

Niepmann, Friederike; Schmidt-Eisenlohr, Tim

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Friederike Niepmann
Tim Schmidt-Eisenlohr

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Banks in International Trade Finance: Evidence from the U.S.

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Abstract

Banks play a critical role in facilitating international trade by guaranteeing international payments and thereby reducing the risk of trade transactions. This paper uses banking data from the United States to document new empirical patterns regarding the use of letters of credit and similar bank guarantees. The analysis shows that the volume of banks' trade finance claims differs substantially across destination countries. Controlling for exports, claims are hump-shaped in country credit risk and increase with the time to import of a destination market. They also vary systematically with global conditions, expanding when aggregate risk is higher and funding is cheaper. The response to changes in these macro factors is not uniform. Trade finance claims adjust the least in countries with intermediate levels of risk, which rely the most on letters of credit to settle payments. We show that a modification of the standard model of payment contract choice in international trade is needed to rationalize these empirical findings.

Key words: trade finance, multinational banks, imports, exports

Niepmann: Federal Reserve Bank of New York (e-mail: friederike.niepmann@ny.frb.org).
Schmidt-Eisenlohr: University of Illinois at Urbana-Champaign (e-mail: t.schmidteisenlohr@gmail.com). The authors especially thank Sydnee Caldwell and Geoffrey Barnes for excellent research assistance. For useful comments, they also thank Andrew Bernard and Catherine Thomas, as well as participants in workshops at the Federal Reserve Bank of New York and New York University. The views expressed in this paper are those of the authors and do not necessarily reflect the position of the Federal Reserve Bank of New York or the Federal Reserve System.

1 Introduction

Banks play a critical role in international trade. While they provide pre-export and pre-import loans to firms, financial intermediaries also facilitate the settlement of international payments. They issue letters of credit and extend similar guarantees, which reduce the risk that importers and exporters default on their obligations to deliver or to pay.¹ There is the notion that letters of credit are relevant but who relies on these instruments, how large the demand for letters of credit is and how demand varies over time is largely unexplored.

Answering these questions is of interest for several reasons. First, there is a growing literature that studies empirically the link between finance and trade, but mostly in reduced form.² Letters of credit represent a key channel through which financial conditions could affect exports and imports. Second, there are several theoretical papers on payment contract choice in international trade that predict when exporters use letters of credit.³ Yet these theories have hardly been tested due to a lack of available data. Third, a detailed understanding of the business is central to policy makers as most development banks run large trade finance programs and confirm letters of credit in emerging and developing countries.⁴

Based on a unique dataset collected by U.S. regulators, this paper investigates the use of letters of credit in international trade, uncovering new empirical patterns. It is the first work to analyze trade finance in the U.S. and to employ data that varies both over time and across destination countries. This allows us to study implications of the payment contract choice model developed in Schmidt-Eisenlohr (2013) that have not been considered. The analysis shows that while the basic model can explain the observed response of bank trade finance to global macroeconomic factors, it cannot rationalize important dimensions of heterogeneity

¹In a letter of credit, a bank acts as an intermediary. The bank ensures that the importer commits to paying before the exporter produces and only pays the exporter if he documents that the goods were produced and shipped. In this way, the risk that the importer or the exporter defaults on his obligation to deliver or to pay is mitigated.

²See, for example, Beck (2002), Beck (2003), Amiti and Weinstein (2011), Paravisini et al. (2011), Manova (forthcoming), and Schmidt-Eisenlohr (2013).

³See Schmidt-Eisenlohr (2013), Glady and Potin (2011), Ahn (2011) and Olsen (2013) for models that predict when letters of credit are used. Other related theoretical papers are Antràs and Foley (2011), Eck et al. (2012), and Hoefele et al. (2012).

⁴For example, the International Finance Corporation (IFC), an entity of the World Bank Group, has a large program to confirm letters of credit. See IFC (2012) for details.

across countries. We present a simple modification to the model that generates the patterns in the data, thereby improving on existing theory.

The dataset used in this paper captures the trade finance activities of all large U.S. banks with foreign counter-parties and primarily reflects confirmed letters of credit and similar bank guarantees that facilitate U.S. export activity. The statistics presented in the beginning of the paper reveal that bank trade finance is very relevant for the U.S. In the second quarter of 2012, the total stock of trade finance claims held by U.S. banks amounted to 20 percent of total U.S. exports. Almost all countries are covered: in the same quarter, trade finance claims were spread over 138 different foreign countries. The trade finance business is highly concentrated with the top 5 banks accounting for 92 percent of the business in 2012. We also find that trade finance claims relative to exports increased during the financial crisis in 2008/2009.⁵

Beyond providing key statistics on the trade finance business of U.S. banks, this paper documents several new relationships. (i) The volume of bank trade finance relative to exports increases when global risk rises. To proxy for changes in global risk, we use the volatility index (VIX), which measure the expected volatility of the U.S. stock market over the next month and reflects risk attitudes of both U.S. and global investors. (ii) Bank trade finance decreases when global interest rates rise. This holds when global funding conditions are proxied by the 3-month London Interbank Rate (LIBOR) or by the Fed Funds Rate.

(iii) Banks' trade finance claims increase with the time to trade. Trading time is captured by three different measures across destination countries: distance, the time to import and the share of goods shipped by vessel as opposed to shipments by air. All three variables have a positive and significant effect on the volume of bank trade finance, which strongly suggests that financing costs increase with the time to trade. (iv) Bank trade finance is hump-shaped in country risk, that is, the trade finance claims of U.S. banks are largest in countries with intermediate levels of default risk. (v) The response of bank trade finance to changes in global conditions (in the VIX and the LIBOR) is heterogeneous across countries. Bank trade finance responds the least in countries with intermediate levels of risk, which

⁵The overall picture that emerges is consistent with evidence from Italy documented in Del Prete and Federico (2012).

rely most on banks to facilitate trade.

In addition to documenting these patterns at the aggregate level, we show that the same factors that increase bank trade finance also trigger entry by banks into a destination market and affect concentration. The larger U.S. exports to a country are and the longer the time to trade is, the larger the number of banks that serve the destination market and the less concentrated is the business. Similarly, in countries with intermediate levels of risk, more banks are active that are, on average, smaller. This suggests that fixed costs play an important role for banks in the supply of trade guarantees.

The empirical findings are consistent with a modified version of the trade finance model in Schmidt-Eisenlohr (2013). In the model, firms have the choice between three different payment forms. First, they can agree to trade on open account terms, in which case the exporter produces first and the importer pays after receiving the goods. Second, they can trade on cash-in-advance terms. Then the importer pays first and the exporter produces after receiving the payment. Third, trading partners can use banks to facilitate trade. This can be desirable because banks are able to reduce the risk that the importer or the exporter defaults on her obligation.⁶ In this case, the importer obtains a letter of credit from a local bank for a fee, which is confirmed by a bank in the country of the exporter and guarantees that the exporter is paid. The latter payment method is reflected in the bank data analyzed in this paper.

The model predicts that trading partners choose among the three payment methods to optimally trade off differences in financing costs and default probabilities between the two countries. In contrast to Schmidt-Eisenlohr (2013), in which the letter-of-credit fee is fixed, the fee, in this paper, consists of a fixed monitoring cost plus a variable cost related to the expected loss of the confirming bank, which increases in the importer's default probability. Without this modification, the hump-shaped relationship between the volume of trade finance claims and credit risk and the heterogeneous responses to global conditions is not predicted by the theory. With the adjustment, the model is able to explain all of the empirical findings.

⁶See Olsen (2013) for a micro-foundation of why banks are able to reduce the risk of non-payment.

Consistent with the observation that trade finance claims expand relative to exports when the VIX rises, the theory shows that the profitability of letters of credit increases when the default risk increases proportionately in both the exporting and the importing country. The theoretical result only needs the assumption that banks are sufficiently good at mitigating risk.

An increase in global interest rates has the opposite effect. When interest rates increase by the same amount in both countries, letters of credit become more expensive than the two alternatives and are used less (in line with finding (ii)). This is because both the exporter and the importer have to do some pre-financing under this payment form.

The empirical finding that the volume of banks' trade finance claims is hump-shaped in destination country risk is the third pattern that can be understood within the payment contract choice model. In the modified model, the higher the risk is that the importer defaults, the higher is the cost of a letter of credit. When trading partners trade on cash-in-advance terms, the risk on the importer's side is eliminated because the exporter only produces after receiving the payment. With high levels of payment risk in the destination country, cash-in-advance is therefore the preferred financing form. In contrast, if the risk in the importing country is low, open account is optimal because it is not worthwhile for the trading partners to incur the letter of credit fee. Letters of credit are thus most preferred at intermediate levels of destination country payment risk.

Finally, we show that the model can also generate the observed heterogeneous response to changes in global conditions. When almost all firms in countries with intermediate levels of risk trade based on bank guarantees, while low and high risk countries use also one of the other payment methods, changes in interest rates and risk lead to substantial payment contract switching in low and high risk countries. Countries with intermediate risk show hardly any response and the observed use of letters of credit is less elastic in those countries.

Policy interventions are often motivated by the perception that there is a lack of bank trade finance. Our results suggest a nuanced view on the public provision of guarantees for trade. On the one hand, we find that there is payment contract switching, that is, firms choose between different payment forms depending on interest rates and risk conditions as

predicted by the model. Hence in some cases, low levels of bank trade finance might reflect firms' choices. On the other hand, the use of letters of credit is inelastic in destination countries with intermediate levels of risk. Even when interest rates rise and global risk goes down, trading partners do not switch to alternative financing forms. In these countries, a limited supply of letters of credit may be harmful to trade.

Literature While the evidence on trade finance has increased in recent years, it is still very limited and is mostly based on voluntary surveys of banks, which provide only an incomplete picture.⁷ In this paper, we analyze data on bank trade finance, which banks are required to provide to U.S. regulators and which has not been studied before.

There are only few works that analyze information on the use of letters of credit and bank trade finance in general. Glady and Potin (2011) provide a model of payment contract choice and use SWIFT transactions data for the year 2006 to test it. This data contains details on the number of letter-of-credit transactions between different countries but not on the values of these transactions. The authors find that the use of letters of credit increases in country risk. Their empirical results also suggest a hump-shaped relationship, a finding which is, however, not predicted by their theory and not discussed by the authors.

In recent empirical work, Del Prete and Federico (2012) study the effect of financial shocks on trade based on detailed information on bank trade finance in Italy. They observe bank loans and guarantees separately for exports and imports, but, in contrast to this paper, do not have information on the partner countries. Thus our work, unlike previous research, exploits information on the value of trade finance by destination country. In addition, it spans a much larger time period— 1997 until 2012— which allows us to study the behavior of trade finance over the business cycle.

Without elaborating on differences across countries, Ahn (2013) investigates whether financial shocks in 2008/2009 affected the use of letters of credit based on matched bank-importer-exporter data from Columbia. Both Antràs and Foley (2011) and Hoefele et al.

⁷See, in particular, surveys by the International Monetary Fund (IMF) and the International Chamber of Commerce (ICC) in ICC (2009) and IMF (2009). Results from the first four IMF surveys have been summarized by Asmundson et al. (2011). The ICC has started collecting more comprehensive data in its so-called Trade Register, which is, however, not accessible to researchers. See ICC (2013).

(2012) use firm-level data to study how the choice between cash-in-advance and open account is affected by country characteristics. However, they have no or only very limited information on letter-of-credit transactions.

Entry into markets and the concentration of the trade finance business by destination country, analyzed in section 3.2 of this paper, have not been studied before. The analysis of entry links to work in Niepmann (2013) on the international activities of banks. As in Niepmann (2013), we find evidence that fixed costs are highly relevant for banks when entering foreign markets.

The role of time to trade was first studied empirically in Hummels and Schaur (forthcoming). Schmidt-Eisenlohr (2013), Bourgeon et al. (2012), and Paravisini et al. (2011) investigate how trading time affects the response of trade to changes in financial conditions. This paper provides more direct evidence that financing costs indeed increase with the time to trade.

By modifying Schmidt-Eisenlohr (2013) to match the data, this paper also contributes to the theoretical literature on trade finance. Several other papers have studied the choice between payment forms. Antràs and Foley (2011) extend the model in Schmidt-Eisenlohr (2013) to a dynamic setting. Glady and Potin (2011) introduce heterogeneous firms and asymmetric information to the framework. Hoefele et al. (2012) derive new predictions on the role of industry complexity. Ahn (2011) studies the effect of changes in aggregate default risk on the ratio of exports over domestic sales. In his model, letters of credit reduce the commitment problem of the importer to a lesser extent than in this paper. This leads to the opposite prediction that, in a crisis, as both importer risk and bank risk rise, letters of credit become relatively less attractive. None of the aforementioned papers derives predictions that match the empirical patterns documented here.

The paper is structured as follows. Section 2 provides details on the data source and aggregate statistics. Section 3 presents key patterns in the data. Section 4 discusses the theoretical model and shows that it is consistent with the empirical findings. Section 5 concludes.

2 Data

2.1 Data source

Data on the trade finance claims of U.S. banks is from the Country Exposure Report (FFIEC 009). U.S. banks that have more than \$30 million in total foreign assets are required to file this report and, among other requirements, have to provide information on their trade finance related claims against parties residing in foreign countries. Trade finance related loans to firms with residency in the U.S. or bank guarantees that cover U.S. obligations are not reported. The observed measure of trade finance thus represents only a fraction of the overall trade finance activities of the U.S. banking sector but it captures the activities of all large banks with foreign parties. Claims are reported on a consolidated basis, that is, they also include the loans and guarantees extended by the foreign affiliates of U.S. banks. While several different instruments are potentially reported, the data mainly reflects confirmed letters of credit and similar bank guarantees that are used to finance trade transactions between U.S. exporters and foreign importers. A detailed discussion of the data and the reporting instructions are given in appendix B.

A letter of credit is an instrument to increase the reliability of payment in a trade transaction. It works as follows: An importer asks her bank to issue a letter of credit on her behalf. This letter is then sent to the exporter. It guarantees that the issuing bank pays the agreed contract value to the exporter if a set of conditions are fulfilled. These conditions typically include delivering a collection of documents to the bank, e.g., shipping documents that confirm the arrival of the goods in the destination country. However, there is still a risk that the guaranteeing bank defaults on its obligation. To address this concern, there is the option to ask a bank in the country of the exporter to confirm the letter of credit. The confirming bank agrees to pay the exporter if the issuing bank defaults.

If a U.S. bank confirms a letter of credit of a foreign importer that, for example, resides in Spain, then the bank has claims on a Spanish party that will be liquidated through the proceeds of international trade. These claims are recorded in the financial exposure report and are equivalent to the value of the goods that are exported from the U.S. to Spain.

Banks' trade finance claims by destination country are available at a quarterly frequency starting from 1997.⁸ Quarterly trade data is from the IMF's Directions of Trade Statistics. Additional data sources are reported in the data appendix.

2.2 The trade finance business of U.S. banks

Bank trade finance in the aggregate The dataset captures a substantial amount of trade finance in the U.S. Over the period from 1997 until the middle of 2012, the trade finance claims of all reporting U.S. banks represent on average 14 percent of U.S. quarterly exports in goods. Quarterly exports are a good basis for comparison because trade finance is typically short term. Using data from international banks participating in the Trade Register, ICC (2013) calculates that the average maturity of a confirmed letter of credit is 70 days, while the average maturity of an importer letter of credit is estimated to be 80 days.

In the last 15 years, there have been substantial changes in the trade finance business of U.S. banks. As the solid line in Figure 1 shows, total trade finance claims were relatively flat until 2006 at about \$20-30 billion.⁹ Since then bank trade finance has risen quite sharply to reach more than \$70 billion by 2012. Figure 1 also indicates how the ratio of bank trade finance over exports, depicted by the dotted line, evolved between 1997 and 2012. We call this measure the trade finance intensity. Over the observed period, it roughly followed a u-shape reaching 20 percent in 2012.

In addition to these general patterns, three more specific features of the data stand out. First, there was a peak in 1998 both in terms of volumes and trade finance intensity, at the time of the Asian crisis. Second, in the recent 2008-2009 financial crisis bank trade finance first increased and then declined steeply. Figure 2 zooms into the crisis period

⁸Until 2005, they are reported on an immediate borrower basis, that is, a claim is attributed to the country where the contracting counter-party resides. From 2006 onwards, claims are given based on the location of the ultimate guarantor of the claim (ultimate borrower basis). See <http://www.ffiec.gov/> for more details. This reporting change does not appear to affect the value of banks' trade finance claims in a systematic way. Consequently, we use the entire time series without explicitly accounting for the change. Statisticians at the Federal Reserve of New York, who are familiar with the reporting instructions, confirm that risk transfers, which make values on the immediate borrower basis diverge from those on an ultimate borrower basis, are less relevant for trade finance products.

⁹The aggregate numbers exclude observations for one bank that changed its trade finance business fundamentally in the reporting period.

displaying growth rates for trade finance claims and exports separately. There is a striking divergence between trade finance growth and export growth in the fourth quarter of 2007. In this period, trade finance claims jumped by 42 percent while exports only increased by 7.2 percent. Starting from the third quarter in 2008, both trade finance and export growth rates were negative for three consecutive periods. The biggest drop in trade finance and exports occurred in the second quarter of 2009 with both indicators falling by roughly 18 percent. The observed pattern is in line with the following interpretation. The initial increase in 2007 was driven by a higher demand for bank trade finance due to the riskier global environment. However, when the major crisis hit in 2008, two effects came into play. Trade volumes declined, reducing the demand for trade finance. In addition, the supply of trade finance was lower because banks faced liquidity problems and contracted lending and guarantees. These two effects dominated the demand generated by the increased risk and led to a decline in overall trade finance claims. The pattern of trade finance during the crisis is consistent with evidence from Italy in Del Prete and Federico (2012), who also find that bank trade finance first increased and then decreased.

The final observation concerns the period after 2009. Since 2010, trade finance claims have risen sharply. One factor that explains the recent growth in U.S. bank trade finance and trade finance intensity is that firms have substituted away from European bank to U.S. banks. In the aftermath of the recent crisis, several European banks exited the trade finance business, especially in Asia, and banks from other countries took over.¹⁰ The low-interest rate environment over the past years may also have contributed to the rise. As we will show, bank trade finance generally expands when funding conditions ease.

Geographical distribution The trade finance activities of U.S. banks vary widely across countries both in terms of the absolute values of trade finance claims and in the trade finance intensities. The upper panel of figure 3 shows the top countries in terms of average absolute values of trade finance claims from 2006 q1 until 2012 q2. Not surprisingly, several countries that exhibit the highest trade finance claims are also top trading partners (see the middle

¹⁰Decomposing the increase shows that a larger part of the growth was indeed due to activities in Asia. See <http://wongchienmi.files.wordpress.com/2012/02/trade-finance-focus-cmw.pdf> for a business report on trade finance in Asia from May 2012.

panel) over the same period. China and Mexico, for example, are in the top 5 in terms of both measures.

