**2005**			**2006**		
Interest bearing liabilities:	*Avg Bal*	*Interest*	*Avg Cost*	*Avg Bal*	*Interest*	*Avg Cost*	*Avg Bal*	*Interest*	*Avg Cost*
Warehouse LOC	1,349,435	53,650	3.98%	2,863,982	147,339	5.14%	6,374,157	356,796	5.60%
Repo agreements	4,976,437	124,637	2.50%	7,184,534	260,423	3.62%	8,979,463	461,801	5.14%
Commercial paper	744,335	16,541	2.22%	2,160,859	76,993	3.56%	2,511,157	126,854	5.05%
Notes payable	118,592	4,770	4.02%	213,935	10,384	4.85%	354,902	20,883	5.88%
Deposits	7,188,799	199,598	2.78%	0	0	0.00%	5,215	207	3.97%
CDOs				706,355	26,485	3.75%	2,797,000	156,754	5.60%
Trust preferred securities				65,836	5,029	7.64%	256,953	22,744	8.85%

Table A.2: Summary Statistics

Panel A of this table presents the summary statistics of the HMDA sample used for matching with the BBx database. The HMDA dataset is first filtered to consist of mortgages (i) sold for private securitization, (ii) sold to non-bank institutions such as insurance companies, credit unions, mortgage banks or other finance companies. This subsample of loans sold to non-GSEs is further filtered to contain only owner occupied, first lien, single family homes. Similarly, the BBx database is also filtered to consist of owner occupied, first lien, single family homes. Panel B of this table presents the matched BBx-HMDA dataset. The matching is carried exactly on four loan characteristics, namely loan amount, loan purpose, occupancy type and lien type. Additionally, loans are matched on the geographic location of the property as shown in Figure A.1. LTI stands for loan-to-income ratio. LTV stands for loan-to-value ratio.

Panel A: ***Unmatched HMDA sample***

	CommBanks	Thrifts	CreditUnions	AMC	IMC
Tot Loan Number (1000s)	553.10	536.29	29.34	714.85	2597.68
Tot Loan Volume ($Bil)	116.40	127.33	4.55	184.59	584.74
Avg Loan Amount (1000s)	210.45	237.42	155.23	258.23	225.10
Avg Borrower Inc. (1000s)	86.56	94.49	70.72	102.33	89.68
Avg LTI Ratio (%)	2.65	2.68	2.40	2.70	2.68

Panel B: ***Matched BBx-HMDA sample***

	CommBanks	Thrifts	CreditUnions	AMC	IMC
Tot Loan Number (1000s)	339.04	396.19	8.97	716.09	1666.18
Tot Loan Volume ($Bil)	81.55	105.20	1.70	192.44	393.42
Avg Loan Amount (1000s)	240.54	265.53	189.19	268.74	236.12
Avg FICO	674.86	675.30	673.23	678.96	670.85
Avg LTV Ratio (%)	83.78	81.99	83.14	82.46	82.52

Table A.3: Summary Statistics

Panel A of this table presents the summary statistics of the matched BBx-HMDA sample. The headers of the columns indicate the number of HMDA matches for a given BBx loan. The matching is carried exactly on four loan characteristics, namely loan amount, loan purpose, occupancy type and lien type. Additionally, loans are matched on the geographic location of the property as shown in Figure A.1.

Panel A: ***BBx Logic matching across years***

			Number of Matches (%)				
Year	BBx Unmatched (#)	BBx Matched (%)	One	Two	Three	Four	$\geq$ Five (%)
2004	879,377	74.70	36.72	21.38	13.02	8.24	20.64
2005	1,237,355	79.87	32.09	19.48	12.75	8.62	27.06
2006	989,129	78.63	35.49	20.41	12.66	8.35	23.09

Panel B: ***HMDA matching across years***

Year	IMCs (%)	AMCs (%)	Others (%)
2004	60.14	59.84	60.10
2005	63.97	73.20	66.27
2006	58.48	71.69	61.45

Table A.4: Summary Statistics

This table presents the top 10 independent mortgage companies (IMCs) and parents of the top 10 affiliated mortgage companies (AMCs). The values for the loan volume and loan number are aggregated over the 2004–2006 period.

Top Ten IMCs	Loan Volume ($ Bil)	Loan Number (1000s)	Top Ten AMC Parents	Loan Volume ($ Bil)	Loan Number (1000s)
BEDFORD HOME LOANS INC.	186.0	1073.64	COUNTRYWIDE FC	546.0	2676.45
NEW CENTURY MORTGAGE CORP.	119.0	655.34	HSBC HOLD. PLC	132.0	928.99
AMERICAN HOME MORTGAGE	118.0	561.47	SUNTRUST BANK	106.0	580.62
OPTION ONE MORTGAGE CORP.	95.0	548.56	ABN AMRO HOLD. NV.	96.7	530.74
WMC MORTGAGE CORP.	72.7	382.20	FIRST HORIZON NAT. CORP.	90.5	512.80
PINNACLE MORTGAGE	63.1	363.07	GMAC BANK	89.3	545.08
PPH MORTGAGE CO.	62.3	366.35	WACHOVIA CORP.	82.8	410.99
MHL FUNDING CORP.	54.2	241.70	JP MORGAN CHASE & CO	63.9	336.69
AEGIS LENDING CORP.	47.6	278.64	CITIGROUP	61.8	443.20
TAYLOR, BEAN, & WHITAKER	47.4	275.02	WELLS FARGO & CO	47.5	275.34

Table A.5: State Anti-Predatory Lending Laws

This table provides the data for anti-predatory lending laws for U.S. states gathered from [25]. The numbers reported in this table are from the combined index based on the pre- and post-mini-HOEPA laws that were in effect in 2004–2005. The table has been sorted based on the Enforcement measure.

StateName	Enforcement	Coverage	Restriction
Arizona	0.00	0.00	0.00
Delaware	0.00	0.00	0.00
Louisiana	0.00	1.81	0.67
Minnesota	0.00	6.46	0.55
Montana	0.00	0.00	0.00
New Hampshire	0.00	0.00	0.00
North Dakota	0.00	0.00	0.00
Oregon	0.00	0.00	0.00
Rhode Island	0.00	1.93	2.01
South Dakota	0.00	0.00	0.00
Tennessee	0.00	0.00	0.00
Washington	0.00	0.00	0.00
Wisconsin	0.00	0.00	0.00
Alaska	0.64	1.69	2.68
Iowa	0.64	1.93	2.68
Nebraska	0.64	1.93	0.00
Michigan	0.96	6.74	2.16
New York	1.76	2.15	1.91
West Virginia	1.76	5.60	1.64
Hawaii	1.92	0.85	0.67
Mississippi	1.92	1.93	0.67
Missouri	1.92	1.81	0.67
Vermont	1.92	1.57	2.68
Florida	2.10	0.00	1.64
Arkansas	2.11	3.66	4.07
Connecticut	2.11	2.67	3.25
Georgia	2.11	1.72	3.00
Pennsylvania	2.11	0.00	1.36
Texas	2.11	0.86	1.36
Illinois	2.46	3.74	1.91
Massachusetts	2.46	2.15	3.82
New Jersey	2.46	2.15	2.73
Alabama	2.57	1.57	2.68
Idaho	2.57	1.81	1.34
Kansas	2.57	1.93	2.68
Utah	2.57	3.54	4.87
Virginia	2.57	1.81	0.00
Wyoming	2.57	0.85	2.68
Nevada	2.81	0.00	0.00
California	3.33	4.09	2.03
North Carolina	3.33	3.42	4.61
District Of Columbia	3.39	5.67	3.25
Maryland	3.97	3.01	3.23
Colorado	4.03	1.88	4.32
Ohio	4.03	1.93	2.03
South Carolina	4.32	2.80	4.87
Indiana	4.39	3.23	4.34
Maine	4.39	1.57	3.23
Oklahoma	4.68	0.97	4.87
Kentucky	4.74	2.43	2.85
New Mexico	5.03	6.10	5.96

Table A.6: Mortgage Credit Growth: Unique BBx-HMDA Matches

This table examines the changes in the broad measures of loan origination before and after the 2005 BAPCPA between IMCs and AMCs. The dataset is at the mortgage originating firm-county-quarter level. The dataset is restricted to only unique matches where one BBx loan is matched to one HMDa loan. The dependent and independent variables are the same as in the baseline regression specifications in Table 2. All regressions include *Firm FE* and *County*×*Quarter FE*. *T*-statistics displayed in parentheses are robust and clustered at the *County* level. *, **, and *** indicate significance greater than 10%, 5%, and 1% respectively.

Depvar:	g_LoanVol (1)	g_LoanNum (2)	AvgIntRate (3)	AvgLTI (4)
dPostBAPCPA×dIMC	0.09*** (7.81)	0.11*** (11.57)	-0.14*** (-8.04)	0.03** (2.54)
Avg FICO			-0.01*** (-31.91)	0.00* (1.91)
Avg LTV			0.04*** (38.27)	
ARM Loans(%)			-0.23*** (-8.37)	0.13*** (10.85)
Alt-A Loans(%)			0.40*** (17.46)	-0.04*** (-3.15)
Subprime Loans(%)			1.02*** (36.09)	-0.06*** (-3.70)
LowDoc Loans(%)			0.19*** (13.16)	-0.10*** (-12.26)
Firm FE	✓	✓	✓	✓
County×*Quarter FE*	✓	✓	✓	✓
N	96483	96483	79724	78787
Adj. R^2	0.040	0.039	0.547	0.356

Table A.7: Mortgage Credit Growth: Highest Probability Match

This table examines the changes in the broad measures of loan origination before and after the 2005 BAPCPA between IMCs and AMCs. The dataset is at the mortgage originating firm-county-quarter level. The dataset is restricted only to the highest probability matched HMDA loan for a given BBx loan. The dependent and independent variables are the same as in the baseline regression specifications in Table 2. All regressions include *Firm FE* and *County*×*Quarter FE*. *T*-statistics displayed in parentheses are robust and clustered at the *County* level. *, **, and *** indicate significance greater than 10%, 5%, and 1% respectively.

Depvar:	g_LoanVol (1)	g_LoanNum (2)	AvgIntRate (3)	AvgLTI (4)
dPostBAPCPA×dIMC	0.10***	0.11***	-0.09***	0.05***
	(12.65)	(15.91)	(-8.05)	(6.07)
Avg FICO			-0.01***	0.00
			(-46.61)	(1.44)
Avg LTV			0.04***	
			(55.78)	
ARM Loans(%)			0.00	0.07***
			(0.05)	(9.05)
Alt-A Loans(%)			0.33***	-0.01
			(19.42)	(-1.55)
Subprime Loans(%)			0.86***	-0.03**
			(42.73)	(-2.46)
LowDoc Loans(%)			0.23***	-0.08***
			(23.20)	(-12.09)
Firm FE	✓	✓	✓	✓
County×*Quarter FE*	✓	✓	✓	✓
N	187227	187227	163798	161762
Adj. R^2	0.068	0.074	0.593	0.379

Table A.8: Mortgage Credit Growth: County-Quarter Level

This table examines the changes in the broad measures of loan origination before and after the 2005 BAPCPA between IMCs and AMCs. The dataset is at the mortgage originating county-quarter level. The dependent and independent variables are the same as in the baseline regression specifications in Table 2. Additionally, county-level population growth and per-capita income growth rates are included as county-level controls. All regressions include *County FE* and *Quarter FE*. *T*-statistics displayed in parentheses are robust and clustered at the *County* level. *, **, and *** indicate significance greater than 10%, 5%, and 1% respectively.

Depvar:	g_LoanVol (1)	g_LoanNum (2)	AvgIntRate (3)	AvgLTI (4)
dPostBAPCPA×dIMC	0.08*** (7.92)	0.08*** (8.38)	-0.12*** (-8.85)	0.05*** (5.65)
dIMC	-0.13*** (-17.83)	-0.13*** (-20.91)	0.16*** (18.26)	0.00 (0.69)
County-level Controls:				
Population growth	1.41** (2.20)	0.66 (1.21)	-0.00 (-0.00)	0.73 (1.45)
PCI growth	-0.24 (-1.15)	-0.20 (-1.08)	0.07 (0.29)	-0.44*** (-2.75)
Competition growth	-0.06*** (-2.97)	-0.06*** (-3.46)	0.01 (0.20)	0.01 (0.40)
Loan-mix Controls:				
Avg FICO			-0.01*** (-30.91)	0.00 (1.22)
Avg LTV			0.05*** (42.70)	
ARM Loans(%)			0.23*** (8.97)	0.09*** (5.82)
Alt-A Loans(%)			0.31*** (8.91)	-0.02 (-1.08)
Subprime Loans(%)			0.74*** (19.03)	0.01 (0.44)
LowDoc Loans(%)			0.20*** (9.12)	-0.12*** (-8.73)
County FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
N	38356	38356	36508	36505
Adj. R^2	0.112	0.145	0.726	0.463

Table A.9: Mortgage Credit Growth Robustness: Alternate Specifications

This table examines the changes in the broad measures of loan origination before and after the 2005 BAPCPA using alternate specifications for the dependent variable and the event window. The dataset is at the mortgage originating firm-county-quarter level. The dependent variables in Panel A are the log of total volume of loans (*Log_LoanVol*) and the log of total number of loans (*Log_LoanNum*) made by a mortgage originating firm in a given county and quarter. In Panel B columns (1)–(2), *dPostBAPCPA* takes the value 1 for four quarters from 2005Q4 to 2006Q3 and 0 for four quarters from 2004Q4 to 2005Q3. In Panel B columns (3)–(4), *dPostBAPCPA* takes the value 1 for eight quarters from 2005Q4 to 2007Q3 and 0 for eight quarters from 2003Q4 to 2005Q3. In Panel B columns (5)–(6), the placebo event window is a non-overlapping window with the baseline regression event window in Table 2. For these specifications, *dPostBAPCPA* takes the value 1 for six quarters from 2002Q4 to 2004Q1 and 0 for six quarters from 2001Q2 to 2002Q3. All regressions include Firm FE, County×Quarter FE. *T*-statistics displayed in parentheses are robust and clustered at the County level. *, **, and *** indicate significance greater than 10%, 5%, and 1% respectively.

