Does Trade Insurance Matter?

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Abstract

This study introduces a new index of product-level reliance on insurance in international trade transactions. It is based on the use of letters of credit, which allow trading parties to avoid trade-related risks, such as non-payment, delayed payment or payment dispute. The index, constructed using unique data from Turkey, is available for 1,196 HS4 products. To shed light on how letters of credit facilitate trade, the index is combined with worldwide bilateral trade data. The results indicate that products relying heavily on trade insurance saw a larger decline in exports to destinations affected by the 2008-2009 financial crisis than other products did. They also registered an increase in the intra-firm share of exports sent to crisis-affected countries.

Keywords: Trade insurance, Trade finance, 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. An exporter sending goods abroad faces the risk of not receiving a payment, the payment being disputed or delayed. It is possible to require payment in advance, but this in turn shifts all the risk onto the importer. A letter of credit (LC) offers a solution, as it shifts the risk onto a third party, a bank. In an LC-financed transaction, the importer's bank promises to pay for the goods on behalf of the importer provided the delivery of the goods has been made, as reflected in the shipping documents. In this way, the risk of non-payment or non-delivery of pre-paid goods is eliminated.[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 being 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 the 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 stem in large part from product characteristics that increase the demand for insurance.

The purpose of this paper is twofold. First, it introduces a new index capturing product reliance on LCs, called *Trade Insurance Intensity*, or *TII* hereafter. Second, it demonstrates that the lack of trade finance - or, more precisely, inability to purchase trade insurance - contributed to the Great Trade Collapse which occurred in 2009, in the aftermath of the global financial crisis. We show that products relying more heavily on trade insurance experienced a more severe decline in exports to countries affected by the 2008 financial crisis. This is a novel finding as the contribution of trade insurance to the Great Trade Collapse has received relatively little attention so far and has not been assessed using global trade data.

This conclusion is corroborated by an analysis of trends in intra-firm exports. Intra-firm

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

trade is not subject to risks of default or payment delay and thus should be more resilient than arms-length trade when no trade insurance is available for purchase. 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). Considering the share of intra-firm trade in total exports is appealing because it allows us to control for all the unobserved factors that may be affecting total exports of a given product to a particular crisis-affected destination in a given time period, such as decline in demand, the impact of worsening conditions in the importing industry, etc.

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, month 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 engages in imports and exports in a very large number of products with over 200 partner countries. 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 in particular years. *TII* is available for 1,196 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. The index reveals considerable variation across products within industries.

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 and lower cost to eliminate the risk.

We use the *TII* indicator to assess the contribution of the disruption of trade insurance supply to the major trade collapse of 2008-9, triggered by the financial crisis. This application is interesting in its own right, but it is also meant to give an example of potential uses of the new measure. More importantly, it strengthens 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

[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.

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), the lack of access to financing (Amiti and Weinstein, 2011; Paravisini et al., 2015; Chor and Manova, 2012) and the interplay of uncertainty and higher ordering costs for foreign (relative to domestic) inputs (Berman et al., 2018).

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 219 countries covering the period 2002-09.

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 results are robust to controlling for origin-destination-product, origin-destination-year, and product-year fixed effects. They hold 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 10% of trade lost during the Great Trade Collapse.

We complement our analysis with additional data on intra-firm trade. Intra-firm trade (as opposed to arms-length transactions) eliminates the risk of non-payment, payment delay or dispute, thus we conjecture that exports of products heavily reliant on trade insurance registered an increase in the intra-firm share relative to other products when destined for crisis-affected countries. 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 0.5 percentage point increase in intra-firm trade, corresponding to 5% of its average value in the data, destined for crisis-affected markets. This is a much more stringent test of the trade insurance channel, as by focusing on the share of intra-firm trade we implicit take into account all other factors that may be affecting exports of a particular product to a particular crisis-affected destination in a given time period.

These intuitive and statistically significant results 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 its 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. This barrier is likely to be distorting since it has a greater impact on smaller businesses that cannot rely on intra-firm trade. Moreover, our results illustrate another reason why multinational firms are more resilient to financial crises. Finally, our findings also suggest 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. The proportion of differentiated products among an industry inputs has been in turn 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.

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 Why a product-specific measure is informative

There exist four main methods of structuring financing terms in an international trade transaction: *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. An LC 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.

LCs protect the seller against the buyer (i) refusing to accept the shipment and the associated payment obligations; (ii) refusing to pay for the goods received (fraud); (iii) intentionally delaying the payment; (iv) disputing the terms of the contract (e.g., whether the goods are of specified quality) in order to reduce the payment obligation.

The fundamental principle of an LC is that it deals with documents and not with goods. The payment obligation is independent from the underlying contract of sale or any other contract in the transaction. The bank's obligation is defined by the terms of the LC alone, and the contract of sale is not considered. Thus the bank is obliged to pay, regardless of whether the contract between the buyer and the seller is subject to contractual issues. The LC does not permit of any dispute with the buyer as to the performance of the contract of sale being used as a ground for non-payment or reduction or deferment of payment.[3] Whilst the bank is under an obligation to identify that the correct documents exist, the bank is not responsible for investigating the underlying facts of each transaction, whether the goods are of the sufficient – and specified – quality or quantity. Because the transaction operates on a negotiable instrument, it is the document itself which holds the value – not the goods to which it refers. This means that the bank need only be concerned with whether the document fulfils the requirements stipulated in the letter of credit.

