INNOVATION, PRODUCT QUALITY, COMPLEXITY, AND DURATION OF INTERNATIONAL TRADE

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INNOVATION, PRODUCT QUALITY, COMPLEXITY, AND DURATION OF INTERNATIONAL TRADE

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SUMMARY

Factors affecting products arrive and duration in international market are examined. Intellectual property rights (IPR) and innovation are suggested to influence exports of new products. Product quality and complexity are suggested to impact duration of trade relationships by theories. Trade data are collected from UN Comtrade and Feenstra et al (2002). Results indicate that IPR protection increases the number of new products exported to U.S. for poor countries. In addition, products with higher quality have longer trade duration and larger trade growth. More complex goods are more likely to survive than simple goods. Findings suggest that technology and innovation play an important role determining trade patterns.

CHAPTER 1

INTELLECTUAL PROPERTY RIGHTS, INNOVATION, AND EXPORTS

1.1 Introduction

Although the impact of intellectual property rights (IPR) protection has been intensively debated for many years, an agreement on Trade-Related Aspects of Intellectual Rights (TRIPs) was reached only in 1994. Although many countries have significantly increased their IPR protection the debate continues. Proponents of IPR protection argue that lax enforcement in destination countries hurts the profits of an innovator and reduces exports from an innovating country. Therefore, to promote international trade, destination countries and particularly developing countries should increase their IPR protection. Opponents, however, assert that more stringent IPR would strengthen monopoly power of innovators who would reduce their exports in order to charge higher prices. Both the theoretical and empirical literature examine how IPR protection of developing destination countries affects their imports from developed innovator countries. Thus, the literature has largely focused on the presumption that developed countries are the only innovators and has investigated the effect of destination country's IPR protection on developed country exports, either to other developed or developing countries. In this paper we offer a different perspective on this issue and examine the effect of stronger IPR protection of exports of all countries, including developing ones, an issue few, if any, studies have addressed.

We investigate how own IPR protection affects innovation and exports. Numerous papers examine whether intellectual or patent rights of trade partners affect exports of sourcing countries, especially exports from developed to developing countries. However, these studies do not consider the impact of strengthening of own IPR on own exports. The potential consequences of strengthening IPR include but are not limited to stimulating domestic innovation (Chen and Puttitanun 2005) and expanding inward technology transfers and foreign direct investment (Branstetter et al. 2011). Branstetter et al. (2011) also found that after reforming IPR countries increase the number of new products exported to the United States.

Another strand of the literature examines the link between innovation and international trade. The Krugman (1979) model predicts that innovation could introduce new products or expand the variety of products. Since Krugman (1979) many studies have explored the effect of innovation on exports of new products. Other studies have examined the role of innovation in product quality or productivity (Grossman and Helpman, 1991a, 1991b; Eaton and Kortum, 2001, 2002). However, to the best of our knowledge, this paper is the first to empirically investigate the link between own IPR protection and exports in terms of the number of new products and total value.

We use U.S. imports recorded at both the 10-digit HS and 2-digit SIC levels along with NBER patent data to examine three hypotheses. The first one states that strengthened IPR stimulates innovation. The second one states that strong IPR protection increases the number of new products exported, while the third one states that stronger IPR promotes aggregate exports. We treat joining the TRIPs agreement as an exogenous shock affecting intellectual property rights for all countries. We use the number of patents granted by the United States Patent and Trademark Office (USPTO) as a measure of innovation and the Ginarte and Park (1997) index (GP) as a measure of IPR protection. To take account of frequent changes of HS codes, we apply the Pierce and Schott (2012) algorithm to identify HS codes that were not affected by reclassifications.

We find that stronger IPR increases patenting in the U.S. In addition, stronger IPR increases the variety of exports to the U.S. for developing countries. We also find that both stronger IPR protection and innovation increase total exports. We conduct a number of robustness checks. First, we use data with original HS codes without accounting for their frequent changes. Second, we use citation-weighted patent counts rather than original counts. These results confirm our main findings. In addition, we find that both the effects of IPR on innovation and those of innovation on exports vary significantly across industries. For patent-sensitive industries, stronger IPR protection stimulates innovation and increases exports, but for patent-insensitive industries, neither effect is significant.

1.2 Implications of Intellectual Property Rights Protection

As discussed in Section 1.1, strengthened patent rights may attract more inward technology transfers and foreign direct investment (FDI). This may in turn improve exports by enhancing the productivity and the competitiveness of local firms. Yang and Maskus (2009) used a strategic two-firm and two-country model to analyze the export market involving IPR protection and found that strengthened IPR not only promotes technology spillovers from outside countries but also encourages domestic innovation. Chen and Puttitanun (2005) illustrated that innovation increases as IPR increases in developing countries. Local firms in developing countries might benefit from technology spillovers through FDI or licensing and domestic innovation because of strengthened IPR protection. Based on the above analysis, we formulate three testable hypotheses:

1. Stronger IPR protection stimulates domestic innovation activities.

2. Stronger IPR protection increases the variety of exported products.

3. Stronger IPR protection and innovation both increase total value of exports.

To examine the effect of intellectual property rights protection we use the Ginarte and Park (1997) measure. Their index is constructed in two steps. The first step entails assigning an index value, in the zero to one range in five dimensions: 1) coverage of patent protection, 2) membership in international patent agreements, 3) provisions for loss of protection, 4) enforcement mechanism, and 5) duration of patent term. The second step sums up these five measures to obtain the GP index, calculated every five years from 1960 to 2005. A higher value of GP index indicates stronger IPR protection. GP index of many countries increased significantly from 1990 to 1995, which is most likely due to many countries signing the TRIPs agreement in 1994. Therefore, we assume all countries have stronger IPR protection after 1994.

1.3 Data

Our empirical investigation relies on data on U.S. imports, standard gravity equation variables, data on openness and exchange rates, and data on innovation and patents.

1.3.1 Trade and related data

We use two types of U.S. imports data: 10-digit HS and 2-digit SIC data.[1] The former one provides U.S. imports from 1989 to 2006 recorded at the 10-digit HS level. These data are particularly useful to examine the growth within surviving products, the intensive margin, as well as products adding and dropping, the extensive margin. The other trade data set we use are U.S. imports from 1989 to 2005 recorded at the 2-digit SIC level. We use imports at the 2-digit level because patent data could only be linked to 2-digit SIC codes.

There are several issues to keep in mind with HS data. The HS classification is updated frequently for several reasons. For example, the World Custom Organization (WCO) makes adjustments to reflect technology developments, which this paper attempts to capture. Another example is that the U.S. Census may split a single HS code into several new codes in order to report trade data at a more detailed level. The U.S. Census can also replace several codes with a single one if the amount of trade does not warrant multiple codes to be maintained. Since we cannot disentangle these changes and to avoid potential bias caused by code changes, we utilize the Pierce and Schott (2012) concordance algorithm to track unchanged HS codes over the sample period. To make sure these are newly exported codes/products, we count them as new only in the second year in the data. For example, a particular HS code exported to the U.S. in 1990, 1992, 1993 from country i would be counted as a new product in 1992 not 1990. Our approach provides a lower bound for

[1] Both data sets come from Peter Schott's website,
http://faculty.som.yale.edu/peterschott/sub_international.htm

estimates of new product growth if they exist. Our approach can be thought of as requiring that a new product become somewhat entrenched in a country's export portfolio in order for it to be counted. We use the counts of new HS codes rather than trade volume because the emergence of new products reflects innovation better as the volume of trade in new products will always be small since there was no time to grow them. This also avoids the the partial year issue discussed by Bernard et. al. (2017).

Gravity variables come from the CEPII database, which provides the bilateral distance between countries and whether they share a common official language and a common border. The distance variable is defined by the distance between the capital cities of country i and the U.S. All continuous variables are used in log values. The openness and exchange rate come from the Penn World Table. The sample involving HS imports contains 159 countries. The SIC sample involving patents contains 57 countries in 12 2-digit manufacturing industries. The second sample has a small number of countries because patent data and GP indices of some countries and industries are not available for all years. The data set is an unbalanced panel data due to missing values.

1.3.2 GP index and patent data

The GP index comes from Ginarte and Park (1997) and Park (2008). To be consistent with trade data, we focus on GP index data from 1990-2005. Since R&D expenditure data are very limited, we use the number of patent applications filed with the USPTO to measure innovation. In addition, R&D expenditures may be a better measure of inputs in the innovation process, while patent counts more appropriately reflect output of the innovation process. Patent data come from the NBER patent database compiled by Hall et al. (2001). The NBER patent data set consists of detailed information about patents granted by the USPTO between 1976 and 2006 such as patent classes, the unique assignee number, the original country, the application year, and the grant year.

Using NBER patent data we must address several issues. One is that since the patent classification system differs from the industry classification system, we need to match patent classes with SIC codes in order to match patent data with trade data. The USPTO has developed a concordance for these two classifications, in which each patent class has one or more corresponding 2- or 3-digit SIC code(s). Because we cannot expand two digits to three, we collapse the patent classes into 12 two-digit SIC industries. For patent classes with multiple corresponding SIC industries, we assign equal weights to each industry. For example, if one patent class has three corresponding SIC industries, then each industry has one-third of the patent count. We apply a different weighting scheme as a robustness check.

Another issue is that some researchers argue that patent counts do not reflect innovation precisely and argue in favor of using citation-weighted patent counts. Because the relative importance of patents is not determined by IPR protection, we use non-citation-weighted patent counts as a proxy of innovation and the results do not vary significantly. Finally, the patent has two indices of time: the application year and the grant year. Because the innovation took place in the year the patent was applied for not the year in which it was granted, we use the application year rather than the grant year.

1.4 Impact of IPR on Exporting and Patenting of New Products

1.4.1 Specifications

We examine how intellectual property right protection affects exports of new products first. Since most countries strengthened their IPR protection after 1994 when the TRIPs agreement was reached, we treat this agreement as an exogenous shock to intellectual property rights for all countries and compare the number of newly exported varieties before and after 1994. The specification follows Branstetter et al. (2011), but we create a different dummy variable, $post94$ for all countries, which is equal to one if the year is greater or equal to 1994 and zero otherwise. This variable differs from Branstetter et al. (2011) who use a dummy variable for 16 IPR reforming countries. The specification we use is:

$$\begin{aligned} product\_count_{it} = \beta_0 + \alpha_i + \gamma_t + \beta_1 post94 + \beta_2 lnopenness_{it} + \beta_3 lnGDPPC_{it} \\ + \beta_4 lnexchange\_rate_{it} + \epsilon_{it} \end{aligned} \tag{1.1}$$

where the dependent variable $product\_count_{it}$ is defined as the number of new products exported to the U.S. from country i in year t; α_i and γ_t are country and year fixed effects, respectively; $openness_{it}$ denotes the ratio of total trade value, the sum of imports and exports, over GDP for country i in year t; and $GDPPC_{it}$ and $exchange\_rate_{it}$ are real value of GDP per capita and the exchange rate (foreign currency per $1), respectively. The variable we are interested is $post94$, which indicates stronger IPR since 1994, and we expect that it has a positive effect on the number of new products. Because rich countries export a much higher number of products than the poor countries, we expect some variations across countries and divide the sample into two sub-samples: OECD and non-OECD countries.

If foreign countries do export more new products to the U.S., and if these changes are the consequence of stronger IPR, then this would also be reflected partially by the number of patents applied by foreign countries in the U.S because exporters want to obtain protection for these new goods. The patent specification is:

$$\begin{aligned} lnPatent_{it}^{j} = \beta_0 + \alpha_{ij} + \beta_1 lnGPindex_{it} + \beta_2 lnopenness_{it} + \beta_3 lnGDPpc_{it} \\ + \beta_4 lnexchange\_rate_{it} + \epsilon_{it}^{j} \end{aligned} \tag{1.2}$$

where the dependent variable $Patent_{it}^{j}$ represents the number of patents of country i in industry j applied for in the U.S. in year t; $GPindex_{it}$ measures IPR protection in country i in year t; and α_{ij} is country-industry pair fixed effects. All other variables are the same as in equation (1.1). Here we use the GP index rather than the dummy variable, $post94$, because we want to compare the number of products exported before and after 1994 in equation (1.1), but in equation (1.2) we want to capture how the number of patents changes as IPR protection changes. In addition, we do not include year fixed effects because there are many observations with either zero or few patent applications in consecutive years at the industry level which leads to small variations.

1.4.2 Results

Since the dependent variables of equations (1.1) and (1.2) are count variables, we use both Poisson and the log-linear regressions. The results of estimating equations (1.1) and (1.2) are presented in Tables 1.1 and 1.2, respectively.

From Table 1.1 we find that in both specifications, only non-OECD countries benefit from strengthened IPR protection resulting from joining the TRIPs agreement. The coefficients of $post94$ are positive and significant in two models for non-OECD countries (Poisson regression is significant at the 10 percent level). The interpretation is that an average increase in the number of new products exported to the U.S. after 1994 is about 1.28 and 1.53 per year in the two specifications. The negative coefficients for the OECD countries are possibly due to two reasons. One is that these countries already have very strong IPR protection before 1994 and the main target of the TRIPs agreement are developing countries. In addition, OECD countries already export a large variety of products, making it difficult for them to export additional ones (since they may not be able to produce the ones they are not exporting, for example).[2] This result is robust to splitting the sample into four groups by GDP per capita and the coefficients of $post94$ are positive and significant only for least-developed and lower-middle income countries as we show below.

Table 1.2 provides the results of estimating equation (1.2). Here we use OLS as the baseline model because some patents are assigned to multiple industries and result in non-integer patent counts. In these cases, we assign equal weights for each industry. For example, if a patent is assigned to 3 industries, then each industry has one-third of the patent. The results show that the higher GP index is associated with more patent applications in the

[2] See Table 2 in Besedeš and Prusa (2011).

Table 1.1: Impact of IPR on exports of new products

	Poisson (count)			OLS (Log(count))		
Variables	All	Non-OECD	OECD	All	Non-OECD	OECD
post94	-0.517***	0.250*	-1.886***	0.129	0.428***	-1.888***
	(0.168)	(0.128)	(0.290)	(0.0898)	(0.0887)	(0.181)
lnopenness	-0.315**	-0.0627	-0.0227	-0.144	0.0646	-0.281
	(0.158)	(0.146)	(0.332)	(0.0982)	(0.103)	(0.216)
lnGDPPC	0.232	-0.409*	1.947***	0.0730	0.0386	2.503***
	(0.252)	(0.236)	(0.553)	(0.0974)	(0.0985)	(0.274)
lnexchange	0.160**	0.0139	0.382***	0.0776***	0.0301*	0.404***
	(0.0813)	(0.0514)	(0.0610)	(0.0179)	(0.0169)	(0.0414)
Constant				4.813***	3.940***	-18.63***
				(1.055)	(0.906)	(2.599)
Country FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	2,454	1,946	508	2,434	1,926	508
R^2				0.904	0.894	0.758
Number of countries	160	128	32			

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.2: Impact of IPR on patents

	Poisson (count)			OLS (Log(count))		
Variables	All	Non-OECD	OECD	All	Non-OECD	OECD
lnGPindex	7.329***	0.638	8.725***	0.906***	0.140	0.894***
	(1.606)	(0.527)	(1.770)	(0.212)	(0.229)	(0.403)
lnopenness	-3.636***	-0.736	-4.143***	-1.411***	0.00292	-3.373***
	(0.779)	(1.248)	(0.814)	(0.319)	(0.514)	(0.373)
lnGDPPC	1.471	0.663	1.735	-0.0169	0.197	-0.112
	(1.090)	(1.550)	(1.118)	(0.400)	(0.724)	(0.441)
lnexchange	1.419***	0.0709	1.678***	0.146***	0.0201	3.236***
	(0.300)	(0.0651)	(0.305)	(0.0338)	(0.0314)	(0.240)
Constant	-8.325	-2.866	-11.63	5.826***	-0.432	15.72***
	(8.577)	(10.59)	(9.559)	(3.144)	(5.707)	(3.915)
Country-industry FE	Y	Y	Y	Y	Y	Y
Observations	1,135	268	867	1,135	268	867
R^2				0.821	0.695	0.853

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

U.S. for all countries. However, this effect varies between OECD and non-OECD country. Specifically, the number of patents would increase by 0.894% as the GP index increases by 1% for OECD countries. For non-OECD countries, the GP index does not have a significant effect on patent applications in either specification. Poisson regressions indicate that the GP index has no significant effect on patent applications for non-OECD countries. For OECD countries in Poisson models, the coefficient of the GP index is positive and significant, but implausibly large, indicating that Poisson model may not be appropriate for the OECD sample. These findings suggest that stronger IPR protection stimulates innovation only for rich countries. Therefore, inward technology transfers may be the main channel of increasing exports of new products for poor countries.