Panel A: ***Change in Levels (log)***

	Levels	
Depvar:	Log_LoanVol (1)	Log_LoanNum (2)
dPostBAPCPA×dIMC	0.03*** (4.07)	0.04*** (4.87)
Lagged Depvar	0.56*** (66.17)	0.58*** (67.41)
Firm FE	✓	✓
County×Quarter FE	✓	✓
N	295932	295932
Adj. R^2	0.607	0.561

Panel B: ***Alternate Time Periods***

	4Q Before/After		8Q Before/After		Placebo Test	
Depvar:	g_LoanVol (1)	g_LoansNum (2)	g_LoanVol (3)	g_LoansNum (4)	g_LoanVol (5)	g_LoansNum (6)
dPostBAPCPA×dIMC	0.08*** (7.02)	0.08*** (8.26)	0.05*** (5.51)	0.06*** (7.01)	-0.00 (-0.19)	-0.01 (-0.96)
Firm FE	✓	✓	✓	✓	✓	✓
County×Quarter FE	✓	✓	✓	✓	✓	✓
N	217025	217025	334839	334839	104177	104177
Adj. R^2	0.041	0.042	0.054	0.058	0.032	0.029

Table A.10: Mortgage Credit Growth Robustness: Discontinuity in Growth of Number and Volume of Loans

Panel A and B fit a non-parametric local linear polynomial using a triangular kernel within half and twice the optimal bandwidth (OB) proposed by [28] respectively. The dependent variable in both panels is either the growth in the *number* or *volume* of mortgage originations at each FICO score from the pre- to post-BAPCPA period covering 2004Q2 to 2007Q1. The Indicator variable *dThreshold* is equal to 1 if the FICO score is greater than 620 (580) for low (full) documentation loans, and 0 otherwise. *T*-statistics displayed in parentheses. *, **, and *** indicate significance greater than 10%, 5%, and 1% respectively.

Panel A: ***Local linear polynomial fit within half the optimal bandwidth (0.5×OB)***

	Low-Doc Loans (FICO Threshold=620)		*Full-Doc Loans (FICO Threshold=580)*	
Depvar:	g_LoanVol (1)	g_LoanNum (2)	g_LoanVol (3)	g_LoanNum (4)
d_Threshold	0.18*** (4.75)	0.18*** (6.25)	0.15*** (2.67)	0.07 (1.29)
N	29	29	21	21

Panel B: ***Local linear polynomial fit within twice the optimal bandwidth (2×OB)***

	Low Doc Loans (FICO Threshold=620)		*Full Doc Loans (FICO Threshold=580)*	
Depvar:	g_LoanVol (1)	g_LoanNum (2)	g_LoanVol (3)	g_LoanNum (4)
d_Threshold	0.10*** (4.79)	0.10*** (6.52)	0.16*** (5.91)	0.13*** (4.31)
N	115	115	83	83

Table A.11: Mortgage Credit Growth Robustness: Variation Across Counties with APL laws

This table examines the changes in the broad measures of IMC loan origination before and after the 2005 BAPCPA between counties bordering states with weak and strong anti-predatory lending (APL) laws. The dataset is at the mortgage originating firm-county-quarter level. States are sorted in ascending order based on the strength of the enforcement of APL laws presented in Table A.5. States in the top and bottom half are classified as weak-APL states and strong-APL states respectively. In panels A and B, neighboring counties are defined as counties within 30 miles and 50 miles respectively across borders of states with weak and strong APL laws. In panel C all counties in weak- and strong-APL states are included and no distance cut-off is used. The dummy variable *dWeakAPLCounty* is equal to 1 if a county belongs to a weak-APL state and is 0 otherwise. The dependent variable and rest of the control variables are the same as in Table 2. All regressions include *Firm FE*, *County*, and *Quarter FE*. *T*-statistics displayed in parentheses are robust and clustered at the *County* level. *, **, and *** indicate significance greater than 10%, 5%, and 1% respectively.

Panel A: ***Neighboring counties classified as within 50 miles***

Depvar:	g_LoanVol (1)	g_LoanNum (2)	AvgIntRate (3)	AvgLTI (4)
dPostBAPCPA×dWeakAPLCounty	0.07*** (3.85)	0.07*** (3.95)	-0.03 (-1.03)	0.04** (2.43)
Loan-mix Controls			✓	✓
Firm FE	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
N	58004	58004	51810	51178
Adj. R^2	0.035	0.037	0.569	0.341

Table A.11 (continued)

Panel B: ***Neighboring counties classified as within 100 miles***

Depvar:	g_LoanVol (1)	g_LoanNum (2)	AvgIntRate (3)	AvgLTI (4)
dPostBAPCPA×dWeakAPLCounty	0.04***	0.04***	-0.00	0.00
	(3.04)	(3.31)	(-0.21)	(0.18)
Loan-mix Controls			✓	✓
Firm FE	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
N	107849	107849	96397	95253
Adj. R^2	0.031	0.033	0.560	0.309

Panel C: ***Variation across states***

Depvar:	g_LoanVol (1)	g_LoanNum (2)	AvgIntRate (3)	AvgLTI (4)
dPostBAPCPA×dWeakAPLCounty	0.02*	0.02**	0.00	0.06***
	(1.70)	(2.20)	(0.17)	(4.93)
Loan-mix Controls			✓	✓
Firm FE	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
N	241040	241040	217659	214742
Adj. R^2	0.032	0.034	0.580	0.353

APPENDIX B

MISCELLANEOUS SECTION FOR CHAPTER 2

B.1 Variable Definitions

B.1.1 Rating-level variables

- *dCDS* is an indicator variable equal to one if the rating change takes place when the CDS trades on the underlying firm, and 0 otherwise.

- *Previous Rating* is the credit rating level prior to the rating change. It is expressed as the natural logarithm of the cardinal rating scale; see Table B.1 for the mapping

- *Abs Rating Change* is the absolute value of the difference in rating scale change between after and before rating change events.

- *Days Since Last Rating* is the natural logarithm of the number of days between the previous rating change in the same direction for the same bond issue, but by another rating agency. Following Jorion, Liu, and Shi (2005), the number of days is set to 60 (a) if both rating agencies rate on the same day, (b) if the rating by the second rating agency is in the opposite direction,or (c) if the rating change by the other rating agency is more than 60 days.

- *Earnings Ann Related* is an indicator variable equal to one if there is an earnings announcement within (-1,+1) days of the rating change event day, and 0 otherwise.

- *dDowngrade* is an indicator variable equal to one if the bond experiences a rating downgrade event, and 0 otherwise.

B.1.2 Firm-level variables: Firm fundamentals

- *Sales* is the firm's quarterly sales (saleq) reported in COMPUSTAT.
- *Assets* is the firms' quarterly total assets (atq) reported in COMPUSTAT.
- *Operating income* is the quarterly operating income (oiadpq) reported in COMPUSTAT.
- *Profitability* is the firm's quarterly ratio of *Operating income* to *Sales*.
- *Total debt* is the firm's total debts (dlcq + dlttq) reported in the quarterly COMPUSTAT.
- *Leverage* is the firm's *Total debt* divided by its *Assets*.
- *Market value of equity* is the market value of equity calculated using the monthly CRSP database, i.e. share price $\times$ total shares outstanding.
- *Book value of equity* is the book value of equity. It is the total assets minus total liability plus tax credit (atq$-$ltq + txditcq) calculated using quarterly COMPUSTAT.
- *Mkt-to-Book* is the monthly ratio of *Market value of equity* divided by the *Book value of equity*.
- *Avg Volatility* is the monthly standard deviation of daily stock returns caculated using data from CRSP.
- *Avg Trading Volume* is the monthly trading volume on the stock reported in CRSP.
- *Avg Return* is the monthly stock return obtained from CRSP.

B.1.3 Firm-level variables: CDS trading variables

- *Analyst Coverage* is the number of analyst EPS forecasts in the 90 days prior to the earnings announcement date. (source: I/B/E/S)

- *Analyst Dispersion* is the standard deviation of analyst EPS estimates made in the 90 days prior to the earnings announcement date scaled by the actual reported EPS. (source: I/B/E/S)

- *Institutional Ownership* is the ratio of total shares held by institutional investors to the total shares outstanding for a given stock. (source: Thomson-Reuters Institutional Holdings (13F) Database)

- *Stock Illiquidity* is the monthly average stock illiquidity defined as the squared root of the [9] measure. It is the monthly average of the following daily values where Ret_t and Price_t are daily return and price of the stock:

  $\sqrt{1000000 * |\text{Ret}_t| / (\text{Volume} \times \text{Price}_t)}$.

- *Bond Illiquidity* is the number of outstanding bond issues in a given month (see [115]).

- *Debt Outstanding* is a proxy for hedging demand. It is the residual from regressing total amount of bond debt outstanding on the number of bond issues.This variable measures the amount of bond debt outstanding for a firm that is linearly unrelated to the number of its bond issues.

- *Forex Derivative Hedging* is the average amount of foreign exchange derivatives used for hedging purposes (i.e. non-trading purposes) relative to total assets of the lead syndicate banks and bond underwriters that the firm has done business with in the past five years. Banks' derivatives usage data is obtained from Bank Holding Company (BHC) Y9-C filings. Data on the firm's lead bank syndicate is obtained from LPC Dealscan, and the firm's underwriter information is obtained from Mergent FISD.

B.1.4 CDS & Bond variables

- *CDS Spread* is the average monthly 5-year CDS spread from CMA and MARKIT databases.
- *Bond Yield* is the trade-weighted average monthly bond yield calculated from the TRACE database.
- *CDS Spread Change* is the logarithmic difference in average monthly 5-year CDS spreads between the current and previous months.
- *Bond Yield Change* is the logarithmic difference in trade-weighted average bond yields between the current month and previous months.
- *CDS Slope* is the difference between the monthly average 10-year CDS spreads and the monthly average 1-year CDS spreads.
- *CDS-implied Rating Class* is the firm's credit rating class, on the scale of 1 to 6, that is backed out non-parametrically using CDS spreads. See Section 2.5.1 for more details.
- *Credit Rating Class* is the credit rating level mapped to the rating class scale. See Table C.2 for the mapping.
- *Credit watch dummy* indicates whether the firm (or bond issue) is put on credit watch prior to a credit rating change. This monthly indicator variable takes the value 1 from the month of the watch announcement to the month of the rating change event or until "Off Watch" or "Not On Watch" is announced. Only negative watches are considered for downgrades and only positive watches were considered for upgrades. A credit watch announced 180 days or more prior to when a firm is re-rated is not considered to be related to the rating change

event. Credit watch data is obtained from Mergent FISD and Moody's Default Risk Database (MDRS).

- *Market Cap* is the monthly market value of equity.

- *Market Leverage* is defined as (Total debt + Market value of equity)/(Market value of equity) calculated at a quarterly frequency.

- *Long Term Debt-to-Asset* is the ratio of long term debt to total assets (dlttq/atq) calculated using quarterly COMPUSTAT.

- *ERP* is the firm's annualized equity risk premium implied by the dynamic of CDS term structure.

- *Subordinate* is an indicator variable equal to one if the bond is subordinated. We obtain bond characteristics from Mergent FISD, CUSIP Master file, and Moody's Default Risk Database (MDRS).

- *Callable* is an indicator variable equal to one if the bond is callable or redeemable, and zero otherwise.

- *Issue Size* is the offering amount of the bond at primary issue.

- *Maturity* is the maturity of the bond in years.

- *Treasury Slope* (10yr-1yr) is the difference between the 10-year and 1-year Treasury rates.

- *Bond return* is the raw bond return around the rating change event (t = 0) calculated over the $[-k, +k]$ event days as:

$$BondReturn_{t=0} = \frac{BondPrice_{t+k} - BondPrice_{t-k} + AccruedInterest}{BondPrice_{t-k}}.$$

  We use the shortest event window possible depending on the availability of bond trading history. The maximum window of $k = 7$ days is used, otherwise bond event-period return is not computed.

- *Daily bond index* is the weighted (equal or value) index of bond returns grouped according to Moody's six major rating categories.

B.1.5 Bankruptcy & Distress regression variables

- *Bankruptcy* is defined as when the firm experiences a credit default event as defined in Moody's Ultimate Recovery Database (Moody's URD).

- *Net Income-to-Assets* is the ratio of net income to total assets (niq/atq) obtained from quarterly COMPUSTAT.

- *Total Liabilities-to-Assets* is the ratio of total liabilities to total assets (ltq/atq) obtained from quarterly COMPUSTAT.

- *Relative Size* is the logarithmic of the firm's market value of equity divided by the total NYSE/AMEX market equity value. It is calculated monthly using data from CRSP.

- *Excess Return* is the monthly return on the firm minus the value-weighted NYSE/AMEX index return.

