ESSAYS ON RESOURCES AND INNOVATION

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

SUMMARY

External resources play a crucial role in fostering innovation by allowing individuals and firms to actively seek new knowledge and create novel products alongside their routine operations. In my dissertation, I investigate the impact of external resources in three distinct forms: consumers, award authorities, and foreign governments. Online user reviews are an important external information source for both consumers and producers. While the impact of reviews on consumer purchasing behavior has drawn much attention in the literature, whether it can influence producers in terms of future product development remains unclear. In Chapter 1, I examine the role of user reviews on product development and assess how the impact varies across different types of reviews. Analyzing textual data from a two-sided platform using NLP techniques, I evaluate the effect of review ratings on video game updates. The empirical results show that games with more design-related reviews have a higher probability of updates in the following month when users are not satisfied. Moreover, incumbent firms with more resources and capabilities can learn from reliability-related reviews for more complicated product development. The developed updates are positively correlated with the re-engagement of inactive users. My findings show that producers learn from users to absorb ideas about subsequent product development, and the relationship is heterogeneous across different dimensions of the reviews and producers. I discuss the strategic implications of the results for further development by producers, as well as the importance of platform review systems governance.

While innovations are often critical to the growth of firms, such firm-level outcomes emerge from the actions of organizational members who seek novel knowledge. Chapter 2 (co-authored with Jessica Li) develops and tests a model examining how status gain impacts individual novel knowledge adoption and subsequent performance. The model is tested using longitudinal data from a sample of book authors. Results indicate that status gain is associated with a higher level of novelty adoption, and the effect is more pronounced when

the authors do not have other sources of income. Adoption is positively associated with subsequent performance, measured by online ratings and easiness of passing through the publishers. This chapter contributes to knowledge management literature by demonstrating the unique effect of status gain on individual-level knowledge searching and adding to the evidence on how these two activities are present at the individual level.

The last external resource that I am examining is government support, which has been accounting for regional innovation growth. in Chapter 3 (co-authored with Kedong Chen and Xiaojin Liu), I analyze the unintended consequences of foreign government policies on domestic inventors. In 2009, the Chinese government launched the policy of "national innovative cities" to support the innovation of firms in selected regions. But the unintended consequence of the policy is unclear at the inventor level, in particular on those foreign inventors who have experience working with Chinese firms that are exposed to the policy intervention. Our research is guided by the research question: *How does government support influence foreign inventors who have collaborated with domestic firms before?* By employing the difference-in-differences (DiD) technique in the quasi-experimental setting, we examine the influence of government intervention on foreign partners. We find that foreign inventors who have established relationships with firms in selected cities experience an increase in collaborators and innovations. We further show that inventors with less patent stock take better advantage of cross-border government support. Taken together, the findings of the study suggest that government support can facilitate unintended cross-border knowledge flows and strengthen the innovation performance of "treated" foreign inventors.

Overall, this dissertation enhances our comprehension of how firms and individuals respond to changes in external resources.

CHAPTER 1

ENLIGHTENED BY USERS: IMPACT OF ONLINE USER REVIEWS ON PRODUCT DEVELOPMENT IN A TWO-SIDED PLATFORM

1.1 Introduction

Online feedback mechanisms have become the most common way for consumers to express their attitudes toward products, which also provides producers with a potentially valuable external information source. Especially on two-sided platforms, online reviews facilitate information exchange within user communities, and they replace the consumer survey as the most common way to understand the consumer population for firms. The formulation of user communities in the platform-hosted environment has important implications for many management activities, including customer retention and product development (Dellarocas, 2003). As a result, a considerable amount of academic research has examined how firms respond to online user communities and user reviews (Gans et al., 2021; Zhu & Liu, 2018). While most prior literature focuses on the advertising and pricing behaviors of producers (Archak et al., 2011; Ba & Pavlou, 2002; Hollenbeck et al., 2019), few studies have estimated the impact of user reviews on product innovation and development. Bertschek and Kesler (2022) provide indirect evidence by reporting that the probability of introducing a product innovation is positively correlated with firms' adoption of online communication via a Facebook page. However, while using online communication could provide information flows to firms, the adoption of Facebook might be a mix of advertising and consumer service rather than an attempt to learn from users. Another exception is the work done by Karanam et al. (2021). They find that apps that echo novel ideas from users enjoy an increase in downloads. However, they do not demonstrate to what extent the development is a consequence of learning from users.

While producers generally value user communities on platforms regarding their impact on marketing, there exists a challenge for both scholars and managers. The knowledge exchange within the user communities is informative for firms, but the large quantity and disorganized nature make it hard to identify the useful ones. Therefore, whether producers take advantage of user reviews as an information source in addition to a marketing approach remains unclear. It also remains unknown to what extent information is more insightful for product development. A case study by Zhang et al. (2018) shows that the information embedded in online reviews is correlated with the revision of smartphone features. However, empirical and quantitative studies that discuss the relationship between platform-hosted user communities and product development are scarce. In this paper, I attempt to answer these important questions: (a) Are user reviews an external information source for producers? (b) Do different dimensions of the reviews have heterogeneous impacts? (c) Do firms react differently to user reviews? (d) What is the value of the updates?

To investigate the impact of reviews in user communities on product development and subsequent performance, I examine the relationship between online reviews of game players and game development. The video game platform setting is a more appropriate setting than Facebook both because it is not an advertising channel and there is ample evidence that game producers value consumer opinions due to its informative characteristics (Xu & Ni, 2022). While Twitter is abundant with voices with extreme feelings (Gans et al., 2021), the design of platforms enables all users to leave messages with little extra cost. Using a unique dataset from the largest online video game platform, *Steam*, I report that after controlling for unobserved heterogeneity, the probability of product development increases with the count of design-related reviews, and such impact is heterogenous across producers. Moreover, updates have a positive impact on inactive user re-engagement but have little impact on new user attraction.

This paper speaks to multiple streams of research. First, it contributes to the literature of online reviews. Miller et al. (2009) emphasize the importance of firms' online strategy as the diffusion of opinions becomes rapid. As a result of its popularity, scholars have extensively examined the impact of online user reviews and their characteristics on consumers and producers. I join the discussion by examining the relationship between user review and product development on the producers' side. Second, it contributes to the discussion of user communities. User communities have become a common search source for external knowledge, and scholars are asking how the environment shapes the openness of the communities (Garriga et al., 2013). I show in addition to corporate-hosted communities, which are designed for ideators, innovation can be triggered by collecting ideas from consumers with limited knowledge about product development on third-party platform-hosted communities. Third, this paper speaks to online platforms and ecosystem research. This benefits the platform owner by generating more sales in the short term and bringing in more complementors to enjoy the network effect. By showing that user reviews can improve the complementor's output, I provide new insights for platform owners to motivate complementors' innovative efforts and hence align with the platform's value creation and evolution strategy (Panico & Cennamo, 2022). I also show evidence that complementor innovation has a significant impact on the performance of the products in terms of user loyalty. Last but not least, by investigating the heterogeneity across the producers, I join the discussion of IT competency through the lens of the resource-based view. Organizational learning has been pointed out as having a significant role in mediating the relationship between IT competency and firm performance (Tippins & Sohi, 2003). I show that learning is not exogenous but dependent on firm-specific characteristics in the first place, including size, experience, and age. These firm-specific resources and capabilities are correlated with how firms strategically learn from external resources.

1.2 Theoretical Development

1.2.1 User Communities

Shah and Nagle (2019) define user communities as "organizations composed primarily of users working collaboratively, voluntarily, and with minimal oversight to freely and openly develop and exchange knowledge in an area of common interest around an artifact." The value of user communities has been widely discussed, and how firms interact with the communities varies. While it is common for firms to organize communities to support knowledge exchange among users, they can also simply participate in a user community that users or third parties govern. The former example would be the IBM open-source software project, where IBM backs influential communities (firm-hosted user community), and the latter includes the online discussion boards of platforms such as Reddit (platform-hosted user community). The user communities vary in different dimensions, including participant motivation and firm governance.

First, in a corporate-hosted user community designed for innovation, the participants significantly differ from the normal users in the discussion groups on a third-party platform regarding motivations. Von Hippel (1976) points out that innovation activity does not necessarily originate from inside the firm, and many successful innovations of scientific instruments were created and tested by users. Firms host communities to invite users who draw from a knowledge set that differs from firms (Lettl et al., 2009; Von Hippel, 2005). By doing so, firms are able to leverage such information to complement their own knowledge and boost corporate innovation. This intended collaboration with user communities requires higher control and has been well-documented by multiple studies (Baldwin & Von Hippel, 2011; Bayus, 2013; Chatterji & Fabrizio, 2014; Di Gangi et al., 2010; Dong & Wu, 2015). Most firm-hosted user innovation communities are likely to consist of early adopters who are willing to share their innovations and are responsive to firm recognition (Jeppesen & Frederiksen, 2006; Jeppesen & Laursen, 2009; Schweisfurth & Raasch, 2015). Yet a large proportion of users do not share these characteristics: they remain silent in firm-hosted user innovation communities but active in platform-hosted communities. In platform-hosted user communities, participants also exchange knowledge and information about the artifact. These users 1) draw from different knowledge and skill sets from firms and ideators and 2) narrowly focus on their own needs (Chatterji & Fabrizio, 2012), in contrast to ideators attuned to the firm's needs. Users on corporate-hosted communities provide information for producers intentionally, but users on platforms speak to impact management and other customers (Chevalier et al., 2018). Jeppesen and Laursen (2009) report that ideators can benefit from solving innovation-related problems on the firm-host platform, but it is not the same case for common users. For example, in a video game platform setting, the users in the game community are not ideators who actively collaborate with the firms, and neither are they experts in developing games. Therefore, the primary motivation for user reviews is not to provide innovative ideas and benefit from solving the problem but to express their feelings and share knowledge with community members.

Second, firms have less control over the platform-hosted user communities. In a firm-hosted user community, firms have governance strategies to maintain the integrity of the master rules (Nickerson et al., 2017) and diagnose the potential of the ideas (Sivam et al., 2019). For example, the administrators in Wikipedia make sure that the contribution from the user community is relevant to the topics. However, in a user community hosted by third-party platforms, firms do not have control over the knowledge exchange, indicating that discussions might be distant from the knowledge firms seek. For example, the discussion about a restaurant on Yelp includes the environment, service, and food. A manager who wants to learn about local residents' preference for foods cannot set keys to induce discussion, and therefore, the discussion about the environment and service is less valuable to the owner. The lower control level in platform-hosted user communities suggests that the knowledge is less organized and can not be as effective as those in firm-hosted user communities where firms can moderate the discussion to help corporate innovation.

Despite the differences across the communities, corporate can still benefit from user reviews in the platform-hosted communities. Common benefits include learning from the discussion to conduct innovation and product development, branding, product support, and talent recruitment (Shah & Nagle, 2019). Platforms, as third parties, provide information infrastructure to facilitate information exchange; therefore, these online platforms constitute a vital information resource for the firms (Loh & Kretschmer, 2023). Future customers may utilize abundant information when evaluating the product and making purchasing decisions. On the other side of the market, producers can, in principle, listen to the voice of consumers and strategically respond accordingly (Chen & Xie, 2005). As online review platforms can help improve the overall welfare through learning the preference of users (Fang, 2022), rational firms ought not to make strategic moves accordingly. For example, hotels may spend less on advertising or service improvement when they receive highly satisfactory evaluations from an online platform, as they know that their users are satisfied with the current service (Hollenbeck et al., 2019). Regarding the reviews and discussions in the communities, producers are also aware of the importance for the performance. On eBay, sellers spend more effort on product quality when they find that user reviews cannot be revoked (Ye et al., 2014). They also reply to unsatisfied consumers on the platform when products are unfavorably rated (Zervas et al., 2017), which in turn can motivate consumers to contribute more information about the product quality. Besides the branding effect of the user communities and user reviews on the platforms, the exchange of knowledge among users is also insightful for innovation and product development. Motivated by nonpecuniary benefits, they discuss their unmet needs within the communities (Shah & Tripsas, 2007)), which provides the firms with a critical opportunity to learn and further develop their products (Antorini et al., 2012; Ogawa & Piller, 2006). However, the process of learning from user communities has been discussed more in corporate-hosted user communities where firms have higher control over the knowledge exchange. Since firms pay attention to the platform-hosted user communities and the communities do contain informative discussions, I complement the findings by analyzing the impact of platform-hosted user communities on the product development of the producers.

1.2.2 Review content and its implications

As corporate cannot effectively set rules for the reviews in platform-hosted user communities, managers and scholars need to identify the valuable reviews from others. Karanam et al. (2021) argue that among the ideas generated by users, values are higher when the differentiating ideas are contextually close or imitating other apps. Therefore, a major focus of research on users' reviews is to investigate the heterogeneity of the reviews in terms of values. There are generally two approaches the platform provides to the potential consumers, by dimensions and by helpfulness. As learning from user communities is essentially learning what the primary unmet needs among the users are, these two widely used approaches also provide solutions for producers when learning. A trending feature on the platforms is the multidimensional rating system. Knowing the heterogeneity of reviews, platforms have adopted multiple ways to help users sort helpful reviews and locate helpful reviews. For example, Amazon invites customers of coffee to rate features, including flavor, freshness, and value for money, separately. The multidimensional system explicitly scores different facets of the review under the belief that different dimensions of reviews may have varying implications for users and producers. When provided dimensional rating choices, consumers recall specific attributes since they become cognitively accessible (Schneider et al., 2021), and such dimensional information may have varied subsequent impacts. For example, Siering et al. (2018a) find that service-specific reviews instead of value-specific sentiment drive and predict the recommendation of the users in the airline industry. And in the settings of interior designs of auto models, Kong et al. (2020) conclude that ratings and reviews associated with functional and hedonic product attributes primarily affect perceived helpfulness and sales, respectively. Due to the various economic implications of the product dimension, when multidimensional rating is not explicitly available, corporate still has the motivation to synthesize the knowledge from the unstructured text to understand the multidimensional performance of their products. As different dimensions of products may involve different levels of product development, the impact of reviews may vary. For example, the functional part of auto design and hedonic design require different inputs from the producers, and hence corporate cannot respond equally regarding further improvement and development.

Another approach is to sort the reviews by helpfulness, and much of the literature focuses on how to predict helpfulness to consumers based on review features (Hong et al., 2017; Mudambi & Schuff, 2010). For example, Mudambi and Schuff (2010) measure review depth by counting length and find that the count of words has a positive effect on the perceived helpfulness of the review. Cao et al. (2011) find that reviews with extreme opinions are perceived as more helpful than neutral ones. Siering et al. (2018b) report that content characteristics such as semantic styles and reviewer characteristics such as reviews expertise help improve the prediction of review helpfulness. Extending the research stream from the demand side to the supply side, identifying helpful reviews could help producers sort reviews to reduce information overload. Most platforms provide methods to sort reviews based on consumer votes (e.g., how many other consumers find this review helpful), and whether producers benefit from such a sorting method deserves investigation. As helpfulness effectively measures the weight of knowledge in the user communities, it should have implications for future product development, and producers have the motivation to scrutinize the most salient ones.

1.2.3 User reviews and firm capabilities

While it is generally agreed that IT can be a part of the strategic value of the firms, the intersection between innovation management and IS emphasizes the heterogeneity of the organizations (Aral & Weill, 2007; Zhu & Kraemer, 2002). The classic resource-based view and dynamic capabilities perspective argue that firms possess resources and capabilities through which they achieve competitive advantage and renew them to stay competitive in the changing business environment (Teece et al., 1997). Therefore, the difference in capabilities across the firms determines their success in learning from the rapid-changing market and consumer demands. Grounded in resource-based theory with a focus on firm-specific resources and capabilities, scholars examine how internal factors, in addition to the industry structure, can shape and interact with the relationship between information systems and the competitive advantages of the firms (Clemons, 1986; Mithas et al., 2011; Ravichandran et al., 2005). For example, the ability to employ the information through information infrastructure depends on a variety of organizational features such as organizational structure (Wu et al., 2019), financial commitment (Zhu & Kraemer, 2005), and IT knowledge base (Joshi et al., 2010). Among the performance metrics, IT knowledge base is especially critical for firm-level innovation productivity (Kleis et al., 2012; Wu et al., 2020), and one of the reasons is that IT competency enables firms to learn from external actors such as partners and consumers. This includes the differences in the capability of listening to stakeholders to sense potential environmental changes or spot new opportunities in the process of organizational learning. For example, data analysis and information absorption are challenging, but firms with such capability can outperform their competitors in expanding the search space of existing knowledge during the R&D process, especially for incremental process improvements (Wu et al., 2020).

Taking these arguments together, I argue that firm heterogeneity in resources and capabilities is important when discussing the impact of user reviews on product development. In the video game industry, there are at least two types of producers: large firms such as Electronic Arts and small game studios. They significantly differ in the efficiency of using user reviews. First, the firm-level capability is accumulated through experience and stored in human capital. Large firms have many more resources and capable employees with the ability to respond to user demands. The resources and process when acquiring knowledge from user communities are specific to firms, which impacts the success of organizational learning (Sivam et al., 2019). On the other hand, small studios in the video game industry are usually composed of around 20 employees, which means limited resources in research and development. A significant proportion of the small studios funded through Kickstarter lack the capability to hire talent, indicating less stored human capital in absorbing information. Second, Wu et al. (2020) point out that external information learning through data analysis mainly benefits incremental process improvement. As large firms focus on process innovation and incremental product innovation more (Almeida & Kogut, 1997; Cohen & Klepper, 1996), they benefit from user reviews due to the motivation to exploit in the existing knowledge space. Meanwhile, the small studios are more ambitious and invent more in less crowded areas. As learning from user communities includes both problem-finding and solution-finding (Nickerson et al., 2017), firms may shape problem formulation differently due to their value-creation strategy. How small studios delve into user-generated texts to assist their product development might differ from the large firms due to their needs in innovation and R&D. Therefore, they accumulated different sets of capabilities in learning, catering to their unique demands.

Despite the differences in resources and capabilities, small studios still are able to improve their capabilities through multiple approaches, including accumulating experience and collaborating with other firms. By gaining experience in the industry and specific knowledge about product R&D, they can effectively resemble large incumbents in terms of the pattern of product development.

1.2.4 Value of updates

There is no doubt about the value of updates on the platform as innovations (Kircher & Foerderer, 2022; Miric & Jeppesen, 2020). Platforms, as the block builders, connect the review of the users to producers and benefit from the sales of the complementor's innovative products. While empirical studies have shown that the volume of reviews has been widely proven to be positively correlated with sales performance (Duan et al., 2008; Liu, 2006;

Zhu & Zhang, 2010), what remains unclear is whether at least some of the reasons can be attributed to the updates.

This question concerns scholars and practitioners is the value of the updates of existing products: Do updates matter for the performance of firms? As the marginal cost of producing updates is effectively zero, producers in the software industry are widely using updates to enter the market in time (Arora et al., 2006). In the sector of the software industry, patches are regarded as welfare-enhancing (Kim et al., 2009), and firms are widely using the strategy to release the product earlier with defects (Choudhary & Zhang, 2015). The reason is that when facing a large but competitive market, they are able to sell the virtual goods in a larger quantity with earlier but buggies strategy. Moreover, after the publishment, successful patches can increase the loyalty of the consumers, even then they would have no unsatisfactory with the problematic products (Sousa & Voss, 2009). Such loyalty would be valuable for producers who have large installation bases, but a proportion of the users are not active. For example, in the online retailing industries, the customer intention to reuse can be moderated by the assurance of reliability and satisfaction (Malhotra et al., 2017). As reuse is also profitable in addition to new user attraction, the assurance by updating is valuable for the sellers. On top of that, updates can significantly help small startups to interact with crowdfunding investors, and hence improve project outcomes (de Kok, 2022). Therefore, updates are preferable for the platform owner and the complementor producers.

1.3 Data and Methods

1.3.1 Empirical Setting and Data

Marketing and IT management studies have extensively examined the importance of reviews and content on the platform for both consumers and producers across sectors, using books (Godes & Silva, 2012), movies (Chen et al., 2012), hotels (Hollenbeck et al., 2019), and restaurants (Li, 2018) as the research settings. However, innovation and product development, especially the incremental ones, can hardly be observed by scholars in these industries: once the product is published, seldom do users see any further development about the existing ones. Therefore, in this paper, I use the video game industry as my research context to investigate the research questions. The video game industry has been used for studies in online user reviews and product development, given its unique features for two reasons. First, similar to the software industry, the published game can be further modified and developed as a strategic move. The update history of the games enables one to examine the trajectory of the product development. Second, users of video games are encouraged to leave reviews on the games, and the cost of leaving reviews is much lower, indicating the reviews are more representative of the whole population compared to the other industries. A project manager from *Blizzard*, a famous game developer and publisher that has released Diablo and the Warcraft series, claims in my interview that the video game industry is heavily community-based, and feedback from existing users is vital in the way that it helps attract potential players. He says:

> We care a lot about ratings and reviews. We listen to our existing users' feedback because we believe that the existing users are good representatives of the whole market that we are serving, and basically, we are creating value by meeting their demands. And as a consequence, we tend to focus more on negative feedback since we try our best to eliminate them. As we do try to integrate the users' ideas into our products, it is hard to claim to what extent our development can be attributed to user's feedback, since the development process is complicated, and it is challenging for us to identify valuable feedback. We receive thousands of reviews from different sources, and unless we can find a pattern, most of them cannot be embraced directly since the reviews per se do not contain valuable information

Steam, a digital distribution platform for video games, was launched in September 2003. It is now the most prominent digital distribution platform for PC gaming. By 2019, it had over one billion registered accounts, with 90 million active users per month. It had over 30,000 games by 2019, with an additional 20,000 downloadable content extensions to games (DLCs). *Steam* provides a community discussion for every single game. *Steam* creates individual shopping pages for each game that contain a large amount of information about the game: publication date, language, update history, DLCs, and user reviews. This setting enables me to collect a large sample of user reviews and ratings and track product development. Learning from customers is not rare in the industry of video games. Xu and Ni (2022) show that video game producers are uncertain about consumers' game evaluation, and thus they try to learn through the sales prior to the official publishment. This paper extends their research by showing that producers continue to learn after the program launch, and they can subtly learn from the textual reviews in addition to the sales performance.

In this study, I collect review information from a sample of games officially published in 2016 and 2017. I select all the games that exceed 1 million sales until the end of 2021 and remove the games that are not listed on the platform for various reasons. The sample criteria guarantee that the products are successful, indicating that they are not terminated quickly due to reasons such as lack of revenue. The sample includes 263 unique games, and I collect user review text from three years prior to the official publishment to four years post publishment. As *Steam* allows developers to list the game on the platform before entirely complete, the beta-test product can also be purchased and reviewed. I also match the reviews with the sales and active user data from *Steam Spy*, which monitors the data using *Steam* API (Rietveld & Ploog, 2022).

