# Does Trade Insurance Matter?

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**Abstract**

Using unique data from Turkey, this study compiles a measure of product reliance on trade insurance. The measure is based on the use of letters of credit, which allow trading parties to avoid trade-related risks, such as non-payment or non-delivery of pre-paid goods. Combing the new measure with bilateral trade figures for 98 countries shows that products relying heavily on trade insurance saw a larger decline in exports to destinations affected by the recent financial crisis than other products did. Products relying heavily on trade insurance also registered an increase in the intra-firm share of exports sent to crisis-affected countries. This result is intuitive as intra-firm trade is much less risky than arms-length transactions.

Keywords: Trade insurance, Financial crisis, Risk, Letter of credit, Intra-firm trade

JEL codes: G01; F14; F23.

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# 1 Introduction

Trading goods across international borders is more risky than trading within national borders. The trading partners are located in different countries that may be separated by a large distance which results in long shipping times, are subject to different laws and may speak different languages. Thus it is crucial for the trading partners to agree on how to share the risks associated with their transaction.

There exist three primary ways of structuring financing in international trade. Under *open account*, the importer pays after the arrival of the goods in the destination and the exporter is exposed to the risk of non-payment. Alternatively, under *cash in advance* the importer pays before the exporter ships the goods to the destination, and thus it is the importer who faces the risk of not receiving the pre-paid goods. Finally, the trading partners may shift the risk onto a third party by purchasing a *letter of credit* (LC). In an LC-financed transaction, the importer's bank promises to pay for the goods on behalf of the importer provided the exporter meets all requirements specified in the contract. In this way, the risk of non-payment or non-delivery of pre-paid goods is eliminated. A substantial fee is typically charged by a bank issuing an LC.[1]

There is a lot of variation across countries and importing firms in the extent to which LCs are used and hence trade-related risks are insured. The choice of LC as a payment method is determined by various factors, including the quality of institutions, level of competition in partner countries, and the length of the relationship with a given trading partner (see Schmidt-Eisenlohr, 2013; Antràs and Foley, 2015; Demir and Javorcik, 2018).

This paper draws attention to differences *across products* in their reliance on LCs to insure trade-related risks. Such differences appear to be substantial. For instance, among 1208 different products (defined according to 4-digit Harmonized System (HS) classification) imported by Turkey in 2006, no LCs were used in 250 cases, while in 151 cases LCs covered at least 20% of the import value. In 29 of 1208 products, LCs covered at least 50% of the import value. These differences may stem mostly from product characteristics that increase the demand for insurance against non-payment or non-delivery.

The purpose of this paper is threefold. First, we introduce a new index capturing product reliance on LCs, which we call *Trade Insurance Intensity*, or *TII* hereafter. Second, we demonstrate that products relying more heavily on trade insurance experienced a more severe decline in exports to countries affected by the 2008 financial crisis. This result is not surprising because the financial crisis made it difficult, if not impossible, to purchase LCs.

[1] The exporter may further eliminate the risk of the importer's bank defaulting by using services of another bank in their country to confirm an LC.

Third, we show that the share of intra-firm exports increased for goods relying heavily on trade insurance and destined for crisis-afflicted countries (relative to other goods and other destinations). This is intuitive because intra-firm trade is much less (if at all) subject to risks of default or non-delivery and thus may be more resilient than arms-length trade when no trade insurance is available for purchase. Considering the share of intra-firm trade in total exports is appealing for another reason. It allows us to control for all the factors that may be affecting total exports of a given product to a particular crisis-affected destination in a given time period, such a decline in demand, the impact of worsening conditions in the importing industry, etc. This result therefore confirms that our *TII* indicator does capture dependence on trade insurance and that our results on the role of trade finance during financial crises are not driven by unobserved product characteristics. Finally, we explore further the relationship between insurance dependence and intra-firm trade by focusing on a non-crisis period. We find that intra-firm trade share is higher for insurance-intensive goods exported to destinations with underdeveloped financial markets, where availability of LCs may be limited.

To construct our product-level measure of trade insurance intensity we use detailed import and export data from Turkey disaggregated by the trading firm, 6-digit HS product code, source country, year and payment method. Turkish data are very suitable for this purpose for several reasons. Turkey is a fast-growing OECD country that ranks among the top twenty largest economies in the world. It imports a very large number of products from over 200 destinations reflecting a diversified supplier base. And, most importantly, it collects detailed information on payment terms used in international trade transactions.

When constructing the *TII* measure, we remove variation due to different partner countries and different trading firms in particular years. *TII* is available for 1203 4-digit HS products. It is based on the years 2003-2006, chosen to avoid the period of the recent financial crisis. We focus on multiple years to avoid capturing idiosyncratic shocks, though we show that constructing the index using data from individual years does not affect much the rankings. Our index reveals considerable variation across products within industries. For instance, “Nickel mattes; nickel oxide sinters and other intermediate products of nickel metallurgy" (HS7401) are among the products with the lowest value of *TII*, while another product “Nickel; waste and scrap" (HS7503), belonging to the same 2-digit HS heading, is among products with the highest *TII* value.

The *TII* measure exhibits intuitive correlations with several product characteristics, such as, demand volatility, time to ship and transaction size. A negative demand shock may make the buyer disinclined to accept and pay for the shipment. A longer delay due to the shipping time increases the risk of an adverse exchange rate or price movement, and thus may prompt one of the trading partners to try to renegotiate the contract.[2] If a given product tends to be shipped in bulk, due to its inherent characteristics, the large transaction value gives the trading partners a greater impetus to eliminate the risk.[3]

When aggregated to the industry-level, *TII* exhibits no correlation with standard industry-level finance dependence measures, such as the widely used measure of reliance on external financing constructed by Rajan and Zingales (1998) and others. This is not surprising, as *TII* is designed to capture something very different. Indicators of external finance dependence intend to capture the amount of desired investment that cannot be financed through internal cash flows generated by the same business. In contrast, *TII* intends to capture the need to insure sales against non-payment and is not directly related to the firm's or industry's financing needs.

We present two applications of *TII* to questions widely studied in international economics. The first application focuses on the "Great Trade Collapse" of 2008-9, triggered by the financial crisis. The second application is related to intra-firm trade and firms' choice between sourcing from third-party companies or internalizing their international sourcing within their own networks of foreign affiliates. These applications are interesting in their own right, and they are also meant to give examples of potential uses of the new measure. More importantly, they strengthen our argument that *TII* captures product-level variation that matters for international trade decisions.

Between the third quarter of 2008 and the second quarter of 2009, the world witnessed the Great Trade Collapse – the steepest fall of world trade in recorded history and the deepest fall since the Great Depression (Baldwin, 2009). The existing literature has investigated several factors which contributed to this phenomenon, namely the shift away from demand for durable goods (Levchenko et al., 2009; Eaton et al., 2016), increased protectionism (Evenett, 2009) and the lack of access to financing (Amiti and Weinstein, 2011; Paravisini et al., 2015; Chor and Manova, 2012).

This study points out yet another factor – the inability of the trading partners to insure the transaction risk. We conjecture that a banking crisis in the destination country makes it difficult for an importer to purchase a letter of credit and thus has an adverse impact on trade by eliminating the trading parties' ability to insure the transaction risk. This effect goes beyond the impact of a banking crisis on access to credit, which is the channel usually mentioned in the literature. To study this issue we combine the *TII* measure with bilateral trade figures at the 4-digit HS level for 98 countries covering the period 2002-09.

[2]Hummels and Schaur (2010) show theoretically and empirically that transit lags act as trade barriers for firms facing volatile demand and that the likelihood and extent to which firms employ (fast but expensive) air shipments is increasing in the volatility of demand they face.

[3]See Section 2.3 for a more detailed discussion.

Our analysis shows that a lessened ability to insure trade-related risks had a negative impact on international trade flows during the recent financial crisis. More specifically, we find that products that rely heavily on trade insurance registered a larger decline in exports destined for crisis-affected destinations than other products did. The negative impact of a bank crisis on imports was 6.9% more severe for products in the 5*th* quintile of the *TII* measure than for the ones in the first quintile. The results are robust to controlling for origin-destination-product, origin-destination-year, and product-year fixed effects. They hold when we use a continuous measure of *TII*, when we allow for a differential impact of the crisis on products with high dependence on external financing or products with a high elasticity of demand. The results are also robust to controlling for other product characteristics. In sum, these results imply that the recent financial crisis affected trade flows not only through the lack of access to financing and working capital, but also through the lack of guarantees against trade-related risks. A back-of-the-envelope calculation suggests that the insurance channel may have been responsible for about 7% of trade lost during the Great Trade Collapse.

The second application focuses on intra-firm trade. We hypothesize that intra-firm trade (as opposed to arms-length transactions) is more prevalent in products with greater need for trade insurance, as keeping transactions within firm eliminates the risk of non-payment or non-delivery of pre-paid orders. We further conjecture that exports of such products registered an increase in the intra-firm share relative to other products when exports were sent to crisis-affected countries. We also hypothesize that the propensity to keep exports of insurance-intensive products within firm is attenuated when exports are destined for countries with well-developed financial markets, because a well-functioning financial market can provide guarantees that eliminate such risks and hence the need to keeping transactions within firm.

We utilize data on intra-firm exports by US firms disaggregated by country of destination and 4-digit HS product codes. We show that a one-standard-deviation increase in the *TII* index was associated with a 1.1 percentage point increase in intra-firm trade destined for crisis-affected markets. Focusing on the non-crisis period, we show that a one-standard deviation increase in *TII* boosts the share of related-party trade by 2.7 percentage points (or 15% of its mean in 2006) when a country moves from the 90*th* (Spain in 2002) to 10*th* percentile (Dominican Republic in 2005) of the financial development index. These findings illustrate yet another reason why multinational firms may be have an advantage when it comes to exporting.

The intuitive and statistically significant results obtained in the two applications give us confidence that the *TII* index captures what it is intended to measure. We envision a plethora of other settings where this measure could be applied. After all, product-specific need for trade insurance is likely to affect the choice of a firm's product portfolio, the likelihood of entering export markets, the cost of hedging trade-related risks and ultimately profitability. All of these aspects matter for potential investors and shareholders.

