The Impact of a Higher Cost of Credit on Exporters: Evidence from a Change in Banking Regulation*

Joao Monteiro† Pedro Moreira‡

November 2024

Abstract

How do exporters react to changes in the cost of credit? To answer this question, we exploit an exogenous variation in banking regulation that increases the cost of financing for exports in the European Union. Using a unique data set that combines customs, firm-level, and credit registry data on Portuguese firms, we find that in response to an increase in the cost of credit, exports fall by 8 percent through the intensive margin. In the extensive margin, we also show a sharp drop in entry and an increase in firm exit. Within a firm, we document that firms reduce their dependence on bank credit by adjusting their product mix as firms shift towards products with low dependence on working capital and bank credit. We also provide direct evidence of the mechanism through which the change in banking regulation operates. We find that loan rates for exporters increase and that loan amounts fall by 7 percent. We then turn to aggregate trade data for all E.U. countries. We find an overall decline in exports, but countries with undercapitalized banks drive this decline or where bank equity is scarce. This finding suggests that the banking system's health is an important determinant of how exports react to an increase in the cost of credit. Using a multi-sector Ricardian model, we show that welfare in E.U. countries declines due to a depreciation in terms of trade. Welfare in countries that import goods from the E.U. also declines due to increased import prices.

Keywords: Trade Finance, Product Mix, Lending Channel

JEL Codes: G22, G30, F10, J23

*Joao Monteiro would like to thank his committee, Effi Benmelech, Marty Eichenbaum, Dimitris Papanikolaou, Mitchell Petersen, and Jacopo Ponticelli for their continued guidance and support. Monteiro thanks Filipe Correia (discussant), Carola Frydman, Joao Guerreiro, Fergal Hanks, Filippo Mezzanotti, Laura C. Murphy, Mounu Prem, Sergio Rebelo, Miguel Santana, Paola Sapienza, and Vikrant Vig for helpful comments and discussions. Joao Monteiro also acknowledges the support of FCT under grant 2022.10595.BD. We also thank participants in seminars at the Kellogg Finance Department, the Northwestern Economics Department, the Bank of Portugal, the 2023 Lubrafin Conference, and the Bank of Italy-EIEF Financial Intermediation Workshop. All errors are our own. The views expressed in this article are those of the authors and do not necessarily represent those of Banco de Portugal or the Eurosystem.

†Einaudi Institute for Economics and Finance. Email: joao.monteiro@eief.it.

‡Banco de Portugal. Email: pedro.moreira@bportugal.pt.

1 Introduction

How does the cost of the credit affect international trade? It is well established that shocks to the cost of credit affect the level of firm production (Khwaja and Mian, 2008; Chodorow-Reich, 2014; Benmelech et al., 2016) . This exposure is more pronounced for firms with a longer product cycle, like exporters. The recent empirical literature on trade and finance (Manova, 2013; Paravisini et al., 2015) has argued that the effect of credit shocks on firm production takes place only through the intensive margin. However, this stands in contrast with the theoretical literature. In the Melitz model, not only is the extensive margin fundamental in understanding trade flows, but a shock to the cost of credit should also affect firm entry and exit. Moreover, the recent theoretical literature (Mayer et al., 2014) has highlighted that shocks may affect the firm's product mix as firms often sell multiple products. Both dimensions may introduce greater persistence to the effects of a temporary negative shock, as firms will need additional time and resources to recover from the shock. Moreover, changes to a firm's product mix may also change its exposure to risk and affect its ability to grow. In this paper, we investigate the consequences of an increase in the cost of credit on exports by looking at the three channels – intensive margin, extensive margin, and product mix.

Exporters depend more on credit than firms selling only in the domestic market. There are long time lags between production and shipment and shipment and delivery. For example, in the EU, a product may take up to a month to transit from a factory to a ship (Djankov et al., 2010) . Throughout these lags, exporters need to pay their suppliers. This creates a need for working capital, which credit can help to fill. Exporters also face counterparty risk, as collecting payment from an importer in a different country may be challenging in the event of default. Therefore, exporters often rely on banks as intermediaries to alleviate this friction. As banks usually have closer relations and affiliations with foreign banks and have developed procedures to manage counterparty risk efficiently, they often have a comparative advantage in enforcing payments. Moreover, the role of banks as intermediaries is even more pronounced when either the exporter or the importer is in a country with weak contractual enforcement (Antràs and Foley, 2015).

The most common type of credit in international trade is trade finance. In its simplest form, trade finance is a working capital loan guaranteed by a letter of credit obtained from a foreign bank. We explore the consequences of an increase in the cost of trade finance for some destinations while keeping the cost fixed for all other destinations. The increase in the cost of trade finance results from a change in macroprudential regulation introduced by the implementation of Basel III.

Basel III introduces significant changes to banks' risk management. Under this regulation, banks must maintain a minimum level of equity relative to risk-weighted assets.[1] A high-risk weight is given to a high-risk asset, requiring the bank to hold more equity as part of its mandatory capital requirements. Basel III changes the risk weights used in trade finance. The new regulation assigns a higher risk weight to banks in non-OECD countries (high-risk countries) while leaving the risk weight intact for banks in OECD countries (low-risk countries). As a result, from the bank's perspective, the cost of providing a trade finance loan to an exporting firm selling to a high-risk country increases. Since the bank will likely pass part of this cost to exporters, the marginal cost of exporting to a high-risk destination increases.

We use a unique data set of Portuguese firms to understand the impact of this increase in the cost of credit. Portugal is an ideal setting to study the effects of this shock because most Portuguese exporters are small, financially constrained, and rely exclusively on bank credit to finance their working capital. Moreover, a significant share of Portuguese exports is directed to high-risk countries. Our data set contains

[1] Risk-weighted assets are the sum of all assets in the balance sheet of a bank, where each asset is multiplied by an assigned risk weight.

detailed information on exports by destination and by product for the universe of Portuguese exporters. We supplement these data with credit registry information, in which we observe all loans obtained by Portuguese firms and information on loan amounts, maturities, and interest rates. The data will allow us to conduct a within-firm analysis of the consequences of the increase in the cost of credit by comparing the evolution of exports to high-risk destinations with the evolution of exports to low-risk destinations.

At the firm level, we find that, on average, exports to high-risk destinations decrease by around 8 percent compared to low-risk destinations. At the aggregate level, Portuguese exports also declined, which suggests that exporters cannot fully offset the decline in exports to high-risk destinations with an increase in exports to low-risk destinations. We also find that firm entry into high-risk destinations declines by over 5 percent while exit from these countries remains unchanged. We explain this asymmetry in the effects on entry and exit with the presence of sunk costs of entry, as documented by Alessandria and Choi (2007). Given these sunk costs of entry, a firm that has already entered a market may choose to keep exporting to that destination (even though it is decreasing the level of exports), while firms considering entry to that location may decide not to enter.

We next turn to the exporters' product mix. We create a novel classification of products based on their dependence on working capital and bank credit. This measure depends on the product's cash conversion cycle, which is the time it takes the firm to convert cash it invests in inventories into cash obtained from sales. At the firm level, we find that products with a high dependence on bank credit explain the bulk of the drop in exports to high-risk destinations. This finding validates our mechanism, which operates through the working capital channel, and illustrates how firms adjust to changes in the cost of credit by changing their product mix. In response to an increase in the cost of credit, firms skew their product mix towards products with low dependence on working capital and bank credit to reduce their overall costs.

We can also investigate the effect of the increase in the cost of credit introduced by Basel III on loan rates and amounts obtained by exporters. We split the exporters in our sample based on their exposure to high-risk destinations, where exposure is measured as the share of exports going to high-risk destinations before the introduction of Basel III. We find that exporters with high exposure to high-risk destinations face an increase of 13 basis points in the interest rates on their loans compared to firms with low exposure. This effect is small compared to the change in exports, and the difference in magnitudes is driven by two other margins of adjustment used by treated exporters, which introduces a negative bias in our estimation of the effect on interest rates. First, exporters also reduce their loan amounts – firms with high exposure to high-risk destinations cut their loan amounts by 7 percent compared to low-exposure firms. Moreover, exporters also reduce the number of loans they obtain. We find that the probability that a firm with high exposure to high-risk destinations obtains a loan declines by 7 percent compared with low-exposure firms.

We then investigate the consequences of Basel III across all EU countries by using bilateral trade data at the country-destination-product level. We find that exports to high-risk destinations decline by 5 percent relative to exports to low-risk destinations and that this drop is mainly driven by products with a high dependence on credit. We also use these data to investigate the banking system's health role in transmitting this cost-of-capital shock. Banks face a regulatory constraint – their capital ratio must be above a given threshold. An increase in risk weights, such as the one introduced by Basel III, decreases the capital ratio. If the bank's capital ratio is high enough, then Basel III should not lead to any change in bank behavior. Similarly, if the bank has easy access to external equity financing, it can offset the increase in risk weights by increasing equity. Using our data, we find that EU countries with undercapitalized banks or where bank equity is scarcer exhibit a sharper export drop. These findings show that countries with healthier banking systems can increase their presence in high-risk destinations compared to countries with weaker banking systems, conditional on the shock.

We turn to a model to understand the welfare implications of the changes in trade flows caused by the increase in the cost of credit. The model will not only evaluate the costs of Basel III in international trade but also allow us to understand to what extent exporters can offset the decrease in exports to high-risk destinations with an increase in exports to low-risk destinations. We use a Ricardian trade model with multiple countries and sectors, as in Caliendo and Parro (2015). In this model, trade exists because of differences in productivity – firms import goods from countries with a comparative advantage in producing them. We include financial frictions in a tractable way – exporters must pay for their factors of production in advance and, therefore, borrow from banks. We consider a shock to these interest rates and calibrate the shock to match the causal effect of Basel III on exports in the EU. As this model does not have frictions in the credit market, this calibration will deliver an estimate of the *shadow cost* of Basel III on trade, which is an important statistic to evaluate the effects of this policy change. The decline in exports to high-risk destinations in the EU is rationalized by an increase of 1.8 percentage points in interest rates. Note that this increase differs substantially from the effect we document for Portuguese exporters, as that estimation has a downward bias.

Using our model, we find that welfare in high-risk countries declines by 0.04 percent as the price of imports increases. This increase in the price of imported inputs increases marginal costs, effectively reducing these countries' comparative advantage. EU countries also exhibit a decline in welfare of 0.09 percent. To put this number in context, using a similar model, Caliendo and Parro (2015) estimate that the total welfare gains from NAFTA to the US are around 0.06 percent, suggesting that Basel III leads to an economically significant drop in welfare. Most of this decline in welfare is caused by a depreciation in terms of trade, which is the ratio of the price of exports to the price of imports. As the cost of capital increases, global demand for EU exports declines due to a price increase. This decline in demand leads to a decrease in domestic factor prices, which depresses marginal costs and reduces the price of exports. As the price of exports declines, so does welfare, as EU countries can now afford fewer imports for a given quantity of exports.

Our model suggests that the increase in the cost of capital caused by implementing Basel III is similar to an overall decline in productivity. Before the increase in the cost of capital, EU exporters relied on their ability to source cheap credit to export goods to developing countries. The introduction of Basel III erodes that comparative advantage. For developing countries, whose competitiveness is partially driven by low wages, Basel III increases marginal production costs as the price of imported inputs increases.

The overall impact of Basel III on welfare is beyond the scope of this paper. This paper focuses only on the costs through its effects on international trade. However, Basel III was implemented because policymakers believed banks were mispricing their loans to exporters, as interest rates were too low. Thus, increasing interest rates should also lead to welfare gains as the mispricing is corrected. Those welfare gains must, however, be balanced against the welfare costs we compute.

Related Literature. Our paper contributes to a growing literature focusing on the role of credit in international trade.[2] Some papers, like Gertler and Rogoff (1990), Matsuyama (2005), and Chor (2010), have highlighted that credit is an important source of comparative advantage.[3] In this literature, Manova (2013)

[2] There is also a broader literature focusing on the effects of credit on real activity, focusing on the firm side, like in Paravisini (2008); Khwaja and Mian (2008); Chodorow-Reich (2014); Huber (2018) or Benmelech et al. (2016). However, exporters are usually more sensitive to credit shocks, as shown by Minetti and Zhu (2011).

[3] There is also a literature studying trade finance, which is the most common form of financing for exporters. Some examples include Schmidt-Eisenlohr (2013), Antràs and Foley (2015), and Niepmann and Schmidt-Eisenlohr (2017).

shows that financial frictions substantially drag international trade. In the Great Recession, Chor and Manova (2012) and Ahn et al. (2011) show that credit played a crucial role in explaining the drop in trade flows. Other papers have focused on how financial frictions affect the impact of other shocks – Caggese and Cuñat (2013) study trade liberalizations, Manova (2008) studies credit liberalizations, Chaney (2016) studies currency appreciations, and Becker et al. (2013) study financial development. Using historical data, Xu (2022) finds that countries more exposed to bank failures observe a permanent export decline.

The paper most closely related to ours is Paravisini et al. (2015), who use the 2008 Peruvian sudden stop as a shock to credit to exporters. They find that this credit shock only affects exports through the intensive margin. We contribute to this literature in two ways. First, we find that the extensive margin and the product mix are essential to understanding the effects of credit shocks on exports.[4] Second, the nature of our shock allows us to speak to the nature of substitution across destinations and products *within* a firm. Therefore, we can show how firms change their activities in one segment in response to a shock in another, as in Giroud and Mueller (2019).

We also contribute to a literature that studies the design of macroprudential policy and its impact on real activity. Kashyap et al. (2004), Hanson et al. (2011), Kashyap et al. (2011), Repullo and Suarez (2013), and Bahaj and Malherbe (2020) study the optimal design of banking regulation. On the empirical side, Gropp et al. (2019), Aiyar et al. (2014a) and Aiyar et al. (2014b) show that banks respond to risk-weight increases by reducing lending.

Outline. The rest of the paper proceeds as follows. Section 2 describes the institutional framework and the changes introduced by Basel III. Section 3 describes the data and presents summary statistics. Section 4 discusses the empirical strategy and presents the results for the comparison between countries. Section 5 presents results for the effect on lending conditions. Section 6 extends our results to a sample of E.U. countries using aggregate data. Section 7 introduces a structural model. Section 8 concludes.

2 Trade Finance and Basel III

Trade finance is the oldest form of credit used in international finance and has been used by exporters since at least the 19th century. The goal of trade finance is to resolve two fundamental problems in international trade: (1) international transactions take longer to execute than domestic transactions and (2) the parties involved (exporters and importers) often have very limited recourse in the event of default. For example, using a sample of manufacturing firms in 180 countries, Djankov et al. (2010) report that the median time between production and shipment is 21 days. Hummels and Schaur (2013) show that the typical good imported into the U.S. by sea spends 20 days in a vessel. Moreover, and as highlighted by Amiti and Weinstein (2011), importers are usually not obligated to pay until 90 days after receiving the shipment.

In its simplest form, trade finance involves four players, as we describe in Figure 1. In the domestic country, which in our example is Portugal, there is an exporter and a domestic bank. In the destination country, there is an importer and a foreign bank.

[4] There is evidence of how exporters change their product mix in response to shocks. In the theoretical literature, Mayer et al. (2014) study how changes in the competitive environment lead exporters to change their product mix. De Loecker (2011) argues that changes in the product mix are an essential part of a firm's response to trade shocks. Using data from wine producers, Mendes (2020) shows that firms adjust to adverse credit shocks by skewing their product mix towards low-quality wines. In response to adverse demand shocks, Friedrich and Zator (2022) show that low-leverage exporters expand their product mix.

The process has five stages. In the first stage, the exporter and the importer negotiate a sales contract which specifies all characteristics of the transaction (e.g. price, volume, payment, and delivery terms). At this stage, the importer requests a letter of credit from the foreign bank in order to serve as a guarantee of payment. In the second stage, the exporter obtains a working capital loan from the Portuguese bank to cover production costs, using the letter of credit as collateral. In the third stage, production takes place and the goods are shipped. In the fourth stage, the foreign bank issues a banker's acceptance to the exporter, which is a guarantee of future payment with a maturity of around 90 days.[5] The exporter then sells the banker's acceptance to the Portuguese bank, usually at a discount. The Portuguese bank then replaces the claim on the exporter with a claim on the foreign bank in its balance sheet. In the fifth stage, the foreign bank pays the banker's acceptance with a foreign bill and the process ends. Default may take place at any stage of this process.

In the beginning of the process, the Portuguese bank has a on the exporter. This claim is not different from a standard working capital loan given to a domestic firm. However, at some point, this claim is replaced by a claim on a foreign bank. Therefore, in trade finance, there is an element of off-balance sheet risk since the payment of the loan depends on a foreign bank and not only on the exporter.

There are other financial instruments that are used in trade finance. Antràs and Foley (2015) present three: cash-in-advance, open account terms (which do not require direct intermediation by banks) and documentary collection terms (which, like the letter of credit process we described above, requires financial intermediation). They further show that, for large firms selling to countries with strong contract enforcement, products which do not requires direct intermediation are preferred. In terms of magnitude, Niepmann and Schmidt-Eisenlohr (2017) use SWIFT data from 2007 to 2012 to show that bank-intermediated trade represents around 15 percent of global trade volume, while other estimates suggest a magnitude close to 47 percent.

2.1 Treatment of trade finance under Basel III

Basel III, which was approved in all E.U. countries in 2013 and was implemented on January 1, 2014, is an internationally agreed-upon set of regulations developed by the Basel Committee on Banking Supervision in response to the Global Financial Crisis of 2007-2009.[6] There were three main changes that were with this new set of regulations: (1) a tightening of capital requirements with new rules on how to compute capital ratios, (2) the introduction of macro-prudential controls (e.g. capital buffers) and (3) a framework to address excess leverage and liquidity risk.

The capital ratio can be written as

$$\text{Capital ratio} = \frac{\text{Tier 1 capital}}{\sum_k \omega_k \text{Asset}_k}$$

where the numerator is Tier 1 capital (equity and disclosed reserves), and the denominator is total risk-weighted assets, where ω_k is the weight assigned to a particular asset. Risk weights are meant to reflect the risk of the asset: a risky asset should have a larger risk weight. For example, a AAA rated bond has a risk weight of 0.1 while a bond with a rating below B- has a risk weight of 1. Before Basel III, the risk weights

[5] Banker's acceptances, which are sometimes called bills of exchange, can have a maturity of up to 180 days.

[6] In the E.U., there are two documents outlining Basel III regulations. One is the E.U. directive 2013/26 of June 26th 2013, which outlines the basic principles, and the other is the more thorough E.U. regulation 575/2013 of November 30th 2013. These two pieces of legislation are then transcribed by all E.U. countries and become law in all E.U. countries.

associated with short-term claims on foreign banks (regardless of the country of the foreign bank) were fixed at 0.2. Under Basel III, these weights now depend on the rating of the foreign bank. Trade finance loans where the foreign bank is classified as low-risk still receive a risk weight of 0.2 while trade finance loans where the foreign bank is classified as high-risk now receive a risk weight of 0.5.[7] This change implies that the bank's marginal cost of providing a trade finance loan where the foreign bank is high-risk increases, while that same marginal cost remains constant if the foreign bank is low-risk.

As we do not observe the rating of the foreign bank, we use the OECD's measure of sovereign risk as a proxy and divide destinations into two groups: OECD countries are classified as low-risk and countries outside of the OECD are classified as high-risk.[8] Using sovereign ratings as a proxy for foreign bank ratings will not lead us to underestimate the risk of the foreign bank – it is unlikely that we will assign a high rating to a bad bank in a low-risk country. In fact, bank ratings tend to be better than sovereign ratings, particularly in emerging countries.[9] In our empirical analysis, we compare the evolution of exports to high-risk countries with the evolution of exports to low-risk countries. Foreign banks in low-risk countries are always viewed as low-risk. Some banks in high-risk countries might also be viewed as low-risk which may lead us to find smaller (in absolute value) effects of Basel III on exports. Therefore, the measurement error in our proxy will lead to a dampening of our results.[10]

To understand the potential magnitude of this shock, we consider a simple model of a bank. Consider a bank that can invest in three assets: a risk-free asset F, a risky asset A and trade finance T. Total assets are given by $F + A + T$. The bank's tier 1 capital is given by E. Under these assumptions, the capital ratio for this bank is given by

$$\text{Capital ratio} = \frac{E}{\omega_F F + \omega_A A + \omega_T T}$$

where ω_i represents the risk weight applicable to asset class i. Suppose that bank wants to keep the capital ratio, total assets and tier 1 capital constant.[11] In Basel III, $\omega_F = 0$. Assume also that the bank takes returns on all asset classes as exogenous. The marginal cost of trade finance is the opportunity cost of increasing trade finance T by one unit. The opportunity cost is the return the bank loses on its remaining assets. Given

[7] In Articles 120 and 121 of E.U. regulation 757/2013 of June 2013, trade finance loans where the foreign bank is an unrated institution and maturity is higher than 3 months receive a risk weight of 0.5. Unrated institutions are banks or other financial institutions that do not have a credit rating and are generally banks with a very high default risk. For example, most banks in low-income countries can be assumed to be unrated and therefore high-risk (BIS, 2015).