1.5 The Effects of IPR and Patents on Total Exports

1.5.1 IPR and exports

In the above section, we found evidence of intellectual property rights protection increasing exports of new products. In this section, we move further to examine the impact of IPR on total exports. We estimate a gravity equation using the following specification:

$$\begin{aligned} lnexports_{it}^{j} &= \theta_0 + \theta_1 lnGPindex_{it} + \theta_2 lndist_i + \theta_3 language_i \\ &\quad + \theta_4 border_i + \theta_5 lnGDPPC_{it} + \theta_6 lnpop_{it} + \theta_i + \gamma_j + \delta_t + \epsilon_{it}^{j} \end{aligned} \tag{1.3}$$

where $exports_{it}^{j}$ represents the total value of exports to the U.S. from country i in industry j at year t; pop_{it} is the population of country i at year t; $dist_i$ is the distance of capital cities between country i and the U.S; $language_i$ and $border_i$ are dummy variables, which represent whether country i shares a common official language and a border with the U.S., respectively; and θ_i, γ_j, and δ_t are country, industry, and year fixed effects, respectively. Since the GP index is calculated every 5 years, we use data in 5-year intervals for estimation.

Table 1.3: Impact of IPR on total exports

	Baseline (OLS)			OLS	OLS	FE
Variables	All	Non-OECD	OECD	All	All	All
lnGPindex	0.576***	1.007***	1.118***	0.602***	5.436***	0.511***
	(0.277)	(0.416)	(0.281)	(0.285)	(1.075)	(0.138)
lnpop	1.372*	2.306	2.321***	1.179	2.939***	1.306***
	(0.744)	(3.566)	(0.457)	(0.753)	(0.752)	(0.403)
lnGDPPC	0.188	0.136	0.189	0.186	0.631	0.208
	(0.251)	(0.514)	(0.169)	(0.251)	(0.378)	(0.129)
lndist	-3.281***	-3.553	-24.12***	-2.846***	-1.488	
	(0.602)	(2.614)	(4.232)	(0.574)	(0.913)	
language	1.947***	1.481	14.52***	1.590***	-1.356	
	(0.353)	(1.179)	(2.599)	(0.313)	(0.847)	
border	-1.033		-29.14***	-0.413	-1.551	
	(1.349)		(5.857)	(1.349)	(1.051)	
Constant	24.65***	24.40**	211.2***	21.19***	-3.618	-2.605
	(2.627)	(11.65)	(37.78)	(2.465)	(9.730)	(1.632)
Country Dummy	Y	Y	Y	Y	N	N
Year Dummy	Y	Y	Y	Y	N	Y
Industry Dummy	Y	Y	Y	N	Y	N
Country-year Dummy	N	N	N	N	Y	N
Country-industry FE	N	N	N	N	N	Y
Observations	1,829	413	1,416	1,829	1,829	1,829
R^2	0.776	0.758	0.792	0.682	0.811	0.743

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.3 presents the results of the impact of IPR on total exports. Column 1 shows the result of equation (1.3) representing the baseline model for all countries. The results indicate that the GP index has a positive and significant effect on exports: exports would increase by 0.576% if the GP index increases by 1%. This positive effect is true for both non-OECD and OECD countries as indicated in Column 2 and 3. Columns 4-6 use alternative fixed effects, and their results are robust except in Column 5 the effect of GP index is much bigger than that in the baseline model and all gravity variables become insignificant. Population has a positive effect on exports which suggests that the exporter's market size of may matter, though the effect is not always precisely estimated. GDP per capita seems to have no effect on exports, which is possibly due to the correlation with population. Distance and common language have expected signs and effects on exports. The coefficient on common border is negative, but is not statistically significant. These findings indicate that strengthened IPR promotes total exports, which is important for policy makers. Increasing IPR protection may be a useful tool to encourage growth of exports particularly for lower IPR protection countries.

1.5.2 Patents and exports

Besides the impact of intellectual property rights protection on exports, innovation might influence exports too. Therefore, we examine whether patents, a measure of innovation, affect total exports. The specification is the same as equation (1.3) but we use the number of patents replacing the GP index. To be consistent with equation (1.3), we also use data for five-year panels to fit the model.

Table 1.4 presents the impact of patents on exports. Column 1-3 are baseline models. The coefficient on patents in Column 1 indicates that exports would increase by about 0.472% as patents increase by 1% in both specifications. The effect of patents on exports is positive and significant for both non-OECD and OECD countries, and the magnitude is larger for non-OECD countries as shown in Column 2 and 3. The results of Column 4,

Table 1.4: Impact of patents on exports

	Baseline (OLS)			OLS	OLS	FE
Variables	All	Non-OECD	OECD	All	All	All
lnpatent	0.472***	0.709***	0.417***	0.465***	0.660***	0.115***
	(0.0661)	(0.127)	(0.0642)	(0.0520)	(0.104)	(0.0296)
lnpop	1.450*	0.0830	1.902**	1.405*	5.708***	1.476***
	(0.773)	(4.023)	(0.775)	(0.777)	(0.142)	(0.392)
lnGDPpc	-0.117	0.104	-0.454	-0.0664	-1.693***	0.230*
	(0.317)	(0.568)	(0.321)	(0.309)	(0.247)	(0.128)
lndist	-2.335***	-1.115	-22.28***	-2.426***	-6.552***	
	(0.648)	(2.720)	(6.651)	(0.588)	(0.488)	
language	0.975***	0.239	13.44***	1.150***	3.436***	
	(0.454)	(1.193)	(4.056)	(0.369)	(0.434)	
border	-0.470		-27.03***	-0.378	-5.147***	
	(1.434)		(9.229)	(1.405)	(0.511)	
Constant	19.36***	10.37	202.1***	18.92***	55.89***	-2.968*
	(2.757)	(11.59)	(58.93)	(2.543)	(6.018)	(1.642)
Country Dummy	Y	Y	Y	Y	N	N
Year Dummy	Y	Y	Y	Y	N	Y
Industry Dummy	Y	Y	Y	N	Y	N
Country-year Dummy	N	N	N	N	Y	N
Country-industry FE	N	N	N	N	N	Y
Observations	1,829	425	1,417	1,829	1,842	1,842
R^2	0.792	0.755	0.811	0.732	0.842	0.729

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

controlling for country and year fixed effects only, are similar to Column 1. In Column 5 we control for country-year pair and industry fixed-effects in which all coefficients are bigger than Column 1. The coefficient on patents in Column 6 is much smaller than in Columns 1 and 2, but is still highly statistically significant. Other variables have similar effects as in equation (3). Therefore, these findings show that patents have a robust positive and significant impact on exports although the coefficients are slightly smaller than IPR.

1.6 Robustness checks

1.6.1 Original HS codes

We use original 10-digit HS codes to check whether results in Table 1.1 depend on the particular way of dealing with changes in HS codes. Table 1.5 provides the results of equation (1.1) using original HS codes without applying the Pierce and Schott algorithm. We found that the main variable of interest, $post94$, has a smaller coefficient relative to Table 1.1 for non-OECD countries in the log-linear model, but is still positive and significant. However, for the Poisson model, the coefficient is significantly negative, which is possibly due to high initial conditions. In fact, the number of original HS codes in the first three years are much higher than in later years. Therefore, if we exclude the initial years (i.e. exclude years 1989-1991) in the Poisson model, then the coefficient of $post94$ becomes positive and significant, although the magnitude is much smaller than in Table 1.1. These findings indicate that results are robust and not determined by the way we utilize HS codes. In addition, we divide the sample into four groups according to the country development measured by GDP per capita. The results are consistent with Table 1.1 and Table 1.5, in the sense that the $post94$ variable has positive and significant effects only for least-developed and lower-middle income countries.

Table 1.5: Original HS codes

Panel A	Poisson(count)			
Variables	Non-OECD	Non-OECD91	OECD91	All91
post94	-0.0320**	0.0770***	-1.207***	-0.344***
	(0.0161)	(0.0167)	(0.0232)	(0.0129)
lnopenness	-0.0934***	-0.101***	-0.0547*	-0.368***
	(0.0158)	(0.0172)	(0.0289)	(0.0137)
lnGDPpc	-0.246***	-0.178***	1.154***	0.207***
	(0.0207)	(0.0226)	(0.0392)	(0.0196)
lnexchange	0.0287***	0.0419***	0.274***	0.154***
	(0.00304)	(0.00373)	(0.00812)	(0.00344)
Observations	1,992	1,882	479	2,361
Number of countries	128	128	32	160

Panel B	OLS(log(count))		
Variables	Non-OECD	OECD	All
post94	0.319***	-1.481***	0.0855
	(0.0857)	(0.115)	(0.0798)
lnopenness	-0.0613	-0.253*	-0.259***
	(0.0880)	(0.144)	(0.0843)
lnGDPpc	0.0270	1.591***	0.0425
	(0.0810)	(0.226)	(0.0838)
lnexchange	0.0505***	0.277***	0.0870***
	(0.0171)	(0.0261)	(0.0174)
Constant	5.088***	-8.572***	6.735***
	(0.746)	(2.186)	(0.903)
Observations	1,981	508	2,489
R^2	0.911	0.851	0.924

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All specifications include country and year fixed effects

1.6.2 Citation-weighted patents and exports

Some researchers argue that patent counts cannot reflect innovation activity precisely. The citation-weighted patents may be a better measure of innovation. We use Trajtenberg's (1990) citation-weighted patent counts instead of original patent counts, whose weighting scheme is the following: $wpatent_{jit} = \sum_{k}^{n_{jit}}(1 + g_k)$ where k represents a patent; g_k is the number of citations received by patent k; and n_{jit} is the number of patents issued to country j in industry i at year t. The result of weighted-patents on total exports is provided by Table 1.6. The findings are very similar to Table 1.4. Although magnitudes are slightly smaller than the baseline model, the effect of weighted-patents on exports is still significant. As weighted-patents increase by 1%, total exports would increase by 0.0815% to 0.318% depending on model selection. In addition, we also test the effect of GP index on weighted patents. The results are almost the same as in Table 1.2.

1.6.3 Estimates by industry

Responses of innovation and exports on IPR protection might vary significantly across industries. We use Poisson and OLS regressions to estimate these two effects industry by industry. Table 1.7 shows coefficients on GP index in three models by each industry: First two columns run regressions of patents on GP index using Poisson and log-linear estimators, respectively. The third one estimates the impact of GP index on total exports.[3] We find that for patent-intensive (by number of patents) industries in the Poisson regression (column 1), such as chemicals and allied products (SIC 28), industrial machinery and equipment (SIC 35), electrical and electronic equipment (SIC 36), and instruments and related products (SIC 38), GP index has a robust positive effect on the number of patent applications. For patent-insensitive industries, GP index has an insignificant effect on patent applications and even negative effects for some industries, such as food and kindred products (SIC 20) and stone, clay, glass and concrete products (SIC 32). In column 2, the results of log-linear

[3] The full tables are available upon request

Table 1.6: Citation-weighted patents

Variables	OLS	FE
lnwpatent	0.318***	0.0815***
	(0.0516)	(0.0285)
lnpop	1.463**	1.477**
	(0.729)	(0.647)
lnGDPpc	-0.0814	0.237
	(0.299)	(0.233)
lndist	-2.512***	
	(0.615)	
language	1.099***	
	(0.442)	
border	-0.589	
	(1.355)	
Constant	20.15***	-3.109
	(2.487)	(2.852)
Country Dummy	Y	N
Year Dummy	Y	Y
Industry Dummy	Y	N
Country-industry FE	N	Y
Observations	1,842	1,842
R^2	0.788	0.729

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.7: Impact of the GP index on patents and exports by industry

	Poisson	OLS	OLS
Dependent variable	# of patents	lnpatents	lnexports
Independent variable	lnGPindex	lnGPindex	lnGPindex
SIC 20 – Food and kindred products	-1.557*	-0.697	0.758**
	(0.798)	(0.624)	(0.310)
SIC 22 – Textile mill products	1.276	1.908*	0.463
	(1.260)	(1.082)	(0.986)
SIC 28 – Chemicals and allied products	1.544***	0.321	-0.00484
	(0.153)	(0.346)	(0.234)
SIC 29 – Petroleum and coal products	0.174	0.465	0.584
	(0.713)	(0.416)	(0.878)
SIC 30 – Rubber and miscellaneous plastic products	-0.795**	-0.989***	0.431
	(0.376)	(0.358)	(0.399)
SIC 32 – Stone, clay, glass and concrete products	-1.514***	-0.751	0.601**
	(0.534)	(0.500)	(0.300)
SIC 33 – Primary metal industries	-1.299*	-1.653**	0.610**
	(0.678)	(0.784)	(0.284)
SIC 34 – Fabricated metal products	-0.289	0.203	0.654
	(0.257)	(0.521)	(0.441)
SIC 35 – Industrial machinery and equipment	0.413***	0.524	0.434
	(0.152)	(0.331)	(0.315)
SIC 36 – Electrical and electronic equipment	0.318**	0.501	0.666*
	(0.156)	(0.398)	(0.360)
SIC 37 – Transportation and related products	0.358	0.296	0.602
	(0.398)	(0.349)	(0.462)
SIC 38 – Instruments and related products	0.453**	1.565***	0.397
	(0.207)	(0.449)	(0.330)

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

specification differ slightly from Poisson results in which the GP index has a significant effect only on textile and allied products (SIC 22) and instruments and related products (sic 38) industries. The impact of IPR protection on total exports also differs across industries as depicted in column 3. Stronger IPR increases total exports of both patent-sensitive and patent-insensitive industries such as electrical and electronic equipment and stone, clay, glass and concrete products, respectively, which implies IPR protection affects innovation and exports differently.

1.6.4 Bilateral trade

In this section we evaluate export performance under the influence of IPR protection in the world market rather than in the U.S. market only. Bilateral trade data come from the CEPII database, which provides trade data for most countries from 1948 to 2006. However, because of the GP index is limited, we focus on the years from 1965 to 2005. The independent variables include population, GDP per capita for both the origination and destination countries. We also include gravity variables such as distance, common language, and common border as in equation (1.3). Variables we are interested in are GP index of both the exporter and the importer. Results are shown in Table 1.8. Columns 1-3 display OLS estimates. Column 2 adds country development interactions based on column 1 and column 3 adds year dummies. The last 3 columns have a similar structure but using the country-pair fixed-effects model. The development level of a country is defined by the World Bank: least developed, lower-middle income (lmc), upper-middle income (umc), and high income countries (hic). We find that stronger IPR protection of the destination country significantly increases bilateral trade, which confirms the results in the literature. IPR protection of the origination country, in which we are interested, is positively and significantly associated with trade for all countries. However, if we control for the country development level, stronger IPR possibly harms the least developed countries. The other three groups of countries benefit from strengthened IPR. Furthermore, if we control for time fixed effects, only the upper-middle income and high income countries gain from stronger IPR protection. In terms of magnitudes, high income countries have the largest coefficient, which implies that other groups of countries may decrease production as it becomes more difficult to imitate products, and the effects of IPR protection on exports varies across countries. For least developed and lower-middle income countries, stronger IPR protection does not significantly increase exports.