More generally, our results suggest that an insufficient supply of trade insurance services (due to a sudden banking crisis or a low level of financial development) constitutes a substantial "behind-the-border" barrier to trade. Moreover, this barrier is likely to be distorting since it has a greater impact on smaller businesses that cannot rely on intra-firm trade. It also suggests that the disruption of the supply of trade insurance is a factor that aggravated the negative impact of financial crises. This is a dimension of the trade-finance nexus that has been rarely explored in the existing literature, which mainly focuses on provision of external finance rather than on provision of ways to handle uncertainty and risk inherent to commercial transactions.

Understanding differences in product reliance on trade insurance is important for policy choices. It may help direct state-run export insurance programs to the right sectors. It may help predict which firms, sectors or even countries may be more adversely affected by financial crises in their main export markets. Our results also suggest that the ownership structure (domestic versus foreign) of exporters may matter in this respect.

Our paper is related to several strands of the existing literature. The first strand encompasses studies that develop innovative industry- or product-specific indices that matter for economic decisions. This strand includes the work of Rajan and Zingales (1998) who developed a measure of industry reliance on external financing that has been widely used by many applied economists. It also includes the classification of products into homogenous, referenced-priced and differentiated groups proposed by Rauch (1999), and applied to a wide range of questions. Similarly, the proportion of differentiated products among an industry inputs has been the basis of the contract intensity index built by Nunn (2007). The TII index developed in this study can be viewed as a complement to the existing indices and can allow researchers consider a fuller range of product characteristics that matter for economic decisions.

The second strand of related literature encompasses studies (reviewed earlier) aiming to explain the Great Trade Collapse. We contribute to the literature by isolating the impact of access to guarantees against trade-related risks on international trade flows.

Finally, our work is related to the literature on intra-firm trade. Recent theoretical developments on firms' outsourcing strategies have highlighted the crucial role of contractual imperfections in deciding whether to use foreign suppliers rather than to internalize foreign production through direct investments (see Antras (2003) and Antras and Helpman (2004) and, for a literature review, Antras and Yeaple (2014) and Antras (2016)). The fact that contracts between an importer and a foreign supplier cannot be fully enforceable generates a risk for both parties. If each of them has to invest in the development of a customized input that is not fully contractible, a classic hold-up problem arises. This creates an incentive to invest in the foreign country to produce the intermediate goods in-house. The existing empirical studies show that the share of intra-firm trade decreases with the degree of contractibility of the inputs and with the institutional quality in the foreign country (see Bernard et al., 2010; Carluccio and Fally, 2012; Nunn and Trefler, 2013; Antras and Chor, 2013; Corcos et al., 2013; Antras, 2016). We contribute to this literature by pointing out another reason for intra-firm trade, namely protection against non-payment. We further show that well developed financial markets that provide insurance instruments, such as letters of credit, are able to mitigate this risk.

Our paper is structured as follows. The next section describes the data and explains how the *TII* index is constructed. In Section 3, we present the empirical results on the Great Trade Collapse, while Section 4 shows the finding related to intra-firm trade. Section 5 concludes the study.

# 2 Trade Insurance Intensity Measure: *TII*

## 2.1 Data

We construct our measure of trade insurance intensity (*TII*) using confidential micro-level international trade data from Turkey. The data set is provided by the Turkish Statistical Institute and covers the universe of Turkey's imports and exports. It includes information on the monthly value of imports (including freight and insurance costs) and exports (reported on f.o.b. basis) as well as the breakdown of financing disaggregated by the importing/exporting firm, 8-digit HS product code, country of origin/destination and year. To avoid the period of the recent financial crisis, we construct our measure based on figures for 2003-2006.

The dataset includes information on four main financing terms: open account, cash in advance, documentary collection, and letter of credit. Under open account terms, goods are delivered before a payment is made by the importer. This is the safest method for the importer and the riskiest one for the exporter. Under cash-in-advance terms, the exporter receives the payment before ownership of the goods is transferred. This method eliminates the payment risk on the part of the exporter, and all the risk is borne by the importer.

Transactions on documentary collection terms are settled by banks through an exchange of documents. Although documentary collection terms do not involve a payment guarantee in case the importer defaults on payment, this method may partially eliminate the transaction risks as the importer does not pay prior to shipment and the exporter retains ownership of the goods until the importer pays for the goods or accepts to pay at a later date. The final method, letter of credit, eliminates the risk to both parties.

Our measure *TII* is constructed based on the intensity of the use of letters of credit. A letter of credit is a guarantee issued by the importer's local bank (issuing bank) that a payment will be made to the exporter, provided that the conditions stated in the LC have been fulfilled. The importer's bank charges (often a substantial) fee for issuing an LC. The exporter can also request its local bank to confirm the LC. If confirmed, the exporter‘s bank (the confirming bank) takes on the responsibility for making payments if the importer's bank fails to transfer the payment by the due date. The LC is the most secure instrument available to international traders.

During the period under consideration (2003-2006), about 20% of Turkish imports and 15% of exports were backed by LCs. Transactions relying on LCs were found in 4,280 of 4,900 6-digit HS products, with the average share of LC-backed trade across all 6-digit HS product categories reaching 9%.

The aggregate figures for the use of LCs, i.e., 20% of the total value of Turkish imports and 15% of exports, are very close to the use of LCs by importers located in middle income countries – which include Turkey– as reported by Niepmann and Schmidt-Eisenlohr (2017) based on SWIFT data. There exists, however, considerable heterogeneity in the use of LCs across products/industries (Demir et al., 2017). This is the variation we exploit to construct our risk sensitivity measure.

## 2.2 Constructing the *TII* measure

Our measure of trade insurance intensity is based on the prevalence of LC use and thus captures reliance on payment guarantees. The choice of LC as a payment method is determined by various factors. For instance, Schmidt-Eisenlohr (2013) and Antràs and Foley (2015) present a model that predicts that the use of LCs decreases in the quality of institutions in the importing country. Trade partners' scope for misbehavior is also an important determinant of the use of LCs. We conjecture that the choice of LC as a payment method is additionally determined by the nature of the traded product. Therefore, we construct our measure at the product level, while removing the variation coming from different partner countries and different importing firms in particular years.

Table A.6 in appendix presents the variation in the use of LCs explained by each dimension, namely firm, product and trade partner country, in each year of our sample period. Each cell reports the adjusted $R^2$ value obtained from a regression of a binary variable, which takes the value one for LC-financed transactions and zero otherwise, on various fixed effects. The sample is monthly trade data (imports, exports, or pooled imports and exports) at the firm-product-country level, disaggregated by financing terms, at time $t = 2003 - 2006$. Three results emerge. First, the share of variation explained by each dimension remains relatively stable over time for each sample. Second, for both imports and exports, the largest share of the variation in the use of LCs is explained by firm-level factors. However, importer characteristics matter more than exporter characteristics. Third, while product-level factors matter less than the firm-level factors, they matter more than country-level factors for imports (or when imports and exports are jointly considered). In particular, they explain about 7% of variation in the use of LCs for imports (as opposed to 2% of variation explained by trading partners in 2006).

To construct *TII*, we first estimate the following regression using monthly data for the 2003-2006 period:

$$\mathbb{1}\{m = LC\}_{fikct} = \alpha_{fict} + \sum_{d=1}^{12} \mathbb{1}\{month = d\} + \alpha_k + \epsilon_{fikct}, \tag{1}$$

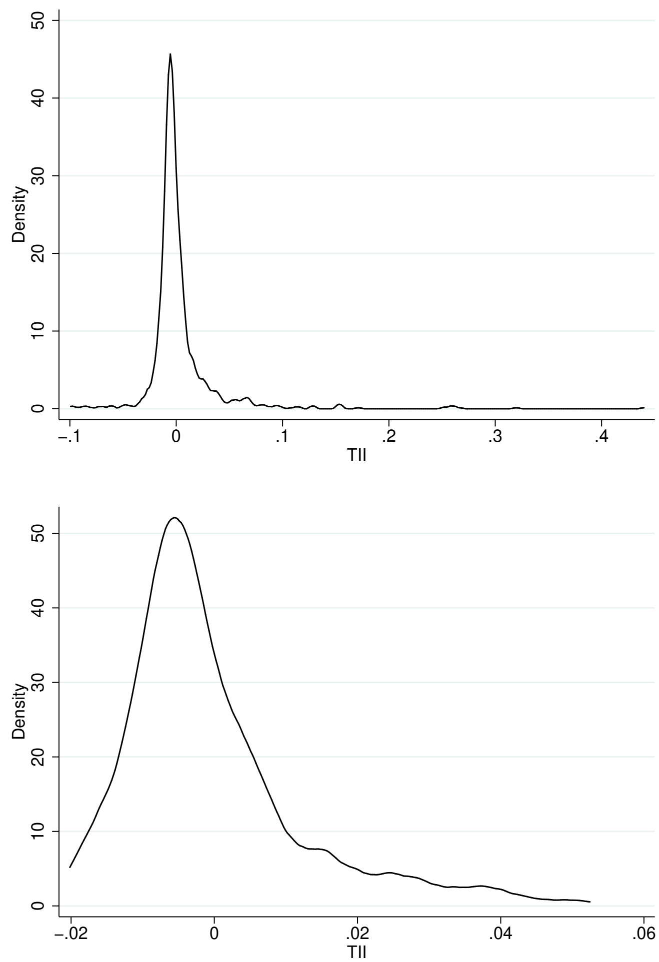
where the dependent variable is a binary variable that takes on the value one when the payment method ($m$) is LC, and zero otherwise for trade flow $f = \{import, export\}$ by Turkish firm $i$, HS6 product $k$ with a trade partner located in country $c$ at time $t$. We add flow-firm-country-time fixed effects ($\alpha_{fict}$), 6-digit HS product fixed effects ($\alpha_k$) and monthly dummies. The estimated product fixed effects capture trade insurance intensity of each 6-digit HS product.[4] By construction, $\hat{\alpha}_k$ is orthogonal to firm- and country-level factors. We then construct our *TII* measure as the median value of the estimated product fixed effects within each 4-digit HS product code $p$, i.e., $TII_p = median(\hat{\alpha}_k)$. Our measure is available for 1203 goods, of which 1096 are manufacturing products.