Table B.1: Classification of credit rating codes

The table presents the mapping of rating codes issued by S&P, Fitch, and Moody's to the cardinal scale, as well as to the rating class. The rating codes used by S&P and Fitch are similar but are different from those used by Moody's. Moody's uses code from Aaa down to C to rate bonds whereas S&P and Fitch rate bonds from AAA down to D. Within the 6 classes from AA to CCC for S&P and Fitch, the rating agencies have three additional gradations with modifiers (+,none,-). For examples, S&P's AA rating class is subdivided into AA+, AA, AA-. Similarly, Moody's has three additional gradations with modifiers 1,2,3 from Aaa to Caa. We transformed the credit ratings of the three rating agencies into a cardinal scale starting with 1 as AAA(Aaa), 2 as AA+(Aa1), 3 as AA(Aa2), and so on until 23 as the default category. The rating class mapping is from [91]. Fitch differs from the other two agencies in that it provides three ratings for default. We follow [90] by using 23 instead of 22 as the cardinal scale for Fitch's default category, which is the average of three default ratings – i.e., DD.

Description	S&P	Moody's	Fitch	Cardinal scale	Rating class
Investment grade					
Highest grade	AAA	Aaa	AAA	1	1
High grade	AA (+,none,-)	Aa (1,2,3)	AA (+,none,-)	2, 3, 4	1
Upper-medium grade	A (+,none,-)	A (1,2,3)	A (+,none,-)	5, 6, 7	2
Medium grade	BBB (+,none,-)	Baa (1,2,3)	BBB (+,none,-)	8, 9, 10	3
Speculative grade					
Lower medium grade	BB (+,none,-)	Ba (1,2,3)	BB (+,none,-)	11, 12, 13	4
Speculative	B (+,none,-)	B (1,2,3)	B (+,none,-)	14, 15, 16	5
Poor standing	CCC (+,none,-)	Caa (1,2,3)	CCC (+,none,-)	17, 18, 19	6
Highly speculative	CC	Ca	CC	20	6
Lowest quality	C	C	C	21	6
In default	D		DDD/DD/D	23	6

Table B.2: Probit model for CDS trading: First-stage IV model

We report probit regression results for the probability of CDS trading. The dependent variable is the firm-quarter indicator variable that is equal one if CDS contract trades on the underlying firm's debt in this quarter, and zero otherwise. The explanatory variables include firm-level characteristics, CDS-trading controls, and the instrument variable proxying for the probability of CDS trading. The instrumental variable (IV) that we use is *Forex Derivative Hedging* (see also [132]). It is defined as the average amount of foreign exchange derivatives used for hedging purposes relative to total assets of the lead syndicate banks and bond underwriters that firms have done business with in the past five years. We obtain data on firm's lead syndicate bank and underwriters from Dealscan and FISD, respectively. See Appendix B for description of other variables. Industry and year fixed-effects are included. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

	Probability of CDS trading
Instrumental variable	
Forex Derivative Hedging (%)	0.04***
	(4.84)
Firm-level controls	
Sales (log)	0.40***
	(21.14)
Profitability	-0.54***
	(-4.81)
Leverage	0.28***
	(3.19)
Market-to-Book	-0.01*
	(-1.89)
Rating Scale (log)	-0.30***
	(-6.01)
Avg Volatility (log)	-0.05
	(-1.58)
Avg Trading Volume (log)	0.12***
	(6.23)
Avg Return	0.15
	(1.16)
CDS-trading controls	
Analyst Coverage (log)	0.03
	(1.53)
Analyst Dispersion	0.00**
	(1.96)
Institutional Ownership	0.26***
	(5.10)
Stock Illiquidity	-3.28***
	(-4.92)
Bond Illiquidity	0.66***
	(33.22)
Debt Outstanding (log)	0.40***
	(20.15)
Observations	17850
Incremental Pseudo R^2	1.1%
Pseudo R^2	0.4854

Table B.3: The propensity score matched sample

This table presents matched sample diagnostics. Panel A shows the probit model used in the propensity score matching. We estimate firms' probability of having CDS trading in each month. The dependent variable in the probit model is the firm-month indicator that is equal one if CDS contract trades on the underlying firm's debt this month, and zero otherwise. All independent variables are lagged by one month. The first column in Panel A (Before matching) reports results estimated using the full sample for which data are available. The second column in Panel A (After matching) reports results estimated using the CDS-traded and propensity-score matched firms. Firms for which CDS contracts trade at any point in our sample period (1996-2010) are identified as the treatment group, i.e. traded-CDS firms. Firms in the control group used in the matching are those in the full sample that never have CDS contracts traded at any point in our sample period , i.e. non-traded-CDS firms. Each traded-CDS firm (treatment firm) is matched with up to five non-traded-CDS firms (control firms) based on their propensity scores of having CDS trading. Industry and year fixed effects are included in the regressions. *, **, and *** indicate statistical confidence greater than 10%, 5%, and 1%, respectively. Panel B reports pairwise comparisons of the variables used for matching for the CDS treatment firms, and the matched control firms. Panel C reports industry distributions (Fama-French 12 classification) for the CDS treatment firms, and the matched control firms.

Table B.3 (continued)

Panel A: Propensity score matched sample

	Before matching	After matching
Sales (log)	0.43***	0.12*
	(41.60)	(1.73)
Profitability	-0.44***	-0.25
	(-7.50)	(-0.66)
Leverage	0.02	-0.66*
	(0.35)	(-1.68)
Mkt-to-Book	-0.00*	-0.00
	(-1.84)	(-0.19)
Rating Scale(log)	-0.33***	-0.36**
	(-11.20)	(-2.47)
Avg Return	0.05	1.07**
	(0.74)	(2.41)
Avg Volatility (log)	-0.05**	0.05
	(-2.52)	(0.42)
Avg Trading Volume (log)	0.08***	0.00
	(7.71)	(0.05)
Analyst Coverage (log)	-0.03**	-0.05**
	(-2.37)	(-1.96)
Analyst Dispersion	0.00***	0.00
	(4.49)	(0.88)
Institutional Ownership	0.38***	0.13
	(13.87)	(0.82)
Stock Illiquidity	-3.14***	-1.42
	(-7.99)	(-0.43)
Bond Illiquidity	0.64***	0.21***
	(60.12)	(3.07)
Debt Outstanding (log)	0.38***	0.29***
	(37.11)	(3.36)
Observations	59539	1025
Pseudo R^2	0.49	0.09

Table B.3 (continued)

Panel B: Sample means of firm variables used in the propensity-score matching

	Before matching			*After matching*		
	Mean		(Diff)	Mean		(Diff)
	Treated	Control	T-stats	Treated	Control	T-stats
Sales (log)	7.75	6.70	151.98	7.22	6.79	6.15
Profitability	0.14	0.15	-8.70	0.16	0.15	0.48
Leverage	0.68	0.69	-8.04	0.68	0.70	-1.77
Mkt-to-Book	2.80	2.47	15.31	2.65	2.62	0.12
Rating Scale	8.41	9.63	-59.39	8.44	9.60	-2.28
Avg Return	0.01	0.01	-1.76	0.02	0.00	1.79
Avg Volatility (log)	-4.00	-3.95	-14.74	-4.02	-4.00	-0.61
Avg Trading Volume (log)	-0.83	-1.70	107.21	-1.32	-1.46	1.19
Analyst Coverage (log)	2.11	1.86	54.82	1.94	1.81	2.67
Analyst Dispersion	5.59	5.31	1.36	7.09	5.41	0.73
Institutional Ownership	4.27	4.25	10.41	4.25	4.27	-0.98
Stock Illiquidity	0.02	0.03	-64.73	0.02	0.03	-1.92
Bond Illiquidity	2.02	1.46	103.92	1.74	1.59	2.56
Debt Outstanding (log)	0.38	-0.21	96.95	0.20	-0.11	2.99

Panel C: Industry distribution of firms in the matched sample

FamaFrench 12 Industry Classifications	Treatment Sample (%)	Control Sample (%)
(1) Consumer Non-durables	7.34	5.44
(2) Consumer Durables	2.10	2.51
(3) Manufacturing	13.29	13.81
(4) Energy, Oil, Gas, and Coal Extraction	6.64	5.86
(5) Chemicals and Allied Products	4.55	5.44
(6) Business Equipment	6.99	6.69
(7) Telecommunciations	5.59	5.02
(8) Utilities	9.44	8.37
(9) Wholesale, Retail, and Services	10.14	7.11
(10) Healthcare	4.55	5.86
(11) Finance	19.58	22.18
(12) Others	9.79	11.72

B.1.6 Descriptives of the credit rating change sample

Panel A of Table B.4 summarizes the number of upgrades and downgrades along with the size of their rating changes over each year. There are about 2.1 downgrades for every upgrade, which is more or less consistent with previous studies.[1] We observe clustering of upgrades and downgrades in certain years over the 15-year period, and we find that 42% of all downgrades occurred in 2001-2002 and 2007-2009, which correspond to the post-Internet bubble and the recent financial crisis periods, respectively. On the other hand, 39% of all upgrades occurred in pre-Internet bubble period, i.e. 1997-1998, and when the market volatility level is historically low, i.e. 2006-2007, as measured by the VIX index. The size of the rating change is the absolute value of the change in the rating scale. The average size of the rating change does not vary significantly over the years. There are 1416 downgrades and 689 upgrades during the period when the underlying firms have CDS contracts traded. On the other hand, there are 3249 downgrades and 1482 upgrades during the period when the underlying firms do not have CDS contracts traded. For downgrades (upgrades), the mean size of the absolute rating change for an issue without CDS trading is 1.69 (1.38), and for an issue with CDS trading, it is 1.55 (1.27). Table B.4 shows that the start dates of CDS trading in our sample begin in 2001, when we observe only 12 downgrades on firms that have CDS contracts traded. Nevertheless, the number of firms that have CDS contracts traded increases significantly in subsequent years. In fact, Panel A shows that the numbers of downgrades on firms with and without CDS contracts traded are roughly comparable after 2005.

In order to control for the differences between these two types of firms, we consider a subsample of firms for which CDS starts trading at some point during our sample

[1] Our number is closer to that of [47], who report twice as many downgrades as upgrades over their sample period of 1970 to 1987. In contrast, [90] report 4 downgrades for every upgrade from 1998 to 2002.

period. We refer to this sample as the "Traded-CDS". Panel B of Table B.4 reports the sample size of traded-CDS sample. The average size of rating change for the sample is 1.45 before CDS trading starts and 1.49 after CDS trading starts.

Table B.5 presents the distribution of the absolute magnitude of rating changes for the pre- and post-CDS trading periods. Panel A reports the distribution year by year, while Panel B reports absolute rating changes for "within-letter-grade", "across-letter-grade", and "across-investment" rating changes. A rating change is defined as "within-letter-grade" if it is within the same alphabet letter (e.g., A+, A, A-). All other rating changes are classified as "across-letter-grade". Among the across-letter-grade changes, those that change between investment grade to speculative grade, and vice versa, are considered " across-investment" grade changes. Table B.1 in the appendix summarizes rating categories that belong to the investment and speculative grades.

B.1.7 Other robustness tests for stock price reactions to rating changes

The abnormal returns of firms around credit rating events could be affected due to factors which are unrelated to the rating event. In this case, the CARs would not average out to zero in the cross-section. This problem can be alleviated by using standardized CAR (SCAR) instead of CAR. We define SCAR as $SCAR_i(-1,+1) = \frac{CAR_i(-1,+1)}{\sigma(AR_i)\sqrt{3}}$, where $\sigma(AR_i)$ is the standard deviation of the one-period mean abnormal return, and the factor of $\sqrt{3}$ accounts for the length of the event window (-1,+1), which is equal to 3 days. We carry out all the univariate analysis, the regression analysis, and the matched sample analysis using SCAR instead of CAR as a measurement of abnormal returns and obtain the same conclusions.

In order to rule out the possibility that our results are due to outliers, we winsorize each of the CAR and SCAR specifications at the 1% level. We also test for the difference in the mean of stock price reactions between the pre- and post-CDS groups using bootstrapped standard errors. In both cases, we find that the results do not change qualitatively. In addition, we conduct various other subsample analyses based on credit rating agencies, industry type, across-investment-grade rating change, and we find that our results are robust.

We verify that our main conclusion holds for rating changes that are within-investment-grade, as well as those that are across investment grade. Using only traded-CDS firms, we find that stock price reactions to rating downgrades in the pre-CDS-trading period is -1.72% for "within investment grade" rating changes, while it is -9.13% for "across investment grade" rating changes. However, in the post-CDS-trading period, we find that stock price reactions to rating downgrades is -0.84% and -2.86% for "within investment grade" and "across investment grade" rating changes, respectively. In both cases we find the difference in CAR(-1,1) to be positive and statistically different from zero. The difference in CARs between the pre-CDS-trading and post-CDS-trading periods for "within investment grade" rating change is 0.88% with a t-statistic of 1.82, while the for "across investment grade" rating change is 6.28% with a t-statistic of 3.60.

Apart from the instrumental variable analysis and the matched sample analysis described in Sections 2.4.4–2.4.5, we apply a "placebo test" test to further rule out a concern that our results are related to changes in certain market conditions over time — e.g., changes in volatility. To do this, we first generate random pseudo CDS introduction dates. Then we apply the standard event study methodology to these randomly generated pre- and post-CDS periods. We find that the difference in the stock price reactions between these pseudo pre- and post-CDS periods is not significantly different from 0. Overall, using a host of robustness tests, we confirm that the abnormal stock return around credit rating downgrades is muted after CDS contracts trade on the underlying firm's debt.

B.1.8 Bond price reactions to rating changes

We examine the impact of the CDS market on corporate bond pricing as a channel through which CDS trading attenuates firms' equity price reactions to credit rating downgrades. The basic idea in the cost of capital calculation is that the market value of the firm's assets must equal the market value of the firm's debt plus the market value of the firm's equity. Any impacts on the firm's debt value can affect its equity return through changes in the firm's total assets. We examine whether bond prices also react less to credit rating downgrade announcements when firms have CDS trading on their debt.