Table 1.8: IPR protection and bilateral trade

	OLS				Country-pair FE		
Variables	All-countries	Interaction	Year-dummies		All-countries	Interaction	Year-dummies
lnpop_o	0.474***	0.504***	0.531***		-0.402***	-0.309**	-0.0990
	(0.0348)	(0.0293)	(0.0294)		(0.132)	(0.138)	(0.205)
lngdpcap_o	0.502***	0.266***	0.475***		0.433***	0.395***	0.485***
	(0.0293)	(0.0397)	(0.0517)		(0.0579)	(0.0562)	(0.0776)
lnpop_d	0.409***	0.432***	0.460***		-0.0777	-0.0641	0.144**
	(0.0199)	(0.0205)	(0.0206)		(0.112)	(0.121)	(0.0596)
lngdpcap_d	0.416***	0.173***	0.384***		0.392***	0.365***	0.459***
	(0.0235)	(0.0308)	(0.0276)		(0.0374)	(0.0352)	(0.0289)
lndist	-0.615***	-0.631***	-0.634***				
	(0.0403)	(0.0344)	(0.0331)				
language	0.213***	0.349***	0.363***				
	(0.0581)	(0.0549)	(0.0546)				
border	0.656***	0.717***	0.681***				
	(0.0893)	(0.0836)	(0.0814)				
GPindex_o	0.158***	-0.0917*	0.0177		0.216***	-0.00843	0.0116
	(0.0468)	(0.0526)	(0.0508)		(0.0354)	(0.0933)	(0.0954)
GPindex_d	0.145***	-0.0985*	0.0190		0.168***	0.0118	0.0323*
	(0.0179)	(0.0215)	(0.0139)		(0.0176)	(0.0158)	(0.0144)
lmc_gp_o		0.151***	0.0589			0.193	0.155
		(0.0444)	(0.0477)			(0.129)	(0.132)
umc_gp_o		0.309***	0.153***			0.297**	0.268*
		(0.0522)	(0.0551)			(0.134)	(0.139)
hic_gp_o		0.509***	0.275***			0.363***	0.341***
		(0.0618)	(0.0663)			(0.126)	(0.141)
lmc_gp_d		0.195***	0.0985***			0.140***	0.101***
		(0.0144)	(0.0105)			(0.0294)	(0.0269)
umc_gp_d		0.299***	0.140***			0.177***	0.151***
		(0.0212)	(0.0137)			(0.0380)	(0.0355)
hic_gp_d		0.515***	0.272***			0.236***	0.212***
		(0.0256)	(0.0159)			(0.0411)	(0.0300)
Constant	-2.327***	0.891**	-1.254***		-4.111***	-3.867***	-5.579***
	(0.364)	(0.352)	(0.440)		(0.262)	(0.268)	(0.754)
Observations	92,789	92,789	92,789	92,789	92,789	92,789	
R^2	0.629	0.629	0.703	0.475	0.481	0.485	
Number of paired					10,924	10,924	10,924

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.7 Conclusion

In this paper we provide an assessment of the effects of IPR protection on innovation and exports using data on exports to the U.S. We show that stronger IPR protection increases the number of new products exported to the U.S. for developing countries. We also find that IPR has a robust impact on innovation, which in turn has a significant impact on total exports. However, these effects vary significantly across industries.

These findings have important policy implications especially for developing countries. Some researchers argue that stonger IPR protection in developing countries may experience reduced production and even economic development. Others argue stronger IPR protection might stimulate domestic innovation and promote inward technological spillovers, which might benefit exports both on the extensive and intensive margin and particularly the former one. Our findings show that only poor countries gain in terms of extensive margin. Strengthened intellectual property rights protection may reduce production for some industries but countries gain as a whole. For example, Branstetter et al. (2011) find that patent reform promotes overall industry development and increases new product exports for reforming countries. Although it might reduce production in the short term, increasing IPR protection could be a useful tool for economic development in the long term, especially for the developing and lower IPR protection countries.

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CHAPTER 2

PRODUCT QUALITY, TRADE DURATION, AND TRADE GROWTH

2.1 Introduction

Product quality plays an important role in international trade and evidence indicates that the quality of products in international markets varies significantly across countries. On one hand, higher quality brings good reputation for producers. On the other hand, higher quality requires higher costs. Producers face a trade-off between quality and costs. Although a substantial amount of trade models point to the importance of product quality, there are few empirical studies addressing how product quality affects trade over time because of the lack of quality data. More recent literature has empirically studied the effects of quality on international trade using various approximations of quality. Hallak (2006) uses unit values as a proxy of product quality and examines how product quality determines the direction of trade. He finds that rich countries import relatively more high-quality goods. Schott (2004) shows that product quality is a key factor of how countries specialize in production. Hummels and Klenow (2005) find that richer countries produce higher quality goods and export more units. Hallak (2009) develops a model predicting and verifying empirically that exporters sell products of higher quality at higher prices conditional on size. Baldwin and Harrigan (2011) propose a model incorporating quality into Melitz's (2003) model to explain instances of no trade between a pair of countries, zeros in the bilateral trade matrix, which standard trade models fail to explain.

Another strand of product quality literature is to estimate the quality of exported products. Khandelwal (2010) estimates the quality of products exported to the U.S. using a standard industrial organization method. Hallak and Schott (2011) estimate differences in product quality across countries and find that unit value could be a poor approximation for quality. Unlike the above two papers focusing on the demand side, Feenstra and Romalis (2014) model both demand and supply sides and estimate the quality and quality-adjusted prices for most countries over 1984-2011. By modifying the Hallak (2006) method, Henn et al. (2013) estimate product quality from unit values. First, they assume that price is a linear function of product quality, exporter income per capita, distance between the exporter and importer, and other unobservable factors. Second, they specify and estimate a quality-augmented gravity equation. Finally, product quality is calculated by using the estimated coefficients from the second step. Since Henn et al. (2013) estimates of quality have the longest time period and richest country sample, we use their measures of product quality in our paper. We will discuss this data set in detail in section 2.3.

In our model, we assume product quality varies across time, which means producers could adjust their quality to compete with rivals according to consumers' preferences. Therefore, if exporters' quality continues to be worse than others, consumers would purchase goods from their rivals, with such firms being more likely to exit the market. On the other hand, quality can significantly affect the cost of production. If costs increase too fast as quality increases, producers would not make any profits. Therefore, producers need to lower costs as well as maintain quality at some level. Thus, our hypothesis is that product quality may influence the probability of firms' survival.

As Besedeš et al. (2014) examine how credit constraints affect trade growth, we develop a similar model investigating how product quality affects trade growth. In our model, consumers have preferences for both quantity and quality. They treat products exported from different countries differently. Therefore, exporting firms have to choose the price and quality of their products. Following the Baldwin and Harrigan (2011) model, we assume that quality affects marginal costs positively, but the magnitude of the effect of quality on marginal costs may vary across countries and industries. Based on this assumption, we derive the relationship between quality and trade growth, which predicts that the effect of quality on growth depends on the value of parameter of quality affecting marginal cost. In addition, our model implies that the relationship between product quality and total imports also depends on that parameter.

We test the above hypotheses and predictions using data on disaggregated bilateral trade flows and data on product quality. Our trade data are annual 5-digit SITC revision 1 imports from 1962 to 2005 for all countries in the UN Comtrade database. Data on product quality come from the IMF Export Diversification and Quality Database. This database provides 1- to 4- digit SITC product quality from 1962 to 2010.

Our paper contributes to the literature by examining how product quality affects duration and growth of trade. For middle and high income countries, our empirical findings show that exports of products with higher quality are more likely to survive, that higher product quality is positively related to trade growth, and that quality is positively related to total trade value. Besedeš and Prusa (2006) show that product differentiation affects the duration of trade relationships. Araujo et al (2016) find that if an importer has higher institutional quality, then the trade relationship would be longer. In our paper, we contribute to the duration literature by studying how product quality influences the duration of trade relationships.

2.2 Conceptual Framework

We begin by theoretically analyzing the effect of product quality on the probability of firms' survival in export markets and trade growth. We assume that consumers can perceive the quality of products from various origin countries. In addition, the marginal cost of the producer depends on product quality. Formally, we assume that the international market consists of $e = 1, 2, ..., E$ countries. Each country has monopolistically competitive firms which produce differentiated varieties and may export to all other countries. We arbitrarily pick one Export (e) country and one Import (i) country, and examine the trade flow from an Exporter to an Importer.

2.2.1 Quality and hazard

Baldwin and Harrigan (2011) incorporate product quality into the Melitz (2003) model and derive the relationship between exports and quality: Higher quality products are more likely to be exported. The key difference between these two models is that the former allows firm heterogeneity in productivity and quality while the latter only allows heterogeneity in productivity. Baldwin and Harrigan (2011) assume firms' marginal cost is positively associated with quality and the typical firm takes its quality and marginal cost as given when it chooses prices. By solving for the marginal firm's export decision, they find that only firms with sufficiently high-price/high-quality goods will export. The Baldwin and Harrigan (2011) model crucially depends on how quality affects marginal costs and their assumption is that marginal costs increase slowly with quality, which indicates that higher quality is positively associated with higher operating profit. However, some countries may incur large costs of increasing quality even slightly. In particular, low-income countries which lack technology and skilled labor required to improve quality may face large increases in production costs associated with increasing the quality of their products. In addition, some industries are characterized by small variations in quality, as is the case with many agricultural products. To increase quality of such products large costs associated with significant investments in technology and labor may be required. If the effect of increased costs dominates the effect of the higher price caused by higher quality, these products are more likely to cease being exporting. In addition, Grossman and Helpman (1991a,b) quality ladder model shows that firms can improve the quality of products and increase the chance of exporting by investing innovative activities We then have the following hypothesis:

Hypothesis 1. Higher quality products are more likely to survive. However, the effect may vary across countries and industries.

2.2.2 Trade growth

Consumer preferences

Following Besedeš et al (2014), we define the utility function as CES with a numeraire but incorporating product quality into consumer preferences:

$$u_t(d) = z_t + \lambda_t \sum_{e\geq 1} \sum_{d\geq 0} \left(\sum_{v\in v_{ed}} (\theta_{vt}(d) x_{vt}(d))^{\frac{\sigma-1}{\sigma}} \right) \tag{2.1}$$

where x_{vt} and θ_{vt} are individual consumption and quality of differentiated variety v in period t, v_{ed} is the set of total varieties supplied by exporter e for d consecutive years, and σ is the elasticity of substitution. λ_t is a period-specific demand shifter. Price of the numeraire, z_t, is normalized to one.

The budget constraint is given by

$$z_t + \textstyle\sum_e \sum_d (\sum_{v\in v_{ed}} p_{vt}(d) x_{vt}(d)) = I_t$$

where I_t is the total income. Individual demand for variety v in period t is derived as

$$x_{vt}(d) = \theta_{vt}^{\sigma-1}(d) \left(\frac{\sigma-1}{\sigma} \frac{\lambda_t}{p_{vt}(d)} \right)^{\sigma} \tag{2.2}$$

Firm's profit

Assume labor is the only input of production and all costs are measured as units of labor. Fixed cost is denoted as F. We assume that marginal cost, c, is related to quality. Note that quality varies across varieties and over time. Similar to Baldwin and Harrigan (2011), we assume quality affects marginal cost as follows:

$$c_{vt} = \theta_{vt}^{k}, \quad k > 0$$

Here we only assume $k > 0$ which implies that quality is positively related to marginal cost. But the strength of the positive relationship may vary across industries and countries within an industry. For some industries, a slight increase in quality may lead to a huge increase in marginal cost implying that $k > 1$. We also assume that quality and marginal cost are given and firms only need to choose the price to maximize profit. In addition, we assume that there exist iceberg transportation costs, $\tau_e > 1$, so only a portion of shipped goods arrive in the destination country and a firm needs to produce some extra units to meet the demand of the destination country. Then the total output of a firm is $\tau_e x_{vt}$.

We are interested in investigating the growth of trade conditional on a spell of exporting having survived. A spell is defined by consecutive years during which a bilateral trade relationship for a specific product is active. Duration of a trade spell is denoted by $d = 0, 1, 2, ..., D$. Here firms have already decided to export at time t, but there is an exogenous probability that firms may not export or the trade relationship breaks down at $t + n$ as in Araujo et al. (2016). Therefore, we assume the number of new entrants in each period is given by n_e, out of which only $\phi_e(0)$ will succeed in exporting similar to the Besedeš et al. (2014) framework. Define $\phi_e(d)$ as the probability of success of partnership between the exporter and importer with duration d. The total length of duration of a partnership is D. Then, the expected profit of a firm with duration d is:

$$E[\pi_{vt}(d)] = \phi_e(d)p_{vt}(d)x_{vt}(d) - w_e(c_{vt}(d)\tau_e x_{vt}(d) + F) \tag{2.3}$$

where the quantity, x_{vt}, is given by equation (2) and F is the fixed cost.

Solving the F.O.C. with respect to $p_{vt}(d)$ gives us:

$$p_{vt}(d) = \frac{w_e c_{vt}(d)\tau_e}{\phi_e(d)} \frac{\sigma}{\sigma - 1} \tag{2.4}$$

Our model differs from Besedeš et al (2014) in the sense that the price, given by equation (4), varies over time in each origin e and duration d cohort. To simplify our analysis, we assume that firms who have been exporting for d years within an exporting country have the same quality in period t. But quality of the same variety varies across countries and over time. The quantity of variety v exported from e is equal to the consumption of destination country:

$$Q_{evt}(d) = Q_{vt}(d) \equiv L_i x_{vt}(d) \tag{2.5}$$

where L_i is the total number of consumers in the importing country.

Then the aggregate value of exports of a new variety v exported by country e are given by:

$$V_{evt}(0) \equiv n_e \phi_e(0) p_{evt}(0) Q_{evt}(0) = n_e \phi_e(0) L_i \left(\frac{\sigma - 1}{\sigma}\right)^{2\sigma-1} \lambda_t^{\sigma} \left(\frac{w_e \tau_e}{\phi_e(0)}\right)^{1-\sigma} \theta_{vt}^{(\sigma-1)(1-k)} \tag{2.6}$$

The number of firms with duration d is given by:

$$N_e(d) = n_e \phi_e(0) (\widetilde{\phi})^d \tag{2.7}$$

where $\widetilde{\phi} = \phi_e(d \geq 1) > \phi_e(0)$ is the probability of success of a trade relationship for $d \geq 1$.