1.3.2 Dependent Variable

The main dependent variable is $Update_{it}$. The dummy variable equals 1 if game i publishes an Update News in month t. For each game, Steam provides a variety of channels for producers to publish game-specific news and to communicate with players, including *game updates*, *press release*, *steam blog*, and so on. Game developers do not necessarily need to announce the published updates, and they do not have to post in the updates channel – they can generally post in the *all news* channel. To identify the updates, I first extract all items from the *all news* channel for the games in my sample and keep *all news* that are posted on the *Product Release* and *Product Update* channels. I then remove all items posted on game reviews and press cover channels. Finally, I remove all news in the remaining channels without keywords "*update*", "*release*", "*patch*", "*hotfix*", "*change log*" or that lack a version number.

1.3.3 Independent Variables

The main challenge is to differentiate the dimensions embedded in the review text. Given the amount of data, it is impossible to classify those reviews manually, and thus I use machine learning techniques to extract the information. Unsupervised machine learning algorithms can be used in review analysis for extracting topics from text automatically. For example, Timoshenko and Hauser (2019) use such a method to mine consumers' needs from user-generated content. However, since unsupervised algorithms will extract the most salient information, which happens to be game categories (e.g., shooting, sports, or multi-players), they do not lend themselves well to my data and research goal. Therefore, I make use of a supervised machine learning algorithm to recognize the dimensions of the reviews.

BERT is a technique for Natural Language Processing (NLP) pre-training developed by computer scientists. To tailor the algorithm to my data, I manually label a subsample of reviews in multiple dimensions and then train the model in order to identify the information embedded in review texts in terms of these dimensions. As Steam does not provide a multidimensional rating system, I classify the reviews into four dimensions: reliability (bugs, glitches, and optimizations), aesthetics (graphics and sounds of the game), story (storyline and characters), and gameplay (game features and game mode). I randomly select 800 positive reviews and 800 negative reviews, and manually label them as 1 or 0 in terms of these four dimensions. Table 1.1 illustrates the examples of the concordance between review text and classifications. I manually recognized reviews for both positive and negative reviews regarding these dimensions.

Table 1.1: Examples of Mannually Labeled Reviews

Review Text	Reliability	Aesthetics	Story	Gameplay
...was a game that I played during my mid childhood. I was hoping that they would fix the game issues (Physics, Camera, and Mouth syncing) before releasing it to steam, but I guess it's free money to just add a resolution option and remake the chao transfer tool into a departure tool. Otherwise, it's still a fun game. Still a fun storyline.	1	0	1	0
It's incredibly satisfying killing the orcs, making small mazes, messing around with the various traps and weapons...I love how each play through can be different and custom to how YOU want to play. It's also on sale a LOT (along with the DLCs which are fun as well for ∼$1 each), definitely worth it. Highly recommend. :)	0	0	0	1
A surprisingly entertaining game with clever character design, Funny voice acting, great art and amazing music at all points. Although it does come with some minor problems, none of them are bad enough to hinder the great experience the game provides	0	1	1	0
The cut scenes and movie like game play where the enemy just keep coming until you figure out what you need to do, and having to play the same 3 to 5 minute section of game over and over again because the save points are so far apart was bad, but what was terrible was the number of times the game just crashed in a row (up to 8 tonight in the last half hour), which is why I can't recommend the mac version of this game.	1	0	0	0

After training the NLP model with the manually labeled reviews, I test its prediction accuracy on another 200 positive reviews and 200 negative reviews. These 400 reviews are also manually labeled in the four dimensions based on the contents to verify the reliability of the machine prediction. The accuracies of the tuned model for these dimensions are shown below in Table 1.2. This result is comparable to previous research where the accuracy of sentiment analysis reaches 94% by deep learning, 74.2% by Naïve Bayes, and

76.46% by Support Vector Machine (Day & Lin, 2017), and 70% to 74% where the deep learning model is used to identify the informative of the consumers' review (Timoshenko & Hauser, 2019). As the story, aesthetics, and gameplay cannot be modified easily through updates, I combine them together as a *Design* dimension.

Table 1.2: NLP Model Performance

	Reliability	Design		
		Aesthetics	Story	Gameplay
Accuracy	0.865	0.932	0.910	0.816

I apply this fine-tuned machine learning model to the reviews of the game in the sample. For example, the game *Stardew Valley* received 172 reviews in January 2017, with 10 in reliability, 23 in aesthetics, 7 in story, and 102 in gameplay. For each dimension, I calculate the score. Among the 10 reliability-oriented reviews, 2 are positive and 8 are negative, which yields the $ReiliabilityScore_{it}$ = 0.2 and $Reiliability_{it} = 10$. Similarly, I calculate all the ***Design Score*** and ***Design Count*** for the selected game samples.

The detailed description of variables in my research model is presented in Table 1.3. The descriptive statistics are in Table 1.4, and the correlations are in Table 1.5. In Figure 1.1, I provide a locally-weighted scatterplot of data to show the dynamic patterns of games. Panel A shows that the likelihood of product development increases first and then decreases with time. Panel B shows that the relationship between the number of users and time is an inverse-U shape, and it is not perfectly correlated with the number of reviews. Panel C shows that reliability is less commonly mentioned than game design in the reviews, while Panel D shows that the scores of the two dimensions are not parallel: the reliability score is much lower; the game design score corresponds with the overall score, and both of them increase first and stay stable after official publish.

Table 1.3: Construction of Variables

Construct	Variable	Description
Dependent Variable	$Update_{it}$	1 if game i published an update on month t, 0 otherwise.
Independent Variables	$Log(Reliablity)_{it}$	The log of 1 plus total review count mentioning reliability posted for game i on month t.
	$Log(Design)_{it}$	The log of 1 plus total review count mentioning design posted for game i on month t.
	$ReliablityScore_{it}$	The percentage of positive out of all the reviews mentioning reliability posted for game i on month t.
	$DesignScore_{it}$	The percentage of positive out of all the reviews mentioning design posted for game i on month t.
	$ReliablityHelpful_{it}$	1 if the percentage of reliability reviews of game i on month t exceeds the median of the percentages for the focal game across all months, 0 otherwise.
	$DesignHelpful_{it}$	1 if the percentage of design reviews of game i on month t exceeds the median of the percentages for the focal game across all months, 0 otherwise.
	$Firm_i$	1 if game i is published by a firm with more than 50 employees, 0 otherwise.
	$ProducerAge_{it}$	The age of the developer of game i on month t, in year.
	$Experience_{it}$	Number of games that the developer of game i published before the focal game.
	$Collaboration_i$	1 if game i is collaborated by multiple game developers, 0 otherwise.
Control Variables	$Log(Count)_{it}$	Log of 1 plus all review count posted for game i on month t.
	$Log(Users)_{it}$	Log of 1 plus average daily active users for game i on month t.
	$Log(Owners)_{it}$	Log of 1 plus accumulating owners (sales) for game i on month t.
	Age_{it}	The age of the game i on month t, in months.
	$Positive_{it}$	The average attitude for reviews posted for game i on month t.
	$Promotion_{it}$	1 if game$i$ has a non-updated related promotion on month t, 0 otherwise.

Table 1.4: Descriptive Statistics

Panel A. Descriptive Summary

	Mean	SD	Min	Max	N
Update	0.241	0.428	0	1	13,305
Log(Reliablity)	2.559	1.469	0	9.558	13,305
Log(Design)	3.507	1.554	0	9.187	13,305
ReliablityScore	0.818	0.213	0	1	13,305
DesignScore	0.817	0.19	0	1	13,305
ReliablityHelpful	0.607	0.488	0	1	13,305
DesignHelpful	0.593	0.491	0	1	13,305
Firm	0.387	0.487	0	1	13,305
Producer Age	12.959	10.181	0	53	13,305
Experience	6.957	17.283	0	90	13,305
Collaboration	0.228	0.419	0	1	13,305
Log(Count)	5.062	1.598	0.693	10.542	13,305
Log(Users)	6.531	2.002	0.304	14.859	13,305
Log(Owners)	13.897	1.319	6.909	18.311	13,305
Age	27.986	19.024	-24	60	13,305
Positive	0.817	0.158	0	1	13,305
Promotion	0.179	0.383	0	1	13,305

Panel B. Between and Within SD

	Mean	SD	Min	Max	N
Update	0.241	0.428	0.226	0.363	263
Log(Reliablity)	2.559	1.469	1.19	0.875	263
Log(Design)	3.507	1.554	1.343	0.825	263
ReliablityScore	0.818	0.213	0.122	0.176	263
DesignScore	0.817	0.19	0.124	0.145	263
ReliablityHelpful	0.607	0.488	0.113	0.477	263
DesignHelpful	0.593	0.491	0.095	0.483	263
Log(Count)	5.062	1.598	1.426	0.782	263
Log(Users)	6.531	2.002	1.882	0.749	263
Log(Owners)	13.897	1.319	0.964	0.903	263
Age	27.986	19.024	5.572	18.405	263
Positive	0.817	0.158	0.122	0.103	263
Promotion	0.179	0.383	0.124	0.363	263

1.3.4 Specifications

The baseline specification is

$$\begin{aligned} Y_{it+1} =& f(\alpha_0 + \beta_0 \times X_{it} + \beta_1 \times log(Reliability_{it} + 1) + \beta_2 \times ReliabilityScore_{it} \\ &+ \beta_3 \times log(Design_{it} + 1) + \beta_4 \times DesignScore_{it} + \delta_t + \gamma_i + \epsilon_{it}) \end{aligned}$$

Table 1.5: Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	*Update*	1																
2	*Log(Reliablity)*	0.203	1															
3	*Log(Design)*	0.137	0.793	1														
4	*ReliablityScore*	-0.11	0.062	0.181	1													
5	*DesignScore*	-0.129	0.076	0.212	0.601	1												
6	*ReliablityHelpful*	0.134	-0.127	-0.15	-0.16	-0.139	1											
7	*DesignHelpful*	0.171	-0.08	-0.11	-0.132	-0.184	0.433	1										
8	*Firm*	-0.031	0.241	0.236	-0.102	-0.106	-0.011	-0.008	1									
9	*Producer Age*	-0.122	0.134	0.181	-0.021	-0.014	-0.059	-0.076	0.678	1								
10	*Experience*	-0.099	0.057	0.036	-0.049	-0.043	0.001	-0.005	0.435	0.45	1							
11	*Collaboration*	-0.038	0.014	-0.034	-0.078	-0.086	0.019	0.005	0.227	0.319	0.303	1						
12	*Log(Count)*	0.16	0.82	0.909	0.18	0.21	-0.187	-0.15	0.188	0.137	0.031	-0.05	1					
13	*Log(Users)*	0.259	0.719	0.713	0.02	0.029	-0.073	-0.029	0.332	0.254	0.048	0.029	0.762	1				
14	*Log(Owners)*	-0.029	0.377	0.346	-0.02	-0.037	-0.246	-0.269	0.122	0.138	-0.051	-0.003	0.383	0.479	1			
15	*Age*	-0.336	-0.11	-0.057	0.117	0.117	-0.391	-0.498	0.021	0.179	0.031	0.027	-0.065	-0.079	0.412	1		
16	*Positive*	-0.157	0.089	0.251	0.733	0.84	-0.164	-0.184	-0.13	-0.019	-0.058	-0.098	0.249	0.032	-0.037	0.141	1	
17	*Promotion*	-0.263	-0.017	0.025	0.069	0.084	-0.055	-0.051	-0.031	-0.009	-0.009	-0.023	0.033	-0.035	-0.005	0.075	0.098	1

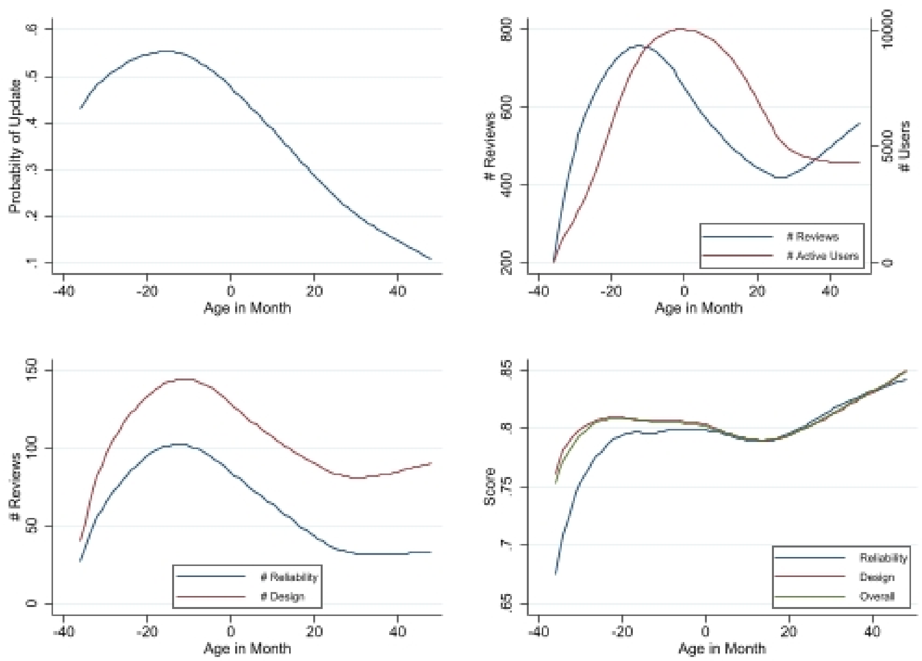


Figure 1.1: Game and Review Trend

where Y_{ist} is the dummy variable for updates for game i on month t. X_{it} are the time-variant market controls including user count, overall score, age, and promotion information. I include game-fixed effects and time-fixed effects, which account for many omitted variables and sources of endogeneity.

1.4 Results

1.4.1 Baseline Results

The baseline results of the linear probability models are presented in Table 1.6. Column (1) only includes the controls, and it is evident that active users have a positive impact on the probability of updates, while the accumulated sale record has a negative impact. From column (2), which controls for monthly active users and accumulated copies sold, it is evident that the aggregate count of user reviews has a positive impact on the likelihood of a product update in the following month, but the coefficient magnitude of active users shrinks. A ten percent increase in the number of posted reviews is expected to lead to a 0.315 percent increase in the update likelihood. Column (3) substitutes the total review counts with the counts of reliability and design reviews, and the magnitude of the coefficient on reliability review counts is statistically insignificant at conventional levels, while the coefficient on the count of design reviews is only significant at 10% level: if the count of monthly design reviews increases by ten percent, the producer is expected to increase the update likelihood by 0.152 percent.

Moreover, it is also interesting that the ratings of the reviews matter in columns. This is consistent that less satisfactory products should be invested in more attention for further polish. I further investigate the different dimensions of ratings generated by machine learning algorithms to investigate whether they interact with the count of the reviews to motivate the producers to learn. In column (4), I examine whether the sentiment *Positive* interacts with the two types of reviews in terms of impacts on product development. The variable *Positive*, which captures the overall satisfaction level of the users in the focal month, does not interact significantly with the reliability reviews, but with design reviews. Producers are more likely to react to the design reviews when users express negative feelings through reviews, which is significant at the conventional level.

However, it is still counterintuitive that firms fail to react to reliability reviews. In

Table 1.6: Baseline Regression: Impact of User Reviews on Product Development

	(1) *Update*	(2) *Update*	(3) *Update*	(4) *Update*	(5) *Update*	(6) *Update*
Age	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Promotion	0.093***	0.094***	0.094***	0.093***	0.094***	0.093***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
log (Owners)	-0.042***	-0.039***	-0.041***	-0.042***	-0.041***	-0.042***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
log (Users)	0.052***	0.028**	0.036***	0.034***	0.037***	0.034***
	(0.009)	(0.012)	(0.011)	(0.012)	(0.011)	(0.011)
Positive	-0.150***	-0.164***	-0.159***	0.078		
	(0.044)	(0.045)	(0.044)	(0.048)		
log (Count)		0.033***				
		(0.009)				
log (Reliability)			0.007	0.014	0.007	0.025
			(0.008)	(0.033)	(0.008)	(0.018)
log (Design)			0.016*	0.099***	0.015	0.083***
			(0.009)	(0.032)	(0.009)	(0.019)
Reliability Score					(0.019)	(0.02)
					(0.016)	(0.028)
Design Score					-0.075***	0.073**
					(0.022)	(0.031)
*log (Reliability) * Positive*				-0.009		
				(0.04)		
*log (Design) * Positive*				-0.098***		
				(0.037)		
log (Reliability)						-0.022
** Reliability Score*						(0.019)
log (Design)						-0.078***
** Design Score*						(0.02)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Game FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13230	13230	13230	13230	13230	13230

Standard errors in parentheses, clustered at game level
* p<0.10, ** p<0.05, *** p<0.01

column (5), I dissemble the overall ratings Positive into Reliability Score and Design Score to address the concern that reliability reviews might be dominated by design reviews. I further interacted the dimensions ratings with review counts respectively in column (6), but the interaction term is only significant for design reviews but not reliability reviews. In Figure 1.2, for each game, I divide the observations into 5 quantile bins regarding the overall ratings and examine the coefficient of two types of reviews, respectively. It is

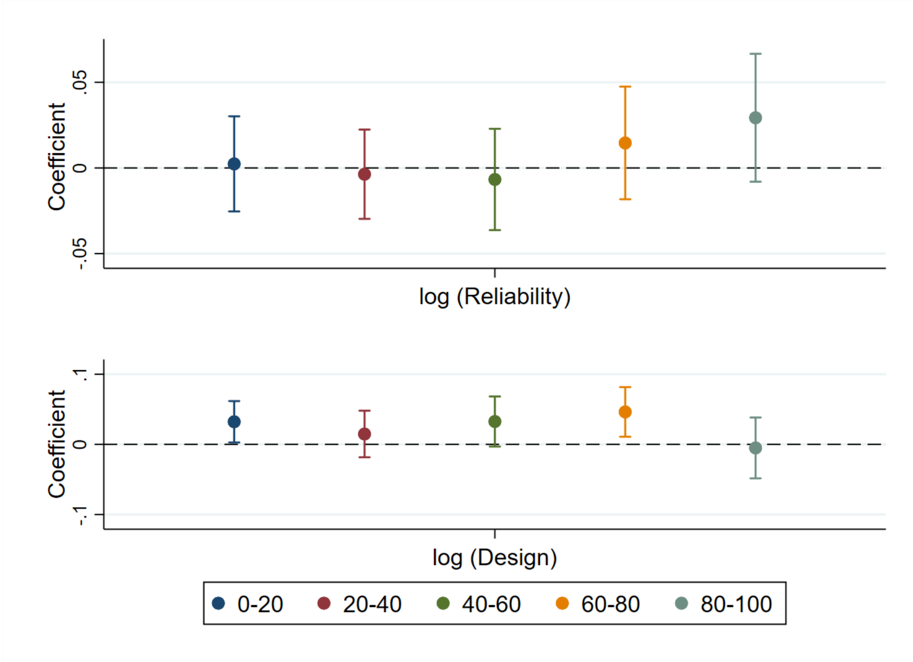


Figure 1.2: Coefficients of Review Counts by Ratings

evident that design reviews can significantly trigger the update when the ratings are low.

Given the average likelihood of updates is 0.241, producers do not publish updates every month. This means that updates might be a response to the reviews from the two or three months before, in addition to the previous month. Therefore, in Table 1.7, I use different lags between the independent variable and the dependent variable to address this concern. It is evident here that using a one-month lag is appropriate since it yields the highest R-squared value, and using a two-month lag also yields similar results regarding our main variables of interest. Using three months or four months is not appropriate here since even the impact of the count of users and overall ratings would not be reflected. In Table A.1 in the Appendix, I also replicate the main regression models using a 2-month lag, and despite the difference in magnitude, the main results persist. In Table A.2 in the Appendix, I add a 2-month lag to the main regression models. Both AIC and BIC decrease, but the magnitude of the coefficient only changes slightly. Our main result that the count of reviews has a positive impact on update probability in the following month holds.

The result is in line with the marketing studies where ratings have a significant impact

Table 1.7: Optimal Lag Selection

	(1)	(2)	(3)	(4)
	$Update$	$Update$	$Update$	$Update$
Age	-0.011***	-0.006***	-0.005***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Promotion	0.094***	-0.053***	-0.059***	-0.047***
	(0.016)	(0.010)	(0.008)	(0.010)
log (Owner)	-0.039***	-0.032***	-0.023***	-0.020**
	(0.009)	(0.008)	(0.008)	(0.008)
log (Users)	0.028**	0.023**	0.011	0.001
	(0.012)	(0.011)	(0.011)	(0.011)
log (Count)	0.033***	0.021**	0.020**	0.028***
	(0.009)	(0.009)	(0.009)	(0.009)
Ratings	-0.164***	-0.149***	-0.058	-0.056
	(0.045)	(0.043)	(0.041)	(0.044)
Time &Game FE	Yes	Yes	Yes	Yes
Lag	1 Month	2 Months	3 Months	4 Months
R^2	0.138	0.122	0.115	0.111

Standard errors in parentheses, clustered at game level
* p¡0.10, ** p¡0.05, *** p¡0.01

on other consumers' behavior (Chevalier et al., 2018; Moe & Trusov, 2011). While future customers rely on review ratings from existing customers to make decisions about the unknown but fixed quality, producers make decisions about product development when they find consumers are unsatisfied. What is unknown to them is the preference of the customers in terms of the game design, so they pay more attention to the volume of the reviews and the textual information in the reviews. Therefore, for producers, the importance of reviews is the information embedded in the high volume of the design reviews, which represents the consumers' taste when ratings fail to meet their expectations. More reviews can provide information about the direction of the product development when they attempt to cater to frustrated users. Overall, the results show that the different dimensions of reviews have heterogeneous impacts on product development activities. Reliability-related reviews are not valued by the producers, whereas design-related reviews are relevant for product improvement when ratings of the product are low.