Similar to our analyses for stock returns, we consider a rating change event on a debt's issuer as one observation. We calculate the daily bond price using the trade-weighted average of all the prices reported during that day (see also [17]). In a number of cases, there are multiple bond issues per issuer. These multiple issues usually experience rating changes on the same day. In order to avoid double counting events, we study the return of a weighted bond portfolio (equal or value weighted) for each firm. We construct both the equal- and value-weighted portfolios using all the issues written on a firm, and we find that the results are not qualitatively affected by the weighting methods. To save space, we present only the results that are based on the value-weighted portfolios.

Unlike the stock sample analysis, bond trading is relatively thin. For instance, based on the filtered sample in 2006–2007, we find that each bond issue, on average, trades on only 30 days per year. Conditional on the day that we observe trades, there are approximately 3.48 trades per day. To compute abnormal bond returns, we follow the method advocated in [17] by differencing the raw returns with the benchmark of indices. We match returns to six benchmark indices based on Moody's six major rating categories (Aaa, Aa, A, Baa, Ba, and B), and the equivalent S&P and Fitch rating categories (See the mapping in Appendix Table B.1). Matching further on additional dimensions yields an inadequately small sample because the majority of bonds do not trade daily. We construct daily bond return indices based on the above six rating categories. For each rating category, we calculate the daily index return using all of the bonds rated in that category. We exclude bonds that are re-rated on the day the index is constructed. Since few bonds trade on a daily basis, the composition of the index changes daily. As suggested by [17], the bond index return is computed using the value-weighted average to reflect the daily change in index composition.

The cumulative bond return is first calculated at the issue level using transaction prices observed immidately before and after the event day. Because bonds do not often trade daily, the closest observations to the event day may be several days away. We pick the closest pre-event and post-event bond trades around the event day (Day 0) in the (-7,+7) event window. If we do not observe bond trades within (-7,+7) days relative to the event date, the rating change observation is excluded. On average, the closest transaction prices are observed on event-days -2.7 and +2.4 relative to the event date.[2] The cumulative abnormal return for the bond price is calculated by subtracting the cumulative bond return with the cumulative bond index return over the same window period. Finally, the bond market reaction to a rating change event for a firm is calculated as the value-weighted average returns of all of the issues traded around the event date.

Appendix Table B.10 displays the number of upgrades and downgrades and the sizes of rating changes per year in the bond sample. There are about twice the downgrades for every upgrade in the bond event-study sample, which is similar to the stock sample (Table B.10). Relative to the stock sample, we find significantly fewer rating events. This is because TRACE and NAICS databases had limited bond

[2]Sampling over smaller event windows such as (-3,+3) and (-5,+5) lead to a very small sample of unique firms. On the other hand, extending the sampling window – e.g., (-15,+15) would increase the bias due to confounding information arrivals (see [138], and [53]).

coverage during the early years. We rely on NAICS bond database before 2002, which reports only bond trades executed by national insurance companies. For TRACE, it was not until March 2003 that it began to cover all the bonds with an issue size of at least \$100 million that were rated "A" or higher. Nevertheless, in subsequent years, the coverage has steadily increased. The Traded-CDS sample for bonds is constructed in the same manner as for the stocks. Panel B of Table B.10 shows a large reduction in the number of observations from the Full sample to the Traded-CDS sample. The number of unique firms in the Traded-CDS sample is only 123 (as opposed to 672 unique firms for the full sample) Therefore, we rely mainly on the Full sample when interpreting the results.

Table B.11 reports the mean bond cumulative abnormal returns (CAR) for the pre- and post-CDS trading periods. The results in Panel A are based on the full sample. Consistent with prior literature ([77]), we find that bond prices react significantly to downgrades (-2.39%) but little to upgrades (0.0%). We find that average bond price reactions to rating upgrades in the post-CDS period is negative, but not significant. Panel A shows the mean of bond CARs to downgrades are negative and significant at the 1% level for both pre-CDS and post-CDS periods. However, the magnitude of bond price reaction is significantly weaker in the post-CDS period. The mean CARs for the pre- and post-CDS cases are -3.37% and -1.44%, respectively, and their difference is significant at the 1% level. To rule out concerns that our results are due to outliers, we verify that the difference in the means of bond CARs to rating downgrades is statistically significant using the bootstrapped standard error. As for upgrades, the difference between bond price reactions in the pre- and post-CDS cases is not significant. This set of results is consistent with our findings on stock price reactions to rating change announcements.

Panel B of Table B.11 displays results for the Traded-CDS sample, which represents firms that have CDS traded at some point during 1996–2010. Again, we find that the overall bond price reaction to downgrades is negative (-1.94%) and significant at the 1% level. Consistent with our hypothesis, the magnitude of the bond price reaction is weaker in the post-CDS period (-1.61%) than in the pre-CDS period (-2.61%), although not significant. The fall in statistical power is likely due to the small sample size. Also, most of the post-CDS downgrades for the bond sample occur during the crisis, i.e. 2007-2009, which could systematically amplify the magnitude of bond price reaction to rating downgrade announcements.

B.1.9 Primary market bond yields

This section tests whether CDS spreads are useful relative to credit ratings in explaining the primary market bond yields. Table B.9 reports the cross-sectional regression results where the dependent variables are corporate bond yields, in basis points, observed at their primary bond issuance. We report results for four regression specifications. We include rating-level, firm-level, and bond-issuance-level controls in the regressions. Where appropriate, the control variables are lagged by one period. Industry, year, and rating agency fixed-effects are also included. Appendix B describes the control variables. We use lagged CDS quotes that are traded immediately prior to the bond issuance in order to avoid the endogeneity concern that bond yields and CDS spreads are jointly determined.

In regression models (I) and (II), we compare the relative explanatory power of *Credit Rating* and *CDS Spread* to explain the cross section of primary market bond yields. *Credit Rating* is expressed on the cardinal scale (see Table B.1 for mapping), and *CDS Spread* is expressed in basis points. The coefficient on *Credit Rating* in regression model (I) is 17.18 and significant at the one percent level, suggesting that credit ratings are useful for explaining the cross-section of newly issued bond yields. However, we find that once *CDS Spread* is introduced as a variable in the regression (see regression model (II)), the size of coefficient on *Credit Rating* decreases by a third to 6.18. We also find a substantial increase in adjusted R^2 when *CDS Spread* is added to the list of explantory variables —from 58.3 to 71.5 percent. We conclude that CDS spreads significantly help explain the cross-sectional variations in primary market bond yields in addition to credit ratings.

Because the *Credit Rating* variable is discrete while the *CDS Spread* is a continuous variable, we facilitate their comparison by expressing them as credit rating classes, which range from 1 to 6. The mapping between credit rating scales to credit rating classes is shown in Table B.1. For CDS spreads, we use the CDS-implied rating classes calculated non-parametrically in Section 2.5.1. Regression models (III) and (IV) in Table B.9 report results where both CDS spreads and credit ratings are converted to the same unit of measurement, i.e., credit rating classes. We find that the results remain qualitatively similar when using rating classes to define credit ratings and CDS spreads. There is a substantial increase in adjusted R^2 when *CDS-implied rating class* is added to the list of explantory variables – from 57.9 percent in regression model (III) to 71.1 percent in regression model (IV). Overall, we find that CDS spreads provide incremental information for the pricing of primary market bond issuance.

B.1.10 CDS-implied equity risk premia

This Appendix section describes how we empirically estimate the equity risk premia implied from CDS spreads as shown in equation (22) of the main paper. For convenience, we replicate the equation below

$$ERP^T_{t+\tau} \equiv -\left(\frac{\log E^{\mathbb{P}}_t\left[S^T_{t+\tau}\right] - \log E^{\mathbb{Q}}_t\left[S^T_{t+\tau}\right]}{\sqrt{\int_t^{t+\tau}\sigma^2_{S,u}du}}\right)\cdot\sqrt{\int_t^{t+\tau}\sigma^2_{E,u}du}, \qquad (25)$$

The equation above shows that calculating implied equity premium requires evaluating the $\mathbb{Q}$- and $\mathbb{P}$-measure expectations of future T-year CDS spreads. The expected risk-neutral CDS spreads can be represented using the firm's forward CDS spread,

$\log E_t^{\mathbb{Q}}\left[S_{t+\tau}^T\right] = F_t^{\tau\times T}$, where $F_t^{\tau\times T}$ is the forward T-year CDS spread contracted at time t for delivery at time $t+\tau$.

As a result, we can write the CDS Sharpe ratio in equation (25) as

$$SR_{t+\tau} = \frac{\log E_t^{\mathbb{P}}\left[S_{t+\tau}^T\right] - F_t^{\tau\times T}}{\sqrt{\int_t^{t+\tau} \sigma_{S,u}^2 du}}. \tag{26}$$

Relying on the established approach in [38] who estimated bond risk premia using the term structure of forward rates, [62] suggest that CDS Sharpe ratio in equation (26) can be estimated from the term structure of forward CDS spreads for contracts with maturities $T_k \in T = \{1,3,5,7\}$,

$$\overline{SR}_{t+\tau} = \frac{1}{4}\sum_{T_k\in T} \frac{\log S_{t+\tau}^{T_k} - F_t^{\tau\times T_k}}{SD_{t+\tau}},$$

where $SD_{t+\tau}$ refers to the sample standard deviation of daily CDS spread returns between t and $t+\tau$. The above method yields time-series of CDS Sharpe ratio estimated from daily cross-maturity CDS spreads and CDS forward spreads. In order to extract the common component similar to that in [38], we regress daily time-series of $\overline{SR}_{t+\tau}$ on $\mathbf{F}_t = \left(1, S_t^1, F_t^{3\times 1}, F_t^{5\times 1}, F_t^{7\times 1}\right)$, a vector of one-year CDS spread and one-year CDS forward spreads that start in 1, 3, 5, and 7 years. That is, we estimate

$$\overline{SR}_{t+\tau} = \gamma' \cdot \mathbf{F}_t + \varepsilon_{t+\tau}. \tag{27}$$

The fitted value of the estimated Sharpe ratio is then used for the implied equity premium calculation, which according to equation (22), is given by

$$\widehat{ERP}_{t+\tau} = -\widehat{\gamma}\cdot \mathbf{F}_t \widehat{\sigma}_{E,t,\tau}, \tag{28}$$

where $\widehat{\sigma}_{E,t,\tau}$ denotes the time-t conditional equity volatility estimated as the sample standard deviation of daily equity returns from $t-\tau$ to t.

For our empirical analysis, we estimate one-year CDS-implied equity risk premium in equation (28) on a daily basis for each firm in the sample. We use a one-year estimation window in the regression model (27) to obtain $\widehat{ERP}_{t+\tau}$ with τ equal to one year. In order for firms to be eligible for the $\widehat{ERP}_{t+\tau}$ calculation, it must have sufficient data on CDS quotes at maturities 1, 3, 5, 7, and 10 years.

Table B.12 reports results from constructing monthly portfolio sorts based on CDS-implied equity risk premia (ERP*)*. In Panel A, we report the mean characteristics of quintile sorted portfolios that are formed monthly based on ERP. The means of portfolio characteristics are calculated using equal weights. Because the start dates of CDS trading differ across firms, the number of firms available in monthly cross-sections also varies, but mostly increase from 2001 through 2010. On average, there are 72 firms available for quintile portfolio sorting each month. Panel A of Table B.12 shows no monotonic pattern in portfolio characteristics sorted based on CDS-implied equity premia. The equity risk premia estimated from CDS spreads are not related to firms' size or market-to-book values. We also do not find that ERP is monotonically explained by firms' cross-sections of credit ratings, as well as CDS spread levels.

Panel B of Table B.12 reports average one-year return of five portfolios sorted monthly based on ERP, credit ratings, and CDS spreads. We assign equal weight to firms in each porfoltio. We find a clear and distinct monotonic pattern in equity returns across the five portfolios. Firms with higher equity risk premia implied by their CDS spreads earn higher returns, consistent with the prediction of structural models, e.g. [104]. The difference in one-year average returns between the highest (5) and lowest (1) ERP portfolios is economically large, with the magnitude of about 24% per year. The t-statistic associated with this magnitude is 13.0, suggesting an overwhelmingly strong statistical significance. [62] find the difference between the highest and lowest portfolios sorted by one-month ERP is about 1.51% per month after the risk-free rate (i.e., 18.12% per year). Thus, our results are roughly in line with theirs.

Panel B also shows that average one-year returns of portfolios sorted monthly based on credit ratings and CDS spreads do not monotonically explain the cross-section of equity returns. The finding is similarly weaker when we sort portfolios based on the level of CDS spreads alone. We do not find any significant difference in one-year portfolio returns between the highest (5) and lowest (1) CDS spread firms. Overall, Panel B shows that ERP estimated from CDS term structures are informative of equity returns, while the level of CDS spreads alone are not. Further, the findings suggest that ratings issued by credit rating agencies are not a good measure of default risk premium, and hence cannot explain cross-section of equity returns equally well relative to the ERP estimated from CDS spreads.

Table B.4: Distribution of bond rating changes

The sample consists of 4,665 downgrades and 2,171 upgrades of taxable corporate bonds issued by U.S. firms from January 1996 to December 2010. The sample is split between rating changes that occur in the presence of CDS trading (post-CDS period) and in the absence of CDS trading (pre-CDS period) on the underlying firm's debts. Panel A reports year-by-year distribution of rating changes. Count represents the number of rating changes. Size represents the mean of the cardinal value of the new rating minus the cardinal value of the old rating. Bond ratings are converted to a cardinal scale measured on a 23-point scale (see Appendix A for the mapping). Panel B reports the number of rating changes and the average sizes of rating changes for the "Full Sample" and the "Traded-CDS". The full sample represents the entire sample period consisting of firms that have and do not have CDS traded on their debts. Traded-CDS sample consists only of firms that have CDS trading at any point in our sample period, i.e from 1996 to 2010.