We can express the value of exports of all firms with duration d as a function of exports of new exporters, $V_{evt}(0)$:

$$V_{evt}(d) \equiv N_e(d) p_{evt}(d) Q_{evt}(d) = V_{evt}(0) \left(\frac{\phi_e(0)}{\phi_e(d)}\right)^{1-\sigma} (\widetilde{\phi})^d \tag{2.8}$$

This result allows us to derive the value of exports by all firms from country e with "exporting age" $D \geq 1$ as a function of exports by new exporters, $V_{evt}(0)$:

$$\sum_{d=0}^{D} V_{evt}(d) = V_{evt}(0)[1 + \sum_{d=1}^{D} \left(\frac{\phi_e(0)}{\widetilde{\phi}}\right)^{1-\sigma} (\widetilde{\phi})^d] \tag{2.9}$$

From equation (2.9), we can derive the export growth of variety v from country e with $D \geq 1$:

$$G_{evt}(d) = \sum_{d=0}^{D} V_{evt}(d) - \sum_{d=0}^{D-1} V_{ev(t-1)}(d) = V_{evt}(0) \left(\frac{\phi_e(0)}{\widetilde{\phi}} \right)^{1-\sigma} \widetilde{\phi}^{D} \tag{2.10}$$

Substitute $V_{evt}(0)$ into equation (2.10) and export growth can be expressed as:

$$G_{evt}(d) = n_e \phi_e(0) L_i \left(\frac{\sigma - 1}{\sigma} \right)^{2\sigma - 1} \lambda_t^{\sigma} \left(\frac{w_e \tau_e}{\widetilde{\phi}} \right)^{1-\sigma} \widetilde{\phi}^{D} \theta_{vt}^{(\sigma-1)(1-k)} \tag{2.11}$$

Taking log value of (2.11), we obtain the log value of export growth as

$$\begin{aligned} \ln G_{evt}(d) = (2\sigma - 1) \ln \left(\frac{\sigma - 1}{\sigma} \right) + \ln(n_e Li) + (1 - \sigma) \ln(w_e \tau_e) \\ + \sigma \ln \lambda_t + \ln \phi_e(0) + (\sigma - 1 + D) \ln \widetilde{\phi} + (\sigma - 1)(1 - k) ln \theta_{vt} \end{aligned} \tag{2.12}$$

From equation (2.12), we can see that the effect of product quality on trade growth depends on the value of k (since $\sigma > 1$) controlling for everything else. If $k > 1$, the marginal cost increases quickly with quality. In this case a firm's revenue and operating profit fall with quality. If $0 < k < 1$, by contrast, marginal cost increases slowly with quality. If this is true operating profit increases as quality increases. As we discussed above the value of k may vary across countries and industries. Then the effect of quality on growth of trade may be different for different country and industry groups. If we assume $0 < k < 1$, then we have the following hypothesis:

Hypothesis 2. Growth of trade is positively related to product quality, ceteris paribus.

Similarly, from equation (2.8) we can show that the level of imports within a spell are positively related to product quality of the same period t if $0 < k < 1$. Then we have the following hypothesis:

Hypothesis 3. Level of imports of each year within a spell are positively associated with the product quality of the same period.

2.3 Data and Empirical Methods

2.3.1 Bilateral trade and product quality data

To verify our theoretical predictions, we need trade flow data and the associated quality of products. We combine two main data sets in our study. The bilateral trade flow data come from the UN Comtrade Database, which provides annual industry-level imports and exports data. We use data on imports recorded using the 5-digit SITC revision 1 classification for years ranging from 1962 to 2005. We use data reported by importers because they are more accurate than exporter reported data.

Data on product quality come from the IMF Export Diversification and Quality Databases (Henn et al. 2013). To construct the quality data, Henn et al. (2013) first simply assume that the trade price (unit value) is a linear function of unobservable product quality, exporter income per capita, distance between the importer and exporter, and other unobservable factors. Next, they substitute quality into the common bilateral gravity equation as an interaction term with the importer's income per capita. After rearranging quality as a function of price, all variables on the right-hand side of the gravity equation are observable. The following step is to estimate the gravity equation for each of the 851 SITC 4-digit categories using the two-stage least squares method. Finally, all quality estimates are normalized by their 90th percentile in product-year combination and aggregate estimates across importers using trade values as weights. Data provide the 4-, 3-, 2-, and 1-digit SITC quality, and overall country-level average quality for each exporter in sample periods. We use 4-digit quality values ranging between 0 and 1.2 for years from 1963 to 2010.

Figure 2.1 presents the distribution of product quality. From Figure 2.1 we can see that product quality is skewed and concentrates around 1. Figure 2.2 gives an example of quality changes for four sectors in four countries: United States, Germany, South Korea, and China. We can see that the U.S. and Germany have higher quality than China for all of the four sectors, while the quality of South Korean products is between them. For Heating and Cooling equipment, China has the lowest quality but experiencing a large increase since 1990. The U.S. and Germany have a similar pattern of quality evolution which is relatively stable over the sample period, while South Korea catches Germany around 2000. We also notice that Clothing of Textile Fabric and Heating and Cooling Equipment have larger quality difference than Dried Fruit and Lubricating Oils and Greases industries. This illustrates that the effect of quality on the probability of trade relationships ceasing vary across industries. For industries with a small range of product quality, firms may have no incentive to increase quality since it may increase costs significantly yet provides small differentiation from rivals' goods.

We use standard gravity variables in our analysis. Data on these variables come from the CEPII database which provides both the exporter's and importer's GDP, the distance between them, and whether they share a common border and a common language.

We examine the effect of product quality on trade relationships based on a unit of observation being a continuous trade spell involving an exporter, an importer, and a specific product. More specifically, we focus on consecutive years, beginning with a clearly observed starting point, during which a trade relationship is active or a trade spell. A trade spell slightly differs from a trade relationship. The latter denotes an exporter-importer-product triplet, while the former defines the consecutive years during which a relationship is active allowing for a trade relationship to have multiple active trade spells, something which we observe in data with some degree of regularity.

Our sample observations are the intersection of two sources available from 1962 to 2005. After we merge the above two data sets, we have a total of 14,574,526 observations and 257 distinct 4-SITC sectors. Our data structure consists of spell-episodes with positive trade. Put another way, it consists of exporter-importer-product spells with positive trade over consecutive years. There are a total 5,784,321 exporting spells with a total of 8,790,205 years of growth since some relationships only exist in one year.

Table 2.1 shows that the majority of observed spells of trade have a very short duration,

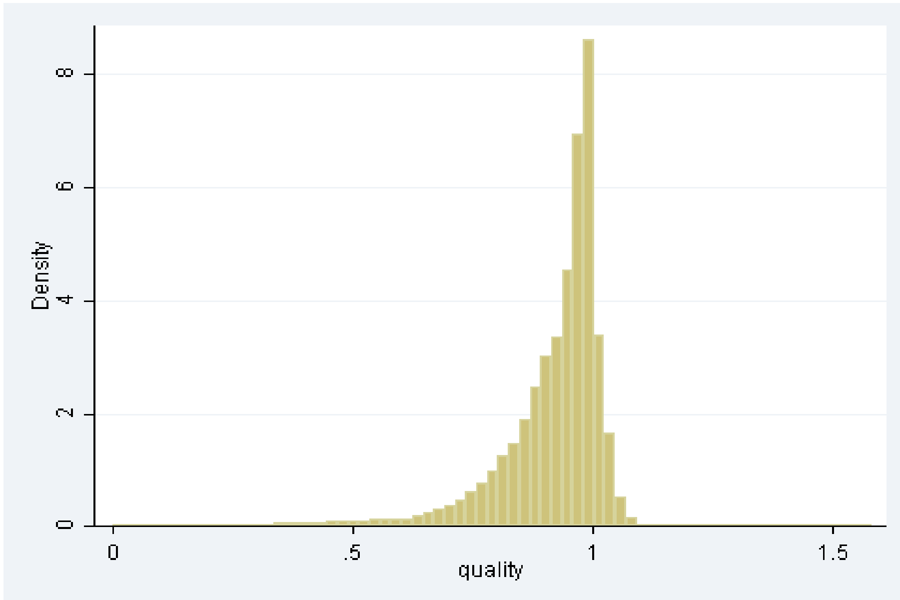

Figure 2.1: Quality Distribution

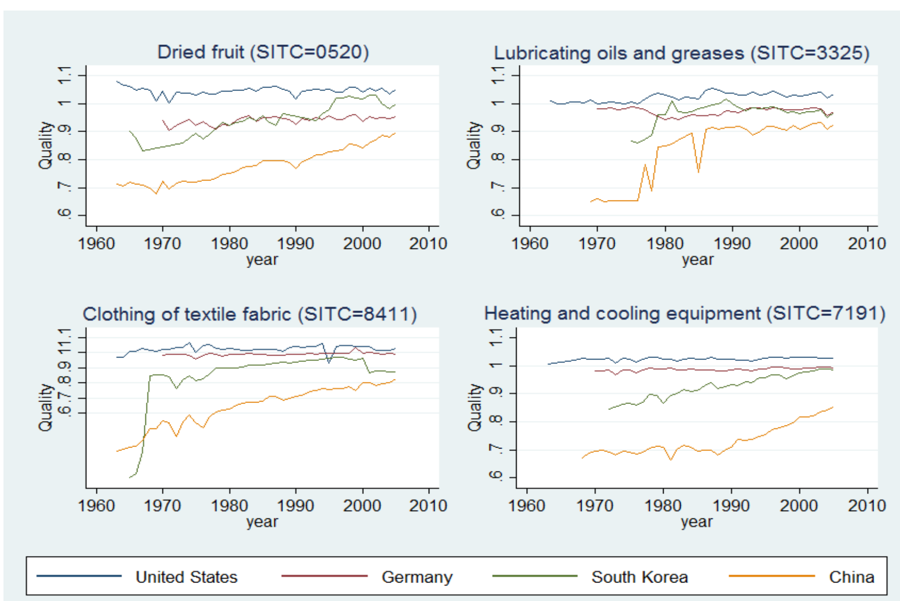

Figure 2.2: Quality Changes for 4 Sectors

Table 2.1: Distribution of Spell Length

Spell length	Number of spells	Fraction
1	2,874,453	49.7%
2	893,135	15.4%
3	439,474	7.6%
4	265,918	4.6%
5	197,373	3.4%
6	167,865	2.9%
7	112,739	1.9%
8	96,629	1.7%
9	79,194	1.4%
10	84,033	1.5%
11-20	336,530	5.8%
21-30	90,723	1.6%
31-44	146,255	2.5%
Total	5,784,321	100.0%

with approximately half of all spells lasting one year and about 90% being observed for 10 or fewer years. Our hazard estimation sample is smaller by 2,375,717 observations due to three factors. The majority of these observations, 1,349,738 to be precise, are lost because of missing values of product quality. The second factor is left censored observations which is caused by the nature of survival data. To be specific, there are 1,080,184 missing observations due to left censoring. The reason for left censoring is that for all spells which are active in the first year in which an importing country reports data, we cannot observe the actual starting year of that relationship. For example, if the U.S. reports imports in 1962 which is the first year of our trade data, then all spells involving U.S. imports in 1962 are left censored, and we omit such spells from our analysis. The remaining omitted observations are caused by the missing values of gravity data.

2.3.2 Empirical methods

Hazard estimation

The hazard is the probability of exports of variety v from country e to importing country i in spell s ceasing at time $t+1$ conditional on it having survived until time t, $P(T^v_{sei} \leq t+1 | T^v_{sei} \geq t)$, where T^v_{sei} is a random variable measuring the survived duration of spell sei. Many papers studying the duration of trade relationships have followed Besedeš and Prusa (2006) and estimate various versions of continuous-time Cox proportional hazards models. However, Hess and Persson (2011) show that discrete-time models are more suitable to estimate hazards in large trade data sets because of three major concerns. The first one is that the continuous-time models cannot deal well with tied duration times which leads to biased estimates. Trade data have many tied failure times by nature since the number of spells usually dwarfs the time dimension of the data. Secondly, it is difficult to control for unobserved heterogeneity in the Cox model as estimation requires evaluation of a multidimensional integral. If one were to model unobserved heterogeneity at the level of trade relationships, the dimensionality of this integral would equal the number of trade relationships in our data, which is more than 2 million. Finally, the Cox model imposes a restrictive assumption of proportional hazards which is questionable empirically. By contrast, the discrete-time models can handle all three drawbacks without difficulties.

We define the hazard of a spell trade ceasing, h^v_{seit} and estimate the hazard of exports ceasing at time $t+1$ by random-effects probit model as

$$\begin{aligned} h^v_{seit} &= P(T^v_{sei} \leq t+1 | T^v_{sei} \geq t) \\ &= \Phi(\theta^v_{et}(d) + \ln d(t)_{seit} + \ln V^v_{seit} + \ln GDP_e + \ln GDP_i + X_{ei} + \epsilon^v_{sei}) \end{aligned} \tag{2.13}$$

where θ^v_{et} represents the quality of variety v of exporter e at year t, $lnd(t)_{seit}$ is the log of age of spell s in year t, $\ln V_{seit}$ is the log of bilateral trade volume of spell s in year t between e and i, $\ln GDP_e$ and $\ln GDP_i$ represent the GDP of exporter and importer, X_{ei}

is a vector of bilateral time-invariant gravity variables (distance, common border, common language), while ϵ^v_{sei} captures the relationship-specific random effect.

Growth and level of imports estimation

To investigate the effect of quality on trade growth, we estimate the following equation:

$$g^v_{seit}(d) = \alpha + \delta_e + \gamma_i + \lambda_t + D_s + \mu_s + V + \beta \ln \theta^v_{et} + X + \epsilon^v_{seit} \qquad (2.14)$$

where $g^v_{seit}(d) = \ln G^v_{seit}(d) - \ln G^v_{sei(t-1)}(d-1)$ is the difference of log value of trade value of variety v within the spell s between e and i, α is a constant, δ_e and γ_i represents the exporter and importer fixed effects respectively, λ_t is the calendar year fixed effects, D_s is the spell length fixed effects, μ_s is the spell fixed effects, V is the 4-digit SITC industry fixed effects, X is a vector including the spell age, GDP of both countries, gravity variables, and first year trade value of the spell. ϵ^v_{seit} is the error term.

We apply a similar specification to investigate the effect of quality on the level of imports at the same period but excluding the initial trade value as an independent variable.

2.4 Results

2.4.1 Duration

Hypothesis 1 states that the probability of a trade relationship ceasing (surviving) is negatively (positively) related to product quality. To test the relationship empirically, we use random-effects Probit model to estimate the specification given by equation (2.13).

Results are presented in Table 2.2. The first column is the baseline model including all countries and industries. We divide countries into three groups by country development: low-, middle-, and high-income countries. The country sub-group results are given by Column 2-4. As we discussed above, we want to examine whether product quality affects hazard of trade relationships differently across industries. Then we divide industries into manufacturing (4-digit SITC range from 4000-9000) and non-manufacturing. Column 5 and 6 present the results. From the baseline model, we find that the higher quality is negatively related to the hazard rate, which confirms our hypothesis. However, the effect of quality on hazard varies across countries and industries. For low-income countries and non-manufacturing industries, higher quality is associated with higher hazard. This implies that the benefit of higher quality is offset by increased costs, which causes firms to exit the market. We also note that trade relationships in high-income countries are more likely to survive than middle-income countries as quality increases. All other variables have expected effects on hazard and are consistent with the literature. For example, longer lived spells (longer duration) are less likely to cease. Also larger spells are more likely to survive. The larger are the GDP of both exporter and importer the less likely is trade to cease as well.

Interpreting the magnitude of Probit coefficients depends on other variables' value and the starting value of quality. Figure 2.3 plots the predicted hazard for different quality level keeping other explanatory variables at the mean values against the spell age using the baseline specification. We can see that the predicted probability of ceasing decreases as the relationship survives longer. The upper-left plots the predicted hazard for all countries. The hazard decreases as quality changes from zero to mean value. But there is no significant difference when quality moves one standard deviation away from mean value. For low-income countries, predicted hazard increases as quality changes from zero to mean value. For middle- and high-income countries, predicted hazard decreases as quality increases from zero to mean, but the effect is much larger for high-income countries.

We can conclude that product quality has a positive effect on the probability of survival in international markets in general. Intuitively, consumers would prefer the goods with higher quality over those with lower quality conditional on prices. However, this effect varies across countries. For middle- and high-income countries, higher quality may help exporters stay longer in the market despite the likely higher costs associated with it. The negative relationship between quality and hazard only holds for manufacturing industries.