The lower graph of Figure 3 displays the 25 countries with the highest ratio of trade finance claims to U.S. exports. The set of countries differs considerably from the one in the top graph. Three factors apparently impact the trade finance intensity of a country: risk, distance and offshore center status. While we conduct a detailed econometric analysis of the different factors, the countries can be easily assigned to one or more of these characteristics. High risk countries in the top 25 include, among others, Uzbekistan, Malawi and Zambia. All countries in the list but Bermuda and Barbados are far away from the U.S.. Offshore centers in the top 25 are Bermuda, Mauritius, Maldives, Macao and Barbados, indicated with patterned bars in the graph.¹¹

Offshore centers are excluded from the analysis in section 3 because the data shows that these countries attract large amounts of bank trade finance even in the absence of corresponding trade flows.¹² The share of trade finance claims in offshore centers in banks' total claims amounted to 5 percent of total claims in 2012, down from around 9 percent in 2006. For comparison, the share of offshore exports in total U.S. exports was 3.4 percent in 2006 and 3.8 percent in 2012.¹³

Bank-level statistics How important is the trade finance business for banks? In the first quarter of 2012, total trade finance claims corresponded to approximately one percent (0.72 percent) of the foreign assets, guarantees and unused commitments of all FFIEC reporting banks (including those with zero trade finance claims). This figure masks that, for some banks, the trade finance business is an important part of their foreign operations.

Table 1 shows statistics for banks with positive trade finance claims in the respective quarter. In early 2006, the 21 active firms had claims of \$1038 million on average. These increased to an average of \$3853 million in 2012 for the 19 remaining banks. The average

¹¹The country with the highest trade finance intensity is Bermuda with a ratio of 3.85. Countries can have trade finance intensities that are larger than 1 if trade transactions take more than three months or if some of the trade finance activities are not related to U.S. exports with that country.

¹²We discuss the behavior of trade finance claims in offshore centers in more detail in appendix B.

¹³For a list of countries designated as offshore centers, see the data appendix.

share of trade finance claims in total foreign assets, unused commitments and guarantees of each bank decreased from 12.8 percent to 9.4 percent over the same period. On average, trade finance claims as the share of each bank's total balance sheet increased over the same period.

Trade finance is a more concentrated business in comparison with the overall banking industry. In the first quarter of 1997, the top 5 banks had a joint share of 66 percent in total bank trade finance claims. Nine years later, this share had increased to 92 percent, remaining stable until 2012.¹⁴ For comparison, the share of the top 5 banks in total bank assets was 39 percent in 1997 q1, 73 percent in 2006 q1 and 80 percent in 2012 q1 based on the sample of banks that reported positive trade finance activities in at least one quarter over the sample period.¹⁵ Del Prete and Federico (2012) report similar patterns for Italy and find that the market for bank guarantees is more concentrated than the overall trade finance business of banks.

Our data also allows us to analyze the country coverage over time. Altogether banks had positive trade finance claims in 120 countries in the first quarter of 2006 compared to 138 in the same quarter in 2012. Similarly, the average number of countries per bank increased over this period. Banks held claims in an average of 26 destination countries in 2012, up from 22 countries in 2006. As for total claims, the distribution of destination countries across banks is highly skewed. In 2012, 50 percent of banks were active in less than 10 countries. Only around 20 percent of banks had trade finance with more than 35 countries.

¹⁴Real concentration could be lower because we do not observe the trade finance claims of banks that fall below the reporting threshold. Let us suppose that all other commercial banks in the U.S. (additional 6158 banks in 2012 q1) had \$30 million of foreign assets (the reporting threshold) and let us suppose that 9.4 percent of these assets were trade finance claims in 2012 q1 (the mean exposure of banks in the data). Total trade finance claims would then be around \$90 billion and the top 5 banks would have 72 percent of the business. Thus even when taking a very conservative stance on the non-observed components of bank business, the implied concentration of the business remains very high.

¹⁵The actual degree of concentration of the U.S. banking industry is lower. In these calculations several large and many middle-sized U.S. banks are not included because they do not engage in trade finance.

3 Empirical Patterns

In this section, we document several patterns that have not been shown before and that are highly robust features of the data. (i) Banks' trade finance claims vary systematically with aggregate risk and global funding conditions. (ii) Bank trade finance increases in the time to trade and (iii) is hump-shaped in the default risk of a destination. (iv) The response of trade finance claims to changes in aggregate risk and interest rates depends on the risk of a destination country. Countries with intermediate levels of risk adjust the least.

3.1 The effect of aggregate factors

Bank trade finance increases in global risk We start by analyzing the effect of changes in global risk on bank trade finance. The Volatility Index, called VIX, measures expected volatility on the U.S. stock market over the next 30 day period. Although it is based on developments in the U.S., the index reflects conditions in global capital markets. It moves up when the price for portfolio insurance increases, i.e. if aggregate uncertainty rises and investors become more fearful. Figure 4 plots the ratio of aggregate U.S. trade finance to U.S. exports and the VIX over time. The graph documents a clear positive relationship between the two variables. While the VIX measures primarily uncertainty, it also moves with global default risk.¹⁶ Therefore, in times when global default risk, uncertainty and risk aversion are higher, a larger share of trade is backed by bank guarantees.

Changes in aggregate risk potentially affect both the demand side and the supply side. A letter of credit is an instrument to mitigate risk. In times of higher default risk or higher uncertainty, firms may find it more desirable to reduce the risk of a trade transaction and hence use banks. At the same time, it is possible that banks also change their supply and pricing of letters of credit. In particular, they could demand a higher fee for the same level of risk when times get riskier as their cost of risk-adjusted capital might be higher. This

¹⁶The VIX is highly correlated with average country risk measured by the Economist Intelligence Unit's country risk index. The correlation coefficient between the log of the VIX and average credit risk is 30 percent. The VIX is our preferred measure of global risk because it is available at a longer horizon than the EIU risk measure which starts in 2000 only. For a description of the EIU risk measure, see the next section.

would generate a countervailing force which would limit the expansion of bank trade finance in riskier times.¹⁷ Given that we find that the overall effect of aggregate risk on bank trade finance is positive, we conclude that the demand effect dominates the supply effect.

Bank trade finance decreases in interest rates In a next step, we study the response of bank trade finance to changes in aggregate funding conditions. Figure 5 shows the ratio of trade finance to exports over time together with the 3-month LIBOR, the rate at which banks borrow and lend to each other on the London interbank market. The LIBOR is highly positively correlated with country-specific interbank lending rates and hence reflects global funding conditions. The graph indicates that trade finance intensity and the LIBOR are strongly negatively correlated. When global interest rates are higher, bank trade finance is reduced. If funding is cheaper, bank trade finance expands relative to exports. The explanation for why bank trade finance and global interest rates co-move contemporaneously lies in the short-term nature of the business. Trade-related loans and guarantees can respond more quickly than other balance sheet items that have, on average, longer maturities.

Table 2 confirms what figures 4 and 5 conveyed. It shows the results from OLS regressions where the log of the trade finance claims, aggregated over all banks and countries, is regressed on the VIX and the LIBOR, respectively, as well as additional controls (the log of aggregate U.S. imports, exports, and U.S. GDP). As an alternative to the LIBOR, we use the 3-months fed funds rate in column (4).¹⁸ Columns (1) to (4) exhibit highly significant coefficients on interest rates and the volatility index. The effects are economically meaningful. An increase in the VIX of one standard deviation from the mean increases trade finance claims by 4.8 percent. Equivalently, an increase in the LIBOR of one standard deviation from the mean decreases trade finance claims by 10.7 percent. The regressions indicate robust macro-economic relations. Controlling for exports, imports and U.S. GDP, aggregate trade finance claims are higher if funding is cheaper and if global risk is higher.

¹⁷According to IMF surveys summarized in Asmundson et al. (2011), banks, in fact, increased prices for letters of credit over the period from 2007 until 2009.

¹⁸The sample period is 1998 to 2011. The year 1997 is excluded because of one bank the business strategy of which has a significant impact in the aggregate. In all other regressions, we also include the year 1997 because time-fixed effects are able to mostly take care of this issue.

3.2 Country-level determinants: time to trade and risk

3.2.1 Bank trade finance is larger the longer the time to trade

An important determinant of banks' trade finance claims is the time to trade. If a U.S. bank confirms a foreign letter of credit at time t , its trade finance claims increase by the value of the obligation that is guaranteed in that period. The time of the underlying trade transaction determines how long this guarantee remains on the bank's books. Therefore, the longer trade takes, the longer claims are recorded and the larger the observed stock variable is.

Figure 6 presents preliminary evidence for a positive relationship between trade finance claims and the time to trade proxied by distance. It plots the trade finance intensity (trade finance over exports) of country c against the log of its distance from the U.S. in the first quarter of 2006. The figure clearly indicates that the trade finance claims of U.S. banks relative to exports increase with the distance to the trading partner.

To test for this relationship formally, we run several OLS regressions. We regress the log of trade finance claims in country c at time t on the log of exports as well as three different proxies for the time to trade: distance from the U.S., the share of goods transported by vessel (as compared to air) computed from product-level trade data with information on transport modes, and a measure of the time goods need to enter the destination country available from the Doing Business Indicators of the World Bank.¹⁹ The two latter proxies are available for the years starting from 2006. As information on import times is only available at an annual frequency, regressions are based on aggregated annual data. All regressions include time-fixed effects. Standard errors are clustered at the destination country. Table 3 presents the results.

The coefficient on exports is highly significant and close to 1 in columns (1) to (3). This shows that banks' trade finance claims strongly covary with U.S. exports. As expected, the estimated coefficients on the three proxies for trading time are all positive and highly significant. Controlling for the volume of trade, banks' trade finance claims are larger, the

¹⁹Time to import was first used in Djankov et al. (2010).

further away the destination country, the bigger the share of goods shipped by vessel and the longer the time needed to import goods.

IV approach The regressions reported in columns (1) to (3) of table 3 suffer from a potential endogeneity problem. As trade finance and exports are likely to be determined by unobserved common factors and there is a two-way relationship, the estimated coefficients may be biased. In order to address this issue, the log of exports is instrumented by the log of population. The size of the population is an excellent instrument because it is highly correlated with exports. At the same time, population should affect the supply of bank trade finance only through its effect on exports.

The IV regressions are shown in columns (4) to (9) of table 3. Columns (4), (6) and (8) present the results of the first stage regression where the endogenous variable, the log of exports, is regressed on the instrument, the log of population, and all other exogenous variables. In all three regressions, the population coefficient is positive and significant at a 1 percent significance level. All proxies for trading time have a negative effect on exports as one would expect. The R^2 is high, ranging between 35 and 68 percent.

The second stage results are shown in columns (5), (7) and (9). Compared to columns (1) to (3), the results are qualitatively the same. The magnitudes of all coefficients increase compared to the OLS specification, which suggests that the estimates are biased downward when endogeneity is not accounted for. Due to the IV approach, it is now possible to interpret the export coefficient as the elasticity of trade finance claims with respect to exports. The estimate of 1.1 displayed in column (5) indicates that a 10 percent increase in exports, increases the annual trade finance claims of banks by 11 percent. The estimates are very similar when regressions are run on bank-level data and time- and bank-fixed effects are controlled for.

The results in this section show that banks' trade finance claims increase in the time to trade. This finding has implications for the relationship between trading time and trade finance costs. The time a trade finance claim remains on the books of a bank should determine the fee that a bank charges for the extended guarantee. The longer a bank guarantees

the obligation of a trading party, the higher the bank’s opportunity costs and the higher the price that the bank charges. Thus there should be a direct link between time and costs. In this regard, we provide more direct evidence than previous research on the relationship between trading time and trade finance costs. Due to a lack of data, other works have been limited to showing that the effect of interest rates on trade depends on the distance between the trading partners.²⁰

3.2.2 Bank trade finance is hump-shaped in destination country risk

Another key determinant of bank trade finance is country risk. In order to proxy destination country risk, we use the country risk index provided by the Economist Intelligence Unit (EIU), which is available for the period from 2000 to 2011. The higher the index, the higher the default risk. To test for the effect of risk on trade finance, the following equation is estimated:

$$\begin{aligned} \log(tf_{ct}) = & \beta_1 \log(exp_{ct}) + \beta_2 \log(GDPpc_{ct}) + \beta_3 \log(distance) + \\ & + \beta_4 risk_{ct} + \beta_5 (risk_{ct})^2 + \alpha_t + (\alpha_c) + \epsilon_{ct} \end{aligned} \quad (1)$$

The log of trade finance claims is regressed on the log of exports, the log of distance as well as risk and risk squared. To account for other factors that might be correlated with risk and affect bank trade finance, the log of nominal GDP per capita is also included as a control variable.²¹ Regressions are again run on annual data, aggregated over all banks and summed over four quarters. OLS regression results are reported in table 4. All columns include time-fixed effects. Column (2) and (4) also control for country-fixed effects.

Columns (1) and (2) of table 4 include the variable risk but exclude risk squared. The coefficient on risk is positive in column (2) at a 10 percent significance level. It implies that banks’ trade finance claims are larger, the larger the credit risk in the destination country.

²⁰Schmidt-Eisenlohr (2013) introduces an interaction between distance and net interest rate margins into a standard gravity estimation. He finds that the longer the distance between trading partners, the larger the negative impact of financing costs on trade. This result has been confirmed with French firm level data by Bourgeon et al. (2012).

²¹Results become stronger if GDP per capita is left out as this variable is highly correlated with country risk.

In column (3), risk squared is also included as a regressor. Now, both coefficients related to risk and risk squared are significant. The coefficient on risk squared is negative and the coefficient on risk is positive, suggesting a hump-shaped relationship between bank trade finance and country risk. In other words, bank trade finance, controlling for exports, is highest in countries with intermediate levels of default risk. In column (4), which includes country-fixed effects, the coefficient on risk squared has the correct sign but is not significant. When correcting for endogeneity via IV, as discussed in the next paragraph, the significance levels increase substantially.

IV results are presented in table 5. Odd-numbered columns show the coefficients from first stage regressions. The log of population has a high predictive power for exports in all four first stage regressions, and the R^2 is large, which indicates that we have a good instrument at hand. Even-numbered columns in table 5 show the second stage results. Compared to the OLS regressions in table 4, the results now clearly suggest a non-linear relationship between risk and bank trade finance. The coefficients on risk and risk squared are highly significant in the specification that both exclude (column (6)) and include (column (8)) country-fixed effects.

Figure 7 shows the predicted level of the log of trade finance as a function of country risk. According to the estimates in column (4) of table 4, the peak of the hump is reached at a value of 62.75, which corresponds to the risk levels of Kenya in 2007 and of Pakistan in 2009, for example. The hump-shaped relationship between trade finance claims and country risk is economically relevant. Based on the same estimates, if Brazil (risk index of 39 in 2012) became as risky as Tunisia (risk index of 61.5 in 2012), U.S. bank trade finance claims would increase by approximately 39 percent. If Tunisia had the same credit risk as Jamaica (risk index of 71 in 2012), trade finance claims in Tunisia would decline by 5 percent. We will argue in section 3.3 that the curvature of the hump depends on aggregate risk and interest rate conditions. So differences in trade finance claims between countries with different risk levels are even more pronounced when global risk is low and when interest rates are high.

Results do not change when the log of imports is included in the above OLS regressions. They also hold when regressions are run at the bank-level and include bank-, time- and

country-fixed effects. Section 3.4 discusses several other robustness checks in more detail. Altogether, we find strong evidence that bank trade finance is hump-shaped in destination country default risk.

3.2.3 Exports, time to trade and country risk as triggers of entry

So far, we have documented that bank trade finance is larger in countries with a larger export market, longer transaction times and intermediate levels of country risk. In this section, we investigate whether the same factors that determine bank trade finance in the aggregate, also trigger entry by banks into markets and systematically affect concentration at the country-level.

Three different measures of entry are considered that address different moments of the within-country bank distribution: the number of banks active in a given country, the size of the smallest bank active in a given market, and the share of the largest three trade finance providers in total trade finance. The first measure corresponds to the extensive margin and captures competition. The second variable allows us to analyze whether there is a pecking order, i.e., whether there is a systematic relationship between bank characteristics, such as bank size, and entry. The size of bank b is measured by the total trade finance claims of bank b in country c at time $t - 1$. The third measure is a direct measure of concentration. For each country, we compute the share of the three banks with the largest trade finance claims in total claims. If small banks that enter a market are able to attract a significant market share, then the share of the top 3 banks should be low.

The three different variables are regressed on country observables that affect the aggregate volume of bank trade finance as we have shown: time to trade, risk and exports. In addition, nominal GDP per capita is included in the regressions to control for other factors that may affect entry. Specifically, the regressions take the following form:

$$y_{ct} = \beta_1 \log exports_{ct} + \beta_2 \log(GDPpc_{ct}) + \beta_3 \log dist_c + \beta_4 \text{sea share} + \beta_5 risk_{ct} + \beta_6 (risk_{ct})^2 + \alpha_t + \epsilon_{ct}, \quad (2)$$

where y_{ct} stands either for the number of banks, the minimum bank size or the share of the top 3 banks. We report results from OLS regressions based on quarterly data. In addition, estimates from OLS and IV regressions on aggregated annual data are presented. All regressions include time-fixed effects. Standard errors are clustered at the country level.

Number of banks Columns (1) to (3) of table 6 show regression results where the dependent variable is the log of the number of banks active in each market. The positive and significant coefficient on exports in column (1) suggests that, as expected, the number of banks that have positive trade finance claims in a given market increases with the exports that the country receives from the U.S..

Two proxies of the time to trade, distance and the share of goods shipped by sea, are included in the regressions. Both variables should have a positive effect on the number of active banks. Distance, however, also affects the fixed costs that firms face when operating in a foreign market. The further away a country, the less familiar U.S. banks may be with the business environment and the more costly it may be to acquire information.²² Thus distance has potentially two countervailing effects on profitability. The estimated distance coefficient displayed in column (1) is positive but insignificant suggesting that both described forces are at play. In contrast, the share of goods shipped by sea has a positive and significant effect on the number of banks, consistent with the previous findings.²³

The third factor that affects market size is risk. As shown, the market for bank trade finance is largest for intermediate levels of risk. In line with these findings, the coefficients on risk and risk squared in column (1) indicate that the number of banks that operate in a given market is also largest for intermediate levels of risk. When regressions are run on annual data (column (2)) and exports are instrumented by population (column (3)), the significance levels of the coefficients generally decline. The positive effect of exports and the share of goods shipped by vessel remain, however, highly significant.²⁴

²²For example, Felici and Pagnini (2008) find evidence that distance is a barrier to entry in the Italian banking market.

²³We do not present regressions result where the time to import from the Doing Business Indicators is included instead of the share of goods shipped by vessel. Estimated coefficients on time to import have the expected signs but are significant only at a 15 to 20 percent significance level.

²⁴First stage regression results are suppressed. As in the IV regression shown before, the log of population

Minimum bank size The second dependent variable used in our analysis is the size of the smallest bank that has positive trade finance claims in a given country measured by banks' total trade finance claims at time $t - 1$. Columns (4) to (6) of table 6 show how this size cutoff varies with country characteristics.²⁵ The signs on the coefficients of interest should be the opposite to those in columns (1) to (3) where the number of banks is the regressand. This is indeed the case. The effect of exports on the minimum size is negative suggesting that the size of the smallest bank decreases with U.S. exports to this market. The coefficient on the sea transport share also has the expected sign although it is not significant at standard significance levels. The effect of distance is positive and significant in columns (5) and (6) that are based on annual data. The further away a country from the U.S., the larger the smallest bank that operates in that market. The fixed cost effect therefore dominates the effect of distance on market size. The signs on the variables risk and risk squared are fully in line with the argument that a larger market size triggers entry: The size of the smallest active bank is smallest in countries with intermediate levels of risk. This pattern also holds on the annual data and when exports are instrumented by population.