[8] The OECD publishes sovereign ratings for most countries. These ratings are used by banks to determine the risk weights applicable to assets involving exposure to foreign banks.

[9] In fact, in the initial proposed Basel III regulations risk weights applicable to trade finance loans had a so-called sovereign floor. Under this sovereign floor, the rating of the foreign bank could not be better than the rating of the country where the foreign bank is located. This was later waived after pushback from banks (BIS, 2015). For claims on foreign banks which are not trade finance loans this sovereign floor is still in effect.

[10] Firms might also react to the increase in the cost of credit by changing the banks with which they work. Firms in countries which we classify as high-risk might move from high-risk banks to low-risk banks. This reaction also introduces measurement error which is correlated with the shock. However, this action will also dampen the results as the cost of credit should not increase if the letter of credit is provided by a low-risk bank.

[11] The assumption that the bank would not want to change its capital is grounded in empirical evidence. For example, Gropp et al. (2019) find that in response to an increase in capital ratios, banks respond not by increasing their equity, but by reducing their risk-weighted assets. They do this by reducing lending to corporate and retail customers. In our example, they will do this by reducing their investment in risky asset A.

our assumptions, the marginal cost is given by

$$\begin{aligned}\text{Marginal cost} &= r_f \times (-\Delta F) + r_A \times (-\Delta A) \\ &= r_f + \underbrace{\frac{\omega_T}{\omega_A} \times (r_A - r_F)}_{\text{risk premium}},\end{aligned} \tag{1}$$

which is the sum of the risk-free rate plus a risk-premium which depends on the ratio of the weights of trade finance and risky assets (in excess of the weights applicable to risk-free assets). This expression captures the idea that the marginal cost of trade finance has to be proportional to divestment on risky assets. To invest in trade finance, the bank can divest from risk-free assets in order to keep total assets constant. However, doing so increases risk-weighted assets. Therefore, the bank also needs to divest from risky assets, which also tend to have higher returns, in order to keep the capital ratio constant. The divestment on risky assets will depend on the ratio of the risk-weights.

Basel III increases ω_T for high-risk countries. Therefore, the marginal cost of providing trade finance increases. Assume that the risk-free rate is the same before and after Basel III. We also assume that $r_A - r_F = 1\%$. To obtain an estimate of ω_A we divide risk-weighted assets by total assets for Portuguese banks in 2013 using data from the ECB's quarterly report for Q4. We estimate that the marginal cost of a trade finance loan given to an exporter selling to a high-risk country (and where the foreign bank is high-risk) increases by 49 percentage points due to the increase in the risk weight. If banks pass this cost (or a fraction of this cost) onto exporters, this will lead to an increase in the cost of credit, and on the firms' marginal costs.

There is little direct evidence on how banks reacted to Basel III. One important source is the International Chamber of Commerce, which represents over 45 million companies in over 100 countries. In 2014, they published "Rethinking Trade & Finance", which focused in the impact of Basel III on export finance. They carried out a survey among export finance professionals within banks. Among these professionals, 78 percent have stated that Basel III has increased the cost of doing export finance and 69 percent have claimed that Basel III has led banks to increase the prices they charge customers.

This report also provides some evidence about the risk characteristics of trade finance. Using data from 24 banks and reflecting more than 4.5 million transactions (representing an an exposure of around 2.4 trillion dollars), they find that for the type of trade finance we have described the customer default rate is 0.033 percent. A debt instrument with the same corporate default rate would have, according to Moody's, a rating between Aa and Aaa. Therefore, trade finance remains an asset with a low default risk.

3 Data

We build a data set which has detailed information on annual export volumes for all Portuguese firms, decomposed by destination and by product. We also use credit registry data, which has information on all loans obtained by Portuguese firms. Finally, we supplement this data with firm-level balance sheet information.

3.1 Data sources

Trade data We use a data set from Statistics Portugal, which has monthly information on all exports and imports of Portuguese firms by firm, source/destination country and product classification, from 2011 to

2018. The product classification in this data set is the European Combined Nomenclature, which is an 8-digit classification employed by the European Union. This classification adds 2 additional digits to the Harmonized System, which is a 6-digit classification. In our work, we will aggregate goods to the Harmonized System heading, which consists of the first 4 digits. We then further aggregate this data set to the annual level, in order to match the balance sheet and income statement information, which is also at an annual level.[12]

Credit and accounting data We use the Portuguese credit registry, the *Informação Individual de Taxas de Juro*, which is managed by the Bank of Portugal, and which has data on all new loans and loan renegotiations between 2013 and 2018. Until December 2014, all banks with an annual volume of new loans to firms greater than 50 million Euros had to report the details of all new loans. From January 2015 onwards, this obligation was extended to all banks. For each loan, we can identify the date of origination, the bank, the firm, the interest rate, maturity, loan amount and type of loan. However, we cannot directly identify trade finance in this data set. We exclude financial firms. We also exclude overdrafts and renegotiated loans. We complement the credit data with information on the balance sheet and income statements of all Portuguese firms from the *Informação Empresarial Simplificada*. This data set is a joint project of the Ministry of Justice, the Ministry of Finance, Statistics Portugal and the Bank of Portugal. All Portuguese firms are required to report this information, and so this data set represents the universe of Portuguese firms.

Merged data We cannot directly merge the credit and accounting data set with the trade data set due to legal restrictions imposed by the Bank of Portugal and Statistics Portugal.[13] However, we observe total exports in both data sets, although the source of the variable is different. Therefore, we match each firm in the credit and accounting data set with a firm on the trade data set that is in the same sector (where sector is defined at the 5-digit level, which is the finest classification possible) and which minimizes the absolute difference in exports. This method is the best possible matching algorithm subject to legal restrictions. We identify $11,246$ exporters on the credit and accounting data set.[14] These firms are matched with $6,453$ exporters on the trade data set, using the algorithm we described above.[15] There are $4,079$ unique matches, i.e., there are $4,079$ firms from the trade data set that are matched to a single firm in the credit data set.

3.2 Summary statistics

Portuguese exports of goods in 2013 totaled 47 billion Euros, approximately 27 percent of GDP. In 2013, Portugal exported to 189 destinations. The main destination for Portuguese exports is the E.U., and its main trade partners are Spain, that accounts for 24 percent of total exports of goods, France (12 percent) and Germany (12 percent). The fourth-largest trade partner was Angola, which accounted for 7 percent of total exports of goods. Overall exports to high-risk destinations represent 23 percent of total exports in 2013. The main exports are minerals (24 percent of total exports of goods), machinery (15 percent) and chemicals (13 percent). We plot the evolution of Portuguese exports in Figure 2.

[12]The data also exhibits a great deal of seasonality, and so aggregating it to an annual level removes these effects.

[13]The credit and accounting data set is anonymized while the trade data set is not. Therefore, merging both data sets would break the anonymization.

[14]We define exporters as firms whose annual exports are at least 5 percent of their total sales, as in Niepmann and Schmidt-Eisenlohr (2017). This assumption can be relaxed and the results will not qualitatively change. However, increasing this threshold will reduce the number of exporters, which will negatively impact the power of our analysis in Section 4.

[15]We observe more exporters in the credit and accounting data set because we are including some firms which are exporting services, while the trade data set only reports the exports of goods.

If we look at panel (a), we see four different periods. The first period, from 2000 to 2008, exhibits a remarkable increase in exports of around 80 percent. During the Great Recession and the sovereign debt crisis (from 2008 to 2011), Portuguese exports fall sharply and then quickly recover. The drop in exports is usually attributed to a drop in credit supply, which explains the so-called Great Trade Collapse (Chor and Manova, 2012). After the financial crisis and until 2013 there is a small increase in exports. After 2013, there is a drop in exports followed by another quick recovery. In panel (b), where we plot the share of Portuguese exports to high-risk countries, we see a very large increase in this share until 2013. Between 2000 and 2013, the share of exports to high-risk destinations more than doubles, which shows that exports to high-risk destinations grew faster than exports to low-risk destinations. In particular, during the Sovereign Debt Crisis, this share accelerates as Portuguese exports to high-risk destinations increase sharply. This increase is driven by a fall in domestic demand as well as a fall in demand in E.U. countries. As documented by Almunia et al. (2021), in response to a fall in domestic demand, exporters in Southern Europe increased their exports. However, as business cycles are very correlated across E.U. countries, this increase in exports was directed towards emerging countries, which are also high-risk countries. After 2014, which is the year in which Basel III is introduced, we see a sharp and persistent decline in the share of exports going to high-risk destinations.

Table I presents summary statistics on the Portuguese exporters in our sample. The average Portuguese exporter sells 15 products in 5 destinations, with an average number of products per destination of 11. However, the distribution is very skewed to the right, because the median values are much smaller than the means. Therefore, there are some firms that are present in many destinations and which sell many products. For exporters, their main product, which we define as the best-selling product in all destinations, represents, on average, 45 percent of its total exports, and their main destination represents 24 percent of total exports. If we look at the HHI, which is a measure of concentration, we see the same picture: exports across destinations are highly concentrated so are exports across products.

On average, 71% of a firm's exports go to high risk destinations, although the distribution is effectively bimodal, with a lot of mass around 0 and around 1. Note that, since the share of aggregate exports that goes to high-risk destinations is 23.3%, it must be that there are some large firms (in terms of export volume) that are mostly selling to low-risk destinations. Exporters obtain an average of 16 loans in 2013, although this is driven by some outliers, and the median value is 5. Exporters obtain, on average, these loans from 2 different banks. The median loan maturity is 134 days, which is within the range we would expect for trade finance (90 to 180 days).

4 Effect on Exports Across Destinations

The introduction of Basel III leads to an increase in the cost banks face when providing a trade finance loan to an exporter selling in a high-risk destination. Banks pass this cost onto exporters, which leads to an increase in marginal costs for the firm. In this Section, we investigate the consequences of this increase in the cost of credit on exporters. We focus on three margins of adjustment: the intensive margin (the volume of exports), the product mix (changes in the types of products an exporter sells) and the extensive margin, which is related to entry and exit into high-risk destinations.

4.1 Intensive margin: what happens to the volume of exports?

To motivate our empirical strategy, we start by presenting a partial equilibrium model of trade with firm heterogeneity as in Melitz (2003). Consider a firm i which is deciding how much to export of product p to destination d The firm faces an isoleastic demand curve $y_{ipd} = A_{pd} p_{ipd}^{-\sigma}$ where $\sigma > 1$ is the price elasticity and A_{pd} is a demand shifter which the firm takes as given. Production follows a linear technology $y_{ipd} = \varphi_{ip} l_{ipd}$ where φ_{ip} is productivity and l_{ipd} is labor demand. The firm has market power on the product market but is a price taker in the labor market. The firm faces exogenous and constant iceberg costs: in order to sell one unit in destination d it must produce $\tau_d \geq 1$ units. Finally, the firm also faces a financial friction – the firm must pay a share $\theta \in [0, 1]$ of its labor costs in advance. To do so, it must borrow at an interest rate $R_{id} \geq 1$, which it takes as given.

The marginal cost of selling product p in destination d is given by

$$\mathcal{M}_{ipd} = \frac{w_t \tau_d}{\varphi_{ip}} \cdot (\theta R_{id} + 1 - \theta),$$

which is a product of two terms: the first term represents the technological costs of production with iceberg costs, and the second term reflects the financial friction. We can interpret $\mathcal{R}_{id} \equiv \theta R_{id} + 1 - \theta$ as the average interest rate the firm faces – due to the working capital constraint, the firm finances a share θ of its wage bill with external financing and a share $1 - \theta$ with internal funds, which have an interest rate of zero. We can then write the logarithm of the volume of exports, or total sales, as

$$\begin{aligned} \log \text{Exports}_{ipd} &= c + (1 - \sigma) \log \tau_d + (1 - \sigma) \log w + (\sigma - 1) \log \varphi_{ip} \\ &\quad + \log A_{pd} - (\sigma - 1) \log \mathcal{R}_{id}, \end{aligned}$$

where c is a constant. We want to compare the evolution of exports to high-risk destinations with the evolution of exports to low-risk destinations within a firm-product pair to estimate the effects of a change in interest rates. Thus, we can use use destination fixed effects to capture the effect of iceberg costs and firm-product-year fixed effects to capture changes in wages and productivity. Therefore, net of the fixed effects, changes in exports can be written as

$$d \log \text{Exports}_{ipd} = d \log A_{pd} - (\sigma - 1)\, d \log \mathcal{R}_{id}. \tag{2}$$

Equation (2) summarizes both our identification strategy and its main challenge. On one hand, we can estimate the effect of the shock to the cost of credit on exports by comparing exports to high-risk destinations with exports to low-risk destinations for a given firm-product pair. On the other hand, the presence of demand shocks may confound our analysis. In particular, if demand shocks are correlated with the risk weight of the destination country, they may bias our results.[16] If they are not correlated, they will be random shocks which will be captured by the error term. To address this possibility, we include a vector of time-varying destination controls.

If demand shocks are uncorrelated with the risk weight of the destination, we can use a two-way fixed

[16]For example, suppose that German demand for Portuguese wine increases while Chinese demand for Portuguese wine decreases by the same amount. This asymmetric shock will not be captured by the firm-product-year fixed effect as the average within a firm-product-year is zero. However, it will introduce a source of variation which is correlated with the change in interest rates we expect. In particular, suppose interest rates do not change. This asymmetric demand shock will generate a decrease in exports to high-risk destinations relative to exports to low-risk destinations.

effects estimator to estimate the impact of the shock to credit introduced by Basel III on exports. The average treatment effect will then capture

$$\text{ATT} = -(\sigma - 1)\left\{\mathbb{E}\left[d \log \mathcal{R}_{id} \mid d \in \text{High-risk}\right] - \mathbb{E}\left[d \log \mathcal{R}_{id} \mid d \in \text{Low-risk}\right]\right\},$$

which should be negative as interest rates should increase by more for exporters selling to high-risk destinations.

4.1.1 Estimation

We want to compare the evolution of exports to high-risk destinations with the evolution of exports to low-risk destinations. To do so, we divide destinations into two groups - high-risk and low-risk according to their OECD sovereign rating in 2013 - and estimate the following regression[17]

$$\log \text{Exports}_{ipdt} = \lambda_{ipt} + \mu_d + \beta X_{dt} + \gamma Z_{dt} + u_{ipdt}, \tag{3}$$

where

$$Z_{dt} \equiv \mathbf{1}\left\{d \in \text{High-risk}\right\} \times \mathbf{1}\left\{t \geq 2014\right\}. \tag{4}$$

On the left hand side of (3), we have the logarithm of the value of exports of firm i and product p to destination d at time t. On the right hand side we include firm-product-year fixed effects, destination fixed effects, and time-varying destination controls. The inclusion of firm-product-year fixed effects, while it allows us to control for all shocks happening at the firm or product level, comes at a cost as we lose half of our observations. In particular, we only use firms that sell to both a high-risk and a low-risk destination. The inclusion of destination fixed effects is particularly important in this type of exercise because of the need to control for iceberg costs and other unobservable trade costs. We include destination-level controls X_{dt}: log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. These controls are meant to capture any change in demand at the destination level. The coefficient γ estimates the average treatment effect on exports. The errors are clustered at the firm level following the recommendations in Bertrand et al. (2004). Also note that this regression excludes zeros, i.e., it excludes firms that do not export to a particular destination-product before or after Basel III. Therefore, this regression will only estimate the pure intensive margin effect, ignoring the entry or exit of firms into specific destinations.

The structure of fixed effects in equation (3) implies that we are using variation within firms to estimate the causal effects of Basel III on the volume of exports. Given the structure of the shock, this identification strategy is superior to an identification that relies on variation across firms. However, most of the literature that focuses on the effect of credit shocks has relied on variation across firms. The distinction between the two approaches is not innocuous and we will return to in in Section A.2.

Our estimation requires two assumptions. First, we need that the shock (the implementation of Basel III) is exogenous relative to exporting decisions of Portuguese firms. In particular, it must be that Basel III is not implemented taking into account the specific conditions of the Portuguese exporting market. As Basel III is a multinational piece of macro-prudential regulation and Portugal is not even a member of the

[17] All OECD countries are classified as low-risk, including Greece or Portugal. Most countries outside of the OECD are classified as high-risk. For example, China is a high-risk country.

Basel Committee on Banking Supervision, it's unlikely the rules in Basel III are driven by the actions of Portuguese exporters. A second assumption is related to anticipation. If Portuguese firms anticipated the components of Basel III and its impact on the cost of credit for exporters our estimates will be biased. Most of the firms in our sample are small and so we can reasonably assume that managers do not have a high level of sophistication. Therefore, the only way in which they are able to understand the impact of Basel III is through an increase in interest rates. However, this would require that Portuguese banks increase interest rates before Basel III, which would decrease their profits.

We estimate equation (3) using data from 2011 to 2018 and present the results in Table II.

We find that, across all specifications, exports to high-risk destinations decline relative to exports to low-risk destinations as a consequence of Basel III. In our preferred specification, which is column (4), our empirical analysis shows that, in response to the increase in the cost of credit caused by the implementation of Basel III, exports to high-risk destinations decline by almost 8 percent relative to exports to low-risk destinations. If this loss of exports is not compensated by increased exports to other destinations, then this finding suggests that total Portuguese exports could decline by as much as 2 percent.[18][19] We can also allow the average treatment effect to vary over time. We present the results of this analysis in Figure 3.

We find that, following 2013, there is a persistent decline in exports to high-risk destinations consistent with an increase in the cost of funding exports to these destinations. The decline is not immediate – there is smaller decline in 2014 followed by a larger decline in 2015 which is then persistent until 2018. However, this comparison also features pre-trends as the evolution of exports to high-risk destinations is not parallel with the evolution of exports to low-risk destinations before 2013.

The presence of pre-trends presents an econometric challenge. If we compare the average evolution of exports to high-risk destinations after 2013 with the period before, we obtain a coefficient with a positive bias. Therefore, our estimator will be a lower bound, in absolute value, of the effects of Basel III on exports. However, the presence of pre-trends also opens the door to alternative explanations for the data.

In Figure 2 we observed an increase in the share of Portuguese exports going to high-risk destinations between 2000 and 2013. Moreover, after 2011, there is an acceleration of this increase due to the reaction of Portuguese firms to the Eurozone crisis. The forces underlying this increase are not fully captured in our empirical model. In particular, the increase in exports to high-risk destinations due to the Eurozone crisis cannot be captured by the destination controls because it is not driven by demand, but rather by supply. It cannot be captured by the firm-product-year fixed effects because it varies across destinations as exporters increase their presence in destinations outside of the E.U.. Therefore, we attribute the presence of pre-trends to both the long-run trend of increased exports to high-risk destinations and to the consequences of the Eurozone crisis.

However, there is an alternative explanation – demand for Portuguese exports from high-risk destinations declines after 2013.[20] This possibility would explain the data and is consistent with the model we presented. However, this decrease in demand cannot be common across all exporters. In Appendix A we show that after 2013 there is a decline in exports from E.U. countries to high-risk destinations. However,

[18]To compute this, we multiply the coefficient by the share of exports going to high-risk destinations in 2013.

[19]The two main high-risk destinations to which Portugal exports are Brazil and Angola. Both of these countries experienced an economic downturn around 2013, which could bias our results. To address this, we estimate equation (3) and include either a past colonial links indicator or a common language indicator interacted with time fixed effects to fully absorb the variation coming from countries speaking Portuguese. We present the results in Table A.I in Appendix A. We still obtain a negative and significant average treatment effect.

[20]Another possibility is that there is an increase in tariffs within high-risk destinations for goods coming from Portugal or, more generally, from E.U. countries. In Figure A.7, we show that this is not the case. In fact, after 2013, tariffs on goods from the E.U. imposed by high-risk countries decrease. This dampens the negative effects on exports we identify.

this is not true for exports from countries outside of the E.U. (most of which did not implement Basel III): in 2013, the share of exports from non-E.U. countries to high-risk destinations was 41 percent; in 2018 this share was 42 percent.[21] Therefore, the alternative explanation is that demand for Portuguese exports from high-risk destinations declines after 2013, but that demand for exports for the same product from any other exporter outside of the E.U. does not change. This alternative explanation is, however, inconsistent with our findings in Section 5. A decrease in demand for Portuguese exports would lead to a decrease in the demand for credit on the part of Portuguese exporters as their production decreases. This decrease in demand for credit should lead to a decline in interest rates. Instead, we find evidence of an increase in interest rates, which is not consistent with the change in demand but is consistent with the effects of Basel III on credit supply.