Another feature that may moderate the relationship between reviews and product development is the helpfulness of the reviews. The reason that counts of the reviews fail to trigger learning might be that a great proportion of the reviews are not useful. For example, a general expression such as "The game is awesome, and I like it" may encourage other potential users but does not contain any valuable information for firms to extract. Therefore, in Table 1.8, I investigate whether the perceived helpfulness of the reviews alters the impact of reviews. The reason is that helpfulness represents the load of information, and it should have an impact on the producer's decision if they are trying to learn from the reviews on the platform. I follow two widely used approaches to discuss helpfulness: by length and by other users' votes. The reviews are considered helpful either when they are longer than 20 words or when they are voted "helpful" by at least another user. The word-count approach is widely used in the marketing and information management literature, as it has been found to predict the perceived helpfulness and informativeness of the reviews (Kim et al., 2006; Mudambi & Schuff, 2010; Salehan & Kim, 2016). The latter approach is used by the Steam platform, and both users and producers can sort the reviews by the count of other users' agreements. In column (2) and column (3), I only take the helpful reviews into count, and compared to the baseline regression, the count of helpful reviews is significant at the conventional level. The coefficient increases from 0.016 in Table 6 to 0.026. In column (4) to column (7), the helpful reviews are the ones that are longer than 20 words. I then create a dummy variable, *ReliabilityHelpful*, which equals one if the proportion of reliability-related reviews that are scored as helpful in any given month exceeds the median for the whole sample, and I apply the same process to generate *DesignHelpful*. The goal is to examine whether producers are aroused when the proportion of useful reviews is high. In other words, the analysis is to examine whether firms are more encouraged to learn when they find that the majority of the reviews are helpful. However, the interaction effect is insignificant for both ways of measurement. It suggests that the producers learn from the helpful design reviews, but they are insensitive to the situation where helpfulness "density" is high.

Table 1.8: OLS - Helpfulness of Reviews

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Update	*Update*	*Update*	*Update*	*Update*	*Update*	*Update*
log (Reliability)	0.007	0.013*	0.015*	0.008	0.003	0.008	-0.001
	(0.008)	(0.007)	(0.007)	(0.008)	(0.010)	(0.008)	(0.010)
log (Design)	0.016*	0.026***	0.024***	0.018*	0.009	0.018*	0.017*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)
Reliablity Helpful				0.014*	-0.003	0.015**	-0.014
				(0.008)	(0.016)	(0.007)	(0.016)
Design Helpful				0.021**	-0.019	0.012	0.005
				(0.009)	(0.021)	(0.008)	(0.022)
log (Reliability)					0.006		0.011*
** Reliability Helpful*					(0.007)		(0.006)
log (Design)					0.012*		0.001
** Design Helpful*					(0.006)		(0.006)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Game FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Helpful Measure		Length	Vote	Length	Length	Vote	Vote
Observations	13230	13230	13230	13230	13230	13230	13230

Standard errors in parentheses, clustered at game level
* p<0.10, ** p<0.05, *** p<0.01

1.4.2 Heterogeneity across producers and mechanisms

Organizational learning literature suggests the importance of the capability of firms, and therefore I examine the characteristics of the developers as the moderators. Results are shown in Table 1.9. Column (1) replicates the baseline regression in Table 1.6. In Column (2), I interact the counts with the dummy Firm, which equals 1 when the game is produced and published by large firms and equals 0 when the game is produced by an indie game studio or individual game developers. While video games are often produced by firms composed of coders and graphic designers, it is possible for an individual or team with less than ten members to produce an innovative game but at the cost of some dimensions of games, such as the low-resolution image. The coefficient of the interaction term with reliability review counts is significant and positive at the 5% level, suggesting that individuals and studios are less likely to take advantage of the reliability reviews for subsequent product development compared to firms. Figure 1.3 shows the coefficients for individuals, studios, and firms, respectively. Individual developers do not learn from both types of reviews, and firms react differently from studios. Studios, like the whole sample population, respond to design reviews, while firms respond to reliability reviews.

The reason is that large firms, compared to small start-ups, are more likely to be engaged in incremental innovation and process innovation. Product development in the software industry is an amalgam of both process innovation and product innovation, but process innovation emphasizes the "way of developing, implementing and maintaining Information System" (Mustonen-Ollila & Lyytinen, 2003). The reliability aspect of video games focuses on the process of production: how to deliver the story and play of the game to the users with fewer reliability issues. And the patched codes and way of optimization enjoy economies of scale since they can be leveraged in future products. On the other hand, the design of the games only applies to the focal product and can hardly be referred to by future products. Therefore, reliability is leaned toward process and incremental innovation, while design is leaned toward product innovation. And on top of that, the development of reliability is more challenging than design reviews. Development of design is about "adding" novel elements to the existing products, while the development of reliability is about "replacing". As the reliability of the game is tightly coupled, the complex process involved in replacement includes finding out the mistakes and then correcting them, which costs the producers more to update (MacCormack et al., 2017). Therefore, small firms underperform their large competitors in terms of response to reliability reviews.

In column (3), I interact the count of two-dimension reviews with producer age respectively and find that the interaction with reliability reviews count is significantly positive, which young firms underperform in terms of meeting the reliability-related demand of users. Similar to manufacturing and service industries, learning curves also apply to producers in software developers regardless of the size (Fong Boh et al., 2007). Modification surrounding game reliability is challenging and costly, and results indicate that only

Table 1.9: OLS - Heterogeneity of Producers

	(1) Update	(2) Update	(3) Update	(4) Update	(5) Update
log (Reliability)	0.007	-0.008	-0.011	-0.001	-0.008
	(0.008)	(0.011)	(0.013)	(0.009)	(0.010)
log (Design)	0.016*	0.014	0.022	0.019*	0.027**
	(0.009)	(0.012)	(0.014)	(0.010)	(0.011)
Firm log (Reliability)*		0.035**			
		(0.016)			
*Firm * log (Design)*		0.008			
		(0.018)			
*Producer Age * log (Reliability)*			0.001**		
			(0.001)		
*Producer Age * log (Design)*			-0.001		
			(0.001)		
Experience log (Reliablity)*				0.001***	
				(0.000)	
Experience log (Design)*				-0.000	
				(0.000)	
Collaboration log (Reliability)*					0.061***
					(0.018)
Collaboration log (Design)*					-0.045**
					(0.019)
Time FE	Yes	Yes	Yes	Yes	Yes
Game FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	13230	13230	13230	13230	13230

Standard errors in parentheses, clustered at game level
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

aging firms with great experience can accomplish such kinds of updates. Note that there are small studios, usually in Europe, has been established for years. Similarly, in column (4), I interact with the experience of the producers, and in column (5), I interact with the collaboration indicator. Producers learn from the user reviews regarding reliability as they have more project experience and when they are collaborating with others. By accumulating domain experience and partnering with other developers, producers, including small studios, can learn from the user reviews about reliability, in addition to the design which they generally focus on.

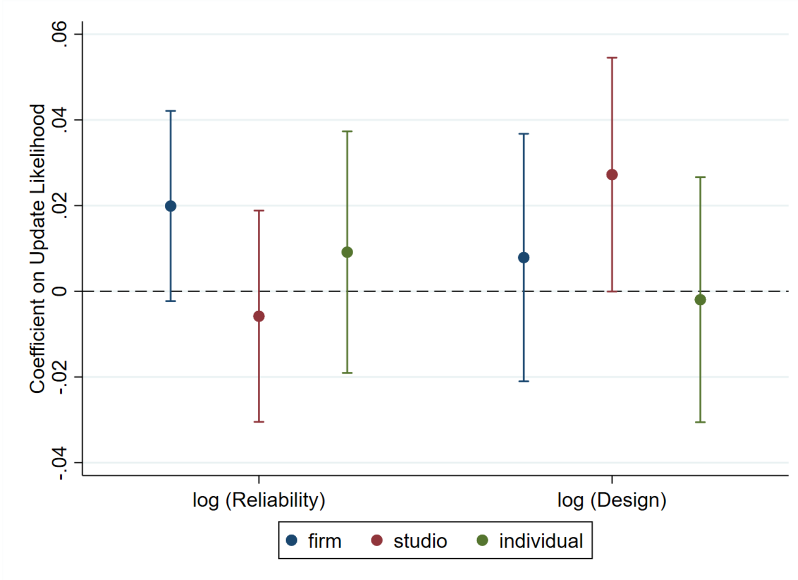


Figure 1.3: Coefficients of Review Counts by Producer Type

1.4.3 Performance of updates

Last, I examine the impact of updates on the performance of products. Results have shown that user reviews positively impact the update, contingent on the ratings, type of reviews, and the type of producers. However, what also concerns the scholars and practitioners is the value of the updates: Are updates matter for the performance of products? As the marginal cost of producing updates is effectively zero, producers in the software industry are widely using updates to enter the market in time (Arora et al., 2006). Empirical studies have shown that the volume of reviews has been widely proven to be positively correlated with sales performance (Duan et al., 2008; Liu, 2006; Zhu & Zhang, 2010). And what remains unclear is whether at least some of the reasons can be attributed to the updates. Therefore, I examine the impact of updates on users in Table 1.10

In Column (1), I examine the impact of updates on total users. After controlling for the existing users, the regression captures the relationship between updates and new customers. However, there is no correlation at the conventional level. In Column (2), I examine the impact of updates on active users. In Column (3) and (4), I run the seemingly unrelated regressions (SUR) to simultaneously estimate the relationship (Duan et al., 2008) between

Table 1.10: Impact of Updates

	(1) $log(Owner)_{t+1}$	(2) $log(User)_{t+1}$	(3) $log(User)_{t+1}$	(4) $Update_{t+1}$
Model	OLS	OLS	SUR	SUR
Update	0.001	0.023*	0.023**	0.236***
	(0.006)	(0.014)	(0.011)	(0.011)
Promotion	0.025***	0.168***	0.168***	0.148***
	(0.007)	(0.018)	(0.018)	(0.009)
Age	0.006***	0.007***	-0.035***	-0.002***
	(0.001)	(0.002)	(0.003)	(0.000)
Ratings	-0.049**	0.040	0.040	-0.127***
	(0.025)	(0.119)	(0.003)	(0.030)
log (Owner)	0.886***	0.075***	0.075***	-0.029***
	(0.011)	(0.012)	(0.012)	(0.006)
log (Users)	0.015	0.665***	0.665***	0.017***
	(0.010)	(0.033)	(0.020)	(0.007)
log (Count)	0.019*	0.063***	0.063***	0.007***
	(0.010)	(0.021)	(0.017)	(0.021)
Time FE	Yes	Yes	Yes	Yes
Game FE	Yes	Yes	Yes	Yes
Observations	13230	13230	13230	13230

Standard errors in parentheses clustered at game level
*p<0.10, ** p<0.05, *** p<0.01"

updates and user counts, and the results are robust: every time the producers publish an update, the active user count in the following month increases by 2.3%. The difference between owners and active users is that the measurement of users focuses on user retention and reactivation. All the results indicate that while updates can hardly attract new users in a short time, it has a positive impact on consumer loyalty by keeping existing users active. As games can profit from in-game purchases, active users are important sources of revenue streams for producers, especially when the games reach a certain stage of the product life cycle. In Figure 1.4, I replicate the regression in Column (2), adding the interaction of age in year with updates, and graphically show the coefficients of the interaction terms. The baseline is the observations with less than one year old. It is evident from the graphic that the updates can significantly increase the number of active users when products reach the later stage of their life cycles.

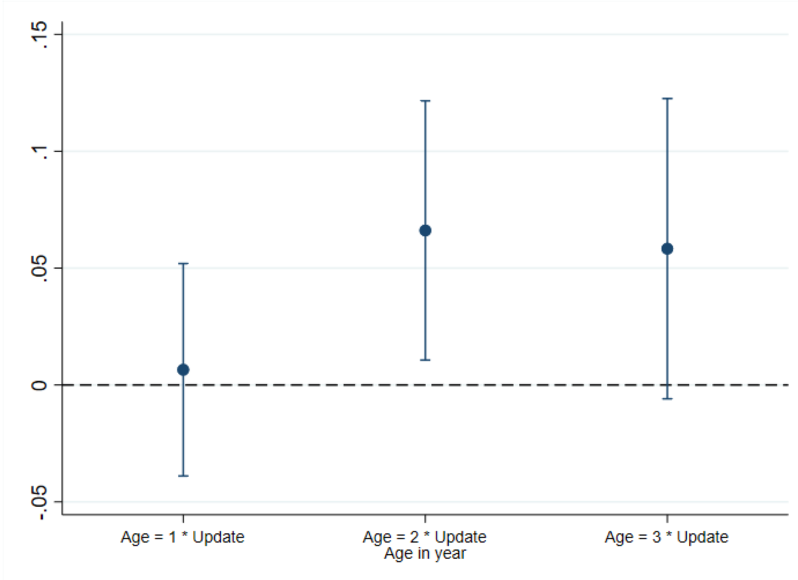


Figure 1.4: Coefficients of Interactions between Age and Update

1.4.4 Robustness checks

A major concern is that the producers may decide to save the ideas for new products instead of publishing updates when faced with complaints about reliability and quality. In fact, there is evidence that the comments on the previous generation of a product have a significant impact on the current generation (Li et al., 2022b). Therefore, it is necessary to rule out the alternative possibility that producers may shift focus onto new products instead of updating the game after negative feedback.

I address the concern by investigating the probability of publishing DLC. The majority of the DLCs, an extension of games to which the consumer already has access, require a small payment (Ozuem et al., 2017). DLCs are not aimed at fixing glitches at all. DLCs contain large-scale paid content, including new game modes, maps, and expansions. DLCs are a cyclical form of commodification, and companies are reliant on DLCs for revenue continuity since they fill the gaps between sequels (Lizardi, 2012). Updates barely alter the core game or its storyline but instead, focus on optimization issues. They are installed free and automatically. But DLC has a separate webpage, and producers market themselves independently of the original game. Some games, such as SMITE, are free-to-play but provide DLC for customers with a certain charge. Therefore, DLC and updates identify different facets of product strategy: updates capture developments of existing products, while DLCs focus on generating revenue by developing and marketing new products. Therefore, the usage of DLC can be viewed as an alternative for game updates, and hence I use it to run the robustness check.

In Table 1.11, I run a bivariate probit model in column (3) and compare it with univariate OLS models to address this concern. If producers avoid publishing updates but save ideas to develop new DLC as a response to the online reviews, differences across the coefficients would be observed across models. I only consider the sample of studio producers who take advantage of design reviews to publish updates. Columns (1) and (2) of the table show the result of OLS models for DLC and updates for the selected sample, respectively, and column (3) shows the bivariate probit model. The significance does not change, suggesting that the potential interaction between the decision to publish a DLC and an update does not undermine the results already reported. To facilitate comparison, I note that the average marginal effect of log (Design) on updates is 0.023 percent, compared with the 0.025 obtained in the OLS specification.

Besides, to strengthen the belief that the above results are credible, I perform a placebo treatment test in Table 1.12, using reviews mentioning the price of the products. The concern is that count of reviews are capturing other possible market performance record instead of a source of organizational learning. The test is informative because user reviews about price cannot affect the likelihood of updates after controlling for promotions, but the purported flaw would operate in a similar way. After controlling for the actual treatment, which guarantees the independent variables are not contaminated (Eggers et al., 2021), I replicate two main results in Column (1) and Column (3) and two corresponding placebo tests in Column (2) and Column (4). Both the significance and the magnitude of the coefficients do not change.

Another concern is that the result is not driven by producers or users but by the nature

Table 1.11: Robustness Check: DLC vs Updates

	(1)	(2)	(3)	
	Update	*DLC*	*Update*	*DLC*
Model	OLS	OLS	Bivariate Probit	
Age	-0.010***	-0.002*	-0.047***	-0.029*
	(0.002)	(0.001)	(0.010)	(0.017)
Promotion	0.132***	0.019**	0.964***	0.548***
	(0.022)	(0.007)	(0.093)	(0.105)
log (Users)	0.017	0.011**	0.185***	0.236***
	(0.014)	(0.005)	(0.060)	(0.089)
log (Owners)	-0.036***	-0.010**	-0.247***	-0.214**
	(0.010)	(0.005)	(0.059)	(0.089)
Positive	-0.117**	-0.034	-0.640**	-0.683
	(0.051)	(0.023)	(0.277)	(0.418)
log (Reliability)	-0.004	-0.003	-0.013	-0.036
	(0.011)	(0.004)	(0.053)	(0.058)
log (Design)	0.025**	-0.001	0.126**	-0.010
	(0.011)	(0.005)	(0.060)	(0.072)

Standard errors in parentheses clustered at game level
*p<0.10, ** p<0.05, *** p<0.01”

of games. It is possible that some types of games are more likely to be produced by large firms, and the feature of the games requires the producer to come up with updates on a frequent basis. For example, single-player games differ from multi-player games in many ways, including revenue-generating strategy, demands of complementary assets (contract or ownership of internet servers), direct network effect, and so on. These features may confound the relationship between user reviews and updates. To address the concern, I generate a series of dummies associated with game features and then interact with the review counts respectively. The results are shown in Table A.3, and none of the features is significant.

1.5 Conclusion

In this study, I investigate whether producers learn from their users and which type of user knowledge is more informative for them. Using a dataset from the video game plat-

Table 1.12: Robustness Check - Placebo Test

	(1) *Update*	(2) *Update*	(3) *Update*	(4) *Update*
log (Reliability)	0.014	0.012	-0.011	-0.013
	(0.033)	(0.035)	(0.013)	(0.013)
log (Design)	0.099***	0.095***	0.022	0.019
	(0.032)	(0.034)	(0.014)	(0.015)
log (Price)		0.011		0.006
		(0.037)		(0.011)
*log (Reliability) * Positive*	-0.009	-0.008		
	(0.040)	(0.041)		
*log (Design) * Positive*	-0.098***	-0.097**		
	(0.037)	(0.040)		
*log (Price) * Positive*		-0.006		
		(0.045)		
*log (Reliability) * Firm Age*			0.001**	0.002**
			(0.001)	(0.001)
*log (Design) * Firm Age*			-0.001	-0.000
			(0.001)	(0.001)
*log (Price) * Firm Age*				-0.000
				(0.001)
Time FE	Yes	Yes	Yes	Yes
Game FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	13230	13230	13230	13230

Standard errors in parentheses clustered at game level
*p<0.10, ** p<0.05, *** p<0.01"

form *Steam*, I find that updates of producers are positively correlated with the count of user reviews under certain circumstances. Specifically, when the product is poorly rated, producers are more likely to respond with an update to the game and learn from the design-related reviews but not the reliability reviews. They also benefit from the number of helpful reviews but not the density of helpfulness. Moreover, I identify that the firms can effectively take advantage of the reliability reviews compared to individual game developers and studios. As reliability is associated with replacement and process innovation, only producers with more experience are capable of responding to them by publishing development. Updates are beneficial for performance since they can effectively re-engage inactive users.

The evolution of platforms and ecosystems attracts great attention from both scholars and platform owners. Platform owner has great power when entering the competition over the complementors because they know which product space is more popular Zhu and Liu (2018), and Wen and Zhu (2019) argue that the entry of platform owners shifts complementor innovation to unaffected areas. My result complements the story by adding that even when the platform owner is absent, small studios fail to compete in reliability since they must somehow overlook the developed consumers (regardless of their dissatisfaction with reliability) and delve into new content by differentiation. Overall, this paper points to the dynamic paths of complementors of the platform in terms of product development and shows that if they can seek help through existing but unorganized user review, they can at least earn a better position in the competition.

These results have implications for both third-party complementors and platforms concerned with using reviews to direct their innovation efforts. While large firms outperform their competitors in reacting to users' voices regarding modifying existing products, small startups should reconsider how to allocate their resources toward incremental product development by listening to the users. But more importantly, for the platform owners, a multi-dimension review system, rather than the unidimensional scores most platforms continue to use, would be more informative for producers. In a two-sided market platform setting, platform architecture characteristics such as generativity greatly impact complementary innovation (Anderson et al., 2014). There is evidence that as platforms gain a dominant position in the market, they shift the attention from a wide population of complementors to selective ones (Rietveld et al., 2020). The selected complementor group normally does not include the products of studios and hence puts them into disadvantage in follow-up innovation. However, a ready-to-use information pool can be helpful for producers who are looking for external knowledge to incorporate, especially for individual game developers confronting information overload. And as the platform also profits from sales of a well-maintained game, my findings offer support to the idea that these platforms should improve and design online communication systems among users appropriately to encourage product development from the other side of the market. As other commonly used platform governance approaches such as awarding (Claussen et al., 2013), synthesis of the user reviews can nudge the developers into more innovation by avoiding information overload and thereby saving costs for the producers.

There remain several avenues for further research. First, I revealed that the platform-hosted user community could be used by the producers to generate ideas for incremental product development. I consider the scenario where producers are making a commitment to the games and investigate under such assumption whether user review would be a great motivation and assistance. As I restrict the sample to the successful games and rule out the alternatives by examining the development of DLC, it would highly be the case that the producers continue to work on those successful games. However, it is also true that other producers with less successful games would abandon the existing game and launch new projects when the games received negative reviews. It is interesting to ask under what circumstance the producers would continue to improve the unwelcomed products in contrast to diversifying their products. Even for those successful games, it is interesting to ask when the firms use the reviews to support the development of the current product and when firms save the ideas for new products in the future, such as sequels. Second, Foerderer

(2020) finds that the interfirm knowledge spillover among platform complementors leads to more innovation measured by app updates. Similarly, producers, especially large ones, can get access to the reviews of competitors' products and absorb them for their own benefit, if necessary, since the information is public. From the perspectives of platform owners, this would definitely create more value through the perfection of games. However, as the learning capability is disproportionately biased towards large corporate, the interaction between large firm production teams and small firms' user groups might drain the users from the small firms in the long run. Whether it is beneficial for small firms or platforms remains unclear.

CHAPTER 2

NOVEL AND NOVELTY

2.1 Introduction

In organizations, employees are tasked with applying their existing expertise and knowledge to carry out routines and accomplish work (Deken et al., 2016; Nelson & Winter, 1982). Meanwhile, they also have the option to search for and adopt new knowledge, which serves as the foundation for future innovation and the adoption of new technologies (Arts & Fleming, 2018; March, 1991). Balancing these two activities proves challenging, particularly at the individual level, due to the difference in effort required (Gibson & Birkinshaw, 2004; March, 1991; Tushman & O'Reilly III, 1996).

Considering that an organization's innovative capability and direction heavily rely on its intellectual human capital (Rothaermel & Hess, 2007) and the stock of existing knowledge possessed by its employees(Smith et al., 2005), the pressure to innovate within today's competitive business environment permeates from top managers to employees. Consequently, the seeking of novelty has become a highly desirable behavior for employees with creative responsibilities (Scott & Bruce, 1994). However, as the return of adopting novel knowledge is uncertain and takes a longer time, individuals, including both employees and managers, tend to sleep on the existing knowledge and execute routine work.

Within organizations, leaders' awareness of ambidexterity, which involves balancing the exploration of new norms and the exploitation of existing norms, permeates the organization top-down and significantly impacts organizational performance in terms of creativity and productivity (Katou et al., 2021). Additionally, employees' adoption of novel knowledge and new norms plays a crucial role in facilitating knowledge diffusion within the organization. Over the long term, the adoption of novel and distant knowledge can contribute to the existing knowledge stock and foster innovative creations for the organization (Greenwood et al., 2019; Rothaermel & Hess, 2007). Consequently, it is crucial to avoid inertia and promote the adoption of new knowledge at the individual level, irrespective of an individual's position, for the development of organizations. In fact, organizations have implemented programs to encourage individuals to seek new knowledge and explore new ideas. Therefore, closely examining the individual level is imperative for researching the adoption of novel knowledge and holds significant implications for organizational innovation.