It is worth reiterating the points made above. The propensity to rely on an LC may be determined by the characteristics of the country where the trading partner is located. To avoid the fees associated with obtaining an LC, a Turkish importer may be willing to buy on cash-in-advance terms from a country with a sound business climate, efficient courts and very good contract enforcement, such as, Germany, but not from a country with poor institutions, such as, China. Such country-specific time-varying or time-invariant factors

[4]We drop cases where the the number observations per $k$ is less than 10.

will be purged from our measure by firm-product-country-year fixed effects included in equation (1). Similarly, some importing firms may be better positioned to obtain an LC than others, perhaps because of their favorable credit rating. This factor and other time-varying factors specific to particular importers at a particular point in time will be taken out by firm-product-country-year fixed effects. All of this means that the variation captured in our measure comes only from differences in LC use across products traded by a given firm in a given market in a given year.

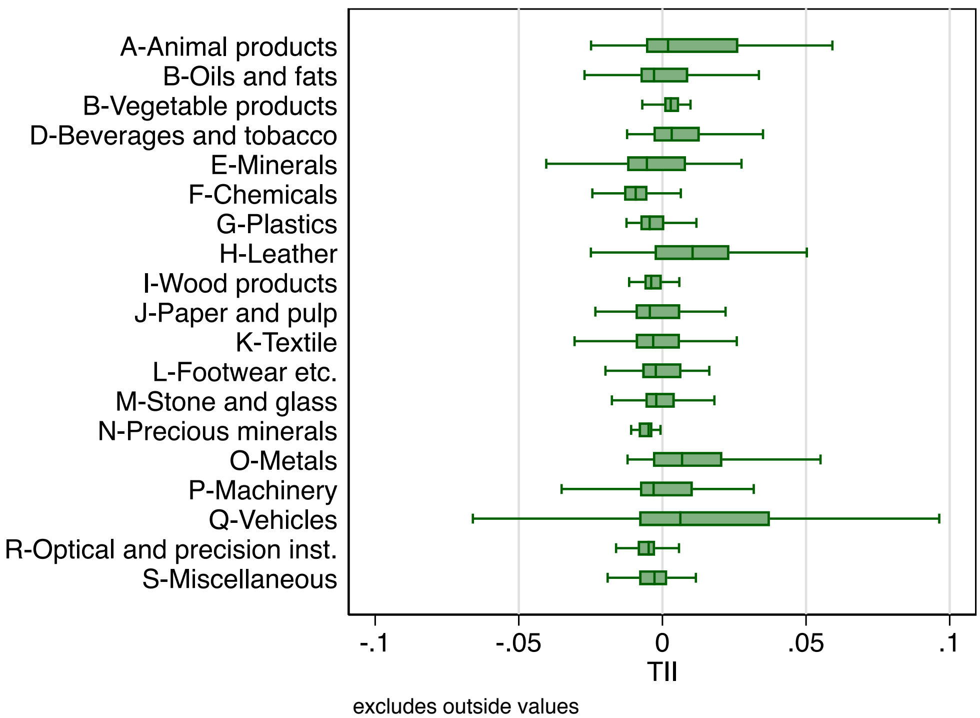
Figure 1: Distribution of *TII* across 4-digit HS product codes




*Notes:* The figures plot the distribution of *TII* across 4-digit HS product codes. The upper panel shows the whole distribution, and the lower panel shows the trimmed distribution at the 5/95%.

Figure 1 shows the distribution of *TII* across 4-digit HS product codes. The measure varies between -0.0062 and 0.4398 it has a mean of 0.003, a median of -0.003 and a standard deviation of 0.034 (see Table A.7). The distribution is positively skewed and shows considerable variation across products. As presented in Figure 2, which shows 25th, 50th and 75th percentiles of *TII* by broad product categories, leather, metals, and transport vehicles have relatively high median values of the *TII* measure. In contrast, chemicals have the lowest median value. This figure also illustrates large variation in *TII* values within industries.

Figure 2: Median, 25th and 75th percentiles of *TII*, by industry




*Notes:* The figure shows the median value of *TII* for each industry. The box sizes show the range between the the 25th and the 75th percentiles.

In Table A.8, we list products with the highest values of *TII*. These match the industry-level patterns as they include metals and minerals (Ferrous products obtained by direct reduction of iron ore; Iron ores and concentrates; Ferrous waste and scrap; Crude petroleum oils; Coal, briquettes, ovoids and similar solid fuels manufactured from coal), and transport vehicles (Rail locomotives; Tugs and pusher craft).

Finally, to check whether *TII* is stable over time, we estimate a variant of equation (1) separately for individual years:

$$\mathbb{1}\{m = LC\}_{fikc} = \delta_{fic} + \sum_{d=1}^{12} \mathbb{1}\{month = d\} + \delta_k + \epsilon_{fikc}, \tag{2}$$

We recover the estimated product fixed effects $\hat{\delta_k}$ and construct *TII* at the 4-digit HS product level for 2003, 2004, 2005 and 2006 separately. The rank correlation between the baseline measure and the one obtained from individual years is above 0.86, implying that the rankings are quite stable over time. As illustrated in Figure A.5, rankings of of 4-digit HS products based on the baseline measure and the one obtained from individual years correlate significantly with each other, and the rankings overlap for most of the top and bottom-*TII* products.

## 2.3 *TII* versus other product characteristics

Next we exploit the product-level factors that are correlated with our measure.

Table A.10 and Figure 3 (panel a) show that products with more volatile demand tend to use LCs more intensively.[5] A negative demand shock may induce the importer to refuse to accept a shipment and make a payment. Therefore, higher demand volatility increases the risk that the buyer may want to walk away from the deal without accepting the goods and making the payment, thus increasing the need for insurance.

As illustrated in Figure 3 (panel b) and Table A.10, products that tend to be shipped by sea use LCs more intensively.[6] This could be explained by the fact that maritime transport is slow and the probability of default increases with shipping time (Berman et al., 2013). A longer shipping time also increases the risk of an adverse exchange rate or price movement and thus may prompt one of the trading partners to try to renegotiate the contract.

Table A.10 and Figure 3 (panel c) show that products that tend to be shipped in larger volumes use LCs more intensively.[7] This pattern is consistent with the findings of Niepmann and Schmidt-Eisenlohr (2017) based on SWIFT data. Trading partners may have a greater incentive to insure larger shipments. Moreover, as banks also charge a fixed fee when issuing/confirming LCs, purchasing an LC is relatively cheaper for products that tend to be traded in larger volumes.

*TII* also correlates positively with the industry-level contract intensity measure proposed by Nunn (2007) (see Table A.10 and Figure 3, panel d). This measure aims to capture

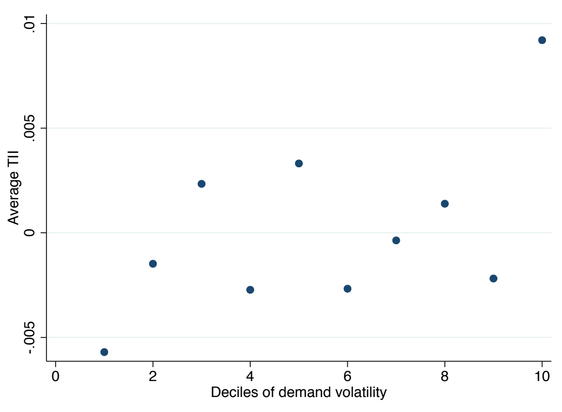
[5]Demand volatility is measured as the median of the coefficient of variation of import values within a country and 4-digit HS product across months. It is constructed using monthly UNCOMTRADE data on imports for the year 2016. It is similar in spirit to the measure of risk content of exports compiled by Di Giovani and Levchenko (2012) based on output volatility figures.

[6]We use the 4-digit HS product-specific share of ocean transport in total exports from the EU-27 to the US in 2005 based on Comext (Eurostat) data.

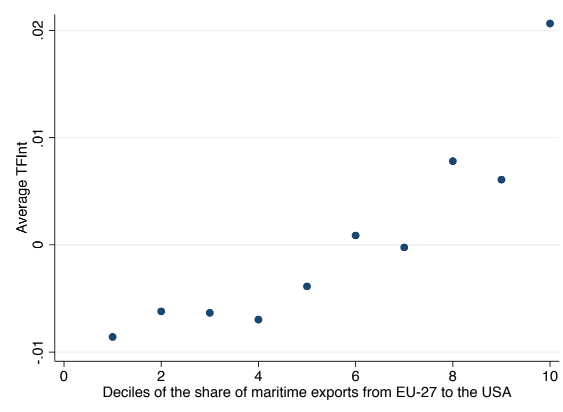
[7]The indicator of shipment size by 4-digit HS product has been constructed based on French individual monthly custom declarations for 2008. It is defined as the logarithm of the (median) value of monthly French firm-level export values, after controlling for destination and firm fixed effects.