Panel A: Distribution of number and size of bond rating changes by year

Year	Downgrades				Upgrades			
	Pre-CDS		Post-CDS		Pre-CDS		Post-CDS	
	Count	Size	Count	Size	Count	Size	Count	Size
1996	16	1.31			31	1.23		
1997	149	1.39			206	1.35		
1998	251	1.65			195	1.52		
1999	310	1.63			147	1.23		
2000	428	1.73			128	1.34		
2001	556	1.92	12	1.25	99	1.42		
2002	510	1.74	72	1.25	66	1.45	4	1.00
2003	226	1.76	109	1.25	85	1.47	20	1.05
2004	131	1.63	108	1.31	97	1.33	73	1.25
2005	110	1.49	128	1.59	71	1.76	95	1.25
2006	98	1.23	170	1.60	95	1.22	132	1.17
2007	101	1.60	181	1.56	81	1.26	134	1.22
2008	112	1.56	290	1.62	58	1.24	77	1.31
2009	178	1.70	258	1.83	35	1.57	43	1.81
2010	73	1.42	88	1.27	88	1.38	111	1.28
Total	3249	1.69	1416	1.55	1482	1.38	689	1.27

Panel B: Distribution of number and size of bond rating changes by sub-sample

Sample	Downgrades				Upgrades			
	Pre-CDS		Post-CDS		Pre-CDS		Post-CDS	
	Count	Size	Count	Size	Count	Size	Count	Size
Full sample	3249	1.69	1416	1.55	1482	1.38	689	1.27
Traded-CDS sample	803	1.45	1029	1.49	300	1.22	574	1.29

Table B.5: Sample distribution by magnitude of rating changes

The sample consists of 4,665 downgrades and 2,171 upgrades of taxable corporate bonds issued by U.S. firms from January 1996 to December 2010. The sample is split between rating changes that occur in the presence of CDS trading (post-CDS period) and in the absence of CDS trading (pre-CDS period) on the underlying firm's debts. In Panel A, *Freq* represents the number of rating changes. Bond ratings are converted to a cardinal scale measured on a 23-point scale. *Scale change* represents the absolute change, in cardinal value, of the new rating minus the old rating. *Pct* represents the percentage of rating changes observed in each scale change group. Panel B reports the distribution of rating changes for three rating-change classifications. A rating change is classified as "Within letter grade" if it is within the same letter group (e.g., A+, A, A-). All other rating change events are classified as "Across letter grade" as their change is from one letter group to a different letter group. We classify a rating change as"Across Inv Grade" if the change is from an investment grade to a speculative grade or vice-versa. Investment grade rating for S&P and Fitch corresponds to rating levels of BBB and above. Investment-grade rating for Moody's corresponds to rating levels of Baa and above.

Panel A: Sample distribution by absolute magnitude of rating changes

	Downgrades				Upgrades			
Scale change	Pre-CDS		Post-CDS		Pre-CDS		Post-CDS	
	Freq	Pct(%)	Freq	Pct(%)	Freq	Pct(%)	Freq	Pct(%)
1	1945	59.86	979	69.14	1168	78.81	557	80.84
2	802	24.68	272	19.21	206	13.90	102	14.80
3	299	9.20	82	5.79	56	3.78	19	2.76
4	106	3.26	39	2.75	26	1.75	4	0.58
5	42	1.29	22	1.55	7	0.47	5	0.73
6	20	0.62	10	0.71	5	0.34		
7	15	0.46	7	0.49	5	0.34		
8	10	0.31	2	0.14	1	0.07	2	0.29
9	5	0.15			2	0.13		
10	3	0.09			1	0.07		
11	2	0.06	2	0.14	3	0.20		
12					1	0.07		
14			1	0.07	1	0.07		
Total	3249	100.00	1416	100.00	1482	100.00	689	100.00

Panel B: Sample distribution within and across rating

	Downgrades				Upgrades			
	Pre-CDS		Post-CDS		Pre-CDS		Post-CDS	
	Freq	Pct(%)	Freq	Pct(%)	Freq	Pct(%)	Freq	Pct(%)
Within letter grade	1714	52.75	655	46.26	592	39.95	258	37.45
Across letter grade	1535	47.25	761	53.74	890	60.05	431	62.55
Across Inv grade	367	11.30	206	14.55	167	11.27	79	11.47

Table B.6: Stock price reactions to bond rating changes: Robustness I

This table reports regression results of stock price reactions to bond rating changes. The sample consists of credit rating change events on taxable corporate bonds issued by U.S. firms from January 1996 to December 2010. The dependent variable is the cumulative abnormal return (CAR) calculated over the 3-day event window (-1,+1) using the *market model*. Panel A consists of the full sample and includes Industry×Year fixed effects to control for time-varying industry-level fixed effects. Panel B consists of only non-financial firms. All the variables are defined in B.1. *dCDS* is an indicator variable equal to one when the firm has CDS contracts traded on its debt, and zero otherwise. Coefficients on other controls have been omitted to conserve space. Robust t-statistics are clustered at the firm-level and reported in brackets below each estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

Panel A: Time-varying industry-level FE

	Downgrades	***Upgrades***
	Full sample	**Full sample**
	(I)	(I)
dCDS	1.25*	0.14
	(1.80)	(0.53)
Rating controls	✓	✓
Firm controls	✓	✓
CDS-trading controls	✓	✓
Fixed effects	Ind×Year	Ind×Year
Observations	4176	1972
Adjusted R^2	0.126	0.009

Table B.6 (continued)

Panel B: Non-financial firms

	Downgrades				***Upgrades***			
	Full sample			**Traded-CDS**	**Full sample**			**Traded-CDS**
	(I)	(II)	(III)	(IV)	(I)	(II)	(III)	(IV)
dCDS	2.61***	1.80**	1.53**	2.62***	-0.34	-0.11	-0.04	-0.14
	(4.35)	(2.44)	(2.45)	(3.75)	(-1.40)	(-0.44)	(-0.14)	(-0.33)
Rating controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓	✓	✓	✓	✓
CDS-trading controls	✓	✓	✓	✓	✓	✓	✓	✓
Fixed effects	Ind	Ind & Year	Ind ×Year	Ind	Ind	Ind & Year	Ind ×Year	Ind
Observations	3333	3333	3333	1559	1623	1623	1623	729
Adjusted R^2	0.126	0.129	0.136	0.082	0.001	-0.004	0.010	-0.004

Table B.7: Stock price reactions to bond rating changes: Robustness II

This table reports regression results of stock price reactions to bond rating changes. The sample consists of credit rating change events on taxable corporate bonds issued by U.S. firms from January 1996 to December 2010. In Panel A the dependent variable is the cumulative abnormal return (CAR) calculated over the 3-day event window (-1,+1) using the *Fama-French 3 factor model*. In Panel B the dependent variable is the cumulative abnormal return (CAR) calculated over the 3-day event window (-1,+1) using the *market model*. All the variables are defined in B.1. *dCDS* is an indicator variable equal to one when the firm has CDS contracts traded on its debt, and zero otherwise. In Panel B *dDowngrade* is an indicator variable equal to one if the rating change is a downgrade, and zero for an upgrade. We also interact all rating controls with *dDowngrade*. Coefficients on other control variables have been omitted to conserve space. Robust t-statistics are clustered at the firm-level and reported in brackets below each estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

Panel A: Fama-French 3 factor adjusted CAR

	Downgrades				***Upgrades***			
	Full sample			**Traded-CDS**	**Full sample**			**Traded-CDS**
	(I)	(II)	(III)	(IV)	(I)	(II)	(III)	(IV)
dCDS	1.86***	1.52**	1.12*	2.29***	-0.17	-0.06	0.04	0.05
	(3.09)	(2.18)	(1.69)	(3.36)	(-0.74)	(-0.22)	(0.15)	(0.12)
Rating controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓	✓	✓	✓	✓
CDS-trading controls	✓	✓	✓	✓	✓	✓	✓	✓
Fixed effects	Ind	Ind & Year	Ind ×Year	Ind	Ind	Ind & Year	Ind ×Year	Ind
Observations	4176	4176	4176	1775	1972	1972	1972	834
Adjusted R^2	0.123	0.124	0.127	0.092	0.002	0.003	0.017	-0.001

Table B.7 (continued)

Panel B: Pooled Downgrades & Upgrades

	Full sample			Traded-CDS
	(I)	(II)	(III)	(IV)
dCDS×dDowngrade	1.61***	1.65***	1.48**	1.38*
	(2.70)	(2.81)	(2.56)	(1.83)
dDowngrade	-3.23***	-3.30***	-3.09***	-3.13***
	(-8.51)	(-8.14)	(-7.16)	(-4.29)
dCDS	0.28	0.05	-0.18	0.88
	(0.76)	(0.13)	(-0.44)	(1.62)
Rating controls	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓
CDS-trading controls	✓	✓	✓	✓
Fixed effects	Ind	Ind & Year	Ind ×Year	Ind
Observations	6148	6148	6148	2609
Adjusted R^2	0.133	0.134	0.138	0.091

Table B.8: Diff-in-diff downgrade CAR regression: 1–to–1 matching without replacement

This table reports diff-in-diff regression analysis of stock price response CAR(-1,1) to bond downgrades for the propensity-score matched sample. One non-traded-CDS (control) firm is matched to one traded-CDS (treated) firm without replacement, with a caliper of 10% and common support. Panel A reports the main diff-in-diff regression results for the matched sample. Panel B reports matching diagnostics via a probit regression before and after matching. All the variables are defined in B.1. Coefficients on other controls have been omitted to conserve space. For Panel A, robust t-statistics are clustered at the firm-level and are reported in brackets below each estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

Panel A: 1:1 Matched Sample

	Diff-in-diff		***Subsamples (diagnostics)***			
			Treatment	Control	Post-CDS	Pre-CDS
	(I)	(II)	(III)	(IV)	(V)	(VI)
dTreatment×dCDS	3.19***	3.02**				
	(2.60)	(2.53)				
dCDS	-0.22	-1.65	2.41**	-0.14		
	(-0.20)	(-1.05)	(2.18)	(-0.11)		
dTreatment	-1.12	-1.46			2.18**	-0.78
	(-1.25)	(-1.53)			(2.34)	(-0.93)
Rating controls	✓	✓	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓	✓	✓
CDS-trading controls	✓	✓	✓	✓	✓	✓
Fixed effects	Ind	Ind & Year	Ind	Ind	Ind	Ind
Observations	1368	1368	793	575	855	513
Adjusted R^2	0.110	0.111	0.111	0.108	0.111	0.129

Table B.8 (continued)

Panel B: 1:1 Matching Diagnostics via Probit Regression

	Before matching	***After matching***		***Before matching***	***After matching***
Sales (log)	0.43***	-0.11	Avg Trading Volume (log)	0.08***	-0.06
	(41.60)	(-0.92)		(7.71)	(-0.52)
Profitability	-0.44***	0.58	Analyst Coverage (log)	-0.03**	0.02
	(-7.50)	(0.97)		(-2.37)	(0.14)
Leverage	0.02	0.11	Analyst Dispersion	0.00***	-0.00
	(0.35)	(0.21)		(4.49)	(-1.31)
Mkt-to-Book	-0.00*	-0.01	Institutional Ownership	0.38***	-0.10
	(-1.84)	(-0.44)		(13.87)	(-0.36)
Rating Scale(log)	-0.33***	-0.55*	Stock Illiquidity	-3.14***	-7.80
	(-11.20)	(-1.80)		(-7.99)	(-1.37)
Avg Return	0.05	0.58	Bond Illiquidity	0.64***	-0.08
	(0.74)	(0.72)		(60.12)	(-0.60)
Avg Volatility (log)	-0.05**	0.31	Debt Outstanding (log)	0.38***	0.01
	(-2.52)	(1.38)		(37.11)	(0.06)
Observations	59539	324			
Pseudo R^2	0.49	0.04			

Table B.9: Primary market bond yields regression

This table reports regression results for the determinants of primary market bond yields. The sample consists of coporate bonds issued by firms that have CDS contracts trading on their debt. The dependent variables are corporate bond yield spreads (in bps) observed at issuance. Regression models (I) and (II) examine the explanatory power of credit rating levels and lagged CDS spreads. *Credit Rating* is the rating level, in cardinal scale, issued by the credit rating agency. *CDS Spread* is the firm's 5-year CDS spread (in bps) last observed prior to the bond issuance date. In regression models (III) and (IV), credit rating and CDS-implied rating are expressed as rating class, i.e. between 1 to 6; see Table B.1 for mapping. *CDS-implied rating class* is calculated using the nonparametric method described in Section 2.5.2. We include various issuance-level and firm-level controls in the regressions. *Subordinate* is an indicator variable equal to one if the issued bond is a subordinate debt, and zero otherwise. *Callable* is an indicator variable equal to one if the issued bond has a callable option. *Issue Size* is the log of the notational amount (in $) of the bonds issued. *Maturity* is the maturity of the issued bond. Firm-level characteristics are calculated using information in the quarter prior to bond issuance; see C.2 for details. *Treasury Slope* is the difference between 10-year and 1-year Treasury yields. All regressions include industry, year, and rating agency fixed-effects. Robust t-statistics are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

Table B.9 (continued)