While scholars have pointed out that individuals are at the core of an organization's ability to explore and adopt novel knowledge (Gibson & Birkinshaw, 2004; Mors, 2010; O Reilly & Tushman, 2004), research on when these behaviors occur at the individual level remains limited, while most scholars have studied them at the organizational level (Fang et al., 2010; Lee & Meyer-Doyle, 2017; Stettner & Lavie, 2014). It is partially attributed to the theoretical assumptions that it is difficult for individuals to develop routines to execute routines and seek novelty at the same time (Gupta et al., 2006; Lee & Meyer-Doyle, 2017). However, as more micro-level data and field experiment becomes available, a few recent papers have found that at the individual level, people shift attention to new knowledge field or start new norms when performance incentives are weakened (Lee & Meyer-Doyle, 2017), the knowledge inflow is bottom-up and horizontal Mom et al., 2007, individuals move close to new peers spatially (Lee, 2019), prolonged favorable feedback is given (Billinger et al., 2021), and fewer peer awards are exhibited (Burtch et al., 2022). While the picture still remains incomplete, these studies have made valuable progress in our understanding of the predictors by pointing out that novel knowledge adoption propensity is influenced by motivation. A more specific example comes from Lee and Meyer-Doyle (2017). They show higher performance-based incentives may have a negative effect on employee intrinsic motivation and hence lead them to engage in more exploitation work. As for managers and top executives, Mom et al. (2019) argue there is a positive relationship between motivationenhancing leadership and managers' willingness to change or adapt their behavior through intrinsic motivational orientation. We continue to the stream of literature and echo Greenwood et al. (2019) to further pivot another motivation for adopting new practices – status gain. Specifically, we ask the following questions: When individuals experience a status gain within their domain, will they adopt new practices and novel knowledge or continue to stick to the existing knowledge domain? How does the decision of novel knowledge adoption at the individual level influence the subsequent performance? We argue that factors that can support motivation will shift the individual direction of knowledge adoption, and we develop hypotheses concerning status gain pertaining to the change of individual motivation. By doing so, we join the conversation to understand the knowledge adoption of organizations by investigating the knowledge adoption at the individual level.

We theorize that status gain enhances an individual's motivation to adopt novel knowledge, attributed to increased slack resources and self-confidence. Furthermore, we posit that this impact is particularly pronounced among individuals who have received status recognition in their respective focal areas. Drawing on foundational research on creativity performance and knowledge adoption, we subsequently evaluate the performance outcomes following the adoption of new practices. We argue that the adoption of novel knowledge is advantageous for the focal individual due to the learning effect it brings about, as well as the subjective nature of assessment criteria by the audience, which increases the likelihood of successful adoption outcomes.

Our empirical setting leverages the most significant awards in the literature world in the US. Although the change of status is generally slow and predictable through institutionalized practices, it is also common to observe sudden status gain when individuals win approvals from multiple actors through competitions or awards (Gould, 2002; Maoret et al., 2022). For example, in our setting of the world of literacy, awards can confer a status gain on the recipients since it is a recognition from fellow creative fellows and critics and implies a sudden entry into an elite group (Jensen & Kim, 2015). We have selected a sample of book authors who have achieved status gain by winning awards or receiving award nominations. Through the analysis of novel knowledge adoption and performance among these selected authors, we leverage the extensive data available on the largest online book review platform. This dataset offers comprehensive information on the authors' works and reader evaluations. By matching this data with external award information and demographic data, we are able to identify the impact of the status gain on knowledge adoption activities and assess its heterogeneous effects across the authors. This unique dataset provides us with valuable insights into the relationship between status gain, knowledge adoption, and performance among book authors. Our findings are in line with the argument that symbols of status change, such as prizes, can motivate creative workers to enter competitive fields and persist in efforts to innovate (Brunt et al., 2012; Moser & Nicholas, 2013). As high-status individuals enjoy access to tangible and intangible resources that can be utilized in creation (Bothner et al., 2012), when individuals experience status gain— an increase in relative standing, prestige, or worth in their group (e.g., being promoted, winning an award, receiving a prestigious assignment; Marr and Thau (2014)), they are more likely to be motivated to engage in new writing topics and adopt new knowledge into their professional creative work.

This study makes several contributions. First, it contributes to the literature on knowledge adoption by examining an individual-level antecedent. While knowledge management and knowledge adoption literature focus on the supply side of the knowledge source and attempt to answer the question of where individuals can search for knowledge source (for example, (Matusik & Hill, 1998)), we take an approach to understand when individuals start to search novel information and adopt them intentionally.

Second, we speak to the literature on status change by providing insight into the aftermath of status gain. Since the work on middle-status conformity by Phillips and Zuckerman (2001), researchers have focused on how status impacts individuals in terms of their economic decision and creative production. Building on the relationship between conformity and status, we argue that individuals with increased status do not compare to their social peers but also their historical profile. As knowledge adoption is an important aspect of these economically significant decisions, we aim to empirically extend the research to show how status awards can be used to deviate individuals from their own routine work. By doing so, we provide implications for organizations to predict innovation-related behaviors of those who recently gained status and had access to more resources.

Third, we contribute to the ongoing discussion on the relationship between status and performance by demonstrating that certifications from critics play a significant role in influencing individuals' decisions between pursuing established, productive traditions and adopting risky novelties. Previous research on the connection between status and performance has yielded conflicting findings. Our research highlights the importance of considering novelty when seeking to explain the decoupling of performance from status in industries where individual-level adoption of novelty is limited. By shedding light on this important activity, our study provides valuable insights into understanding how performance is influenced when status and novelty adoption are decoupled within specific industries.

Last, we contribute to the discussion of gatekeepers in the creative industry (for example, Godart et al., 2023). Unlike the technology industry, the creative industry lacks objective evaluation metrics, driving critics and gatekeepers to play important roles in measuring symbolic and aesthetic performance (Slavich & Castellucci, 2016). Therefore, understanding the gatekeepers and critics is the essence of penetrating the creative industry in future economic and management research. We point out how status gains assist creative workers in winning the approval and support of prominent gatekeepers, generally conservative, in maintaining their legitimacy.

2.2 Theory and Hypotheses

2.2.1 Status Gain and Novelty Adoption

Novel knowledge adoption remains an important question for organizations as knowledge is critical for production improvement and economic development (Anthony, 2018). Organizations can structurally separate into subgroups to efficiently explore a wide range of ideas and empower the diffusion of current knowledge (Fang et al., 2010; Tushman & O'Reilly III, 1996), and similarly, individuals make decisions on how they divide their time and effort between new and existing businesses (Gibson & Birkinshaw, 2004), which has a strong impact on knowledge- and innovation-intensive assignments (Hatch & Dyer, 2004). Research has suggested that individuals are inclined to exploit extant knowledge instead of exploring new knowledge due to the high possibility of failure related to novelty exploration (Denrell & March, 2001; March, 1991). There are three common requirements for individuals to incorporate novel elements into their routines: the availability of new information, the attention to the new information, and the adaption of operational processes (Greenwood et al., 2019). The processes of adopting novel practices, which are nontrivial and cognitively demanding, often lead individuals to hesitate when incorporating new information into their daily work routines.

However, research suggests that the motivation mechanism, coupled with status gain and loss, can play a pivotal role in individuals' decisions to acquire and adopt new knowledge within their professional work. Specifically, status gain, such as receiving a promotion or winning an award, can result in greater slack resources (Azoulay et al., 2014; Bothner et al., 2012; Lambooij et al., 2007), enabling individuals to search for novelty. Slack resources refer to excess resources beyond what is required for routine operations (Nohria & Gulati, 1996). As resources and opportunities tend to be disproportionately allocated to high-status individuals (Sørensen, 1996), status gain signals an influx of resources. For example, Oscar winners and nominees receive more casting invitations for new movies compared to their competitors (Jensen & Kim, 2015), and high-status scientists are more likely to be cited and form alliances with unfamiliar partners after receiving awards from prestigious institutions (Azoulay et al., 2014). As these additional resources surpass what is necessary for routine work, a portion of the newly acquired resources falls into the category of slack resources, which can be utilized for searching and integrating novelty (Nohria & Gulati, 1996). Engaging in the search for novel ideas involves multiple experiments and consumes significant resources. Thus, high-status individuals have a more feasible opportunity for such endeavors compared to the pre-award period (Lee & Meyer-Doyle, 2017).

Indeed, slack resources have been identified as an important precursor to searching for new knowledge and ideas within organizations, as they facilitate experimentation, a crucial process in integrating novelty into routine work (Cyert, March, et al., 1963; Greve, 2007; Lavie et al., 2010; Levinthal & March, 1993; Nohria & Gulati, 1996). Similarly, at the individual level, slack financial resources enable employees to invest in their own human capital growth, thereby fostering new knowledge generation (Wang et al., 2016). The additional rewards associated with innovative work do not adequately compensate for the investment risk (Foster et al., 2015), making novelty-seeking affordable only to those with more than sufficient resources. The term ”slack search,” coined by Cyert, March, et al. (1963), captures the idea of search arising from excess resources.

Resources do not solely refer to tangible assets such as financial capital. Intangible resources, such as reputation and connections, can also have an impact on novelty adoption. Rogan and Mors (2014) discovered that a heterogeneous network, even if sparsely connected, could enable managers to explore less redundant knowledge, which is essential for recombining with existing knowledge in the search for new clients and project adoption. As high-status individuals are more likely to connect with external contacts due to their visibility and fame, they have a higher likelihood of accessing remote knowledge and integrating it into their work. For instance, consider the commercialization activities of high-status scientists. Commercialization typically falls outside the realm of scientists’ expertise, and they may lack the necessary knowledge. Research on university-industry relations has shown that academic researchers who are recognized by their peers and awarded grants are more inclined to explore external commercialization alliances and gain insights into commercialization practices (Perkmann et al., 2013). This is possible because, compared to low-status scientists, industry partners are within their reach, allowing them to adopt commercialization knowledge into their routine work, thereby introducing novelty for the scientists.

Moreover, status gain plays a role in encouraging individuals to adopt novel knowledge by increasing self-confidence and the tendency to take risks, both historically and socially. Similar to exploration, which is often associated with uncertain, distant, and potentially negative outcomes (March, 1991), the adoption of new knowledge does not typically result in positive, immediate, and predictable outcomes. Consequently, the risks associated with the search and adoption of new knowledge may discourage individuals, as they generally exhibit risk aversion when making decisions related to personal payoff (Holt & Laury, 2002; Wiseman & Gomez-Mejia, 1998). However, when individuals experience status gain, they also gain increased confidence in their ability to navigate unfamiliar situations because they interpret the gain as a signal of their capability (Chatterjee & Hambrick, 2011). Status gain generally enhances motivation and productivity in one's career (Chan et al., 2014), making individuals more likely to underestimate the probability of failure and seek new knowledge externally compared to their low-status period (Galasso & Simcoe, 2011). In fact, Li et al. (2022a) discovered that CEO's status gain, as measured by winning a significant award, led to an elevated sense of self and entitlement, which sometimes resulted in misconduct behaviors such as fraud.

Furthermore, in addition to changes in status compared to past performance, an upward shift in social status order can trigger divergent behavior, as status associated with awards serves as an anchor in the social status hierarchy relative to others. According to the middle-status conformity theory, individuals situated in the middle of the status hierarchy tend to conform to conventional behavior. However, high-status individuals are less likely to succumb to conformity pressures, as they possess a sense of security in their role incumbency and exhibit a greater inclination towards risk-taking (Phillips & Zuckerman, 2001). They are more likely to experience an increase in self-efficacy and actively search for new norms that challenge existing inertia (Tarakci et al., 2018). When they feel secure in their position within the status hierarchy, they become norm breakers. Faced with pressures, they may respond by focusing on authenticity and exclusivity rather than conforming to the actions of others (Favaron et al., 2022). Hence, considering the effects of increased slack resources and risk-taking tendencies, we propose the following hypothesis.

Hypothesis 1 (H1): *Following a status gain, individuals are more likely to adopt novel knowledge compared to the pre-status gain period.*

When examining the factors that shape the orientation of new knowledge adoption, it is necessary to consider individual experience, demographics, skills, organizational context, and resources (Kacperczyk & Younkin, 2017; Nagle & Teodoridis, 2020), as these can either facilitate or hinder the tendency to adopt novel knowledge. Therefore, we also explore the heterogeneity across individuals to investigate the mechanism of status gain on novelty adoption.

One important factor that may influence how individuals respond to status gain is the relative significance of the shift. For some individuals, the gain in status and subsequent benefits are substantial, while for others, it may be less influential. Specifically, if the awarded authors already possess sufficient resources and self-confidence prior to the status gain, they may be less motivated to exert additional effort compared to competitors who are in need of such recognition. The incentive provided by the awards will be amplified when creative work is prominent within the profession relative to other tasks (Chown, 2020). As discussed in the previous section, status gain provides individuals with slack resources. It is crucial to note that how individuals perceive and value these slack resources will determine whether they redirect their efforts toward novelty adoption. Individuals who highly value the additional resources and increased confidence are more likely to capitalize on the influx of resources for searching and adopting novel knowledge. Conversely, those who perceive the status gain as a minor addition to their existing resources and motivation may be less driven by the status gain itself. To be more specific, in the case of a full-time creative worker, the incentive based on their creative output will likely be greater compared to part-time creative workers whose creative work may not be as prominent.

Hypothesis 2 (H2): *Holding other paid jobs moderates the positive relationship between status gain and novel knowledge adoption, such that the positive relationship is likely to be stronger for individuals who do not hold other paid jobs (than for individuals who do).*

2.2.2 The Performance Implications of Novel Knowledge Adoption

New knowledge adoption is an important source of creation, but not all novelty adoption is successful and leads to higher performance. Therefore, besides the decision to adopt new knowledge, it is important to examine whether the adoption leads to better performance. While scholars have extensively examined performance at the organizational level, studies at the individual level are sparse. Generally speaking, engaging in novel domain leads to uncertain and often negative returns in the short run (March, 1991), and balancing new norm adoption and executing existing paths is beneficial for firms to hedge the risks associated with novelty (Lavie et al., 2010). Again, while resource allocation organizational separation between these two activities to balance is feasible and common for firms, individuals can only focus on only one in a certain time window. Although sharing some similarities, new knowledge adoption at the individual and organizational levels requires different processes that may uniquely influence overall performance. For example, new knowledge can potentially be less accessible for individuals as facilitating management approaches, such as hiring new domain experts, are less available at the individual level if the individual does not have the resources to find a collaborator. New knowledge and norms may also have a large impact at the individual level because the responsibility to seek and gain new knowledge falls on one focal person rather than a group of people. Moreover, rational firms can divest in order to keep high status in the industry when unsuccessful adoption happens (Wang & Jensen, 2019), but individuals have few alternatives to avoid the impact if the adoption turns out to be less satisfying. Therefore, it is important to examine the unique performance effect of knowledge adoption at the individual level.

We posit that a higher level of knowledge adoption is positively correlated with individual performance. When individuals adopt novel knowledge, they venture into domains in which they lack experience and expertise. This process typically involves a learning curve due to limitations in cognitive and time resources (Adler & Clark, 1991; Jain, 2013). Engaging in new knowledge domains means a higher percentage of an individual's task profile lies outside their area of expertise. However, exploration activities have positive long-term consequences as they facilitate adaptation to environmental changes (Lavie et al., 2010).

In rapidly changing markets, the ability to adopt novel knowledge can provide economic advantages by enabling actors to catch up with industry leaders in terms of industry knowledge and more efficiently absorb information from external sources compared to those with limited experience in novelty adoption. At the individual level, Lee and Meyer-Doyle (2017) apply the concept of ”exploratory competence” to individuals and argue that the capability for search and experimentation can be accumulated. Prior exploration experiences enhance subsequent knowledge acquisition and decision-making under conditions of uncertainty.

The adoption of novel knowledge by high-status individuals is not an exception, even though it is triggered by resources and confidence rather than a goal of competence growth. For individuals who attain high status, public recognition serves as an endorsement of their past success in learning ability. They have effectively acquired knowledge about the industry during their pre-award career period, and it is highly likely that their experience can be leveraged to contribute to the new field. The process of adopting novel knowledge is more of an integration process rather than starting from scratch, meaning it builds upon their existing knowledge sets and experiences. Their previous domain experience enables them to leverage assets and experiences, such as complementary tools (Allen & Choudhury, 2022).

With their higher status, these individuals can appropriate more resources and assistance, allowing them to better understand the evolving context and effectively adopt novelty into production. Their deliberate efforts to understand the industry in the past have developed their superior learning abilities, and they are competent in applying similar processes of idea searching and management in the post-award period. For instance, Fini et al. (2022) demonstrate that entrepreneurial scientists exhibit greater impact because they work on topics that are new to them during the entrepreneurship process, integrating this knowledge into their existing domains. As a result, they can outperform their competitors by recombining novel knowledge to form a new and valuable knowledge pool, leveraging their proven learning ability.

Therefore, we hypothesize the following:

Hypothesis 3 (H3): *Individuals' novelty knowledge adoption will be positively related to their subsequent performance.*

Furthermore, beyond the objective outcomes driven by novelty, the subjective judgment of performance by the audience, relying on the producer's status, also has an impact on the relationship between performance and the adoption of novel knowledge. The production of a novel adopted product is often not straightforward, and status "helps" evaluators and gatekeepers interpret the novelty in favor of the producer. Evaluators require additional cognitive resources to understand unfamiliar and novel information, highlighting the tension between the desire for novelty and path dependence. Status awards divert evaluators' attention from unreliable indicators, such as gender (Botelho & Gertsberg, 2022), making the authority of the creators more salient. Research on status suggests that although status and quality are only weakly correlated (Gould, 2002), evaluators tend to use status as a reference when assessing performance, be it current or potential (Merton, 1968). As the audience believes that individuals possess the desired characteristics when they experience status gain in the industry, evaluators rely on cognitive heuristics, assuming that focal actors will perform the valued characteristics without carefully confirming if this is indeed the case. The leverage of existing status and related skills during assessments is particularly true when the audience cannot accurately evaluate the quality of the idea (Kovács & Sharkey, 2014) or in a niche market where experimentation is more feasible (Sgourev, 2013). In such cases, high-status individuals have a competitive advantage over their competitors when entering the market, as the judgment of quality in the new domain is somewhat ambiguous and lacks authority due to a lack of established practices. Since the outcome is based on different and distant knowledge sets, evaluators are unsure about the standards (Theeke et al., 2018), leading to a lower likelihood of questioning inconsistent work but rather interpreting it as creativity. For example, in the cultural industry setting where novelty is highly valued, Younkin and Kashkooli (2020) found that the audience tends to be conservative when assessing products that marginally break the norm, as they apply existing criteria and struggle to fit these marginally norm-breaking products within their evaluation framework. However, a product that adopts a novel and distant knowledge can significantly mitigate this confusion, as the audience fails to apply their existing criteria to the novel product. High-status individuals can leverage their authority to define the ways of interpretation, resulting in a higher performance outcome. In fact, for high-status individuals, the criteria within the existing domain are often stricter due to the high expectations of evaluators. As expectations rise with reputation and status, the adoption of knowledge into their new product becomes more beneficial, as expectations in the existing field are much higher (Smirnova et al., 2022).

The effect is amplified in industries that have no clear and objective assessment criteria such that performance is assessed by the members and audience. Without a clear standard, as in technology industries, the creative industry heavily relies on the expectations of the audiences. In these industries, novelty adoption is, in fact, more desirable since the authority of high-status individuals can help shape and build new norms. When these renowned individuals start to contribute to the marginal content knowledge field, their contributions are more likely to be valued by the community as they appreciate the attention relocated to the novel field, and they believe their effort could help push the field forward (Safadi et al., 2021).

Therefore, we hypothesize the following:

Hypothesis 4 (H4): *Individuals' novelty adoption will be more likely to be viewed as successful by industry gatekeepers after status gain.*

2.3 Empirical Setting

2.3.1 Performance in Literacy World

The adoption of new knowledge in the culture industry differs from that in the tech industry due to reasons. First, because the audience and readers' evaluation criteria stay fairly stable, competition in the cultural industry drives producers to differentiate themselves from others incrementally instead of revolutionary innovation (Lampel et al., 2000). To achieve product differentiation without breaking any aesthetic conventions, it is common for cultural professionals to recombine existing styles outside their previous knowledge scale and adopt new knowledge to meet the consumer expectation of 'novelty.' Second, products in creative industries, including publishing and film, are extremely complex to develop and circulate by authors alone, and therefore intermediary assistance is of necessity for the success of publishing. As the financing agencies and gatekeepers, intermediaries helped rationalize the development process since the maturation of the industry (Tschang, 2007). Characterized by risk aversion, the conservative view of the intermediaries determines that audience hardly observe dramatic breakthrough in the contents of the cultural industry but more incremental innovation, which is mostly minor changes and recombination. Despite the difference in the notion of novelty adoption, they require the same effort in exploring field-specific knowledge and the process of integration. Book authors always have the freedom to continue to work on genres they have already published in and amply their influence, but they sometimes choose to adopt knowledge that is novel to them. They have to proactively seek and accumulate substantial new external information. Moreover, the balance between novelty adoption and routine execution in an entrepreneurship setting can be extended to the literacy world as authors resemble entrepreneurs in their ways of production. The role associated with novelty adoption includes experimenting with new approaches towards new knowledge or markets, while the opposite role includes applying and improving existing competencies and knowledge (Volery et al., 2015). Entrepreneurs can actively engage in exploration activities such as exploring new possibilities and reaching out to external network resources, and similarly, authors manage their orientation and decisions. They have to rebuild their knowledge base and create variety in experience when they adopt, and it is challenging for even the most successful authors. The novel knowledge adoption for authors requires resources, including time and investment for authors as it does for other risk-taking entrepreneurs. For example, JK Rowling started her career with the fantasy novel series *Harry Potter* in 1997. She then wrote *The Casual Vacanc*y in 2012, which discussed class, politics, and social issues. These genres are not fundamentally new to the readers, but the recombination with her pre-existing styles and plot lines requires her to adopt new knowledge. She did ”a vast amount of research on Sikhism”, yet she also ”concedes that her works share common themes”.