Thus *the nature of the product traded matters for how desirable it is to use an LC*. Sellers of products with structurally more volatile global demand or heavy products, that tend to be shipped by sea and have longer transport times, face a higher risk of the buyer changing her mind and attempting to cancel the order. Differentiated products and products that tend to be customized to the buyer's specification face a higher risk of the buyer disputing whether the terms of the contract have been met, which may be due to product characteristics not being precisely specified due to omission or misunderstanding. The risk of default also

[3]The only exception to this may be fraud. For example, a dishonest seller may present documents which seem to comply with the LC and receive payment, only for it to be later discovered that the documents are fraudulent. This would place the risk on the buyer, but it also means that the issuing bank must be stringent in assessing whether the presented documents are legitimate.

depends on specific features of the market on which the products are traded. Exporters primarily need LCs to protect themselves against importers intentionally delaying payment or attempting to pay less by questioning product quality or specifications. This is more likely to occur in markets where purchasing firms have relatively thin margins, more difficult access to credit or a high bargaining power vis-a-vis the exporter. Exporters of perishable goods are particularly vulnerable as perishability means that there is little time to call off the transaction and find an alternative buyer. As will show later in this section, product-specific dimension explains a considertable share of variation in LC usage.[4]

In summary, there is not one particular product characteristic that makes LCs more desirable. Rather it is an array of factors that determine product-specific demand for trade insurance. We will come back to this issue later in this section when we examine the link between *TII* and product characteristics.

2.2 Why constructing *TII* using Turkish data is appropriate

While constructing our *TII* indicator on observations based solely on Turkish trade might reflect some specificities of the country's productive and financial systems, we believe that this does not detract from the fact that the index contains general and useful information on insurance dependence of products traded around the world.

There are several considerations in choosing the data to be used for constructing the *TII* measure. First, one would like to use information from a country with a large trading portfolio in order to maximize the product coverage of the index. Second, one would like to focus on a country with a reasonably well developed banking sector that is capable of both issuing and confirming LCs. At the same time, it is useful to choose an emerging market rather than a G7 country, as less than perfect contract enforcement increases the need for using LCs on the import side, thus increasing prevalence of LCs and amplifying variation across products. Finally, one needs to choose a country where data on trade financing terms are available.

Turkey fulfills all of the criteria listed above. With its population of over 80 million, Turkey is one of the most important emerging markets. It is a large open economy trading with more than 200 countries exporting about 1,050 4-digit HS products and importing about 1,100 4-digit HS products. About 40% of its trade is with the European Union, with whom Turkey has a customs union in manufacturing goods. Although its institutions have been improving, they are still at the level representative of an emerging market.

[4]Obviously, factors specific to the partner country and the trading firms matter a great deal, but for the most part these will be purged from our index, as explained later in this section.

During the sample period that we use to construct *TII* (2003-2006), Turkish banking system was healthy, with strong balance sheets, low levels of non-performing loans, and capital levels above regulatory minima. This was possible thanks to a comprehensive reform program in the financial sector backed by the International Monetary Fund in the aftermath of the 2001 crisis and strong commitment by the Turkish authorities to harmonization with the EU acquis. The 2003-2006 period is also characterized by high growth rates and rising incomes, with real per capita income growth averaging at about 6% per annum. Such strong economic performance and successful economic reforms, accompanied by ample liquidity in international markets, led to a significant surge in foreign direct investment into Turkey. The banking sector benefited from inflows of foreign direct investment, and as a result, the share of total banking sector assets held by foreigners reached 25%.

During the sample period, about 20% of the total value of Turkish imports and 15% of exports used LCs. These figures 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.

And most importantly, Turkey is unique among emerging markets and developed countries in mandating reporting of financing terms in all international trade transactions. To the best of our knowledge no other country collects such information for both imports and exports. Moreover, reporting of financing terms in Turkey has to be backed by documentation, which mean that the data collected are highly reliable.

Our index will be constructed using data on both import and export flows, which means it will capture demand for LCs from exporters in a large number of countries around the world selling to Turkey and as well as Turkish exporters supplying a variety of countries. Thus we would expect it to be fairly representative of the global demand for LCs. Focusing on Turkish exports to a variety of markets (where LCs are issued) will also mean that we should not be concerned about specificity of the Turkish financial sector affecting the index.

Finally, the econometric results presented in the following sections show that our indicator has strong explanatory power for the patterns and trends in international trade flows that do not involve Turkey.

2.3 Data

We construct our *TII* measure 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. Most importantly for our purposes the dataset distinguishes between the four main financing terms: open account, cash in advance, documentary collection, and letter of credit.[5]

Our *TII* index is constructed based on the intensity of the LC use in both import and export transactions. To avoid the period of the recent financial crisis, we construct our measure based on figures for 2003-2006. Our baseline measure focuses on all trading partners, but in robustness checks we will consider alternative measures defined just on subsamples of partner countries. We pool exports and imports transactions together to eliminate the possibility that particularities of the Turkish financial sector affect availability of LCs across products.

During the period under consideration, about 20% of Turkish imports and 15% of exports were backed by LCs. Transactions relying on LCs were found in 92% of the 4-digit HS products, with the average share of LC-backed trade across all 4-digit HS product categories reaching 9%. 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.

2.4 Constructing the *TII* index

Our trade insurance intensity index 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. While most of this literature on trade finance focuses on firms and countries characteristics, we explore the extent to which 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 in particular time periods.

Table A.1 in appendix presents the variation in the use of LCs explained by each dimension, namely firm, product and 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 (pooled imports and exports) at the firm-product-country

[5]One can think of the data set as consisting of transaction level data aggregated to firm-flow-product-financing term-partner country-month level.

level, disaggregated by financing terms. Three results emerge. First, the share of variation explained by each dimension remains relatively stable over time for each sample. Second, the largest share of the variation in the use of LCs is explained by firm-level factors. Third, while product-level factors matter less than the firm-level factors, they matter as much as the country-level factors.

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

$$\mathbb{1}\{p = LC\}_{fikcm} = \alpha_{ct} + \sum_{y=1}^{12} \mathbb{1}\{month = y\} + \alpha_{k4} + \epsilon_{fikcm}, \tag{1}$$

where the dependent variable is a binary variable that takes on the value one when the payment method (p) is LC, and zero otherwise for trade flow $f = \{import, export\}$ by Turkish firm i, 8-digit HS product k with a trade partner located in country c in month-year m. We add country-year fixed effects (α_{ct}), 4-digit HS product fixed effects (α_{k4}) and dummies for calendar months to capture seasonal effects. The estimated product fixed effects capture trade insurance intensity of each 4-digit HS product.[6] By construction, $\hat{\alpha}_{k4}$ is orthogonal to country-level factors. Our measure is available for 1,196 goods, of which 188 are agricultural and agri-food products.