Figure 3: *TII* and other product characteristics

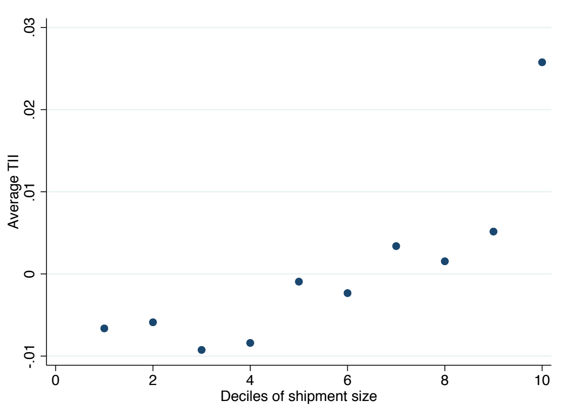
(a) Demand volatility



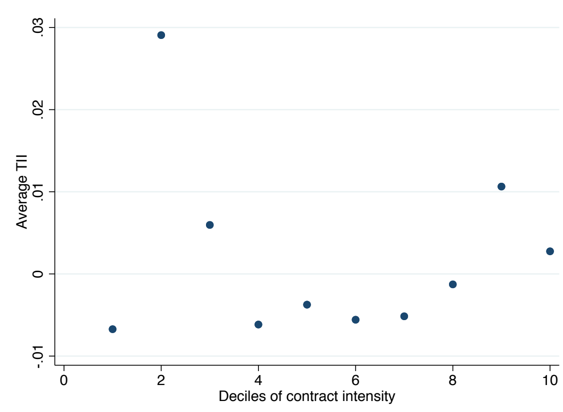

(b) Shipping time




(c) shipment size




(d) Contract intensity



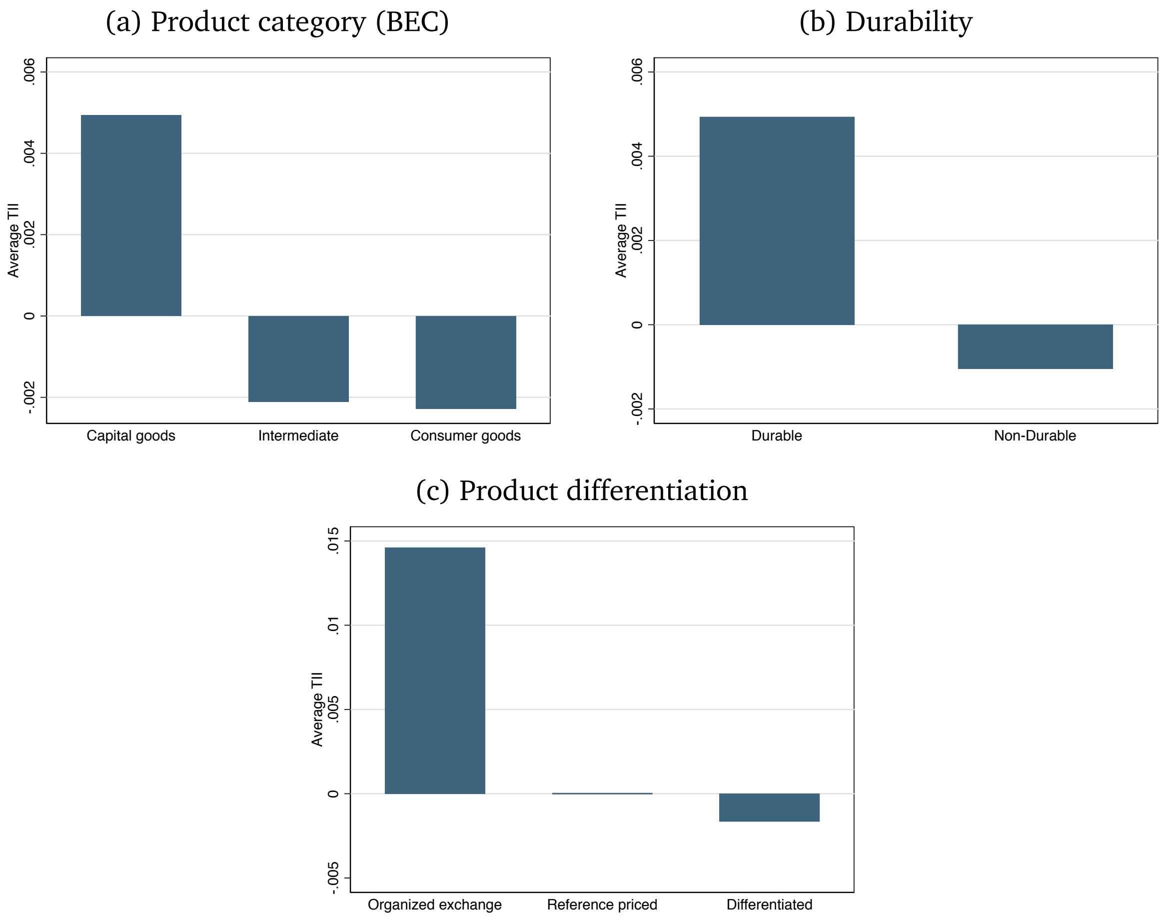

*Notes:* The figures show the the association between *TII* and for each decile of demand volatility (panel a), the share of maritime exports from EU-27 to the US (panel b), shipment size which is defined as the logarithm of the (median) value of monthly French firm-level export values for the year 2008, after controlling for destination and firm fixed effects, and the contract intensity measure proposed by Nunn (2007) (panel d).

the share of the intermediate inputs that require relationship-specific investments.[8] The positive correlation with *TII* might reflect the fact that it is more difficult to resell customized products in the case of the importer refusing to accept a shipment.

Figure 4 shows that capital goods as well as goods that are durable and less differentiated tend to rely more on LCs. For less differentiated goods, this could be explained by the possibility that obtaining LCs when importing such products is less costly. Under the Basel

[8]It is defined as the share of inputs that fall into the differentiated product category (as classified by Rauch (1999)).

Figure 4: Average *TII* by product type




framework, a lower credit conversion factor applies when the traded good can serve as collateral (Demir et al., 2017) Assuming that more homogenous goods can be collateralized more easily, trading firms would rely more on LCs when trading such goods.

A simple regression in Table A.11 aims to shed more light on how well various product characteristics explain variation in the *TII* measure. When all the variables mentioned above enter the regression, they jointly explain about 11% of variation in *TII*. Our only supply-side related measure (non-differentiated dummy) has almost no explanatory power (see the second column).

Several observations emerge from this section. First, correlations between *TII* and product characteristics seem quite intuitive and thus boost our confidence in the index. Second, although the prevalence of LC use is an equilibrium outcome and thus driven by both demand and supply factors, our measure seems to be more strongly correlated with the demand factors. Third, product characteristics explain only a small share of variation in the index, which suggests that our measure captures something that is different from what can be collectively captured by the product characteristics considered.

## 2.4 *TII* versus financial dependence

The next question we tackle is whether our measure captures something different from what is captured by the standard measures of financial dependence used in the literature. As explained above, it should be the case, as the primary purpose of LC is to insure against the risk of non-payment and non-delivery.

Table 1: Correlations between *TII* and standard financial dependence measures

| | External Finance Dependence (RZ) | Inventory Ratio (IR) | Asset Tangibility (AT) | Trade Credit Int. (TCI) |
|---|---|---|---|---|
| **TII** | -0.037 | 0.051 | -0.021 | -0.012 |
| RZ | - | $0.136^{a}$ | $-0.294^{a}$ | $-0.054^{c}$ |
| IR | - | - | $-0.669^{a}$ | 0.031 |
| AT | - | - | - | $0.195^{a}$ |

*Notes:* Significance levels: c: $p < 0.10$, b: $p < 0.05$, a : $p < 0.01$.

We consider simple correlations of *TII* with the standard measures of financial dependence. The first measure (RZ) captures the need for external borrowing to finance capital expenditures. It was constructed by Rajan and Zingales (1998) as the share of capital expenditures that is not financed by internal cash flows. The second measure (IR) captures the short-term working capital needs of firms in an industry and is defined as the ratio of inventories to sales. The third measure (AT) focuses on the availability of assets that can be used as collateral to obtain external financing and is constructed as the share of plant, property, and equipment in total assets. The final measure (TCI) captures the intensity of firms' reliance on supplier financing in an industry and is defined as the ratio of the change in accounts payable to the change in total assets. We obtain RZ, AT, and IR from Kroszner et al. (2007) who constructed them as the 1980-1999 period average for the median US firm in each 3-digit NAICS industry. TCI is obtained from Fisman and Love (2003) who constructed the measure using US data for the 1980-1989 period.

Table 1 shows that *TII* is not correlated with any of the standard measures of financial dependence and thus captures a different source of variation. This is comforting, if not unexpected, as our measure is designed to capture relying on trade insurance, and not financial dependence.

It is worth noting that the standard measures are more aggregated, i.e., they capture industry-level variation, while our measure is product-specific and available for 1203 different products. Moreover, *TII* shows considerable variation within 2-digit HS headings. As visible in Figure A.6, the coefficient of variation of RZ is by construction concentrated around zero within 2-digit HS headings, while that of *TII* shows notable dispersion. This indicates that *TII* captures a lot of information and variation even within industries.

All of these observations taken together, further our belief that *TII* captures information that is distinct from reliance on external financing or the need for trade credit, and thus differs substantially from the proxies typically used in the literature.

# 3 Application of *TII*: The Great Trade Collapse

Our first application examines whether products relying heavily on trade insurance are more adversely affected during financial crises. To isolate the effect of interest from possible confounding factors, our identification is based on the occurrence of bank crises across countries during the 2007-2008 financial crisis and the variation of the *TII* index across products.

## 3.1 Data and empirical specification

We use bilateral trade data for the 2003-2009 period available from BACI.[9] The dataset covers 98 countries and more than a thousand 4-digit HS product codes, implying 67,007,794 possible trade relationships, of which 20% (13,375,723) are strictly positive. Since we construct the *TII* measure using Turkish data, we exclude Turkey from the data set. In our main analysis, we focus on manufacturing goods, which gives us 12,825,760 non-zero trade flows, though we show that our results are robust to including agricultural products.

We merge the bilateral trade data with data on bank crises obtained from Laeven and Valencia (2013). We focus on the Great Recession period (2007-2009). Table A.9 lists the countries in our dataset that experienced a bank crisis. We further augment the dataset with industry-level (3-digit NAICS codes) measures of financial dependence, which have been widely used in the literature (e.g. Beck, 2003; Chor and Manova, 2012; Manova et al., 2015).

Our econometric specification examines whether trade of products that rely more heavily on trade insurance reacted differentially to bank crises in exporting and/or importing

[9]The database is proposed by the CEPII, cf. Gaulier and Zignago (2010).

countries. We estimate the following equation:

$$\begin{aligned} \ln(\text{Exports}_{odpt}) &= \beta_1 \text{TII}_p \times \text{Crisis}_{dt} + \beta_2 \text{TII}_p \times \text{Crisis}_{ot} \\ &\quad + \delta_{pt} + \delta_{odp} + \delta_{odt} + \varepsilon_{odpt}. \end{aligned} \tag{3}$$

where $\text{Exports}_{odpt}$ is the value of exports of 4-digit HS product $p$ from origin country $o$ to destination country $d$ in year $t$. $\text{Crisis}_{ot}$ (respectively $\text{Crisis}_{dt}$) are dummy variables equal to 1 if the origin (destination) country experienced a bank crisis in year $t$, and 0 otherwise. $TII_p$ is our index of trade insurance intensity for a 4-digit HS product $p$. We control for a large range of possible confounding factors with fixed effects by product-year, origin-destination-product, and origin-destination-year. We cluster standard errors by product to allow for possible correlation between disturbances of trade flows within products.