Share of the top 3 Finally, we look at concentration as an outcome variable. It is measured by the share of the top 3 banks in each destination market. Consistent with the results on minimum bank size, we find that the largest players are more important in countries to which the U.S. exports less. This can be seen from the negative and highly significant coefficient on exports in columns (7) to (9) of table 6. As in columns (5) and (6), the distance coefficient is significant and positive, which again suggests that distance is a barrier to entry. The share of goods shipped by sea, in contrast, reduces concentration. The relationship between risk and concentration is also as expected: the share of the top 3 banks is lowest in countries with intermediate levels of risk.

These results imply that the same factors that drive the volume of bank trade finance in the aggregate also determine the extensive margin of bank trade finance and concentration. The larger the market for bank trade finance, the smaller is the smallest bank active and

is highly significant and the R^2 of the first stage is high.

²⁵Niepmann (2013) also uses the minimum size of banks in a given country to study bank entry into foreign markets.

the smaller is the market share of the top 3 banks in a given market. The fact that bank entry follows a pecking order so that larger banks operate in the smaller markets is a strong indication that fixed entry costs play a key role in the trade finance activities of banks.

3.3 Heterogeneous responses to global conditions

The preceding analysis has shown that bank trade finance is systematically affected by global conditions. At the same time, trade finance differs across countries. Therefore, the question naturally arises whether changes in global funding conditions and the risk environment impact all destination countries in the same way or whether effects are asymmetric. In order to test for heterogeneous responses of bank trade finance across countries to changes in global conditions, different versions of the following equation are estimated:

$$\begin{aligned}
 \log(tf_{ct}) &= \beta_1 \log(exp_{ct}) + \beta_2 \log(GDPpc_{ct}) + \beta_3 risk_{ct} + \beta_4 (risk_{ct})^2 & (3) \\
 &+ \beta_5 (risk_{ct} \times \log(global\ factor_t)) + \beta_6 ((risk_{ct})^2 \times \log(global\ factor_t)) \\
 &+ \alpha_t + \alpha_c + \epsilon_{ct},
 \end{aligned}$$

where the variable *global factor* corresponds either to the VIX or the LIBOR. As before, we run regressions on annual data and cluster standard errors at the destination country.

3.3.1 The response to changes in the VIX is u-shaped in country risk

Figure 4 illustrated that aggregate bank trade finance expands when global risk rises. In order to check whether an increase in risk increases bank trade finance equally across countries, we estimate the effect of an interaction term between the log of the VIX and the EIU risk measure. Table 7 presents the results. Columns (1) to (3) exclude time-fixed effects, which allows us to estimate the level effect of the VIX on bank trade finance as this variable only varies over time. Columns (4) to (6) include time- and country-fixed effects. Columns (3) and (6) are obtained from IV regressions where the log of exports is instrumented by the log

of population as before.²⁶ The other columns show results from OLS regressions.

Start by considering column (1) of table 7. The estimated coefficient on the VIX is positive and significant at a 10 percent significance levels. The coefficient on the interaction between the log of the VIX and country risk is negative and significant, which implies that countries with higher risk respond less to an increase in global risk. This effect is robust to the inclusion of time-fixed effects (see column (4)). Column (2), (3), (5) and (6) of table 7 include an interaction term between the log of the VIX and risk squared. In all columns, the interaction with risk is negative, and the interaction with risk squared is positive. This suggests that the response to an increase in the VIX is u-shaped, the change being lowest in countries with intermediate levels of risk. The coefficient on the interaction with risk squared is only significant in column (6), but the results based on an alternative risk measure presented in the next section strongly support the non-linear response.

Figure 8 plots the estimated response of trade finance claims to a change in the VIX for different country risk levels based on the estimated coefficients in column (3). The graph clearly shows that the estimated response to a change in global risk is close to zero for countries with intermediate levels of risk and strongly positive for countries with low and high levels of default risk. According to the respective point estimates, if the VIX increases by 10 percent, the trade finance claims of U.S. banks in Chile, which has a risk index of 28 in 2012, increase by around 3.8 percent. In contrast, trade finance claims in China, whose risk index takes a value of 42 in 2012, are not predicted to increase.

3.3.2 The response to changes in the LIBOR decreases in country risk

In a next step, we study whether the response to changes in global funding conditions is also heterogeneous across countries. When interest rates rise, bank trade finance generally declines. An interaction term between the log of LIBOR and country risk allows us to check whether countries with different risk levels respond differently. Results are presented in table 8. As before, country-fixed effect are included in all columns.

²⁶The first stage regressions that underly the IV regressions in tables 7 and 8, which are not displayed, indicate as before that population has a high predictive power for exports.

Column (1) displays a negative and significant coefficient on LIBOR. The positive and significant coefficient on the interaction between the log of LIBOR and country risk indicates that this negative response is smaller in countries with higher credit risk. In columns (2) and (4), the regression is estimated using IV. In columns (3) and (4), time-fixed effects are added. The results remain essentially unchanged.

Figure 9 plots the estimated effect of a change in the LIBOR for countries with different risk levels using the estimated coefficients in column (2). The graph shows that countries with low risk levels show the strongest negative response to an increase in interest rates. The change in trade finance is closer to zero for countries with intermediate levels of credit risk. According to the point estimates in column (4), if the LIBOR increases by 10 percent, the trade finance claims of U.S. banks in Spain decrease by roughly 1 percent. In contrast, the trade finance claims in China would hardly be affected. There is also evidence that the response to changes in interest rates is non-linear in credit risk based on an alternative measure of risk discussed in the next section. The additional results imply a hump-shaped response with low and high risk countries adjusting the most.

3.4 Robustness

This section presents and discusses several robustness checks. First, an alternative measure of country risk is used to test for the hump-shaped relationship and for the heterogeneous response to changes in global factors. Second, we present a different IV strategy. Third, trade finance intensity is used as the dependent variable. Finally, we include private credit over GDP as additional control variable to account for a potential omitted variable problem.

An alternative measure of country risk An alternative measure of country risk comes from the Alliant Insurance Company. The firm provides an inverse measure of default risk, which reflects the likelihood that industries and companies experience future losses and which is derived from historical insurance loss data. This series is available from the fourth quarter of 2003 onwards. The higher this measure, the lower the risk of non-payment. While the EIU risk measure covers a larger time period, the Alliant risk measure is observed for a larger

number of countries.

Table 9 is based on the risk measure from Alliant, testing for the relationship between default risk and trade finance claims. Standard errors are, in general, larger compared to table 4 but we still find a significant effect of risk. The negative coefficient on the risk measure in columns (1) and (5) indicates that trade finance claims are lower in countries with a higher probability of repayment. When risk squared is added as regressor, the effect of risk is not significant. However, when GDP per capita is excluded from the regressions, which is highly correlated with country risk, there is evidence of a hump-shaped response also based on the second risk measure.

Tables 10 and 11 are equivalent to tables 7 and 8, respectively. The coefficients related to the Alliant risk measure confirm that the response to changes in the VIX and the LIBOR is heterogeneous across countries. There is even stronger evidence for a u-shaped response to changes in the VIX based on this alternative index. In addition, there is also evidence that countries respond to changes in global interest rates in a non-linear way. The interaction of the LIBOR with risk squared is negative and significant in columns (3) and (6) of table 8. These results imply that bank trade finance adjusts the least in countries with intermediate levels of credit risk when global conditions change.

Controlling for imports and alternative IV strategies While trade finance claims mostly reflect confirmed letters of credit and similar instruments that support U.S. export activity, the data also captures pre-export loans to foreign exporters extended by the foreign affiliates of U.S. banks abroad as we argue in appendix A2. Trade finance claims, controlling for time- and country-fixed effects, also covary with U.S. imports. In the previous regressions, the log of imports was excluded. However, including it does not change the results in any substantive way, and the conclusions remain unchanged.

As an additional robustness check, we next control for total trade in the OLS specification. In addition, we instrument total trade by population. It would be desirable to include both exports and imports separately and to have two instruments, one for each variable. It is, however, difficult to find two valid and strong instruments given that imports and exports

are highly correlated. Table 12 shows results for the effect of time to trade on trade finance claims and for the hump shape. When the log of U.S. trade with destination c is included as a regressor and instrumented by the log of population, the same patterns emerge as before.

Trade finance intensity as the dependent variable An alternative to the IV approach consists of using trade finance intensity as the dependent variable measured. This regression directly tests how the share of exports that is backed by bank guarantees responds to exogenous variables. Table 13 presents the results for the key specifications of this paper. Again, the positive effect of trading time, the hump shape as well as the heterogeneous response to global conditions are confirmed.

Additional controls Trading partners may have a choice between using a U.S. bank or the bank in the other trading partner's country to finance trade transactions. If this ability to substitute is correlated with the independent variables, the regressions may suffer from an omitted variable bias. To control for this, we include private credit over GDP from the Financial Structure Database of the World Bank in the estimations. This measure captures the degree of financial development in the destination country. Table 14 presents regressions where private credit over GDP is added as a regressor. The variable is significant if country-fixed effects are not included, indicating that trade finance claims are lower in countries with higher ratios of private credit over GDP. This suggests that there is a substitution effect and that trading partners use non-U.S. banks more when the non-U.S. party is located in a country with a well functioning banking sector. The new control, however, does not explain much of the within-country time variation in banks' trade finance claims (see column (4)). When the additional control variable is included, all coefficients of interest have signs that are consistent with the previous findings and are, except for the coefficient on the share of goods shipped by vessel, highly significant.

Together, these robustness checks indicate that the empirical relationships that we uncover are highly robust features of the data.

4 Explaining the Patterns

The previous section documented several new relationships in the data. The use of banks to facilitate trade transactions expands when global risk increases and when funding conditions ease. U.S. exporters rely the most on bank guarantees when exporting to destinations with intermediate levels of default risk. At the same time, bank trade finance in these countries is much less elastic when global conditions change. How can these patterns be rationalized?

Models of payment contract choice in line with Schmidt-Eisenlohr (2013), Antràs and Foley (2011), Glady and Potin (2011), and Hoefele et al. (2012) distinguish between three different payment methods: cash-in-advance, open account and letters of credit. The data used in this paper reflects the latter payment method. In this section, we study in how far the existing theory generates the empirical findings documented in this paper. It turns out that the benchmark model is successful in explaining the response of bank trade finance to changes in global conditions. However, the hump-shaped relationship and the heterogeneity in the response to global risk and interest rates across countries are beyond its scope. We show that when the letter-of-credit fee of the original model is assumed to increase in the default risk of the destination country, the model predictions are fully consistent with the empirical findings.

4.1 Model setup

In the model, exporters and importers have the choice between three payment contracts: cash-in-advance (CIA), open account (OA) and letter of credit (LC). It is assumed that one exporter is matched with one importer and that they play a one-shot game. Both firms are risk-neutral. The exporter has all bargaining power and makes a take-it-or-leave-it offer to the importer specifying the type of contract, the price and the quantity. R denotes the sales value of the goods in the destination country and K the production costs in the source country. $1+r$ and $1+r^*$ reflect the financing costs in the source country and the destination country, respectively.

Firms can be of good and bad type. A good firm always fulfills a contract. A bad firm

breaks it whenever this is profitable. The share of good firms in the source country is given by η and in the destination country by η^* . If a firm does not voluntarily fulfill a contract, its trading partner can go to court and can try to enforce it. This is successful with exogenous probabilities λ and λ^* in the source and the destination country, respectively.

4.1.1 Cash-in-advance

Cash-in-advance is the case where the importer first pays for the goods and then the exporter delivers them. Due to the time delay between the pre-payment and the arrival of the goods at the destination, the importer needs to pre-finance the transaction at her local interest rate $1 + r^*$. The exporter, in turn, receives the payment before incurring the production costs. This gives rise to a commitment problem because the exporter can decide to keep the money without producing and delivering the goods. Exporters that are of good type (share η) always fulfill the contract whereas bad exporters (share $1 - \eta$) always try to deviate. If an exporter defaults on the contract, the importer brings her to court, which successfully enforces the contract with probability λ .

The exporter, who has all bargaining power, chooses the optimal pre-payment C^{CIA} to maximize her expected profits, taking the enforcement probability λ into account.²⁷ She also respects the participation constraint of the importer. Expected profits of a good exporter can be derived as:

$$E[\Pi_E^{CIA}] = \frac{\eta + (1 - \eta)\lambda}{1 + r^*} R - K. \quad (4)$$

Because the importer pre-finances the transaction, the profitability of cash-in-advance decreases in the financing costs in the destination country $1 + r^*$. The commitment problem is on the exporter side. Therefore, stronger contract enforcement and a larger share of good firms in the source country (higher λ and η) increase the expected profits from cash-in-advance.

²⁷Two cases need to be distinguished: A pooling and a separating case. Under pooling, a bad exporter imitates the good exporters, under separating she chooses a different strategy that reveals her type. Following Schmidt-Eisenlohr (2013), we assume that conditions are such that only the pooling case arises. This is the case if $\frac{R}{K} > \frac{(1+r^*)}{\eta}$. See appendix C for details and a formal derivation of all results.

4.1.2 Open account

Open account is the case where the exporter first sends the goods and then the importer pays for them. The exporter incurs the production costs and delivers the goods to the importer before receiving the payment. Hence, the exporter has to finance the working capital over this period at her interest rate $1+r$. The commitment problem is now on the importer's side. She receives the goods before paying for them. Good importers (share η^*) pay the agreed price in any case, while bad importers (share $1-\eta^*$) try to get away without paying. In this case, the exporter goes to court, which successfully enforces the contract with probability λ^* .

The exporter maximizes expected profits respecting the participation constraint of the importer.²⁸ The exporter's expected profits result as follows:

$$E[\Pi_E^{OA}] = \frac{\eta^* + (1-\eta^*)\lambda^*}{1+r}R - K. \quad (5)$$

Under open account, pre-financing is done by the exporter. Consequently, higher source country financing costs $1+r$ reduce her expected profits. Since the commitment problem is on the importer's side, better contract enforcement and a higher share of good firms in the destination country (higher λ^* and η^*) both increase the profitability of open account.

4.1.3 Letter of credit with fixed fee

A letter of credit is typically issued by a bank in the destination country. It guarantees the payment of the agreed upon price against documents that confirm the arrival of the goods in the destination. Additionally, a letter of credit can be confirmed by a bank in the source country. The confirming bank guarantees the payment of the bank in the destination country. When the risk that the issuing banks defaults is zero, there is no reason for the exporter to ask for a confirmation of the letter of credit. The original model in Schmidt-Eisenlohr (2013) implicitly assumes this and considers only a simple letter of credit. We first

²⁸As we focus on the case where both type of importers participate in trade, the relevant constraint is the participation constraint of good importers. See Appendix C for the details.

present the original formulation where the letter of credit fee is exogenous. In a next step, we present a modification that allows for the possibility that the issuing bank defaults and derive the fee that the importer has to pay for a confirmed letter of credit.

For its guarantee, an issuing bank demands a fee from the importer. Assume that this fee f^{LC} is proportional to the transaction value of the letter of credit C^{LC} . When a letter of credit is used, the exporter only sends the goods once she has received the letter. Conversely, the goods only arrive at the importer after she has committed to the payment by making her bank issue the letter. Under perfect third party verifiability, it is possible for the bank to only pay out the money to the exporter if the exporter has indeed produced and sent off the goods. In this way, a letter of credit can fully resolve the commitment problem of the exporter and the importer at the same time.

Again, the exporter maximizes expected profits, respecting the participation constraint of the importer. This delivers the following profits:²⁹

$$\Pi_E^{LC} = \frac{R}{(1 + f^{LC}(1 + r^*))(1 + r)} - K. \quad (6)$$

As discussed, a letter of credit fully resolves the commitment problems on both sides of the transaction. Thus, enforcement probabilities λ and λ^* and the shares of good and bad exporters η and η^* do not affect profits. The importer, however, has to pay the letter of credit fee f^{LC} . While this payment takes place at the beginning of the transaction, sales revenues R are only realized after a time delay. Therefore, the importer has to pre-finance the fee at her interest rate $1 + r^*$. Similarly, before being paid, the exporter has to pre-finance her working capital K at the source country interest rate $1 + r$. Profits from a letter of credit transaction thus decrease in the financing costs in both countries, $1 + r$ and $1 + r^*$, as well as in the letter of credit fee f^{LC} .

When comparing the expected profits from the three financing forms in equations (4), (5) and (6), the tradeoffs involved in choosing between them are clear. Cash-in-advance and open account each eliminate the commitment problem on one side of the transaction. In contrast, a letter of credit eliminates the risk on both sides but implies an additional

²⁹Note that by resolving the commitment problem, a letter of credit eliminates all uncertainty.

cost in the form of the fee f^{LC} . The optimal choice of the exporter can also be studied graphically. The left panel in figure 10 plots the profit factors of the three payment forms against destination country risk λ^* . Cash-in-advance and a letter of credit fully resolve the importers' commitment problem so that both profit factors are independent of destination country risk. Accordingly, profit factors are represented by two horizontal lines. Profits from open account decrease in destination country risk as illustrated by the downward-sloping line. Choosing the payment form with the highest profit factor, exporters, in our example, prefer open account when destination risk is low and a letter of credit when this risk is high.

4.1.4 Letter of credit with endogenous fee

So far, the model corresponds to Schmidt-Eisenlohr (2013). We now endogenize the letter of credit fee f^{LC} . Substitute $\tilde{\lambda} = \eta + (1 - \eta)\lambda$ and $\tilde{\lambda}^* = \eta^* + (1 - \eta^*)\lambda^*$ and assume that there is a competitive banking sector offering letters of credit.³⁰ The letter of credit fee consists now of two components. First, the provision of a letter of credit requires monitoring and administrative expenses by the issuing bank, which are proportional to the transaction value of the letter of credit C^{LC} . Total monitoring costs are mC^{LC} . Second, the issuing bank defaults on its obligation with some probability. This probability is proportional to the risk of default in the destination country and is given by $\alpha(1 - \tilde{\lambda}^*)$. This assumption is plausible because the default risk of a bank should, by and large, be determined by the risk conditions in the local market.

Given that the issuing bank might default on its obligations, there is scope for the exporter to ask her bank to confirm the letter of credit.³¹ Under perfect competition in the banking market, a confirming bank charges its expected loss from the guarantee $CC = \alpha(1 - \lambda^*)C^{LC}$. Adding the monitoring and administrative costs to the expected loss from default, the total

³⁰If banks had market power and charged a markup over their marginal cost of providing a letter of credit, results would not change qualitatively. Markups would, however, magnify the effect of destination country risk on the cost of letters of credit.