If we use the variation in exports from countries outside of the E.U. to high-risk destinations as the counterfactual for the changes in demand, then we conclude that demand for Portuguese exports does not change between 2013 and 2018. In this case, we can interpret the coefficients in Figure 3 as the average treatment effects. If demand increases after 2013, then the coefficients in Figure 3 are upper bounds of the true average treatment effect. In Appendix A we use the method developed in Rambachan and Roth (2022) to compute confidence intervals in this case. We still obtain negative, persistent, and statistically significant effects on exports after the introduction of Basel III.

4.1.2 Heterogeneity across countries

We can also estimate equation (3) by decomposing high-risk countries into three groups based on their OECD sovereign rating in 2013: (1) countries with a sovereign rating of 2 (e.g. China), (2) countries with a sovereign rating of 3 (e.g. Brazil), and (3) countries with a sovereign rating between 4 and 7 (e.g. Turkey).[22] We use heterogeneity in sovereign risk within high-countries as a proxy for the likelihood that a bank is classified as high-risk. For example, we expect there to be some banks in China which are classified as low-risk. However, most Turkish banks should be considered high-risk.[23] This analysis is valuable because the probability that the foreign bank involved in the trade finance loan is high-risk (and would therefore receive a risk weight of 0.5) increases with the sovereign risk of the country (BIS, 2015). Moreover, this decomposition is the one used by the E.U. to define risk weights applicable to claims on foreign banks which are not trade finance loans and so banks are familiar with this classification. We present the result of this decomposition in Table III.

Basel III should lead to a larger increase in costs of banks lending to exporters selling in destinations with higher risk. Therefore, our mechanism predicts that countries with higher risk weights should experience a larger decline in exports. We find that, across all specifications, the decline in exports is more pronounced for high-risk destinations with higher risk. In our preferred specification, which is column (4), we find that exports to countries with a medium sovereign risk (e.g. China) do not change relative to the evolution of exports to low-risk destinations. For countries with worse sovereign ratings we find a decline in exports

[21] In Table C.I in Appendix C we also show that there is no evidence of a decline in exports from countries outside of the E.U. to high-risk countries for all products. In fact, there is some evidence of an increase in exports to high-risk destinations after 2013.

[22] The OECD published sovereign ratings for most countries. The ratings range from 0 to 7, where 0 is a very safe country and 7 is a very risky country. All OECD countries have a rating of 0 or 1, and are considered low-risk countries. These ratings do not change during the period of analysis.

[23] In our empirical analysis, we have implicitly assumed that all treated countries are treated with the same intensity. This is not the case as the increase in risk weights is not identical to all high-risk countries. The existence of different treatments or different treatment intensities may imply that using the two-way fixed effects estimator will not lead to a consistent estimator of the average treatment effect, as highlighted by De Chaisemartin and d'Haultfoeuille (2022) and Goldsmith-Pinkham et al. (2022). In Table A.III we show that our estimates are robust to the presence of this issue.

which is monotonic in the sovereign risk rating.

4.2 Effect on the product mix

From equation (2), we can write the change in exports, net of changes in demand and fixed effects, as

$$d \log \text{Exports}_{ipd} = -(\sigma - 1) \times \underbrace{\frac{\theta_p R_{ipd}}{\theta_p R_{ipd} + 1 - \theta_p}}_{m_{ipd} \in [0,1]} \times d \log R_{ipd}, \tag{5}$$

where we allow the share of marginal costs the firm must finance to vary across products. For example, some products like pharmaceuticals might take longer to produce when compared with other products, like coffee. From equation (5) we can then see that for a common shock to interest rates and conditional on the same average interest rate, products with a higher share of marginal costs that require external financing (a higher θ_p) should exhibit a larger decline in exports.

We want to compare different products according to their need for working capital loans. However, there is no readily available data set which would allow us to compute this measure at the product level. We therefore follow the approach of Rajan and Zingales (1998) and Chor and Manova (2012), who use Compustat data to compute measures of credit dependence by U.S. industry.[24] We compute our measure of credit dependence at the firm level in 2013 and then aggregate it at the 3-digit NAICS level by taking a weighted average of the measure, using firm sales as the weight. We then use the methodology in Pierce and Schott (2009) to match 3-digit NAICS industries to 4-digit product codes.[25]

The literature has often relied on measures such as these which are computed using U.S. data. This has some advantages. Note that our goal is to compute a measure of technological dependence on credit and which is not impacted by firm dependence on bank credit or a country's lack of financial development. As Compustat data has a large number of large firms, we can be confident that we are able to remove non-technological motives for dependence on bank credit. Furthermore, as the U.S. has the most developed financial system in the world, we can also think of this estimate as an estimate for the technological dependence on credit. An alternative would be the use our micro data for Portugal to compute this measure. This approach would have the advantage of being directly applicable to the Portuguese case. However, this is also a problem because, in Section 6, we conduct a similar exercise with aggregate data for E.U. countries and so we cannot use a Portuguese-based measure for German exports. Therefore, in order to have a consistent measure, we need to choose a single country.[26]

[24]In particular, they tend to focus on measures of long-term dependence on external capital. Their focus is more on how investment requires external capital. In our analysis, our focus in on short-term dependence on external capital.

[25]We choose 3-digit NAICS industries to balance the need for a sufficiently broad set of industries with the need to have a sufficiently large number of firms per industry. We aggregate the firm-level data to the industry level using firm sales as the weight. The industry-to-product match occasionally generates multiple industries being matched to the same product. In those circumstances, the industry-level measures are aggregated using as weights the total industry sales.

[26]Our method for estimating θ_p has an additional problem, as we conduct the exercise using sales data that mixes domestic sales and exports. Ideally, we would like to compute this in a data set that has either one or the other. For example, there may be a sector which ends up with a high θ_p but where the true θ_p is low but most sales are exports to a country that is very far away. Therefore, we could be picking up the effect of distance rather than the technological dependence on credit. In order to check whether or not this is a problem, we can compute the correlation between our measure of credit dependence and the average distance by product between the U.S. and the destination. We compute the average distance by taking the weighted average of the distance between the most populated city in the U.S. and the most populated city in the destination country and weighing this term by the share of exports of that product that go to the particular destination. This correlation is 0.06 and so we are confident that the estimation of θ_p is not affected by this problem. In addition, if we were to use another country like Portugal, which has a higher concentration of exports in a few countries, our measure could display a greater bias.

Our measure is the cash conversion cycle (CCC), which expresses the time (measured in days) it takes for a firm to convert its investments in inventory and other resources into cash flows from sales. This is an ideal measure for an exporter's dependence on credit because it measures how long each net input Euro is tied up in the production and sales process before its gets converted into cash received. This measure takes into account how much time the firm needs to sell its inventory, how much time it takes to collect receivables and how much time it has to pay its bills. The CCC for firm i at time t is computed as

$$\begin{aligned}\text{CCC}_{i,t} = &\left(\frac{\text{Avg. Inventory}_{i,t}}{\text{COGS}_{i,t}} + \frac{\text{Avg. Accounts Receivable}_{i,t}}{\text{Sales}_{i,t}}\right) \times 365 \text{ days} \\ &- \frac{\text{Avg. Accounts Payable}_{i,t}}{\text{COGS}_{i,t}} \times 365 \text{ days},\end{aligned}$$

which depends on the ratio of the average inventory to the cost of goods sold, the ratio of the average accounts receivable to sales, and the ratio of the average accounts payable to the cost of goods sold. The averages in the denominator are the average of the beginning and ending balance of inventory, accounts receivable, or accounts payable. A high CCC means that there is a long time lag between the investment in inventories and received payments. Therefore, a low CCC is better than a high one, and a high CCC implies a greater dependence on credit to overcome the long lag between production and cash from sales.[27]

We group products into two groups: products with a cash conversion cycle above the median (high dependence products) and products with a cash conversion cycle below the median (low dependence products).[28] As with the exercise when we compare firms according to their dependence on bank credit, we need that a product which is classified as high dependence would have been classified as high dependence under the true measure of product dependence on credit. However, we do not need that, within each bin, the ranking of products according to our measure is identical to the ranking of products according to the true measure of dependence on credit. Given this assumption, we estimate an augmented version of equation (3) where we include a third difference across these two products groups we have defined. We include firm-product-year and destination fixed effects, as well as a vector of time-varying destination controls. We cluster errors at the firm level. In our exercise, we define the low dependence products as the reference group. We present the results of this exercise in Table IV using data from 2011 to 2018.

Across all specifications, we conclude that the decline in exports to high-risk destinations relative to the evolution of exports to low-risk destinations is more pronounced for products with a high dependence on bank credit. In fact, in our preferred specification in column (4), almost all of the decline in exports to high-risk destinations is driven by a drop in exports of products with a high dependence on bank credit. This finding not only validates our mechanism, which operates through the working capital channel, but also illustrates how firms adjust to changes in the cost of credit by changing their product mix. In response to an increase in the cost of credit, firms skew their product mix towards products with a low dependence on working capital and bank credit to reduce their overall costs.

We have shown that there is substantial heterogeneity in terms of the treatment effects. Note that, given

[27] In our classification, products in manufacturing have a larger cash conversion cycle. For example, cars have a cash conversion cycle of 130 days, and engines have a cash conversion cycle of 121 days. Chemicals also have a long cash conversion cycle: pharmaceutical products have a cash conversion cycle of 124 days and fertilizers have a cash conversion cycle of 117 days. Agricultural products have low cash conversion cycles: coffee has a cash conversion cycle of 44 days, meat products have a cash conversion cycle of 42 days and flour products have a cash conversion cycle of 42 days.

[28] In Appendix A, we present the distribution of the cash conversion cycle. We also show that low-credit and high-credit products are very similar in terms of trade elasticities and in terms of product use (intermediates, capital or consumption). We also show that each of these groups represents around 50 percent of total Portuguese exports, and half of total Portuguese exports to high-risk countries.

our model, it is possible to have substantial heterogeneity across firms even if the increase in interest rates is identical. The presence of heterogeneous treatment effects may imply that estimates of the average treatment effect computed with a two-way fixed effect estimator are misleading. In particular, De Chaisemartin and d'Haultfoeuille (2020) have shown that the average treatment effect computed with two-way fixed effect estimator is a weighted average of all individual treatment effects. However, the weights are not necessarily all positive, even though they must add to one. Therefore, it is possible to have individual treatment effects which are all positive and obtain an estimate of the average treatment effect which is negative. To address this issue, we can use the alternative estimator developed by De Chaisemartin and d'Haultfoeuille (2020) which is robust to the presence of heterogeneous treatment effects. We find that results are largely identical to the ones we obtain from the two-way fixed effects estimator. We present these results in Table A.II.

4.3 Extensive margin – effects on entry and exit

We turn now to the extensive margin. As in Melitz (2003), we assume that, in order to be able to export to destination d, a firm must pay a fixed cost of entry $f_d > 0$ which is measured in units of labor. Therefore, firm i will only export product p to destination d at time t if $\pi_{pdt}(i) \geq f_d w_t$, i.e., if the operating profit is not smaller than the fixed costs of entry. We can write this condition as

$$\varphi_{ip} \geq \frac{\sigma}{\sigma-1}\left(\frac{A_{pd}}{\sigma}\right)^{1/(\sigma-1)} \tau_d f_d^{1/(1-\sigma)} w^{\sigma/(\sigma-1)} \mathcal{R}_{ipd} \tag{6}$$

which defines a threshold for the exporting decision. As the interest rate increases, the threshold increases as well and firms with lower productivities will exit destination d. Furthermore, entry into destination d by new firms decreases as they face reduced expected profits. Therefore, the unobserved financing costs represent a latent variable which influences the exporting decision. In this simple model, we predict that net entry into high-risk destinations should decline in response to an increase in credit costs. In our empirical analysis, we look at the effects on entry into high-risk destinations and exit from high-risk destinations separately. However, the elasticity of the threshold with respect to a change in interest rates is lower for the extensive margin than it is for the intensive margin. The elasticity of the volume of exports with respect to interest rates is given by $(\sigma-1) \times m_{ipd}$ while the elasticity of the extensive margin threshold is only m_{ipd}. Therefore, the effects on the extensive margin should be smaller than the effects on the intensive margin.[29]

4.3.1 Estimation

Our goal is to separately identify the effects of Basel III on entry and exit. We define an entrant as a firm which is exporting product p to destination d in year t but did not export that product to that destination in year $t-1$. An exiting exporter is a firm which was exporting product p to destination d in year $t-1$ but is no longer exporting that product to that destination in year t. Therefore, we define the entry and exit rates as

$$\text{Entry rate}_{pdt} = \frac{\text{Number of entrants}_{pdt}}{\text{Number of exporters}_{pdt}}, \quad \text{Exit rate}_{pdt} = \frac{\text{Number of exiting exporters}_{pdt}}{\text{Number of exporters}_{pd,t-1}}.$$

[29] To be more precise, the effects on the extensive margin depend on two factors: (1) the elasticity of the threshold and (2) the mass of firms around the threshold. If there is no bunching of firms around the threshold, the elasticity of the extensive margin should be smaller than the elasticity of the intensive margin.

We want to compare the evolution of the entry and exit rates for high-risk destinations with the evolution of these rates for low-risk destinations. To do so, we estimate the following equations:

$$\text{Entry rate}_{pdt} = \lambda_{pt} + \mu_d + \beta X_{dt} + \gamma Z_{dt} + u_{idt}, \tag{7}$$

$$\text{Exit rate}_{pdt} = \lambda_{pt} + \mu_d + \beta X_{dt} + \gamma Z_{dt} + u_{idt}, \tag{8}$$

where Z_{dt} is defined as in equation (4). We include product-year and destination fixed effects, as well as time-varying destination controls. Errors are now clustered at the destination level. We present the results of this analysis in Table V.

We find that entry into high-risk destinations declines by 2.5 percentage points when compared with entry into low-risk destinations, and that this decline is robust across various specifications. As the average entry rate in 2013 is 48 percent, this represents a decline of 5 percent in the entry rate. There is an increase in exit from high-risk destinations of 1.3 percentage points. However, this increase is not statistically significant. In Table A.IV in Appendix A, we show a decomposition of the effects on entry and exit by group of high-risk countries. We find that there is a small increase in exit for countries with an OECD sovereign rating between 4 and 7 and that the effects on entry are driven by countries with either medium risk (OECD sovereign rating of 2) or very high risk (OECD sovereign rating between 4 and 7).[30] We plot the effects on entry into and exit from high-risk destinations over time in Figure 4.

The decline in entry is not immediate as we can see in panel (a) – there is a steady decline until 2017 and then a stabilization. On the other hand, the effects on exit, while small, are immediate as the entry rate jumps in 2014 and then remains stable as we can see in panel (b). We attribute this difference in timing to the difference in how exporters learn about the higher costs of credit. Incumbents need credit on a regular basis and so will immediately learn that interest rates on loans relative to exports to high-risk destinations have increased. Consequently, they immediately exit. Possible entrants will only learn about this increase in interest rates when they ask the bank for the conditions on a possible loan to finance exports to high-risk destinations, which may take some time.

We find no effects on exit from high-risk destinations. Therefore, there is a asymmetric effect on the extensive margin – there are no effects on exit while there are some effects on entry. This asymmetry has been documented before but in response to temporary shocks. Alessandria and Choi (2007) motivate this asymmetry by assuming that the fixed cost exporting firms pay to continue exporting to a destination is lower than the entry cost. This explanation also holds for permanent shocks. If the fixed costs of continuing to export to a destination are smaller than the costs of entering the destination, entry will be more reactive than exit. To understand this, note that a firm will only enter into a location if the operating profits are at least as large as the continuation cost and a share of the total cost of entry, amortized over the lifetime of the firm.[31] A firm will exit a location if and only if operating profits fall below the continuation costs. Therefore, the threshold for entry is larger than the threshold for exit. As consequence, a fall in operating profits will generate a larger reaction in entry than exit.

Our finding that the extensive margin is a relevant channel through which credit shocks affect trade is new in the literature. In their study of the effects of a credit shock on Peruvian exporters, Paravisini et al.

[30] In Tables A.V and A.VI in Appendix A we show that our findings are not driven by the presence of heterogeneous treatment effects. In Table A.VII and A.VIII in Appendix A we also show that they are not influenced by the contamination bias discussed in De Chaisemartin and d'Haultfoeuille (2022) and Goldsmith-Pinkham et al. (2022). We find that there is a decline in entry for countries with very high risk (OECD sovereign ratings between 4 and 7) and there are no effects on exit.

[31] This share will depend on the discount factor of the firm. For example, if the firm discounts the future at an interest rate r, the threshold is $\pi \geq f_c + r f_x > f_c$.

(2015) find no effects on entry or exit, which is at odds with most trade models with firm heterogeneity as in Melitz (2003). There are two possible reasons why we find a change in entry when the literature has not. First, we focus on a permanent shock, while most of the literature has relied on temporary shocks. Second, we use six years of data after the shock. In contrast, Paravisini et al. (2015) use only three years.

5 Effect on credit conditions

We have thus far focused on the impact of Basel III on exports. However, Basel III is a shock that affects the marginal costs of firms, which then affect sales. Therefore, we can look at the interest rates obtained by exporters in order to confirm that there is in fact an increase in marginal costs. In principle, we would like to compare the evolution in interest rates in trade finance loans for a high-risk and a low-risk destination, for the same firm and product. However, this comparison is not possible as we are not able to perfectly identify loans as trade finance loans and we are not able to allocate loans to specific destinations within a particular firm.

To overcome this problem, we compare firms based on their exposure to high-risk destinations, in the spirit of Khwaja and Mian (2008). If a firm is very exposed to high-risk destinations, there is a higher probability that a particular loan (conditional on it being a trade finance loan) is directed at a high-risk destination. This also requires the assumption that the probability that a particular loan can be allocated to exports does not vary with the share to high–risk destinations. Therefore, if we are able to perfectly control for differences across firms, and we compare this loan to one obtained by a firm that is not very exposed to high-risk destinations, we obtain an estimate of the treatment effect on interest rates. We then allocate firms to two groups based on their exposure to high-risk destinations: firms with a share of exports to high-risk destinations above the cross-sectional median will be classified as high-exposure and firms below the median will be classified as low-exposure.[32]

This analysis also allows us to separate the effects of heterogeneity in the shock from the effects of heterogeneity in incidence. In our model in Section 5, we can write the impact of a change in interest rates in exports, net of other shocks, as

$$d \log \text{Exports}_{ipd} = -(\sigma - 1) \times m_{ipd} \times d \log R_{ipd}.$$

We have argued that by comparing exports to high-risk and to low-risk destinations within a firm, we are estimating the effects of an heterogeneous change in interest rates. However, there is another possible explanation. If there is a common shock $d \log R_{ipd} = d \log R$, our findings can also be rationalized by heterogeneity in incidence m_{ipd}. In particular, if incidence is larger for high-risk destinations than it is for low-risk destinations, our results can be explained even with a common shock to interest rates.[33] In this Section, we will therefore show direct evidence of an heterogeneity in interest rates in order to exclude the possibility that our findings are driven solely by heterogeneous incidence.

We use a data set which is now at the firm-year-bank-loan level, i.e., we observe data on loan k obtained by firm i from bank b in year t. We include only exporters, and we also observe their degree of exposure

[32] In this classification, we exclude firms that sell only to low-risk destinations and firms that sell only to high-risk destinations. We do this in order to be consistent with the empirical analysis in Section 4, where the inclusion of firm-product-year fixed effects as well as the interaction term between the year fixed effects and the indicator variable classifying destinations as high-risk implies that firms that sell only to one type of destination are not included in the regression.

[33] If this is the case, our findings are still causal as long as we interpret incidence as an exogenous characteristic. The different lies in the interpretation of the results.

to high-risk destinations in year t. We include all new loans with maturities less than 180 days. These two filters imply that we are only considering loans that are either trade finance or sufficiently similar such that they provide a good control group.