Table 2.2: Hazard Regression (RE Probit)

	Base model	Low-income	Middle-income	High-income	Manufacturing	Non-manufacturing
Quality (ln)	-0.0664***	0.0300***	-0.0441***	-0.319***	-0.0993***	0.0143***
	(0.00286)	(0.00750)	(0.00444)	(0.00667)	(0.00445)	(0.00416)
Duration (ln)	-0.552***	-0.608***	-0.570***	-0.540***	-0.557***	-0.511***
	(0.000701)	(0.00419)	(0.00142)	(0.000826)	(0.000761)	(0.00187)
Trade size (ln)	-0.107***	-0.0765***	-0.0969***	-0.115***	-0.106***	-0.115***
	(0.000240)	(0.00113)	(0.000423)	(0.000304)	(0.000262)	(0.000620)
Importer GDP (ln)	-0.00848***	-0.00410***	-0.00247***	-0.00843***	-0.0121***	0.00331***
	(0.000227)	(0.00123)	(0.000408)	(0.000293)	(0.000248)	(0.000582)
Exporter GDP (ln)	-0.0471***	-0.0938***	-0.0812***	-0.0316***	-0.0524***	-0.0306***
	(0.000296)	(0.00183)	(0.000583)	(0.000378)	(0.000334)	(0.000667)
Distance (ln)	0.0822***	0.00540	0.0756***	0.0914***	0.0892***	0.0663***
	(0.000591)	(0.00387)	(0.00110)	(0.000747)	(0.000651)	(0.00147)
Contiguity	-0.0929***	-0.186***	-0.0533***	-0.146***	-0.0946***	-0.102***
	(0.00239)	(0.00977)	(0.00332)	(0.00422)	(0.00266)	(0.00554)
Common language	-0.0135***	0.00798	-0.00189	-0.0377***	-0.0128***	-0.0313***
	(0.00129)	(0.00534)	(0.00228)	(0.00169)	(0.00141)	(0.00326)
Constant	1.000***	1.856***	1.317***	0.775***	1.016***	0.958***
	(0.00598)	(0.0354)	(0.0106)	(0.00777)	(0.00660)	(0.0148)
Observations	12,198,809	421,603	3,609,775	8,167,431	10,230,538	1,968,271
Relationships	2,609,873	140,421	909,441	1,560,011	2,215,996	393,887

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

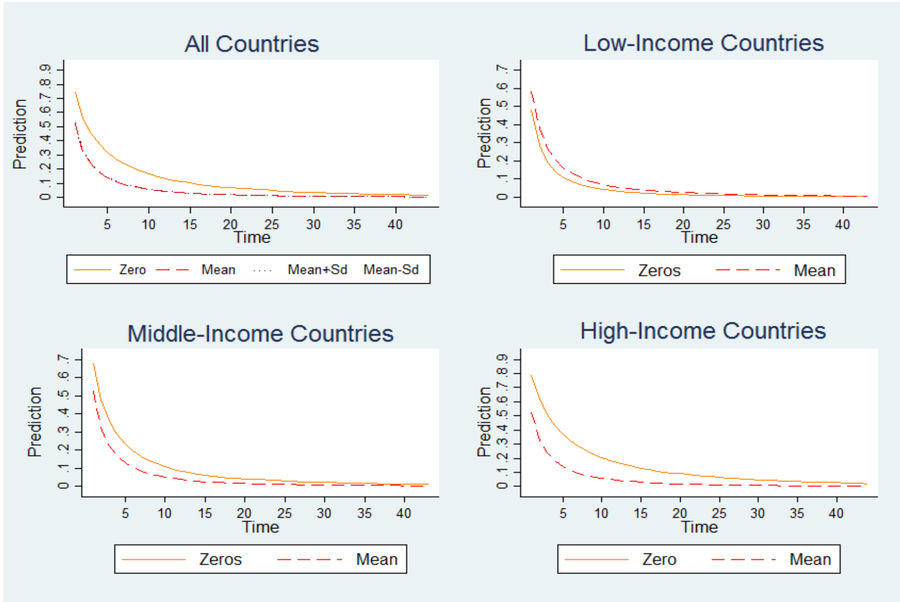

Figure 2.3: Predicted Hazard

For non-manufacturing industries, goods are close to being homogeneous and have small variations in quality. A slightly increased quality may bring significant increase in costs for those industries. Then higher quality does not lead to longer duration.

2.4.2 Trade growth

Hypothesis 2 states that higher product quality is positively associated with trade growth if $0 < k < 1$. In particular, we examine the growth rate of trade conditional on spell survival. Empirically, we can examine the coefficient of quality, β, by estimating equation (2.14). If $\hat{\beta}$ turns out to be positive, then it implies that $0 < k < 1$ which makes our assumption sensible. To estimate equation (14), we use the OLS method adding exporter, importer, year, spell number and spell length, 4-digit SITC industry fixed effects besides the variables we used in the hazard regression. Note that we use the initial trade value instead of current value of a spell in the growth regression because the dependent variable, the growth rate, is calculated from current value.

Table 2.3 presents the results of the growth regression. We divide the our sample into subsamples as in Table 2.2. The baseline model, Column 1, shows that the coefficient of quality is 0.0691 (indicating $0 < k < 1$), which implies that trade would increase by 0.0691% as an exporter's product quality increases by 1% controlling for other variables. This confirms our hypothesis in section 2.2. The positive effect of quality on trade growth is robust for all countries and industries except for most developed countries. The reason is probably that high-income countries keep exporting high quality goods then quality plays a small role determining trade growth. Higher quality increases growth for both manufacturing and non-manufacturing industries. But the effect of quality on the former is about 9 times larger than that on the latter. Unlike Besedeš et al. (2014), we find that the growth of trade within a spell increases as the relationship lasts longer. The initial trade value has a negative effect on growth too. Specifically, the growth would be lower by 0.017% if the initial value increases 1% from the base model. The GDP of exporter and importer have positive effects on growth. The gravity variables are consistent to the literature findings. The longer the distance, the lower the growth because of larger transportation costs. Sharing a common border and a common language result in faster growth of trade.

The findings show that product quality has a positive effect on trade growth. We are interested in investigating the channel behind this effect. One can argue that high quality products may have small initial trade values since they are more expensive, which leads to the positive relationship between quality and growth, as smaller starting relationships grow faster. Araujo et al (2016) indeed find that lower institutional quality results in larger trade growth because those institutions result in lower initial trade values. Therefore, we want to examine whether higher quality is negatively related to initial trade values. If so, then it could provide one explanation for larger growth of high quality products. We estimate the following specification:

$$\ln imports^{v}_{seit}(0) = \alpha + \delta_e + \gamma_i + \lambda_t + \mu_s + V + \beta ln\theta^{v}_{et}(0) + X + \epsilon^{v}_{seit}$$

The dependent variable is the value of imports in the first year of a spell. Explanatory variables are the same as the growth regression, but excluding the duration variable since we only consider first year trade values. However, our empirical test shows that product

Table 2.3: Growth Regression (OLS)

	Base model	Low-income	Middle-income	High-income	Manufacturing	Non-manufacturing
Quality (ln)	0.0321***	0.0671***	0.154***	0.0365***	0.123***	0.0139**
	(0.00461)	(0.0212)	(0.00844)	(0.00844)	(0.00849)	(0.00625)
Duration (ln)	-0.297***	-0.394***	-0.358***	-0.271***	-0.292***	-0.336***
	(0.00123)	(0.00747)	(0.00242)	(0.00149)	(0.00139)	(0.00267)
Initial Trade (ln)	-0.109***	-0.163***	-0.139***	-0.0993***	-0.113***	-0.0956***
	(0.000300)	(0.00214)	(0.000651)	(0.000348)	(0.000339)	(0.000658)
Importer GDP (ln)	0.154***	0.114***	0.180***	0.151***	0.162***	0.122***
	(0.00225)	(0.0150)	(0.00487)	(0.00260)	(0.00249)	(0.00521)
Exporter GDP (ln)	-0.0133***	0.0255***	0.0468***	-0.0682***	-0.0201***	-0.0117***
	(0.00231)	(0.0130)	(0.00407)	(0.00314)	(0.00265)	(0.00481)
Distance (ln)	-0.0472***	-0.0245***	-0.0420***	-0.0552***	-0.0558***	-0.0286***
	(0.000804)	(0.00926)	(0.00200)	(0.00100)	(0.000914)	(0.00175)
Contiguity	0.0414***	0.0509***	0.0371***	0.0371***	0.0453***	0.0344***
	(0.00225)	(0.0206)	(0.00471)	(0.00267)	(0.00253)	(0.00501)
Common language	0.0242***	0.00630	0.0131***	0.0306***	0.0318***	0.00879**
	(0.00171)	(0.0107)	(0.00380)	(0.00209)	(0.00193)	(0.00373)
Observations	8,127,769	217,921	2,074,295	5,835,551	6,761,889	1,365,880
R^2	0.038	0.058	0.049	0.035	0.038	0.039

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

quality has no significant impact on first year imports. This implies that higher quality being positively associated with larger growth is not because higher quality is associated with lower initial imports. We present the results in the Table 2.4.

Table 2.4: Initial Trade Value Regression

	Initial trade value
	OLS
Quality (ln)	0.000360
	(0.00818)
Importer GDP (ln)	0.206***
	(0.00342)
Exporter GDP (ln)	0.0660***
	(0.00364)
Distance (ln)	-0.0358***
	(0.00155)
Contiguity	0.0379***
	(0.00566)
Common language	-0.0432***
	(0.00309)
Constant	7.148***
	(0.0766)
Observations	4,067,145
R^2	0.259

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.4.3 What is driving trade growth?

Table 2.3 shows that quality has positive impact on growth for all three groups of exporting countries although the magnitudes differs. However, trade growth could be driven by demand from importing countries. Then we re-run the growth regression including interactions between quality and exporter- and importer-income groups. Table 2.5 presents the results. Column 1 shows the estimation results including all countries. Column 2-4 presents the results for low-, middle- and high-income exporting countries respectively. From Column 1 we can find that only interactions between high-income and middle-income importing countries with quality have positive impact on trade growth. It implies that demand for high quality goods from middle- and high-income importers plays an more important role in trade growth.

Table 2.5: Interaction between quality and country development (OLS)

	All countries	Low-income	Middle-income	High-income
Duration (ln)	-0.297***	-0.394***	-0.358***	-0.271***
	(0.00123)	(0.00747)	(0.00242)	(0.00149)
Initial Trade (ln)	-0.109***	-0.163***	-0.139***	-0.0993***
	(0.000300)	(0.00214)	(0.000651)	(0.000348)
Importer GDP (ln)	0.154***	0.115***	0.179***	0.151***
	(0.00225)	(0.0150)	(0.00487)	(0.00260)
Exporter GDP (ln)	-0.0139***	0.0260***	0.0487***	-0.0684***
	(0.00232)	(0.0130)	(0.00407)	(0.00314)
Distance (ln)	-0.0469***	-0.0240***	-0.0422***	-0.0553***
	(0.000810)	(0.00927)	(0.00200)	(0.00100)
Contiguity	0.0411***	0.0510***	0.0366***	0.0371***
	(0.00225)	(0.0206)	(0.00471)	(0.00267)
Common language	0.0244***	0.00608	0.0127***	0.0306***
	(0.00171)	(0.0107)	(0.00380)	(0.00209)
High-exporter*Quality	0.0196			
	(0.0157)			
Middle-exporter*Quality	-0.00524			
	(0.0149)			
High-importer*Quality	0.0494***	0.0302	0.128***	0.0349***
	(0.0143)	(0.0420)	(0.00860)	(0.00925)
Middle-importer*Quality	0.0372***	-0.00321	0.131***	0.0642***
	(0.0152)	(0.0480)	(0.0123)	(0.0144)
Low-importer*Quality	-0.0784***	0.0437		
	(0.0168)	(0.0459)		
Observations	8,127,769	217,921	2,074,295	5,835,551
R^2	0.038	0.058	0.049	0.035

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.4.4 Level of imports

Hypothesis 3 states that imports are positively related to product quality of the same period if $0 < k < 1$. Our empirical results confirm the assumption about $0 < k < 1$. Then we would expect that the value of imports would be positively related to product quality too.

To test the prediction, we estimate a similar specification as the growth regression except that we use imports instead of the growth rate as the dependent variable. We exclude the initial trade value as an independent variable.

Table 2.6 presents the results of the estimation. The coefficient of quality is about 0.0735 and significant at 1% level, which confirms our prediction. The interpretation of the magnitude is that the imports would increase by 0.0735% as product quality increases by 1%. This is consistent with the intuition that consumers would buy goods with higher quality conditional on prices. Since the quality data we used reflect price information, product quality being positively related to contemporaneous imports of the same period is not surprising. Also, we can find that imports are larger for longer lived spells. The larger the GDP of both the exporter and the importer, the larger the trade.

Table 2.6: Level of Imports Regression

	Value of imports (ln)
	OLS
Quality (ln)	0.0735***
	(0.00519)
Duration (ln)	0.560***
	(0.00100)
Importer GDP (ln)	0.420***
	(0.00214)
Exporter GDP (ln)	0.110***
	(0.00233)
Distance (ln)	-0.167***
	(0.000876)
Contiguity	0.235***
	(0.00277)
Common language	0.0442***
	(0.00182)
_Constant	6.241***
	(0.0548)
$Observations$	13,093,971
R^2	0.492

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.5 Robustness checks

2.5.1 Alternative specifications for growth and level estimations

For the growth and imports estimations, we use exporter, importer, year, 4-digit SITC industry, spell number, and spell length fixed effects. However, some unobserved characteristics may be captured by exporter-importer pair fixed effects. Then we estimate a specification using exporter-importer pair fixed effects instead of using exporter and importer fixed effects separately and keep all other fixed effects. In addition, we use exporter-year and importer-year fixed effects as an alternative specification. The results are presented in Table 2.7. Column 1 and 2 display the results using exporter-importer pair fixed effects. Column 3 and 4 present the estimations using importer-year and exporter-year fixed effects. We can find that product quality is positively related to trade growth and imports. The magnitude of the effect of quality on growth is slightly smaller than that in the baseline specification, while the magnitude of quality for level of imports is slightly bigger than that in the baseline specification.

2.5.2 Aggregate 3-digit SITC

We next check whether the results are driven by the disaggregation of SITC classification. We re-estimate the effect of quality on hazard and trade growth using 3-digit SITC data. The results are presented by Table 2.8 and 2.9 respectively. We can find that the results of hazard estimations are consistent with 5-digit SITC data. Higher quality is associated with lower hazard for middle- and high-income countries. The only difference is that the effect of quality on hazard for non-manufacturing industries is negative at the 3-digit level while the effect is positive at the 5-digit level. However, the impact of quality on trade growth differs to some degree by aggregating industries. At the 3-digit level, the positive relationship between product quality and trade growth only holds for middle-income countries and manufacturing industries. One possible explanation is that quality loses some variation due to aggregation which results in an insignificant effect on growth.