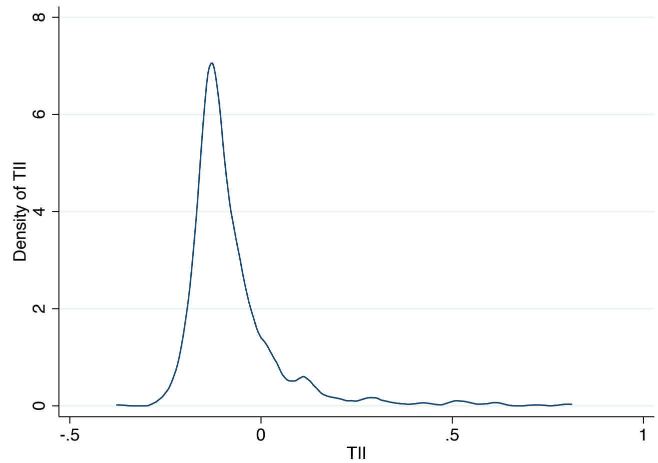
It is worth reiterating the points made above. The propensity to rely on an LC may be determined by the characteristics of the country where the trading partner is located. To avoid the fees associated with obtaining an LC, for instance, a Turkish importer may be willing to buy on cash-in-advance terms 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 will be purged from our measure by country-year fixed effects included in equation (1). This means that the variation captured in our measure comes from differences in LC use across products traded with a given country in a given year.

In robustness checks, we will experiment with alternative definitions of the *TII*, including a measure based on trade with just OECD countries, a measure based just on imports and a measure defined as a simple share of trade on LC terms. In other words, we will consider a different sample of trading partners, a different trade flow and a different methodology for constructing the index.

Figure 1 shows the distribution of *TII* across 4-digit HS product codes. The measure varies between -0.38 and 0.82 it has a mean of -0.08, a median of -0.11 and a standard deviation

[6]We drop cases where the the number observations per 4-digit HS product code is less than 10.

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.

of 0.13 (see Table A.2). 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, metals and machinery have relatively high median values of the *TII* measure. In contrast, precious minerals have the lowest median value. This figure also illustrates large variation in *TII* values within industries.

In Table A.3, we list products with the highest values of *TII*. These match the industry-level patterns as they include metals and minerals (such as ferrous products, tar, crude petroleum oils, pitch coke, etc.), and transport vehicles (such as, rail locomotives). The former group of products often involves bulk shipments going by sea. The latter products tend to be customized. In addition, the list includes military weapons (which are also highly customized products) and live bovine animals (for which transit delays may be detrimental).

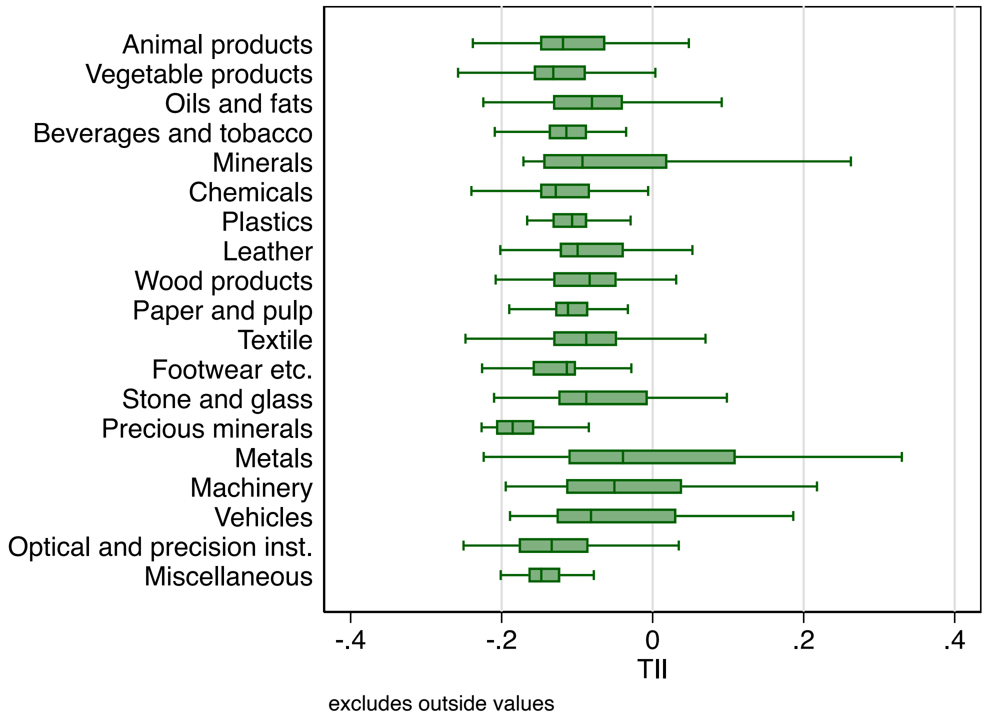
2.5 *TII* versus other product characteristics

As mentioned earlier, the need for insurance is a function of an array of product characteristics, rather than a single factor. Nevertheless, it is instructive to examine which product characteristics are correlated with our measure.

Products that tend to be shipped by sea use LCs more intensively (see Table A.4 and Figure 3).[7] 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

[7] 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.

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.