We expect that bank crises affect more severely exports of products that use trade insurance more intensively because bank crises make it difficult, if not impossible, to purchase LCs and thus insure against trade-related risks. This means that we expect $\beta_1 < 0$, as a crisis in the importing country makes it harder to purchase an LC. It is possible that a crisis in the exporting country may matter as well because it makes it harder for traders confirm an LC (and thus $\beta_2 < 0$), though this effect is unlikely to be large. LCs are typically issued by large banks that during normal times are unlikely to go out of business and hence the need to insure against the bank not fulfilling the contract is minimal, when compared to the need for insuring against a non-payment by the foreign trading partner. This will indeed turn out to be true. As a matter of fact, the crisis in the origin country will not matter at all, so in subsequent specifications we will focus only on crises in destination countries and replace product-year fixed effects with origin-product-year fixed effects:

$$\ln(\text{Exports}_{odpt}) = \delta_1 \text{TII}_p \times \text{Crisis}_{dt} + \gamma_{opt} + \gamma_{odp} + \gamma_{odt} + \varepsilon_{odpt}. \tag{4}$$

One challenge we face is that we do not know precisely when the 2007/2008 bank crisis ended in each country. Therefore, we drop all years after 2009. The treatment dummies take the value of one for two years in countries hit by a crisis in 2008 and three years for those where the crisis started in 2007 (US and UK).[10]

[10]We eliminate Nigeria from the sample as a bank crisis started there only in 2009.

## 3.2 Estimation results

Table 2: The Great Trade Collapse: Baseline results

| Dep. Var.: $\ln(Exports_{odpt})$ | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Sample | Manufacturing | Manufacturing | All | Manufacturing |
| $\text{TII}_p\times$ | **-0.647a** | **-0.653a** | **-0.601a** | **-0.894a** |
| $\text{Crisis}_{dt}$ | (0.210) | (0.194) | (0.184) | (0.218) |
| $\text{TII}_p\times$ | 0.280 | | | |
| $\text{Crisis}_{ot}$ | (0.175) | | | |
| $\text{Durable}_p\times$ | | | | -0.005 |
| $\text{Crisis}_{dt}$ | | | | (0.010) |
| $\text{TimeToShip}_p\times$ | | | | 0.002 |
| $\text{Crisis}_{dt}$ | | | | (0.014) |
| $\text{Size}_p\times$ | | | | -0.0001b |
| $\text{Crisis}_{dt}$ | | | | (0.000) |
| $\text{Non-Differentiated}_p\times$ | | | | 0.019b |
| $\text{Crisis}_{dt}$ | | | | (0.009) |
| $\text{DemandVolatility}_p\times$ | | | | 0.087a |
| $\text{Crisis}_{dt}$ | | | | (0.020) |
| $\text{IncomeElasticity}_p\times$ | | | | -0.145a |
| $\text{Crisis}_{dt}$ | | | | (0.036) |
| No. Obs. | 12825760 | 12749702 | 13576068 | 12338126 |
| $R^2$ | 0.869 | 0.879 | 0.879 | 0.879 |
| Fixed effects | pt,odp,odt | opt,odp,odt | opt,odp,odt | opt,odp,odt |

*Notes:* Significance levels: c: $p< 0.1$, b: $p < 0.05$, a : $p < 0.01$. Standard errors, clustered by 4-digit HS codes, are shown in parentheses.

The estimation results provide evidence in line with our main hypothesis. The first regression in Table 2 shows that the negative impact of a bank crisis in the importing country is significantly stronger for products using trade insurance intensively than for other products. This estimated effect is statistically significant and economically meaningful. A one-standard-deviation increase in the *TII* measure (i.e., 0.035) is associated with a 2.2% larger decline in trade when a crisis hits the importing country.

As expected, a crisis in the exporting country does not appear to affect products relying on trade insurance in a differential manner. Therefore, in subsequent specifications we focus only on banking crises in the importing countries and estimate equation 4. The results from the augmented specification, presented in the second column of Table 2, confirm our conclusions. The interaction term between *TII* and destination country bank crisis indicator is statistically significant at the one percent level. Its magnitude is almost exactly the same as in the previous column. In column 3, we include agricultural goods in the sample. The estimated coefficient remains statistically significant at the one percent level, though its magnitude is slightly smaller.

In the last column, we add interactions with the other product characteristics presented above: durability, reliance on maritime transport, average shipment size, non-differentiated product dummy, demand volatility. We also control for product's income elasticity of demand since it is an obvious determinant of inter-sectoral variation in the trade impact of economic crises.[11] The coefficient of interest remains statistically significant at the one percent level, and its magnitude increases by a third. In line with expectations, we also observe that a crisis in the importing country has a stronger negative effect on trade in products with higher income elasticity.

Next, we investigate jointly the role of external finance dependence and sensitivity to trade-related risks. Tables A.12 reproduces our benchmark specification while allowing for a differential impact of crises on industries with a high reliance on external financing. Our main result remains robust to the additional controls, implying that the financial crisis affected trade flows primarily through the lack of guarantees against trade-related risks. The interaction terms between a crisis indicator and dependence on external financing ($RZ$) and reliance on supplier financing ($TCI$) do not appear to be statistically significant, which is broadly in line with the findings reported by Levchenko et al. (2010) that the trade impact of the financial crisis was *not* more severe for industries that depend more on external finance. In contrast, we find that products originating in industries with greater working capital needs ($IR$) were more affected by the crises, while products from industries with greater availability of collateralizable assets ($AT$) were less affected.

In the first column of Table A.13, we investigate how the impact of the financial crisis on high-*TII* products varied over time. We do so but by splitting each crisis dummy into a dummy for the first year of the crisis and a dummy for the subsequent years. We find that the impact of the crisis in the destination country increases over time. In column 2, we present non-parametric estimates, where we replace the continuous *TII* variable with dummies for each quintiles of the *TII* distribution (the first quintile being the omitted category). All of the interaction terms are statistically significant and the impact of the effect is larger for products in higher quintiles of the *TII* distribution. The coefficients indicate that the negative impact of a bank crisis on imports is $1 - e^{-0.022} = 2.2\%$ more severe for

[11]We rely on the elasticities estimated by Caron et al. (2012). Using the Global Trade Analysis Project (GTAP) database they estimate income elasticity of demand for 36 manufacturing sectors. Their estimates do not cover the entire GTAP nomenclature. In particular, they do not have the elasticities for "Iron and Steel" and "Non-Ferrous Metals". In order to minimize loss of information, we have assigned to these two sectors the average of elasticity for "non-metallic minerals" and "fabricated metal products" (which are actually very close from to each other). We therefore obtain an estimate of the income elasticity of demand for 1135 HS4 products. These elasticities are very weakly correlated with our *TII* variable (correlation is only -0.0314 and not statistically different from zero).

Table 3: Quantification of the role of trade insurance during the Great Trade Collapse

| Quintile of TII index | 1*st* | 2*nd* | 3*rd* | 4*th* | 5*th* | Total |
|---|---|---|---|---|---|---|
| Trade value 2007 (billion US$) | 829 | 1683 | 1085 | 781 | 2111 | 6489 |
| Trade value 2009 (billion US$) | 696 | 1403 | 978 | 673 | 1573 | 5323 |
| Trade collapse (bn. US$) | 336 | 792 | 423 | 314 | 1352 | 3217 |
| Trade collapse (% of predicted trade) | 32.5 | 36.1 | 30.2 | 31.8 | 46.2 | 37.7 |
| Counterfactual: Role of trade insurance | | | | | | |
| Trade collapse due to insurance channel: | | | | | | |
| In billion US$ | - | 31.2 | 38.9 | 38.8 | 115.7 | 224.6 |
| As % of trade collapse | - | 3.9 | 9.2 | 12.4 | 8.6 | 7.0 |

products in the 2rd quintile of *TII* than for the ones in the first. Going to the 3th quintile raises this difference to $3.8\%$ and going to the 4th and the 5th quintile raises it to $5.4\%$ and $6.9\%$ respectively. While the results discussed above are about the impact of bank crises on the value of bilateral trade (the intensive margin), in the last column we check whether the results also hold for the extensive margin. We replace the dependent variable with a dummy indicating a strictly positive trade flow and report the linear probability estimates. The estimated coefficient is much smaller in magnitude than those found before, but the main conclusion holds.

Finally, in Table 3, we use the non-parametric estimates reported in the second column of Table A.13 to quantify the role played by trade insurance in the Great Trade Collapse. In this exercise, we focus on imports of non-agricultural products by countries that experienced a bank crisis in 2008. The first two rows of the table display the actual value of total imports in 2007 and 2009 for the five groups of products corresponding to each quintile of the *TII* distribution. In the third row, we propose a simple quantification of the trade collapse. We calculate the growth rate of each bilateral import flow for each product between 2005 and 2007. Then we apply this growth rate to the values observed in 2007 in order to obtain the value of bilateral trade that would have been observed in 2009, had trade continued to grow at its 2005-2007 rate. The trade collapse is the difference between the predicted values and the observed 2009 trade. The aggregates by quintiles of *TII* reported in the table show that the 2009 imports by countries that experienced a bank crisis were more than 37% lower than predicted. As shown in the lower panel of the table, the contribution of trade insurance to this sudden decline of trade is non-negligible. We assume that trade loss due to lack of trade insurance for the products in the first quintile of *TII* was zero. Then, by using the estimated coefficients from the second column of Table A.13, we calculate the trade loss due to lack of trade insurance for the second through fifth quantile relative to the first quintile. As presented in the first row of the lower panel of Table 3, the aggregate trade decline in 2009 that can be attributed to reliance on trade insurance is estimated to be US$ 224.6 billion. This amount accounts for 7% of total predicted trade collapse.

# 4 Application of *TII*: Intra-firm trade

Our second application focuses on intra-firm trade, which is typically not subject to the risk of non-payment or non-delivery. First, we focus on the prevalence intra-firm trade in high-*TII* products exported to markets affected by a financial crisis. And second, we consider a more general relationship between the share of intra-firm trade, *TII*, and financial development of the export market.

We use data on intra-firm exports by US firms disaggregated by country of destination and 4-digit HS product codes.[12] In our baseline exercise, we consider country-product pairs with positive intra-firm exports in at least one year during the period considered.

## 4.1 High *TII* products, intra-firm trade and financial crises

If intra-firm trade is not subject to the usual trade-related risks, we expect it to be more resilient to crises in the destination markets. More specifically, we anticipate to see higher reliance on intra-firm trade in high *TII* products destined for destinations afflicted by a financial crisis. Understanding drivers of intra-firm trade is interesting in its own right, but it also offers an additional advantage. By considering *the share* of intra-firm trade in total exports, we are controlling for all other factors that may be affecting exports of a given product to a particular crisis-affected destination in a given time period, such a decline in demand, the impact of worsening credit conditions in the importing industry, etc.