By changing themes and topics, authors are not aiming for efficiency and implementing their existing knowledge, but rather they engage in research and recombination of their knowledge base to create new products, which is at the core concept of novelty. It is worth noting that although authors’ adoption contribution may not introduce anything completely new to the world as a patent does in the technology industry, the cognitive process involved in eventually producing a book with a topic that is new to the authors themselves is similar, and the tendency to reach beyond their limits is akin to that of researchers in the technology field. Therefore, it is reasonable to believe that publishing in experienced topics or genres and exploring new topics and genres fits the definition of novelty adoption in the literature (Jansen et al., 2006).

In fact, the discussion about authors' novelty and innovation is not new to both practitioners and scholars. For instance, Colson Whitehead, the winner of the 2016 National Book Award for Fiction, spent 11 years honing his skills and researching over 2,000 accounts of slavery to complete his highly acclaimed book, The Underground Railroad (Brockes, 2017). He was honored with the Wall Street Journal Innovator Awards in 2021, alongside other entrepreneurs, highlighting his reinvention of literature by "mashing up genres, eras, cultures." Additionally, Wu and Zhu (2022) studied how competition affects the novelty of creative workers in a novel writing platform market, measuring the novelty of books based on the subjective judgment of readers.

However, as researchers, we seldom observe failed explorative works that attempt to adopt novel knowledge (Hu et al., 2017). The main reason for this is that poorly performed products are often terminated before they are published, except that failed clinical trials in pharmaceutical R&D can be observed. However, we believe that it is less of a concern in research settings where the tendency and output of adoption are highly correlated for prestigious authors. For example, Lee and Meyer-Doyle (2017) measure the searching activities of sales employees as a propensity for exploration, assuming that as long as individuals attempt to acquire new information and search for new products to sell, they are highly likely to succeed and consequently be observed by researchers. Similarly, authors who have the desire to adopt new knowledge are likely to eventually succeed in transforming their attempts into output, given that knowledge acquisition for writing ideas is not as challenging as R&D for technological innovation. Additionally, as renowned authors, they would not be prevented from publishing their output, given their recent popularity. Therefore, we argue that the observations collected from the publication dataset can effectively capture the exploration and exploitation activities of the authors.

As for the performance of the product in the literary world, we measure it in two ways. First, we measure the ratings of the books from readers, which is a widely used metric in the literature to test H3. While both ratings and sales can be used to measure the success of a product, ratings on online platforms do not necessarily have a direct impact on sales (Hu et al., 2014). We argue that the online rating system provides a better test for our hypothesis because sales, especially post-award sales, capture not only the quality of the book but also the marketing activities of the publishers as intermediaries. Nevertheless, online ratings of books accurately reflect the assessment of the creative work by readers when controlling for advertising power. A book with high sales might be poorly rated but written by a famous author, whereas a highly rated book demonstrates its reception among its target audience, even if it attracts a relatively small population. Therefore, we measure the performance of authors using online ratings, as authors may decide to adopt genre knowledge that is less popular among their existing readers, but once they are recognized by the audience, they can be considered successful in their attempt.

Second, we attempt to measure how easy it is for authors to publish books with novel knowledge adoption through the same publishers. Using ratings as the only performance measurement ignores the fact that low-quality books, despite their novelty, would be terminated before being published, making it difficult to observe failures in the dataset. However, the unique characteristics of the industry allow us to address this concern. As risk-averse intermediaries, publishers have a preference for assisting authors in publishing categories that have proven market success. Publishers and editors specialize in certain genres of books, and authors, if they wish to succeed, must collaborate with publishers who have expertise in those genres. Especially for experienced authors, it is common for them to discuss the product with assigned editors before they start writing. Therefore, authors who have established connections with editors may face challenges when trying to publish books with novel ideas due to a lack of domain understanding. They often seek assistance from new publishers to get the novel product published because their existing publisher may lack confidence in the success of an unfamiliar genre. However, once the quality of the book can persuade editors with its promising sales, switching to a new publisher becomes unnecessary. Therefore, the ease of passing through gatekeepers can be used as a measurement of performance for our H4: for books that adopt novel information, only high-quality ones can be produced without changing to a new publisher. Using publisher switch as a measurement for success alleviates the concern of upward bias that may be truncated by 'survivorship,' in the sense that negotiations between authors and publishers generally happen before the actual production of the book. The reason is that termination of the product often occurs at the ideation phase of production, making it rare for "failed adoptions" to exist, where authors adopt novel knowledge and complete books but fail to get them published, particularly for renowned authors.

2.3.2 Status in Literacy World

Awards and recognition issued through public and competitive procedures denote status (Perretti & Negro, 2006). Even awards with limited direct economic value, such as CEO awards by media sources, are desirable as a formal recognition and certification of accomplishments and status, particularly within certain industries (Jensen et al., 2022; Kovács & Sharkey, 2014; Malmendier & Tate, 2009). While status is typically accumulated over time and experience, receiving prestigious awards represents a sudden status gain within the industry, surpassing other candidates. The use of performance-based awards as symbols of status is widely accepted by researchers (Azoulay et al., 2014; Jensen & Kim, 2015; Jensen et al., 2022), especially in the cultural industry, including the literary world (Kovács & Sharkey, 2014). Winning a literary award indicates that a book has been read and recognized by insiders such as critics and other authors, who essentially form the elite group within the industry. Therefore, receiving awards accurately captures a sudden status gain by signifying entry into this group. In creative industries, the opinions of critics who determine the awards play a crucial role in providing values and structures to the industry

(Godart et al., 2023), and recipients of their recognition experience an increase in status when awarded.

2.3.3 Data and Sample

To test our hypotheses, we collected panel data from Goodreads.com, a leading source of information on books and authors (Kovács & Sharkey, 2014) using Python. The sample includes authors who received nominations for or won major book awards from 2007 to 2017. We collected all books published by these authors from 1990 to 2020, with the goal of studying the change before and after status gain.

Measures

Status gain. We operationalize status gain as receiving major book awards. To ensure that the awards represent a significant shift in status, we use the awards that have been studied in Kovács and Sharkey (2014), which include the Man Booker Prize, the National Book Award, the National Book Critics Circle Award, and the PEN/Faulkner Award, which are all considered prestigious book awards.

Novelty Adoption. As discussed, the adoption of new knowledge can be demonstrated by the genres of their books. However, genre information is not provided directly by the Goodreads website but is tagged by numerous readers. We collected the five most used tags for each book used by the readers. We manually excluded the tags unrelated to genre such as 'to-read' and 'e-book'. We compare the most used five tags for a focal book with those for previous books of the same author to measure the novelty of the knowledge. For example, the top 5 tags of the book *Portrait of a Killer: Jack the Ripper - Case Closed* were nonfiction, history, crime, mystery, and biography, three of which were new in the author's publications, as his/her previous books were all tagged crime and mystery, but not nonfiction, history, or biography. In this case, we assigned this focal book a score of 3 (i.e., the number of new genres) for novelty adoption. Operationalizing it as a continuous variable is in line with previous research on exploration and exploitation as two ends of a continuum (Perretti & Negro, 2006).

Performance. We collect the ratings of the books from Goodreads. The demographics of the user statistics have shown that the users of the website are a good representation of the reading population. Therefore, the reviews of the focal books on the website can capture the overall opinion towards the published books. We calculate the average ratings if more than one book was published by the focal author in the focal year.

Control variables For each author-year observation, we also collect the author's career age, gender, and number of book pages. For pages, we calculate the average if more than one book was published by the focal author in the focal year. We also construct a dummy variable winner, which equals 1 when the author wins the award and equals 0 when the author is only nominated. We also collect information on whether the author was holding jobs other than writing (1 = yes and 0 = no). The most common jobs include university lecturers and faculties. We controlled whether the book reached 300 reviews in total. There is concern that the popularity of the platform may impact how long it takes to reach 300 reviews. However, given that 40% of the books in our sample, which are written by the most successful authors, do not reach the 300 reviews threshold and those that reach the threshold generally take quite a short time (mean = 187 days), we believe that to treat whether the books can reach the threshold as a dummy variable is appropriate. If a book is about to be a hit on the market, it accumulates reviews quickly. Time does not help those books that sell poorly.

As described, the refined dataset includes the books of the authors throughout 30 years, which allows us to measure the yearly exploration, performance, and quantity of production for each author. This panel data format enables us to adopt the fixed-effect ordinary least squares (OLS) model with robust standard errors clustered at the individual level to control for the time-invariant heterogeneity when testing our hypothesis.

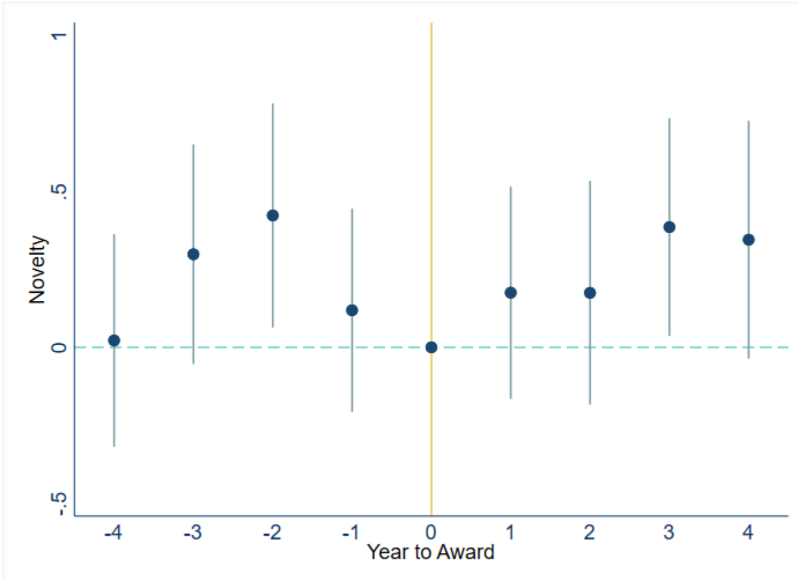


Figure 2.1: Event Study Graph

2.4 Results

Table 2.1 presents descriptive statistics for the variables, and Figure 2.1 graphically shows how individual novelty adoption changes four years before and after awards, after controlling for individual fixed effect and year fixed effect. We observe a slightly higher likelihood of novelty adoption after the awards. Figure B.1 also shows the novelty adoption before and after the awards within a longer time window. However, as authors explore new ideas when they start their careers, we observe a higher novelty adoption likelihood at the very beginning.

Table 2.2 reports the fixed-effect OLS model results, controlling for unobserved heterogeneity across individuals and years. We drop the publications in the year following the awards/nominations in the regression analysis for the concern that these might be the books written before the award but published to take advantage of the popularity. The standard errors are robust and clustered at the author level. In column (1), only the control variables are included in the model. The main result is shown in column (2), confirming our hypothesis that individuals experiencing status gain have a positive and statistically significant

Table 2.1: Variable Construction and Descriptive Statistics

Variable	Construct	Mean	SD
Exploration	Count of tags that have not been used with the focal author before	1.96	1.26
Status Gain	=1 if after winning/being nominated	0.41	0.49
Performance	The average rating for books published in the focal year	3.73	0.74
N. of Pages	Average number of pages offor books published in the focal year	298.7	191.3
Career Age	Year since the first book published	11.95	6.24
Gender	=1 if male	0.58	0.49
Membership	=1 if member of the platform	0.05	0.22
Other jobs	=1 if has other jobs	0.09	0.28
New Publisher	‘=1 if switch to a new publisher	0.8	0.4

Table 2.2: Fixed-Effect OLS Panel Linear Regression for Novelty Adoption (H1)

	(1) Novelty	(2) Novelty	(3) Novelty	(4) Novelty	(5) Novelty
Controls					
Career Age	-0.093***	-0.130***	-0.024***	-0.109***	-0.029***
	(0.019)	(0.022)	(0.006)	(0.012)	(0.005)
Log (Pages)	-0.034	-0.024	-0.021	-0.008	
	(0.08)	(0.083)	(0.032)	(0.054)	
Variables of Interests					
Status Gain		0.722***	0.178**		0.127**
		(0.226)	(0.076)		(0.066)
*Status Gain **				0.322**	
Treatment				(0.16)	
Constant	4.146***	3.995***	0.929***	3.827***	0.758***
	(0.491)	(0.504)	(0.179)	(0.334)	(0.032)
N	593	593	593	1281	1122
Author Fixed Effect	Y	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y	Y
Samples	Winner & Nominee	Winner & Nominee	Winner & Nominee	Winner, Nominee, & Control Group	Winner & Nominee
Measurement of Novelty	# of New Tag	# of New Tag	3 New Tag Dummy	# of New Tag	3 New Tag Dummy

Notes. Standard errors in parentheses, clustered at author level.* p <0.10, ** p <0.05, *** p <0.01

impact on subsequent novelty adoption. Specifically, after status gain, the count of new tags associated with post-award books increases by 0.72 (the average count of new tags is 1.96). In column (3), we introduce a new dummy variable that equals 1 if the average count of new tags for an author-year observation is larger than 3. This aims to explore a more drastic adoption of new information, ruling out the possibility that readers use slightly different tags to describe the same genre. The result shows that the probability of adopting novel information in the production increases by 18% when authors experience status gain.

To address the potential confounding effect of unobserved variables and career stage on both status gain and novelty adoption, we collected an additional sample of control authors using the recommendation system of the platform. Control authors were selected based on the following criteria: never having won significant awards throughout their lifetime, having their first book published within five years of the treated author's first book, and having a similar total count of published books. Column (4) in the model estimates the coefficient of interest using this control sample. The specific specification for the model is as follows:

$$Novelty_{it} = \beta Treat_i \times StatusGain_{it} +_{it} + \delta_i + \gamma_t + \epsilon$$

By comparing the results from the treated authors to those of the control authors, we can better isolate the effect of status gain on novelty adoption while controlling for potential confounding factors related to career stage and unobserved variables.

The coefficient of interest in our analysis remains consistent with our hypothesis, indicating a significant increase in the likelihood of adopting novel information after a status gain compared to control samples.

It is important to note that our estimation represents an upper bound for the variable of interest since there are gaps in the observations where focal individuals have no books published. Ignoring these observations could introduce bias to our results, as the absence of production could indicate either the preparation for the next project or other activities related to existing books, such as marketing efforts. By including these observations in our analysis, we aim to provide a more comprehensive understanding of the relationship between status gain and the adoption of novel information. Therefore, in column (5), we manually assign the count of the new tag in the following criteria: for any given author i with no observation in year t, we assign $Novelty_{it}$ = $Noveltyit + 1$ if $Noveltyit + 1$ is observed. We also assign $Novelty_{it}$ = 0 if both $Noveltyit + 1$ and $Noveltyit + 2$ are not observed. The assumption is that for authors, it sometimes takes two years to finish and publish a book. Therefore, a year with no publication but followed by a year with publication indicates a project spanning two consecutive years. On the other hand, three consecutive years with no publication indicates that at least the first year of the consecutive years is not dedicated to a successful novelty adoption. Additionally, we create a dummy variable similar to column (3), which equals 1 if the average count of new tags for an author-year observation is larger than 3. The magnitude of the coefficient shrinks compared to the regression in column (3), but it remains significant at the 5% level.

We further examine the heterogeneity across individuals to explore boundary conditions. Table 2.3 presents the results, with column (1) replicating the baseline findings from Table 2.2. In column (2), we investigate whether having another job influences exploration activities. The negative and significant coefficient of the interaction term suggests that authors who have another job are less likely to engage in exploring new book genres. This aligns with our argument that the slack resources brought by status gain are not decisive for them compared to their competitors. Writing as a career, being more unstable and unpredictable compared to waged jobs such as university lecturers, makes authors rely more on the resources derived from status gain. This result confirms our H2 and indicates that when the status increase is not directly related to their core work field, the motivating effect is diminished.

In column (3), we examine first-time winners/nominees, column (4) explores gender differences and column (5) investigates the difference between winners and nominees. However, none of these factors yield significant results. While Kovacs and Sharkey (2014) compared winners to finalists and found that increased status gain attracts more audience for actors, we do not report the difference between winners and nominees as our focus is on different sides of the market. Their study observed that publicity disproportionately benefits winners on the consumer side in the short run, whereas the impact is shared more equally on the producer side. Both winners and nominees experience recognition among fellow authors and critics regarding their subsequent novelty creation.

In Table 2.4, we use fixed-effect OLS panel linear regression to examine the relationship between post-status gain novelty adoption and performance using user reviews. In

Table 2.3: Fixed-Effect OLS Panel Linear Regression for Moderating effect (H2)

	(1) Novelty	(2) Novelty	(3) Novelty	(4) Novelty	(5) Novelty
Career Age	-0.130***	-0.127***	-0.129***	-0.138***	-0.130***
	(0.022)	(0.023)	(0.022)	(0.026)	(0.022)
Log (Pages)	-0.024	-0.025	-0.026	0.001	-0.026
	(0.083)	(0.084)	(0.083)	(0.092)	(0.083)
Status Gain	0.722***	0.805***	0.461	0.698**	0.747***
	(0.226)	(0.233)	(0.437)	(0.321)	(0.236)
Status Gain * Other Career		-0.957**			
		(0.440)			
Status Gain * First Time Win			0.280		
			(0.400)		
Status Gain * Gender				0.033	
				(0.295)	
Status Gain * Winner					-0.137
					(0.290)
Constant	3.995***	4.050***	4.014***	3.726***	4.011***
	(0.504)	(0.503)	(0.506)	(0.552)	(0.504)
N	593	593	593	488	593
Author FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y

Standard errors in parentheses, clustered at author level
* p<0.10, ** p<0.05, *** p<0.01

column (1), we report the baseline model, which shows that the popularity of a book on the platform, as measured by reaching a certain threshold of review count, does not have a significant impact on reader ratings. In column (2), we add the variables for novelty adoption and status gain to the regression. The results indicate that novelty adoption has a positive impact on ratings, while status gain has a negative impact on performance. This finding aligns with previous research that suggests novelty adoption is generally beneficial for knowledge creators. In column (3), we interact the variable for adoption activities with status gain to capture the effect of post-status novelty adoption. The result shows that the interaction term is not statistically significant, even at the 10% level, indicating that post-award novelty adoption is at least as beneficial as adoption that occurs in the pre-award period. In column (4), we use Tobit regression to estimate models with left- and right-censoring at 1 and 5, respectively, which represent the lowest and highest ratings on the platform. The results remain consistent with the previous models.

Table 2.4: Regression for Performance of Novelty Adoption (H3)

	(1) Rating	(2) Rating	(3) Rating	(4) Rating
Career Age	-0.163***	-0.149***	-0.151***	0.008
	(0.033)	(0.034)	(0.033)	(0.033)
Log (Pages)	0.038	0.026	0.020	0.019
	(0.081)	(0.077)	(0.078)	(0.045)
Membership	0.448**	0.473**	0.480**	0.448***
	(0.183)	(0.185)	(0.185)	(0.148)
Reviews	0.018	0.095	0.096	0.021
	(0.105)	(0.116)	(0.118)	(0.085)
Status Gain		-0.247*	-0.372**	-0.329**
		(0.143)	(0.185)	(0.147)
Novelty		0.132***	0.101**	0.079**
		(0.038)	(0.049)	(0.033)
Status Gain * Novelty			0.063	0.048
			(0.066)	(0.046)
Constant	4.216***	3.899***	4.011***	3.974***
	(0.454)	(0.477)	(0.496)	(0.356)
N	435	435	435	435
Author FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Regress Model	OLS	OLS	OLS	Tobit

Standard errors in parentheses, clustered at author level
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Overall, the results confirm our H3 and suggest that post-status novelty adoption is positively related to performance. Individuals, upon gaining access to slack resources and experiencing self-entitlement, are more likely to adopt more novel knowledge in subsequent work. While some may argue that such attempts could be bold and reckless due to overconfidence, we show that post-awards novelty adoption does not underperform pre-awards adoption. This lack of underperformance might be an outcome of cautious exploration. However, there is also no evidence to suggest that high-status individuals are more likely to benefit from novelty adoption compared to novelty adoption in the pre-awards period.

In the final analysis, we examine whether the difficulty of getting novel books published through gatekeepers is influenced by status in Table 2.5. In columns (1) and (2), we show that while the performance of the author's last book does not have any impact on changing publishers, it is common for authors to switch publishers when working on novel topics. Publishers, being conservative gatekeepers, often prefer authors to focus on topics that have already proven to be successful. Therefore, authors frequently seek new publishers when pursuing novel writing ambitions. However, in column (3), when we interact status gain with novelty, we find that an increase in status helps authors pass through old gatekeepers with their novelty writing. While ratings on the platform, to some extent, reflect the objective quality of books due to the large population of raters, the discussion of publisher switches focuses more on the subjective performance of the product. Furthermore, there is a concern that low-quality books are more likely to be terminated by existing publishers before being published. By investigating the negotiation phase between authors and publishers, we aim to address this concern by examining the pre-release stage. Our findings indicate that status gain can significantly reduce the "failure rate" of novel books, regardless of the subsequent reactions or potential termination. In summary, the results are in line with H4 and suggest that status gain can facilitate the acceptance of novelty writing by gatekeepers, providing authors with a better chance of getting their novel books published. This finding highlights the importance of status in overcoming barriers in the publishing process and increasing the chances of success for authors pursuing novel topics.

2.5 Discussion

In this paper, we discuss the relationship between status gain and novelty adoption. We found that after status gain, individuals are more likely to adopt novel information compared to the pre-status gain period. Specifically, our results show that the average new tags associated with books increase by 0.72 after status gain, a significant increase given that

Table 2.5: OLS for Switch Gatekeepers (H4)

	(1) New Publisher	(2) New Publisher	(3) New Publisher
Career Age	-0.011	-0.018**	-0.018***
	(0.007)	(0.007)	(0.007)
Quantity	0.040***	0.040***	0.036***
	(0.013)	(0.013)	(0.013)
Membership	-0.033	-0.046	-0.055
	(0.064)	(0.067)	(0.065)
Last Performance	-0.009	0.008	0.013
	(0.031)	(0.032)	(0.032)
Novelty		0.073***	0.119***
		(0.015)	(0.021)
Status Gain		0.089	0.297***
		(0.082)	(0.107)
*Status Gain * Novelty*			-0.100***
			(0.031)
Constant	0.941***	0.771***	0.670***
	(0.135)	(0.139)	(0.136)
Observations	550	550	550

Notes. Standard errors in parentheses, clustered at author level.* p <0.10, ** p <0.05, *** p <0.01

the average number of new tags across lifetimes is 1.96. This finding adds to the stream of research examining the antecedents of individual exploration (Rogan & Mors, 2014). Our analysis also demonstrates the role slack resource plays in the relationship between status gain and novelty adoption activities by showing that the relationship is moderated by individual task distributions. Consistent with the idea that novelty adoption is a resource-intense activity, we found that those with other sources of income engaged in fewer adoption activities after status gain. This implies that motivation of status and recognition are more likely to be effective for individuals with limited resources. The competency trap (Levinthal & March, 1993) has been widely discussed since incumbents get locked in exploitation and become incapable of renewal when faced with changing external environment. We echo the insight that the balance between organizational exploration adoption ”manifests itself in the specific actions of individuals throughout the organization” (Gibson & Birkinshaw, 2004) and add to the solutions to confront with competency trap by manipulating the status of individuals. While it is reported that experts tend to focus on their area of expertise in the latter stages of careers (Mannucci & Yong, 2018), our study points out that status change can be leveraged by managers and executives to increase individuals' propensity of new knowledge adoption which address the concern of creativity drain associated with expertise.