Dependent variable: Primary market bond yields (bps)	(I)	(II)	(III)	(IV)
Credit Rating (cardinal scale)	17.18***	6.18***		
	(9.84)	(4.57)		
CDS Spread (bps)		0.58***		
		(9.91)		
Credit Rating class			49.23***	12.76***
			(9.13)	(2.97)
CDS-implied Rating class				56.34***
				(15.51)
Issuance-level controls				
Subordinated	23.66**	23.87***	21.44**	25.61***
	(2.30)	(3.10)	(2.21)	(3.19)
Callable	-3.83	-0.42	-1.57	-1.23
	(-0.52)	(-0.07)	(-0.21)	(-0.20)
Issue Size (log)	51.16***	48.86***	49.99***	46.89***
	(5.40)	(4.89)	(5.37)	(5.27)
Maturity (yrs)	0.87***	1.09***	0.90***	1.17***
	(3.70)	(5.77)	(3.92)	(5.62)
Other controls				
Sales (log)	-19.57***	-21.89***	-19.13***	-21.04***
	(-4.24)	(-5.30)	(-4.06)	(-5.41)
Profitability	-17.88	-11.96	-21.07	-18.18*
	(-1.49)	(-1.05)	(-1.62)	(-1.75)
Long-Term Debt-to-Assets	8.89	-43.01	7.69	-43.84
	(0.27)	(-1.55)	(0.24)	(-1.61)
Leverage	0.83	-1.89	0.48	-2.59**
	(0.65)	(-1.57)	(0.36)	(-2.16)
Treasury Slope (10yr-1yr)	5.02	1.43	7.17	3.05
	(0.68)	(0.21)	(0.98)	(0.46)
Rating-type FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2208	2208	2208	2208
Adj. R^2	0.583	0.715	0.579	0.711

Table B.10: Distribution of bond rating changes: Bond market reaction sample

We report the distribution of bond rating change events used in the bond market reaction analysis. The full sample consists of 2,336 downgrades and 1,019 upgrades of taxable corporate bonds issued by U.S. firms from January 1996 to December 2010. The sample is split between rating changes that occur in the presence of CDS trading (post-CDS period), and in the absence of CDS trading (pre-CDS period) on the underlying firm's debts. Panel A reports year-by-year distribution of rating changes. Count represents the number of rating changes. Size represents the mean of the cardinal value of the new rating minus the cardinal value of the old rating. Bond ratings are converted to a cardinal scale measured on a 23-point scale (see Table B.1 for the mapping). Panel B reports the number of rating changes and the average sizes of rating changes for the "Full Sample" and the "Traded-CDS". The full sample represents the entire sample period consisting of firms that have and do not have CDS traded on their debts. Traded-CDS sample consists only of firms that have CDS trading at any point in our sample period, i.e from 1996 to 2010.

Panel A: Distribution of number and size of bond rating changes by year

Year	Downgrades				Upgrades			
	Pre-CDS		Post-CDS		Pre-CDS		Post-CDS	
	Count	Size	Count	Size	Count	Size	Count	Size
1996	3	1.00			2	1.00		
1997	8	1.25			16	1.31		
1998	22	1.50			23	1.35		
1999	35	1.43			21	1.14		
2000	71	2.15			17	1.82		
2001	140	2.31	11	1.18	29	1.97		
2002	208	1.96	47	1.26	16	1.19	3	1.00
2003	94	1.93	83	1.22	32	1.41	15	1.07
2004	48	1.56	92	1.33	40	1.40	38	1.16
2005	81	1.65	122	1.64	43	1.67	74	1.26
2006	71	1.38	164	1.80	82	1.48	133	1.11
2007	79	1.59	151	1.74	64	1.69	130	1.22
2008	95	1.48	240	1.66	32	2.69	70	1.69
2009	160	1.87	244	1.70	33	2.18	53	2.51
2010	36	1.44	31	1.23	16	1.25	37	1.59
Total	1151	1.81	1185	1.61	466	1.64	553	1.40

Panel B: Distribution of number and size of bond rating changes by sub-sample

Sample	Downgrades				Upgrades			
	Pre-CDS		Post-CDS		Pre-CDS		Post-CDS	
	Count	Size	Count	Size	Count	Size	Count	Size
Full sample	1151	1.81	1185	1.61	466	1.64	553	1.40
Traded-CDS sample	237	1.48	465	1.58	55	1.09	296	1.35

Table B.11: Bond price response to credit rating downgrades and upgrades

This table reports cumulative abnormal returns (CAR) of bond price to credit rating downgrades and upgrades.The full sample consists of 2,336 downgrades and 1,019 upgrades of taxable corporate bonds issued by U.S. firms from January 1996 to December 2010. Table B.10 in the appendix reports the distribution of bond rating changes used in this analysis. Panel A reports results for the full sample, while Panel B reports results for the traded-CDS sample. The traded-CDS sample (Panel B) consists only of firms that have CDS trading at any point in our sample period. In each panel, the sample is split between rating changes that occur in the presence of CDS trading (Post-CDS period) and in the absence of CDS trading (Pre-CDS period) on the underlying firm's debts. Cumulative abnormal bond return is defined as the firm's value-weighted bond portfolio's excess return against the bond return of a matching portfolio based on Moody's six major rating categories (Aaa, Aa, A, Baa, Ba, and B). The event window is the shortest trading window within (-7,+7) calendar days relative to the rating change event day. T-statistics are displayed in square brackets. *, **, and *** indicate significance greater than 10%, 5%, and 1%, respectively.

Panel A: Full sample

	Downgrades		Upgrades	
	Mean CAR(%)	Count	Mean CAR(%)	Count
Pre-CDS	-3.37***	1151	0.12	466
	(-10.25)		(1.11)	
Post-CDS	-1.44***	1185	-0.11	553
	(-4.44)		(-1.10)	
Difference (Pre−Post)	1.93***		-0.23	
	(4.18)		(-1.57)	
Total	-2.39***	2336	-0.00	1019
	(-10.32)		(-0.06)	

Panel B: Traded-CDS sample

	Downgrades		Upgrades	
	Mean CAR(%)	Count	Mean CAR(%)	Count
Pre-CDS	-2.61***	237	0.09	55
	(-4.01)		(0.26)	
Post-CDS	-1.61***	465	-0.25**	296
	(-3.46)		(-1.74)	
Difference (Pre−Post)	1.00		-0.34	
	(1.35)		(-0.93)	
Total	-1.94***	702	-0.20	351
	(-5.14)		(-1.49)	

Table B.12: CDS-implied equity risk premium and portfolio characteristics

This table reports means of portfolio characteristics and one-year average portfolio returns sorted by CDS-implied equity risk premia (ERP). The sample consists of U.S. firms that have CDS contracts with maturity of 1, 3, 5, 7, 10 years trading on their debts. We calculate daily CDS-implied ERP with one-year horizon for each reference entity using its CDS term structure. We follow the method in [62] for calculating ERP, which is motivated by [38] who estimated bond risk premia using the term structure of forward rates. Section 2.7 describes the procedure for calculating ERP. In Panel A, we report the mean characteristics of quintile sort portfolios that are formed monthly based on based on CDS-implied ERP. The means of portfolio characteristics are calculated using equal weights and the sorting is done at the beginning of each month. Because the start dates of CDS trading differ across firms, the number of firms available in monthly cross-sections also varies, but mostly increase from 2001 through 2010. We require a minimum of 20 firms in the cross section to execute the portfolio sorts. *Size* is the log of firm's market capitalization. *Mkt-to-Book* is the ratio of a firm's market value of total assets to its book value of total assets. *Credit rating* is the average firm's credit ratings, in cardinal scale, given by the three agencies: Moody's, Fitch, and S&P. *CDS spread* is the 5-year CDS spread level of the firm. In Panel B, we report average one-year equity returns of portfolios sorted monthly based on ERP, credit ratings, and CDS spreads. The fifth (highest) quintile portfolio corresponds to firms with the highest ERP, lowest-rated firms, and largest CDS spreads. Newey-West t-statistics adjusted for 11 lags are reported in brackets below the average portfolio returns in Panels B–C. *, **, and *** indicate significance greater than 10%, 5%, and 1%, respectively.

Panel A: Portfolio characteristics sorted by CDS-implied ERP

	Average values				
	ERP	Size	Mkt-to-Book	Credit rating	CDS spread
1 (lowest ERP)	-0.005	15.753	2.486	9.105	0.015
2	0.005	21.289	2.931	7.913	0.006
3	0.009	22.842	2.806	8.151	0.007
4	0.016	18.925	2.635	8.739	0.011
5 (highest ERP)	0.034	12.095	2.392	10.016	0.025

Panel B: Average one-year returns of single-sorted portfolios

	Average one-year return		
	Sorted by ERP	Sorted by Credit ratings	Sorted by CDS spreads
1 (lowest)	-0.141***	-0.044***	-0.011*
	(-10.81)	(-3.80)	(-1.44)
2	-0.042***	-0.018*	-0.015**
	(-4.76)	(-1.53)	(-1.89)
3	-0.012*	-0.023**	-0.018**
	(-1.55)	(-1.97)	(-1.90)
4	0.020**	-0.018*	-0.032***
	(2.31)	(-1.44)	(-2.75)
5 (highest)	0.086***	0.012	-0.020
	(7.10)	(0.69)	(-1.12)
5−1	0.227***	0.056***	-0.009
	(13.16)	(2.64)	(-0.46)

APPENDIX C

MISCELLANEOUS SECTION FOR CHAPTER 3

C.1 Variable Definitions

- *Total assets* = atq
- *Average assets* = ((Total assets) + (lagged Total assets))/2
- *Market value* = prccq*cshoq - (Total assets-ltq + txditcq) + total assets
- *Market-to-book ratio* = (Market value)/(Total assets)
- *Total debt* = dltcq + dlttq
- *Leverage ratio* = (Total debt)/(Total assets)
- *Macro q* = (prccq*cshoq+dlttq+dlcq-invtq)/lagged ppentq
- *Net worth* = atq - ltq
- *Tangible net worth* = actq + ppentq + aoq - ltq
- *Current ratio* = actq/lctq
- *Cash scaled by assets* = cheq/(Total assets)
- *Operating income scaled by average assets* = oibdpq/(Average assets)
- *Interest expense scaled by average assets* = xintq/(Average assets)
- *Capital expenditures quarterly* = capxy adjusted for fiscal quarter accumulation
- *Cash acquisitions quarterly* = aqcy adjusted for fiscal quarter accumulation
- *Capital expenditures scaled by average assets* = Capital expenditures quarterly/(Average assets)

- *Investment* = Capital expenditures quarterly/(Lagged ppentq)
- *Net debt issuance* = (Total debt-Total lagged debt)/(Lagged total assets)
- *Sales* = saleq
- *Operating costs* = Sales-(Operating income)
- *Sales scaled by average assets* = Sales/(Average assets)
- *Operating costs scaled by average assets* = Sales/(Average assets)
- *Beta* = Borrower's market model beta calculated using daily stock returns for a given firm over the estimation period of one year ranging from one month prior to the loan announcement day and extending back one year.
- *Runup* = Cumulative return of the borrower's stock during the estimation period of one year ranging from one month prior to the loan announcement day and extending back to one year.
- *Idiosyncratic risk* = Standard deviation of the prediction errors (i.e., borrower's stock return residual) during the estimation period of one year ranging from one month prior to the loan announcement day and extending back to one year.
- *Loan Size* = The total deal amount in a given package.
- *Relative Loan Size* = The total deal amount divided by total assets of the firm at the point when the loan is made.
- *Maturity* = The maturity of a package or deal, measured in months.
- *Loan Spread* = The all-in-drawn spread over LIBOR in basis points for a given loan.
- *Number of lenders* = The number of lenders at loan syndication.
- *Lending Relationship* = The number of loans to borrower i by bank m scaled by the total number of loans to the borrower made until then.

- *Loan Types* = Loans are classified as (a) *Revolvers:* if the LoanType field in Dealscan consists of *Revolver*, *364-Day*, *Demand Loan*, or *Limited Line*; (b) *Term loan A:* if the LoanType field in Dealscan consists of *Term Loan A*; (c) *Term Loan B:* if the LoanType field in Dealscan consists of *Term Loan*, *Term Loan B* to *Term Loan E*.

- *CR Distance* = $\mathbb{1}_{CurrentRatio_{it}} \times (CurrentRatio_{it} - CurrentRatio^0_{it})$ where $\mathbb{1}_{CurrentRatio_{it}}$ is an indicator variable equal to one if the firm-quarter observations are bound by a current ratio covenant. $CurrentRatio^0_{it}$ is the current ratio covenant threshold and $CurrentRatio_{it}$ is the current ratio in quarter t for firm i.

- *NW Distance* = $\mathbb{1}_{NetWorth_{it}} \times (NetWorth_{it} - NetWorth^0_{it})$ where $\mathbb{1}_{NetWorth_{it}}$ is an indicator variable equal to one if the firm-quarter observations are bound by a net worth covenant. $NetWorth^0_{it}$ is the net worth covenant threshold and $NetWorth_{it}$ is the net worth in quarter t for firm i.

- *Analyst Coverage* = The number of analyst EPS forecasts made in the 90 days prior to the earnings announcement date. It is calculated using I/B/E/S unadjusted estimates and actual files. We adjust for any stock splits using adjustment factors obtained from the CRSP dataset (cfacshr) to ensure that EPS values in the Estimates and Actuals are on the same basis.

- *Analyst Dispersion* = The standard deviation of analyst EPS estimates made in the 90 days prior to the earnings announcement date scaled by the actual reported EPS. It is calculated using I/B/E/S Unadjusted Estimates and Actual files.

- *Institutional Ownership* = The ratio of total shares held by institutional investors to the total shares outstanding for a given stock. Institutional holding data are obtained from Thomson-Reuters Institutional Holdings (13F) Database.