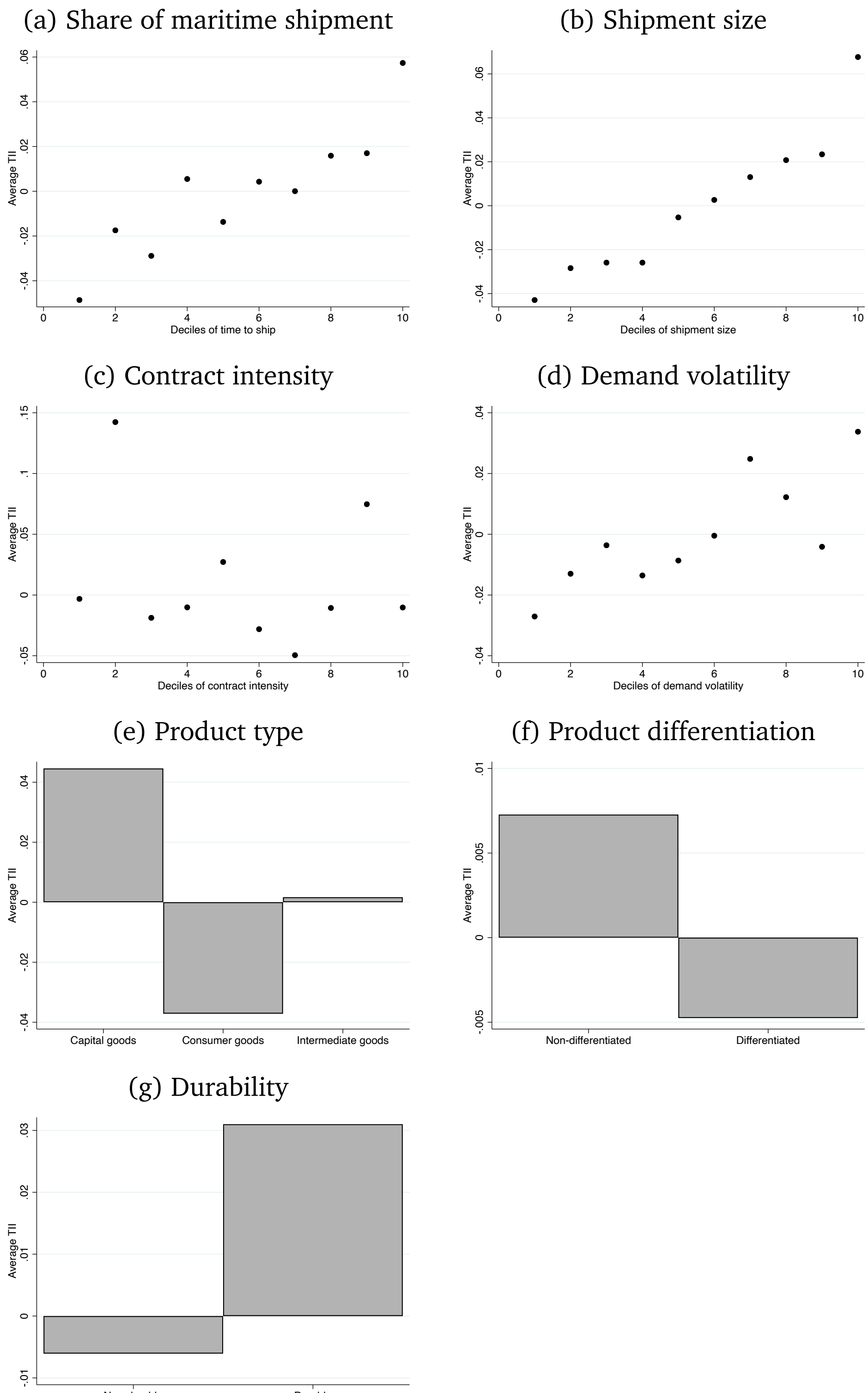
time also increases the risk of an adverse exchange rate or price movement and thus may prompt one of the trading partners to try to renegotiate the contract.

As visible in panel b of Figure 3 and confirmed in Table A.4, products that tend to be shipped in larger volumes use LCs more intensively.[8] 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 bank LC fees include a fixed component 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), though this relationship is less pronounced (see Table A.4 and Figure 3, panel c). This measure aims to capture the share of the intermediate inputs that require

[8] The indicator of shipment size by 4-digit HS product is based on French 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: Average *TII* by product type



Notes: The figure shows the average value of *TII* for each category or decile as stated on the x-axis. *TII* is demeaned in the full sample to have a zero mean.

relationship-specific investments.[9] 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.

As expected, demand volatility presents an upward-sloping pattern (see panel d in Figure 3).[10] It confirms high LC dependence of goods with highly volatile demand. As visible in Table A.4, this relationship is statistically significant.

Figure 3 also shows that capital goods as well as goods that are durable tend to rely more on LCs.[11] The opposite is true for consumer goods, presumably because orders are made for large batches of goods with the same (or at least well specified) characteristics. The pattern for differentiated goods suggests that low level of differentiation is associated with high reliance on LCs, reflecting the need to insure slow bulk shipments of commodities.[12] These patterns are confirmed by the results in Table A.4.

The next question we tackle is whether our index 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 an LC is to insure against the risk of non-payment, payment delay or attempts to renegotiate the contract or refusal to accept a delivery.

We consider several 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.[13]

Column (9) of Table A.4 shows that while *TII* is correlated positively with IR, AT and TCI, it captures a different source of variation as evidenced by the low R^2 value. This

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

[10] Our indicator of demand volatility is the coefficient of variation of monthly bilateral export flows. It is calculated from Comtrade data, from which we have excluded flows involving Turkey.

[11] We use the classification by broad economic categories (BEC) provided by the United Nations Statistics Division.

[12] We use the conservative classification proposed by Rauch (1999).

[13] 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.

is comforting, if not unexpected, as our measure is designed to capture relying on trade insurance, and not financial dependence. It is also worth noting that the standard measures of financial dependence are more aggregated, i.e., they capture industry-level variation, while our measure is product-specific and available for 1,196 different products.

When all the variables mentioned above enter the regression, they jointly explain about 15% of variation in *TII*. It would be reasonable to expect that there are numerous additional broad industry-level factors that correlate with *TII*, but omitted from this specification. Thin margin are just one of possible examples. This is confirmed by results presented in the last column of the table: adding 2-digit HS-level fixed effects increases the value of the R^2 to 38%. In this specification, the coefficients on the share of shipments by sea, average shipment size, demand volatility and IR retain their size and statistical significance.

Three main messages emerge from this section. First, correlations between *TII* and product characteristics seem quite intuitive and thus boost our confidence in the index. Second, *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. Third, broad-industry level characteristics, together with share of ocean shipping and average shipment size, explain slightly less than two-fifths of variation in the index, leaving more than half of the variation unexplained. This suggests that our measure captures something that is different from what can be collectively captured by the widely-used observed product characteristics.