Our study also suggests that after exploration activities occur in the post-status gain period, performance does not decrease. We observed an increase in average ratings for novel products produced both before and after status gain. This suggests that the adoption of novelty, whether it occurs before or after status gain, can positively impact performance outcomes. Furthermore, our study emphasizes the role of status gain in persuading gatekeepers to accept and support the production of novel products. Gatekeepers, often conservative in their decision-making, may be more inclined to reject unfamiliar or unconventional ideas. However, the status gain can act as a signal of credibility and expertise, increasing the likelihood of acceptance and support for novel products. By considering the challenges of observing only "successful adoptions," we attempted to address the issue by examining the switch of gatekeepers as a potential avenue for less successful adoptions. Our findings suggest that status gain can assist individuals in overcoming the challenges associated with getting their novel ideas published by providing them with additional persuasive power and influence.

By disentangling exploration's performance effect at the individual level, we attend to calls to understand the 'multifaceted performance implications of exploration and exploitation in various contexts' (Lavie et al., 2010, p.138). We hope to inform policymakers and managers about managing exploration activities strategically. By investigating the effect of status on exploration versus exploitation, we hope to inform managers about possible changes in exploration activities for those who experience status gain.

Our paper is not without limitations. First, our dataset only includes authors who won awards from 2007 to 2017, which means that for the majority of them, we can only observe the subsequent performance within a ten-year window. If we can trace individuals in a career-long span, we can further analyze how performance evolves dynamically. Also, although we control for time-invariant but important personal characteristics through fixed-effect models such as gender, other author-related factors can complement our analysis. For example, marriage could discourage one from pursuing aggressive decisions, which may demotivate individuals to engage in exploration activities (Roussanov & Savor, 2014). Second, authors are more similar to entrepreneurs who are responsible for their own job. Although the process of adoption also involves interaction with others such as publishers, embedding in an organization such as a corporate could possibly have different insights for any given individual. Despite the limitations, we believe this study answers calls to examine exploration and its impact at the individual level (Lavie et al., 2010; Lee & Meyer-Doyle, 2017), and generalizes the research of status (such as Matthew Effect) from scientific output to creative production in the setting of entrepreneurs and creative workers.

CHAPTER 3

GOVERNMENT SUPPORT AND CROSS-BORDER KNOWLEDGE FLOWS

3.1 Introduction

Knowledge flows enhance the process of innovation, making them crucial for the economy. External R&D knowledge gained across countries is critical for innovative activities for countries (Peri, 2005). However, it's important to note that knowledge flows tend to be geographically localized within specific regions. There is evidence that ways can help overcome the barrier. Firm collaborations, goods import, and foreign direct investment (FDI) are the proven ways of supporting the flow of knowledge. For example, MacGarvie (2006) reports that importers can learn from the firms that they import overseas. Similarly, multinational corporations (MNCs) driven by FDI are superior in gaining cross-border knowledge through organizational culture, systems, and structures that facilitate the flow of knowledge (Almeida et al., 2002). The reason that cross-border knowledge spillovers remain an important locus of analysis is that, in contrast to the diminishing effect of state borders over time, the influence of geographic localization on knowledge flows remains persistent(Singh & Marx, 2013). This persistence can be at least partly attributed to various political factors, especially immigration policy and travel visas leading to the localization of knowledge (Orazbayev, 2017).

In this paper, we aim to address an important question: Do government subsidies in one country facilitate knowledge flows to inventors in other countries? While the primary purpose of government support is to enhance domestic innovation capacity rather than encourage cross-border knowledge flows, it has a significant impact on firms' oversea innovation. Domestic firms have the tendency to file for patents globally, which in turn leads to an unintended but positive outcome of government subsidies on overseas innovation.

Nevertheless, as empirical evidence shows that the emigration and mobility of inventors do not result in a loss of knowledge and innovative production in their home countries through knowledge remittances (Fackler et al., 2020; Oettl & Agrawal, 2008), knowledge flows out of country border through oversea patenting should not be a concern for the government. In fact, it can help rejuvenate internal innovation activities and cross-border collaborations. Similar to foreign direct investment and exports, knowledge flow is bilateral when domestic firms are encouraged by the local government to explore innovation activities in foreign countries. Consequently, the unintended outcome of knowledge flows should be viewed as a beneficial side effect rather than a detrimental one.

This research adopts a difference-in-differences (DiD) technique, which examines the impact of policy interventions on foreign inventors who collaborated with Chinese firms benefiting from government support, compared to a control group of inventors who collaborated with Chinese firms unaffected by the policy. The results show that Chinese government support for innovative cities results in the ”treated” international inventors increasing their collaborators (including both the US and Chinese inventors), patent filing in the US, and forward citations. Our analysis also shows that the increase in co-inventors can be attributed to new Chinese collaborators, but the increase in the forward citation cannot fully be attributed to Chinese inventors citing activities. Additionally, foreign inventors with a lower knowledge stock have a greater ability to benefit from the overseas policy.

We investigate this question in the setting of Chinese cities, some of which experienced an exogenous policy intervention through innovation-related government subsidies. China started a process of policy with the goal of building ”national innovative cities,” and it aims to develop local innovation infrastructure and help local firms with product and process innovation. The primary purpose of the policy is not to encourage knowledge exchange internationally, but scholars have observed that Chinese firms enhance their global competitiveness by filing more patents in foreign countries post-treatment (Chen et al., 2023). However, as Chinese firms widely collaborate with inventors in other countries to overcome the liability of foreignness, what remains unclear is whether their foreign collaborators can benefit from the Chinese policy shock.

This research makes a significant contribution to the existing literature by examining how government actions that improve the domestic innovation system result in cross-border knowledge flow, which is challenging and has been mainly achieved by immigrants and foreign direct investment. However, this study sheds light on an additional implicit avenue for such knowledge flows—the unintended yet positive effect of government subsidies. These policies incentivize domestic firms to collaborate with foreign inventors, resulting in a mutually beneficial outcome for both countries. This win-win situation demonstrates the importance of understanding how cross-border knowledge exchange can be shaped by local innovation policy. Furthermore, in contrast to the research that primarily relies on firm-level data, we utilize individual-level data in our study. Recognizing the critical role of inventors as the micro-foundations of the firm-level innovation performance, by disaggregating the analysis to the level of inventors, we demonstrate how these key actors perform and facilitate the knowledge flows.

3.2 Literature Review and Hypothesis Development

3.2.1 Domestic Government Support and Foreign Inventor Network

Political stimulation has been a crucial driver for firm-level innovation, and a variety of approaches have been discussed by scholars, including public procurement and prize (Murray et al., 2012). Most of these policies have been widely proven effective in terms of their impact on firm innovation (Bloom et al., 2002; González et al., 2005), although some approaches, such as direct earmark funding, sometimes are unrelated to innovative performance, particularly in the context of China in the 1990s (Guan & Yam, 2015). Among the commonly employed innovation tools, government-funded R&D subsidies have garnered significant attention. It has been extensively proven effective (Bronzini & Piselli, 2016; Jaffe & Le, 2015), despite some debate regarding its potential crowding out private funding. R&D subsidies can notably stimulate private R&D, especially for small firms (Lach, 2002), and significantly increase the likelihood of patent application of the firms (Bronzini & Piselli, 2016). In the specific context of East Asia, where we base our study, Hu and Mathews (2005) take a close look at the national innovative capacity across five East Asia nations and report that public funding from the government plays an important role in those countries' catch-up strategies. And empirically, firms awarded government subsidies will apply for more patents than their counterfactual competitors.

Government subsidies, in addition to their direct impact on R&D financing, can serve as a motivator for awarded private firms to engage in R&D programs with positive externalities. The reason is that it may confer a signaling effect (Feldman & Kelley, 2006) and enable the firm to prototype their technology (Howell, 2017). External organizations perceive the receipt of government support as an endorsement of the quality, and hence the awarded firms have advantages over competitors, such as improved access to long-term financial resources (Meuleman & De Maeseneire, 2012). Furthermore, the awarded firms are more likely to form technological collaborations with other partners. They tend to be more adventurously when selecting partners (Ahn et al., 2020), and potential partners also see the awards as a positive signal (Bianchi et al., 2019).

With the prevalence of international collaboration, the impact of political support extends beyond national borders. As the support effectively provides slack resources to promote innovation and mitigate uncertainties, which include liabilities of foreignness, firms increase innovation regardless of national boundaries (Chen et al., 2023). They are more inclined to seek overseas partnerships and collaborate with foreign inventors when engaging in patenting activities abroad than working alone. Firstly, cross-border patenting is critical and meaningful in protecting their innovation outcome in the international product market, but patenting overseas is not as easy as domestic applications due to the liability of foreignness (Gomes-Casseres et al., 2006). Firms need to interact with the host country in the patenting phase. Therefore, to mitigate these challenges and reduce costs, firms, driven by the increased tendency for cross-border innovation resulting from government support, actively seek partnerships with experienced foreign inventors who can provide valuable knowledge and network reach. But more importantly, the benefit of cross-border innovation is higher when collaborating with foreign inventors in the long run. Collaboration serves as a catalyst for inter-organizational learning, and when subsidies enable firms to approach foreign inventors to collaborate, it creates opportunities for knowledge exchange between two distant parties. As a result of the support incentives, firms become adventurous and more likely to search for partners that are out of their existing value chain (Ahn et al., 2020), including foreign academia and industrial partners who can bring in new knowledge to recombine. They can gain new knowledge through alliances with cross-border partners, which would enhance their innovative competence in both short and long term (Kavusan et al., 2016; Schildt et al., 2012). Therefore, government-supported firms are more likely to collaborate with foreign inventors to expedite the patenting process, and through the process of collaborations, both parties gain knowledge flow from distant countries.

However, the impact of government subsidies on foreign inventors remains unclear. Considering that cross-border innovation enables knowledge flow, we argue that inventors who collaborate with firms receiving government support in host countries also indirectly benefit from the subsidies. When examining how an inventor can be impacted positively by distant knowledge, we first focus on an inventor's collaboration networks, given the emphasis that innovation research places on network and productivity, as well as star inventors and scientists' ability to influence others, as an important locus of analysis. That is, the expansion of the network, besides facilitating existing knowledge circulation and the finding of new knowledge combinations (Paruchuri, 2010), also helps new inventors to grow and gain experience (Akcigit et al., 2018). These insights about the beneficial effects of overseas policy align with the increasing dominance of collaboration in the organization of knowledge-based activities. Especially given knowledge spillovers are often spatially bounded, inventors that organize their R&D efforts in larger groups are better positioned to gain access to knowledge produced remotely and influence larger populations.

Although these effects resemble the beneficial influence of R&D policy on foreign inventors, research does not have a clear idea of how the collaboration and network can be shaped by other countries policies. DeCarolis and Deeds (1999) argue alliance with other organizations is a visible representative of knowledge flows. Building upon this perspective, we contend that foreign inventors can establish more co-inventor relationships following the policy intervention if they are associated with government subsidies. The reason is that inventors are inclined to extend efforts to increase their visibility to others (Paruchuri & Awate, 2017), and with the help of overseas policy, the impacted foreign inventors are more likely to patent more together with the firms which are eligible for the subsidiaries (Chen et al., 2020). Therefore, as a result of the increased patent outcomes, these inventors experience growth in both their knowledge stock and visibility, rendering them more likely to be sought after by other inventors as potential collaborators. Especially for firms seeking opportunities to overcome the liabilities of foreignness, the ”treated” foreign inventors possess relevant experience that sets them apart from others.

To summarize, once a dense, cross-border, interfirm collaboration network is triggered by a policy in a country, the collaborating inventors in another country can take great advantage of the alliances (Schilling & Phelps, 2007). The collaboration triggered by the policy increases their knowledge stock. And the collaboration, in turn, shows that the foreign inventors are competent and promising alliance choices for other firms and inventors who are actively seeking potential collaborators, which will lead to an increase in the number of co-inventors. Therefore, we raise our first hypothesis:

HYPOTHESIS 1 (H1). *Foreign inventors who co-invented with domestic firms increase the number of their collaborators following government supports.*

3.2.2 Domestic Government Support, Knowlege Spillover, and Innovation

What is also implied in the benefit of collaboration, given the fact that learning is bilateral, is that foreign inventors also have the opportunities to learn from the firms that they are working with. When government support, particularly from developing countries, helps domestic firms search beyond national borders and absorb advanced knowledge, it also helps local knowledge spillovers to other countries. In other words, international inter-organizational learning through FDI, MNCs, and collaborations benefits both the host country and the home country. The knowledge base between the home country and the host country is different but not necessarily inferior. For example, besides that MNCs can learn from the host countries' knowledge base, there is a great chance that they can also transfer unique knowledge to the host countries' networks (Perri & Peruffo, 2016). Evidence also shows that foreign institutional investors have a positive impact on invested firms' innovations due to multiple reasons, and one of the major mechanisms is that such cross-border networks enhance knowledge flows from investors' economy (Luong et al., 2017).

Similarly, cross-border collaborations that are stimulated by government support can also benefit foreign collaborating inventors in terms of learning and productivity. When government support promotes domestic firms to patent overseas, knowledge flows are also triggered as a byproduct of cross-border collaborations. The collaborations are close in terms of the technology field by nature since firms in one country tend to work with partners with high technological proximity, which facilitate effective learning. The impact of learning depends on the industry attributes, as the gaps between foreign companies and domestic companies may lead to varying learning effects (Alvarez & Molero, 2005). There is evidence that FDI cannot contribute to knowledge flow when the gap of technology between two countries is huge (Fons-Rosen et al., 2017), as the knowledge flow is realized by inventor mobility. The co-invention relationship in nature is more technologically proximate than FDI. Therefore, not only do domestic firms receiving government subsidies have the opportunity to learn through the alliance process, but foreign inventors involved in these collaborations also gain access to and absorb distant knowledge through their partnerships. And as a result of knowledge diffusion and learning, foreign inventors benefit from the gain in knowledge sources and therefore increase their innovative capacity (Roper & Hewitt-Dundas, 2015).

Therefore, we argue that as foreign inventors gain access to overseas government subsidiaries, they get access to the knowledge flow and increase their innovative output. Hence we propose the following hypothesis.

HYPOTHESIS 2 (H2). *Foreign inventors who co-invented with domestic firms increase the number of innovation outputs following government supports.*

In addition to the quantity of innovation, we also argue that the quality of innovation increases after the policy intervention. There is no evidence that such an increase of patents in the foreign is a single outcome of fiscal incentives, as the cash or tax credits reward cannot directly benefit the cross-border partners. Instead, it is an outcome of knowledge transfer and learning, as stated. What makes learning different from knowledge exchange between two local firms is that the knowledge sets are distant. Almeida (1996) report that MNCs not only use more local knowledge than similar domestic firms but also contribute to a knowledge pool as local patents cite these MNCs more. Similarly, Yang et al. (2010) argues that the process of knowledge transfer is not one-direction. The recombination of cross-border knowledge creates a spillover knowledge pool, which would, in turn, create opportunities for recombined knowledge to be learned by other inventors who can get access to the pool. Thus, the foreign inventors associated with government-supported firms increase innovation capacity through recombining distant knowledge sets, and these outputs are more likely to be novel and generative.

To summarize, a noteworthy consequence of knowledge spillovers is that it can generate recombination of distant knowledge. Such recombination is valuable and desirable for firms (Rosenkopf & Almeida, 2003) as it can help the firms to create more valuable knowledge and make breakthrough (Fleming, 2001), especially when the innovation is a result of knowledge recombination from distant organizations but close technology sectors (Rosenkopf & Nerkar, 2001). This fits with the benefit of cross-border alliances: the knowledge should be close enough to foster the partnership, but they are different and distant organizations. The most direct representative of the knowledge recombination is the outputs of the foreign inventors following the policy intervention, as they are familiar with these two different knowledge sets. When distant knowledge joins the local knowledge pool, the knowledge gets more attention within the local network of foreign inventors. And as a result, the new recombined innovation will receive more citations.

HYPOTHESIS 3 (H3). *Foreign inventors who co-invented with domestic firms receive increased citations with government support*

3.3 Research Method

3.3.1 A Quasi-Experimental Setting

To examine our theoretical arguments, we rely on a quasi-experimental setting in which China staggeringly introduced policy interventions across cities. Therefore, domestic government and domestic firms refer to the Chinese government and Chinese firms, while foreign partners refer to the United States inventors. The Chinese government has initiated a series of policies aiming at improving the innovation capabilities of cities and regions. In 2009, China's National Development and Reform Commission (NDRC) formulated the administrative regulations to renovate Shenzhen as the first national innovative city in China and promulgated the policy for implementation (Shenzhen Government, 2009). In the subsequent years, China's Ministry of Science and Technology (MOST) followed up with NDRC and co-developed the policy of "constructing national innovative cities" (MOST, 2010; MOST and NDRC, 2016). The policy was adopted at the city level in China. By 2017, there had been 61 cities that enacted the policy (see Table C.1 in Appendix for a complete list).

Based on the government publication (MOST and NDRC, 2016), city governments who enacted the policy take the following actions: (1) reform the policies, including technology, economy, and administration, (2) accumulate and provide elements that promote innovation, such as talents, research labs, subsidies, tax reduction, information, and technology, (3) transform innovation outcomes (e.g., patents) to concrete products/services, (4) cultivate entrepreneurship, (5) upgrade the infrastructure, (6) stimulate researchers and talents, (7) improve related services (e.g., legal services), (8) enhance investment and financing systems (e.g., financial product innovation for firms), (9) improve the living conditions for the people, and (10) create an innovation-oriented ecosystem. In general, city governments provide financial and institutional benefits to the residing firms to encourage their innovation in domestic and international markets and further enhance the innovation capability of the city.

The enactment of the innovative city policy serves as a quasi-experimental setting for our theoretical and empirical inquiry. This setting ensures the exogeneity of the policy enactment to firms and individuals, as the policy is determined by the Chinese government at the national level. The city governments implement the policy based on upper-level guidance. We provide contextual support and empirical verification in Section 3.3.5 that the policy is not driven by firms' or individuals' decisions, strategies, or activities. In this sense, such policies offer plausibly exogenous variation in a firm's innovation performance and strategy.

3.3.2 Data and Variables

To clarify the impact of government support on foreign partners' collaboration and knowledge spillover, we collected data and assembled a sample from two main sources. First, we identified the government support and timing following the previous literature (Chen et al., 2020). Table C.1 in Appendix presents the years when certain Chinese cities enacted the innovative city policy. Second, we identified the cross-border collaboration activities and partners using the U.S. patent data on the PatentsView platform[1]. The U.S. patent data is widely used in the literature to study firms' and/or inventors' innovation activities(e.g., Cirillo, 2019). The U.S. patent data contain details about patent applications and grants in the U.S. from firms and individuals around the world.

We filtered patents with Chinese assignees. For those patents, non-Chinese inventors are foreign inventors to domestic (Chinese) firms. We first examine all non-Chinese inventors and then report the results of US-employee inventors in the following analysis. For each foreign inventor, we recorded their collaboration with Chinese firms, whether they collaborate with firms residing in innovative cities and in which year, their patents, and the citations they receive from future patents (i.e., forward citation). To obtain the year of their collaboration with firms in innovative cities, we cross-matched the two data sources by the locations (cities) of the assignees (firms or individuals) of a patent. A foreign inventor may work with firms in multiple innovative cities and/or at different times. We mark the earliest year as the foreign partner's first experience with government support. In general, for each foreign inventor, we quantify their collaboration intensity with Chinese firms, their innovation performance, and the knowledge spillover activities and examine how government support affects these metrics. We only include individuals who have patent outputs in three separate years. This means that each individual in our analysis must file patents in three distinct years. The final unbalanced longitudinal panel dataset has 12,162 observations, including 1,845 foreign inventors with years from 2005 to 2018. We selected a time range of 2005 to 2018 to cover the entire period of the innovative city policy and make it long enough for the empirical analysis.

[1] https://www.patentsview.org/download, accessed on August 12, 2020

3.3.3 Dependent Variables

Number of Collaborators.

For a foreign inventor, the number of collaborators measures the number of (both Chinese and non-Chinese) inventors who file patents jointly with the foreign partner in a year. If a foreign inventor files multiple patents with the same inventor, we consider the inventor only once in this measure. Again, we propose to see as foreign inventors get access to new knowledge flow, they are more likely to form collaborations with others as well.

Number of Patents.

The number of patents measures the innovation outcome that the foreign partner authors have in a year. The patents include those filed by Chinese and non-Chinese assignees. This measurement captures the outcome of knowledge flow from domestic to foreign partners.

Number of Citations.

We use the number of citations to capture the value of the innovation outcome at the foreign partner level. For a foreign partner, the number of citations is the total number of forward citations (i.e., from future patents) to all the existing granted patents by an inventor in a year. As hypothesized, the foreign innovation triggered by the domestic policy should be more valuable as it recombines distant knowledge, and we expect to see an increase in the number of citations for the treatment group after the treatment.

3.3.4 Independent Variables

Government Support.

The analysis examines the role of the exposure experience to government support in China on collaborators' innovation performance. *Government Support* is a binary variable indicating whether the focal inventor has experience or not in working with Chinese firms which are from cities receiving innovative city policy. Specifically, the variable takes the value of *1* when an inventor had such an exposure to the enactment of this type of city policy in a year and for all the subsequent years for this collaborator ("treatment group"), and *0* when an inventor working in China does not have such an exposure ("control group"). The treatment and control group includes two types of foreign inventors: (1) inventors who have collaboration experience with Chinese firms before the policy shock and (2) inventors who start to establish relationships with Chinese firms after the policy shock. Our assumption for the second type of inventors is that these inventors can be approached by both firms in selected cities and non-selected cities. After they found a collaborating relationship, the treatment group can indirectly enjoy the subsidiary while the control group cannot. Our measure development mimics the commonly used DiD estimator (e.g., Bertrand et al., 2004; Bertrand & Mullainathan, 2003; Flammer & Kacperczyk, 2016), which can help identify the treatment effect of the exposure to government support through the DiD technique. Specifically, we examine the change in inventors' citation performance before and after having exposure to government support (first difference) between the treated and control cities (second difference).