- *Stock Illiquidity* = The monthly average stock illiquidity defined as the squared root of the Amihud measure. It is the monthly average of the following daily values:

$$\sqrt{1000000 * |\text{Ret}_t| / (\text{Volume} \times \text{Price}_t)},$$

where Ret_t and Price_t are daily return and price of the stock.

- *Forex Derivative Hedging* = The average amount of foreign exchange derivatives used for hedging purposes (i.e., non-trading purposes) relative to total assets of the lead syndicate banks and bond underwriters that the firm has done business with in the past five years. Banks' derivatives usage data is obtained from Bank Holding Company (BHC) Y9-C filings. Data on the firm's lead bank syndicate are obtained from LPC Dealscan, and the firm's underwriter information is obtained from Mergent FISD.

- *Non-Interest Income* = Item number BHCK4079 from the FR Y-9C reports expressed as a percentage of total income (BHCK4074 + BHCK4107)

- *Loans Securitized* = Sum of residential loans sold and securitized (BHCKB705), other consumer loans sold and securitized (BHCKB709), commercial loans and industrial loans (C&I loans) sold and securitized expressed as a percentage of total loans and leases (BHCK2122). Data for these items is available from 2001 Q2 onwards.

- *CD Bought* = the total credit derivatives on which the reporting bank is the beneficiary, which is reported as item number BHCKA535 from 1997 Q1 to 2005 Q4, and the sum of item numbers BHCKC969, BHCKC971, BHCKC973, BHCKC975 from 2006 Q1 onwards expressed as a percentage of total assets (BHCK2170).

- *CD Sold* = the total credit derivatives on which the reporting bank is the guarantor, which is reported as item number BHCKA534 from 1997 Q1 to 2005 Q4, and the sum of item numbers BHCKC968, BHCKC970, BHCKC972, BHCKC974 from 2006 Q1 onwards expressed as a percentage of total assets (BHCK2170).

C.2 Additional Tables & Figures

Figure C.1: Investment vs distance to violation: Polynomial Fit

This figure plots investment vs distance to covenant violation. Distance to covenant violation is defined as the negative of the relative covenant distance for every firm-quarter observation $(-\frac{Ratio-CovenantThresholdRatio}{CovenantThresholdRatio})$. In case both, net worth and current ratio covenants are present, the tighter of the two is chosen to compute the distance to covenant violation. The plot displays the mean investment for bins defined along the distance to covenant violation. The solid lines represent the fitted values of a third-degree polynomial in distance to covenant violation.

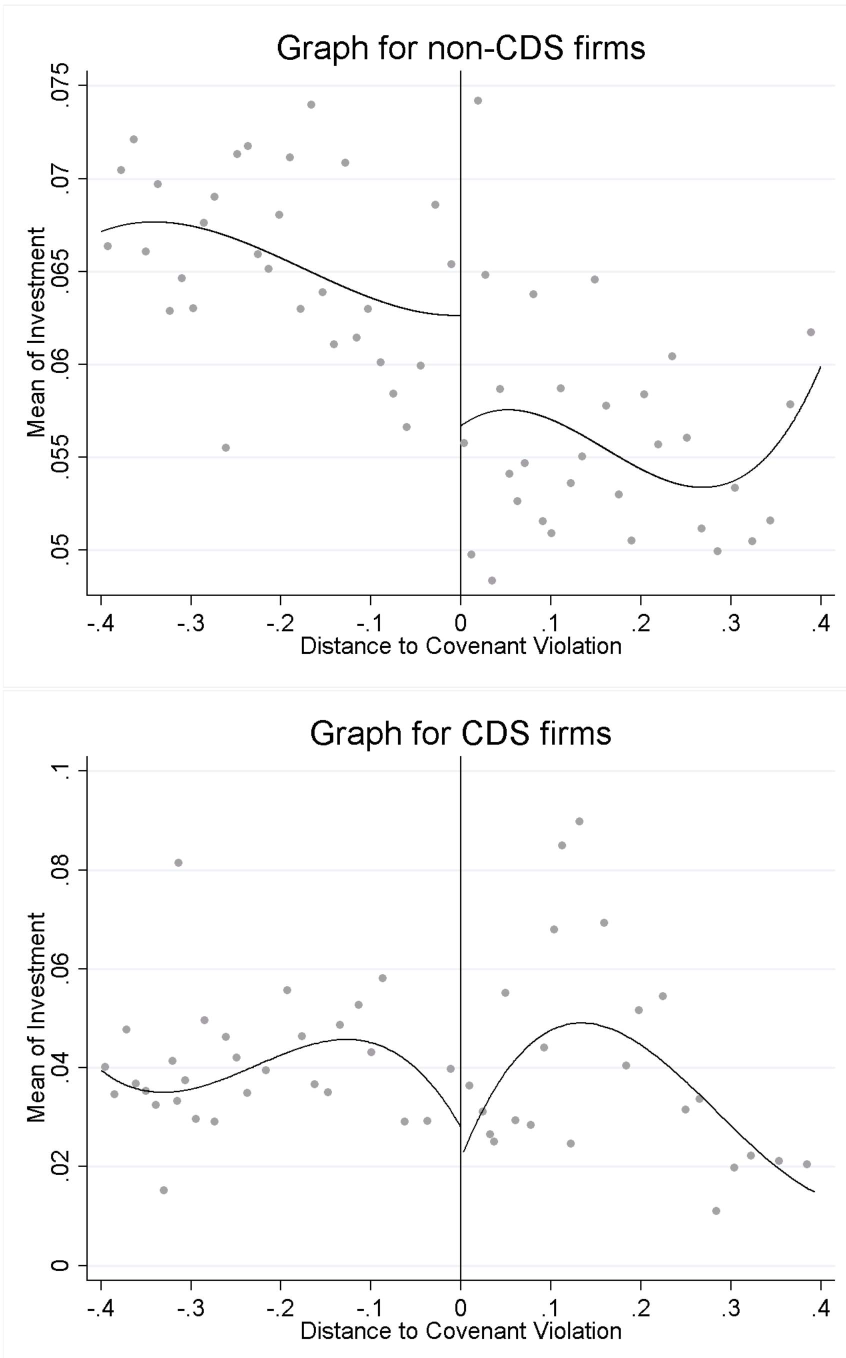


Table C.1: 2SLS IV regressions: Distress and outperformance

This table conducts a 2SLS IV regression using a linear probability model for firms after a covenant violation in the presence and absence of traded CDS on its underlying debt. Firm exits in our sample are classified based on the CRSP delisting codes and Moody's URD database. Financial failure from the CRSP codes is defined as liquidation (400 – 490), bankruptcy (574). Failure in URD is defined as missed/delayed interest/principal payments, bankruptcy, or distressed exchange. Other forms of firm exit include mergers (200 – 290) or going private (573). Distress and outperformance is defined based on [66] and [67] as the firms in the bottom and top 5% of the entire universe of firms in the CRSP based on the past three-year of cumulative return. The instrument for CDS trading is the average amount of forex derivatives used for hedging purposes relative to total assets of the lead syndicate banks and bond underwriters with which the firms have conducted business in the past five years.

The data is constructed at firm-quarter level. The main independent variable of interest is CDS IV, which is obtained from the first stage where d_CDS is instrumented. d_CDS is an indicator variable equal to one if a CDS is traded on the underlying firm's debt for that firm-quarter observation, and zero otherwise. t-statistics displayed in parentheses are robust to within-firm correlation and heteroscedasticity. *, **, and *** indicate significance greater than 10%, 5%, and 1%, respectively.

	All Exits	**Distress Related**	**Non-distress Related**	**Equity Distress**	**Equity Outperformance**
	(1)	(2)	(3)	(4)	(5)
CDS IV	-0.05*	-0.01	-0.04	0.08	-0.10**
	(-1.81)	(-0.86)	(-1.58)	(1.45)	(-2.16)
d_Rated	-0.00	0.00	-0.00	-0.04	0.01
	(-0.00)	(0.27)	(-0.17)	(-1.41)	(0.18)
Assets(log)	0.00	0.00	0.00	-0.02	0.01
	(0.71)	(0.34)	(0.63)	(-1.45)	(1.16)
Profitability	-0.15**	-0.14***	-0.00	-0.30***	0.06
	(-2.36)	(-2.65)	(-0.12)	(-4.52)	(0.76)
Book Leverage	-0.03	0.02	-0.05	0.17*	-0.02
	(-0.72)	(0.43)	(-1.60)	(1.65)	(-0.26)
Interest Expense/Assets	0.95**	0.55	0.40	-0.10	-0.37
	(2.08)	(1.42)	(1.24)	(-0.11)	(-0.50)
Market-to-Book	-0.00	0.00	-0.01	-0.04***	0.10***
	(-0.21)	(0.63)	(-0.82)	(-3.74)	(5.23)
Initial Covenant Tightness	-0.00	0.00	-0.01	0.01	-0.01
	(-0.22)	(1.55)	(-1.26)	(0.57)	(-1.10)
N	14506	14506	14506	14358	14358
Adj. R^2	0.04	0.06	0.02	0.10	0.16
Industry FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Table C.2: Propensity of CDS trading: First-stage IV regression

This table conducts the first stage of the IV regression (reported in Table C.1) using a probit model. The instrument for CDS trading is the average amount of forex derivatives used for hedging purposes relative to total assets of the lead syndicate banks and bond underwriters with which the firms have conducted business in the past five years. The independent variable is *d_CDS*, which is an indicator variable equal to one if a CDS is traded on the underlying firm's debt for that firm-quarter observation, and zero otherwise. t-statistics displayed in parentheses are robust to within-firm correlation and heteroscedasticity. *, **, and *** indicate significance greater than 10%, 5%, and 1%, respectively.

	Probit Model	
	(1)	(2)
Instrument		
Forex Derivative Hedging (%, log)		0.16***
		(2.64)
Firm-level controls		
d_Rated	1.00***	0.99***
	(9.31)	(9.19)
Assets(log)	0.75***	0.74***
	(13.54)	(13.09)
Profitability	-0.13	-0.12
	(-0.44)	(-0.41)
Book Leverage	0.82***	0.81***
	(3.70)	(3.65)
Market-to-Book	-0.10**	-0.11**
	(-2.39)	(-2.54)
Monthly Volatility (log)	-0.26***	-0.26***
	(-5.37)	(-5.44)
Monthly Trading Volume (log)	0.20***	0.21***
	(4.47)	(4.49)
Monthly Return	-0.02	-0.02
	(-0.29)	(-0.24)
CDS-trading controls		
Analyst Coverage (log)	0.03	0.03
	(0.79)	(0.81)
Institutional Ownership	0.07	0.07*
	(1.61)	(1.65)
Stock Illiquidity	0.17	0.17
	(1.22)	(1.24)
Analyst Dispersion	0.00	0.00
	(0.26)	(0.26)
N	74330	74330
Pseudo R^2	0.5810	0.5820
Industry FE	✓	✓
Year FE	✓	✓

Table C.3: Firm quality at loan issuance

This table regresses various measures of firm quality on *d_CDS* at loan issuance dates. *d_CDS* is an indicator variable equal to one if the loan announcement occurs when CDS is traded on the underlying firm's debt, and zero otherwise. Controls include *firm-level* characteristics, such as whether the firm has a rating, which may indicate different access to credit markets, *firm size*, *leverage*, *market-to-book*, *profitability*, and *current ratio*, and *CDS-trading* controls that may affect the probability of CDS trading such as *analyst coverage*, *institutional ownership*, *stock illiquidity*, and *analyst dispersion*. The control variables are defined in detail in the Appendix. t-statistics displayed in parantheses are robust to within-firm correlation and heteroscedasticity. *, **, and *** indicate significance greater than 10%, 5%, and 1%, respectively.

Risk measures regressed on 1-quarter lagged variables

	Altman Z-score (1)	**Intangible Assets** (2)	**Interest Coverage** (3)	**Cash-Flow Volatility** (4)
d_CDS	0.178***	0.001	0.020	0.001
	(3.35)	(0.14)	(1.41)	(0.46)
d_HasRating	0.007	-0.011	0.009	-0.002
	(0.14)	(-1.18)	(0.67)	(-0.84)
Assets (log)	0.122***	0.076***	0.010	-0.011***
	(3.17)	(9.10)	(1.17)	(-5.42)
Book Leverage	-5.536***	0.026	0.416***	0.019**
	(-29.66)	(1.03)	(10.71)	(2.56)
Market-To-Book	1.563***	-0.030***	-0.022***	0.010***
	(34.39)	(-5.20)	(-3.64)	(6.88)
Profitability	1.516***	0.026	-0.141**	-0.045***
	(7.40)	(1.24)	(-2.23)	(-4.47)
Current Ratio	0.657***	-0.027***	-0.006	0.001
	(17.50)	(-7.77)	(-1.11)	(0.90)
Analyst Coverage (log)	0.011	-0.001	-0.002	0.000
	(0.60)	(-0.42)	(-0.47)	(0.45)
Institutional Ownership	0.001	-0.001	-0.013*	-0.005***
	(0.04)	(-0.49)	(-1.72)	(-3.28)
Stock Illiquidity	-0.054	0.001	0.006	0.001
	(-0.63)	(0.03)	(0.17)	(0.24)
Analyst Dispersion	-0.008	-0.001	0.007*	-0.000
	(-0.97)	(-1.58)	(1.94)	(-0.01)
N	17060	8302	17544	17648
Adj. R^2	0.905	0.889	0.287	0.685
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Table C.4: Loan Announcement CAR Regressions: Within-Lender Analysis

The table report regression results of stock price reactions to firm loan announcements. The dependent variable is the cumulative abnormal return (CAR) calculated over the 3-day event window (-2,+2), where day 0 represents the loan announcement event day. CAR is calculated using the market model. Our main variable of interest is *d_CDS*, which is an indicator variable equal to one if the loan announcement occurs when CDS is traded on the underlying firm's debt, and zero otherwise. *d_TradedCDS* is an idicator variable equal to one if the firm in our sample has CDS traded on the debt at any point during our sample period, and zero otherwise. We control for *Loan-level* characteristics, *Pre-announcement* characteristics, *Firm-level* characteristics, and *CDS-Trading* characteristics which are defined in detail in the appendix section. The observations in this sample are at lender-package level. t-statistics displayed in parentheses are robust to within-firm correlation and heteroscedasticity. *, **, and *** indicate significance greater than 10%, 5%, and 1% , respectively.