3 Application of *TII*: The Great Trade Collapse

Our first application examines whether products relying heavily on trade insurance are more adversely affected by reduced supply of trade insurance. 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 Developments in trade finance during the crisis

The 2007-2008 financial crisis offers a good setting for testing our hypothesis as it caused a severe crunch in the supply of trade finance. These reasons for this supply shock are summarized well by the industry report (ICC Banking Commission, 2009):

*As the financial crisis unfolded, **the availability of trade finance declined** and **its cost increased** because of **growing liquidity pressure** in matured markets, the **general scarcity of capital**, unprecedented **increases in the cost of funding** and a perception of **heightened country and counterparty risks**. The contraction in trade finance was also fueled by the **loss of critical market participants, such as Lehman Brothers**, a **drying up of the secondary market** for short-term exposure (as banks and other financial institutions deleveraged) and the volatility of commodity prices. Banks in developed countries are also required to **hold more capital at home** and are **providing less liquidity to banks in emerging economies**. In addition, **the implementation of the Basel II Accord** on banking laws and regulations, with its increased risk sensitivity of capital requirements in an environment of global recession, has added pressure on banks to hold back on trade finance.* (page 20)

Not surprisingly, where trade insurance remained available, its costs incrased. Over half of respondents surveyed by ICC Banking Commission (2009) indicated an increase in issuance fees for LCs. 58% reported an increase in confirmation fees.

At the same time, the demand for insurance was booming:

As the financial crisis spread, the demand for LCs, insurances and guarantees increased, because exporters wanted to be certain importers would pay on schedule. This led to delays in international trade, with goods reportedly being docked for weeks before shipment, as terms of financing were finalized. (page 21)

3.2 Data and empirical specification

Our analysis is based on bilateral trade data for the 2003-2009 period[14] available from BACI.[15] The dataset covers 220 countries and more than a thousand 4-digit HS product codes, generating almost 19 million strictly positive bilateral trade flows. Since we construct the *TII* measure using Turkish data, we exclude Turkey from the analysis.

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.5 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).

[14]Results based on a longer period of time are very similar. They are available upon request.
[15]The database is proposed by the CEPII, cf. Gaulier and Zignago (2010).

Our econometric specification examines whether exports of products that rely more heavily on trade insurance reacted differentially to bank crises in exporting and/or importing countries. We estimate the following equation:

$$\begin{aligned} \ln(\text{Exports}_{odpt}) &= \beta_1 \text{TII}_p \times \text{Crisis}_{dt} + \beta_2 \text{TII}_p \times \text{Crisis}_{ot} \\ &\quad + \delta_{pt} + \delta_{odp} + \delta_{odt} + \varepsilon_{odpt}. \end{aligned} \tag{2}$$

where Exports_{odpt} is the value of exports of 4-digit HS product p from the origin country o to the destination country d in year t. Crisis_{ot} (respectively Crisis_{dt}) is a dummy variable 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 the 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 particular 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 (recall evidence presented above). 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:

$$\ln(\text{Exports}_{odpt}) = \delta_1 \text{TII}_p \times \text{Crisis}_{dt} + \gamma_{opt} + \gamma_{odp} + \gamma_{odt} + \varepsilon_{odpt}. \tag{3}$$

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).[16]

3.3 Estimation results

Table 1: The Great Trade Collapse: Baseline results

Dep. Var.: $\ln(Exports_{odpt})$	(1)	(2)	(3)	(4)
$\text{TII}_p \times$ Crisis$_{dt}$	**-0.127a**		**-0.097b**	**-0.177a**
	(0.039)		(0.042)	(0.051)
$\text{TII}_p \times$ Crisis$_{ot}$	-0.041	-0.035		
	(0.040)	(0.043)		
Durable Good$_p \times$ Crisis$_{dt}$				-0.017
				(0.015)
Non Differentiated$_p \times$ Crisis$_{dt}$				0.008
				(0.009)
Capital Good$_p \times$ Crisis$_{dt}$				0.003
				(0.016)
Consumer Good$_p \times$ Crisis$_{dt}$				-0.040a
				(0.009)
Ocean Shipment$_p \times$ Crisis$_{dt}$				-0.013
				(0.014)
Shipment Size$_p \times$ Crisis$_{dt}$				-0.000c
				(0.000)
Contract Intensity$_p \times$ Crisis$_{dt}$				-0.056b
				(0.025)
Demand Volatility$_p \times$ Crisis$_{dt}$				0.119a
				(0.022)
Income Elasticity$_p \times$ Crisis$_{dt}$				-0.132a
				(0.036)
No. Obs.	17336776	17114717	17151868	15898751
R^2	0.865	0.878	0.875	0.875
Fixed effects	pt,odp,odt	dpt,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 1 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., 0.13) is associated with a 1.6% larger decline in trade when a crisis hits the importing country. As expected, a crisis in

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

the exporting country does not appear to affect products relying on trade insurance in a differential manner (columns 1 & 2). Therefore, in subsequent specifications we focus only on banking crises in the importing countries and estimate equation 3.

The results from the augmented specification, presented in the third column of Table 1, confirm our conclusions. The interaction term between *TII* and destination country bank crisis indicator is statistically significant at the 5% percent level. Its magnitude is broadly comparable to the estimate presented in the first column.

In the last column, we add interactions with the product characteristics discussed earlier to eliminate the possibility that we are capturing effects other than those due to the trade insurance channel. More specifically, we allow crises to have a differential effect on durable products, non-differentiated products, capital goods, and consumer goods. We also allow for a differential effect depending on product reliance on maritime transport, average shipment size, contract intensity, and demand volatility. Finally, we add an interaction between a crisis dummy and product income elasticity of demand since it is an obvious determinant of inter-sectoral variation in the trade impact of economic crises.[17]

Our key result is robust to including these additional controls. The coefficient of interest remains statistically significant at the one percent level suggesting that a financial crisis in the destination country disproportionately hurts exports of products heavily relying on trade insurance. The estimated magnitude goes up indicating that a one-standard-deviation increase in the *TII* measure is associated with a 2.3% larger decline in trade of such products when a crisis hits the importing country. 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.[18]

Table A.6 shows that our baseline results are robust to using alternative definitions of *TII* and samples of countries. In the first column, *TII* is constructed without purging of the country-specific factors affecting the LC use. It is simply the share of the value of LC-based trade with all countries over the sample period. The estimated coefficient on the

[17]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 1153 HS4 products. These elasticities are very weakly correlated with our *TII* variable (correlation is only -0.0209 and not statistically different from zero).