3.3.5 Control Variables

We control the foreign partners' cumulative number of patents to measure the stock of knowledge. We also control for inventor team size, percentage of past oversea collaborators within the inventor teams, and percentage of past patents with Chinese co-inventors to control for the propensity of foreign partners to work with oversea inventors and firms, especially those from China where we observe the policy change.

Difference-in-differences.

To examine whether government support fosters the knowledge flow of foreign inventors, we follow the literature (e.g., Bertrand & Mullainathan, 2003; Dhanorkar, 2019; Flammer & Kacperczyk, 2016; Liu & Bharadwaj, 2020) and apply the difference-in-differences (DiD) technique. Because the time (year) of the innovative city policy ("treatments") is different across inventors working in cities (see Table C.1 in Appendix), we are analyzing a *staggered* quasi-experimental setting. The generalized DiD model, as suggested by Wooldridge (2015, Chapter 14-4), is most suitable for a staggered quasi-experimental setting when multiple treatment groups receive the treatment at different times. Specifically, we estimate the following regression:

$$Y_{ict} = \alpha_i + \alpha_t + \beta_1 \cdot \textit{Gov Support}_{ct} + \boldsymbol{\gamma}' \boldsymbol{X}_{ict} + \varepsilon_{ict} \tag{3.1}$$

where i indexes inventors; t indexes years; α_i and α_t are inventor and year fixed effects, respectively. The dependent variable of interest, Y, is the number of collaborators, number of patents, and forward citations, respectively. *Gov Support* is the post-treatment dummy of the policy enactment of the innovative city as earlier described. $\boldsymbol{X}$ is the vector of control variables. ε is the error term. The analysis uses a Poisson regression for the model because the dependent variable is a count measure. To account for serial correlation of the error term, we cluster standard errors at the inventor level (Flammer & Kacperczyk, 2016). The coefficient of interest is β_1, which measures the effect of government support on cross-border innovation. Our hypothesis predicts that β_1 should be positive and significant for all three models.

Validity of the Identification Strategy

The identification strategy should meet the requirements of inclusion and exclusion restrictions to be valid. First, the inclusion restriction indicates that the treatment (i.e., the enactment of the innovative city policy) needs to trigger relevant changes in foreign inventor behavior. In our context, although the policy enactment provides us with unequivocal treatment and control groups, we cannot directly observe that inventors use Chinese government support to make changes to their innovation and collaboration. Nonetheless, this issue only results in an underestimation of the treatment effect because inventors that utilize the support are pooled with those that do not (see Scott et al. (2021) for a similar argument). Therefore, the DiD design is still valid (Angrist & Pischke, 2010).

Second, the exclusion restriction requires that the treatment (the policy enactment) needs to be exogenous with respect to foreign inventor innovation. In other words, the enactment of the policy should not be driven by individual inventors' decisions, strategies, or activities. In this research context, the policy is determined by the (Chinese) national-level government that issues guidance on the implementation to city-level governments. We searched for qualitative evidence that would suggest that the inventor affected and took advantage of the policy enactment. We first examined the headquarters of the firms in our sample, for the concern that foreign inventors are indirectly associated with Chinese firms which might have changed headquarter locations simultaneously. We do not find empirical evidence that firms change their headquarters location during 2005 - 2017. Given that the first year of the innovative city policy is 2009, we claim that it is less likely that inventors, especially foreign inventors, knew the future enactment of the policy beforehand and intentionally pursued the resources by moving. Next, we searched the CNKI database (https://cnki.net/)[2] for information indicating that inventors intentionally take actions such as lobbying to affect the innovation policy. We find no such evidence of inventors affecting the policy enactment. In addition to the contextual evidence, we also visualize the parallel trends assumption in Figure 3.1. The figure illustrates the mean counts of U.S. patents in the U.S. for both the treatment and control groups. In the treatment group, we observe a spike in patent output. There is also a variation for the control groups years before the policy shock. However, the variation decreases as the time approaches the policy intervention.

[2]CNKI is an online publishing platform of China knowledge resources initiated by Tsinghua University and Tsinghua Tongfang Holding Group. It provides "over 90% of China knowledge resources, the widest in title and type coverage and deepest in year coverage in China" and "comprehensive coverage of journals, dissertations, newspapers, proceedings, yearbooks, reference works, encyclopedia, patents, standards, S&T achievements, and laws and regulations" (https://oversea.cnki.net/index/Support/en/Project.html).

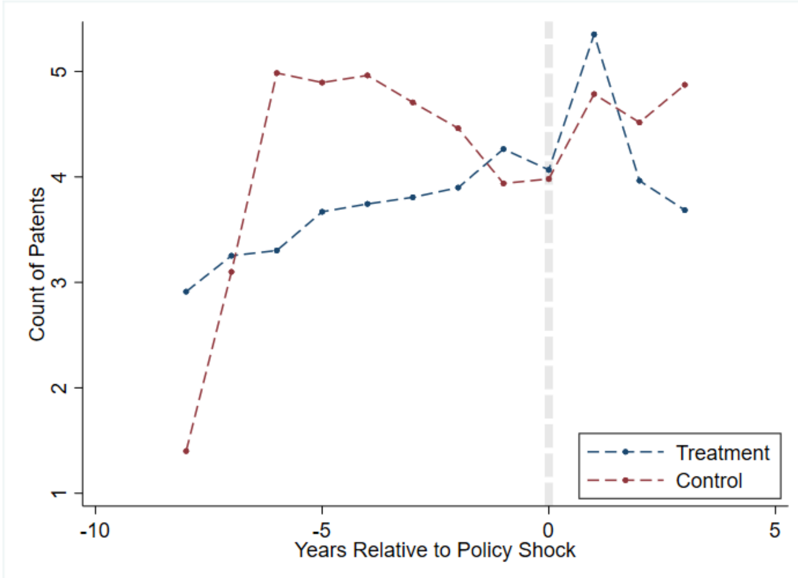


Figure 3.1: Pre Shock Trends: Patents

The identification strategy may also suffer from unobserved differences between treated and control inventors that may affect both innovation and the treatment. Nevertheless, this concern is unlikely to explain our results because (1) we find no evidence of preexisting policy effect as discussed above, and (2) the eventually treated inventors are first in the control group and only later in the treatment group due to the staggered enactment of the policy.

3.4 Analysis and Results

3.4.1 Descriptive Statistics

The summary of descriptive statistics is shown in Table 3.1, and the correlation matrix is shown in Table 3.2. Based on the developed unbalanced sample, on average, the inventors file 3.97 patents per year, and they collaborate with 4.06 inventors every year.

Table 3.3 provides a comparison of our main variables of interest between the control group and the treatment group. Panel A specifically compares the observations from the control group with those from the treatment group prior to the policy intervention. On the other hand, Panel B considers all observations from the entire period. The performance of the treatment group exhibits an increase following the policy implementation, but it is important to note that a significant difference exists between the two groups both before and after the policy intervention.

Table 3.1: Descriptive Statistics

	N	Mean	SD	Min	Max
Number of Patents	12162	3.97	6.187	1	118
Average Team Size	12162	4.06	2.45	1	28
% Foreign Collaborators	12162	0.76	0.35	0	1
% Chinese Collaborators	12162	0.18	0.30	0	1
Number of Collaborators	12162	7.33	9.66	0	212
Government Support	12162	0.36	0.48	0	1
% Chinese Patents	12162	0.18	0.35	0	1
Cumulative Patent Stock	12162	31.39	59.12	1	937
# of Self Citations	12162	0.64	1.74	0	37
# of Other Citations	12162	14.22	30.30	0	445
# of Domestic Citations	12162	0.57	2.02	0	46
# of Citations	12162	15.57	32.36	0	504
Cumulative # of Self Citations	12162	3.35	9.535	0	205
Cumulative # of Other Citations	12162	76.89	220.73	0	3837
Cumulative # of Citations	12162	83.97	235.63	0	4079
Cumulative # of Domestic Citations	12162	2.35	10.02	0	233

Table 3.2: Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Number of Patents	1															
2	Average Team Size	-0.03	1														
3	% Foreign Collaborators	0.06	0.21	1													
4	% Chinese Collaborators	-0.00	-0.01	-0.76	1												
5	Number of Collaborators	0.68	0.39	0.18	-0.07	1											
6	Government Support	0.02	0.04	-0.30	0.40	0.02	1										
7	% Chinese Patents	-0.04	0.07	-0.63	0.83	-0.06	0.41	1									
8	Cumulative Patent Stock	0.59	-0.01	0.08	-0.06	0.60	0.06	-0.09	1								
9	# Self Citations	0.63	-0.03	0.05	-0.03	0.37	0.01	-0.08	0.47	1							
10	# Other Citations	0.46	-0.04	0.09	-0.08	0.48	-0.02	-0.10	0.77	0.41	1						
11	# Domestic Citations	0.36	-0.06	-0.11	0.14	0.20	0.08	0.10	0.38	0.39	0.33	1					
12	# Citations	0.49	-0.04	0.09	-0.08	0.50	-0.01	-0.11	0.78	0.47	0.99	0.36	1				
13	Cumulative # Self Citations	0.44	-0.02	0.03	-0.02	0.31	0.09	-0.07	0.68	0.64	0.53	0.42	0.57	1			
14	Cumulative # Other Citations	0.39	-0.02	0.08	-0.06	0.45	0.05	-0.09	0.84	0.35	0.82	0.30	0.82	0.63	1		
15	Cumulative #Citations	0.41	-0.02	0.07	-0.06	0.46	0.06	-0.09	0.85	0.37	0.82	0.31	0.82	0.67	0.99	1	
16	Cumulative # Domestic Citations	0.26	-0.05	-0.06	0.09	0.19	0.12	0.06	0.46	0.26	0.35	0.67	0.36	0.50	0.40	0.42	1

3.4.2 Hypothesis Testing Results

Table 3.4 reports the estimation results for the testing of the hypothesis. All the analysis uses a Poisson regression for the model, because the dependent variable is a count measure. To account for serial correlation of the error term, we cluster standard errors at the city level Using a fixed effect modeling approach with inventor and year fixed effects unless

Table 3.3: Mean of Treatment Group and Control Group Pre-Policy

Panel A: Mean of Treatment Group and Control Group Pre-Policy			
	Control	Treatment	P value
Number of Innovations	3.61	4.43	0.00
Average Team Size	3.96	4.00	0.61
# of Collaborators	6.51	8.17	0.00
% Foreign Collaborators	0.86	0.79	0.00
Patent Stock	28.25	23.08	0.00
# of Citations	13.95	17.32	0.00
Cumulative # of Citations	54.56	50.68	0.47
Panel B: Mean of Treatment Group and Control Group All Time			
Number of Innovations	3.83	4.55	0.00
Average Team Size	4.05	4.04	0.74
# of Collaborators	7.00	8.74	0.00
% Foreign Collaborators	0.76	0.80	0.00
Patent Stock	28.83	42.20	0.00
# of Citations	14.40	20.52	0.00
Cumulative # of Citations	75.58	119.34	0.00

Table 3.4: Hypothesis Testing Results

Dependent Variables:	# of Collaborators	# of Patents	# of Citations	Cumulative # of Citations
Model:	(1) H1	(2) H2	(3) H3	(4) H3
Variables				
Government Support	0.201***	0.193**	0.150**	0.083***
	(0.030)	(0.078)	(0.059)	(0.029)
Patent Stock	0.002***	0.002***	0.0006***	0.0003**
	(0.0004)	(0.0004)	(0.0002)	(0.0001)
Team Size	0.142***	0.0005	-0.004	-0.003
	(0.020)	(0.010)	(0.003)	(0.003)
% Foreign Collaborators	0.602***	0.247***	0.073	0.026
	(0.065)	(0.074)	(0.076)	(0.041)
% Chinese Patents	0.472***	0.232***	-0.056	-0.064*
	(0.068)	(0.059)	(0.063)	(0.038)
Fixed-effects				
Inventor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	12,194	12,194	11,620	11,620
Squared Correlation	0.77538	0.58669	0.87895	0.98268
Pseudo R^2	0.53366	0.42134	0.81185	0.96249
BIC	80,999.1	71,582.9	98,737.6	126,646.6

Clustered (City) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

specified. Model (1) analyzes the impact of foreign inventors' exposure to the innovative city policy on the number of collaborators. The results indicate that exposure to the innovative city policy has a significant positive effect on the number of collaborators. Foreign inventors who are exposed to the Chinese innovative city policy experience an increase in collaborators by 0.22, suggesting that they gain a degree centrality within the inventor network. The average marginal effect is 0.201, indicating being connected to Chinese firms elgible for the poliy is associated with 0.201 additional collaborators. Model (2) examines the innovation performance, and the results show that the policy benefits the foreign partners by increasing the patents grants by 0.20. This is both statistically and economically significant, given that annually, on average, the number of patents for inventors in our sample is 3.97. Model (3) and model (4) examine the value of the innovations by investigating the forward citations. Both the annual count and cumulative counts of citations reveal that foreign collaborators who have worked with Chinese firms in innovative cities supported by government subsidies receive more total citations compared to those collaborating with firms in other Chinese cities. The recombination of cross-border knowledge flows not only generates more citations but also leads to more innovations for the treated foreign inventors. These results confirm our hypothesis that after the policy intervention, foreign inventors gain more productivity and form more collaborations. Their technology outputs also receive more attention.

We next plot the policy in the count of collaborators and in the count of patents, following the treatment to obtain a broad assessment of the effect of the exotic policy. Figure 3.3 and Figure 3.2 show the differential effect of the policy shock on the differences in co-inventors (Figure 3.3) and innovation output (Figure 3.1) between the treatment group and control group (including year and inventor fixed effects). As observed, the policy leads to an initial increase in both the treatment group's engagement with new inventors and their filing of patents. However, the effect diminishes over time, and there is no significant difference between the two groups two years after the policy shock.

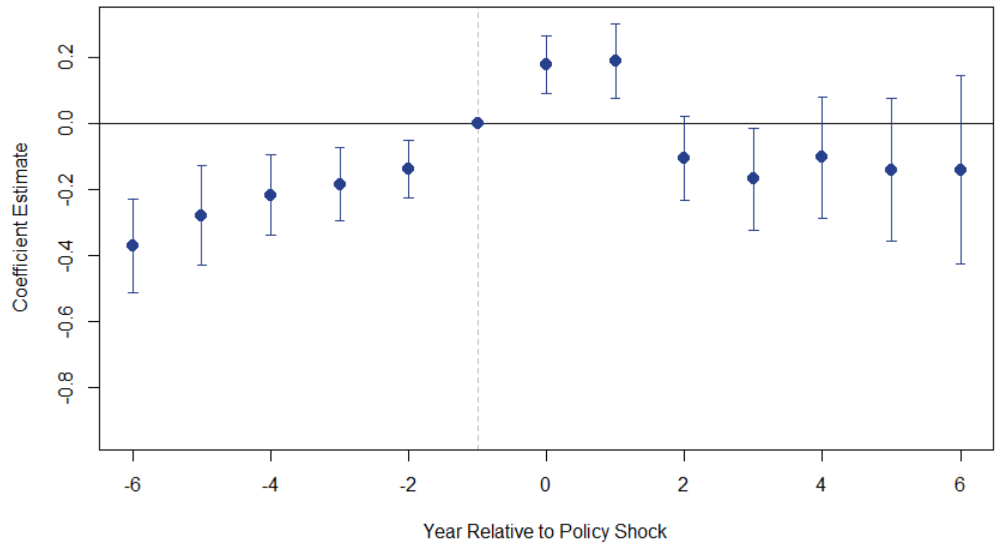


Figure 3.2: Effect on Count of Patents

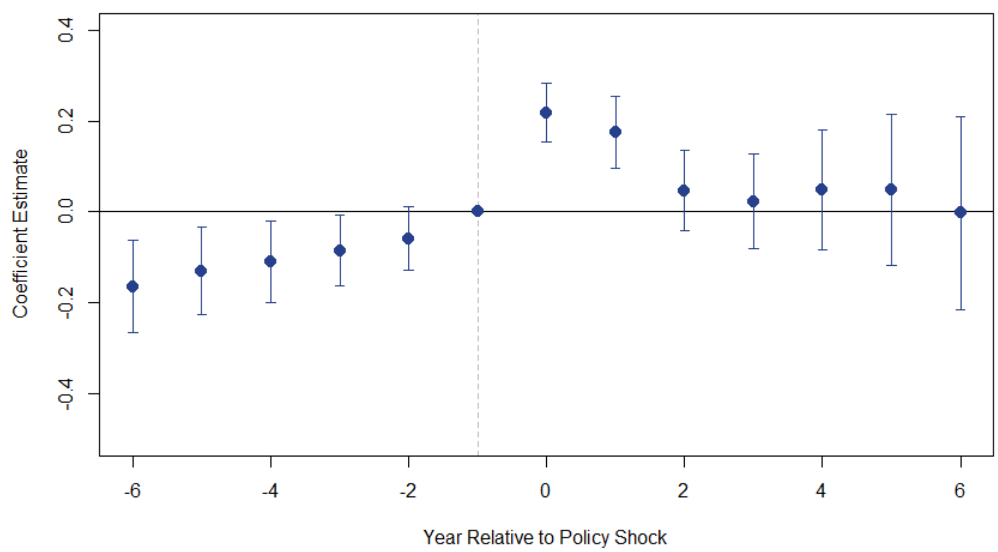


Figure 3.3: Effect on Count of Collabortors

In Table 3.5, we explore the heterogeneity of the foreign partners by examining the interaction between government support and the patent stock of foreign inventors. This analysis helps us understand who benefits more from the overseas policy. The significant and negative coefficient suggests that the policy has a greater impact on those foreign inventors who have a lower patent stock. With the support of oversea government policy, these inventors gain access to valuable resources for innovation, which would be absent for them due to their inferior past performance without the stimulation of oversea government. As a result, they are more likely to expand their co-inventor network and generate more patents without sacrificing the quality of their innovation, as measured by citations.

Table 3.5: Interaction Testing Results

Dependent Variables:	# of Collaborators	# of Patents	# of Citations	Cumulative # of Citations
Model:	(1)	(2)	(3)	(4)
Variables				
Government Support	0.307***	0.357***	0.305***	0.178***
	(0.045)	(0.119)	(0.047)	(0.022)
Patent Stock	0.002***	0.003***	0.001***	0.0007***
	(0.0002)	(0.0004)	(0.0002)	(0.0001)
Team Size	0.142***	-0.0010	-0.005*	-0.004
	(0.020)	(0.010)	(0.003)	(0.003)
% Foreign Collaborators	0.593***	0.239***	0.071	0.029
	(0.068)	(0.072)	(0.078)	(0.044)
% Chinese Patents	0.425***	0.173**	-0.113**	-0.099***
	(0.072)	(0.072)	(0.054)	(0.031)
Government Support	-0.001***	-0.002***	-0.001***	-0.0005***
× Patent Stock	(0.0003)	(0.0005)	(0.0002)	(0.000)
Fixed-effects				
Inventor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	12,194	12,194	11,620	11,620
Squared Correlation	0.77710	0.58903	0.88603	0.98441
Pseudo R^2	0.53538	0.42377	0.81348	0.96293
BIC	80,774.9	71,365.2	98,029.9	125,355.3

Clustered (city) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

3.4.3 Additional Analysis

An alternative explanation suggests that the increase in collaborators and citations may be driven by inventors in China, which might not accurately represent the national level degree of centrality and local economic value. To address this concern, we conducted additional tests to examine the composition of collaborators and citations, as shown in Table 3.6. Model (1) shows that the count of foreign collaborators, identified by inventor location, increases after exposure to the policy, indicating that the treated foreign inventors gain more visibility among foreign inventors. Models (2)-(7) in Table 3.6 report the analysis results on different decomposed citation performances. The findings reveal that the citations from others (excluding self-citations and citations from collaborators) significantly increase for the treatment group. In fact, the increase in citations is not solely driven by cross-citations among Chinese inventors, which suggests a broader expansion of the local knowledge pool. These results support our argument that the combination of distant knowledge significantly enhances the value of U.S. innovation triggered by Chinese policy.

In Table 3.7 (column (1)), we employed text similarity analysis to investigate the citing patents of the treatment group and control group, considering the concern that patents filed by Chinese assignees may be replication or incremental development of existing technologies aimed at gaining government subsidies rather than generating innovative content. The regression results show no significant relationship at the 5% level, indicating that the treatment group relies on prior art to a similar extent as in the pre-policy period. The SEs are clustered at the inventor level here since the residual is likely to be correlated with inventors' and attorneys' language habits.

In columns (2) and (3) of Table 3.7, we divided the citing patents into two categories: those triggered by the policy and those not triggered by the policy. We focused solely on the citation patterns within the treatment group and control group, as this captures the knowledge circulation within the network. If the text similarity between the focal patent and citing patents of a certain category is higher after the shock, it suggests greater proximity between the innovations across borders. Conversely, if the text similarity is lower, it indicates less proximity but potentially greater novelty compared to the category of citing patents. We limited our investigation to the patents which are citing the treatment group and control group, as we wish to investigate the knowledge circulation within the groups. The results show that after the shock, the inventors produce patents in a slightly less novel manner, as they are more proximate to the citing non-policy patents but weakly less proximate to the citing policy-patents. In other words, the treatment group produces more incremental innovation, but these innovations are not proximate to other policy-triggered patents.