³¹Letter of Credit confirmation transfers the risk of default by the issuing bank from the exporter to the confirming bank. Here, an exporter is risk neutral and is indifferent between letter of credit confirmation and bearing the risk herself, as both choices imply the same expected profits. Assume that, if indifferent, the exporter chooses a confirmed letter of credit. Confirmation would be strictly preferred if exporters were risk averse.

letter of credit fee can be expressed as: $f^{LC} = m + \alpha(1 - \tilde{\lambda}^*)$. Plugging this expression into equation (6), expected profits are:

$$\Pi^{LC} = \frac{1}{(1+r)[1+(m+\alpha(1-\tilde{\lambda}^*))(1+r^*)]}R - K$$

As before, profits from a letter of credit decrease both in the financing costs in the source country and in the destination country, $1+r$ and $1+r^*$. They now also depend on the default probability in the importer's country through the letter of credit fee f^{LC} . The higher the default risk, the lower the profits under this contract choice.

The difference between an exogenous and an endogenous letter-of-credit fee can be understood by comparing the left and the right graph of figure 10. The right graph plots profit factors against destination country risk λ^* for the case in which the letter-of-credit fee is endogenous. The profit factors of cash-in-advance and open account are the same as in the original model shown in the left graph. However, letter-of-credit profits now decline in destination country risk. Because banks are able to reduce risk, letter-of-credit profits decline less steeply in destination country risk than open-account profits. Thus for low levels of destination country risk, open account remains the optimal choice. At intermediate levels of risk, letters of credit are preferred. When the risk in the destination country is high, exporters choose cash-in-advance.

4.2 Generating the results found in the data

4.2.1 Changes in aggregate risk

In the empirical section we found that the use of bank guarantees increases when the Volatility Index rises. The VIX reflects both changes in global default risk as well as changes in uncertainty and risk aversion. In this model, all agents are risk neutral so the variance of profits does not play a role for financing decisions.³² We therefore consider only how changes in global default risk affect the exporters' payment contract choice. Assume that the risks

³²If exporters and importers were risk averse, then letters of credit would become more attractive when uncertainty and the default risk increase.

of non-delivery and non-payment in the source and the destination country, respectively, are both proportional to aggregate risk V .³³ Furthermore, define $\kappa_1 = \min\left\{\frac{1}{1+r^*}, \frac{1+r}{(1+r^*)^2} \frac{\tilde{\lambda}}{\lambda^*}\right\}$. Then, the following proposition can be derived.

Proposition 1 *Suppose that banks are sufficiently efficient in mitigating risk, that is $\alpha < \kappa_1$. Then, the use of letters of credit increases in aggregate risk.*

Proof. See appendix D. ■

As discussed before, a letter of credit is able to resolve the commitment problem both in the source and in the destination country. Cash-in-advance and open account each only resolve the problem in one of the two countries. Letters of credit are therefore best able to cope with a setting of high risk in the source and the destination country. If banks are sufficiently efficient at reducing risk (low α), letters of credit thus become more attractive when aggregate default risk increases.

4.2.2 Changes in aggregate financing costs

Next, consider the effect of a change in aggregate financing costs on the use of letters of credit. Let aggregate financing costs be denoted by L . Assume that this variable corresponds to a world wide base interest rate (like the LIBOR) and that it affects country level interest rates in an additive way.³⁴ Define $\kappa_2 = \left(\frac{1+r^*}{1+r}\right)^2 \frac{1+f^{LC}(1+r^*+1+r)}{(1+f^{LC}(1+r^*))^2}$ and $\kappa_3 = \frac{1+f^{LC}(1+r^*+1+r)}{(1+f^{LC}(1+r^*))^2}$. Then the following proposition holds:

Proposition 2 *Suppose $\tilde{\lambda} < \kappa_2$ and $\tilde{\lambda}^* < \kappa_3$.³⁵ Then, the use of letters of credit decreases in aggregate financing costs.*

Proof. See appendix D. ■

The preceding analysis revealed a drawback of letters of credit. They require pre-financing both in the source and in the destination country. The importer has to pre-finance the

³³That is, assume that $\tilde{\lambda}^* = \frac{\gamma^*}{V}$ and $\tilde{\lambda} = \frac{\gamma}{V}$.

³⁴That is, financing costs in the source country are $1+r = 1+\rho+L$ and costs in the destination country are $1+\rho^*+L$, where ρ and ρ^* are country specific financing cost factors.

³⁵The conditions are quite weak. Anecdotal evidence suggests that letters of credit fees are in the low single digits. Setting $f^{LC} = 0.03$ and assuming real annual interest rates of about 10 percent ($1+r = 1+r^* = 1.025$) delivers an upper bound of 0.95 for the probability of default λ and λ^* . This value is even higher if the letter of credit fee or interest rates are lower.

letter of credit fee, and the exporter has to pre-finance the working capital. In comparison, cash-in-advance and open account only require pre-financing by one of the two parties. This generates the result stated in the proposition: if $\tilde{\lambda}$ and $\tilde{\lambda}^*$ do not exceed the thresholds κ_1 and κ_2 , respectively, the use of letters of credit decreases when financing costs increase symmetrically in the two countries.

This result is illustrated in figure 11. As before, the x-axis denotes destination country risk and the y-axis shows the profit factors. The left panel depicts profit factors when global financing costs are low. In the right panel, all parameters are kept constant but financing costs in the two countries are increased by the same amount. First, note that this reduces the profitability of all three payment forms so that all three lines are shifted downward. Second, comparing the left and the right panel reveals that the profitability of letters of credit decreases by more than the profitability of its alternatives. The range of risk levels for which a letter of credit dominates its alternatives becomes smaller.

4.2.3 Hump shape in destination country risk

While the effects of aggregate financing costs and aggregate risk on the use of letters of credit can also be derived in the benchmark model in Schmidt-Eisenlohr (2013), the result that bank trade finance is hump-shaped in destination country risk, which is proven in the following, only holds with the modified letter-of-credit fee.³⁶

Proposition 3 *Suppose $\alpha < \frac{1}{1+r^*}$ and suppose that each contract type $C \in \{CIA, OA, LC\}$ is used for some $\tilde{\lambda}^* \in [0, 1]$. Then, a letter of credit has the highest relative profitability at intermediate values of $\tilde{\lambda}^*$.*

Proof. See appendix D. ■

Proposition 3 shows that the relative profitability of a letter of credit as compared to the two alternatives changes in the destination country payment probability in a non-linear way. Figure 10 illustrated how profit factors change with destination country risk. As long as $\alpha < \frac{1}{1+r^*}$, the slopes in the right panel of the figure have the displayed ordering and a letter

³⁶With a fixed letter-of-credit-fee, the condition that is needed for proposition 1 to hold simplifies.

of credit is most attractive for intermediate values of destination country risk.³⁷ With a fixed letter-of-credit fee that does not depend on destination country risk (see the left panel of figure 10), the profitability of letters of credit would be independent of λ^* .

Figure 12 plots the difference between the profit factor of a letter of credit and its best alternative. There is a kink at the maximum value, where a firm is indifferent between using cash-in-advance or open account as the second best contract. The observed hump-shaped relationship between the share of exports that are financed by letters of credit and destination country risk can be generated as follows. Assume that there is a continuum of exporters and importers in the source and the destination country. Assume further that each exporter draws a random additive shock to the profitability of letters of credit with a sufficiently large variance.³⁸ Then, there is always an exporter that is indifferent between a letter of credit and an alternative payment method when trading with importers in a given destination country. As a consequence, the share of exporters that use letters of credit increases with the relative profitability of letters of credit. A hump-shaped relationship results.³⁹

4.2.4 Heterogeneous responses

The data shows that the reaction of bank trade finance to changes in aggregate conditions is heterogeneous across countries. In this subsection, we discuss how a slight modification of the model allows us to generate the observed heterogeneous responses. To understand the main intuition, first note that both the response to aggregate risk and the response to aggregate financing costs are around zero for intermediate values of destination country risk. In other words, bank trade finance in these countries does not react much to changes in aggregate conditions. In contrast, estimated responses for high and low risk destination countries show positive absolute values for both aggregate variables. The mechanism suggested by the model implies that there is hardly any response in the intermediate risk countries because, for them, a letter of credit clearly dominates the two alternative payment forms. For destination

³⁷That is, expected profits from cash-in-advance, open account and letter of credit change in the destination country payment probability $\tilde{\lambda}^*$ in the following way: $\frac{\partial \Pi^{OA}}{\partial \tilde{\lambda}^*} > \frac{\partial \Pi^{LC}}{\partial \tilde{\lambda}^*} > \frac{\partial \Pi^{CIA}}{\partial \tilde{\lambda}^*} = 0$. This is shown in corollary 1 in appendix C.

³⁸Any single-peaked distribution with mean zero and a sufficiently large variance can be used.

³⁹In Hoefele et al. (2012), shocks to the profitability of different payment forms are modeled explicitly.

countries with low and high risk, respectively, open account and cash-in-advance are viable alternatives.

To illustrate this point graphically, suppose that there is a mass of firms that are hit by random shocks to the profitability of letters of credit. Furthermore, assume that parameters are such that most importers in countries with intermediate values of risk use letters of credit to finance trade transactions. Figure 13 shows a simulation of the model based on the following parameters: $m = .03$, $\alpha = .7$, $\tilde{\lambda} = .8$, $r = r^* = .08$ $\tilde{\lambda}^* \in [0.7, 1]$. It consists of three graphs. The left graph shows the optimal payment choice in a low risk environment as a function of credit risk in the importing country. The graph in the middle displays the choice after default risks in both countries have increased. When aggregate risk increases, the set of countries in which all firms choose letters of credit increases. The right graph of figure 13 shows the corresponding change in the share of firms that use letters of credit due to the increase in aggregate risk. The response has a u-shape: it is largest for high and low values of destination country risk and small or zero for intermediate values as documented.

We can study changes in aggregate financing costs in a similar way. When interest rates rise, lower risk countries shift towards open account whereas higher risk countries may now decide to trade more on cash-in-advance terms. Figure 14 illustrate this. The figure is based on the following model parameters: $m = .03$, $\alpha = .7$, $\tilde{\lambda} = .8$, $r = r^* = .1$ $\tilde{\lambda}^* \in [0.6, 1]$. The graph on the left hand side shows the optimal payment contract choice as a function of credit risk in the importing country in a low interest rate environment. The graph in the middle depicts the choice after interest rates in both the exporting and the importing country have increased by L . As interest rates rise, firms switch away from letters of credit. The graph on the right hand side shows the change in letters of credit used across destination countries with different risk levels, documenting an inversely u-shaped response. Under the assumption that practically all importers in countries with intermediate risk rely on letters of credit, the model generates heterogeneous responses consistent with the empirical patterns.

5 Conclusions

This paper employs data from the U.S. to quantify the role of banks in trade finance and to document new empirical relationships regarding the use of letters of credit across export destinations and over time. The model of payment contract choice with endogenous costs of letters of credit presented can rationalize all of the empirical findings. The key new assumption, which we add to the benchmark theory developed in Schmidt-Eisenlohr (2013), is that the costs of letters of credit increase in the credit risk of the importing country. This assumption can, in particular, explain the hump-shaped relationship between the use of bank guarantees and credit risk in the destination country.

The presented empirical findings indicate that firms choose between letters of credit and its two alternatives exactly as the model predicts. This suggests that in some instances, bank trade finance may not be missing, but firms may simply prefer a cheaper alternative and settle payments on cash-in-advance or open account terms. At the same time, we find that bank trade finance is less elastic when macro conditions change in those countries that rely most heavily on letters of credit. This might indicate that firms are less able or willing to switch between different payment forms so that a lack of supply might translate into a reduction in exports in these countries. For policy interventions, it is crucial to distinguish between demand effects and supply constraints. A further exploration of which firms, industries and countries are especially constrained in their access to bank guarantees and trade finance, more generally, is a key question for future research.

References

- Ahn, JaeBin**, “A Theory of Domestic and International Trade Finance,” IMF Working Papers 11/262, International Monetary Fund November 2011.
- , “Estimating the Direct Impact of Bank Liquidity Shocks on the Real Economy: Evidence from Letter-of-Credit Import Transactions in Colombia,” 2013. mimeo.
- Amiti, Mary and David E. Weinstein**, “Exports and Financial Shocks,” *The Quarterly Journal of Economics*, 2011, 126 (4), 1841–1877.
- Antràs, Pol and C. Fritz Foley**, “Poultry in Motion: A Study of International Trade Finance Practices,” NBER Working Papers 17091, National Bureau of Economic Research, Inc May 2011.
- Asmundson, Irena, Thomas William Dorsey, Armine Khachatryan, Ioana Niculesca, and Mika Saito**, “Trade and trade finance in the 2008-09 financial crisis,” Technical Report 2011.
- Beck, Thorsten**, “Financial Development and International Trade: Is there a Link?,” *Journal of International Economics*, June 2002, 57 (1), 107–131.
- , “Financial Dependence and International Trade,” *Review of International Economics*, May 2003, 11 (2), 296–316.
- Bourgeon, Pauline, Jean-Charles Bricongne, and Guillaume Gaulier**, “Do Financial Frictions and Trading Time matter for trade? Evidence from French firms,” 2012. mimeo.
- Djankov, Simeon, Caroline Freund, and Cong S Pham**, “Trading on Time,” *The Review of Economics and Statistics*, May 2010, 92 (1), 166–173.
- Eck, Katharina, Martina Engemann, and Monika Schnitzer**, “How Trade Credits Foster International Trade,” Working Papers 116, Bavarian Graduate Program in Economics (BGPE) March 2012.

- Felici, Roberto and Marcello Pagnini**, “Distance, Bank Heterogeneity and Entry in Local Banking Markets,” *The Journal of Industrial Economics*, 2008, 56 (3), 500–534.
- Glady, Nicolas and Jacques Potin**, “Bank Intermediation and Default Risk in International Trade-Theory and Evidence,” 2011. ESSEC Business School, mimeo.
- Hoefele, Andreas, Tim Schmidt-Eisenlohr, and Zhihong Yu**, “Payment Choice in International Trade: Theory and Evidence from Cross-country Firm Level Data,” Working Paper 556, F.R.E.I.T. October 2012.
- Hummels, David and Georg Schaur**, “Time as a Trade Barrier,” *American Economic Review*, forthcoming.
- ICC**, “Rethinking Trade Finance 2009: An ICC Global Survey,” ICC Banking Commission Market Intelligence Report, International Chamber of Commerce 2009.
- , “Global Risks - Trade Finance Report 2013,” Technical Report, International Chamber of Commerce April 2013.
- IFC**, “Global Trade Finance Program Brochure,” Technical Report, International Finance Corporation January 2012.
- IMF**, “Survey Among Banks Assessing Current Trade Finance Environment,” IMF-BAFT Trade Finance Survey, International Monetary Fund 2009.
- Manova, Kalina**, “Credit Constraints, Heterogeneous Firms, and International Trade,” *Review of Economic Studies*, forthcoming.
- Niepmann, Friederike**, “Banking across borders with heterogeneous banks,” Staff Reports 609, Federal Reserve Bank of New York 2013.
- Olsen, Morten**, “How Firms Overcome Weak International Contract Enforcement: Repeated Interaction, Collective Punishment and Trade Finance,” 2013. mimeo.
- Paravisini, Daniel, Veronica Rappoport, Philipp Schnabl, and Daniel Wolfenzon**, “Dissecting the Effect of Credit Supply on Trade: Evidence from Matched Credit-Export Data,” Working Paper 16975, National Bureau of Economic Research April 2011.

Prete, Silvia Del and Stefano Federico, “Trade and finance: is there more than just trade finance? Evidence from matched bank-firm data,” 2012. mimeo.

Schmidt-Eisenlohr, Tim, “Towards a theory of trade finance,” *Journal of International Economics*, 2013, *91* (1), 96 – 112.

A Data Appendix

Data sources

- Trade data: Quarterly trade data is from the IMF's Directions of Trade Statistics; yearly data is obtained by summing over 4 quarters.
- U.S. GDP: Quarterly numbers for the U.S. were taken from the national statistical agency via Haver Analytics' Data Link Express (DLX) Software.
- Nominal GDP per capita: Annual numbers are from the World Bank's World Development Indicators.
- Annual population: World Development Indicators.
- Share of export transported by vessel: Nominal U.S. merchandise imports and exports with information on modes of transport at 3-digit HS commodity code from Census Bureau Trade Data.
- Time to import: Doing Business Indicators from the World Bank.
- Distance: CEPII.
- Libor: 3-months rate downloaded from FRED economic data maintained by the Federal Reserve Bank of St. Louis; quarterly averages calculated from daily data.
- Fed funds rate: 3-months lending rate from Federal Reserve Bank of New York; quarterly averages calculated from daily data.
- VIX: Quarterly/yearly averages calculated from daily data downloaded from Bloomberg Terminal.
- EIU country risk: Quarterly index that combines banking, sovereign and currency risk, provided by the Economist Intelligence Unit, downloaded from Thomson Reuters Datastream.

- Alliant risk measure: Alliant is an insurance company that derives country risk scores from historical insurance loss data. The measure is an estimate of the likelihood that companies incur losses in the future; data downloaded from Bloomberg Terminal.
- Private credit by deposit money banks over GDP: Financial Structure Database, The World Bank, 2012.

Variables

- Offshore Centers: Netherlands Antilles, United Arab Emirates, Bahrain, Bahamas, Belize, Bermuda, Barbados, Cayman Islands, Cyprus, Grenada, Hong Kong, Iman, Ireland, Jordan, Lebanon, Macao, Monaco, Maldives, Malta, Mauritius, Seychelles, Taiwan, Vanuatu, Samoa

B Background on the Data

The exact reporting instructions for the trade finance item in the FFIEC 009 Report are as follows:

“Report total extensions of credit with maturities one year and under [...] that: (1) are directly related to imports or exports and (2) will be liquidated through the proceeds of international trade. Provided these two conditions are met, such credit extensions may include customers’ liability on acceptances outstanding, own acceptances discounted, acceptances of other banks purchased, pre-export financing where there is a firm export sales order, commercial letters of credit, as well as other loans and advances whenever such extensions directly relate to international trade. Include credit extensions for pre-export financing when there is a firm export sales order and the proceeds of the order will pay off indebtedness.”

According to the definition, the data can capture several trade finance products that relate to U.S. exporting— in particular, letters of credit, loans to foreign importers, forfeiting and factoring. Trade financing of U.S. imports is possibly reflected in the data through loans and advances to foreign exporters. If U.S. banks finance third-party exports or imports, letters of credit, pre-export and pre-import loans as well as forfeiting and factoring could be included. The different forms of trade finance are discussed in more detail in the following.

Letters of credit Letters of credit, described in detail in the main text, can show up in the dataset in two ways. First, a U.S. bank can confirm a foreign letter of credit and thereby guarantee expected trade receipts. Second, it can issue a letter of credit to a foreign importer, either directly or through an affiliate located abroad. In these cases, the U.S. bank guarantees obligations of the resident of a foreign country, and this is a contractual agreement that banks have to include in the FFIEC 009 report.

Trade finance loans Banks can also directly lend to exporters and importers to finance their trade transactions. If trading partners do not use bank guarantees, they typically agree to trade either on open account or cash in advance terms. Under open account, the exporter first sends the goods and then the importer pays for them after their arrival. Under cash

in advance, the importer first pays for the goods and then the exporter sends them after the payment is received. In the former case, the exporter may obtain pre-financing from the bank, in the latter case the importer needs to finance the transaction. If a U.S. bank or its foreign affiliate lends to a foreign importer or exporter to pre-finance trade, it should be reported in the FFIEC 009 form.