5.1 Effect on loan conditions

We start by looking at interest rates and loan amounts on all loans obtained by exporters. In this analysis, we compare firms that mainly export to high-risk destinations with firms that mainly export to low-risk destinations. We estimate the following regression:

$$Y_{ikbt} = \alpha_i + \lambda_{bt} + \gamma Z_{it} + \beta W_{ikbt} + u_{ikbt}, \tag{9}$$

$$Z_{it} = \mathbf{1}\{i \in \text{High-exposure to high-risk destinations in 2013}\} \times \mathbf{1}\{t \geq 2014\}. \tag{10}$$

On the left hand side, we have the interest rate or the logarithm of the loan amount for loan k obtained by firm i from bank b in year t. On the right hand side, we include firm, bank-year fixed effects, as well as loan controls, which include loan maturity (in days) and an indicator variable that takes the value of one if the loan is collateralized. We also include a vector of firm controls: log of total sales, the sales-to-asset ratio, the leverage ratio, the EBITDA-to-assets ratio, the growth rate of total sales, labor productivity, the ratio of current-to-total liabilities, the ratio of current-to-total assets, as well as the firm's age squared. Including bank-year fixed effects is particularly important because there are very few banks in Portugal and so idiosyncratic shocks to banks might be very relevant in this setting. The parameter of interest is γ, which is our estimate for the average treatment effect. We cluster the errors at the firm level and present the results of this estimation in Table VI.[34]

Firms that mainly sell to high-risk destinations obtain smaller loans after the implementation of Basel III when compared with firms that mainly sell to low-risk destinations, and this finding is robust across all specifications. In our preferred specification, which is column (3), we find that firms that mainly sell to high-risk destinations obtain loans which are 7 percent smaller than those obtained by firms that mainly sell to low-risk destinations. This number is the same order of magnitude as the effect we document for exports to high-risk destinations (which is around 8 percent). Therefore, the estimated elasticity of exports to loan amounts is very close to one. [35]

Interest rates are far less reactive – in column (3), we find that firms that mainly sell to high-risk destinations are charged an interest rate which is 13 basis points higher when compared with the evolution of interest rates faced by firms that mainly sell to low-risk destinations. The average interest rate faced by firms in 2013 was 7.3 percent was so this is a 1.8 percent increase in interest rates. Part of this asymmetry is driven by the change in loan amounts. Basel III increases the cost of giving a trade finance loan to a firm that sells to a high-risk destination. Therefore, when the firm seeks a loan, it seeks to reduce the interest rate by moving along the demand curve and by obtaining a smaller loan. The lack of reaction in interest rates can also be explained by credit rationing and selection.[36]

[34] We also show, in Table B.I, that the number of loans obtained by a firm in a given year does not change.

[35] One concern with this analysis is that firms may seek financing with either their customers or their suppliers. In fact, we find that receivables decline in this period which suggests that firms are financing themselves with their customers. This finding is also consistent with the idea that receivables are higher for exports to high-risk destinations and so as exports to these destinations decrease, so do receivables. We also find that inventories decline. We present these results in Table A.IX.

[36] We can also look at dynamic effects by allowing the average treatment effect γ in equation (9) to vary over time. We present the results of this estimation in Figure B.1. Loan amounts fall on impact and then continue to decrease until 2017. In 2014 and 2015, interest rates obtained by firms that mainly export to high-risk destinations increase by over 20 basis points when compared with the

5.2 Extensive margin – probability of obtaining a loan

In this Section, we have documented that firms which mainly export to high-risk destinations face higher interest rates and lower loan amounts when compared with firms with that mainly export to low-risk destinations. However, the effect on interest rates is much smaller than the effect on loan amounts. There are two possible explanations for this finding: credit rationing and selection.

Credit markets often yield an equilibrium which features rationing, as shown by Stiglitz and Weiss (1981) in their seminal paper. With credit rationing, the market interest rate does not induce market clearing as demand for credit is higher than supply. In particular, there are borrowers who would be willing to borrow at a higher interest rate but the banks are not willing to lend. Rationing can arise not only from information asymmetries but also from quantity constraints. If banks face regulatory constraints, the equilibrium might also feature rationing: borrowers might be willing to borrow more at the market interest rate, but banks are unwilling to lend. Therefore, in the presence of a shock to credit supply, it is possible that the market interest rate will not change even though the quantity of loans changes. As a consequence, the interest rate may not be a good statistic to infer the consequences of Basel III, as we will estimate the effects on the interest rate with a downward bias. This effect will not exist in loan amounts, because both firms and banks will adjust through quantities.

In our empirical analysis, we observed that net entry into high-risk destinations declines as a consequence of Basel III. The firms that exit from or no longer enter high-risk destinations are those with the lowest productivity. Therefore, the average productivity of firms who still export to high-risk destinations increases. From the perspective of the bank, this increase in average productivity implies that banks, upon meeting a firm which wishes to export to a high-risk destination, will perceive the firm as a low-risk firm. Therefore, the interest rate at which the bank is willing to lend to a firm exporting to a high-risk destination will also decrease. As a consequence, the selection induced by the decrease in net entry into high-risk destinations leads to a downward bias in our estimates for the effect on interest rates.

The two explanations we outlined above, credit rationing and selection, are testable as they both predict that firms that mainly export to high-risk destinations should obtain fewer loans from banks. To test this, we use our credit registry data to estimate the following equation

$$\text{Receives loan}_{it} = \alpha_i + \lambda_t + \gamma Z_{it} + \beta W_{it} + u_{it}, \tag{11}$$

where Z_{it} is defined as in equation (10). On the left hand side, we have an indicator variable which takes the value of 1 if firm i receives at least one bank loan in year t and zero if otherwise. On the right hand side, we include firm and year fixed effects, as well as a vector of firm controls. We cluster errors at the firm level and present the results of the estimation in Table VII.

We are interested in the average treatment effect, which estimates the effect of Basel III on the probability that a firm obtains a loan. We find that firms that mainly export to high-risk destinations observe a decline of 5.9 percentage points in the probability of obtaining a loan when compared with firms that mainly sell to low-risk destinations. This effect is robust to many different specifications. This decline is sizable and, compared with the pre-policy average probability of obtaining a loan, represents a 7 percent drop. Therefore, firms with a high exposure to high-risk destinations obtain fewer loans and, conditional on obtaining a loan, pay higher interest rates and receive smaller loan amounts. The decrease in the probability of obtaining a loan also suggests that the firms that sell to high-risk destinations and still obtain loans are the

evolution of interest rates obtained by firms that mainly sell to low-risk destinations.

firms with the highest quality and smallest risk. Consequently, there is an additional force which dampens the effects we estimate for interest rates.[37]

6 Aggregate Effects on E.U. countries

We have so far focused on the effects of Basel III on Portuguese firms and banks. However, the consequences of this policy are not circumscribed to Portugal as Basel III was implemented in all E.U. countries in 2014. In this Section, we show that the effects of Basel III are common across all E.U. countries. In particular, we show that exports to high-risk destinations decline for most E.U. countries and that this decline is driven by an increase in the cost of credit for exporters selling to high-risk destinations.

To study the effect of Basel III in exports from the E.U. to high-risk destinations, we use aggregate trade data from CEPII.[38] These data are at the exporter-importer-product-year level, where products are identified according the the 6-digit HS code. We aggregate the data to a 4-digit product classification and use focus on the 2008–2018 period. Our data set contains information on 18,175 destination-product pairs.

In the E.U., between 2000 and 2013, overall exports increased 8 percent per year on average. In 2000, exports represented 19 percent of total GDP and in 2013 this share had risen to 24 percent. A large share of this growth is driven by exports to high-risk destinations – exports to high-risk destinations had an average annual growth rate of 13 percent between 2000 and 2013 while exports to low-risk destinations grew 7 percent per year. Therefore, the share of high-risk destinations in total E.U. exports also grew from 20 percent in 2000 to 36 percent in 2013. However, following 2014, the growth rate of exports to high-risk destinations slowed down to 0.24 percent while the growth rate of exports to low-risk destinations slowed down to 0.58 percent. Therefore, E.U. exports behave in a similar way to Portuguese exports – exports to high-risk destinations grew very fast between 2000 and 2013, and then slowed down. In Figure 5, we plot the growth rate of exports to high-risk destinations against the growth rate of total exports for all E.U. countries.

In panel (a), we plot the growth rate of exports to high-risk destinations against the growth rate of total exports for the 2000–2013 period. We find that all but one country are above the 45-degree line. Therefore, between 2000 and 2013, exports to high-risk destinations grew faster than exports to low-risk destinations. This pattern is common across almost all E.U. countries. After 2013, most countries are below the 45-degree line and so we observe a slowdown in exports to high-risk destinations. Moreover, in panel (b), there is a substantial set of countries for which overall exports increase and exports to low-risk destinations decrease. For example, in Italy, total exports increased, on average, by 1.13 percent and exports to high-risk destinations fell by 2 percent.

[37] We can also allow the average treatment effect to vary over time and we present the results in Figure B.2. In response to Basel III, the probability that a firm that mainly exports to high-risk destinations obtains a loan decreases immediately by almost 6 percentage points. This effect is also permanent as this drop in the probability of obtaining a loan continues until 2018. This permanence is consistent with the effects of a permanent increase in the cost of bank credit for firms exporting to high-risk destinations.

[38] The data is available at CEPII. CEPII uses data from COMTRADE, after correcting for differences between import and export values.

6.1 High-risk destinations vs. low-risk destinations

To make a causal link between Basel III and the evolution of exports to high-risk destinations, we estimate the following equation for all E.U. countries using data between 2008 and 2013:

$$\log \text{Exports}_{spdt} = \mu_d + \lambda_{spt} + \beta X_{dt} + \gamma Z_{dt} + u_{spdt}, \tag{12}$$

where the dependent variable is the log of exports of product p from country s to destination d in year t. The right hand side includes destination fixed effects and exporter-product-year fixed effects. We also include time-varying destination controls to absorb all changes in demand for exports. These include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. We are therefore able to control for all changes at the exporter-level-product level and, with the controls, we are also able to absorb possible changes in demand. The parameter of interest is the average treatment effect γ, which multiplies the policy indicator Z_{dt}, which is defined as in equation (4), and takes the value of 1 if destination d is a high-risk country (measured in 2013) and the year is after 2014, and zero otherwise. We present the results of estimating equation (12) in Table VIII.

In columns (1) and (2), which do not include exporter-product-year fixed effects, we find no evidence of a decline in exports to high-risk destinations. In fact, we find that, after 2014, exports to high-risk destinations actually increase relative to exports to low-risk destinations. Once we control for shocks taking place at the exporter-product level in column (3), these results flip and we find that exports to high-risk destinations decrease by 4 percent relative to exports to low-risk destinations. We attribute this difference to the presence of shocks operating at the exporter-product level. For example, the exclusion of exporter-product-year fixed effects would not allows us to control for the presence of unobservable changes in factor prices. Different products may use different input combinations and so including exporter-year fixed effects is not enough to absorb these general equilibrium effects.The inclusion of demand controls also changes our estimate for the average treatment effect. If we compare columns (2) and (4) or columns (3) and (5) we see that when we include demand controls, the estimate decreases. Therefore, there are shocks operating at the destination level that increase demand from high-risk destinations. The presence of these shocks is consistent with the long–run trend we document for exports from the E.U. to high-risk specifications. Our preferred specification is column (5), which includes both exporter-product-year fixed effects and destination controls. We find that exports to high-risk destinations decline by almost 5 percent relative to exports to low-risk destinations.[39]

The effects we find using aggregate data are smaller than those we found using micro data, but go in the same direction. There are two reasons for this. First, Portugal is one of the countries where exports to high-risk destinations fall by most after 2013 and so the effect for Portugal is much larger, in absolute value, than the effect on the average E.U. country. The second reason has to with aggregation. In the empirical analysis in Section 4, we estimate the micro elasticity of exports to a change in the cost of credit. In this exercise, we estimate the elasticity at a higher level of aggregation, which controls for some general equilibrium effects

[39] We can also estimate equation (12) by allowing γ_t to vary over time, and we present the results of this estimation in Figure C.3. The effects of Basel III on exports are persistent, as we had documented in our micro data. Exports to high-risk destinations are declining over time in relative terms and, in 2018, have fallen by almost 7.5 percent relative to the evolution of exports to low-risk destinations. This is consistent with the consequences of a permanent increase in marginal costs arising from an increase in the cost of credit. The effect also takes some time, as the effects in 2014 are much smaller than those in 2015. In Figure C.4 in Appendix C we also report the average treatment effect by group of high-risk country. We find that the decline in exports is more pronounced for countries with higher sovereign risk, consistent with our mechanism.

with our fixed effects, but still involves aggregation at the country level, which may make the estimated elasticity smaller.[40]

6.2 High-credit products vs. low-credit products

We have identified a drop in exports to high-risk destinations relative to exports to low-risk destinations for E.U. countries after 2014, which we have argued is caused by the implementation of Basel III. However, there could be other alternative explanations, such as time-varying demand for E.U. exports which are not captured by our vector of controls. In order to address this possibility, we refine our analysis by adding another source of variation: differences in the use of credit across products. If we take exports to a particular high-risk destination, the marginal costs of products which require more credit should increase by more and so exports of this product should decline by more. To do this comparison, we use the same product classification as in Section 4. We split products into two groups according to their cash conversion cycle in 2013: one group above the median and one group below the median. We then estimate equation (12) by allowing the average treatment effect to vary across product groups. We present the results of this analysis in Table IX.

In column (1), we consider a specification with four layers of fixed effects. We estimate that the average treatment effect for products with low credit dependence is 2.5 percent, which means that exports to high-risk destinations of low-credit products increase by 2.5 percent compared with exports of low-credit products to high-risk destinations. We also find that the average treatment effect for high-credit products is 3.6 percentage points lower than the one for low-credit products. We find that exports to high-risk destinations of high-credit products fall by 3.6 percent relative to exports of low-credit products to high-risk destinations, relative to the same difference for low-risk destinations. Adding year-source-product fixed effects to control for changes in economic conditions at the exporter level and changes in the product supply which may co-vary with the economic cycle changes the results, as shows that even for low-credit products, exports to high-risk destinations decrease by 2.3 percent in column (2). Adding destination controls to the specification in column (1) does not change the results. Our preferred specification is the one in column (4), which includes year-source-product fixed effects and destination controls. We find that exports to high-risk destinations of low-credit products fall by 3 percent, relative to exports of low-credit products to high-risk destinations. However, exports of high-credit products fall by even more. Exports of high-credit products fall by around 6 percent, when we compare exports to high- and low-risk destinations. This is in line with our mechanism, which relies on an increase in marginal costs caused by an increase in the cost of credit. It also removes the possibility of possible shifts in demand in destinations which are not captured by our controls. Our specification also fully controls for common changes in the demand for particular products with our fixed effects. It also controls for destination-specific demand for a particular product as long the relation of this demand with aggregate economic conditions is constant over time. [41][42]

[40] We also estimate (12) for non-E.U. countries as a robustness check and we present the results in Table C.I in Appendix C. In this exercise, the average treatment effect is not statistically different from zero. Furthermore, if we estimate (12) around the Great Recession, which is a period in which there was a drop in credit supply as shown by Chor and Manova (2012) and Ahn et al. (2011), we do not find any difference between exports to high- and low-risk destinations, as we show in Table C.II in Appendix C.

[41] One concern with this exercise is that the distribution of credit dependence is very close to the median. In order to address this concern, we conduct this analysis by comparing products in the upper third of the distribution with products in the lower third of the distribution. The results of this exercise are in Table C.III in Appendix C and are qualitatively identical to those in Table IX.

[42] We also report in Figure C.5 in Appendix C the evolution of the average treatment effect over time. We find that for high-credit products, there is a smooth and persistent decline following 2014.

6.3 Dissecting the mechanism - the role of bank health

Our mechanism relies on the fact that Basel III increases the marginal cost of trade finance for high-risk destinations from the perspective of banks. This increase comes from the fact that, if the bank wishes to keep the capital ratio constant, it must either increase its equity or reduce its risk-weighted assets by selling risky sets to increase its stock of risk-free assets. An increase in bank equity is costly as bank equity is scarce. A decrease in risk-weighted assets generated by the sale of a risky asset and the subsequent purchase of a risk-free asset is also costly as the average return on assets will decrease. Therefore, banks with high capital ratios before the implementation of Basel III should observe a smaller increase in costs. Similarly, banks in countries where bank equity is less scarce should observe a smaller increase in the cost of providing loans to exporters selling to high-risk destinations. We will use the return on equity as a measure of scarcity of bank equity – if the return on equity is high, then bank equity should be scarce.

To do this, we will split E.U. countries into two groups: countries with healthy banking systems and countries with unhealthy banking systems. We use two measures of bank health: the average capital ratio and the average return on equity.[43] According to the first measure, a country has a healthy banking system if its average capital ratio in 2013 is above the median. Similarly, according to the second measure, a country has a healthy banking system if its return on equity in 2013 is below the median. Using either measure, we augment equation (12) by allowing the average treatment effect to vary across country groups and present the results in Table X.

We find that, for countries with a healthy banking system (large average capital ratio), exports to high-risk destinations do not change relative to exports to low-risk destinations. Therefore, for these countries, banks are not changing the interest rates they are charging firms that export to high-risk destinations. All of the decline in exports to high-risk destinations is driven by countries with unhealthy banking systems – exports by these countries to high-risk destinations decline by 11 percent. We find similar results for the return on equity, as all of the decline in exports to high-risk destinations is driven by countries where bank equity is scarce.

The results in this section highlight the importance of bank health in the transmission of Basel III. Although all banks in the E.U. face the same increase in risk weights, some countries are more exposed to the change in regulation. Bank health plays a crucial role in the exposure to Basel III as banks with a higher capital ratio or the ability to cheaply increase equity do not have the need to decrease their loans to firms exporting to high-risk destinations.

7 Model

In our empirical analysis in Section 5, we find that the impact of Basel III on interest rates is limited. We attributed this finding to credit rationing – if the market interest rate does not clear the market, then it is not a useful statistic to understand the impact of Basel III. With credit rationing, banks are unwilling to lend to borrowers offering an interest rate above the market rate. The actual cost of Basel is therefore captured by the shadow cost of credit, not the market interest rate. To compute this shadow cost, we require additional structure, or, in other words, we need a model. As most of our data relates to trade flows, this model must take as inputs interest rates on exports and produce trade flows. Combining the results in the empirical

[43] We use Orbis data which allows us to compute the capital ratio and the return on equity for a number of banks for all E.U. countries. We then aggregate these two measures at the country level by taking the weighted average across all banks in each country, using total assets as the weight.

section and aggregate trade flow data for the European Union, we can invert this mapping to compute the shock to interest rates which rationalize the data. We will interpret this shock as the shadow cost of Basel III.

This analysis relies on three key assumptions. The first assumption is that the model accurately represents the data. We use a state-of-the-art general equilibrium model that features many countries and sectors and which has been used to estimate the consequences of changes in tariffs. From the perspective of firms in high-risk countries, Basel III is equivalent to an increase in tariffs as both lead to a rise in the price of imports. It is therefore crucial that our model can explain both trade flows and the reaction of trade flows to variations in costs of trade. In this model, firms import cheaper intermediate inputs from abroad, which justifies the existence of international trade.

The second assumption is that the effects on aggregate trade flows are well identified. In our empirical analysis using aggregate trade flow data, we argued that we can estimate the causal effect of Basel III by comparing exports to high-risk destinations to exports to low-risk destinations. However, we also suggested that this comparison was not robust to the presence of demand shocks. Therefore, we rely on the triple-difference analysis using variation across products to calibrate the model. We calibrate the model using the effects of Basel III on products with a high dependence on bank credit and products with low dependence on bank credit. These estimates are robust to demand shocks or any other confounders operating at the destination level.

Third, we assume that we can interpret the calibrated shock to interest rates as the shadow cost of Basel III. The shadow cost of credit is the market price that would arise in a model with no frictions in the credit market. In our model, the credit market will operate with perfect information and no market power. Moreover, we will assume that firms must fund their marginal costs with bank credit and therefore have no outside option.

The model will also allow us to calculate the effects of Basel III on welfare through its impact on international trade. However, note that we cannot use this model to understand the overall impact of Basel III on welfare. In our model, the increase in interest rates is exogenous. Bank regulation, however, is not exogenous and its goal is to correct mispricing on the part of banks. The regulator believed that banks were not taking into account the risk of lending to exporters selling to high-risk destinations and so there was an excessive amount of lending to these exporters. Therefore, Basel III could increase welfare for E.U. countries by correcting this friction. The same cannot be said for high-risk countries. For high-risk countries, Basel III means only an increase in the price of imports, which always decreases welfare. Therefore, we should only interpret the change in welfare in our model as the welfare costs of Basel III rather than the welfare implications.

7.1 Model setup

We consider a multi-country multi-sector Ricardian model of international trade as in Caliendo and Parro (2015). The model is static. There are N countries indexed by either n or i and, within each country, there are J sectors indexed by j or k. Throughout the description of the model, subscripts will always denote countries and superscripts will always denote sectors. In this model, trade exists because firms want to purchase the cheapest inputs for production. Households will not consume foreign goods. There are two types of goods within each sector: composite goods and intermediate goods. Composite goods use intermediates from their sector in their production and are non-tradable. Producers of composite goods may import intermediates. Intermediate goods use domestic composite goods from all sectors and labor in production and may be tradable.

We describe the structure of the model in detail in Appendix E. Here, we focus on the main differences we introduce relative to Caliendo and Parro (2015) and show how a change in interest rates affects welfare.