Table 2.7: Alternative specifications

	Exporter-Importer Pair FE		Country-Year FE	
	Growth	Imports	Growth	Imports
Quality (ln)	0.0277***	0.100***	-0.000635	0.0292***
	(0.00469)	(0.0235)	(0.00468)	(0.00518)
Duration (ln)	-0.294***	0.576***	-0.318***	0.592***
	(0.00127)	(0.00613)	(0.00138)	(0.00105)
Initial trade (ln)	-0.112***		-0.108***	
	(0.000311)		(0.000301)	
Importer GDP (ln)	0.172***	0.397***	-0.350	-0.607***
	(0.00241)	(0.0141)	(0.352)	(0.262)
Exporter GDP (ln)	-0.0219***	0.120***	0.367	0.449***
	(0.00247)	(0.0151)	(0.351)	(0.259)
Distance (ln)			-0.0482***	-0.158***
			(0.000807)	(0.000868)
Contiguity			0.0394***	0.233***
			(0.00225)	(0.00275)
Common language			0.0236***	0.0232***
			(0.00171)	(0.00179)
Observations	8,126,324	13,093,971	8,127,718	13,093,940
R^2	0.041	0.367	0.049	0.512

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.6 Conclusion

Product quality plays an important role in international trade. It has already been shown (Hallak 2006 and Schott 2004) that product quality could affect direction of trade and the specialization of production. In this paper, we analyze the effect of product quality on trade duration and growth. We develop a theoretical framework which characterizes firms' choices of price to start a trade relationship. We hypothesize that product quality increases duration of trade as well as the growth of trade in an active spell, both of which are are confirmed by our empirical results. Duration increases in product quality for relatively developed countries and manufacturing industries. Growth of trade increases with quality

Table 2.8: 3-digit SITC Hazard Regression (RE Probit)

	Base model	Low-income	Middle-income	High-income	Manufacturing	Non-manufacturing
Quality (ln)	-0.229***	-0.0154	-0.117***	-0.503***	-0.352***	-0.0563***
	(0.00476)	(0.00977)	(0.00751)	(0.0114)	(0.00741)	(0.00623)
Duration (ln)	-0.501***	-0.567***	-0.536***	-0.471***	-0.499***	-0.488***
	(0.00112)	(0.00504)	(0.00205)	(0.00142)	(0.00128)	(0.00239)
Trade size (ln)	-0.0606***	-0.0450***	-0.0592***	-0.0620***	-0.0552***	-0.0791***
	(0.000317)	(0.00122)	(0.000523)	(0.000426)	(0.000363)	(0.000668)
Importer GDP (ln)	-0.0296***	-0.0198***	-0.0206***	-0.0366***	-0.0384***	-0.0158***
	(0.000405)	(0.00158)	(0.000661)	(0.000571)	(0.000464)	(0.000831)
Exporter GDP (ln)	-0.0830***	-0.113***	-0.108***	-0.0603***	-0.0976***	-0.0541***
	(0.000496)	(0.00225)	(0.000874)	(0.000686)	(0.000591)	(0.000931)
Distance (ln)	0.149***	0.0496***	0.130***	0.167***	0.169***	0.115***
	(0.00112)	(0.00480)	(0.00178)	(0.00160)	(0.00130)	(0.00219)
Contiguity	-0.142***	-0.225***	-0.126***	-0.253***	-0.146***	-0.150***
	(0.00460)	(0.0125)	(0.00616)	(0.0102)	(0.00538)	(0.00875)
Common language	-0.0174***	-0.0493***	-0.00433	-0.0521***	-0.0164***	-0.0522***
	(0.00232)	(0.00690)	(0.00380)	(0.00333)	(0.00266)	(0.00475)
_Constant	0.373***	1.451***	0.804***	-0.0511***	0.358***	0.509***
	(0.0108)	(0.0433)	(0.0169)	(0.0159)	(0.0125)	(0.0214)
Observations	7,149,491	370,815	2,401,088	4,377,588	5,637,613	1,511,878
Relationships	772,551	76,404	314,340	381,807	595,068	177,483

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.9: 3-digit SITC Growth Regression (OLS)

	Base model	Low-income	Middle-income	High-income	Manufacturing	Non-manufacturing
Quality (ln)	0.00406	0.0283***	0.0787***	0.0256***	0.0705***	0.0111***
	(0.00493)	(0.0147)	(0.00787)	(0.00972)	(0.00898)	(0.00649)
Duration (ln)	-0.245***	-0.346***	-0.311***	-0.209***	-0.239***	-0.280***
	(0.00138)	(0.00709)	(0.00251)	(0.00175)	(0.00159)	(0.00280)
Initial Trade (ln)	-0.0770***	-0.141***	-0.103***	-0.0671***	-0.0802***	-0.0764***
	(0.000297)	(0.00197)	(0.000612)	(0.000355)	(0.000347)	(0.000630)
Importer GDP (ln)	0.0951***	0.0766***	0.121***	0.0834***	0.0976***	0.0915***
	(0.00225)	(0.0138)	(0.00476)	(0.00261)	(0.00253)	(0.00496)
Exporter GDP (ln)	-0.0225***	0.0347***	0.0101***	-0.0671***	-0.0317***	-0.0136***
	(0.00228)	(0.0117)	(0.00395)	(0.00311)	(0.00266)	(0.00452)
Distance (ln)	-0.0459***	-0.0447***	-0.0419***	-0.0508***	-0.0587***	-0.0273***
	(0.000814)	(0.00875)	(0.00197)	(0.00102)	(0.000950)	(0.00168)
Contiguity	0.0380***	0.0864***	0.0368***	0.0289***	0.0423***	0.0346***
	(0.00225)	(0.0184)	(0.00452)	(0.00250)	(0.00256)	(0.00472)
Common language	0.0287***	0.00863	0.0217***	0.0341***	0.0393***	0.0109***
	(0.00174)	(0.0102)	(0.00375)	(0.00213)	(0.00200)	(0.00359)
Observations	6,341,301	243,675	1,836,348	4,261,278	5,023,041	1,318,260
R^2	0.026	0.045	0.035	0.022	0.026	0.030

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

for middle income countries and manufacturing industries. Moreover, empirical findings show that duration of a trade relationship increases in size and age of a spell, while the growth of a spell decreases in its initial size.

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CHAPTER 3

PRODUCT COMPLEXITY AND DURATION OF US EXPORTS

3.1 Introduction

The growing literature shows that there is a big difference in trade patterns of complex goods and simple goods. Berkowitz et al. (2006) show that good institutions of exporting countries increase international trade in complex products. Yu et al. (2013) show that trade liberalization increases productivity for firms that produce complex goods and decreases productivity of firms producing simple goods. Ma et al. (2012) investigate how institutions affect exports of complex and simple products. Their findings show that bad institutions, such as poor legal system and corruption, reduce exports of complex goods. But the effect of such institutions on the exports of simple products is uncertain.

Unlike the above papers analyzing trade patterns of complex goods in which the authors simply treat complex goods as differentiated goods, Krishna and Levchenko (2013) measure product complexity as the number of inputs used for each sector. They propose a theoretical model and show that low-income countries specialize in less complex goods. They also verify that less complex industries are more volatile in output. Koren and Tenreyro (2013) find that goods that use many inputs are less vulnerable to shocks to any individual input. By contrast, a product that uses very few inputs will be more volatile. In this paper we follow Krishna and Levchenko's (2013) measure of product complexity and examine whether complex and simple goods behave differently in duration of exports. Our hypothesis is that complex products have longer duration than simple ones.

To test our hypothesis, we use the U.S. 1997 Input-Output (IO) table to calculate the number of inputs used for each sector's production. The larger the number of inputs used, the more complex the sector is. Since the IO table is based on North American Industry

Classification System (NAICS), we collect U.S. exports data based on 6-digit NAICS from 1989 to 2006. We find that more complex sectors are more likely to survive in the export market. In addition, complexity plays no role in trade duration for homogeneous goods, but more complex goods are significantly associated with lower hazard for reference priced and differentiated goods by Rauch's (1999) classification.

Our paper also contributes to the trade duration literature. Besedeš and Prusa (2006b) show that product differentiation affects the duration of trade relationships. Araujo et al. (2016) find that if an importer has higher institution quality, then the trade relationship would be longer. Chen (2012) finds that duration of exports increases with innovation and the effect is stronger for differentiated goods. In our paper, we contribute to the duration literature by studying how sectors' complexity influences the duration of exports.

3.2 Implication of Product Complexity

The existing findings show that complex and simple goods display different trade patterns. These papers, however, do not directly address the issue of duration of trade relationships for complex and simple goods. In this paper, we use Krishna and Levchenko's (2013) measure of product complexity which is calculated by the number of inputs. We can interpret this measurement that more complex goods are more technologically diversified as Koren and Tenreyro (2013). In their paper they propose a theory predicting that the more complex goods are more stable for two reasons. First, a product that uses many inputs will be less affected by shocks to any individual input given the law of large numbers. Second, firms can adjust the combinations of inputs they use to partially offset the shock to any single input. They provide an example explaining the second reason. In the example leading-edge steel producers could process a broad range of iron ore with different qualities while the basic steel producers can only accept high-quality ores as input. Obviously the former are less vulnerable to shocks to the high-quality iron ore. A recent example is that Huawei, a Chinese telecommunication equipment provider, uses several kinds of similar memorial chips producing its smart phones to mitigate the short supply of a major chip. Although this argument is more reasonable when input varieties are substitutes, Koren and Tenreyro (2013) show that the ability to utilize a large number of inputs could lead to lower volatility even when inputs display complementarity. Moreover, it is unlikely that all input varieties are complements when the number of inputs is large enough. In summary, if complex goods indeed are more stable, we would expect that complex goods are more likely to survive in the export market. Our first hypothesis is:

Hypothesis 1. More complex products have longer duration of exports.

Rauch (1999) categorizes commodities into three types: homogeneous, reference priced, and differentiated products. Homogeneous goods are products traded on an organized exchange. Products not sold on exchanges but whose benchmark prices exist are defined as reference priced. All other products are classified as differentiated. Besedeš and Prusa (2006b) show that differentiated goods have the longest trade duration, followed by reference priced products, and then homogeneous goods. We expect that the effect of complexity on export duration varies across different product types. Then our second hypothesis is:

Hypothesis 2. The effect of complexity on export duration is greater for differentiated products than that for homogeneous products.

3.3 Data

Product complexity data come from the U.S. Input-Output table for 1997 provided by the Bureau of Economic Analysis (BEA). In particular, we use the total number of inputs in production as a proxy for product complexity. The number of inputs in IO Table differs significantly ranging from 1 to 363. The simplest product is ”Private Household” with only one input and the most complex good is ”Retail Trade” including 363 inputs. One advantage of the U.S. IO table is that it gives us the information on production linkage between industries at a highly disaggregated level, namely 6-digit NAICS based codes.

Table 3.1: Top and Bottom 5 of U.S Exported Products by Complexity

	NAICS97	Product description	PC: Number of Inputs
Bottom 5	311213	Malt manufacturing	66
	311512	Creamery butter manufacturing	75
	311212	Rice milling	79
	1119A0	Sugarcane and sugar beet farming	83
	314992	Tire cord and tire fabric mills	83
Top 5	333415	AC, refrigeration, and forced air heating	213
	336413	Other aircraft parts and equipment	214
	331111	Iron and steel mills	224
	32619A	Plastics plumbing fixtures and all other plastic products	225
	336411	Aircraft manufacturing	228

Data Source: Bureau of Economic Analysis

There are 470 industries in the 1997 IO tables. The IO Table lists some service sectors like ”Financial Service” and ”Hospital” etc., however, trade data do not include service sectors. The total number of industries in trade data differs that in IO Table. The NAICS based U.S. export data include 237 industries. Table 3.1 lists the top and bottom 5 products of U.S. exports by complexity. The simplest product of U.S. exported is ”Malt Manufacturing” which uses 66 inputs, while the most complex good is ”Aircraft Manufacturing” which uses 228 inputs.

We use the 1997 IO Table for three reasons. First, the product classification is consistent to export data which recorded in 1997 NAICS. Second, we want to investigate the effect of complexity on export duration across three Rauch (1999) product types, which uses SITC classification. Then we need to make concordance between NAICS and SITC. NBER provides the mapping of these two classifications, but it is based on 1997 NAICS. Finally, the BEA updates the IO Table every five year implying that production technology changes not too quickly. And the trade data we used is from 1989 to 2006, then the appropriate choices would only be 1997 and 2002. So we use the 1997 IO Table as a baseline and the 2002 IO Table as a robustness check.

U.S. export data come from Feenstra (1996) and Feenstra et al. (2002). Since 1989 the data set provides 6-digit NAICS based exports. To avoid potential concordance issues of different NAICS versions (NAICS 1997 2002 2007), we use the period from 1989 to 2006 in which records trade data by 1997 NAICS consistently. We can identify all countries which import from U.S. for each sector in a given year. On average, U.S. exports about 237 sectors to about 180 countries. In addition to results based on these data, we perform a number of robustness checks including using alternative measures of product complexity and using trade data based on Standard International Trade Classification (SITC) industry codes.

We transform annual data to spell structure for estimation. A spell is defined as continuous exports of a product from the U.S. to a partner country over a number of consecutive years. If U.S. exports product i to country c continuously from 1989 to 1993 then this represents a spell with length of 5 years. Our final data sample consists of 130,053 observations and 18,835 trade relationships between the U.S. and a destination country.

One important issue in survival analysis is the censoring issue. The data we used is from 1989 to 2006. However, a relationship observed in 1989 may have a starting year in 1989 or earlier. Such spells are said to be left censored and are omitted from our analysis as they present an econometric challenge since it is not known whether 1989 is their first year or some other year in the spell. Similarly, relationships observed ending in 2006 may have truly ended later than 2006. Such spells are said to be right censored. Unlike left censored spells, right censored spells are included in our analysis since their start is observed as is their evolution. The only unknown information about them is their eventual length, a feature easily allowed for by all standard models use to estimate duration or hazard.

3.4 Empirical Specification and Results

3.4.1 Hazard estimation

Trade duration and its determinants is usually examined by estimating a hazard model. The hazard is the probability of exports of variety v from the U.S. to an importing country i in spell s ceasing at time $t + 1$ conditional on it having survived until time t, $P(T_{si}^{v} \leq$

$t+1|T^v_{si} \geq t)$, where T^v_{si} is a random variable measuring the survived duration of spell si. Many papers addressing the duration of trade relationships have followed Besedeš and Prusa (2006a,b) and estimate various versions of continuous-time Cox proportional hazard models. However, Hess and Persson (2011) point out that discrete-time models are more suitable to estimate hazards in large trade data sets because of three major reasons. The first one is that the continuous-time models cannot address tied duration times and lead to biased estimates. Trade data have many tied ceasing times because of the large number of countries and industries over many years. Secondly, the Cox model is difficult to control for unobserved heterogeneity which requires evaluation of thousands even millions of integral. Specifically, the dimensionality of trade relationships would equal the number of trade relationships in our data, which is more than 10,000. Finally and most importantly, the Cox model relies on a very restrictive assumption of proportional hazards which may not be true in many cases particularly in trade data. By contrast, the discrete-time models, such as Probit model, can handle all three drawbacks without difficulties.

We define the hazard of a spell trade ceasing, h^v_{sit} and estimate the hazard of exports ceasing at time $t+1$ using the random-effects Probit model as

$$\begin{aligned} h^v_{sit} &= P(T^v_{si} \leq t+1|T^v_{si} \geq t) \\ &= \Phi(pc^v(d) + lnd(t)_{sit} + lnV^v_{sit} + lnGDP_i + X + \epsilon^v_{si}) \end{aligned} \tag{3.1}$$

where pc^v represents the complexity of product v at year t, $lnd(t)_{sit}$ is the log of age of spell s in year t, lnV_{sit} is the log of U.S. export volume of spell s in year t to country i, $lnGDP_i$ represents the GDP of importer i. X is a vector of gravity variables: Distance, common border, and common language. ϵ^v_{si} captures the relationship-specific random effect.

3.5 Results

3.5.1 NAICS Exports

Hypothesis 1 states that the probability of a trade relationship ceasing (surviving) is negatively (positively) related to product complexity. To test the relationship empirically, we use the random-effects Probit model to estimate the specification given by equation (1).