Forfeiting and factoring If a U.S. exporting firm sells its goods to a foreign buyer on open account terms, this generates accounts receivable on its balance sheet. To raise working capital and to limit the exposure, it can decide to sell these accounts receivable to a financial institution at a discount. There are two options. If a firm sells the whole claim of a specific transaction, this is referred to as forfeiting. Alternatively, it can sell only a fraction of its accounts receivable, which is called factoring. In both cases, a financial institution takes over part of or all of the risk that the exporter would otherwise have to bear. If a U.S. bank participates in these activities, it receives a claim against a foreign buyer that is related to a trade transaction. Forfeiting and factoring should thus be captured in the data.

Table B.1: Different forms of bank trade finance and underlying trade transactions that are potentially captured in the data

	U.S. exports	U.S. imports	Third party trade
Pre-export financing	-	X	X
Pre-import financing (affiliate)	X	-	X
LC issuance (affiliate)	X	-	X
LC confirmation	X	-	X
forfeiting/ factoring	X	-	X

Table B.1 summarizes the previous discussion, listing the different forms of bank trade finance, together with the underlying trade transactions that are potentially included in the data. To get a better understanding of the relative importance of import versus export financing, we begin by exploring relevant correlations in the data.

Table B.2 shows the results from OLS regressions where the log of aggregate trade finance claims at date t in country c is regressed on the log of imports from and the log of exports to country c in the same period. All columns include time-fixed effects. In odd columns,

Table B.2: Country-level regressions, 1997-2011

	Quarterly frequency					
	(1)	(2)	(3)	(4)	(5)	(6)
	all		non-offshore		offshore	
log(imp_{ct})	-0.0212 (0.0755)	0.0985 (0.0710)	0.0810 (0.0580)	0.114 (0.0790)	-0.365* (0.175)	0.00193 (0.145)
log(exp_{ct})	0.754*** (0.0885)	0.380*** (0.0726)	0.661*** (0.0811)	0.422*** (0.0737)	0.992*** (0.191)	0.0357 (0.274)
Observations	6,832	6,832	6,010	6,010	822	822
R-squared	0.541	0.827	0.576	0.834	0.421	0.786

	Annual frequency					
	(1)	(2)	(3)	(4)	(5)	(6)
	all		non-offshore		offshore	
log(imp_{ct})	-0.0427 (0.0715)	0.204*** (0.0725)	0.0427 (0.0575)	0.225*** (0.0765)	-0.327 (0.193)	0.0813 (0.162)
log(exp_{ct})	0.862*** (0.0832)	0.867*** (0.0855)	0.781*** (0.0757)	0.900*** (0.0782)	1.096*** (0.204)	0.562 (0.466)
Observations	1,880	1,880	1,660	1,660	220	220
R-squared	0.668	0.887	0.697	0.895	0.522	0.836
Time FE	yes	yes	yes	yes	yes	yes
Country FE	no	yes	no	yes	no	yes

Clustered standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

country-fixed effects are added. In the upper panel, the regression is run on quarterly data, in the lower panel on annual data. The estimated coefficients suggest that banks' trade finance claims are mainly driven by U.S. exports at a quarterly frequency, while U.S. imports also help explain the time variation at an annual frequency. The financing of U.S. exports seems to play a much bigger role than the financing of U.S. imports. According to Column 2, a 10 percent increase in annual exports makes the trade finance claims of U.S. banks rise by around 9 percent whereas the same change in imports increases claims by only 2 percent.

Columns (3) to (6) of table B.2 show the correlations between trade finance and imports and exports for offshore and non-offshore countries separately. While offshore countries' trade finance is significantly positively correlated with exports in the specification that only

Table B.3: Third country relevance, country-level regressions, 1997-2011

	(1)	(2)	(3)	(4)
$\log(\text{imp}_{ct})$	-0.0297 (0.0715)	0.0691 (0.0634)	-0.0688 (0.0742)	0.0603 (0.0596)
$\log(\text{exp}_{ct})$	0.851*** (0.0978)	0.468*** (0.113)	0.938*** (0.0948)	0.475*** (0.113)
$\log(\text{non-U.S. imp}_{ct})$	0.0893 (0.155)	0.644*** (0.173)	0.0220 (0.159)	0.616*** (0.190)
$\log(\text{non-U.S. exp}_{ct})$	-0.0844 (0.127)	0.258* (0.151)	0.0291 (0.139)	0.261 (0.159)
$\log(\text{GDPpc}_{ct})$			-0.235*** (0.0870)	0.163 (0.246)
Observations	1,854	1,854	1,802	1,802
R-squared	0.661	0.893	0.679	0.893
Time FE	yes	yes	yes	yes
Country FE	no	yes	no	yes

Clustered standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

includes time-fixed effects, standard errors increase substantially when country-fixed effects are added in column 6. As the number of observations drops when offshore countries are considered exclusively, insignificant results could be due to the small sample size. However, the relationships documented in section 3 of the paper are stronger when offshore centers are excluded. This supports the hypothesis that most offshore trade finance claims are not linked to real activity but are driven by other factors.

U.S. banks could also be engaged in the financing of third-party trade. To test for this, the log of non-U.S. exports and imports from and to the destination country c are included as controls. Results are displayed in table B.3. All columns include year-fixed effects. In columns (2) and (4), country-fixed effects are added. The coefficients on non-U.S. trade are significant. However, once the log of GDP per capita is controlled for, only the coefficient on non-U.S. imports remains significant at standard significance levels. This indicates that U.S. banks may also confirm letters of credit of foreign importers that trade with third parties.

Trade finance is a relationship intensive industry. Therefore, banks with foreign offices

may have an advantage when providing trade finance to foreign firms. We find evidence for this in the data. First, we check whether a bank has more trade finance with a country if it has FDI there. Thereto, the previous regression is now estimated at the bank-country level at a quarterly frequency, and a dummy is introduced that takes value 1 if a bank b has at least one foreign affiliate in country c at time t .⁴⁰ Second, we test whether the fact that a bank has FDI in a given country increases the correlation between U.S. exports and U.S. imports and the bank’s trade finance claims. To this end, interaction terms between the FDI dummy and the log of imports and the log of exports, respectively, are included in the regression. The regression equation reads as follows:

$$\begin{aligned} \log(tf_{bct}) &= \beta_1 \log(imp_{ct}) + \beta_2 \log(exp_{ct}) + \beta_3 \text{FDI dummy}_{bct} + \beta_4 \text{FDI dummy}_{bct} \times \log(imp_{ct}) \\ &+ \beta_5 \text{FDI dummy}_{bct} \times \log(exp_{ct}) + \alpha_b + (\alpha_c) + \alpha_{ct} + \epsilon_{bct} \end{aligned} \quad (\text{B.1})$$

Table B.4 reports the results. Columns (1) and (3) control for time- and bank-fixed effects. In columns (2) and (4), country×time-fixed effects are included in addition to bank-fixed effects. Columns (1) and (2) display the results of regressions that only include the FDI dummy. Its effect is positive and highly significant. Hence banks that have at least one foreign affiliate in a destination country have larger trade finance claims in that country.

In column (3), the interaction terms are added as regressors. The corresponding coefficients suggest that the trade finance claims of banks co-vary more with imports from a given country if the bank has a foreign affiliate in that country. The covariation between trade finance claims and U.S. exports, however, is not changed by FDI. The results remain unchanged when country×time-fixed effects are included in column (4). This indicates that foreign offices mainly supply financing in support of U.S. imports, that is, to foreign exporters. Loans to foreign importers by foreign affiliates seem to be less relevant.

These results together with the arguments made before imply that letters of credit and similar guarantees that support U.S. exports are the most important component in the data.

⁴⁰Information on whether a bank has at least one foreign affiliate in a country is inferred from the FFIEC 009 report. The dummy takes value 1 if bank b has positive local assets or liabilities vis-a-vis residents of a country c in period t .

Table B.4: The effect of FDI on trade finance, bank-level regressions, 1997-2011

	(1)	(2)	(3)	(4)
$\log(\text{imp}_{ct})$	0.0449 (0.0302)		-0.0329 (0.0314)	
$\log(\text{exp}_{ct})$	0.241*** (0.0370)		0.260*** (0.0371)	
FDI_{cbt}	0.569*** (0.0874)	0.762*** (0.0626)	-0.463* (0.259)	-0.448 (0.318)
$\text{FDI}_{cbt} \times \text{imp}_{ct}$			0.179*** (0.0555)	0.185*** (0.0666)
$\text{FDI}_{cbt} \times \text{exp}_{ct}$			-0.0406 (0.0692)	-0.0374 (0.0803)
Observations	33,923	57,913	33,923	33,923
R-squared	0.298	0.530	0.305	0.525
Time FE	yes	no	yes	no
Bank FE	yes	yes	yes	yes
Country \times time FE	no	yes	no	yes

Clustered (country-bank) standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Also included are pre-export loans extended to foreign firms, as well as guarantees for third party trade.

C Derivation of the Model

In the following, we derive the optimal contract choice between cash-in-advance, open account and letter of credit for the baseline model with fixed letter of credit fee f^{LC} . The model corresponds to the theory in Schmidt-Eisenlohr (2013). δ , the parameter that captures enforcement costs in the original model, is set to zero. For more details, including an extensive discussion of the underlying assumptions, see Schmidt-Eisenlohr (2013).

C.1 Cash-in-advance

There are two possible cases: a pooling case and a separating case. In the following, we first derive the optimal decision under pooling. We then study the separating case and derive the condition that assures pooling that is given in the main text.

Pooling case Under pooling, the exporter maximizes her expected profits, respecting the participation constraint of the importer. Expected profits between good and bad exporters differ because bad exporters are only forced to produce with probability λ :

$$\text{Good type: } \max_C \mathbb{E} \left[\Pi_{E,g}^{CIA,p} \right] = C^{CIA,p} - K, \quad (\text{C.1})$$

$$\text{Bad type: } \max_C \mathbb{E} \left[\Pi_{E,b}^{CIA,p} \right] = C^{CIA,p} - \lambda K, \quad (\text{C.2})$$

s.t.

$$\mathbb{E} \left[\Pi_I^{CIA,p} \right] = \frac{\eta + (1 - \eta)\lambda}{1 + r^*} R - C^{CIA,p} \geq 0, \quad (\text{C.3})$$

(participation constraint importer)

$$\mathbb{E} \left[\Pi_{E,g}^{CIA,p} \right] = C^{CIA,p} - K \geq 0. \quad (\text{C.4})$$

(participation constraint good exporter)

The optimal payment $C^{CIA,p}$ and optimal expected profits of a good and bad exporter, respectively, are:

$$C^{CIA,p} = \frac{\eta + (1 - \eta)\lambda}{1 + r^*} R, \quad (C.5)$$

$$\text{Good type: } E \left[\Pi_{E,g}^{CIA,p} \right] = \frac{\eta + (1 - \eta)\lambda}{1 + r^*} R - K, \quad (C.6)$$

$$\text{Bad type: } E \left[\Pi_{E,b}^{CIA,p} \right] = \frac{\eta + (1 - \eta)\lambda}{1 + r^*} R - \lambda K. \quad (C.7)$$

Separating First, note that if a good exporter chooses cash-in-advance, a bad exporter always chooses it as well and imitates the good type. This is strictly preferable to revealing her type as a higher pre-payment is received at no additional cost. If, however, good firms do not choose cash-in-advance, a bad firm might want to deviate and choose this contract. This case is considered in the following.

Suppose a good exporter does not choose cash-in-advance. Given the ability to default on the contract, a bad firm might still consider it optimal to offer a cash-in-advance contract, even though this implies revelation of her type. In this case, the importer understands that she deals with a bad firm and adjusts her expected revenue downwards. Her participation constraint becomes:

$$E \left[\Pi_I^{CIA,s} \right] = \frac{\lambda}{1 + r^*} R - C^{CIA,s} \geq 0. \quad (C.8)$$

The pre-payment that makes the participation constraint of the importer bind is:

$$C^{CIA,s} = \frac{\lambda}{1 + r^*} R. \quad (C.9)$$

The expected profit of a bad exporter in the separating case with CIA is thus:

$$E \left[\Pi_{E,b}^{CIA,s} \right] = \frac{\lambda}{1 + r^*} R - \lambda K. \quad (C.10)$$

A sufficient condition for the bad exporter not to choose cash-in-advance is that her expected profits in the separating case are less than the expected profits of a good firm in the pooling

case. That is if:

$$\mathbb{E} \left[\Pi_{E,g}^{CIA,p} \right] > \mathbb{E} \left[\Pi_{E,b}^{CIA,s} \right]. \quad (\text{C.11})$$

Substituting the expected profits into the inequality above and rearranging delivers the condition from the main text:

$$\frac{R}{K} > \frac{1 + r^*}{\eta}. \quad (\text{C.12})$$

C.2 Open account

Now, the exporter can choose between a pooling and a separating strategy. Pooling refers to the case where good and bad importers accept the proposed contract. In the separating case, only bad importers agree to buy the goods at the offered price. In the following, both cases are analyzed and then the pooling condition is derived.

Pooling case

$$\max_C \mathbb{E} \left[\Pi_E^{OA} \right] = \frac{\eta^* + (1 - \eta^*)\lambda^*}{1 + r} C^{OA} - K, \quad (\text{C.13})$$

s.t.

$$\mathbb{E} \left[\Pi_{I,g}^{OA} \right] = R - C^{OA} \geq 0 \quad (\text{C.14})$$

(participation constraint good importer).

It is optimal for the exporter to choose C^{OA} such that the participation constraint of the good importer binds. This implies:

$$C^{OA} = R, \quad (\text{C.15})$$

$$\mathbb{E} \left[\Pi_E^{OA} \right] = \frac{\eta^* + (1 - \eta^*)\lambda^*}{1 + r} R - K. \quad (\text{C.16})$$

Separating The separating case implies the following participation constraint for a bad importer:

$$\mathbb{E} \left[\Pi_{I,b}^{OA,s} \right] = \frac{R - \lambda^* C^{OA}}{1 + r^*} \geq 0. \quad (\text{C.17})$$

A binding participation constraint of a bad importer implies:

$$C^{OA,s} = \frac{R}{\lambda^*}. \quad (\text{C.18})$$

The prepayment C^{OA} exactly offsets the the risk of non-payment by the importer. In expectation the importer thus pays R to the exporter. Expected profits of the exporter are, however, reduced as good importers reject the contract and only bad importers (share $1 - \eta^*$) accept it. Thus expected profits are:

$$\mathbb{E} \left[\Pi_E^{OA,s} \right] = (1 - \eta^*) \left(\frac{1}{1 + r} R - K \right). \quad (\text{C.19})$$

Comparing profits, an exporter strictly prefers a pooling contract if:

$$\frac{R}{K} > \frac{\eta^*(1 + r)}{\eta^* - (1 - \eta^*)(1 - \lambda^*)}. \quad (\text{C.20})$$

C.3 Letter of credit

Under the maintained assumption of perfect third party verifiability, with a letter of credit, the commitment problem between the exporter and the importer is fully resolved. The maximization problem is:

$$\max_C \mathbb{E} \left[\Pi_E^{LC} \right] = \frac{C^{LC}}{1 + r} - K, \quad (\text{C.21})$$

$$\text{s.t. } \mathbb{E} \left[\Pi_I^{LC} \right] = \frac{R - C^{LC}}{1 + r^*} - f^{LC} C^{LC} \geq 0 \quad (\text{participation constraint importer}). \quad (\text{C.22})$$

In the optimum, the participation constraint of the importer binds. The optimal payment and expected profits are:

$$C^{LC} = \frac{R}{1 + f^{LC}(1 + r^*)}, \quad (\text{C.23})$$

$$\Pi_E^{LC} = \frac{R}{(1 + f^{LC}(1 + r^*))(1 + r)} - K \quad (\text{C.24})$$

D Proofs

Profit factors First, note that to compare the attractiveness of the three payment contracts, it is sufficient to compare the expression in front of R , which, in the following, is denoted by π and is called the profit factor.⁴¹ The profit factors under the three payment forms are:

$$\pi^{CIA} = \frac{\tilde{\lambda}}{1+r^*} \quad (D.1)$$

$$\pi^{OA} = \frac{\tilde{\lambda}^*}{1+r} \quad (D.2)$$

$$\pi^{LC} = \frac{1}{(1+r)[1+(m+\alpha(1-\tilde{\lambda}^*))(1+r^*)]} \quad (D.3)$$

Proof of proposition 1 **Proof.** From before, $\tilde{\lambda}^* = \frac{\gamma^*}{V}$ and $\tilde{\lambda} = \frac{\gamma}{V}$. The difference between the profit factors of cash-in-advance and letter of credit is:

$$\pi^{CIA} - \pi^{LC} = \frac{\gamma}{V(1+r^*)} - \frac{1}{(1+r)[1+(m+\alpha(1-\gamma^*/V))(1+r^*)]} \quad (D.4)$$

Taking the derivative with respect to V gives:

$$\frac{\partial(\pi^{CIA} - \pi^{LC})}{\partial V} = -\frac{\gamma}{V^2(1+r^*)} - \frac{(1+r^*)\alpha\gamma^*/V^2}{(1+r)^2[1+(m+\alpha(1-\gamma^*/V))(1+r^*)]^2} \quad (D.5)$$

The derivative is smaller than zero if:

$$\alpha < \frac{1+r}{(1+r^*)^2} \frac{\tilde{\lambda}}{\tilde{\lambda}^*} [1+f(1+r^*)]^2 \quad (D.6)$$

Note that $f \geq 0$. A sufficient condition is thus:

$$\alpha < \frac{1+r}{(1+r^*)^2} \frac{\tilde{\lambda}}{\tilde{\lambda}^*} \quad (D.7)$$

⁴¹These factors are sufficient because under pooling the equilibrium contract only depends on the optimal choice of a good exporters. Bad exporters imitate whichever contract is optimally chosen by good firms.

The difference between the profit factors of open account and letter of credit is:

$$\pi^{OA} - \pi^{LC} = \frac{\gamma^*}{V(1+r)} - \frac{1}{(1+r)[1+(m+\alpha(1-\gamma^*/V))(1+r^*)]} \quad (D.8)$$

Taking the derivative with respect to V gives:

$$\frac{\partial(\pi^{OA} - \pi^{LC})}{\partial V} = -\frac{\gamma^*}{V^2(1+r)} - \frac{(1+r^*)\alpha\gamma^*/V^2}{(1+r)^2[1+(m+\alpha(1-\gamma^*/V))(1+r^*)]^2} \quad (D.9)$$

The derivative is smaller than zero if:

$$\alpha < \frac{1}{1+r^*}[1+f(1+r^*)]^2 \quad (D.10)$$

Note that $f \geq 0$. A sufficient condition is thus:

$$\alpha < \frac{1}{1+r^*} \quad (D.11)$$

■

Proof of proposition 2 Proof. From before, $(1+r) = 1+\rho+L$, and $1+r^* = 1+\rho^*+L$.