To test our hypothesis we estimate the following equation:

$$RelatedShare_{dpt} = \gamma_1 \mathrm{TII}_p \times \text{Crisis}_{dt} + \gamma_{dp} + \gamma_{pt} + \gamma_{dt} + \epsilon_{dpt}. \quad (5)$$

where $RelatedShare_{dpt}$ is the share of US related-party (intra-firm) exports in total US exports of a 4-digit HS product $p$ sold to country $d$ at time $t$. We consider the period 2004-2011. The specification includes product-destination, product-year and destination-year fixed effects, which means that there is no need to include *TII* or a crisis dummy by

[12] The dataset has been made available by Pol Antràs at `https://scholar.harvard.edu/antras/books`.

themselves. Standard errors are clustered at the product level. If our hypothesis is true, we would expect to observe $\gamma_1 > 0$.

Table 4: Intra-firm Trade and the Crisis Period

| Dep. Var.: RelatedShare$_{dpt}$ | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| TII$_p\times$ | **0.161d** | | | | | | |
| Crisis$_{dt}$ | (0.104) | | | | | | |
| TII$_p\times$ | | 0.099 | 0.057 | 0.082 | 0.071 | 0.120 | -0.058 |
| Crisis Year=T$_{dt}$ | | (0.129) | (0.133) | (0.137) | (0.136) | (0.149) | (0.156) |
| TII$_p\times$ | | **0.184c** | **0.187c** | **0.214c** | **0.231c** | **0.325a** | **0.308c** |
| Crisis Year>T$_{dt}$ | | (0.110) | (0.109) | (0.115) | (0.119) | (0.123) | (0.181) |
| TII$_p\times$ | | | 0.005 | 0.005 | 0.004 | 0.002 | 0.009 |
| GDPpc$_{dt}$ | | | (0.005) | (0.005) | (0.006) | (0.007) | (0.010) |
| TII$_p\times$ | | | | 0.608 | 0.456 | 0.604 | 0.193 |
| FD$_{dt}$ | | | | (0.565) | (0.710) | (0.760) | (1.120) |
| TII$_p\times$ | | | | | -0.006 | -0.006 | -0.002 |
| CE$_{dt}$ | | | | | (0.019) | (0.020) | (0.031) |
| Durable$_p\times$ | | | | | | -0.002 | -0.005 |
| Crisis$_{dt}$ | | | | | | (0.005) | (0.006) |
| TimeToShip$_p\times$ | | | | | | 0.008 | 0.014 |
| Crisis$_{dt}$ | | | | | | (0.008) | (0.009) |
| Size$_p\times$ | | | | | | 0.0001a | 0.0002a |
| Crisis$_{dt}$ | | | | | | (0.000) | (0.000) |
| DemandVolatility$_p\times$ | | | | | | -0.008 | 0.006 |
| Crisis$_{dt}$ | | | | | | (0.011) | (0.016) |
| Non-Differentiated$_p\times$ | | | | | | 0.001 | -0.002 |
| Crisis$_{dt}$ | | | | | | (0.006) | (0.007) |
| IncomeElasticity$_p\times$ | | | | | | -0.008 | 0.038 |
| Crisis$_{dt}$ | | | | | | (0.025) | (0.038) |
| No. Obs. | 501799 | 501799 | 462789 | 462789 | 389997 | 379922 | 205025 |
| $R^2$ | 0.511 | 0.511 | 0.519 | 0.519 | 0.516 | 0.515 | 0.706 |
| Fixed effects | pt,dp,dt | pt,dp,dt | pt,dp,dt | pt,dp,dt | pt,dp,dt | pt,dp,dt | pt,dp,dt |

*Notes:* FD and CE denote financial development and contract enforcement indices, respectively. Standard errors, clustered by 4-digit HS codes, are shown in parentheses. Significance levels: d: $p< 0.15$, c: $p< 0.1$, b: $p < 0.05$, a : $p < 0.01$.

The results, presented in Table 4, are in line with our hypothesis. The coefficient of interest ($\gamma_1$) is positive and statistically significant, albeit only at the 15% level, suggesting that US exports of good relying heavily on trade insurance are more likely to take place within firm when destined for crisis-afflicted countries. As it may take time for firms to rearrange the nature of their trade, in column 2 we allow for a differential effect in the first year versus the subsequent years of the crisis. And indeed crises appear to have a delayed effect. While the interaction term between *TII* and the dummy for the first crisis year in the destination market is not statistically significant, the interaction terms with the subsequent crisis years is positive and statistically significant. This result based on a more demanding identification strategy suggests that trade insurance availability played a significant role during the Great Trade Collapse. It also implies that, for trade insurance intensive products, arms-length trade has been more severely affected than risk-immune intra-firm transactions. This supports our claim that the *TII* indicator captures dependence on trade insurance and that the over-reaction of high *TII* products during the crisis is related to a disruption of the supply of such insurance.

In the next three columns, we additionally allow for interactions between *TII* and destination country characteristics, such as the GDP per capita, level of financial development and contract enforcement.[13] While our result of interest remains robust, none of the additional interaction terms appear to be statistically significant. In column 6, we also add interaction terms with the product characteristics we considered earlier. Doing so increases both the significance level (to 1%) and the magnitude of the estimated effect. The magnitude is economically meaningful. A one-standard-deviation increase in the *TII* index is associated with a 1.1 percentage point increase in intra-firm trade. In the last column, we restrict the sample to flows with $RelatedShare > 0$. The coefficient of interest is still found to be positive and statistically significant, albeit smaller in magnitude.

## 4.2 High *TII* products, intra-firm trade and financial development

Table 5: Intra-firm Trade: Baseline results

| Dep. Var.: RelatedShare$_{dpt}$ | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| TII$_p\times$ | **-0.982a** | **-1.119a** | **-0.671a** | **-1.048a** | **-1.377a** |
| FD$_{dt}$ | (0.245) | (0.263) | (0.191) | (0.283) | (0.360) |
| TII$_p$ | **0.591a** | | | | |
| | (0.131) | | | | |
| TII$_p\times$ | | | | 0.008c | 0.006 |
| GDPpc$_{dt}$ | | | | (0.004) | (0.006) |
| TII$_p\times$ | | | | | 0.004 |
| CE$_{dt}$ | | | | | (0.004) |
| No. Obs. | 231534 | 231496 | 231096 | 225716 | 107145 |
| $R^2$ | 0.126 | 0.187 | 0.297 | 0.298 | 0.324 |
| FE | HS2t,dt | pt,dt | pt,dt,HS2d | pt,dt,HS2d | pt,dt,HS2d |

*Notes:* Significance levels: c: $p< 0.1$, b: $p < 0.05$, a : $p < 0.01$. FD and CE denote financial development and contract enforcement indices, respectively. Standard errors, clustered by 4-digit HS codes, are shown in parentheses.

[13] We use the financial development index published by the International Monetary Fund. The index is constructed from subindices capturing depth and efficiency of, as well as access to, financial institutions and markets (Sahay et al., 2015). The contract enforcement index comes from the Doing Business dataset published by the World Bank. It "measures the time and cost for resolving a commercial dispute through a local first-instance court, and the quality of judicial processes index, evaluating whether each economy has adopted a series of good practices that promote quality and efficiency in the court system".

Next we consider a more general relationship between intra-firm trade, *TII* and importer characteristics. We test two hypotheses. First, to the extent that *TTI* proxies for the need for insurance, we expect intra-firm trade to be more prevalent for high *TTI* products. To reduce trade-related risks associated with such products, firms might prefer to reduce arms-length trade and trade more with related parties located in the destination country. Second, we expect this effect to be attenuated when exports are destined for countries with well-developed financial markets. A well-functioning financial market can provide payment guarantees through letters of credit, which would reduce the need for engaging in related-party trade.

We use the same data on intra-firm trade, but now we consider the 2002-2006 period to avoid the crisis years that may be confounding the patterns of interest. We keep country-product pairs with positive intra-firm exports in at least one year during the sample period, thus the final dataset covers 170 countries and 1072 4-digit HS products. As before, we augment the data with country-level financial development index published by the International Monetary Fund.

We estimate the following equation:

$$RelatedShare_{dpt} \quad = \quad \alpha_1 \mathrm{TII}_p + \alpha_2 \mathrm{TII}_p \times \mathrm{FD}_{dt} + \delta_{HS2,t} + \delta_{dt} + \epsilon_{dpt}. \tag{6}$$

where $RelatedShare_{dpt}$ is the share of US related-party (intra-firm) exports in total exports of a 4-digit HS product $p$ exported to country $d$ at time $t = 2002, .., 2006$. $\mathrm{FD}_{dt}$ denotes the financial development index pertaining to country $d$ in year $t$. The specification includes HS2-year and destination-year fixed effects.

To test the robustness of our second hypothesis we include a much richer set of fixed effects and estimate the following model:

$$RelatedShare_{dpt} \quad = \quad \beta_1 \mathrm{TII}_p \times \mathrm{FD}_{dt} + \gamma_{pt} + \gamma_{d,HS2} + \gamma_{dt} + e_{dpt}. \tag{7}$$

We control for a large range of possible confounding factors with product-year, HS2-destination, and destination-year fixed effects. In both specifications, we cluster standard errors by product.

As explained above, we expect the share of related-party trade to be higher for high *TII* products, but the effect should be smaller when products are destined for countries with well-developed financial sector, implying $\alpha_1 > 0$ and $\alpha_2 < 0$ in the first specification and $\beta_1 < 0$ in the second model.

The results are presented in Table 5 starting with the less demanding specification described in equation (6). As visible in column 1, the share of related-party exports by US firms is higher for high *TII* products. When interpreted together with the estimated coefficient on the interaction term, the results provide support for the hypothesis that an increase in *TII* is associated with an increase in the related-party export share, but less so for destination countries characterized by well-developed financial markets.[14] In column 2, we include product-year fixed effects, which means that there is no need to include the *TII* measure by itself. The interaction term remains statistically significant at the one percent level and the estimated magnitude increases slightly. Column 3 presents our baseline specification based on equation (7), which additionally includes HS2-destination country fixed effects. The estimated coefficient on the interaction between *TII* and financial development index implies that a one-standard-deviation increase in *TII* increases the share of related-party trade by 1.7 percentage points (or 10% of its mean in 2006) when a country moves from the 90*th* (Spain in 2002) to 10*th* percentile (Dominican Republic in 2005) of the financial development index.