7.1.1 Trade costs and prices

In this model, trade is costly. There are three different costs of trade: (1) iceberg costs, (2) tariffs and (3) financial frictions. Iceberg costs are standard: delivering one unit one good j from country n to country i requires shipping $d^j_{ni} \geq 1$ units of this good, where $d^j_{nn} = 1$ for all j, n. We also consider ad-valorem flat-rate tariffs: goods imported by country n from country i have to pay a tariff $\tau^j_{in} \geq 0$ applicable over unit prices, and where $\tau^j_{nn} = 0$ for all j, n. Finally, we have financial frictions. Each firm in sector j and country n that wants to export to country i will need to pay all of its cost of production in advance. In order to do so, it will need to borrow from a bank at an interest rate $r^j_{ni} \geq 0$ which the firm takes as given. Firms selling in the domestic market do not face this constraint and so we set $r^j_{nn} = 0$ for all j, n. We can combine these three trade costs in a single factor κ^j_{ni} which multiplies unit costs:

$$\kappa^j_{ni} = d^j_{ni} \times \left(1 + \tau^j_{ni}\right) \times \left(1 + r^j_{ni}\right).$$

In this model, iceberg costs are a deadweight loss. Producing $d^j_{ni} - 1$ requires the use of inputs and this quantity disappears or "melts". In contrast, tariffs are rebated as a lump-sum transfer to the representative household. We assume that the financial friction behaves like iceberg costs, and so the interest paid by firms will not be rebated to households and represents a waste of resources. In practice, this implies that the total value of interest payments appears in the aggregate resource constraint, but not on the household's budget constraint. In contrast, we assume that the revenue earned by tariffs is redistributed lum-sum to households.

7.1.2 Welfare

In this model the natural measure of welfare is real household income, or real GDP. The following Proposition shows that we can decompose changes in welfare into three terms: a terms-of-trade effect, a volume-of-trade effect, and a trade costs effect.

Proposition 1 *The change in welfare in country n arising from a change in interest rates can be written as*

$$\begin{aligned} d\log W_n = &\frac{1}{I_n}\sum_{j=1}^{J}\sum_{i=1}^{N}\left(E^j_{ni} d\log c^j_n - M^j_{in} d\log c^j_i\right) \\ &+ \frac{1}{I_n}\sum_{j=1}^{J}\sum_{i=1}^{N}\tau^j_{in}M^j_{in}\left(d\log M^j_{in} - d\log c^j_i\right) \\ &- \frac{1}{I_n}\sum_{j=1}^{J}\sum_{i=1}^{N}\left(1+\tau^j_{in}\right)M^j_{in}dr^j_{in}. \end{aligned} \tag{13}$$

where W_n is welfare in country n, I_n is total household income (wage income and tariff revenue), E^j_{ni} denotes exports of product j by country n to country i, c^j_n is the marginal cost of producing good j in country n net of trade costs, and M^j_{in} denotes imports of good j from country i to country n.

Proof. In Appendix E. ■

We can interpret the first term as a terms-of-trade effect as it captures the change in the price of exports of country n relative to the change in its imports. Note that the terms-of-trade effect depends only on marginal costs and not on interest rates or tariffs. This happens because the revenue generated by those two frictions is not captured by firms. An increase in terms-of-trade is beneficial for country n because then, conditional on a given quantity, its exports can command more imports in the world market.

The second term measures the welfare gains from changes in the volume of trade, which is measured as the quantity of imports. An increase in the volume of imports increases welfare for two reasons. First, an increase in the quantity of trade, conditional on prices, will lead to an increase in tariff revenue for the country. Second, as imports increase so does productivity as country n can rely on cheaper intermediates.

The third term measures the welfare losses arising from an increase in interest rates. If interest rates in a country i increase for exports to country n then country n will have to pay a higher price for its imports. As a consequence, productivity will decrease in country n and this will generate a loss in welfare. If country n is a high-risk country, then this effect can be thought of as the first-round or direct effect of an increase in interest rates on welfare. This increase in interest rates also has an impact on country i but this happens through general equilibrium effects – as demand for its exports declines, its marginal costs will decline as well. Therefore, we can think of the third term in equation (23) as the direct effect of the increase in interest rates, while keeping all trade flows and prices constant.

Consider a high-risk country. As interest rates increase, the high-risk country will observe a welfare loss from the trade costs effect. This effect increases with the size of E.U. countries (measured here as the value of exports from E.U. countries to the high-risk country). As imports become more expensive, the high-risk country will need to reduce quantity, which will lead to a negative volume-of-trade effect as tariff revenue decreases. Finally, as the country must use more expensive intermediate goods, its marginal costs will increase. If this increase is larger than the change in the price of its imports, the high-risk country may experience a positive terms-of-trade effect.

Consider now a E.U. country. As the interest rates which are imposed on its imports do not change, the cost of trade effect is zero as the direct effect of this increase will not change welfare in E.U. countries. This happens because, if we keep all trade flows and prices constant, welfare in E.U. countries does not change because the increased revenue from interest rates is not distributed to households. An increase in interest rates will decrease global demand for its exports, leading to a decrease in E.U. exports. As its exports decrease, its imports must decrease as well due to the balanced trade equation. Therefore, there will be a negative volume-of-trade effect. Finally, as demand for its exports decrease, domestic demand for factors of production will fall. In particular, labor demand will decrease. As labor supply is perfectly inelastic, this implies that the nominal wage will increase which then leads to a decline in marginal costs. This decline in marginal costs will then lead to a negative terms-of-trade effect (conditional on no movement on the price of imports).

7.1.3 Discussion

Our goal was to write down a model to explain the impact of an increase in interest rates faced by exporters who sell their products to high-risk destinations. In this model, trade exists because of productivity differences across countries. As firms purchase intermediates for production, they import goods if the price of the imported input is lower than the domestically produced input. Therefore, we only have Ricardian motives for trade. We have, for example, abstracted from love-for-variety motives for trade. In our model, each country can buy the same set of products. In a model with this motive for trade, as Krugman (1979) and Melitz (2003), there would be an additional cost on the side of high-risk countries if the set of products they can import and consume decreases. We focus instead on Ricardian trade because we wish to highlight what we call the intermediate good channel: an increase in the costs of trade will make inputs more expensive and that will then affect all production in high-risk countries.

We also focus our attention on a model of the long-run where there are no nominal rigidities or frictions in adjustments. In this model, prices and wages are fully flexible and firms can freely adjust their mix of imported inputs. The exclusion of nominal rigidities is not an innocuous choice. Rodríguez-Clare et al. (2022) have shown that including downwardly rigid nominal wages in a Ricardian model of trade may dampen gains from trade. In particular, they show that in a model with this type of rigidity, welfare gains in the U.S. from the China shock may be reduced due to a temporary increase in unemployment. In our model, this could mean that as E.U. countries observe an increase in interest rates, and as global demand for their exports decrease, the subsequent decrease in labor demand need not cause a decrease in the nominal wage. In a world with nominal rigidities, this shock would cause unemployment in E.U. countries, which could lead to additional welfare losses. Alternatively, if firms were not able to freely adjust their imported inputs, the welfare losses in high-risk countries could be higher as their imports become even more expensive. On the side of E.U. countries, this could mean that demand for their exports would not fall as much which would decrease their welfare losses.[44]

We also exclude the possibility of an adjustment through the extensive margin, i.e. through firm entry or exit. We do this in order to focus on the channel of imported inputs and to obtain a tractable model. Moreover, since we use the results in Section 6 to calibrate the model and the aggregate trade flows regression do not provide any information on entry or exit by firms, there would be a added difficulty in terms of calibration. This choice to focus on the role of intermediate inputs instead of the extensive margin should not have a significant impact in our welfare analysis as Arkolakis et al. (2019) have shown that models of the Melitz-Krugman type will not yield significantly different welfare effects of trade when compared with Ricardian models.

In our model, we assume that the revenue earned through interest rates represents a loss of resources. An alternative would be to assume that this revenue is distributed to households, as we assume for tariffs. This alternative assumption would introduce a new channel through which the increase in interest rates operates. If the interest rate revenue is not distributed, an increase in interest rates reduces welfare because global demand for E.U. exports decreases. Consequently, domestic demand in E.U. countries for factors of production falls, which lowers wages. The reduction in wages leads to a decrease in household income, which in turn causes a welfare loss. If the revenue from interest rates is distributed, there is also a positive income effect. An increase in interest rates will increase the revenue from interest rates *ceteris paribus*, increasing household income. As household income increases, demand increases, stimulating demand for factors and thus increasing wages. Therefore, this additional channel may undo some of the welfare losses.

Given that we use hat algebra to solve the model, not including interest rates as a transfer to households implies that we do not need to specify the initial level of interest rates. This is particularly important because, in a model where interest rates are distributed to households, the initial level of interest rates will have first-order importance in determining the impact of an increase in interest rates on household income. If interest rates are very low, an increase in interest rates will yield a substantial increase in the revenue

[44] In Appendix E.7.2, we look at an equilibrium with low trade elasticities which mimics frictions in adjustment. We find that E.U. welfare losses are smaller and that welfare losses for high-risk countries are larger.

earned by interest rates. If interest rates are high, this effect might be smaller or even negative as revenue from interest rates might decline.[45] Therefore, it is important to have a good source of data with which to calibrate the initial level of interest rates. As we do not have the means to calibrate the initial level of interest rates, we instead assume that they represent an efficiency loss and acknowledge that our results for welfare may represent an upper bound for the welfare costs of Basel III through international trade.

In this model we are also not including the frictions that motivate the existence of Basel III. Basel III was introduced because the regulator believed that banks were mispricing their financial products. In particular, for trade finance products, if banks undervalue the risk exposure to high-risk destinations introduces in their balance sheet, then they are charging interest rates which are too low. In our model, the increase in interest rates is exogenous and there is no risk. Therefore, distributing interest rate revenue to households will not help us in understanding the impact of Basel III. The motivation behind Basel III is not to increase bank profits or dividends, but to correct mispricing. In this paper, we are interested in the costs of Basel III, not the benefits. Consequently, including interest rate revenue as a source of income for households will lead to an underestimation of the costs, without providing any insight on the possible benefits of Basel III.

7.2 Impact of Basel III

Our calibration strategy implies that the model will exactly match the base year, which includes aggregate trade deficits. However, in our model, aggregate trade deficits are exogenous and so any shock will not adjust the countries' trade deficits. In order to address this problem, we follow Caliendo and Parro (2015) and calibrate the model by first eliminating all aggregate deficits. We then use the no-deficit world economy as our base year. Note that this methodology does not imply that sectoral deficits are zero, nor does it directly pin down these values, which are endogenous.

7.2.1 Identification of the shock

The first goal of this section is to estimate the shadow cost of Basel III on international trade. To conduct this estimation, we use the results from our empirical analysis using aggregate trade flow data in Section 6. Using the model we have described in this Section, we then find the shock to interest rates which rationalizes the evolution of exports to high-risk destination. In particular, we assume the following specification for the increase in interest rates:

$$\Delta r_{in}^{j} = \begin{cases} \zeta & \text{if } i \in \text{E.U. and } n \in \text{High-risk and } j \in \text{High-credit}, \\ \phi \times \zeta & \text{if } i \in \text{E.U. and } n \in \text{High-risk and } j \in \text{Low-credit}, \\ 0 & \text{if otherwise.} \end{cases}$$

For high-credit sectors, we assume that interest rates increase by $\zeta \geq 0$ for exports from the E.U. towards high-risk countries. For low-credit products, we assume that interest rates increase by $\phi \times \zeta$ where $\phi \in [0, 1]$. This specification can be micro-founded through a model in which firms need only borrow a fraction ϕ of their marginal costs and can use internal funds to cover the remaining share. In this structure, when $\phi = 1$ we return to the previous model and when $\phi = 0$ we return to the canonical Caliendo and Parro (2015) model. We assume that tradable sectors can be classified as either high-credit dependent or low-credit

[45] We provide an illustration of this possibility in Appendix E.5.

dependent.[46] We can therefore use the two parameters we estimate in our empirical exercise for the year 2018 to calibrate these parameters. Note that, in our exercise, we cannot separately identify the exposure of high-credit and low-credit products. Therefore, if we wish to identify ζ, we can only identify $\phi^{\text{low}}/\phi^{\text{high}}$ and so by imposing that $\phi^{\text{high}} = 1$ we can identify ϕ^{low}.

We use these two parameters $\{\zeta, \phi\}$ to match the average treatment effect on exports to high-risk destinations we observe in the data. Note that this does not mean that we are matching the unconditional growth rate of exports of high-credit goods from E.U. countries to high-risk countries. For each vector of parameters, we simulate a path for exports and estimate a triple-difference regression as in Section 6.[47] We present the results for our estimation exercise in Table XI.

Our model yields an increase in interest rates of 1.75 percentage points on exports from E.U. countries to high-risk countries for high-credit products. We are also able to match the effect on low-credit products by calibrating the exposure ϕ to 0.4. This is in line with our empirical findings where the effects on high-credit products are roughly 60 percent larger. Therefore, for these products, firms only need to pay 40 percent of their marginal costs in advance.[48]

The changes in interest rates we document in Table XI are much larger than the ones in Section 5. In our empirical analysis using credit registry data, we found that interest rates faced by firms that mainly export to high-risk destinations increased only by 13 basis points. The model in this section suggests an increase one order of magnitude above. The difference is explained by the fact that the calibration is capturing the shadow cost of Basel III on interest rates, rather than the market interest rate. In the presence credit rationing, the market interest rate does not reflect the true costs of implementing Basel III. Moreover, as in this model firms cannot exit from or choose not to enter into high-risk destinations, there is no dampening in the estimation of the effect on interest rates. Finally, we also do not allow firms to seek alternative sources of external credit, which also allows to fully capture the effects of Basel III on interest rates. Our estimation strategy in this Section therefore allows us to fully understand the costs imposed by Basel III through its effects on international trade.

We target two conditional moments: the average treatment effect on high-credit sectors and the average treatment effect on low-credit sectors. In Table XII, we present the model fit for four unconditional and untargetted moments for E.U. countries: the growth rate of total exports, the growth rate of exports to low-risk countries, the growth rate of exports to high-risk countries and the change in the share of high-risk countries in total exports.

We closely match the growth rate in exports to high-risk countries using our model. This is not a calibrated moment because our exercise seeks to match the conditional relative growth rate of exports to high-risk countries and this is the unconditional growth rate of exports to high-risk countries, which may include the effects of shocks we do not include in the model. The close match suggests that the conditional and unconditional moments are close and therefore lends weight to our mechanism. We cannot match the growth rate of exports to low-risk countries. This is a direct consequence of our empirical strategy. We use

[46] We classify each of our tradable sectors by using the cash conversion cycle measure. We present a list of the sectors that are classified in each of these groups in Appendix E.

[47] We simulate future exports for all source-destination-product tuples. This generates a panel with two periods, where we observe exports for all source-destination-product tuples. Using only exports from E.U. countries, we regress the logarithm of exports on: (1) source-product-year fixed effects, (2) destination fixed effects, (3) the interaction between a time fixed effect and an indicator variable which takes the value of one if the destination country is high-risk and zero if otherwise (which captures the average treatment effect for products with low credit dependence), and (4) the interaction between a time fixed effect, the high-risk dummy, and a dummy for high-credit products (which captures the difference in average treatment effects between low- and high-credit products.

[48] In fact, to be precise, this result says that for two products with the same marginal costs, a firm producing a low-credit product will only need to obtain 40 percent of what the firm producing the high-credit product would need to borrow.

exports to low-risk countries as a control group. This choice implies that we fully absorb any change in this group of countries using fixed effects. Therefore, changes in demand or unobserved changes in productivity or trade costs are completely absorbed and cannot be matched with our empirical exercise. As a consequence, we also miss the growth in total exports because we underestimate the growth rate of exports to low-risk countries. Finally, we are able to match the change in the share of exports to high-risk countries, although we underestimate the drop in this quantity. This imperfect match comes from the fact that we underestimate the growth rate of exports to low-risk countries.

7.2.2 Effect on welfare

Using the decomposition we presented in equation (13), we can compute the change in real GDP for all countries in our sample as well as the contributions from the change in terms-of-trade, volume-of-trade and credit costs. We present the results in Table XIII.

We begin with E.U. countries who exhibit a welfare loss of 0.09 percent as a consequence of the increase in interest rates. This is not a very large effect but it has been noted by Arkolakis et al. (2012) that the overall impact of trade costs in welfare is small. However, within the context of the usual welfare consequences of trade, this is sizable. For example, Caliendo and Parro (2015) use a very similar model to this one and find that the total gains from NAFTA to the U.S. are 0.08 percent which means that our results are of the same magnitude as NAFTA for the U.S. The cost of trade effect is zero as there is not change in the interest rates for exports from non-E.U. countries. The volume of trade effect is negative but very small. This suggests that the E.U. did not have to greatly reduce imports as a consequence of the change in interest rates. In fact, total E.U. imports declined only by 1.18 percent. The bulk of the effect comes from the terms-of-trade effect. As E.U. exports become less competitive, global demand declines. The consequence of this decline is a drop in demand for factors of production, which must lead to a decrease in their prices. The extreme case is labor: as labor supply is perfectly inelastic, the drop in demand affects the nominal wage one for one. The decline in factor prices and the nominal wage then leads to a decrease in marginal costs, which leads to a decrease in the price of exports. This decline has an advantage: it increases demand for E.U. exports which then has a positive contribution to the volume-of-trade effect. However, this increase in competitiveness also implies that E.U. countries can finance fewer imports for the same level of exports, which decreases welfare. Interestingly, the effect coming from the price of imports is positive, which means that the price of imports falls. This happens because the main trade partners of E.U. countries are E.U. countries. Therefore, the fact that a trading block is raising the interest rates helps reduce welfare losses.

High-risk countries also exhibit welfare losses of 0.04 percent, which are completely driven by the first-round effect of the increase in interest rates. Both the volume-of-trade and terms-of-trade effects are very small. Therefore, high-risk countries do not decrease the quantity of imports by much and their terms-of-trade either remain the same or improve slightly. The improvement in the terms-of-trade is of course driven by an increase in the price of exports which comes from an increase in marginal costs. This increase in marginal costs comes from the increase in the price of imported inputs. Finally, it's also important to note that welfare losses are larger in E.U. countries than in high-risk countries.

8 Conclusion

In this paper, we study how exporters react to an increase in the cost of credit. We examine three channels: the intensive margin, the extensive margin, and product mix adjustments. We find that, in response to an increase in the cost of credit, exporters cut exports to high-risk destinations by 8 percent. Moreover, overall exports do not increase, which suggests exporters cannot offset the decrease in exports with an increase in exports to other locations. On the extensive margin, we find that entry into high-risk destinations declines. We also show that firms' product mix changes in response to this shock. Firms adjusted by shifting towards products with a lower dependence on working capital and bank credit. This finding underscores the importance of product characteristics, such as the cash conversion cycle, in determining a firm's overall exposure to credit shocks. We also find that firms respond to the increase in the cost of credit by reducing the size of the loans they obtain from banks or by obtaining fewer loans overall.

We also use a structural model, which we calibrate using our empirical results to identify the welfare consequences of this increase in the cost of credit. This model combines a Ricardian trade structure with financial frictions. Using the model, we find that the increase in the cost of trade leads to welfare losses for high-risk destinations as the price of imports increases. It also leads to welfare losses for EU countries due to a depreciation in terms of trade caused by an erosion of comparative advantage.

Our analysis focuses on the impact of Basel III on exporters. However, importers may also be reacting to the increase in costs. For example, do overall imports of firms in high-risk destinations fall? Does this decline vary across firms? Do these importers shift their banking relationships to banks that are perceived as low-risk? All of these questions are crucial to understanding the full impact of Basel III on trade, and we leave them for future research.

References

Ahn, JaeBin, Mary Amiti, and David E Weinstein, "Trade Finance and the Great Trade Collapse," *American Economic Review*, 2011, *101* (3), 298–302.

Aiyar, Shekhar, Charles W Calomiris, and Tomasz Wieladek, "Does Macro-Prudential Regulation Leak? Evidence From a UK Policy Experiment," *Journal of Money, Credit and Banking*, 2014, *46* (s1), 181–214.

_ , _ , John Hooley, Yevgeniya Korniyenko, and Tomasz Wieladek, "The International Transmission of Bank Capital Requirements: Evidence From The UK," *Journal of Financial Economics*, 2014, *113* (3), 368–382.

Alessandria, George and Horag Choi, "Do Sunk Costs of Exporting Matter for Net Export Dynamics?," *The Quarterly Journal of Economics*, 2007, *122* (1), 289–336.

Almunia, Miguel, Pol Antràs, David Lopez-Rodriguez, and Eduardo Morales, "Venting Out: Exports During A Domestic Slump," *American Economic Review*, 2021, *111* (11), 3611–62.

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," *Journal of Political Economy*, 2015, *123* (4), 853–901.

Arkolakis, Costas, Arnaud Costinot, and Andrés Rodríguez-Clare, "New Trade Models, Same Old Gains?," *American Economic Review*, 2012, *102* (1), 94–130.

_ , _ , Dave Donaldson, and Andrés Rodríguez-Clare, "The Elusive Pro-competitive Effects of Trade," *The Review of Economic Studies*, 2019, *86* (1), 46–80.

Bahaj, Saleem and Frederic Malherbe, "The Forced Safety Effect: How Higher Capital Requirements Can Increase Bank Lending," *The Journal of Finance*, 2020, *75* (6), 3013–3053.