Then the profit factors are:

$$\pi^{CIA} = \frac{\tilde{\lambda}}{1+\rho^*+L} \quad (D.12)$$

$$\pi^{OA} = \frac{\tilde{\lambda}^*}{1+\rho+L} \quad (D.13)$$

$$\pi^{LC} = \frac{1}{(1+\rho+L)[1+f^{LC}(1+\rho^*+L)]} \quad (D.14)$$

Now, the taking the difference between the profit factors of cash-in-advance and letter of credit delivers:

$$\pi^{CIA} - \pi^{LC} = \frac{\tilde{\lambda}}{1+\rho^*+L} - \frac{1}{(1+\rho+L)[1+f^{LC}(1+\rho^*+L)]} \quad (D.15)$$

Taking the derivative with respect to L gives:

$$\frac{\partial(\pi^{CIA} - \pi^{LC})}{\partial L} = -\frac{\tilde{\lambda}}{(1 + \rho^* + L)^2} + \frac{1 + f^{LC}(2 + \rho + \rho^* + 2L)}{[(1 + \rho + L)[1 + f^{LC}(1 + \rho^* + L)]]^2} \quad (\text{D.16})$$

Plugging the interest rates back in yields:

$$\frac{\partial(\pi^{CIA} - \pi^{LC})}{\partial L} = -\frac{\tilde{\lambda}}{(1 + r^*)^2} + \frac{1 + f^{LC}[(1 + r) + (1 + r^*)]}{[(1 + r)[1 + f^{LC}(1 + r^*)]]^2} \quad (\text{D.17})$$

Which is strictly larger than 0 iff:

$$\tilde{\lambda} < \left(\frac{1 + r^*}{1 + r}\right)^2 \frac{1 + f^{LC}[(1 + r) + (1 + r^*)]}{[1 + f^{LC}(1 + r^*)]^2} \quad (\text{D.18})$$

The difference between the profit factors of open account and letter of credit is:

$$\pi^{OA} - \pi^{LC} = \frac{\tilde{\lambda}^*}{1 + \rho + L} - \frac{1}{(1 + \rho + L)[1 + f^{LC}(1 + \rho^* + L)]} \quad (\text{D.19})$$

Taking the derivative with respect to L gives:

$$\frac{\partial(\pi^{OA} - \pi^{LC})}{\partial L} = -\frac{\tilde{\lambda}^*}{(1 + \rho + L)^2} + \frac{1 + f^{LC}[(1 + \rho + L) + (1 + \rho^* + L)]}{[(1 + \rho + L)[1 + f^{LC}(1 + \rho^* + L)]]^2} \quad (\text{D.20})$$

Plugging the interest rates back in leads to:

$$\frac{\partial(\pi^{OA} - \pi^{LC})}{\partial L} = -\frac{\tilde{\lambda}^*}{(1 + r)^2} + \frac{1 + f^{LC}[(1 + r) + (1 + r^*)]}{[(1 + r)[1 + f^{LC}(1 + r^*)]]^2} \quad (\text{D.21})$$

Which is strictly larger than 0 iff:

$$\tilde{\lambda}^* < \frac{1 + f^{LC}[(1 + r) + (1 + r^*)]}{[1 + f^{LC}(1 + r^*)]^2} \quad (\text{D.22})$$

■

Proof of proposition 3 Proof. We begin by deriving a useful corollary.

Corollary 1 *Suppose $\alpha < \frac{1}{1+r^*}$. Then, expected profits from cash-in-advance, open account*

and letter of credit change in the destination country payment probability $\tilde{\lambda}^*$ in the following way:

$$\frac{\partial \Pi^{OA}}{\partial \tilde{\lambda}^*} > \frac{\partial \Pi^{LC}}{\partial \tilde{\lambda}^*} > \frac{\partial \Pi^{CIA}}{\partial \tilde{\lambda}^*} = 0 \quad (\text{D.23})$$

It is easy to see that $\frac{\partial \pi^{CIA}}{\partial \tilde{\lambda}^*} = 0$ and that $\frac{\partial \pi^{LC}}{\partial \tilde{\lambda}^*} > 0$ and $\frac{\partial \pi^{OA}}{\partial \tilde{\lambda}^*} > 0$. It therefore remains to be shown that $\frac{\partial \Pi^{OA}}{\partial \tilde{\lambda}^*} > \frac{\partial \Pi^{LC}}{\partial \tilde{\lambda}^*}$. Begin by taking the difference of the profit factors of open account and letter of credit:

$$\pi^{OA} - \pi^{LC} = \frac{\tilde{\lambda}^*}{1+r} - \frac{1}{(1+r)[1+(m+\alpha(1-\tilde{\lambda}^*))(1+r^*)]} \quad (\text{D.24})$$

Taking the derivative with respect to $\tilde{\lambda}^*$ gives:

$$\frac{\partial \pi^{OA} - \pi^{LC}}{\partial \tilde{\lambda}^*} = \frac{1}{1+r} - \frac{(1+r^*)\alpha}{(1+r)[1+(m+\alpha(1-\tilde{\lambda}^*))(1+r^*)]^2} \quad (\text{D.25})$$

The derivative is larger than zero if:

$$\alpha < \frac{(1+f(1+r^*))^2}{1+r^*} \quad (\text{D.26})$$

As $f \leq 0$, a sufficient condition for this is:

$$\alpha < \frac{1}{1+r^*} \quad (\text{D.27})$$

The corollary states that as long as banks are sufficiently efficient in reducing risk through letters of credit (small α), the profitability of contracts changes with an increase in the destination country payment probability $\tilde{\lambda}^*$ in the following way: profits from open account increase the most, profits from letter of credit increase by less and profits from cash-in-advance remain unaffected. We can now prove the main result of Proposition 3. $\alpha < \frac{1}{1+r^*}$ implies the ordering of first derivatives as described in corollary 1. If each payment contract is used for some $\tilde{\lambda}^*$, the slopes imply the following order: cash-in-advance for $\forall \tilde{\lambda}^* \leq \bar{\lambda}_1^*$. Open account for $\forall \tilde{\lambda}^* \geq \bar{\lambda}_2^* > \bar{\lambda}_1^*$. Letter of credit for $\forall \tilde{\lambda}^* \in (\bar{\lambda}_1^*, \bar{\lambda}_2^*)$. ■

Table 1: Importance of trade finance business for U.S. banks

	trade finance in \$mio	share in total assets	share in foreign assets
2006 q1			
N	21	21	21
mean	1038.1	.00121	12.76
sd	2254.1	.00168	18.95
2012 q1			
N	19	19	19
mean	3852.6	.00161	9.39
sd	7360.0	.00248	14.40

Table 2: The effect of global risk and funding costs on aggregate trade finance, 1998-2011

	(1)	(2)	(3)	(4)
log(imp_t)	-0.361 (0.232)	-0.972*** (0.276)	-0.151 (0.225)	0.504** (0.189)
log(exp_t)	2.201*** (0.173)	2.259*** (0.267)	2.009*** (0.195)	1.605*** (0.158)
log(GDP_t)	-1.900*** (0.378)	-0.430 (0.382)	-1.900*** (0.305)	-2.514*** (0.261)
log(LIBOR_t)	-0.164*** (0.0201)		-0.157*** (0.0168)	
log(VIX_t)		0.175** (0.0656)	0.127*** (0.0357)	0.0875*** (0.0313)
log(fed funds_t)				-0.152*** (0.0126)
Constant	42.47*** (8.230)	6.680 (7.730)	41.74*** (6.581)	56.04*** (5.904)
Observations	56	56	56	46
R-squared	0.912	0.809	0.925	0.965

Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: The effect of time to trade on bank trade finance

	OLS			IV					
	(1)	(2)	(3)	first (4)	second (5)	first (6)	second (7)	first (8)	second (9)
$\log(\text{population}_c)$				0.771*** (0.0889)		0.739*** (0.0827)		0.921*** (0.0677)	
$\log(\text{exp}_{ct})$	0.859*** (0.0386)	0.933*** (0.0486)	1.029*** (0.0465)		1.119*** (0.0772)		1.242*** (0.0892)		1.149*** (0.0715)
$\log(\text{dist}_c)$	0.502** (0.207)	0.911*** (0.205)	0.853*** (0.207)	-1.767*** (0.301)	0.858*** (0.236)	-1.758*** (0.314)	1.348*** (0.244)	-1.374*** (0.207)	0.957*** (0.216)
sea share _{ct}		0.911** (0.431)				-3.116*** (0.630)	1.933*** (0.558)		
$\log(\text{time to import}_{ct})$			0.822*** (0.171)					-2.071*** (0.202)	1.043*** (0.207)
Observations	1,649	686	667	1,649	1,649	686	686	667	667
R-squared	0.711	0.716	0.743	0.349	0.648	0.417	0.643	0.667	0.734

Clustered standard errors in parentheses. Regression include time-fixed effects.

*** p<0.01, ** p<0.05, * p<0.1

Table 4: The effect of country risk on bank trade finance, EIU risk measure, OLS

	(1)	(2)	(3)	(4)
$\log(\text{exp}_{ct})$	0.994*** (0.0538)	0.995*** (0.124)	0.992*** (0.0545)	1.004*** (0.123)
$\log(\text{distance}_c)$	0.172 (0.257)		0.235 (0.256)	
$\log(\text{GDPpc}_{ct})$	-0.411*** (0.141)	0.745*** (0.282)	-0.344*** (0.152)	0.734** (0.285)
risk_{ct}	-0.0106 (0.0118)	0.0196* (0.0113)	0.0931* (0.0497)	0.0889* (0.0466)
risk_{ct}^2			-0.00104*** (0.000457)	-0.000712 (0.000476)
Observations	910	910	910	910
R-squared	0.683	0.900	0.691	0.901
Time FE	yes	yes	yes	yes
Country FE	no	yes	no	yes

Clustered standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 5: The effect of country risk on bank trade finance, EIU risk measure, IV

	first (1)	second (2)	first (3)	second (4)	first (5)	second (6)	first (7)	second (8)
$\log(\text{population}_{ct})$	1.002*** (0.0747)		1.327*** (0.283)		1.011*** (0.0744)		1.307*** (0.284)	
$\log(\text{exp}_{ct})$		1.073*** (0.0782)		2.205*** (0.463)		1.059*** (0.0759)		2.342*** (0.435)
$\log(\text{GDPpc}_{ct})$	1.021*** (0.103)	-0.453*** (0.148)	0.526*** (0.135)	0.170 (0.357)	0.985*** (0.108)	-0.380*** (0.156)	0.526*** (0.135)	0.0967 (0.360)
$\log(\text{distance}_c)$	-1.177*** (0.272)	0.220 (0.257)			-1.220*** (0.269)	0.274 (0.254)		
risk_{ct}	-0.00301 (0.0110)	-0.00891 (0.0115)	-0.0110** (0.00518)	0.0370*** (0.0142)	-0.0652 (0.0756)	0.0936* (0.0491)	-0.0209 (0.0180)	0.131** (0.0518)
risk_{ct}^2					0.000627 (0.000698)	-0.00103*** (0.000451)	0.000102 (0.000185)	-0.000953* (0.000511)
Observations	910	910	910	910	910	910	910	910
R-squared	0.698	0.679	0.969	0.859	0.702	0.688	0.969	0.852
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Country FE	no	no	yes	yes	no	no	yes	yes

Clustered standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Determinants of entry into the trade finance business

	number of banks		minimum bank size		share of top 3 players			
	qrtly OLS (1)	annl OLS (2)	qrtly OLS (4)	annl OLS (5)	qrtly OLS (7)	annl OLS (8)	annl IV (9)	
$\log(\exp_{ct})$	0.352*** (0.0241)	0.337*** (0.0212)	0.340*** (0.0260)	-0.866*** (0.0700)	-0.924*** (0.0708)	-0.807*** (0.109)	-0.0388*** (0.00762)	-0.0388*** (0.00668)
$\log(\text{GDPpc}_{ct})$	-0.0469 (0.0456)	-0.0495 (0.0433)	-0.0513 (0.0444)	0.213 (0.158)	0.150 (0.161)	0.184 (0.168)	-0.0249 (0.0185)	-0.0255 (0.0181)
$\log(\text{distance}_c)$	0.0438 (0.0754)	0.0400 (0.0756)	0.0416 (0.0752)	0.477* (0.284)	0.409 (0.290)	0.505* (0.290)	0.0939*** (0.0315)	0.0934*** (0.0326)
sea share _{ct}	0.535** (0.214)	0.534** (0.228)	0.535** (0.223)	-0.654 (0.761)	-0.621 (0.692)	-0.629 (0.761)	-0.112* (0.0672)	-0.109 (0.0736)
risk _{ct}	0.0291 (0.0179)	0.0111 (0.0183)	0.0110 (0.0181)	-0.106* (0.0603)	-0.132** (0.0577)	-0.107* (0.0590)	-0.0137** (0.00592)	-0.0110* (0.00583)
risk _{ct} ²	-0.000440** (0.000170)	-0.000249 (0.000170)	-0.000247 (0.000169)	0.00138** (0.000616)	0.00155** (0.000630)	0.00139** (0.000607)	0.000129** (5.77e-05)	0.000100* (5.39e-05)
Observations	1,747	463	463	443	1,699	443	1,661	450
R-squared	0.702	0.751	0.751	0.553	0.496	0.551	0.249	0.315

Clustered standard errors in parentheses. Regressions include time-fixed effects.

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Heterogeneous responses to changes in the VIX, EIU risk measure

	OLS (1)	OLS (2)	IV (3)	OLS (4)	OLS (5)	IV (6)
$\log(\text{exp}_{ct})$	0.889*** (0.130)	0.889*** (0.129)	1.052** (0.483)	0.999*** (0.124)	1.000*** (0.123)	2.282*** (0.438)
$\log(\text{VIX}_t)$	0.690* (0.397)	2.219* (1.208)	2.167* (1.132)			
$\log(\text{LIBOR}_t)$	0.0449 (0.0368)	0.0441 (0.0368)	0.0453 (0.0357)			
$\log(\text{GDPpc}_{ct})$	-0.0554 (0.215)	-0.0512 (0.214)	-0.201 (0.463)	0.766*** (0.290)	0.776*** (0.285)	0.157 (0.359)
risk_{ct}	0.102** (0.0485)	0.327* (0.171)	0.330** (0.158)	0.119** (0.0512)	0.374** (0.176)	0.423*** (0.164)
risk_{ct}^2	-0.000454 (0.000462)	-0.00296 (0.00182)	-0.00298* (0.00167)	-0.000531 (0.000476)	-0.00337* (0.00191)	-0.00384** (0.00175)
$\text{risk}_{ct} \times \log(\text{VIX}_t)$	-0.0145* (0.00817)	-0.0872 (0.0542)	-0.0863* (0.0504)	-0.0152* (0.00853)	-0.0975* (0.0566)	-0.0986* (0.0542)
$(\text{risk}_{ct})^2 \times \log(\text{VIX}_t)$		0.000804 (0.000582)	0.000802 (0.000537)		0.000912 (0.000617)	0.000971* (0.000577)
Observations	910	910	910	910	910	910
R-squared	0.894	0.895	0.894	0.901	0.902	0.857
Time FE	no	no	no	yes	yes	yes
Country FE	yes	yes	yes	yes	yes	yes

Clustered standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Heterogeneous responses to changes in the LIBOR, EIU risk measure

	OLS (1)	IV (2)	OLS (3)	IV (4)
$\log(\text{exp}_{ct})$	0.904*** (0.131)	1.077** (0.443)	1.017*** (0.127)	2.286*** (0.448)
$\log(\text{VIX}_t)$	0.00960 (0.0895)	-0.00738 (0.0820)		
$\log(\text{LIBOR}_t)$	-0.262* (0.147)	-0.272* (0.141)		
$\log(\text{GDPpc}_{ct})$	-0.0518 (0.211)	-0.209 (0.426)	0.769*** (0.280)	0.180 (0.354)
risk_{ct}	0.0572 (0.0435)	0.0611 (0.0405)	0.0731 (0.0444)	0.108** (0.0494)
risk_{ct}^2	-0.000504 (0.000450)	-0.000525 (0.000416)	-0.000586 (0.000454)	-0.000769 (0.000487)
$\text{risk}_{ct} \times \log(\text{LIBOR}_t)$	0.00655** (0.00306)	0.00680** (0.00296)	0.00697** (0.00298)	0.00943** (0.00378)
Observations	910	910	910	910
R-squared	0.895	0.894	0.902	0.858
Time FE	no	no	yes	yes
Country FE	yes	yes	yes	yes

Clustered standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 9: The effect of country risk on bank trade finance, Alliant risk measure

	OLS			IV				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(\text{exp}_{ct})$	0.968*** (0.0503)	0.765*** (0.108)	0.963*** (0.0507)	0.776*** (0.108)	1.071*** (0.0728)	1.691** (0.699)	1.080*** (0.0702)	1.529** (0.657)
$\log(\text{distance}_c)$	0.469** (0.226)		0.476** (0.205)		0.550** (0.232)		0.567*** (0.215)	
$\log(\text{GDPpc}_{ct})$	-0.187 (0.119)	0.161 (0.315)	-0.140 (0.127)	0.128 (0.317)	-0.298** (0.133)	-0.253 (0.447)	-0.266* (0.136)	-0.229 (0.441)
repayment_{ct}	-0.0142* (0.00784)	0.00134 (0.00866)	0.0287 (0.0255)	-0.0242 (0.0277)	-0.0129* (0.00780)	-0.0110 (0.0132)	0.0280 (0.0251)	-0.0522 (0.0405)
repayment_{ct}^2			-0.000418 (0.000263)	0.000305 (0.000315)			-0.000397 (0.000261)	0.000521 (0.000398)
Observations	820	820	820	820	820	820	820	820
R-squared	0.723	0.925	0.728	0.926	0.717	0.903	0.720	0.911
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Country FE	no	yes	no	yes	no	yes	no	yes

Clustered standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 10: Heterogeneous responses to changes in the VIX, Alliant risk measure

	OLS (1)	OLS (2)	OLS (3)	IV (4)	OLS (5)	OLS (6)	IV (7)
$\log(\exp_{ct})$	0.744*** (0.107)	0.751*** (0.106)	0.753*** (0.103)	1.094** (0.540)	0.798*** (0.106)	0.802*** (0.104)	1.610*** (0.588)
$\log(\text{VIX}_t)$	0.0401 (0.105)	-0.508* (0.288)	0.795 (0.629)	0.757 (0.578)			
$\log(\text{LIBOR}_t)$	-0.00300 (0.0377)	-0.00378 (0.0377)	-0.00304 (0.0377)	-0.00596 (0.0368)			
$\log(\text{GDPpc}_{ct})$	-0.129 (0.199)	-0.0992 (0.202)	-0.0764 (0.197)	-0.443 (0.584)	0.275 (0.320)	0.324 (0.312)	0.00449 (0.393)
repayment_{ct}	-0.0219 (0.0271)	-0.0611** (0.0307)	0.106 (0.0803)	0.0941 (0.0772)	-0.0736** (0.0316)	0.0967 (0.0830)	0.0654 (0.0844)
repayment_{ct}^2	0.000310 (0.000308)	0.000421 (0.000301)	-0.00109 (0.000771)	-0.00100 (0.000726)	0.000440 (0.000310)	-0.00110 (0.000788)	-0.000971 (0.000755)
$\text{repayment}_{ct} \times \log(\text{VIX}_t)$		0.0102** (0.00510)	-0.0449* (0.0251)	-0.0454** (0.0226)	0.0127** (0.00524)	-0.0435* (0.0260)	-0.0442* (0.0244)
$\text{repayment}_{ct}^2 \times \log(\text{VIX}_t)$			0.000501** (0.000229)	0.000512** (0.000206)		0.000511** (0.000234)	0.000560** (0.000218)
Observations	820	820	820	820	820	820	820
R-squared	0.925	0.926	0.927	0.924	0.927	0.928	0.911
Time FE	no	no	no	no	yes	yes	yes
Country FE	yes	yes	yes	yes	yes	yes	yes