[18]We do not find a stronger effect of crises on durable goods. This is due to a large number of interaction terms included in column 4. If we included just Durable $\text{Good}_p \times \text{Crisis}_{dt}$, we would obtain a negative and statistically significant effect. The would continue to be true if we allowed for a differential impact of crises depending on the *TII* measure.

interaction between *TII* and Crisis$_{dt}$ is very close to the baseline estimate presented in Table 1 and remains statistically significant at the 5% level. This suggests that our results are not dependent on the methodology used to construct the *TII* index. In columns (2) and (3), we use *TII* indicators built using the same method as the one used for our baseline measure. However, the index in column (2) is based on just import flows with all countries, while the one in column (3) is based on imports and exports between Turkey and OECD countries only. Again, the results are very close to the one reported in Table 1. This gives us confidence that our index is not affected by the pecularities of the Turkish financial sector or the set of partner countries.

Next, we investigate jointly the role of external finance dependence and sensitivity to trade-related risks. Table A.7 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.

Table 2: Quantification of the role of trade insurance during the Great Trade Collapse

Quintile of TII index	1st	2nd	3rd	4th	5th	Total
Trade value 2007 ($B)	1361.3	1314.2	1226.9	1070.4	1833.8	6806.6
Trade value 2009 ($B)	1247.2	1019.5	1018.0	872.1	1473.3	5630.2
Trade collapse ($B)	114.1	294.7	208.9	198.3	360.5	1176.5
Trade collapse (% of 2007 trade)	8.4	22.4	17.0	18.5	19.7	17.3
Counterfactual: Trade collapse due to insurance channel						
Based on estimated coef. in col. (4)						
Billion US$	-	7.9	12.9	18.2	79.2	118.1
% of trade collapse	-	2.7	6.2	9.2	22.0	10.0

In column 1 of Table A.8, 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 increased over time.

In column 2, we split crisis-affected countries into three groups of equal size according to the severity of the crisis, defined based on the observed output loss incurred in each country during the crisis.[19] For countries with with low and medium crisis intensity, the impact of the financial crisis on high-*TII* products was discernible only after the first year. But it was discernible both in the first year of the crisis and in the subsequent years for high intensity crisis countries. Moreover, the size of the estimated effect is increasing in the severity of the crisis.

Finally, in Table 2, we quantify the role played by trade insurance in the Great Trade Collapse. In this exercise, we focus on imports by countries that experienced a bank crisis in 2008. The first two rows of the table display the observed value of total imports in 2007 and 2009 for the five groups of products corresponding to each quintile of the *TII* distribution. The difference between these values measures the trade collapse, reported in the row below. On average the total value of imports to countries that experienced a bank crisis in 2007-2008 was more than 17% lower than the one observed in 2017. It is noteworthy that the fall was much lower for products in the first quintile of the *TII* distribution. In the lower panel of the table, we compute the contribution of trade insurance to this sudden decline of trade. 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 reported in column 4 of Table 1, we calculate the trade loss due to lack of trade insurance for the second through fifth quantile relative to the first quintile. The aggregate trade decline in 2009 that can be attributed to reliance on trade insurance is estimated to be 118.1 billion of US$. This amount, already impressive in absolute terms, accounts for 10% of total observed trade collapse, which is far from being negligible.

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, payment delay or payment dispute.

We conduct a test that complements the baseline analysis of the role of trade insurance during the Great Trade Collapse. Focusing on the share of intra-firm trade, rather than on the flows themselves, results in a more rigorous identification strategy that eliminates

[19]Again, this information is provided by Laeven and Valencia (2013).

possible omitted variable biases. In the process, we complement the recent literature (e.g. Nunn and Trefler, 2013) that identifies intra-firm trade as a means of insuring against the risk associated with cross-border trade relations.

One possible limitation of the specification used in our analysis so far (equation (3)) is that it does not adequately control for destination-product-time specific shocks. Focusing on the *share* of intra-firm trade provides a solution to this problem as it implicitly accounts for product specific demand shocks and helps us isolate the role of trade finance.

If intra-firm trade is not subject to the usual trade-related risks that are mitigated by insurance provided by LCs, 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. 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 as decline in demand, worsening credit conditions in the importing industry, etc.

To test our hypothesis we estimate the following equation:

$$RelatedShare_{dpt} \quad = \quad \gamma_1 \mathrm{TII}_p \times \text{Crisis}_{dt} + \gamma_{dp} + \gamma_{pt} + \gamma_{dt} + \epsilon_{dpt}. \tag{4}$$

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. As in the section above, we restrict the sample to the 2003-2009 period.[20] 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 themselves. Standard errors are clustered at the product level. If our hypothesis is true, we would expect to observe $\gamma_1 > 0$.

We use data on intra-firm exports by US firms disaggregated by country of destination and 4-digit HS product codes.[21]

The results, presented in Table 3, are in line with our hypothesis. The coefficient of interest (γ_1) is positive and statistically significant, indicating that *TTI*-intensive products saw an increase in the share of intra-firm trade in crisis-afflicted countries. In the next column, we additionally allow for interactions between *TII* and destination country characteristics, such

[20]Again, results over a longer period of time are very similar.
[21]The dataset has been made available by Pol Antràs at `https://scholar.harvard.edu/antras/books`.