Becker, Bo, Jinzhu Chen, and David Greenberg, "Financial Development, Fixed Costs, and International Trade," *The Review of Corporate Finance Studies*, 2013, *2* (1), 1–28.

Benmelech, Effi, Carola Frydman, and Dimitris Papanikolaou, "Financial Frictions and Employment during the Great Depression," *Journal of Financial Economics*, 2016.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, "How Much Should We Trust Differences-in-Differences Estimates?," *Quarterly Journal of Economics*, 2004, *119* (1), 249–275.

BIS, "Treatment of Trade Finance Under The Basel Capital Framework," https://www.bis.org/press/p111025.htm 2015.

Boehm, Christoph E, Andrei A Levchenko, and Nitya Pandalai-Nayar, "The Long and Short (Run) of Trade Elasticities," Technical Report, National Bureau of Economic Research 2020.

Caggese, Andrea and Vicente Cuñat, "Financing Constraints, Firm Dynamics, Export Decisions, and Aggregate Productivity," *Review of Economic Dynamics*, 2013, *16* (1), 177–193.

Caliendo, Lorenzo and Fernando Parro, "Estimates of the Trade and Welfare Effects of NAFTA," *The Review of Economic Studies*, 2015, *82* (1), 1–44.

_ , Giordano Mion, Luca David Opromolla, and Esteban Rossi-Hansberg, "Productivity and Organization in Portuguese Firms," *Journal of Political Economy*, 2020, *128* (11), 4211–4257.

Chaisemartin, Clément De and Xavier d'Haultfoeuille, "Two-way Fixed Effects Estimators with Heterogeneous Treatment Effects," *American Economic Review*, 2020, *110* (9), 2964–96.

_ and _ , "Two-way Fixed Effects and Differences-in-Differences Estimators with Several Treatments," Working Paper 2022.

Chaney, Thomas, "Liquidity Constrained Exporters," *Journal of Economic Dynamics and Control*, 2016, *72*, 141–154.

Chodorow-Reich, Gabriel, "The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008–9 Financial Crisis," *The Quarterly Journal of Economics*, 2014, *129* (1), 1–59.

Chor, Davin, "Unpacking Sources of Comparative Advantage: A Quantitative Approach," *Journal of International Economics*, 2010, *82* (2), 152–167.

_ and Kalina Manova, "Off the Cliff and Back? Credit Conditions and International Trade During the Global Financial Crisis," *Journal of International Economics*, 2012, *87* (1), 117–133.

Dekle, Robert, Jonathan Eaton, and Samuel Kortum, "Global Rebalancing with Gravity: Measuring the Burden of Adjustment," *IMF Staff Papers*, 2008, *55* (3), 511–540.

Djankov, Simeon, Caroline Freund, and Cong S Pham, "Trading on Time," *The Review of Economics and Statistics*, 2010, *92* (1), 166–173.

Dobkin, Carlos, Amy Finkelstein, Raymond Kluender, and Matthew J Notowidigdo, "The Economic Consequences of Hospital Admissions," *American Economic Review*, 2018, *108* (2), 308–52.

Eaton, Jonathan and Samuel Kortum, "Technology, Geography, and Trade," *Econometrica*, 2002, *70* (5), 1741–1779.

Friedrich, Benjamin U and Michal Zator, "Flexibility Costs of Debt: Danish Exporters During the Cartoon Crisis," Working Paper 2022.

Gertler, Mark and Kenneth Rogoff, "North-South Lending and Endogenous Domestic Capital Market Inefficiencies," *Journal of Monetary Economics*, 1990, *26* (2), 245–266.

Giroud, Xavier and Holger M Mueller, "Firms' Internal Networks and Local Economic Shocks," *American Economic Review*, 2019, *109* (10), 3617–49.

Goldsmith-Pinkham, Paul, Peter Hull, and Michal Kolesár, "Contamination Bias in Linear Regressions," Working Paper 2022.

Goodman-Bacon, Andrew, "Public Insurance and Mortality: Evidence from Medicaid Implementation," *Journal of Political Economy*, 2018, *126* (1), 216–262.

_ , "Difference-in-differences with Variation in Treatment Timing," *Journal of Econometrics*, 2021.

Gropp, Reint, Thomas Mosk, Steven Ongena, and Carlo Wix, "Banks Response to Higher Capital Requirements: Evidence from a Quasi-Natural Experiment," *The Review of Financial Studies*, 2019, *32* (1), 266–299.

Hanson, Samuel G, Anil K Kashyap, and Jeremy C Stein, "A Macroprudential Approach to Financial Regulation," *Journal of economic Perspectives*, 2011, *25* (1), 3–28.

Huber, Kilian, "Disentangling the Effects of a Banking Crisis: Evidence from German Firms and Counties," *American Economic Review*, 2018, *108* (3), 868–98.

Hummels, David L and Georg Schaur, "Time As A Trade Barrier," *American Economic Review*, 2013, *103* (7), 2935–59.

Kashyap, Anil K, Jeremy C Stein et al., "Cyclical Implications of the Basel II Capital Standards," *Economic Perspectives-Federal Reserve Bank Of Chicago*, 2004, *28* (1), 18–33.

_ , Richard Berner, and Charles AE Goodhart, "The Macroprudential Toolkit," *IMF Economic Review*, 2011, *59* (2), 145–161.

Khwaja, Asim Ijaz and Atif Mian, "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market," *American Economic Review*, 2008, *98* (4), 1413–42.

Krugman, Paul R, "Increasing Returns, Monopolistic Competition, and International Trade," *Journal of* *international Economics*, 1979, *9* (4), 469–479.

Loecker, Jan De, "Product Differentiation, Multiproduct Firms, and Estimating the Impact of Trade Liberalization on Productivity," *Econometrica*, 2011, *79* (5), 1407–1451.

Manova, Kalina, "Credit Constraints, Equity Market Liberalizations and International Trade," *Journal of International Economics*, 2008, *76* (1), 33–47.

_ , "Credit Constraints, Heterogeneous Firms, and International Trade," *Review of Economic Studies*, 2013, *80* (2), 711–744.

Manski, Charles F and John V Pepper, "How do Right-to-Carry Laws Affect Crime Rates? Coping with Ambiguity using Bounded-variation Assumptions," *Review of Economics and Statistics*, 2018, *100* (2), 232–244.

Matsuyama, Kiminori, "Credit Market Imperfections and Patterns of International Trade and Capital Flows," *Journal of the European Economic Association*, 2005, *3* (2-3), 714–723.

Mayer, Thierry, Marc J Melitz, and Gianmarco IP Ottaviano, "Market Size, Competition, and the Product Mix of Exporters," *American Economic Review*, 2014, *104* (2), 495–536.

Melitz, Marc J, "The impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 2003, *71* (6), 1695–1725.

Mendes, Diogo, "Financial Constraints and Product Market Decisions: The Role of Production Cycles," Working Paper 2020.

Minetti, Raoul and Susan Chun Zhu, "Credit Constraints and Firm Export: Microeconomic Evidence from Italy," *Journal of International Economics*, 2011, *83* (2), 109–125.

Niepmann, Friederike and Tim Schmidt-Eisenlohr, "International Trade, Risk and the Role of Banks," *Journal of International Economics*, 2017, *107*, 111–126.

Paravisini, Daniel, "Local Bank Financial Constraints and Firm Access to External Finance," *The Journal of Finance*, 2008, *63* (5), 2161–2193.

_ **, Veronica Rappoport, Philipp Schnabl, and Daniel Wolfenzon**, "Dissecting the Effect of Credit Supply on Trade: Evidence from Matched Credit-Export Data," *Review of Economic Studies*, 2015, *82* (1), 333–359.

Pierce, Justin R. and Peter K. Schott, "A Concordance Between Ten-Digit U.S. Harmonized System Codes and SIC/NAICS Product Classes and Industries," Working Paper 2009.

Rajan, Raghuram and Luigi Zingales, "Financial Development and Growth," *American Economic Review*, 1998, *88* (3), 559–586.

Rambachan, Ashesh and Jonathan Roth, "A More Credible Approach to Parallel Trends," *Working Paper*, 2022.

Repullo, Rafael and Javier Suarez, "The Procyclical Effects of Bank Capital Regulation," *The Review of financial studies*, 2013, *26* (2), 452–490.

Rodríguez-Clare, Andres, Mauricio Ulate, and Jose P Vasquez, "Trade with Nominal Rigidities: Understanding the Unemployment and Welfare Effects of the China Shock," 2022.

Schmidt-Eisenlohr, Tim, "Towards a Theory of Trade Finance," *Journal of International Economics*, 2013, *91* (1), 96–112.

Stiglitz, Joseph E and Andrew Weiss, "Credit Rationing in Markets with Imperfect Information," *American Economic Review*, 1981, *71* (3), 393–410.

Xu, Chenzi, "Reshaping Global Trade: The Immediate And Long-Run Effects of Bank Failures," *The Quarterly Journal of Economics*, 2022, *137* (4), 2107–2161.

Figures

FIGURE 1: Trade Finance

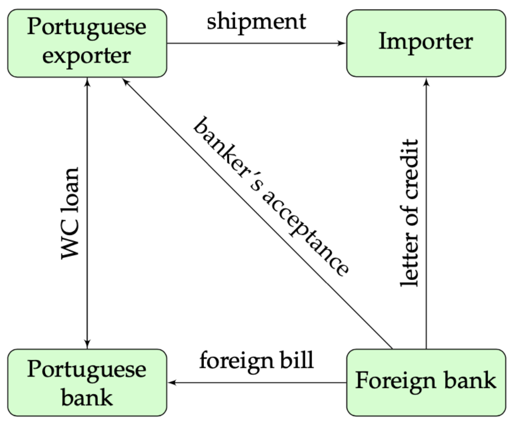
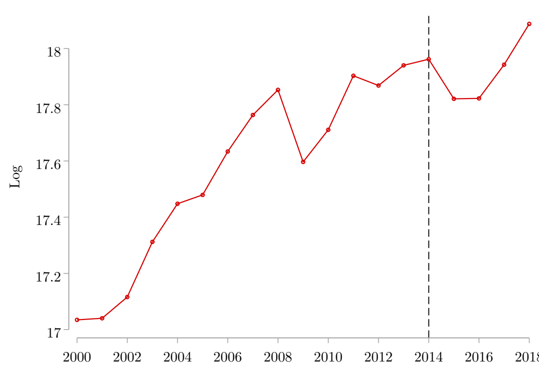


FIGURE 2: Evolution of Portuguese exports

This Figure presents the evolution of Portuguese exports from 2000 to 2018, using data from CEPII. In Panel (a), we show the evolution of total Portuguese exports of goods at current prices. In Panel (b), we present the share of Portuguese exports going to high-risk countries.

(a) Total Exports



(b) Share of exports to high-risk destinations

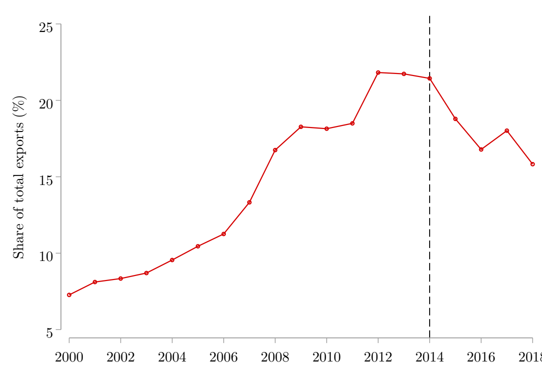


FIGURE 3: Effect on volume of Portuguese exports

This Figure presents the results of estimating regression (3), where the dependent variable is the log of exports of firm i of product p to destination d at time. We use annual data from 2011 to 2018. We present estimates for the average treatment effect over time. We include destination and firm-product-year fixed effects. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. Errors are clustered by firm. We present 95 percent confidence intervals.

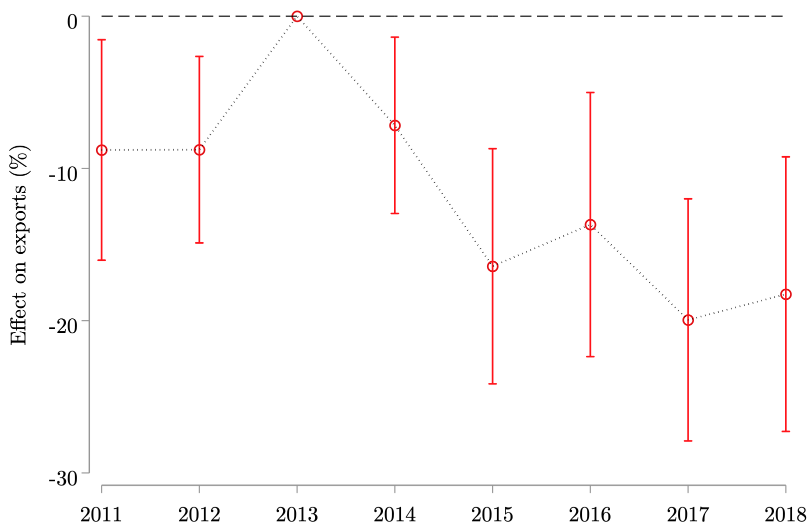
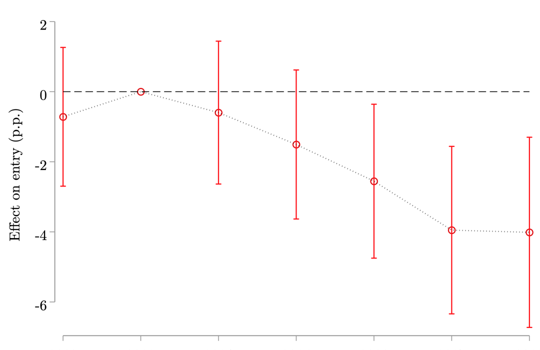


FIGURE 4: Effects on entry and exit into destinations

This figure presents the results of estimating equations (7) and (8), where the dependent variable is the entry rate and the exit rate, respectively, and where we allow the average treatment effects to vary over time. The entry rate is the ratio of the number of entrants at time t to the number of firms at time t and the exit rate is the ratio of number of firms exiting between $t-1$ and t to the number of firms in time $t-1$. We use annual data from 2011 to 2018. We present estimates for the average treatment effect. We include product-year and destination fixed effects. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. Errors are clustered by destination. We present 95 percent confidence intervals.

(a) Entry



(b) Exit

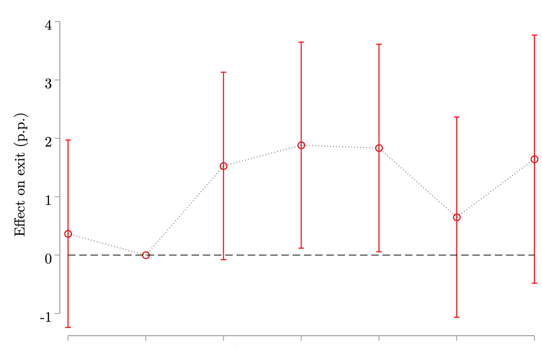
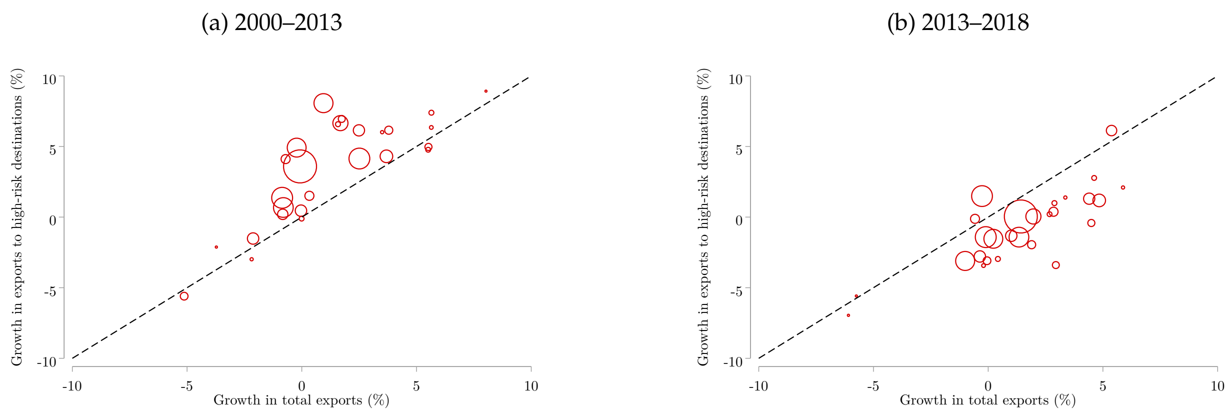


FIGURE 5: Growth rates of exports to high-risk destinations for E.U. countries

This figure plots the average annual growth rates of exports to high-risk destinations against the overall average annual growth rate of total exports for all E.U. countries. We also include a 45-degree line. In Panel (a) we plot the growth rates for the period between 2000 and 2013 and in Panel (b) we plot the growth rates between 2013 and 2018. Growth rates are nominal.



Tables

TABLE I: Summary Statistics

This table presents summary statistics for our sample, for 2013. For each variable, we compute the mean, median, standard deviation, minimum and maximum across all firms. We present summary statistics for the number of destination to which a firm exports, the number of products a firm exports, the average (across destinations) number of products per destination, the share of the firm's main destination in its exports, the share of the firm's best selling product in its exports, the HHI across destinations, the HHI across products, exports to high-risk destinations as a share of total exports, the number of loans obtained, the number of banks from which a firm obtain loans, and loan maturity (in days).

	Mean	Median	SD	Min	Max	N
Number of destinations	4.66	2.00	7.23	1.00	84.00	11,159
Number of products	14.67	5.00	27.69	1.00	342.00	11,159
Average number of products per destination	11.23	3.00	22.92	1.00	294.00	11,159
Share of main destination	0.45	0.11	0.48	0.00	1.00	11,159
Share of main product	0.24	0.00	0.41	0.00	1.00	11,159
HHI for destinations	0.76	0.94	0.28	0.05	1.00	11,159
HHI for products	0.65	0.69	0.32	0.02	1.00	11,159
Share of exports to high-risk destinations	0.71	1.00	0.41	0.00	1.00	8,331
Number of loans	15.72	4.00	46.28	1.00	1,717.00	11,159
Number of banks	1.72	1.00	1.15	1.00	9.00	11,159
Loan maturity (in days)	371	92	661	1	6,995	11,159

TABLE II: Effects on volume of Portuguese exports

This table presents the results of estimating regression (3), where the dependent variable is the log of exports of firm i of product p to destination d at time, and where compare the period between 2011 and 2013 with the period after 2014. We use annual data from 2011 to 2018. We present estimates for the average treatment effect. We include destination and firm-product-year fixed effects, and we also present a specification with destination, time, product and firm fixed effects. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. Errors are clustered by firm. ***,** ,* denote significant at the 10, 5 and 1 percent levels respectively.

	(1)	(2)	(3)	(4)
High-risk × Post 2014	-0.035*	-0.037*	-0.050*	-0.076**
	(0.020)	(0.020)	(0.029)	(0.033)
Share of exports going to high-risk (%)	22	22	22	22
Destination FE	✓	✓	✓	✓
Year FE	✓	✓		
Firm FE	✓	✓		
Product FE	✓	✓		
Firm × Product × Year FE			✓	✓
Destination controls		✓		✓
Observations	1,663,141	1,651,477	895,117	895,042

TABLE III: Effects on volume of Portuguese exports - decomposition by sovereign risk of destination

This table presents the results of estimating regression (3), where the dependent variable is the log of exports of firm i of product p to destination d at time, and where compare the period between 2011 and 2013 with the period after 2014. We use annual data from 2011 to 2018. We present estimates for the average treatment effect decomposed across three groups of high-risk destinations: (1) medium risk countries with an OECD sovereign rating of 2, (2) high risk countries with an OECD sovereign rating of 3, and (3) very high risk countries with an OECD sovereign rating between 4 and 7. We include destination and firm-product-year fixed effects. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. We also interact an indicator variable which takes the value of 1 if the destination country has Portuguese has an official language and zero otherwise with time fixed effects, and we interact an indicator variable which takes the value of 1 if the destination country was a former Portuguese colony after 1945 with time fixed effects. Errors are clustered by firm. ***,** ,* denote significant at the 10, 5 and 1 percent levels respectively.