Clustered standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 11: Heterogeneous responses to changes in the LIBOR, Alliant risk measure

	OLS (1)	OLS (2)	IV (3)	OLS (4)	OLS (5)	IV (6)
$\log(\exp_{ct})$	0.765*** (0.105)	0.773*** (0.105)	1.065** (0.520)	0.815*** (0.106)	0.824*** (0.106)	1.564*** (0.569)
$\log(\text{VIX}_t)$	0.00745 (0.105)	0.00643 (0.104)	-0.0180 (0.103)			
$\log(\text{LIBOR}_t)$	0.271*** (0.101)	-0.0172 (0.205)	-0.0352 (0.191)			
$\log(\text{GDPpc}_{ct})$	-0.0831 (0.201)	-0.0793 (0.199)	-0.388 (0.554)	0.307 (0.314)	0.326 (0.311)	0.0419 (0.376)
repayment_{ct}	-0.0342 (0.0274)	-0.0413 (0.0278)	-0.0540 (0.0363)	-0.0385 (0.0283)	-0.0460 (0.0288)	-0.0798* (0.0419)
repayment_{ct}^2	0.000513* (0.000307)	0.000596* (0.000314)	0.000718* (0.000383)	0.000528* (0.000318)	0.000616* (0.000326)	0.000920** (0.000423)
$\text{repayment}_{ct} \times \log(\text{LIBOR}_t)$	-0.00537*** (0.00181)	0.00727 (0.00832)	0.00850 (0.00795)	-0.00602*** (0.00184)	0.00723 (0.00841)	0.0101 (0.00853)
$\text{repayment}_{ct}^2 \times \log(\text{LIBOR}_t)$		-0.000118 (7.82e-05)	-0.000134* (7.74e-05)		-0.000124 (7.85e-05)	-0.000168** (8.31e-05)
Observations	820	820	820	820	820	820
R-squared	0.927	0.928	0.925	0.928	0.929	0.915
Time FE	no	no	no	yes	yes	yes
Country FE	yes	yes	yes	yes	yes	yes

Clustered standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 12: Controlling for log(trade)

	OLS (1)	OLS (2)	IV (3)	IV (4)	OLS (5)	OLS (6)	IV (7)	IV (8)
$\log(\text{trade}_{ct})$	0.874*** (0.0470)	0.914*** (0.0480)	1.148*** (0.0862)	1.092*** (0.0755)	0.904*** (0.0595)	1.002*** (0.152)	0.975*** (0.0825)	3.222*** (0.679)
$\log(\text{distance}_c)$	0.669*** (0.188)	0.605*** (0.205)	0.999*** (0.235)	0.729*** (0.228)	-0.0459 (0.243)		-0.0219 (0.245)	
sea share _{ct}	0.777* (0.446)		1.691*** (0.540)					
$\log(\text{time to imp}_{ct})$		0.499** (0.212)		0.798*** (0.234)				
$\log(\text{GDPpc}_{ct})$					-0.325** (0.160)	0.605* (0.318)	-0.365** (0.163)	-0.741 (0.696)
risk _{ct}					0.0753 (0.0600)	0.0878* (0.0495)	0.0745 (0.0587)	0.156*** (0.0528)
risk _{ct} ²					-0.000947 (0.000571)	-0.000759 (0.000486)	-0.000930* (0.000564)	-0.00126** (0.000519)
Observations	682	663	682	663	910	910	910	910
R-squared	0.687	0.695	0.624	0.672	0.643	0.896	0.640	0.782
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Country FE	no	no	no	no	no	yes	no	yes

Clustered standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 13: Trade finance intensity as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{distance}_c)$	0.878*** (0.196)	0.734*** (0.220)	0.240 (0.256)			
$\log(\text{GDPpc}_{ct})$			-0.348** (0.147)	0.736*** (0.260)	0.776*** (0.260)	0.777*** (0.256)
risk_{ct}			0.0931* (0.0497)	0.0887* (0.0471)	0.374** (0.175)	0.0726 (0.0448)
risk_{ct}^2			-0.00104** (0.000456)	-0.000711 (0.000478)	-0.00337* (0.00189)	-0.000584 (0.000456)
sea share_{ct}	1.553*** (0.441)					
$\log(\text{time to imp}_{ct})$		0.745*** (0.188)				
$\text{risk}_{ct} \times \log(\text{VIX}_t)$					-0.0975* (0.0565)	
$(\text{risk}_{ct})^2 \times \log(\text{VIX}_t)$					0.000912 (0.000615)	
$\text{risk}_{ct} \times \log(\text{LIBOR}_t)$						0.00694** (0.00295)
Observations	564	558	910	910	910	910
R-squared	0.161	0.214	0.170	0.733	0.736	0.736
Time FE	yes	yes	yes	yes	yes	yes
Country FE	no	no	no	yes	yes	yes

Clustered standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

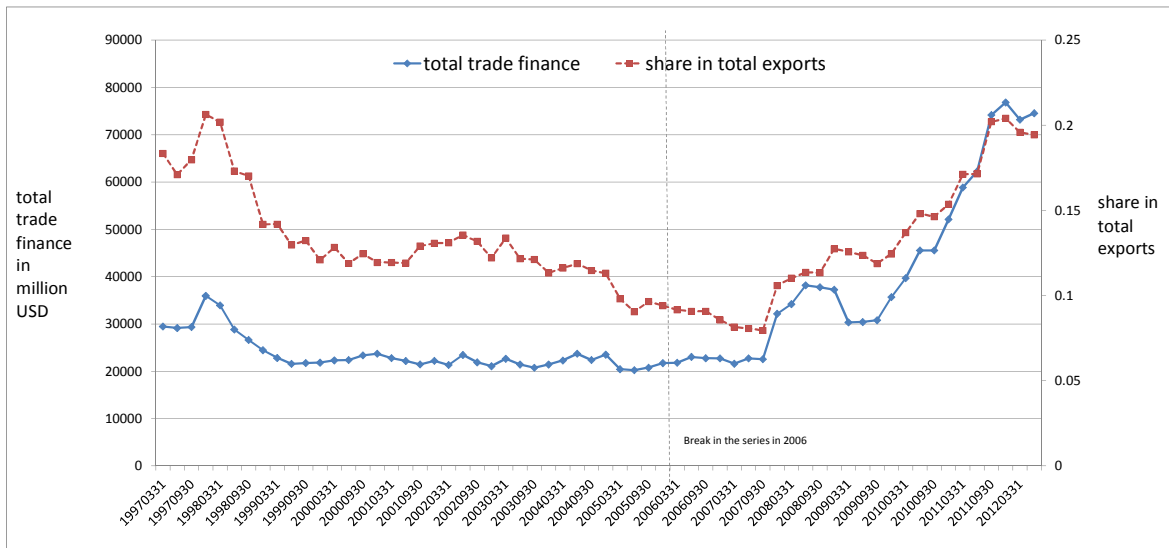
Table 14: Private credit over GDP as additional control

	(1)	(2)	(3)	(4)
$\log(\text{exp}_{ct})$	0.973*** (0.0489)	1.034*** (0.0461)	1.030*** (0.0608)	1.149*** (0.150)
$\log(\text{distance}_c)$	0.858*** (0.217)	0.822*** (0.216)	0.236 (0.253)	
$\log(\text{GDPp}_{ct})$			-0.308** (0.148)	0.594* (0.337)
private credit/GDP _{ct}	-0.00765*** (0.00273)	-0.00215 (0.00227)	-0.0103** (0.00452)	0.00299 (0.00540)
risk _{ct}			0.0641 (0.0493)	0.114** (0.0513)
risk _{ct} ²			-0.000856* (0.000454)	-0.000980* (0.000534)
sea share _{ct}	0.406 (0.508)			
$\log(\text{time to imp}_{ct})$		0.863*** (0.189)		
Observations	512	507	789	789
R-squared	0.728	0.755	0.714	0.910
Time FE	yes	yes	yes	yes
Country FE	no	no	no	yes

Clustered standard errors in parentheses

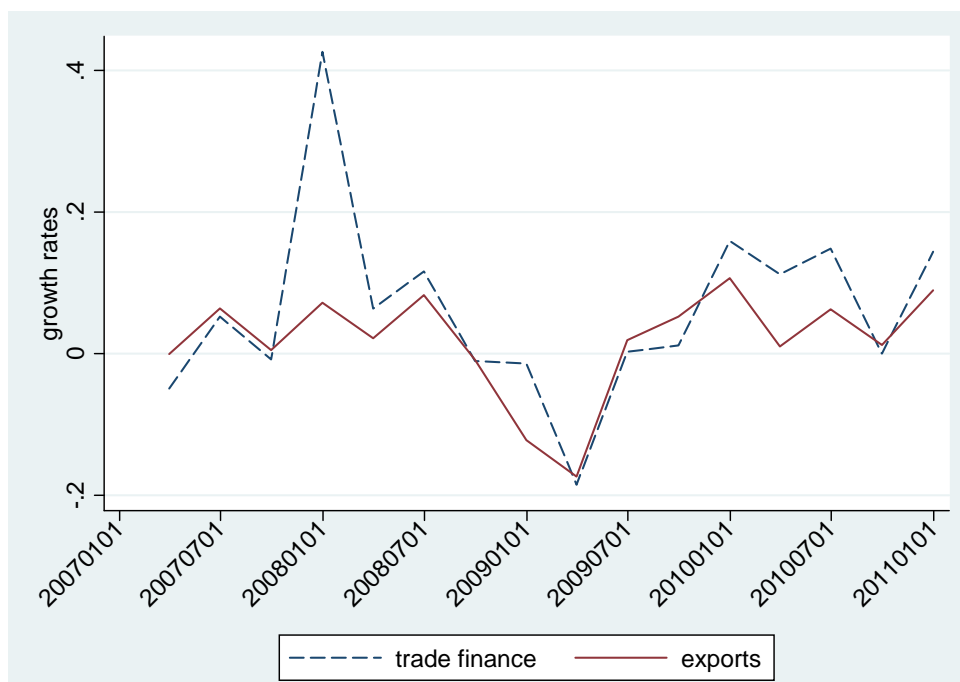
*** p<0.01, ** p<0.05, * p<0.1

Figure 1: Evolution of trade finance over time



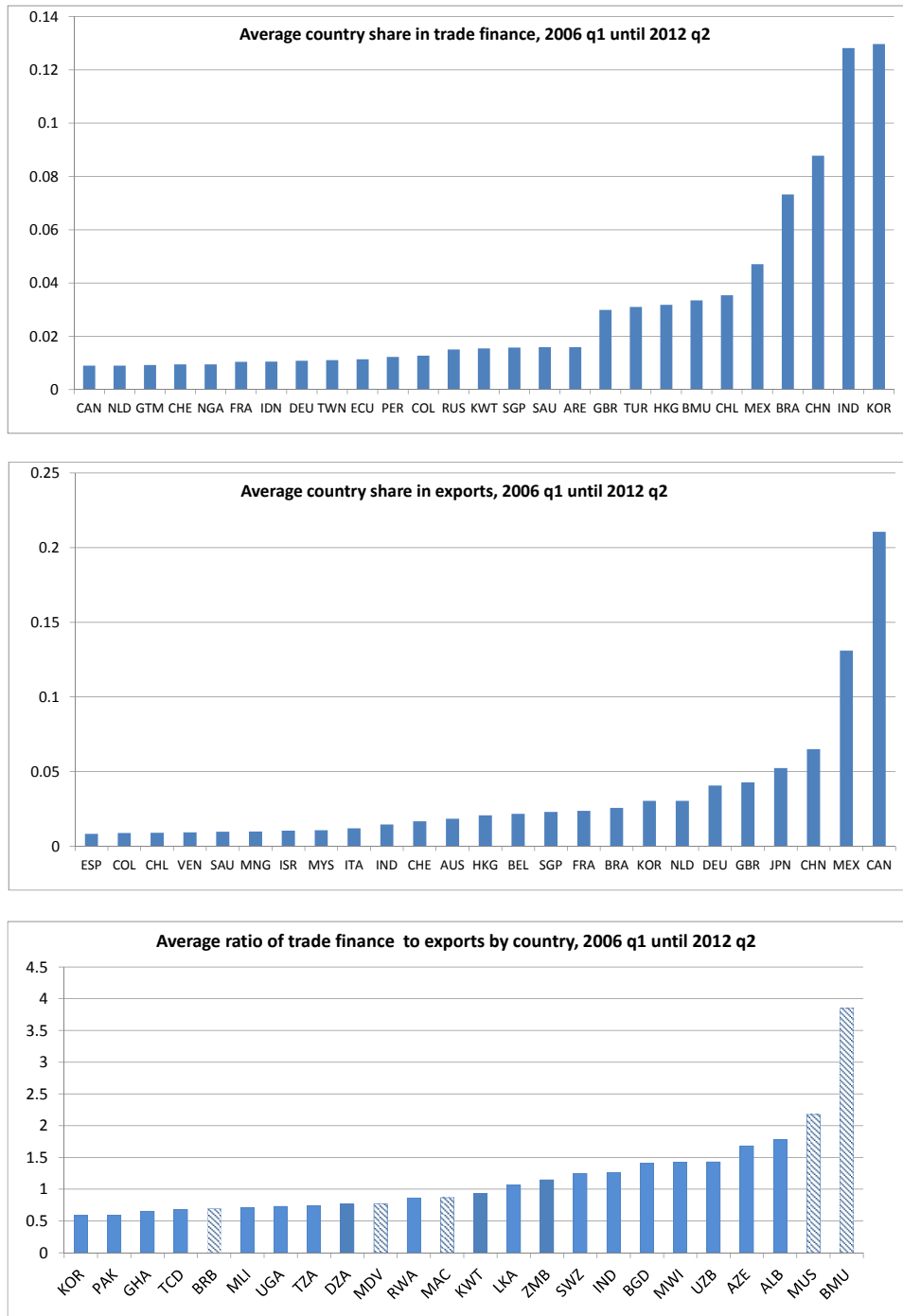
Note: The solid line in the graph shows the evolution of total trade finance claims from 1997 to 2012 (left *y*-axis). The dashed line corresponds to the share of total trade finance claims in total U.S. exports in goods (right *y*-axis). Data sources: FFIEC 009 Report, IMF Directions of Trade Statistics.

Figure 2: Trade finance and export growth during the crisis



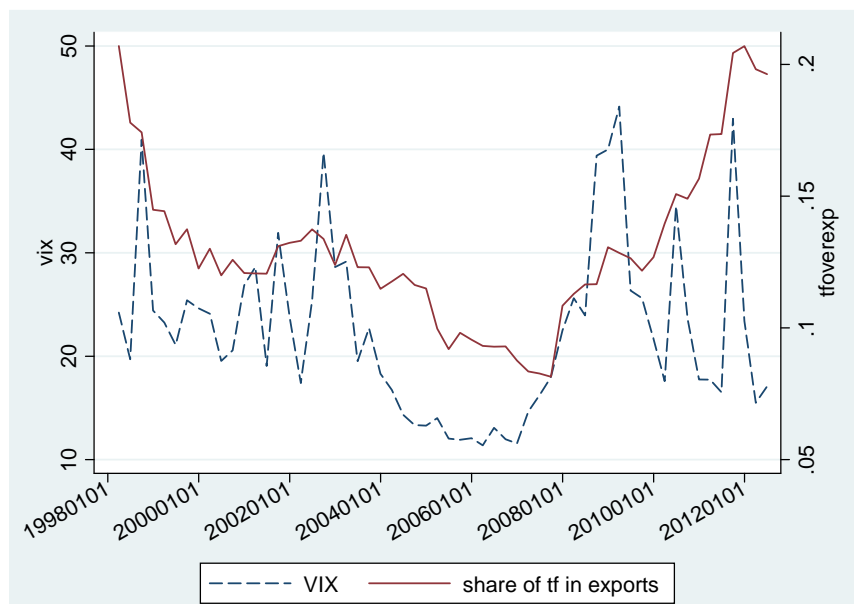
Note: The dashed line in the graph shows the quarterly growth rates of U.S. trade finance claims over the period from 2007 until 2010. The solid line displays the corresponding growth rates of U.S. exports in goods. Data sources: FFIEC 009 Report, IMF Directions of Trade Statistics.

Figure 3: Top countries in terms of trade finance, exports and trade finance intensity



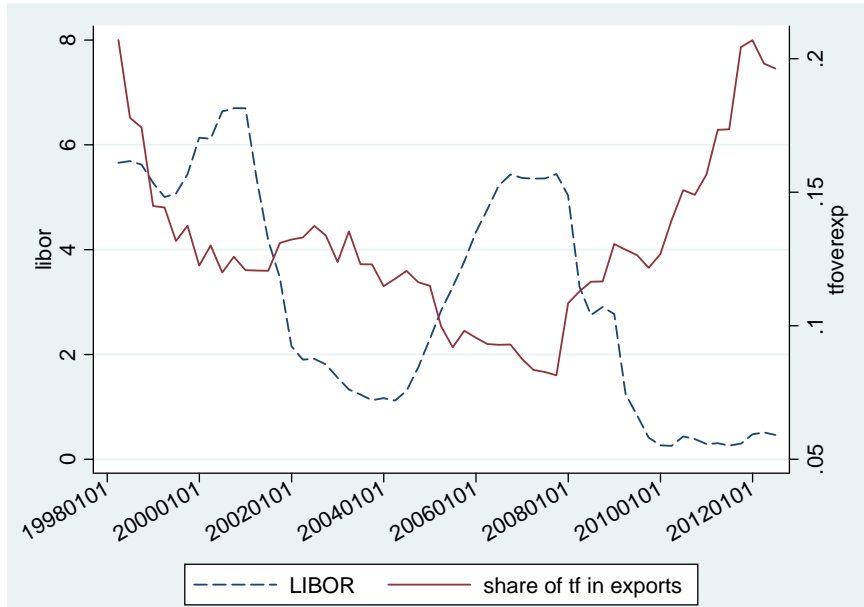
Note: The upper panel shows the top countries in terms of their shares in total trade finance claims averaged over the period from 2006 to 2012. The panel in the middle indicates the top export destinations measured by their average export shares. In the lower panel, those countries are displayed that have the highest average trade finance intensity. Bars with patterns indicate offshore financial centers. Data source: FFIEC 009 report, IMF Directions of Trade Statistics.