In the last two columns of Table 5, we present robustness checks. We augment our baseline specification with interactions between *TII* and per capita GDP or the quality of contract enforcement ($CE$) in the destination country. The former interaction aims to capture the impact of the overall economic development, while the latter the impact of institutional quality and quality of courts in the destination country. In our preferred specification in the last column, the coefficient on *TII*FD* doubles in magnitudes relative to the specification without additional controls, presented in column 3, suggesting that the baseline estimates captured a lower bound on the effect of interest. The estimate implies that one-standard-deviation increase in *TII* increases the share of related-party trade by 2.7 percentage points (or 15% of its mean in 2006) when a country moves from the 90*th* (Spain in 2002) to 10*th* percentile (Dominican Republic in 2005) of the financial development index.

In Table A.14, we include interactions with other product characteristics, such as durability, shipment size, contract intensity, and demand volatility, to test whether they affect the estimate obtained for $\text{TII}_p \times \text{FD}_{dt}$. Our findings remain robust to these additional controls. When an interaction between demand volatility is added in columns 5 and 7, the estimates become quantitatively smaller compared to the estimate from our preferred specification, but they retain their statistical significance.

Finally, Table A.15 presents results obtained from estimating a specification on a restricted sample that excludes observations with $RelatedShare_{dpt} = 0$. The interaction terms of

[14] Values of the FD index range from 0 to 1 with the mean and median of 0.3 and 0.22, respectively.

interest remain significant at the one percent level in all specifications. The estimated magnitudes are larger than in the baseline table, implying that the underlying mechanism, through which financial development affects the relationship between trade-related risks and intra-firm trade is more relevant for the intensive margin of trade rather than the extensive margin.

## 5 Conclusions

In this paper, we construct a product-level measure of trade insurance intensity (*TII*). We do so using information on the prevalence of LC use in Turkish imports and exports disaggregated by the trading firm, 6-digit HS product, source country, year and payment method. When constructing the measure, we purge variation due to the trading firm and source country at a particular point in time. The measure is available for 1203 4-digit HS products. It is quite stable over time and exhibits significant variation within 2-digit HS product groupings.

We find that *TII* is correlated in intuitive ways with some product characteristics, such as, demand volatility, shipment size, time to ship, and others. In our empirical analysis, we show that exports of high *TII* products destined for crisis-hit countries registered a much larger decline than exports of other products did. This finding is in line with the view that the financial crisis negatively affected the supply of LCs, as banks were striving to improve their positions. Moreover, we document an increase in the intra-firm share of exports of high *TII* products sent to crisis-affected countries. This result is intuitive as intra-firm trade can be thought of as a substitute for purchasing trade insurance.

We believe our measure could be used in applications related to finance, international trade and economic growth. For instance, the inability to insure trade-related risks may affect specialization patterns of countries or determine the intensity with which financial shocks propagate across countries. It may drive the geography of supply chains by pushing some production stages to countries with better developed financial sectors. It may also affect firms' incentives for vertical integration or the geography of their sourcing patterns.

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# A Appendix: Tables and Figures

Table A.6: Determinants of the use of LCs

| | t=2003 | t=2004 | t=2005 | t=2006 |
|---|---|---|---|---|
| $f = M, X$ | | | | |
| Firm ($i$) | 0.220 | 0.209 | 0.229 | 0.245 |
| Product ($p$) | 0.052 | 0.049 | 0.050 | 0.051 |
| Country ($c$) | 0.031 | 0.028 | 0.028 | 0.028 |
| Firm-country ($ic$) | 0.511 | 0.491 | 0.514 | 0.527 |
| Firm-product ($ip$) | 0.388 | 0.373 | 0.399 | 0.411 |
| Product-country ($pc$) | 0.243 | 0.225 | 0.224 | 0.223 |
| $f = M$ | | | | |
| Firm ($i$) | 0.322 | 0.310 | 0.336 | 0.357 |
| Product ($p$) | 0.068 | 0.065 | 0.067 | 0.069 |
| Country ($c$) | 0.016 | 0.015 | 0.017 | 0.020 |
| Firm-country ($ic$) | 0.486 | 0.470 | 0.499 | 0.518 |
| Firm-product ($ip$) | 0.544 | 0.524 | 0.561 | 0.573 |
| Product-country ($pc$) | 0.176 | 0.164 | 0.172 | 0.176 |
| $f = X$ | | | | |
| Firm ($i$) | 0.228 | 0.202 | 0.207 | 0.206 |
| Product ($p$) | 0.060 | 0.056 | 0.058 | 0.060 |
| Country ($c$) | 0.068 | 0.061 | 0.059 | 0.060 |
| Firm-country ($ic$) | 0.565 | 0.542 | 0.566 | 0.576 |
| Firm-product ($ip$) | 0.307 | 0.281 | 0.285 | 0.282 |
| Product-country ($pc$) | 0.320 | 0.304 | 0.309 | 0.312 |

*Notes:* Each row shows the adjusted R-squared value obtained from a regression of a binary variable, which takes on the value one for LC-based transactions and zero otherwise, on various fixed effects as listed in the first column. The sample is monthly trade data (imports, exports, or pooled imports & exports) at the firm-product-country level, disaggregated by financing terms, at time $t$. $k$ indicates the level of fixed effects, where $k = \{i, p, c, ic, ip, pc\}$. Firm refers to the Turkish partner in trade transactions.

Table A.7: Summary statistics for *TII*

| Products | All HS4 | Manuf. HS4 |
|---|---|---|
| No. of HS4 products | 1203 | 1096 |
| Mean | 0.003 | 0.003 |
| Std dev. | 0.034 | 0.035 |
| Median | -0.003 | -0.004 |
| 5*th* pctile | -0.020 | -0.020 |
| 10*th* pctile | -0.015 | -0.016 |
| 25*th* pctile | -0.009 | -0.009 |
| 75*th* pctile | 0.005 | 0.005 |
| 90*th* pctile | 0.026 | 0.024 |
| 95*th* pctile | 0.052 | 0.054 |

Table A.8: Top *TII* products

| HS Code | Description |
|---|---|
| 2709 | Petroleum oils; crude |
| 7203 | Ferrous products obtained by direct reduction of iron ore |
| 8445 | Machines for preparing textile fibres; spinning; doubling or twisting machinery |
| 2601 | Iron ores and concentrates |
| 7204 | Ferrous waste and scrap; remelting scrap ingots of iron or steel |
| 1502 | Fats of bovine animals, sheep or goats |
| 8446 | Weaving machines (looms) |
| 8602 | Rail locomotives; (other than those of heading no. 8601), locomotive tenders |
| 2701 | Coal; briquettes, ovoids and similar solid fuels manufactured from coal |
| 8904 | Tugs and pusher craft |

Table A.9: Countries with bank crises

| | | |
|---|---|---|
| Austria | Belgium | Denmark |
| France | Germany | Greece |
| Hungary | Ireland | Italy |
| Kazakhstan | Latvia | Netherlands |
| Portugal | Russia | Slovenia |
| Spain | Sweden | Switzerland |
| Ukraine | UK (2007) | USA (2007) |

*Notes:* The table lists the countries that experienced a bank crisis during the Great Recession according to the database constructed by Laeven and Valencia (2013).

Table A.10: Correlations between *TII* and other product characteristics

| *TII* and | Correlation | Rank correlation | Partial correlation |
|---|---|---|---|
| Demand volatility | $0.0861^{a}$ | 0.0003 | $0.014^{c}$ |
| Share of maritime trade | $0.1726^{a}$ | $0.2187^{a}$ | $0.020^{a}$ |
| Shipment size (log) | $0.2767^{a}$ | $0.3447^{a}$ | $0.009^{a}$ |
| Durable goods | $0.0654^{b}$ | $0.0576^{c}$ | -0.001 |
| Non-differentiated goods | $0.0607^{b}$ | -0.0347 | 0.004 |
| Contract intensity | $0.0602^{c}$ | $0.1239^{a}$ | 0.009 |

*Notes:* Significance levels: c: $p < 0.10$, b: $p < 0.05$, a : $p < 0.01$.

Table A.11: *TII* and other product characteristics

| | (1) | (2) | (3) |
|---|---|---|---|
| Demand volatility | 0.0139c | | 0.0146b |
| | (0.007) | | (0.007) |
| Share of maritime trade | 0.0194a | | 0.0203a |
| | (0.004) | | (0.004) |
| Shipment size (log) | 0.0086a | | 0.0087a |
| | (0.002) | | (0.002) |
| Contract intensity | 0.0128b | | 0.0076a |
| | (0.005) | | (0.005) |
| Durable goods | -0.0007 | | -0.0008 |
| | (0.005) | | (0.003) |
| Non-differentiated goods | 0.0040c | 0.0047c | |
| | (0.002) | (0.003) | |
| N | 977 | 977 | 977 |
| $Adj R^2$ | 0.112 | 0.003 | 0.111 |
| $R^2$ | 0.117 | 0.004 | 0.115 |

*Notes:* Dependent variable is *TII*. Significance levels: c: $p< 0.1$, b: $p < 0.05$, a : $p < 0.01$. Robust standard errors are shown in parentheses.

Table A.12: The Great Trade Collapse: *TII* versus standard financial dependence measures

| Dep. Var.: $\ln(Exports_{odpt})$ | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $\text{TII}_p\times$ | **-0.755a** | **-0.697a** | **-0.759a** | **-0.770a** |
| $\text{Crisis}_{dt}$ | (0.257) | (0.256) | (0.261) | (0.258) |
| $\text{RZ}_p\times$ | 0.017 | | | |
| $\text{Crisis}_{dt}$ | (0.012) | | | |
| $\text{IR}_p\times$ | | -0.596a | | |
| $\text{Crisis}_{dt}$ | | (0.100) | | |
| $\text{AT}_p\times$ | | | 0.170a | |
| $\text{Crisis}_{dt}$ | | | (0.032) | |
| $\text{TCI}_p\times$ | | | | -0.106 |
| $\text{Crisis}_{dt}$ | | | | (0.102) |
| No. Obs. | 12384966 | 12384966 | 12384966 | 12384966 |
| $R^2$ | 0.879 | 0.879 | 0.879 | 0.879 |
| Fixed effects | opt,odp,odt | opt,odp,odt | opt,odp,odt | opt,odp,odt |

*Notes:* Significance levels: c: p< 0.1, b: $p < 0.05$, a : $p < 0.01$. Standard errors, clustered by 4-digit HS codes, are shown in parentheses.