	(1)	(2)	(3)	(4)
Medium risk × Post 2014	-0.012	-0.025	-0.025	-0.032
	(0.052)	(0.052)	(0.051)	(0.053)
High risk × Post 2014	-0.049	-0.088***	-0.086***	-0.062*
	(0.031)	(0.032)	(0.032)	(0.038)
Very high risk × Post 2014	-0.058	-0.119***	-0.116***	-0.096***
	(0.036)	(0.036)	(0.036)	(0.037)
Destination FE	✓	✓	✓	✓
Firm × Product × Year FE	✓	✓	✓	✓
Common language × Year FE		✓		
Former colony × Year FE			✓	
Destination controls				✓
Observations	895,117	894,891	895,117	895,042

TABLE IV: Effects on volume of Portuguese exports - decomposition by product dependence on credit

This table presents the results of estimating regression (3), where the dependent variable is the log of exports of firm *i* of product *p* to destination *d* at time, and where compare the period between 2011 and 2013 with the period after 2014. We use annual data from 2011 to 2018. We present estimates for the average treatment effect for low-credit products, and the difference between average treatment effects for high-credit and low-credit products. We define a product as high-credit if its measure of credit dependence is above the median in 2013. We consider one measure of credit dependence: the cash conversion cycle (CCC). We include destination and firm-product-year fixed effects. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. Errors are clustered by firm. $^{***},^{**},^{*}$ denote significant at the 10, 5 and 1 percent levels respectively.

	(1)	(2)	(3)	(4)
High-risk × Post 2014	-0.008	-0.007	-0.063*	-0.020
	(0.026)	(0.027)	(0.036)	(0.037)
High-risk × High-credit × Post 2014	-0.054*	-0.060**	-0.069*	-0.070*
	(0.028)	(0.026)	(0.039)	(0.038)
Destination FE	✓	✓	✓	✓
Year FE	✓	✓		
Firm FE	✓	✓		
Product FE	✓	✓		
Firm × Product × Year FE			✓	✓
Destination controls		✓		✓
Observations	1,651,763	1,640,139	898,667	888,563

TABLE V: Effects on entry and exit into destinations

This table presents the results of estimating equations (7) and (8), where the dependent variable is the entry rate and the exit rate, respectively. The entry rate is the ratio of the number of entrants at time t to the number of firms at time t and the exit rate is the ratio of number of firms exiting between $t-1$ and t to the number of firms in time $t-1$. We use annual data from 2011 to 2018. We present estimates for the average treatment effect. We include product-year and destination fixed effects. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. We also present the average entry and exit rates for 2013. Errors are clustered by destination.$\star$,$\star\star$ and $\star\star\star$ denote significance at the 10%, 5% and 1% levels, respectively.

	Entry			Exit		
	(1)	(2)	(3)	(4)	(5)	(6)
High-risk × Post 2014	-0.023**	-0.020*	–0.025**	0.041***	0.035***	0.013
	(0.011)	(0.010)	(0.011)	(0.010)	(0.010)	(0.009)
Mean in 2013	.484	.484	.484	.273	.273	.273
Destination FE	✓	✓	✓	✓	✓	✓
Year FE	✓			✓		
Product FE	✓			✓		
Product × Year FE		✓	✓		✓	✓
Destination controls			✓			✓
Observations	202,950	202,494	171,702	193,622	175,617	172,103

TABLE VI: Effect on interest rates and loan amounts

This table presents the results of estimating regression (9), where the dependent variable is the interest rate or the loan amount for loan k obtained by firm i from bank b in year t. We use individual loan data for exporters from 2013 to 2018, and consider only loans with maturities under 180 days. We present estimates for the average treatment effect. The time-varying loan controls include: the loan maturity and a dummy variable that takes the value of 1 if the loan is collateralized and 0 if otherwise. The time-varying firm controls include: log of total sales, the sales-to-asset ratio, the leverage ratio, the EBITDA-to-assets ratio, the growth rate of total sales, labor productivity, the ratio of current-to-total liabilities, the ratio of current-to-total assets, as well as the firm's age and its age squared. Errors are clustered by firm. *,** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Loan amounts			Interest rates		
	(1)	(2)	(3)	(4)	(5)	(6)
High exposure × Post 2014	-0.067**	-0.063**	-0.072**	0.084	0.124*	0.133**
	(0.026)	(0.028)	(0.026)	(0.064)	(0.066)	(0.062)
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓			✓		
Bank FE	✓			✓		
Bank × Year FE		✓	✓		✓	✓
Controls	✓		✓	✓		✓
Observations	793,984	795,077	793,981	793,984	795,077	793,981

TABLE VII: Effects on probability of obtaining a loan

This table presents the results of estimating regression (11), where the dependent variable is an indicator variable which takes the value of 1 if firm i receives at least one bank loan in year t and zero if otherwise. We use individual loan data for exporters from 2013 to 2018, and consider only loans with maturities under 180 days. We present estimates for the average treatment effect. The time-varying firm controls include: log of total sales, the sales-to-asset ratio, the leverage ratio, the EBITDA-to-assets ratio, the growth rate of total sales, labor productivity, the ratio of current-to-total liabilities, the ratio of current-to-total assets, as well as the firm's age and its age squared. Errors are clustered by firm. *,** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)
High exposure × Post 2014	-0.063***	-0.064***	-0.057***	-0.059***
	(0.008)	(0.008)	(0.008)	(0.008)
Mean in 2013	0.79	0.79	0.79	0.79
Firm FE		✓		✓
Year FE		✓		✓
Controls			✓	✓
Observations	66,954	66,954	61,444	61,156

TABLE VIII: Effect on exports to high-risk destinations for all E.U. countries

This table presents the results of estimating regression (12), where the dependent variable is the log of exports of country s of product p to destination d at time t. We use annual data from 2010 to 2018. We present estimates for the average treatment effect. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. We also include destination and source-product-year fixed effects. Errors are clustered by destination.*,** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
High-risk × Post 2014	0.006**	0.011***	-0.040***	-0.002	-0.048***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Year FE	✓				
Destination FE	✓	✓	✓	✓	✓
Source FE	✓				
Product FE	✓	✓		✓	
Year × Source FE		✓		✓	
Year × Source × Product FE			✓		✓
Destination controls				✓	✓
Observations	17,156,788	17,156,788	17,146,341	16,592,948	16,582,259

TABLE IX: Effect on exports to high-risk destinations for all E.U. countries - decomposition by product dependence on credit

This table presents the results of estimating regression (12), where the dependent variable is the log of exports of country s of product p to destination d at time t. We use annual data from 2010 to 2018. We present estimates for the average treatment effect for products with low credit dependence and for the difference in average treatment effects between high and low credit dependence products. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. We also include destination and source-product-year fixed effects. We also present the share of exports of high-credit products within exports to high-risk countries. Errors are clustered by destination.*,** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)
High-risk × Post 2014	0.025	-0.023	0.016	-0.031
	(0.031)	(0.030)	(0.030)	(0.029)
High-risk × High-credit × Post 2014	-0.036***	-0.032***	-0.037***	-0.032***
	(0.011)	(0.010)	(0.011)	(0.010)
Share of high-credit products (%)	42	42	42	42
Destination FE	✓	✓	✓	✓
Year FE	✓		✓	
Source FE	✓		✓	
Product FE	✓		✓	
Source × Product × Year FE		✓		✓
Destination controls			✓	✓
Observations	17,156,788	17,146,341	16,592,948	16,582,259

TABLE X: Effect on exports to high-risk destinations for all E.U. countries - decomposition by bank health

This table presents the results of estimating regression (12), where the dependent variable is the log of exports of country s of product p to destination d at time t. We use annual data from 2010 to 2018. We present estimates for the average treatment effect for countries with high bank health and for the difference in average treatment effects between countries with low bank health and countries with high bank health. We consider two measures of bank health: the average capital ratio and the average return on equity. A country has a healthy banking system if its average capital ratio in 2013 is above the median or if its average return on equity in 2013 is below the median. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. We also include destination and source-product-year fixed effects. Errors are clustered by destination.*,** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Capital ratio		Return on equity	
	(1)	(2)	(3)	(4)
High-risk × Post 2014	0.023	0.012	0.020	0.018
	(0.033)	(0.033)	(0.032)	(0.030)
High-risk × Unhealthy bank × Post 2014	-0.126***	-0.118***	-0.134***	-0.146***
	(0.024)	(0.025)	(0.021)	(0.020)
Destination FE	✓	✓	✓	✓
Exporter × Importer × Year FE	✓	✓	✓	✓
Destination controls		✓		✓
Observations	17,146,341	16,582,259	17,146,341	16,582,259

TABLE XI: Model calibration with heterogeneous effects

This Table presents the results of the calibration of our model with heterogeneous effects. We have two calibration targets: the average treatment effect on products with low credit dependence and the average treatment effect on products with high-credit dependence. We calibrate two parameters: the interest rate shock ζ and the exposure of low-credit products to interest rates ϕ.

		Targets		
Parameters	Value	Value	Data	Model
ζ	1.75 p.p.	Change in exports of high-credit products	-8.24%	-8.35%
ϕ	0.40	Change in exports of low-credit products	-5.31%	-5.39%

TABLE XII: Model fit

This Table presents the fit of our model for E.U. countries. We present four unconditional moments: the growth rate of total exports, the growth rate of exports to low-risk countries, the growth rate of exports to high-risk countries, and the change in the share of high-risk countries in total exports. We focus on the E.U. countries we include in our model: Austria, Denmark, Germany, Finland, France, Greece, Hungary, Ireland, Italy, Netherlands, Portugal, Spain, Sweden and the U.K.

	Data	Model
Growth in total exports (%)	4.72	-1.18
Growth in exports to low-risk countries (%)	7.39	1.00
Growth in exports to high-risk countries (%)	-3.86	-4.01
Change in share of exports to high-risk countries (p.p.)	-1.94	-1.25

TABLE XIII: Changes in welfare

This table presents the effects of the increase in interest rates on the welfare of all E.U. and high-risk countries in our sample. We decompose the change in welfare into three components: a terms-of-trade effect, a volume-of-trade effect, and a trade cost effect. We further decompose the terms-of-trade effect into the effect from the change in the price of exports and the effect from the change in the price of imports. All values represent the percentage change. We also present aggregated effects for all E.U. countries and for all high-risk countries by taking the simple average across all countries in the group.

	Terms of trade				
	Price of exports	Price of imports	Volume of trade	Credit costs	Total
E.U. countries	-0.82	0.73	-0.01	0.00	-0.09
Austria	-0.86	0.76	0.00	0.00	-0.10
Denmark	-0.51	0.48	-0.03	0.00	-0.06
Finland	-0.77	0.69	0.00	0.00	-0.08
France	-0.95	0.87	0.00	0.00	-0.08
Germany	-0.88	0.78	-0.01	0.00	-0.11
Greece	-0.98	0.88	-0.01	0.00	-0.11
Hungary	-1.13	0.91	-0.01	0.00	-0.22
Ireland	-0.74	0.70	0.00	0.00	-0.05
Italy	-0.84	0.78	0.00	0.00	-0.07
Netherlands	-0.75	0.59	0.00	0.00	-0.16
Portugal	-0.81	0.75	0.00	0.00	-0.06
Spain	-0.88	0.80	0.00	0.00	-0.08
Sweden	-0.74	0.68	0.00	0.00	-0.06
U.K.	-0.67	0.61	0.00	0.00	-0.06
High-risk countries	0.31	-0.29	-0.01	-0.04	-0.04
Argentina	0.31	-0.29	-0.01	-0.04	-0.04
Brazil	0.38	-0.36	-0.02	-0.04	-0.04
Chile	0.27	-0.23	0.00	-0.10	-0.06
China	0.45	-0.43	-0.01	-0.04	-0.03
India	0.33	-0.32	-0.01	-0.04	-0.03
Indonesia	0.29	-0.28	-0.01	-0.03	-0.02
Mexico	0.29	-0.26	-0.01	-0.04	-0.02
South Africa	0.32	-0.26	0.01	-0.13	-0.06
Turkey	0.34	-0.28	0.00	-0.14	-0.08

Online Appendix

A Appendix to Section 4

A.1 Addressing pretrends

In general, and as shown by Rambachan and Roth (2022), an event study coefficient can be decomposed as

$$\gamma_t = \tau_t + \delta_t$$

where τ_t is the average treatment effect and δ_t is the difference in trends between high-risk and low-risk destinations. We assume that $\tau_t = 0$ for $t \leq 2013$ and so we exclude the possibility of anticipation. We therefore only observe δ_t for $t \leq 2013$. The identification challenge is therefore to identify τ_t for $t > 2013$. The standard assumption is the parallel trends assumption which states that $\delta_t = \delta = 0$ for all t. Given this assumption, we can use our observable differences in trends and use a simple hypothesis test to check if $\delta_t = 0$ for $t > 2013$.

In our context, δ_t represents the difference in demand from high-risk destinations and low-risk destinations. There is no reason to believe that this relative demand is constant over time, even conditional on controls. We saw in Figure 2 and in Figure C.1 that there is a long secular trend of increased exports to high-risk destinations which will be captured as an increase in relative demand. Moreover, from Table C.I we also know that for non-E.U. countries exports to high-risk destinations do not include. Therefore, we have reason to believe that in our specification $\delta_t > \delta_{t-1}$ for $t > 2014$ and so the assumption of parallel trends is false.

Once we deviate from parallel trends, there are possible paths. The first path is to assume a functional form for δ_t. In our case, as there is a long trend of increase exports to high-risk destinations which resembles a linear function, it is natural to assume a linear trend. This allows us to identify δ_t for $t > 2014$.This method is also similar to a detrending of the data like in Goodman-Bacon (2018). The second path is to make minimal assumptions for δ_t as in Manski and Pepper (2018) and Rambachan and Roth (2022). This second method will only lead to partial identification of the differential trends and therefore to partial identification of the average treatment effects.

We will therefore impose a general class of smoothness restrictions as suggested by Rambachan and Roth (2022). These restrictions are useful in dealing with secular trends which move smoothly over time. This a general case of imposing group-specific linear trends like in Dobkin et al. (2018). It's also the same as the method in Goodman-Bacon (2018) or Goodman-Bacon (2021), who estimates a linear trend using only observations prior to treatment and then subtracts out the estimated linear trend from the observations after treatment. The restriction is

$$|(\delta_{t+1} - \delta_t) - (\delta_t - \delta_{t-1})| \leq M, \quad \forall t \tag{A.1}$$

where M is a non-negative constant which governs the amount by which the slope of δ may vary. If we set $M = 0$ we are assuming a linear trend which is the assumption underlying the linear trends used in the literature.

Under a specific value for M we can compute identification bounds for δ and therefore for τ as well. To compute confidence intervals, we can then use the methods developed in Rambachan and Roth (2022). In

Figure A.1, we present the confidence intervals for the average treatment effects if we assume a linear trend ($M = 0$).

FIGURE A.1: Effects on volume of exports under a linear trend

This Figure presents the results of estimating regression (3), where the dependent variable is the log of exports of firm i of product p to destination d at time. We use annual data from 2011 to 2018. We present estimates for the average treatment effect over time. We include destination and firm-product-year fixed effects. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. Errors are clustered by firm. We present 95 percent confidence intervals for two specifications. In the first one, "No demand shocks", we assume that $\delta_t = 0$ for $t > 2013$. In the second one, "Linear trend", we assume a linear trend by setting $M = 0$ in equation (A.1).

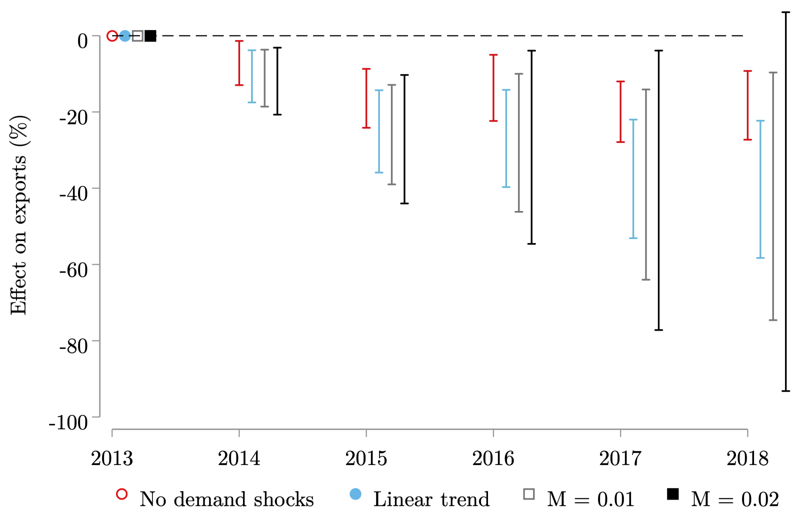
The red series represents the average treatment effect under the assumption that differential trends are zero after 2014. This is the same series we present in Figure 3. The blue series represents the average treatment effect under the assumption of a linear trend in the differential trends δ_t. Under this assumption, the average treatment effects are still negative and statistically significant. Moreover, they may be larger than those estimated under the assumption of zero differential trends after 2014. Therefore, if we follow the method in Goodman-Bacon (2018) and detrend the data we will recover a larger decline in exports to high-risk destinations.

We can also relax the assumption of linearity and allow for $M > 0$. Under this new assumption, we are allowing the slope of the δ_t to change over time. However, we will no longer obtain point identification and will have to rely on partial identification. This alternative assumption allows us to accommodate a change in the slope of the trend. For example, it can include a decreasing trend for the δ_t after 2013. We present confidence intervals for the average treatment effects after 2014 under different values of M in Figure A.2.

Even if we allow for substantial deviations from linearity, we still recover a negative effect on exports to high-risk destinations. Therefore, our results are not dependent on assuming a particular functional form for the evolution of the differential trends.

FIGURE A.2: Effects on volume of exports under smoothness restrictions

This Figure presents the results of estimating regression (3), where the dependent variable is the log of exports of firm i of product p to destination d at time. We use annual data from 2011 to 2018. We present estimates for the average treatment effect over time. We include destination and firm-product-year fixed effects. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. Errors are clustered by firm. We present 95 percent confidence intervals for four specifications. In the first one, "No demand shocks", we assume that $\delta_t = 0$ for $t > 2013$. In the second one, "Linear trend", we assume a linear trend by setting $M = 0$ in equation (A.1). In the third and fourth specifications we assume $M = 0.01$ and $M = 0.02$ respectively.



A.2 Within vs. across firm variation

In this Section, we have relied on variation within firms to identify the causal effects of Basel III. Most of the literature that studies the effect of credit shocks on firms has instead relied on variation across firms, as is the case with Paravisini et al. (2015). This reliance is usually motivated by the nature of the shocks: most experiments involving credit shocks that affect some firms but not others, or affect different firms with different intensities. In our design, the shock affects different destinations within a firm in different ways. Given these two different approaches in the literature, it is important to understand if they will yield different results.

To to explore this possibility, we need to deviate from the canonical Melitz (2003) model we presented in this Section. In that model, an experiment that relies on variation across firms will yield the same elasticities of exports to credit shocks as an experiment that relies on variation within firms. This equivalence comes from the fact that, in that model, production is separable across destinations (and products). Therefore, in order to highlight how "within" and "across" elasticities may be different, we need to assume that production is non-separable across destinations. We are not the first to highlight how this deviation from the assumption of separability may change our understanding of how firms react to shocks. For example, Almunia et al. (2021) argue that non-separabilities in production in Spanish exporters lead to an increase in exports in response to a drop in domestic demand.

We now generalize the canonical model to accommodate non-separabilities in production. For simplicity, we consider the case of a single-product firm that sells to multiple destinations. Firm i selling in destination d faces an isoelastic demand $y_{id} = A_d p_{id}^{-\sigma}$ where $\sigma > 0$ and where we define $\varepsilon \equiv 1/\sigma$. Production for a given destination requires two factors of production: capital and labor. We assume that labor is allocated to each destination: one unit of labor which is used in production for destination d cannot be used for another destination. In contrast, capital will be a common non-rival factor of production: once a firm chooses a level of capital, it will use it for all destinations at the same time. Therefore, capital can be thought of as firm headquarters or all the structure a firm needs for exporting, like having skilled workers who can speak English or deal with customs officers. Thus, the production function for destination d is $y_{id} = \varphi_{id} K_i^{\alpha} L_{id}^{1-\alpha}$ where $\alpha \in [0,1]$, where capital does not depend on the destination but labor does. Note that if we set $\alpha = 0$ we return to the canonical model. We also assume that there is a financial friction: the firm must pay a share θ of its labor costs in advance. Therefore, labor payments for destination d will be $w \times [\theta R_{id} + 1 - \theta]$. We assume that the firm takes the wage and the capital rental rate as given.

There are two alternative experiments. The first one, which is the "across" experiment, involves an increase in interest rates $R_{i^\star d}$ for one particular firm $i^\star$ and all destinations. We then compare the effects of this shock on the volume of exports of firm $i^\star$ to destination d with the change in the volume of exports of another (unaffected) firm i for the same destination. This allows us to compute the "across" elasticity of exports to credit shocks, which is the standard in the literature. The second experiment, which is the "within" experiment, involves an increase in interest rates for all firms i for destination $d^\star$. We then compare, within each firm, the evolution of exports to destination $d^\star$ with the evolution of exports to another destination d. This is the strategy we have followed in this paper. The following Proposition summarizes the differences between the two approaches.