	Lender FE		**Lender FE & Firm FE**	
	(1)	(2)	(3)	(4)
d_CDS	-0.35***	-0.41***	-0.34*	-0.39**
	(-2.78)	(-2.99)	(-1.92)	(-2.14)
d_TradedCDS	0.23**	0.19		
	(1.97)	(1.55)		
N	26755	21108	26755	21108
Adj. R^2	0.048	0.046	0.199	0.208
Deal Purpose FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Firm FE	✗	✗	✓	✓
Lender FE	✓	✓	✓	✓
Loan Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Pre-announcement Controls	✓	✓	✓	✓
CDS-trading Controls	✗	✓	✗	✓

APPENDIX D

MISCELLANEOUS SECTION FOR CHAPTER 4

D.1 Variable Definitions

D.1.1 Risk Measures

- *ES* = the negative of the average of the firms daily returns on 5% worst return days during the calendar year for the firm expressed in percentage terms

- *MES* = the negative of the average firms daily return on 5% worst return days of the market (S&P 500 instead of for the firm) during the calendar year expressed in percentage terms

- ES_{idio} = the residual plus constant upon regressing ES on MES separately for each firm-type expressed in percentage terms

- *Volatility* = the standard deviation of daily firm equity return over the calendar year expressed in percentage terms

- *Beta* = the estimate of the coefficient upon regressing the firms daily return on markets daily return (S&P 500) expressed in percentage terms

D.1.2 Firm-level Variables

- *Total debt* = long-term debt + short-term debt

- *Market value of assets* = (stock price × shares outstanding) at bond issuance + Book value of debt

- *Term spread* = yield spread between the 10- and 1-year treasury bonds

- *Profitability* = operating income after depreciation ÷ sales

- *Long-term debt to total assets* (book leverage) = long-term debt ÷ book value of total assets

- *Leverage (market leverage)* = market value of assets ÷ market value of equity

- *Market-to-Book* = market value of equity ÷ by the book value of equity

- *Asset growth* = $\log(\frac{assets_{i,t}}{assets_{i,t-1}})$ for firm i in quarter t

Table D.1: Names of the sample U.S financial institutions

The table displays the names of the U.S. financial firms in a subsample having a market capitalization of greater than $5 billion. The firms are categorized into 4 groups: Depositories (2-digit SIC code=60); Broker-Dealers (4-digit SIC code=6211); Insurance (2-digit SIC code=60 & 64); Other (2-digit SIC code=61, 62 (except 6211), 65, 67)

Depository	Broker-Dealers	Insurance	Other
BANK OF AMERICA CORP	BEAR STEARNS COMPANIES INC	AFLAC INC	AMERICAN CAPITAL LTD
BANK OF NEW YORK MELLON CORP	BLACKROCK INC	AXA FINANCIAL INC	AMERICAN EXPRESS CO
BANK ONE CORP	DEAN WITTER DISCOVER & CO	AETNA INC	AMERIPRISE FINANCIAL INC
BANKERS TRUST CORP	E TRADE FINANCIAL CORP	ALLSTATE CORP	AVIS BUDGET GROUP INC
CITIGROUP INC	FRANKLIN RESOURCES INC	AMBAC FINANCIAL GROUP INC	CIT GROUP INC
COMERICA INC	GOLDMAN SACHS GROUP INC	AMERICAN INTERNATIONAL GROUP INC	CME GROUP INC
FIRSTAR CORP NEW WIS	LEHMAN BROTHERS HOLDINGS INC	BERKSHIRE HATHAWAY INC DEL	CAPITAL ONE FINANCIAL CORP
FLEETBOSTON FINANCIAL CORP	MERRILL LYNCH & CO INC	CNO FINANCIAL GROUP INC	CIGNA CORP
GOLDEN WEST FINANCIAL CORP	MORGAN STANLEY DEAN WITTER & CO	CIGNA CORP	CREDIT SUISSE FIRST BOSTON USA
JPMORGAN CHASE & CO	SCHWAB CHARLES CORP	CINCINNATI FINANCIAL CORP	EQUITY RESIDENTIAL
M & T BANK CORP		COVENTRY HEALTH CARE INC	FEDERAL HOME LOAN MORTGAGE CORP
MARSHALL & ILSLEY CORP		GENWORTH FINANCIAL INC	FEDERAL NATIONAL MORTGAGE ASSN
NATIONAL CITY CORP		HANCOCK JOHN FINANCIAL SVCS INC	FRANKLIN RESOURCES INC
NORTHERN TRUST CORP		HARTFORD FINANCIAL SVCS GRP INC	GOLDEN WEST FINANCIAL CORP
REGIONS FINANCIAL CORP		HUMANA INC	HEALTH CARE REIT INC
SOVEREIGN BANCORP INC		MBIA INC	ISTAR FINANCIAL INC
STATE STREET CORP		MGIC INVESTMENT CORP WIS	JANUS CAP GROUP INC
SUNAMERICA INC		MARSH & MCLENNAN COS INC	KIMCO REALTY CORP
SUNTRUST BANKS INC		METLIFE INC	NYSE EURONEXT
SYNOVUS FINANCIAL CORP		NATIONWIDE FINANCIAL SERVICES IN	NATIONAL CITY CORP
UNION PLANTERS CORP		PRINCIPAL FINANCIAL GROUP INC	PAINE WEBBER GROUP INC
WACHOVIA CORP		PROVIDENT COMPANIES INC	PROLOGIS
WASHINGTON MUTUAL INC		PRUDENTIAL FINANCIAL INC	SLM CORP
WELLS FARGO & CO		TORCHMARK CORP	TD AMERITRADE HOLDING CORP
WESTERN UNION CO		TRAVELERS COMPANIES INC	

D.2 : A Simple Model.

Following is a simple model that derives bond yields as a function of expected shortfall (ES). This serves as a motivation for our baseline regression specification in Equation 4.4.1.

Let equity - e be given for a firm (Adrian and Shin, 2011)

Let d be the amount of debt to be raised

Let v be the face-value of debt to be repaid by the firm

Let c be the cost of raising too much debt/bankruptcy/financial distress costs

Let $\tilde{r}$ be the random return per dollar invested by the firm with mean μ and variance σ^2

Let r_f be the risk-free rate (opportunity cost of the investor)

Using the above notation, the wealth of the firm can be written as the following.

$$W_{firm} = (e + d)\tilde{r} - v - cd^2$$

The firm's problem is to maximize it's wealth over all cases when wealth is greater than zero as the firm is protected by limited liability.

Firm's problem taking into account the incentive constraint for investors is:

$$\max_{\{d,v\}} \mathbb{E}(W_{firm} \cdot \mathbb{1}_{W_{firm}>0})$$

s.t.

$$\mathbb{E}[\min\{v, [\tilde{r}(e + d) - cd^2]\} \geq r_f d$$

Using Lagrangian multiplier $\lambda > 0$ we can write the optimization problem in the following manner:

$$\max_{\{d,v,\lambda\}} (e+d) \int_{\frac{v+cd^2}{e+d}}^{\infty} rf(r)dr - (v+cd^2)\left[1 - F\left(\frac{v+cd^2}{e+d}\right)\right] +$$
$$\lambda\left(\left[1 - F\left(\frac{v+cd^2}{e+d}\right)\right] v + (e+d) \int_{\frac{cd^2}{e+d}}^{\frac{v+cd^2}{e+d}} \left[r - \frac{cd^2}{(e+d)}\right] f(r)dr - r_f d\right)$$

Differentiating w.r.t v we get:

$$\therefore (\lambda - 1)[1 - F\left(\frac{v+cd^2}{e+d}\right)] = 0 \Longrightarrow \lambda = 1$$

Differentiating w.r.t. d we get:

$$\int_{\frac{cd^2}{e+d}}^{\infty} rf(r)dr - cd^2 f\left(\frac{cd^2}{e+d}\right)\frac{d}{dd}\left(\frac{cd^2}{e+d}\right) + cd^2 f\left(\frac{cd^2}{e+d}\right)\frac{d}{dd}\left(\frac{cd^2}{e+d}\right)$$
$$- 2cd\left[1 - F\left(\frac{cd^2}{e+d}\right)\right] - rf = 0$$

$$\therefore \int_{\frac{cd^2}{e+d}}^{\infty} rf(r)dr - 2cd\left[1 - F\left(\frac{cd^2}{e+d}\right)\right] - rf = 0$$

If $cd^2 \ll (e+d)$ (i.e., bankruptcy costs are small compared to assets of the firm), then:

$$\frac{cd^2}{e+d} \approx 0 \Longrightarrow d \approx \frac{[1-F(0)]\mu - r_f}{2c[1-F(0)]}$$

If $\widetilde{r} \sim N(\mu, \sigma^2)$ then:

$$d \approx \frac{\Phi\left(\frac{\mu}{\sigma}\right)\mu - r_f}{2c\Phi\left(\frac{\mu}{\sigma}\right)} = \frac{1}{c}\left[\mu - \frac{r_f}{\Phi(\frac{\mu}{\sigma})}\right]$$

Briefly, the comparative statics are:

- If the cost of raising debt c is high then, less debt is raised

- If the expected return from the investment is high, then more debt is raised
- If the volatility of the investment is high, then less debt is raised
- If the sharpe ratio of the investment is high, then more debt is raised

To solve for the yield, the participation constraint is binding as $\lambda = 1$.

$$\left[1 - F\left(\frac{v + cd^2}{e + d}\right)\right] v + \int_{\frac{cd^2}{e+d}}^{\frac{v+cd^2}{e+d}} [r(e+d) - cd^2] f(r) dr = r_f d$$

i.e.,

$$\left[1 - F\left(\frac{v + cd^2}{e + d}\right)\right] v + \int_{\frac{cd^2}{e+d}}^{\frac{v+cd^2}{e+d}} [r(e+d) - cd^2 - v] f(r) dr + \int_{\frac{cd^2}{e+d}}^{\frac{v+cd^2}{e+d}} v f(r) dr = r_f d$$

As $W = (e+d)r - v - cd^2;\;\; e + d = a$ (assets)

$$\therefore \left[1 - F\left(\frac{cd^2}{e + d}\right)\right] v + \left[F\left(\frac{v + cd^2}{e + d}\right) - F\left(\frac{cd^2}{e + d}\right)\right] \mathbb{E}(W|W < 0) = r_f d$$

where $\mathbb{E}(W|W < 0)$ is the expected shortfall of wealth

$$\therefore \left[1 - F\left(\frac{cd^2}{a}\right)\right] v + \left[F\left(\frac{v + cd^2}{a}\right) - F\left(\frac{cd^2}{a}\right)\right] w_{firm,0} \mathbb{E}(\widetilde{r}_{firm}|W < 0) = r_f d$$

Let $\mathbb{E}(\widetilde{r}_{firm}|W < 0) = -es$ where $\widetilde{r}_{firm} = \frac{\widetilde{w}_{firm}}{w_{firm,0}}$ is the equity return of the firm.

$$\therefore v = \frac{r_f d + (es) w_{firm,0} \left[F\left(\frac{v+cd^2}{a}\right) - F\left(\frac{cd^2}{a}\right)\right]}{\left[1 - F\left(\frac{cd^2}{a}\right)\right]}$$

Again, if $\frac{cd^2}{a} \approx 0$; $F(0) = 1 - \Phi\left(\frac{\mu}{\sigma}\right) \approx 0$ for typical values (e.g., $\mu = 1.15$; $\sigma = 0.25$), and $F\left(\frac{v}{a}\right) \approx F\left(\frac{d}{a}\right)$, then $y \approx r_f + \frac{(es) w_{firm,0}}{d} \left[F\left(\frac{d}{a}\right)\right]$

$$\therefore log(y - r_f) \approx log(es) + logF\left(\frac{d}{a}\right) - log\,(d) + log(w_{firm,0})$$

or using the log expansion one can write the following:

$$y - r_f = \alpha + \beta.es + controls$$

Further Defining:

Tail-risk of the market is defined as : $es_{mkt,t} = -\mathbb{E}\left[r_{mkt,t} | r_{mkt,t} < -VAR_{mkt,\alpha}\right]$

Tail-risk of the firm is: $es_{i,t} = -\mathbb{E}\left[r_{i,t} | r_{i,t} < -VAR_{i,\alpha}\right]$

Market's return can be written as: $r_{mkt,t} = \omega_i r_{it}$

Therefore tail-risk of the market can be written as:

$es_{mkt,t} = -\mathbb{E}\left[\omega_i r_{i,t} | r_{mkt,t} < -VAR_{mkt,\alpha}\right]$

Taking partial derivatives we can define *mes* as the following:

$$\frac{\partial es_{mkt,t}}{\partial \omega_i} = mes_{i,t} = -\mathbb{E}\left[r_{i,t} | r_{mkt,t} < -VAR_{mkt,\alpha}\right]$$

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