Table 3.2 presents the baseline estimations, in which we use U.S. 6-digit NAICS based exports and calculate the number of inputs for each sector as the measure of product complexity. Column 1 includes all countries. From the baseline estimations, we find that the more complex sectors have a lower hazard rate, which confirms our hypothesis. Put it another way, if a product increases its number of inputs then it's more likely to survive in export market. We divide destination countries into three groups by country development: low-, middle-, and high-income countries. The country sub-group results are given by Column 2-4. The middle-income countries have the largest magnitude for product complexity and the low-income countries have the smallest although the difference is small. This implies that complexity reduces hazard more for exports to middle- and high-income countries. One possible explanation is that complex goods tend to be more expensive and rich countries have the most stable demand for them because of their high income. Another explanation is that complex goods are usually high-tech embedded requiring high ability to use or adopt them. Middle- and high-income importing countries are more likely to master required skills and ability. The effects of other variables are consistent with literature except for Contiguity and Common language. For example, the larger GDP per capita and trade size are related to lower hazard. Common Language has no impact on hazard except for middle-income countries. One possible explanation is that English is the official language for many African countries but trade relationships between US and those countries last short. Contiguity seems to increase hazard which implies that exports is more likely to cease if importing countries share common border with US. It is not consistent with literature and common sense. The reason is probably that there are only a few countries share a border with US, and coefficients of Contiguity disappear due to collinearity in some specifications. These two variables exhibit similar patterns and we do not explain later.

Table 3.2: Baseline: NAICS Exports

	Base model	Low-income	Middle-income	High-income
Product Complexity (ln)	-0.714***	-0.616***	-0.761***	-0.650***
	(0.0300)	(0.0543)	(0.0458)	(0.0768)
Duration (ln)	-0.321***	-0.343***	-0.312***	-0.264***
	(0.00926)	(0.0179)	(0.0143)	(0.0222)
Importer GDP (ln)	-0.150***	-0.230***	-0.149***	-0.0452***
	(0.00516)	(0.0219)	(0.0140)	(0.0235)
Trade Size (ln)	-0.175***	-0.158***	-0.178***	-0.193***
	(0.00341)	(0.00652)	(0.00519)	(0.00854)
Distance (ln)	0.550***	0.543***	0.624***	0.209***
	(0.0209)	(0.0439)	(0.0319)	(0.0549)
Contiguity	1.811***		1.437***	
	(0.556)		(0.449)	
Common language	-0.00125	-0.00404	-0.164***	0.0534
	(0.0162)	(0.0236)	(0.0319)	(0.0503)
_Constant	1.604***	1.848***	1.135***	3.419***
	(0.226)	(0.442)	(0.329)	(0.661)
Observations	130,488	31,733	59,281	22,430
Relationships	18,881	5,680	8,079	2,749

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 3.1 plots the predicted hazard as complexity level (number of inputs) changes. We choose three complexity levels: Mean, 83, and 213 number of inputs. The latter two are the fifth lowest and fifth highest number of inputs from Table 3.1. We find that the predicted hazard decreases significantly as number of inputs increases from 83 to 213. Specifically, the average predicted hazard of 213 inputs is 0.08628 lower than that of 83 inputs across years.

Figure 3.2 plots the predicted hazard for different complexity levels keeping other explanatory variables at mean values against the spell age using the baseline specification. We look at how the predicted hazard changes as product complexity changes across different development level of countries. Specifically, we plot the predicted hazard when complexity moves one standard deviation (sd) away from the mean. The predicted hazard for products with the mean number of inputs at the first year for all countries is 0.3279 rounding 4 digit and that is 0.3434, 0.2983, and 0.2673 for low-income, middle-income and high-income countries respectively. We note that the predicted hazard decreases as complexity increases from the mean minus sd, the mean, to the mean plus sd. The middle-income countries have the largest decrease while the low-income have the smallest, although the difference is very small. We also find that the predicted probability of ceasing decreases as the relationship survives longer, a standard result in the literature.

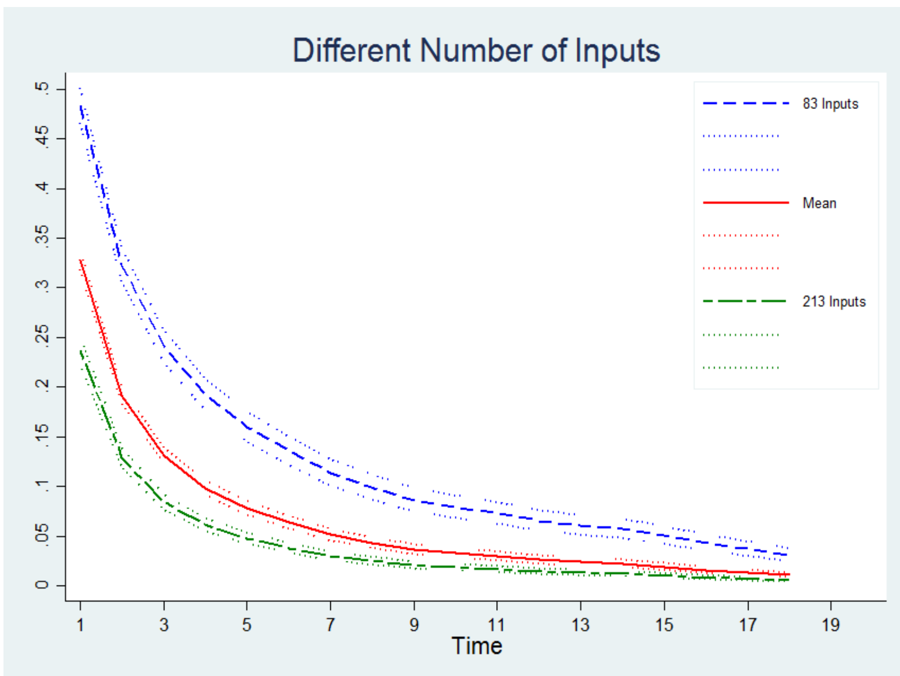

Figure 3.1: Predicted Hazard for Different Number of Inputs

3.5.2 SITC Exports

Hypothesis 2 states that the effect of complexity on trade duration varies across homogeneous and differentiated goods. To test it we make use of concordance from NAICS to SITC classification provided by NBER.[1] The mapping from NAICS to SITC is either one

[1] `http://www.nber.org/lipsey/sitc22naics97/`

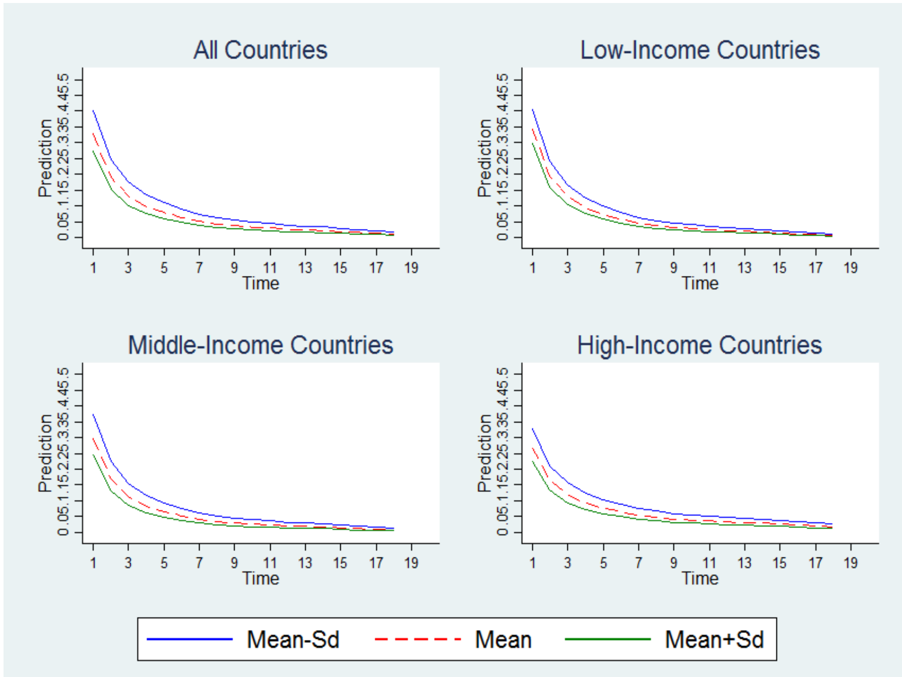

Figure 3.2: Predicted Hazard Across Countries

to one or N to one. For the latter case, we weigh each SITC sector equally which means each SITC sector would be assigned $1/N$ number of inputs if the NAICS sector has just one input. For example, the NAICS code 314110 ("Carpet and rug mills") uses 156 inputs. From the NBER concordance form, it is mapped to five SITC codes: 6592, 6593, 6594, 6595, and 6596. Then each of the five SITC sectors has 31.2 ($156/5$) inputs. We also use an unweighted concordance scheme and keep only one-to-one codes as robustness checks. Those alternative concordance scheme yield similar results as we discuss below. Finally we merge SITC-based product complexity and Rauch (1999) product type classification to the trade data. Figure 3.3 plots the distribution of weighted number of inputs for three product types by Rauch (1999). We can see that differentiated goods have big variations while homogeneous goods have small variations and most of them have very few number of inputs.

Table 3.3 presents the results of hazard estimation using 4-digit SITC U.S. exports. Column 1 presents the results of baseline specification. Column 2-4 provides the results for low-income, middle-, and high-income countries as those in Table 3.2. Comparing the baseline model in Table 3.2, the coefficient of complexity in Table 3.3 is much smaller, but it's still significantly negative. Columns 5-7 present the estimations for homogeneous, referenced priced, and differentiated goods respectively, which we are interested in. We can find that the differentiated products dominate U.S. exports which accounts for about 50% of observations while homogeneous goods account for less than 1% observations. The results show that complexity is not a significant factor affecting export duration for homogeneous goods. But more complex products have lower hazard for referenced price and differentiated goods, and the effect is larger for differentiated goods. This confirms our second hypothesis and is consistent to Besedeš and Prusa's (2006b) finding.

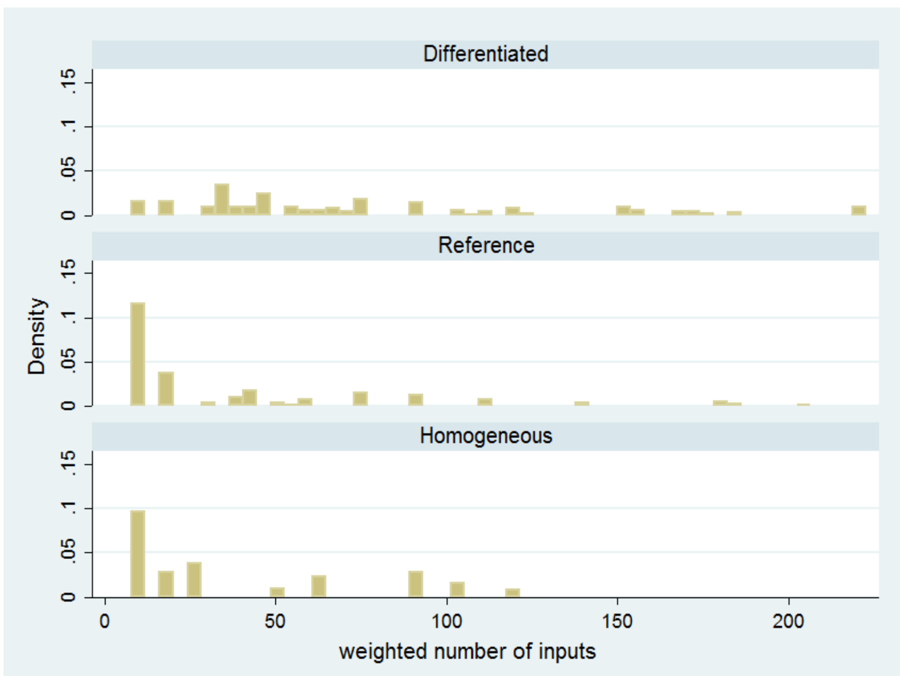

Figure 3.3: Complexity Distribution

Figure 3.4 plots the predicted hazard for different complexity based on the baseline regression of Table 3.3. As we can see that the predicted hazard decreases as number of inputs increases from 83 to 213, and the average predicted hazard of 213 inputs is 0.0173898 lower than that of 83 inputs across years. However, the effect is not so significant as that

Table 3.3: SITC Exports

	Base model	Low-income	Middle-income	High-income	Homogeneous	Reference	Differentiated
Product Complexity (ln)	-0.0918***	-0.0888***	-0.0933***	-0.0856***	0.0410	-0.0360***	-0.179***
	(0.00815)	(0.0177)	(0.0125)	(0.0159)	(0.0320)	(0.0125)	(0.0160)
Duration (ln)	-0.304***	-0.277***	-0.303***	-0.303***	-0.284***	-0.297***	-0.308***
	(0.0115)	(0.0268)	(0.0173)	(0.0226)	(0.0440)	(0.0188)	(0.0163)
Importer GDP (ln)	-0.0892***	-0.186***	-0.109***	-0.0153*	-0.0436***	-0.111***	-0.107***
	(0.00466)	(0.0139)	(0.00776)	(0.00919)	(0.0144)	(0.00746)	(0.00739)
Trade Size (ln)	-0.182***	-0.188***	-0.181***	-0.180***	-0.183***	-0.173***	-0.191***
	(0.00416)	(0.00940)	(0.00640)	(0.00826)	(0.0149)	(0.00650)	(0.00631)
Distance (ln)	0.316***	0.323***	0.392***	0.0838***	0.306***	0.382***	0.317***
	(0.0208)	(0.0598)	(0.0313)	(0.0434)	(0.0740)	(0.0307)	(0.0338)
Contiguity	0.316***		0.455***		-0.208	0.617***	
	(0.175)		(0.251)		(0.371)	(0.245)	
Common language	-0.00458	0.0553	-0.157***	-0.00404	0.0392	-0.0224	-0.0350
	(0.0189)	(0.0349)	(0.0358)	(0.0399)	(0.0694)	(0.0302)	(0.0278)
_Constant	0.289	1.188***	-0.234	1.599***	-0.348	-0.325	0.795***
	(0.187)	(0.521)	(0.269)	(0.403)	(0.659)	(0.273)	(0.303)
Observations	79,602	14,484	35,745	20,158	6,181	29,761	38,522
Relationships	13,311	3,092	5,646	3,029	1,136	5,280	5,998

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

in Figure 3.1. One possible explanation is that the concordance between SITC and NAICS does not precisely reflect the complexity of SITC sectors.

Figure 3.5 plots the predicted hazard for homogeneous, reference priced, and differentiated goods respectively. Since the effect of complexity on homogeneous products is not significant, we focus only on the latter two types of goods. We can find that the predicted hazard display similar pattern as in the Figure 3.2 that it decreases as complexity increases for both reference priced and differentiated products. But the effect for the latter goods is much larger than that for the former.