Figure 4: Co-movement of trade finance intensity and the Volatility Index



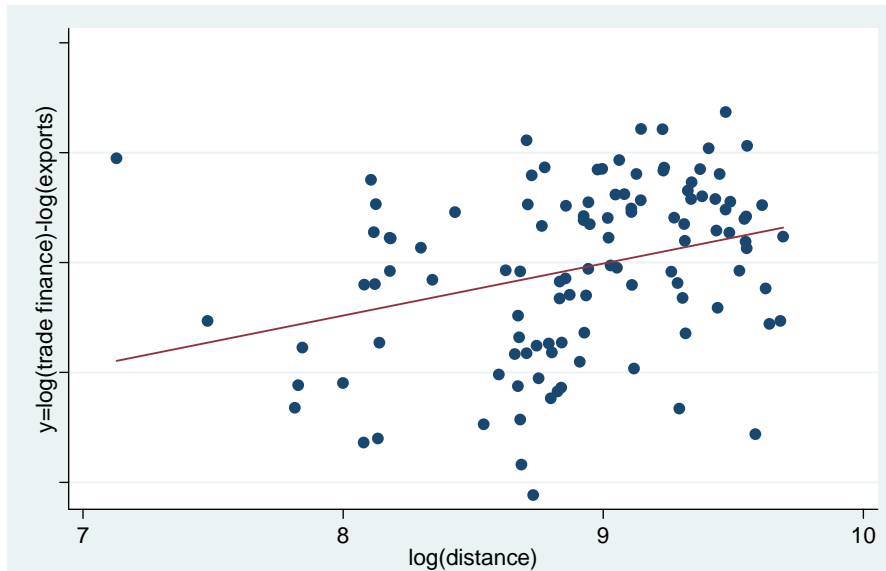
Note: The graph shows the ratio of U.S. trade finance claims to U.S. exports in goods for the period from 1997 to 2012 together with quarterly averages of the Volatility Index, which measures the expected volatility of the U.S. stock market over the next 30 days. Data source: FFIEC 009 report, Bloomberg.

Figure 5: Co-movement of trade finance intensity and LIBOR



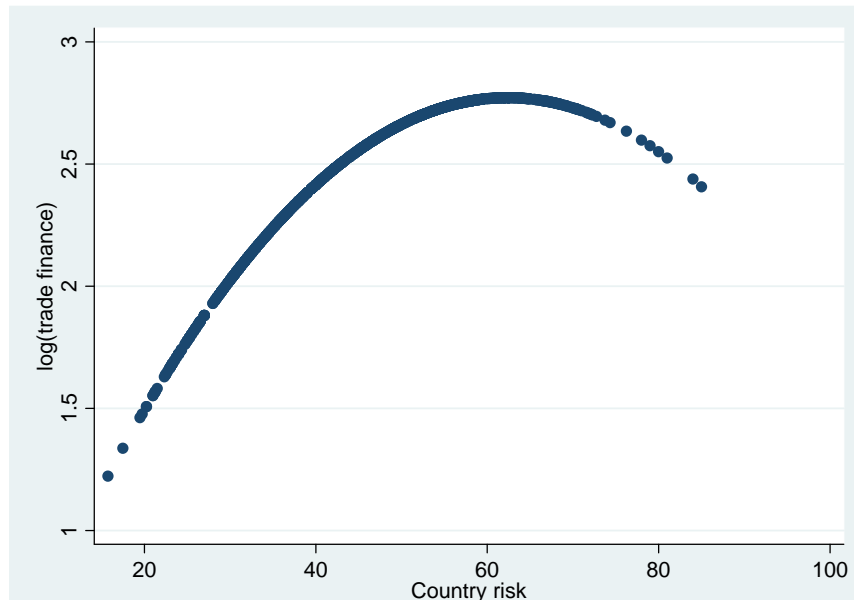
Note: The graph shows the ratio of U.S. trade finance claims to U.S. exports in goods for the period from 1997 to 2012 together with quarterly averages of the 3-month LIBOR. Data source: FFIEC 009 report, FRED Economic Data.

Figure 6: Trade finance and distance, 2006 q1



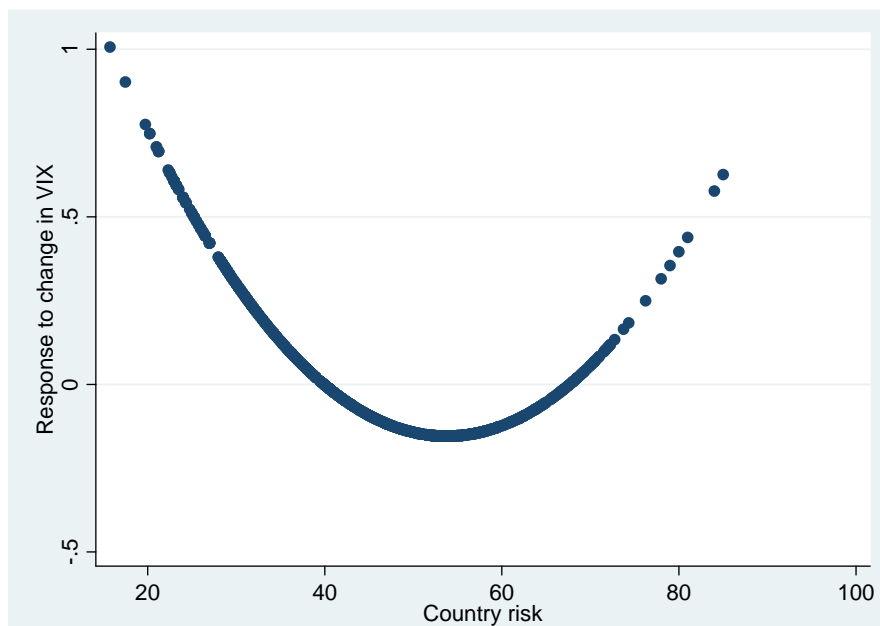
Note: The graph plots the log ratio of a country's trade finance claims against the country's log distance from the U.S.. The line is obtained from fitting a linear regression.

Figure 7: The relationship between bank trade finance and country risk



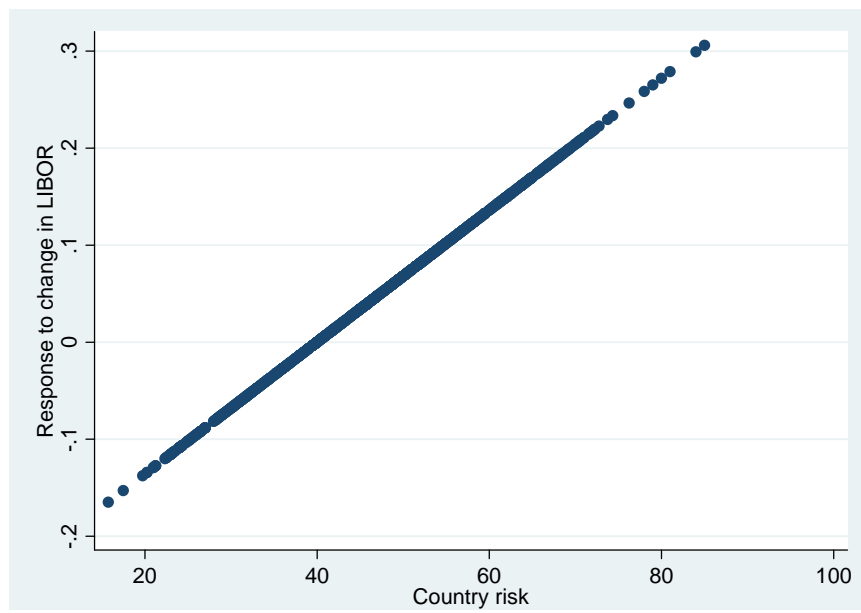
Note: The graph shows the estimated relationship between destination country credit risk and the log of banks' trade finance claims based on the estimates in column (4) of table 4.

Figure 8: Estimated heterogeneous response to changes in VIX



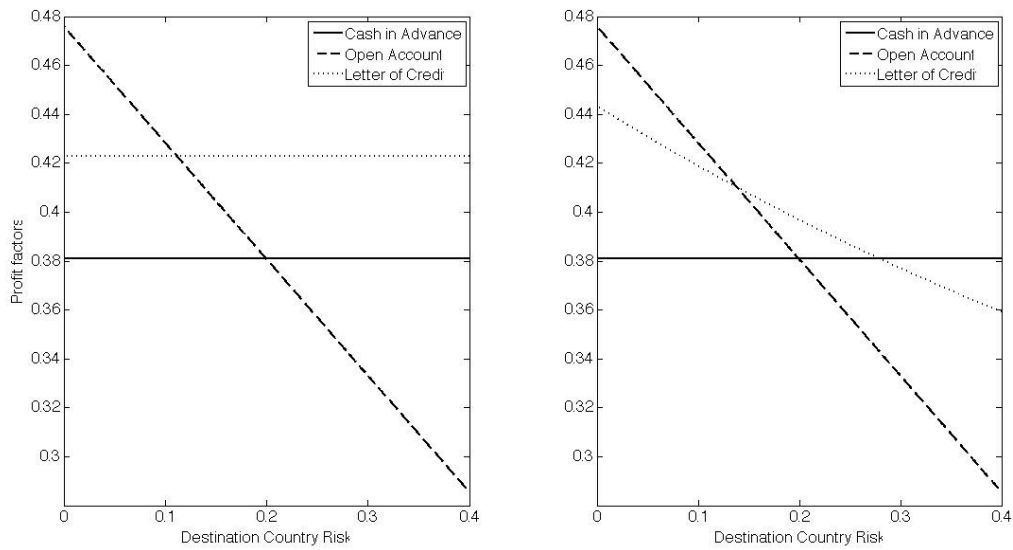
Note: The graph displays the estimated change of banks' trade finance claims as a function of credit risk when the VIX index changes by 1 percent. Calculations are based on the estimates in column (3) of table 7.

Figure 9: Estimated heterogeneous response to changes in LIBOR



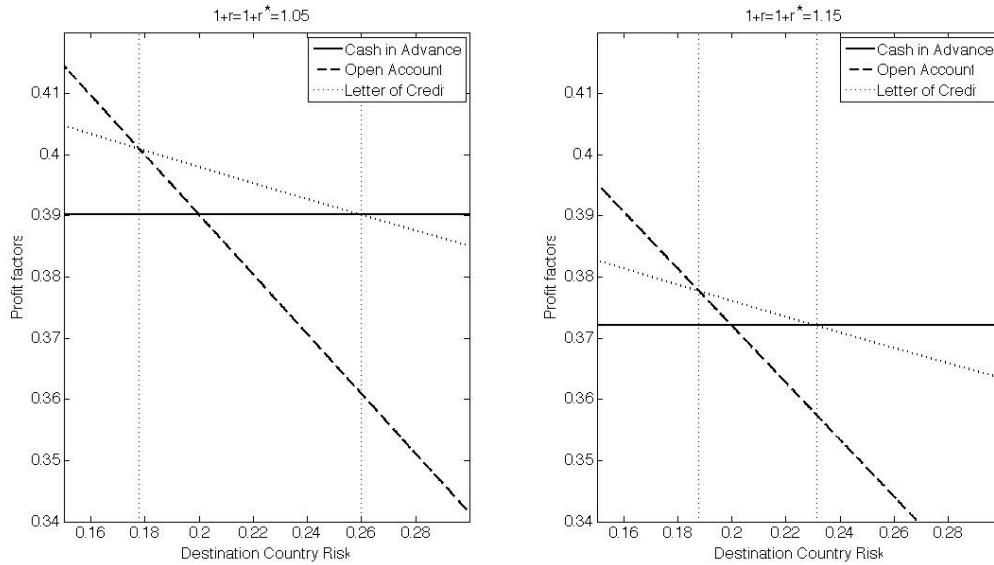
Note: The graph displays the estimated change of banks' trade finance claims as a function of credit risk when the LIBOR changes by 1 percent. Calculations are based on the estimates in column (2) of table 8.

Figure 10: Profitability of letters of credit as a function of credit risk



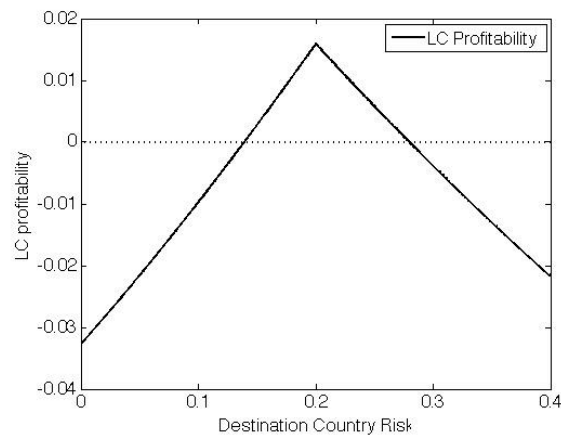
Note: Both panels of the graph plot the exporter's profit factors under the three payment forms (cash-in-advance, open account, and letter of credit) as a function of the importer's default risk λ^* . The left graph depicts the case of a fixed letter-of-credit fee in which letter-of-credit profits are independent of destination country risk. The right graph shows the profit factors in the case of an endogenous letter of credit fee. Then, letter-of-credit profits decrease in destination country risk.

Figure 11: The effect of an increase in aggregate financing costs



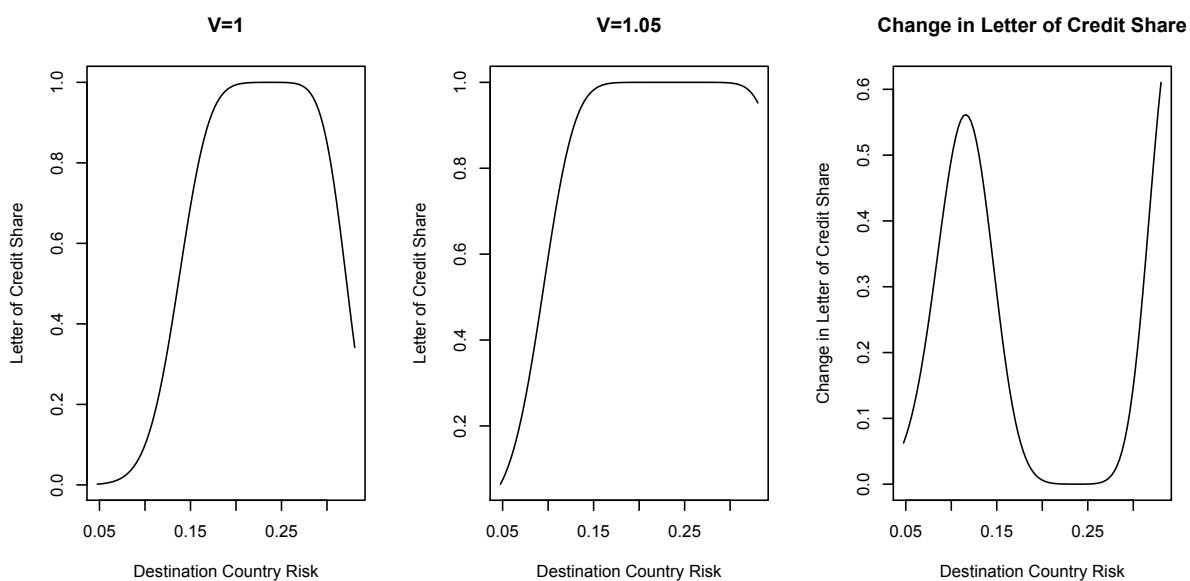
Note: Both panels of the graph plot the exporter's profit factors under the three payment forms (cash-in-advance, open account, and letter of credit) as a function of the importer's default risk λ^* . The left graph depicts profit factors when global financing costs are low. The right graph shows the profit factors after a symmetric increase in the source and destination country financing costs, keeping all other parameters fixed. This reduces profits under all payment forms, the most for letters of credit. The vertical lines show that the range of risk levels for which letters of credits dominate decreases.

Figure 12: Non-linear relationship between letter-of-credit use and destination country risk



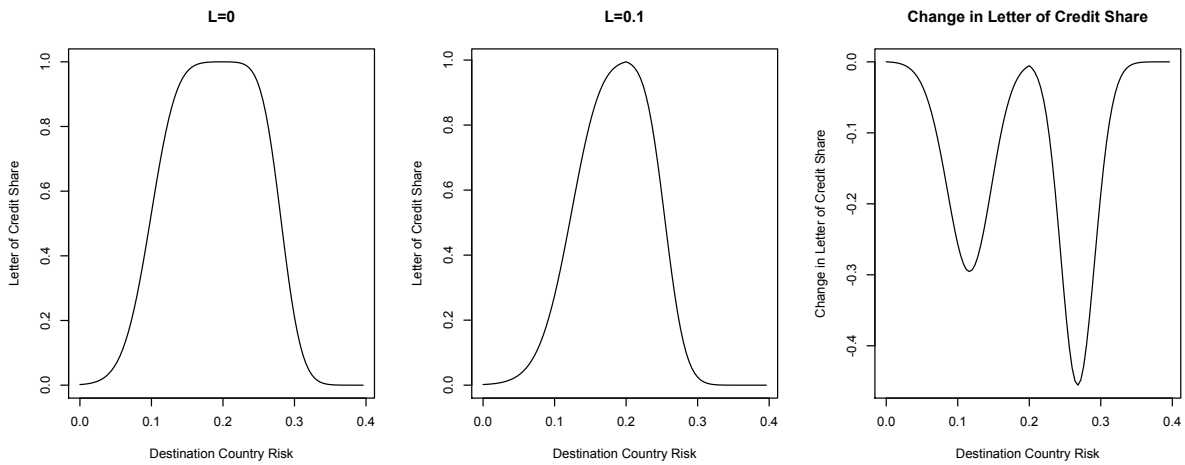
Note: The graph displays the relative profitability of a letter of credit as a function of the importer's default risk. It corresponds to the difference between profits when a letter of credit is used and the profits of the most preferred alternative payment method. At the peak, the exporter is indifferent between open account and cash-in-advance. In the region where the line is above zero, the exporter prefers to arrange the payment through a letter of credit.

Figure 13: Heterogeneous response to changes in VIX in the model



Note: The figure is based on the following model parameters: $m = .03$, $\alpha = .7$, $\tilde{\lambda} = .8$, $r = r^* = .08$, $\tilde{\lambda}^* \in [0.7, 1]$. The left graph shows the optimal payment choice in a low risk environment as a function of credit risk in the importing country. The graph in the middle displays the choice after default risks in both countries have increased. When aggregate risk increases, the set of countries in which all firms choose letters of credit increases. The right graph of the figure reflects the corresponding change in the share of firms that use letters of credit due to the increase in aggregate risk, showing a u-shaped response.

Figure 14: Heterogeneous response to changes in LIBOR in the model



Note: The figure is based on the following model parameters: $m = .03$, $\alpha = .7$, $\tilde{\lambda} = .8$, $r = r^* = .1$, $\tilde{\lambda}^* \in [0.6, 1]$. The graph on the left hand side shows the optimal payment contract choice as a function of credit risk in the importing country in a low interest rate environment. The graph in the middle depicts the choice after interest rates in both the exporting and the importing country have increased by L . As interest rates rise, firms switch away from letters of credit. The graph on the right hand side shows the change in letters of credit use across destination countries with different risk levels, showing a hump-shaped response.