Table 3.6: Composition of Co-inventors and Citations

Dependent Variables:	# Foreign Collaborators	Self Citations	Other Citations	China Citations Citations	Self Citations Cumulative	Other Citations Cumulative	China Citations Cumulative
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Government Support	0.343***	0.614***	0.289***	0.276*	0.323***	0.169***	0.339***
	(0.031)	(0.127)	(0.049)	(0.157)	(0.059)	(0.023)	(0.063)
Patent Stock	0.002***	0.004***	0.001***	0.002***	0.004***	0.0005***	0.002***
	(0.0002)	(0.0010)	(0.0002)	(0.0006)	(0.0006)	(0.000)	(0.0003)
Team Size	0.137***	-0.015	-0.006*	-0.022**	-0.008	-0.004	-0.047***
	(0.018)	(0.014)	(0.004)	(0.011)	(0.007)	(0.003)	(0.006)
% Foreign Collaborator	1.82***	0.194*	0.061	-0.221	0.062	0.030	-0.057
	(0.082)	(0.105)	(0.077)	(0.232)	(0.054)	(0.043)	(0.137)
% Chinese Patents	0.138**	-0.357**	-0.113**	0.809***	-0.088	-0.103***	0.406***
	(0.064)	(0.153)	(0.055)	(0.098)	(0.071)	(0.032)	(0.032)
Government Support	-0.001***	-0.004***	-0.0009***	-0.002***	-0.001***	-0.0004***	-0.001***
$\times$Patent Stock	(0.0002)	(0.0005)	(0.0002)	(0.0004)	(0.0003)	(0.000)	(0.0002)
Fixed-effects							
Inventor	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	12,021	8,540	11,387	7,777	8,540	11,387	7,777
Squared Correlation	0.79629	0.50320	0.88383	0.58562	0.94290	0.98487	0.92222
Pseudo R^2	0.58411	0.34974	0.80952	0.47723	0.77017	0.96239	0.81059
BIC	72,218.0	28,579.5	93,514.0	23,974.8	35,953.1	118,142.3	28,707.2

Clustered (City) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

We further restricted the sample by examining the assignees of the patents throughout our observation window to address the concern that the effect might be an outcome of overseas hiring. In Table 3.8, we created a dummy *US Employee*, which equals 1 for inventors located in the US who had at least one patent assigned to a US-based corporate or research institute. This dummy variable captures the case when inventors were not

Table 3.7: Text Similarity Between Patents and Citations

Dependent Variables:	Text Similarity	Text Similarity with Policy Patents	Text Similarity with None-Policy Patents
Model:	(1)	(2)	(3)
Variables			
Government Support	0.021*	-0.028	0.024**
	(0.013)	(0.167)	(0.010)
Patent Stock	-0.0003**	0.002	-0.0002***
	(0.0001)	(0.002)	(0.000)
Team Size	-0.005	0.015	-0.005
	(0.003)	(0.057)	(0.003)
% Foreign Collaborators	0.0005	-0.052	0.011
	(0.023)	(0.103)	(0.014)
% Chinese Patents	0.010	0.300	0.006
	(0.018)	(0.191)	(0.012)
Fixed-effects			
Inventor	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	2,358	276	2,338
Squared Correlation	0.58331	0.70631	0.56525
Pseudo R^2	-0.58152	2.0417	-0.44646
BIC	319.01	574.98	-414.36

Clustered (inventor) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

employees of Chinese corporations overseas during their entire careers, which ensures they have local networks and the knowledge spillovers have potential economic impact among US firms and inventors. The results obtained are similar to those in Table 3.4, and the interaction term is not significant. This indicates that there is no difference between the two types of inventors. To visually represent these findings, we have included Figure 3.4 and Figure 3.5, which replicates the main results with US employees only sample. The results clearly demonstrate that for inventors who have contributed to US-based corporations at some point in their careers, their innovation output increases following the Chinese policy shock. Furthermore, compared to the findings depicted in Figure 3.1 and Figure 3.2, the effect is similar. Moreover, in Table C.2 in Appendix, we interact government support with dummy variable *Chinese Research*, which equals 1 if collaborating patent is assigned to Chinese research universities. Although Chinese universities in the policy intervented cities do not enjoy certain kinds of benefits such as tax credits, they do enjoy other policies such as merit-based rewards and public infrastructure support. However, they do not hire overseas employees before or after the shock. If the impact is an outcome of overseas hiring, we should be able to observe the heterogeneity across US inventors associated with Chinese universities and those associated with Chinese firms. However, the interaction is not significant at 5% level.

Another concern is the potential bias resulting from corporate actively selecting productive and promising inventors to collaborate with, while ambitious inventors may also approach eligible Chinese firms to gain additional research support. This reverse selection could lead to an upward bias in the estimated effects. In order to address this endogeneity issue, in Table 3.9, we restrict the treatment sample to long-term inventors who had established collaboration relationships prior to the first-round policy shock and the first-round roll-out firms.

However, it is uncommon for Chinese corporations to file patents in the U.S. with foreign inventors prior to the policy, resulting in a relatively small sample size compared to

Table 3.8: US Employees Interaction Results

Dependent Variables:	# of Collaborators	# of Patents	# of Citations	Cumulative # of Citations
Model:	(1)	(2)	(3)	(4)
Variables				
Government Support	0.180***	0.152**	0.148**	0.081***
	(0.052)	(0.077)	(0.064)	(0.029)
Team Size	0.143***	0.0008	-0.003	-0.003
	(0.021)	(0.010)	(0.003)	(0.003)
% Foreign Collaborator	0.602***	0.242***	0.076	0.030
	(0.069)	(0.075)	(0.077)	(0.041)
% Chinese Patents	0.458***	0.216***	-0.062	-0.065*
	(0.067)	(0.055)	(0.061)	(0.037)
Government Support	-0.028	0.118	-0.035	-0.010
× US Employee	(0.060)	(0.111)	(0.104)	(0.068)
Fixed-effects				
Inventor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	12,194	12,194	11,620	11,620
Squared Correlation	0.75964	0.57417	0.87749	0.98224
Pseudo R^2	0.53132	0.41845	0.81155	0.96243
BIC	81,318.2	71,853.4	98,869.7	126,835.3

Clustered (city) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

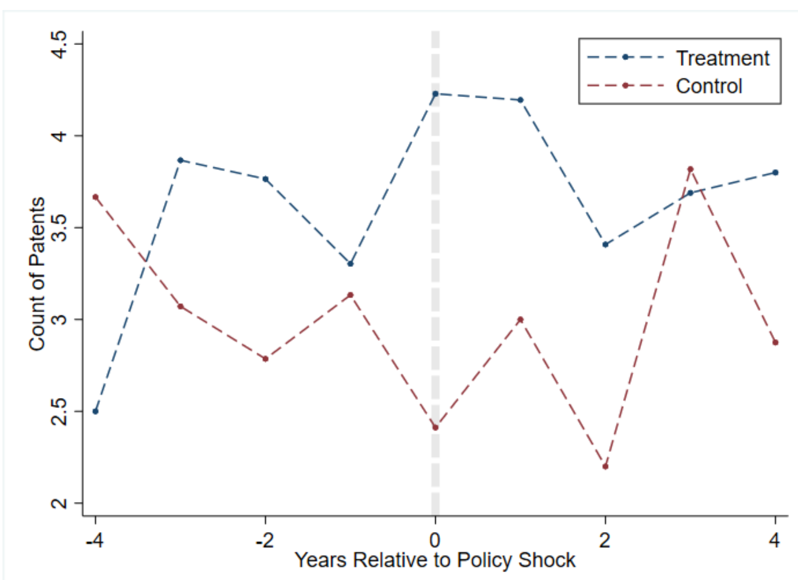


Figure 3.4: # of Patents for US Employees

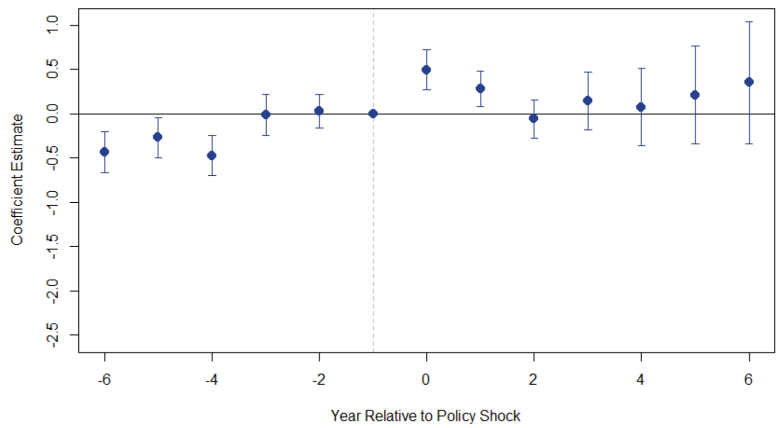


Figure 3.5: Estimate of Coefficients for US Employees

our main models. In columns (1) and (2), we find a significant effect of Chinese government support on the quantity of innovative activities. In columns (3) and (4), we report the quality of inventors also benefits from the exotic government support to catch up and enhance their collaborative activities and innovation output.

Table 3.9: Long Term Inventors Only

Dependent Variables:	# of Collaborators	# of Patents	d# of Collaborators	# of Patents
Model:	(1)	(2)	(3)	(4)
Variables				
Government Support	0.153**	0.153*	0.121**	0.068**
	(0.060)	(0.092)	(0.060)	(0.028)
Team Size	0.140***	0.002	-0.004	-0.003
	(0.021)	(0.009)	(0.003)	(0.003)
% Foreign Collaborators	0.622***	0.251***	0.058	0.022
	(0.060)	(0.061)	(0.074)	(0.040)
% Chinese Patents	0.482***	0.254***	-0.048	-0.060*
	(0.082)	(0.067)	(0.062)	(0.036)
Fixed-effects				
Inventor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	10,284	10,284	10,020	10,020
Squared Correlation	0.74161	0.57387	0.87535	0.98285
Pseudo R^2	0.52979	0.41854	0.80629	0.96253
BIC	68,333.6	59,975.2	88,649.6	113,778.1

Clustered (city) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

3.5 Discussion and Conclusion

Knowledge spills imperfectly among regions, and how to overcome the localization of the knowledge spillovers is a critical research question and policy decision concern. Through a policy-evaluation view, we conceptualize government support as an opportunity for domestic firms to adventurously search for knowledgeable foreign workers and build connections. We first argue that government support from other countries can be a signal for the treated inventors as reliable and outstanding potential partners. We then show that as these inventors recombine the distant knowledge, they tend to be more productive and desirable in terms of the value of the patents. Finally, we examine the heterogeneity of the inventors to investigate who benefits more from the cross-border policy shock.

Using rich inventor-level data from USPTO, we find strong support for our predictions. Importantly, in this setting, we leverage a staggered policy intervention that provides cash rewards to make the innovation less costly and more accessible. Leveraging this exogenous as a quasi-natural experiment, we find that even foreign inventors are more likely to indirectly benefit from the policy by forming more collaborators and increasing productivity. Finally, our effects are amplified among inventors with fewer patent stocks.

This study offers evidence for the literature in several ways. Firstly, it examines the role of government support from an international business perspective. As globalization processes, any local economic innovative capacity development may be impacted by other regions. The unintended consequence of such policies can ultimately stimulate local inventors to access a unique pool of recombinant knowledge, leading to enhanced innovation outcomes. Secondly, this study helps inform the mixed literature on the effects of government subsidies. A major push-back of public subsidies is that they may crowd out private funding, and we show that it has a positive side-effect on building networks which may hedge the negative influence of the financial crowd out.

Finally, our findings have important implications for future research. First, this study does not distinguish the heterogeneity of the industries. As the industry-specific technology gap between the two countries is related to the reason for cross-border collaboration, the heterogeneity across industries may greatly impact the effect of cross-border learning. If the gap is small, learning might be much easier but less valuable. However, if the gap is huge, inventors might not be able to absorb useful knowledge. Therefore, the nature of the industry may have a subsequent impact on the value of signal and learning. Second, future studies could delve into the identity of foreign inventors and examine whether the results differ based on whether the focal inventors work for companies or research institutes. Due to the limited practice of Chinese firms patenting overseas before 2008, we observe few patents with foreign inventors and Chinese assignees prior to the policy intervention. Moreover, even after 2008, most foreign inventors are somehow associated with Chinese corporations. Consequently, our sample size is not large enough to observe collaborations between firms in one country and scholars from universities in another country. Given that industry-university collaborations often commercialize the most advanced technologies, such collaborations deserve significant attention. Therefore, it would be beneficial to obtain data from other countries with a long history of overseas product market presence and patenting.

Appendices

APPENDIX A

USER REVIEWS ON PRODUCT DEVELOPMENT

Table A.1: OLS - Different Lag Use

	(1)	(2)	(3)	(4)	(5)	(6)
	$Update$	$Update$	$Update$	$Update$	$Update$	$Update$
Promotion	0.094***	-0.053***	0.093***	-0.053***	0.093***	-0.053***
	(0.016)	(0.009)	(0.016)	(0.009)	(0.016)	(0.009)
Age	-0.011***	-0.006***	-0.011***	-0.006***	-0.011***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ratings	-0.159***	-0.146***	0.078	0.060	-0.161***	-0.148***
	(0.044)	(0.043)	(0.048)	(0.044)	(0.043)	(0.042)
log (Owner)	-0.041***	-0.034***	-0.042***	-0.034***	-0.040***	-0.033***
	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)
log (Users)	0.036***	0.027***	0.034***	0.024**	0.038***	0.028***
	(0.011)	(0.010)	(0.012)	(0.010)	(0.011)	(0.010)
log (Reliability)	0.007	0.005	0.014	0.048	-0.008	-0.012
	(0.008)	(0.008)	(0.033)	(0.032)	(0.011)	(0.011)
log (Design)	0.016*	0.011	0.099***	0.054*	0.014	0.012
	(0.009)	(0.009)	(0.032)	(0.030)	(0.012)	(0.011)
*log (Reliability) * Ratings*			-0.009	-0.053		
			(0.040)	(0.038)		
*log (Design) * Ratings*			-0.098***	-0.049		
			(0.037)	(0.034)		
*log (Reliability) * Firm*					0.035**	0.039**
					(0.016)	(0.016)
*log (Design) * Firm*					0.008	0.001
					(0.018)	(0.017)
Game & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Lag	1 Month	2 Months	1 Month	2 Months	1 Month	2 Months
R^2	0.137	0.122	0.141	0.125	0.140	0.124

Standard errors in parentheses, clustered at game level
* p¡0.10, ** p¡0.05, *** p¡0.01

Table A.2: Robustness Check - Adding Lag

	(1)	(2)	(3)	(4)
	$Update_{t+1}$	$Update_{t+1}$	$Update_{t+1}$	$Update_{t+1}$
$Promotion_t$	0.094***	0.095***	0.094***	0.095***
	(0.016)	(0.016)	(0.016)	(0.016)
Age_t	-0.011***	-0.011***	-0.011***	-0.010***
	(0.001)	(0.002)	(0.001)	(0.002)
$Ratings_t$	-0.164***	-0.257***	-0.159***	-0.252***
	(0.045)	(0.066)	(0.044)	(0.065)
$log(Owner_t)$	-0.039***	-0.033***	-0.041***	-0.034***
	(0.009)	(0.009)	(0.009)	(0.009)
$log(Users_t)$	0.028**	0.023	0.036***	0.029**
	(0.012)	(0.015)	(0.011)	(0.014)
$log(Count_t)$	0.033***	0.031**		
	(0.009)	(0.012)		
$log(ReliabilityCount_t)$			0.007	0.007
			(0.008)	(0.011)
$log(DesignCount_t)$			0.016*	0.016
			(0.009)	(0.012)
$Ratings_{t-1}$		0.124***		0.121***
		(0.039)		(0.039)
$log(Owner_{t-1})$		0.030		0.032
		(0.020)		(0.020)
$log(Users_{t-1})$		-0.002		-0.007
		(0.009)		(0.009)
$log(Count_{t-1})$		-0.016*		
		(0.009)		
$log(ReliabilityCount_{t-1})$				-0.002
				(0.008)
$log(DesignCount_{t-1})$				-0.009
				(0.008)
Time FE	Yes	Yes	Yes	Yes
Game FE	Yes	Yes	Yes	Yes
AIC	8927.440	8487.161	8934.525	8491.203
BIC	9099.716	8688.768	9114.290	8707.743

Standard errors in parentheses, clustered at game level

* p¡0.10, ** p¡0.05, *** p¡0.01

Table A.3: OLS - Interaction of Game Features

	(1)	(2)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Update	*Update*	*Update*	*Update*	*Update*	*Update*	*Update*	*Update*	*Update*	*Update*
log (Reliability)	0.007	-0.012	0.010	0.009	0.004	0.014	-0.001	0.009	0.011	0.014
	(0.008)	(0.022)	(0.011)	(0.013)	(0.010)	(0.009)	(0.011)	(0.010)	(0.009)	(0.009)
log (Design)	0.016*	0.023	0.010	0.0001	0.015	0.018*	0.024**	0.016	0.011	0.012
	(0.009)	(0.023)	(0.011)	(0.014)	(0.011)	(0.010)	(0.012)	(0.010)	(0.010)	(0.010)
*Game Feature**		0.025	-0.006	-0.003	0.016	-0.026	0.021	-0.007	-0.019	-0.073***
log (Reliability)		(0.023)	(0.016)	(0.017)	(0.017)	(0.020)	(0.017)	(0.017)	(0.021)	(0.024)
*Game Feature **		-0.009	-0.010	0.025	0.008	-0.007	-0.022	-0.000	0.035	0.036
log (Design)		(0.025)	(0.016)	(0.017)	(0.019)	(0.021)	(0.016)	(0.022)	(0.024)	(0.030)
Game Feature		Singleplayer	Multiplayer	Action	RPG	Simulation	Adventure	Casual	Stargegy	Racing
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Game FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13230	13230	13230	13230	13230	13230	13230	13230	13230	13230

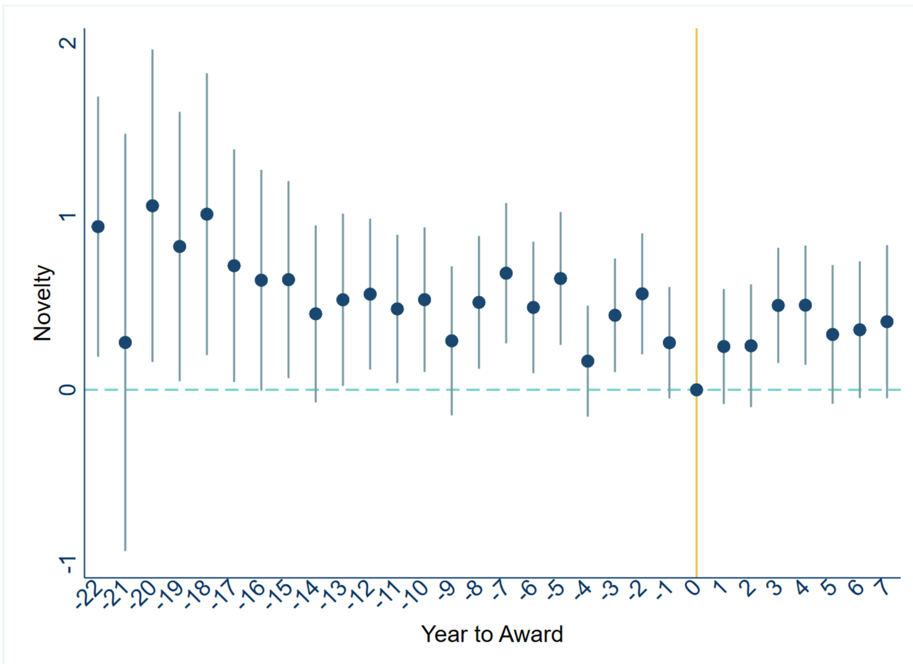
Standard errors in parentheses, clustered at game level

* p¡0.10, ** p¡0.05, *** p¡0.01

APPENDIX B

NOVEL AND NOVELTY

Figure B.1: Event Study



APPENDIX C

INNOVATION CITY

Table C.1: Innovative Cities in China by 2017

Index	Province	City	Policy Year	Index	Province	City	Policy Year
1	Guangdong	Shenzhen	2009	32	Shaanxi	Xi'an	2010
2	Anhui	Hefei	2010	33	Shandong	Jinan	2010
3	Beijing	Beijing	2010	34	Shandong	Qingdao	2010
4	Chongqing	Chongqing	2010	35	Shandong	Yantai	2010
5	Fujian	Fuzhou	2010	36	Shanghai	Shanghai	2010
6	Fujian	Xiamen	2010	37	Shanxi	Taiyuan	2010
7	Gansu	Lanzhou	2010	38	Sichuan	Chengdu	2010
8	Guangdong	Guangzhou	2010	39	Tianjin	Tianjin	2010
9	Guangxi	Nanning	2010	40	Xinjiang Uygur	Changji Hui	2010
10	Guizhou	Guiyang	2010	41	Xinjiang Uygur	Shihezi	2010
11	Hainan	Haikou	2010	42	Yunnan	Kunming	2010
12	Hebei	Shijiazhuang	2010	43	Zhejiang	Hangzhou	2010
13	Hebei	Tangshan	2010	44	Zhejiang	Jiaxing	2010
14	Heilongjiang	Harbin	2010	45	Zhejiang	Ningbo	2010
15	Henan	Luoyang	2010	46	Hebei	Qinhuangdao	2011
16	Henan	Zhengzhou	2010	47	Jiangsu	Lianyungang	2011
17	Hubei	Wuhan	2010	48	Jiangsu	Zhenjiang	2011
18	Hunan	Changsha	2010	49	Nei Mongol	Hohhot	2011
19	Jiangsu	Changzhou	2010	50	Jiangsu	Nantong	2012
20	Jiangsu	Nanjing	2010	51	Xinjiang Uygur	Urumqi	2012
21	Jiangsu	Suzhou	2010	52	Guizhou	Zunyi	2013
22	Jiangsu	Wuxi	2010	53	Henan	Nanyang	2013
23	Jiangxi	Jingdezhen	2010	54	Hubei	Xiangfan	2013
24	Jiangxi	Nanchang	2010		(Renamed to Xiangyang after 2010)		
25	Jilin	Changchun	2010	55	Hubei	Yichang	2013
26	Liaoning	Dalian	2010	56	Jiangsu	Taizhou	2013
27	Liaoning	Shenyang	2010	57	Jiangsu	Yancheng	2013
28	Nei Mongol	Baotou	2010	58	Jiangsu	Yangzhou	2013
29	Ningxia Hui	Yinchuan	2010	59	Jiangxi	Pingxiang	2013
30	Qinghai	Xining	2010	60	Shandong	Jining	2013
31	Shaanxi	Baoji	2010	61	Zhejiang	Huzhou	2013

Table C.2: Interaction with Chinese Organization Features

Dependent Variables:	# of Collaborators	# of Patents	# of Citations	Cumulative # of Citations
Model:	(1)	(2)	(3)	(4)
Variables				
Government Support	0.163***	0.132*	0.163**	0.101***
	(0.052)	(0.073)	(0.080)	(0.035)
Team Size	0.142***	-0.001	-0.004	-0.004
	(0.024)	(0.012)	(0.004)	(0.004)
% Foreign Collaborators	0.537***	0.189***	0.002	-0.014
	(0.035)	(0.053)	(0.039)	(0.021)
% Chinese Patents	0.419***	0.190***	-0.114**	-0.099***
	(0.067)	(0.064)	(0.057)	(0.034)
Government Support	-0.012	0.163	0.052	-0.016
× Chinese Research	(0.043)	(0.100)	(0.175)	(0.116)
Fixed-effects				
Inventor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	10,570	10,570	10,053	10,053
Squared Correlation	0.75748	0.56660	0.87883	0.98249
Pseudo R^2	0.51792	0.41685	0.80717	0.96115
BIC	69,858.6	62,416.7	83,072.5	106,289.8

Clustered (city) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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