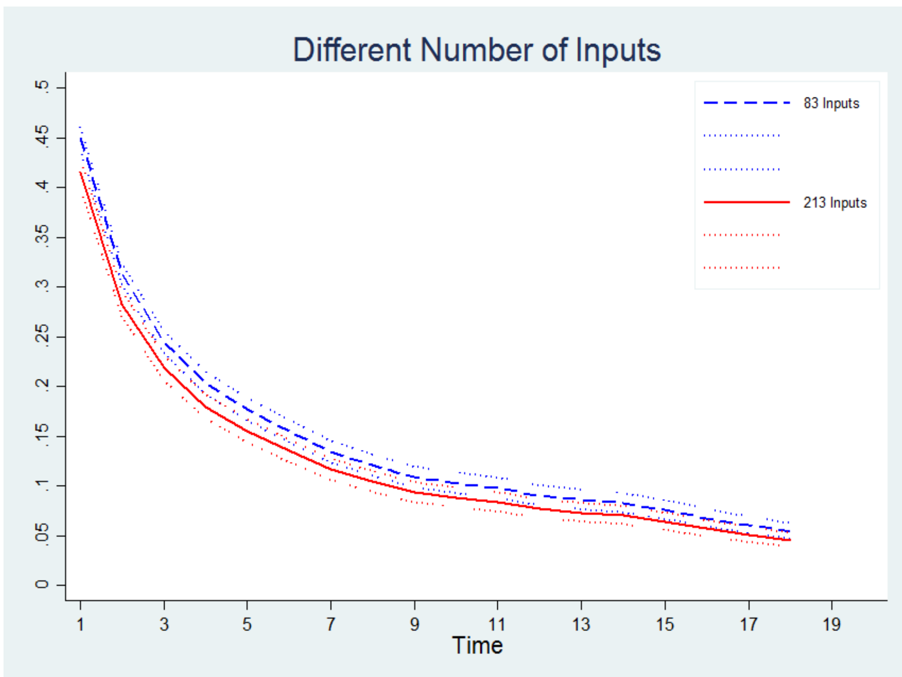

Figure 3.4: Predicted Hazard for SITC Exports

3.6 Robustness Checks

3.6.1 Unweighted SITC Complexity

In Table 3.3, we use equal weights from NAICS and SITC to calculate the number of inputs for each SITC sector. Now we use the unweighted scheme to calculate SITC based complexity. We again refer to the NAICS code 314110 which has 156 inputs and corresponds

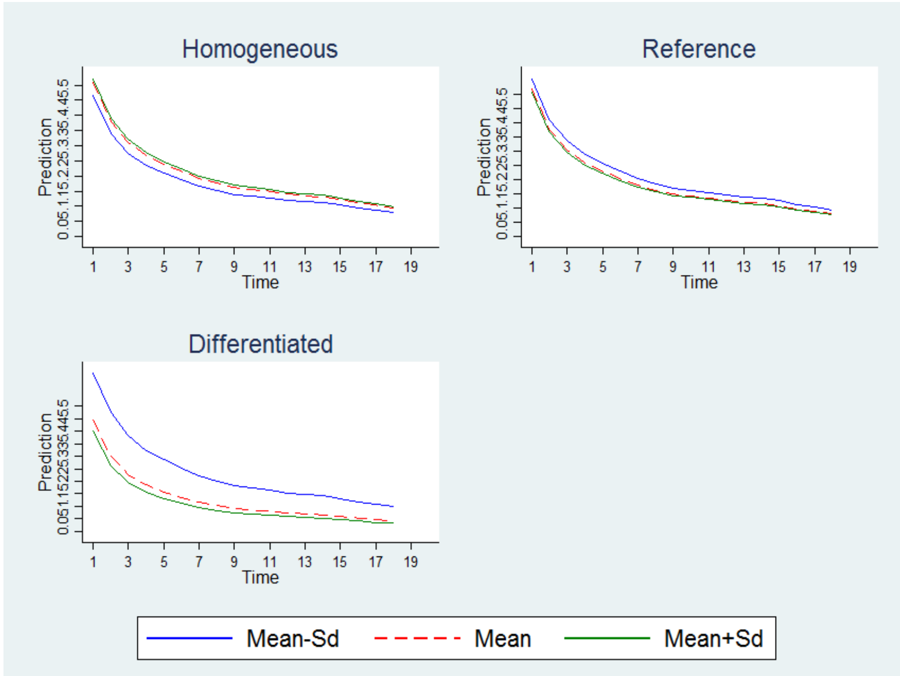

Figure 3.5: Predicted Hazard for Different Product Types

to five SITC codes. Now each of the five SITC sectors has 156, the same as the NAICS code instead of 31.2 for each. Table 3.4 presents the results based on unweighted SITC complexity. We find that the estimation of baseline model is similar to that in Table 3.3. The coefficient of complexity is slightly larger than that in Table 3.3. In addition, the coefficient of complexity on differentiated goods is still significantly negative and slightly increased from -0.179 to -0.287. Complexity has no significant impact on homogeneous goods which is similar to the benchmark results. One difference is that the effect of complexity on referenced goods becomes insignificant using the unweighted scheme.

To avoid any weighting scheme from NAICS to SITC, we keep only one-to-one mapped codes of these two classifications. This procedure reduce observations significantly leading only 24 industries left. Table 3.5 presents the results. The coefficients of complexity increase dramatically in all estimations though the overall effect of complexity on duration is still significantly negative. The coefficient of complexity for homogeneous goods is extremely large and positive and is hard to interpret. The effect of complexity for reference

Table 3.4: Unweighted SITC Complexity

	Base model	Homogeneous	Reference	Differentiated
Product Complexity (ln)	-0.128***	-0.0811	-0.145***	-0.287***
	(0.0315)	(0.125)	(0.0497)	(0.0503)
Duration (ln)	-0.308***	-0.286***	-0.296***	-0.320***
	(0.0115)	(0.0440)	(0.0189)	(0.0164)
Importer GDP (ln)	-0.0845***	-0.0422***	-0.114***	-0.0916***
	(0.00464)	(0.0142)	(0.00760)	(0.00710)
Trade Size (ln)	-0.183***	-0.185***	-0.174***	-0.194***
	(0.00416)	(0.0148)	(0.00650)	(0.00628)
Distance (ln)	0.296***	0.304***	0.386***	0.271***
	(0.0207)	(0.0746)	(0.0308)	(0.0331)
Contiguity	0.249	-0.182	0.584***	
	(0.170)	(0.360)	(0.235)	
Common language	-0.000292	0.0419	-0.0278	-0.0115
	(0.0190)	(0.0690)	(0.0302)	(0.0276)
_Constant	0.768***	0.204	0.333	1.857***
	(0.244)	(0.859)	(0.372)	(0.384)
Observations	79,602	6,181	29,761	38,522
Relationships	13,311	1,136	5,280	5,998

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

priced and differentiated goods are consistent to those in benchmark models.

3.6.2 2002 IO Table

We want to examine whether the effect of product complexity on export duration is driven by the use of 1997 IO Table, so we use 2002 IO Table to obtain product complexity and run the same estimations as baseline models. We only keep unchanged codes from 1997 NAICS to 2002 NAICS. Table 3.6 present the results of NAICS based exports. We can find that the results in Table 3.6 and Table 3.2 are similar. The findings show that more complex goods are associated with lower hazard for all countries. The coefficients of complexity increase in all specifications particularly for high-income countries.

We also want to know how the effect of complexity changes over Rauch (1999) product

Table 3.5: One-to-One Matched SITC and NAICS

	Base model	Homogeneous	Reference	Differentiated
Product Complexity (ln)	-0.531***	9.705***	0.122	-0.720***
	(0.105)	(1.787)	(0.205)	(0.129)
Duration (ln)	-0.312***	-0.352***	-0.304***	-0.291***
	(0.0306)	(0.154)	(0.0664)	(0.0369)
Importer GDP (ln)	-0.0862***	-0.0764***	-0.189***	-0.121***
	(0.0138)	(0.0443)	(0.0335)	(0.0177)
Trade Size (ln)	-0.209***	-0.185***	-0.173***	-0.234***
	(0.0120)	(0.0440)	(0.0265)	(0.0151)
Distance (ln)	0.394***	0.278	0.739***	0.396***
	(0.0663)	(0.179)	(0.129)	(0.0905)
Contiguity	0.431***			
	(0.124)			
Common language	0.0253	-0.269***	-0.178	0.00497
	(0.0566)	(0.141)	(0.127)	(0.0690)
_Constant	2.050***	-45.14***	-3.685**	3.409***
	(0.757)	(8.587)	(1.475)	(1.028)
Observations	11,807	681	2,416	7,942
Relationships	1,756	134	386	1,081

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

types as technology progresses. Then we re-run the estimations as Table 3.3 using the 2002 IO Table. Table 3.7 presents the results. We find that the coefficients of complexity are bigger than those used the 1997 IO Table for three types of products particularly for differentiated goods. This implies that differentiated products benefit most from technology changes in terms of duration. The effects of other variables in Table 3.7 are similar to those in Table 3.3. One key difference is that the impact of complexity on homogeneous goods becomes significant using 2002 IO Table, which indicates that the hazard of homogeneous goods increases as the number of inputs increases. One possible reason is that the cost of input diversification is outweigh the benefit for homogeneous goods.

Table 3.6: 2002 IO Table and NAICS Exports

	Base model	Low-income	Middle-income	High-income
Product Complexity (ln)	-0.857***	-0.819***	-0.844***	-0.893***
	(0.0500)	(0.0924)	(0.0757)	(0.124)
Duration (ln)	-0.336***	-0.345***	-0.338***	-0.271***
	(0.0106)	(0.0201)	(0.0164)	(0.0259)
Importer GDP (ln)	-0.140***	-0.222***	-0.134***	-0.0235***
	(0.00528)	(0.0123)	(0.00809)	(0.0132)
Trade Size (ln)	-0.173***	-0.158***	-0.175***	-0.190***
	(0.00394)	(0.00746)	(0.00603)	(0.00989)
Distance (ln)	0.514***	0.476***	0.590***	0.169***
	(0.0242)	(0.0481)	(0.0376)	(0.0638)
Contiguity	1.566***		1.236***	
	(0.484)		(0.374)	
Common language	0.00630	-0.00848	-0.146***	0.118**
	(0.0185)	(0.0269)	(0.0364)	(0.0589)
_Constant	2.361***	3.260***	1.525***	4.562***
	(0.308)	(0.590)	(0.451)	(0.856)
Observations	99,680	24,726	45,114	16,719
Relationships	14,276	4,365	6,100	2,005

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.6.3 Alternative measure of product complexity

Krishna and Levchenko's (2013) measurement of product complexity is input based, while Hausmann et al. (2011) use a result-based approach to measure product complexity. First, they define diversity to measure how many different products a country is able to make. Second, they define the ubiquity to measure the number of countries that are able to make a particular product. Then the complexity of a product is calculated from the average diversity of countries that make this product, and the average ubiquity of other products that these countries could make. Put it simply, a product is more complex if there are few countries that are able to produce it, and these countries could produce many other goods. The Hausmann et al. (2011) measure of complexity does not directly link to input diversification. However, it takes account of countries' technological capability to produce. If a country is able to produce a broad range of products, it implies that the country has a larger technology capability or a more diversified technology. Then we would expect that the effect of the Hausmann et al. (2011) measure of complexity on trade duration is similar to that in the baseline model.

Since Hausmann et al. (2011) complexity has negative values, we can not take log value and keep its original value in estimation. Other variables are the same as Table 3.3. Table 3.8 presents the hazard estimations using the Hausmann et al. (2011) measure of product complexity. We can find that the coefficients on the Hausmann et al. (2011) complexity measure are very similar to those in Table 3.3. The overall effect of HH complexity on hazard is negative and significant, and it becomes insignificant for homogeneous goods. In addition, its effect is larger for differentiated goods than that for reference priced goods.

Along with the existing literature that link trade duration with product type and the search cost model (Besedeš and Prusa, 2006b; Besedeš, 2008), complexity or technological diversification provide another explanation for trade duration.

3.7 Conclusions

This paper offers an additional empirical evidence that the trade pattern in complex and simple products is different. Specifically, we examine the impact of product complexity on the duration of trade. Using Krishna and Levchenko (2013) and Hausmann et al. (2011) measurements of product complexity, we show that trade relationships involving more complex goods last longer. In addition, the impact of complexity on export duration is stronger for differentiated products than referenced price products, while the impact is insignificant for homogeneous goods.

One extension of interest is to explore the exact usage of each product by other products not simply looking at the number of inputs of each sector, i.e., how different sectors connect to each other. There may exist different types of connections either strong or weak. Then one can investigate how a particular shock to one sector affects trade patterns (including duration) of other sectors. The influence may depend on how sectors connect to each other.

Table 3.7: 2002 IO Table and SITC Exports

	Base model	Low-income	Middle-income	High-income	Homogeneous	Reference	Differentiated
Product Complexity (ln)	-0.158***	-0.0984***	-0.154***	-0.202***	0.0801***	-0.0498***	-0.187***
	(0.00675)	(0.0138)	(0.0101)	(0.0146)	(0.0195)	(0.0143)	(0.0107)
Duration (ln)	-0.312***	-0.330***	-0.310***	-0.272***	-0.279***	-0.300***	-0.310***
	(0.00822)	(0.0174)	(0.0125)	(0.0173)	(0.0273)	(0.0205)	(0.0103)
Importer GDP (ln)	-0.125***	-0.209***	-0.128***	-0.0534***	-0.0895***	-0.119***	-0.157***
	(0.00375)	(0.0100)	(0.00583)	(0.00838)	(0.00983)	(0.00844)	(0.00518)
Trade Size (ln)	-0.163***	-0.141***	-0.168***	-0.168***	-0.170***	-0.195***	-0.177***
	(0.00291)	(0.00594)	(0.00444)	(0.00659)	(0.00833)	(0.00719)	(0.00369)
Distance (ln)	0.396***	0.395***	0.455***	0.105***	0.205***	0.391***	0.511***
	(0.0163)	(0.0394)	(0.0243)	(0.0379)	(0.0418)	(0.0355)	(0.0218)
Contiguity	0.529***		0.571***		-0.0752	-0.271	0.464
	(0.206)		(0.218)		(0.354)	(0.252)	(0.358)
Common language	0.0296**	0.0489**	-0.117***	0.00242	-0.0657	-0.0472	0.00213
	(0.0142)	(0.0235)	(0.0261)	(0.0356)	(0.0445)	(0.0337)	(0.0174)
_Constant	-0.0802	0.304	-0.605***	2.036***	0.844**	-0.0772	-0.654***
	(0.147)	(0.349)	(0.211)	(0.354)	(0.372)	(0.316)	(0.199)
Observations	167,745	36,631	75,199	34,902	14,405	27,430	110,590
Relationships	25,932	6,954	11,037	4,824	2,629	4,688	16,215

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.8: Hausmann et al. product complexity

	Base model	Low-income	Middle-income	High-income	Homogeneous	Reference	Differentiated
Product Complexity	-0.0942***	-0.0890***	-0.0911***	-0.104***	-0.0120	-0.0392***	-0.0851***
	(0.00386)	(0.00848)	(0.00579)	(0.00813)	(0.0140)	(0.00791)	(0.00516)
Duration (ln)	-0.323***	-0.324***	-0.314***	-0.282***	-0.313***	-0.323***	-0.328***
	(0.00555)	(0.0131)	(0.00843)	(0.0111)	(0.0200)	(0.0114)	(0.00737)
Importer GDP (ln)	-0.0829***	-0.295***	-0.153***	-0.0154	-0.0578***	-0.0733***	-0.102***
	(0.00273)	(0.0153)	(0.00771)	(0.0118)	(0.00885)	(0.00517)	(0.00375)
Trade Size (ln)	-0.183***	-0.162***	-0.187***	-0.182***	-0.153***	-0.199***	-0.201***
	(0.00197)	(0.00434)	(0.00297)	(0.00414)	(0.00584)	(0.00391)	(0.00269)
Distance (ln)	0.205***	0.0723***	0.242***	0.0362	0.127***	0.199***	0.246***
	(0.0101)	(0.0268)	(0.0142)	(0.0230)	(0.0298)	(0.0180)	(0.0142)
Contiguity	-0.0459		0.131		-0.537***	-0.0978	0.361***
	(0.0986)		(0.122)		(0.163)	(0.170)	(0.204)
Common language	0.103**	0.0557**	0.126***	-0.00352	-0.000985	0.0463***	0.113***
	(0.00901)	(0.0172)	(0.0157)	(0.0202)	(0.0308)	(0.0173)	(0.0117)
_Constant	0.728***	3.129***	0.861***	1.679***	1.219***	0.988***	0.564***
	(0.0987)	(0.266)	(0.142)	(0.247)	(0.285)	(0.174)	(0.139)
Observations	354,662	67,516	160,459	83,568	26,739	84,986	209,053
Relationships	57,576	13,747	24,802	12,251	5,028	15,014	31,903

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.8 References

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