Table 3: Intra-firm Trade during the Great Trade Collapse

Dep. Var.: RelatedShare$_{dpt}$	(1)	(2)	(3)
TII$_p$ $\times$ Crisis$_{d,t}$	**0.028c**	**0.043b**	**0.049b**
	(0.016)	(0.019)	(0.022)
TII$_p$ $\times$ FD$_{dt}$		0.177b	0.212b
		(0.088)	(0.094)
TII$_p$ $\times$ GDPpc$_{dt}$		-0.002	-0.002
		(0.001)	(0.001)
TII$_p$ $\times$ CE$_{dt}$		-0.001	0.002
		(0.004)	(0.004)
Durable$_p$ $\times$ Crisis$_{dt}$			0.007
			(0.006)
Non-Diff.$_p$ $\times$ Crisis$_{dt}$			0.001
			(0.005)
Capital Good$_p$$\times$ Crisis$_{dt}$			-0.002
			(0.008)
Consumer Good$_p$$\times$ Crisis$_{dt}$			-0.005
			(0.006)
Ocean Ship.$_p$ $\times$ Crisis$_{dt}$			0.003
			(0.007)
Ship. Size$_p$ $\times$ Crisis$_{dt}$			0.000a
			(0.000)
Dem. Vol.$_p$ $\times$ Crisis$_{dt}$			-0.005
			(0.009)
Contract Int.$_p$ $\times$ Crisis$_{dt}$			-0.017
			(0.012)
Income Elast.$_p$ $\times$ Crisis$_{dt}$			0.012
			(0.018)
Nb. Obs	648939	412333	378880
R^2	0.566	0.595	0.591
Fixed effects	pt,dt,dp	pt,dt,dp	pt,dt,dp

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.

as the GDP per capita, level of financial development and contract enforcement.[22] While our result of interest remains robust, none of the additional interaction terms appear to be statistically significant. In column 3, we also add interaction terms with the product characteristics we considered earlier. Doing so increases the magnitude of the estimated

[22]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".

effect. The magnitude is economically meaningful. A one-standard-deviation increase in the *TII* index is associated with a 0.5 percentage point increase in intra-firm trade, which corresponds to 5% of the average value observed in the data.

These results, based on a more demanding identification strategy, corroborate our finding that availability of trade insurance played a significant role during the Great Trade Collapse. They also imply 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 Table A.9, we use alternative definitions of *TII*. The estimates obtained for the parameter of interest γ_1 in equation (4) are very similar in magnitude to its baseline estimate.

5 Conclusions

This study presents a new measure of product-level reliance of trade insurance in international trade transactions, which is constructed based on the use of letters of credit.

Creating this measure is possible thanks to the availability of information on financing terms for Turkish imports and exports, disaggregated by the trading firm, 8-digit HS product, partner country and month. When constructing the measure, we purge variation due to the partner country in a given year. The measure is available for 1,196 4-digit HS products and exhibits significant variation within 2-digit HS product groupings.

The new index is correlated in intuitive ways with some product characteristics, such as, demand volatility, shipment size, time to ship, and others. But the reliance on trade insurance is due to an array of factors rather than a single product characteristic.

Using the index in two empirical applications produces intuitive results, thus boosting our confidence that the index indeed captures what it is intended to capture. First, we show that exports of products heavily relying on trade insurance 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 access liquidity and improve their positions. Second, we document an increase in the intra-firm share of exports of such products sent to crisis-affected countries. Again this result is intuitive as intra-firm trade is less sensitive to contractual risks, such as non payment or payment dispute. By focusing on the share of intra-firm trade we are also able to implicitly control for all other factors that may be affecting exports of a particular 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.

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.1: Determinants of the use of LCs

Fixed effects	t=2003	t=2004	t=2005	t=2006
Firm (i)	0.212	0.196	0.217	0.234
Product ($k4$)	0.039	0.038	0.038	0.039
Country (c)	0.042	0.037	0.034	0.034
Firm-country (ic)	0.488	0.465	0.490	0.506
Firm-product (ik)	0.306	0.289	0.316	0.332
Product-country (kc)	0.191	0.175	0.175	0.173

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 as well as flow-month fixed effects. The sample is monthly trade data (pooled imports & exports) at the firm-product (8-digit HS codes)-country level, disaggregated by financing terms, at time t. $k4$ refers to 4-digit HS product codes. Firm refers to the Turkish partner in trade transactions.

Table A.2: Summary statistics for *TII*

Products	All HS4
No. of HS4 products	1196
Mean	-0.075
Std dev.	0.13
Median	-0.11
5*th* pctile	-0.19
10*th* pctile	-0.17
25*th* pctile	-0.14
75*th* pctile	-0.05
90*th* pctile	0.05
95*th* pctile	0.14

Table A.3: Top *TII* products

HS Code	Description
2706	Tar distilled from coal, from lignite, peat and other mineral tars
2709	Petroleum oils; crude
8608	Railway or tramway track fixtures and fitting
4406	Railway or tramway sleepers (cross-ties) of wood
7207	Iron or non-alloy steel; semi-finished products thereof
2708	Pitch and pitch coke
0102	Bovine animals; live
8607	Railway or tramway locomotives or rolling stock; parts thereof
7203	Ferrous products obtained by direct reduction of iron ore and other spongy ferrous products
7214	Iron or non-alloy steel; bars and rods, not further worked than forged

Table A.4: *TII* and other product characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Durable	0.037a									-0.018	-0.006
	(0.010)									(0.012)	(0.012)
Consumer goods		-0.051a								-0.008	-0.010
		(0.006)								(0.009)	(0.011)
Capital goods			0.050a							0.058a	0.019
			(0.010)							(0.013)	(0.016)
Non differentiated				0.009						-0.007	-0.001
				(0.008)						(0.012)	(0.016)
Contract Intensity					0.002					0.024	-0.062
					(0.021)					(0.036)	(0.071)
Share of ocean ship.						0.068a				0.064a	0.041a
						(0.011)				(0.015)	(0.015)
Mean ship. size (log)							0.033a			0.023a	0.022a
							(0.006)			(0.007)	(0.008)
Demand volatility								0.080a		0.081a	0.104a
								(0.020)		(0.022)	(0.024)
External finance dep. (RZ)									-0.002	-0.009	0.018
									(0.012)	(0.015)	(0.021)
Inventory ratio (IR)									0.483a	0.390b	1.075a
									(0.156)	(0.180)	(0.328)
Asset tangibility (AT)									0.209a	0.259a	0.126
									(0.054)	(0.062)	(0.086)
Trade credit intensity (TCI)									0.251c	0.179	-0.182
									(0.151)	(0.144)	(0.279)
Nb. obs.	1192	1192	1192	1192	1039	1173	1187	1192	1040	1024	1024
R^2	0.012	0.028	0.021	0.001	0.000	0.032	0.053	0.017	0.029	0.148	0.376

Notes: Dependent variable is *TII*. Last column includes 2-digit HS fixed effects. Significance levels: c: $p< 0.1$, b: $p < 0.05$, a : $p < 0.01$. Robust standard errors are shown in parentheses.