Table A.13: The Great Trade Collapse: Extensions

| | (1) | (2) | (3) |
|---|---|---|---|
| $\text{TII}_p\times$ | **-0.317b** | | |
| Crisis Year=$\text{T}_{dt}$ | (0.155) | | |
| $\text{TII}_p\times$ | **-1.021a** | | |
| Crisis Year>$\text{T}_{dt}$ | (0.262) | | |
| $\text{Crisis}_{dt}$ | | | |
| × Bin 2 | | **-0.022b** | |
| | | (0.010) | |
| × Bin 3 | | **-0.039a** | |
| | | (0.011) | |
| × Bin 4 | | **-0.056a** | |
| | | (0.011) | |
| × Bin 5 | | **-0.071a** | |
| | | (0.014) | |
| $\text{TII}_p\times$ | | | **-0.070a** |
| $\text{Crisis}_{dt}$ | | | (0.022) |
| No. Obs. | 12749702 | 12813670 | 22020089 |
| $R^2$ | 0.879 | 0.879 | 0.578 |
| Fixed effects | opt,odp,odt | opt,odp,odt | opt,odp,odt |

*Notes:* Significance levels: c: p< 0.1, b: $p < 0.05$, a : $p < 0.01$. Dependent variable is $\ln(Export_{odpt})$ in columns 1-2, and $[Exports_{odpt} > 0]$ in column 3. Standard errors, clustered by 4-digit HS codes, are shown in parentheses.

Table A.14: Intra-firm Trade: Controlling for other product characteristics

| Dep. Var.: RelatedShare$_{dpt}$ | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| TII$_p$× | **-1.346a** | **-1.299a** | **-1.421a** | **-1.378a** | **-0.776b** | **-1.499a** | **-0.807b** |
| FD$_{dt}$ | (0.365) | (0.361) | (0.359) | (0.360) | (0.323) | (0.374) | (0.326) |
| TII$_p$× | 0.004 | 0.004 | 0.004 | 0.006 | 0.004 | 0.007 | 0.005 |
| GDPpc$_{dt}$ | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| TII$_p$× | 0.003 | 0.004 | 0.003 | 0.004 | 0.004 | 0.004 | 0.004 |
| CE$_{dt}$ | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Durable$_p$× | 0.028 | | | | | | 0.063b |
| FD$_{dt}$ | (0.028) | | | | | | (0.028) |
| TimeToShip$_p$× | | -0.043 | | | | | -0.065c |
| FD$_{dt}$ | | (0.037) | | | | | (0.037) |
| Size$_p$× | | | -0.0004a | | | | -0.0003a |
| FD$_{dt}$ | | | (0.0001) | | | | (0.0001) |
| Differentiated$_p$× | | | | 0.006 | | | -0.011 |
| FD$_{dt}$ | | | | (0.021) | | | (0.022) |
| DemandVolatility$_p$× | | | | | -0.408a | | -0.408a |
| FD$_{dt}$ | | | | | (0.036) | | (0.038) |
| ContractIntensity$_p$× | | | | | | -0.050 | -0.107 |
| FD$_{dt}$ | | | | | | (0.095) | (0.103) |
| No. Obs. | 105665 | 105338 | 105674 | 107145 | 105759 | 104112 | 102553 |
| $R^2$ | 0.325 | 0.325 | 0.325 | 0.324 | 0.328 | 0.322 | 0.327 |

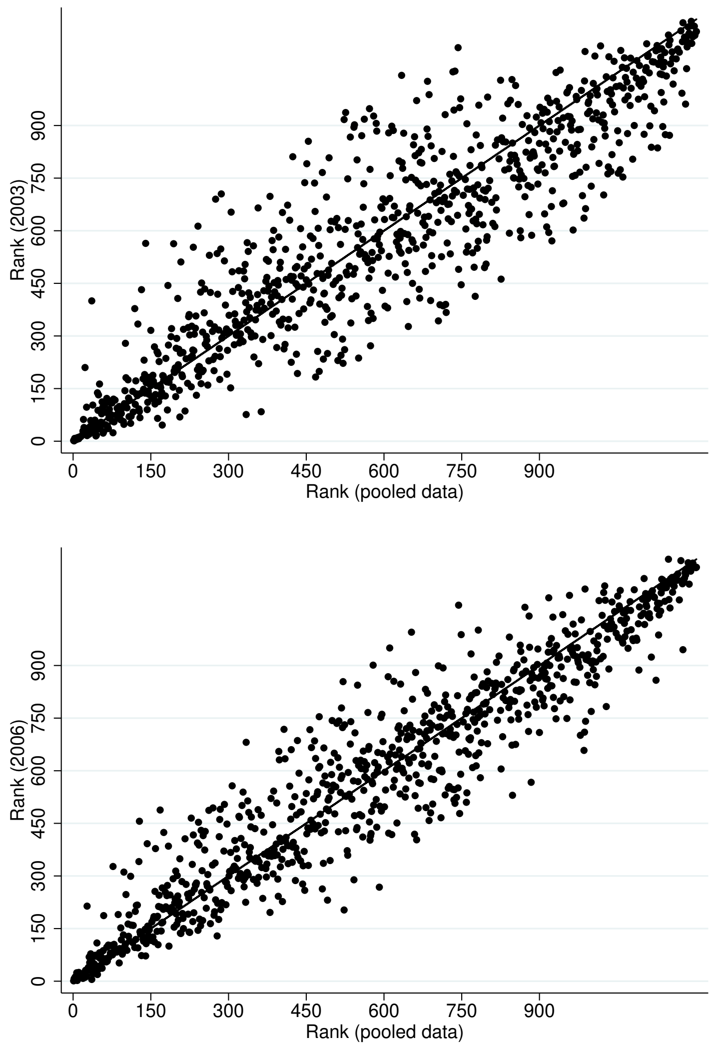
*Notes:* Significance levels: c: $p < 0.1$, b: $p < 0.05$, a : $p < 0.01$. All regressions include product-year, destination-year, and destination-2-digit HS code fixed effects. FD and CE denote financial development and contract enforcement indices, respectively. Standard errors, clustered by 4-digit HS codes, are shown in parentheses.

Table A.15: Intra-firm Trade: Excluding RelatedShare$_{dpt} = 0$

| Dep. Var.: RelatedShare$_{dpt}$ | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| TII$_p\times$ | **-1.169a** | **-1.195a** | **-0.862a** | **-1.470a** | **-2.183a** |
| FD$_{dt}$ | (0.357) | (0.366) | (0.284) | (0.437) | (0.624) |
| TII$_p$ | **0.976a** | | | | |
| | (0.211) | | | | |
| FD$_{dt}$ | -0.003 | | | | |
| | (0.021) | | | | |
| TII$_p\times$ | | | | 0.013b | 0.009 |
| GDPpc$_{dt}$ | | | | (0.006) | (0.009) |
| TII$_p\times$ | | | | | 0.009c |
| CE$_{dt}$ | | | | | (0.005) |
| No. Obs. | 152168 | 152035 | 150666 | 147526 | 69793 |
| $R^2$ | 0.192 | 0.298 | 0.424 | 0.424 | 0.447 |
| FE | hs2,d,t | pt,dt | pt,dt,hs2d | pt,dt,hs2d | pt,dt,hs2d |

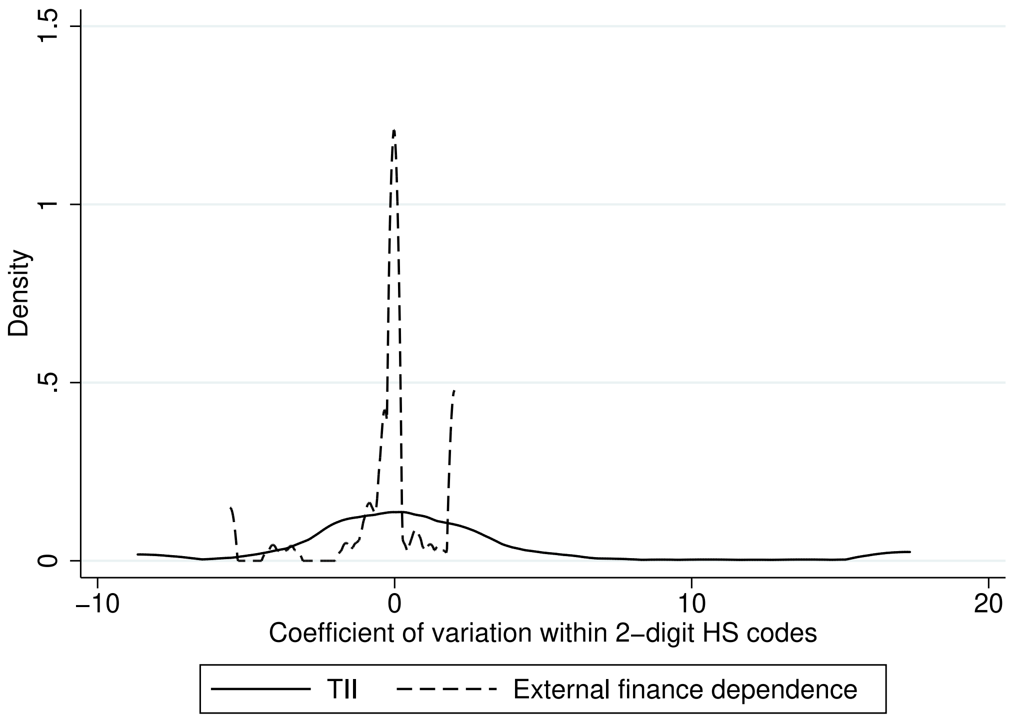
*Notes:* Significance levels: c: p$<$ 0.1, b: p $<$ 0.05, a : p $<$ 0.01. FD and CE denote financial development and contract enforcement indices, respectively. Standard errors, clustered by 4-digit HS codes, are shown in parentheses.

Figure A.5: Stability of *TII* over time




*Notes:* These figures compare rankings of 4-digit HS products based on the baseline measure and the one obtained from two individual years; 2003 and 2006.

Figure A.6: Variation of *TII* within 2-digit HS product codes




*Notes:* The figure shows the distributions of the coefficient of variation of *TII* and the external finance dependence measure (Rajan and Zingales, 1998) within 2-digit HS products.