Table A.5: 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.6: The Great Trade Collapse: Alternative *TII* measures

Dep. Var.: $\ln(Exports_{odpt})$	(1)	(2)	(3)
Countries	All	OECD	All
Flows	Imp. & Exp.	Imp. & Exp.	Imp.
Method	Simple Share	Eq. (1)	Eq. (1)
$\text{TII}_p \times$	**-0.101b**	**-0.111b**	**-0.069a**
Crisis_{dt}	(0.043)	(0.044)	(0.035)
No. Obs.	17148703	17071313	17023195
R^2	0.875	0.875	0.875
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. Standard errors, clustered by 4-digit HS codes, are shown in parentheses.

Table A.7: The Great Trade Collapse: *TII* versus standard financial dependence measures

Dep. Var.: $\ln(Exports_{odpt})$	(1)	(2)	(3)	(4)
$\text{TII}_p \times$	**-0.136a**	**-0.123a**	**-0.155a**	**-0.129a**
Crisis_{dt}	(0.046)	(0.046)	(0.047)	(0.046)
$\text{RZ}_p \times$	-0.014			
Crisis_{dt}	(0.013)			
$\text{IR}_p \times$		-0.555a		
Crisis_{dt}		(0.098)		
$\text{AT}_p \times$			0.204a	
Crisis_{dt}			(0.032)	
$\text{TCI}_p \times$				-0.163
Crisis_{dt}				(0.101)
No. Obs.	18594557	18594557	18594557	18594557
R^2	0.867	0.867	0.867	0.867
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.8: The Great Trade Collapse: Timing and intensity

	(1)	(2)
$\text{TII}_p\times$	-0.020	
Crisis_{d,t_0}	(0.036)	
$\text{TII}_p\times$	**-0.200a**	
$\text{Crisis}_{d,t>t_0}$	(0.048)	
$\text{TII}_p\times\text{Crisis}_{d,t_0}$		**-0.099b**
$\times$ High Intensity_d		(0.050)
$\text{TII}_p\times\text{Crisis}_{d,t>t_0}$		**-0.411a**
$\times$ High Intensity_d		(0.072)
$\text{TII}_p\times\text{Crisis}_{d,t_0}$		0.018
$\times$ Med Intensity_d		(0.048)
$\text{TII}_p\times\text{Crisis}_{d,t>t_0}$		**-0.132b**
$\times$ Med Intensity_d		(0.056)
$\text{TII}_p\times\text{Crisis}_{d,t_0}$		0.003
$\times$ Low Intensity_d		(0.043)
$\text{TII}_p\times\text{Crisis}_{d,t>t_0}$		**-0.118b**
$\times$ Low Intensity_d		(0.051)
No. Obs.	25721635	25721635
R^2	0.858	0.858
Fixed effects	opt,odp,odt	opt,odp,odt

Notes: Significance levels: c: p$<$ 0.1, b: $p < 0.05$, $a: p < 0.01$. Dependent variable is $\ln(Export_{odpt})$. Standard errors, clustered by 4-digit HS codes, are shown in parentheses.

Table A.9: Intra-firm Trade and the Great Trade Collapse: Alternative *TII* measures

Dep. Var.: $\text{RelatedShare}_{dpt}$	(1)	(2)	(3)
Countries	All	OECD	All
Flows	Imp. & Exp.	Imp. & Exp.	Imp.
Method	Simple Share	Eq. (1)	Eq. (1)
$\text{TII}_p \times \text{Crisis}_{d,t}$	**0.040b**	**0.042c**	**0.040c**
	(0.021)	(0.021)	(0.022)
$\text{TII}_p \times \text{FD}_{dt}$	0.212b	0.161	0.233b
	(0.097)	(0.098)	(0.093)
$\text{TII}_p \times \text{GDPpc}_{dt}$	-0.002	-0.002	-0.001
	(0.001)	(0.001)	(0.001)
$\text{TII}_p \times \text{CE}_{dt}$	0.001	-0.001	-0.000
	(0.004)	(0.004)	(0.004)
$\text{Durability}_p \times \text{Crisis}_{dt}$	0.006	0.006	0.006
	(0.004)	(0.004)	(0.004)
Share Non-Diff.$_p \times \text{Crisis}_{dt}$	0.002	0.003	0.002
	(0.005)	(0.005)	(0.005)
Contract Int.$_p \times \text{Crisis}_{dt}$	-0.020c	-0.018	-0.018
	(0.012)	(0.012)	(0.012)
Ocean Ship.$_p \times \text{Crisis}_{dt}$	0.004	0.004	0.004
	(0.007)	(0.007)	(0.007)
Ship. size$_p \times \text{Crisis}_{dt}$	0.000a	0.000a	0.000a
	(0.000)	(0.000)	(0.000)
Dem. Vol.$_p \times \text{Crisis}_{dt}$	-0.004	-0.005	-0.006
	(0.010)	(0.010)	(0.010)
Inc. elast.$_p \times \text{Crisis}_{dt}$	0.011	0.009	0.009
	(0.018)	(0.018)	(0.018)
Nb. Obs	378669	376829	375815
R^2	0.591	0.591	0.591
Fixed effects	pt,dt,dp	pt,dt,dp	pt,dt,dp

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.