Proposition 2 *The "across" and "within" elasticities are given by*

$$\mathcal{E}^{across} = -\frac{(1-\alpha)(1-\varepsilon)}{1-(1-\alpha)(1-\varepsilon)} m_{i^\star d} + [\alpha + (1-\alpha)\kappa_2](1-\varepsilon)\kappa_1 \bar{m}_{i^\star},$$

$$\mathcal{E}^{within} = -\frac{(1-\alpha)(1-\varepsilon)}{1-(1-\alpha)(1-\varepsilon)} m_{id^\star} \leq 0,$$

where $m_{id} = \theta R_{id} / (\theta R_{id} + 1 - \theta) \in [0,1]$ is the incidence of the financial friction, $\bar{m}_i = D^{-1} \sum_{d=1}^{D} s_{id} m_{id}$ is the average incidence of the financial friction for a firm where s_{id} is the share of sales going to destination d, and $\kappa_1, \kappa_2 \in [0,1]$. Furthermore, assuming $m_{id} = m$ for all firms i and destinations d, and excluding the case where both elasticities are zero, $\mathcal{E}^{across} = \mathcal{E}^{within}$ if and only if $\alpha = 0$ and therefore production is separable across destinations.

Proof. In Appendix A. ∎

We start with the within elasticity, which is negative and depends on the degree of non-separability α, the inverse elasticity ε and the incidence of the financial friction in the affected destination m_{id}. If production is separable ($\alpha = 0$), the elasticity is the same as in the model we presented earlier. If the financial friction disappears and $m_{id} = 0$, the elasticity is also zero. How does the shock propagate within a firm? In the affected destination, the relative price of labor increases due to the financial friction. As labor and capital are substitutes, this means that demand for capital increases from a substitution effect. In the unaffected destination, as capital increases, the marginal productivity of labor increases and so the firm wishes to use more labor in the unaffected destination and less in the affected destination. However, this increase in capital also means that labor in the affected destination becomes more productive and so there is an increase in labor in the affected destination. Therefore, there are three effects: (1) a labor shift away from the affected destination due to the increase in the cost of labor, (2) an increase in capital, and (3) a labor increase in both destinations due to the increase in capital. In this simple structure, the second and third effect are identical between affected and unaffected destinations and so the within elasticity only captures the first effect.[49]

The across elasticity has an additional term $[\alpha + (1-\alpha)\kappa_2]\kappa_1 \bar{m}_i$ which captures the two second effects. The term $\alpha\kappa_1\bar{m}_i$ is the result of the increase in capital in all destinations, which is given by $\kappa_1\bar{m}_1$, in production through its product with the capital share. As this affects all destinations in the same way, we use the average incidence of the financial friction. The term $(1-\alpha)\kappa_2\kappa_1\bar{m}_i$ captures the increase in the demand for labor arising from the increase in capital. We can think of the parameter κ_2 as governing the partial elasticity of labor to capital and so the term $\kappa_2\kappa_1\bar{m}_i$ is the increase in labor which comes from the increase in capital. This additional term does not disappear when we compare two firms because the change in the costs of one firm does not affect the other firm. Therefore, the presence of non-separabilities changes the elasticity we are able to estimate.

In our model, the across and the within elasticity will coincide if and only if production is separable. If production is separable, the result is immediate as each firm-destination pair can be thought of as a separate firm. Therefore comparing two destinations for the same firm or two firms for the same destination will yield the same result. The second direction is not as immediate. If all firms are identical in terms of their dependence on working capital and if we observe that the across and within elasticities are identical, it must be that production is separable. This result is more dependent on our functional form assumptions than the first direction. However, it is also intuitive. If all firm-destination pairs are identically exposed to the shock, the only source of differential exposure to the shock is the share of exports to the affected destination. If the elasticities are identical, it must be that this share is irrelevant which is only true if production is separable across destinations.

Therefore, one of our contributions is the estimation of the effect within a firm, which is not the same as the effect across firms unless we are willing to assume separability. In the general case, using elasticities estimated from experiments that rely on variation across firms to estimate the effects of a shock that takes place within a firm will lead to incorrect estimates. In our example, the elasticity within a firm is larger in absolute value than the elasticity across firms. Therefore, using estimates from the literature would lead us to underestimate the effects of Basel III on exports.

A.3 Proof of Proposition 2

A firm i solves the following problem

$$\max \sum_{d=1}^{D} p_{id} y_{id} - rK_i - w \sum_{d=1}^{D} (\theta R_{id} + 1 - \theta) L_{id}$$

subject to the D demand functions and the D production functions. The first order conditions are given by

$$rK_i = \alpha (1-\varepsilon) \sum_{d=1}^{D} p_{id} y_{id}$$

$$w (\theta R_{id} + 1 - \theta) L_{id} = (1-\alpha)(1-\varepsilon) p_{id} y_{id}, \quad d = 1, \ldots, D.$$

[49] This is true because the capital shares (and the elasticities) are identical across destinations. If this was not the case, the effects would not cancel out.

Shocks within a firm: take a firm i and a shock $d\log R_{id^\star} > 0$ for a given destination $d^\star$. Totally differentiating the first order conditions yields

$$d\log K_i = \frac{(1-\alpha)(1-\varepsilon)}{1-\alpha(1-\varepsilon)} \sum_{d=1}^{D} s_{id} d\log L_{id},$$

$$d\log L_{id} = \frac{\alpha(1-\varepsilon)}{1-(1-\alpha)(1-\varepsilon)} d\log K_i - \frac{m_{id}}{1-(1-\alpha)(1-\varepsilon)} d\log R_{id}$$

where $s_{id} \equiv p_{id}y_{id} / \sum_{d=1}^{D} p_{id}y_{id}$ and $m_{id} \equiv \theta R_{id} / (\theta R_{id} + 1 - \theta)$. Solving the system of equations and using the fact that only one destination is shocked yields the following solution

$$d\log K_i = \kappa_1 s_{id^\star} m_{id^\star} d\log R_{id^\star},$$

$$d\log L_{id} = \kappa_2 \kappa_1 s_{id^\star} m_{id^\star} d\log R_{id^\star},$$

$$d\log L_{id^\star} = \kappa_2 \kappa_1 s_{id^\star} m_{id^\star} d\log R_{id^\star} - \frac{m_{id^\star}}{1-(1-\alpha)(1-\varepsilon)} d\log R_{id^\star}$$

where

$$\kappa_1 \equiv \frac{\alpha(1-\alpha)(1-\varepsilon)^2}{1-\alpha(1-\varepsilon)+\alpha(1-\alpha)(1-\varepsilon)^2} \in [0,1],$$

$$\kappa_2 = \frac{\alpha(1-\varepsilon)}{1-(1-\alpha)(1-\varepsilon)} \in [0,1],$$

and $\kappa_1 = \kappa_2 = 0$ when $\alpha = 0$. Using the production function, the change in the value of output is given by

$$d\log p_{id}y_{id} = [\alpha + (1-\alpha)\kappa_2](1-\varepsilon)\kappa_1 s_{id^\star} m_{id^\star} d\log R_{id^\star},$$

$$\begin{aligned} d\log p_{id^\star}y_{id^\star} = {} & [\alpha + (1-\alpha)\kappa_2](1-\varepsilon)\kappa_1 s_{id^\star} m_{id^\star} d\log R_{id^\star} \\ & - \frac{(1-\alpha)(1-\varepsilon)}{1-(1-\alpha)(1-\varepsilon)} m_{id^\star} d\log R_{id^\star}. \end{aligned}$$

We then define the within elasticity as

$$\mathcal{E}^{\text{within}} \equiv \frac{d\log p_{id^\star}y^\star_{id} - d\log p_{id}y_{id}}{d\log R_{id^\star}},$$

which yields a within elasticity of

$$\mathcal{E}^{\text{within}} = -\frac{(1-\alpha)(1-\varepsilon)}{1-(1-\alpha)(1-\varepsilon)} m_{id^\star} < 0.$$

Shocks across firms: take two firms i and $i^\star$. The interest rates for firm $i^\star$ will observe a shock $d\log R_{i^\star d} = \zeta > 0$ for all d. Using the first order conditions, the effect is given by

$$d\log K_{i^\star} = \kappa_1 \bar{m}_{i^\star} \zeta,$$

$$d\log L_{i^\star d} = \kappa_2 \kappa_1 \bar{m}_{i^\star} \zeta - \frac{m_{i^\star d}}{1-(1-\alpha)(1-\varepsilon)} \zeta,$$

where

$$\bar{m}_i \equiv \sum_{d=1}^{D} s_{id} m_{id}.$$

The effect on the volume of sales is given by

$$d \log p_{i^\star d} y_{i^\star d} = \left[\alpha + (1-\alpha)\,\kappa_2\right](1-\varepsilon)\,\kappa_1 \bar{m}_{i^\star}\zeta - \frac{(1-\varepsilon)\,(1-\alpha)}{1-(1-\alpha)\,(1-\varepsilon)} m_{i^\star d}\zeta, \quad d = 1, \ldots, D$$

$$d \log p_{id} y_{id} = 0, \quad d = 1, \ldots, D.$$

We define the across elasticity as

$$\mathcal{E}^{\text{across}} \equiv \frac{d \log p_{i^\star d} y_{i^\star d} - d \log p_{id} y_{id}}{\zeta}$$

and so we obtain

$$\mathcal{E}^{\text{across}} = \left[\alpha + (1-\alpha)\,\kappa_2\right](1-\varepsilon)\,\kappa_1 \bar{m}_{i^\star} - \frac{(1-\varepsilon)\,(1-\alpha)}{1-(1-\alpha)\,(1-\varepsilon)} m_{i^\star d}.$$

Comparison: consider the case where the incidence of the financial friction is common across all firms and destinations and $m_{id} = m > 0$ for all i and d. In this case, it follows that

$$\mathcal{E}^{\text{within}} \leq \mathcal{E}^{\text{across}}.$$

If $\alpha = 0$, then it follows that $\kappa_1 = \kappa_2 = 0$ and we obtain $\mathcal{E}^{\text{within}} = \mathcal{E}^{\text{across}}$. For the other direction, assume that $\mathcal{E}^{\text{within}} = \mathcal{E}^{\text{across}} \neq 0$. This implies that

$$\left[\alpha + (1-\alpha)\,\kappa_2\right](1-\varepsilon)\,\kappa_1 m = 0$$

and so it must be that either $\kappa_1 = 0$ or $\alpha + (1-\alpha)\,\kappa_2$. In order for $\kappa_1 = 0$ it must be that $\alpha = 0$ as $\alpha = 1$ would trivially make the elasticity identical to zero. In the other case, $\alpha + (1-\alpha)\,\kappa_2 = 0$ is equivalent to setting $\kappa_2 = 0$ which is only true when $\alpha = 0$. This completes the proof.

A.4 Additional results

FIGURE A.3: Distribution of Cash Conversion Cycle

This Figure presents the kernel estimate of the density function of the cash conversion cycle across products. We compute the cash conversion cycle for all U.S. firms in Compustat for 2013. The cash conversion cycle is defined as the sum of three components: (1) average inventory / cost of goods sold, (2) average accounts receivable / sales and (3) average accounts payable / cost of goods sold. We then multiply the result by 365. We then aggregate this measure at the industry level by taking the weighed average of the CCC, using the sales of the firm as the weight. We then match each industry to a product. We also show the median of the distribution in the dashed vertical line.

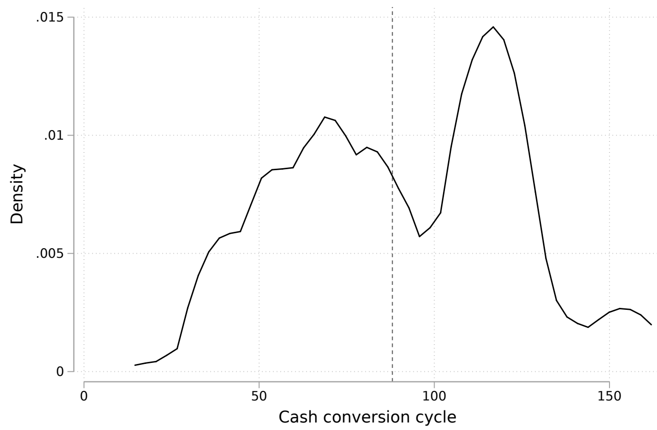


FIGURE A.4: High-credit vs. low-credit products - product uses

This Figure presents the distribution of product uses for high- and low-credit products. We obtain product uses from the BEA classification of products into three groups: capital, intermediate goods and consumption goods.We assign products to the high-credit group or to the low-credit group according to their cash conversion cycle: products above the median are high-credit products and products below the median are low-credit products.

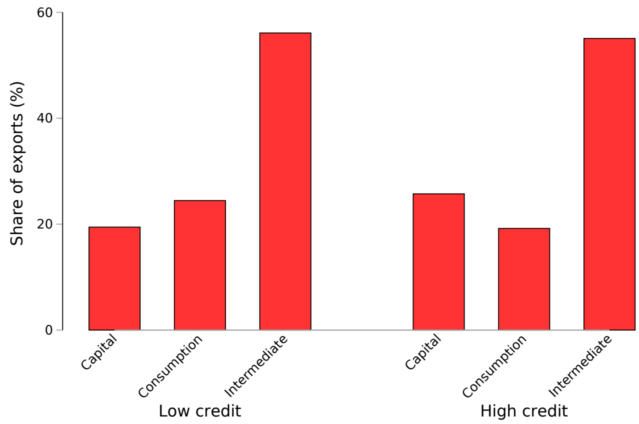


FIGURE A.5: High credit vs. low credit products - distribution of trade elasticities

This Figure presents the kernel distributions of the trade elasticities of high-credit and low-credit products. We obtain trade elasticities from CEPII and aggregate them at the 4-digit product level by taking the averages of the elasticities at the 6-digit level. We assign products to the high-credit group or to the low-credit group according to their cash conversion cycle: products above the median are high-credit products and products below the median are low-credit products. We consider only trade elasticities below 20 in order improve the readability of the plot.

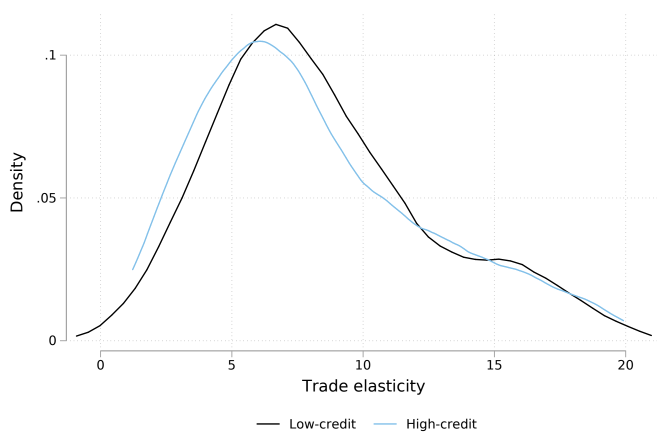
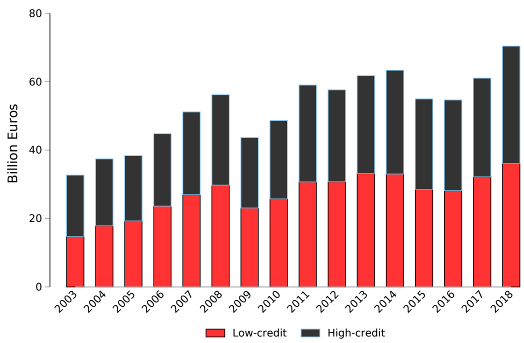


FIGURE A.6: Share of high-credit and low-credit products in exports

This Figure presents the decomposition of total exports in exports of high-credit and low-credit products. We assign products to the high-credit group or to the low-credit group according to their cash conversion cycle: products above the median are high-credit products and products below the median are low-credit products. In panel (a) we present this decomposition over time for total Portuguese exports and in panel (b) we consider exports to high-risk destinations.

(a) Total Exports



(b) Share of exports to high-risk destinations

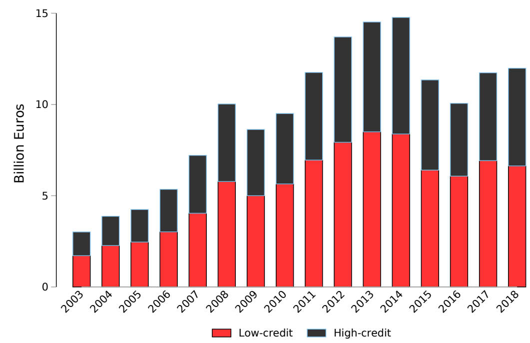


FIGURE A.7: Change in tariffs imposed by high-risk destinations

This figure presents the results of a two-way fixed effects regression of tariffs imposed by high-risk destinations. We use a all tariffs at the importer-exporter-product-year level between 2011 and 2018 (where we aggregate products to the 4-digit level). We include only observations where the importer is a high-risk country. We regress the tariff on an importer-product-year fixed effect and on an exporter fixed effect. We present the coefficients associated with the interaction between a time fixed effect and an indicator variable which takes the value of one if the exporter is an E.U. country. We interpret each of these coefficients as the differential change in tariffs imposed on E.U. countries vs. other countries, relative to a base year (2013). If the coefficient is negative after 2013, it means that high-risk countries are lowering tariffs on goods imported from E.U. countries relative to other countries. We cluster the errors at the importer level and present 95 percent confidence intervals.

TABLE A.I: Effects on volume of exports

This table presents the results of estimating regression (3), where the dependent variable is the log of exports of firm i of product p to destination d at time, and where compare the period between 2011 and 2013 with the period after 2014. We use annual data from 2011 to 2018. We present estimates for the average treatment effect. We include destination and firm-product-year fixed effects, and we also present a specification with destination, time, product and firm fixed effects. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. We also interact an indicator variable which takes the value of 1 if the destination country has Portuguese has an official language and zero otherwise with time fixed effects, and we interact an indicator variable which takes the value of 1 if the destination country was a former Portuguese colony after 1945 with time fixed effects. Errors are clustered by firm. ***,** ,* denote significant at the 10, 5 and 1 percent levels respectively.

	(1)	(2)	(3)	(4)
High-risk × Post 2014	-0.050*	–0.094***	-0.092***	-0.076**
	(0.029)	(0.029)	(0.029)	(0.033)
Share of exports going to high-risk (%)	22	22	22	22
Destination FE	✓	✓	✓	✓
Firm × Product × Year FE	✓	✓	✓	✓
Common language × Year FE		✓		
Former colony × Year FE			✓	
Destination controls				✓
Observations	895,117	894,891	895,117	895,042

TABLE A.II: Effect across destinations - estimator robust to heterogeneous treatment effects

This table presents the results of estimating the average treatment effect on volume of exports to high-risk destinations. We use annual data from 2011 to 2018. We include time fixed effects as well as firm-product-destination fixed effects. We present two estimators. The first one is the two-way fixed effects estimator in which we use OLS with the fixed effect structure we described to compute the average treatment effect. For this estimator, we also report the sum of the positive weights assigned to each of the individual treatment effects. As shown in De Chaisemartin and d'Haultfoeuille (2020), the OLS estimator is a weighted average of the individual treatment effects but the weights are not all positive, even though they must add up to one. The second estimator is the estimator developed by De Chaisemartin and d'Haultfoeuille (2020), which is robust to the presence of heterogeneous treatment effects in our sample. For this second estimator, we also report the number of switchers, i.e. the number of observations which observe a change from untreated to treated (the treatment group). Errors are clustered by firm.*,** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	TWFE	Robust estimator
High-risk × Post 2014	-0.266***	-0.087***
	(0.023)	(0.021)
Year FE	✓	✓
Firm × Product × Destination FE	✓	✓
Observations	1,268,307	128,946
Number of switchers		79,819
Sum of positive weights	1.015	

TABLE A.III: Effect across destinations - estimator robust to multiple treatments

This table presents the results of estimating the average treatment effect on volume of exports to high-risk destinations. We use annual data from 2013 to 2018. We include time fixed effects as well as firm-product-destination fixed effects. We estimate the average treatment effect for each of the risk weight groups, using countries with the lowest risk weight (0.2) as the control group. We present two estimators. The first one is the two-way fixed effects estimator in which we use OLS with the fixed effect structure we described to compute the average treatment effect. The second estimator is the one proposed by De Chaisemartin and d'Haultfoeuille (2022), which is robust to the presence of multiple treatments and to heterogeneous treatment effects. This estimator uses the method developed in De Chaisemartin and d'Haultfoeuille (2022). Errors are clustered by firm.*,** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	OLS	Robust estimator
Medium risk × Post 2014	0.089*	0.276***
	(0.045)	(0.067)
High risk × Post 2014	-0.054*	0.087***
	(0.031)	(0.030)
Very high risk × Post 2014	-0.310***	-0.276***
	(0.024)	(0.067)
Year FE	✓	✓
Firm × Product × Destination FE	✓	✓
Observations	1,268,307	79,819

TABLE A.IV: Effects on entry and exit

This table presents the results of estimating equations (7) and (8), where the dependent variable is the entry rate and the exit rate, respectively. The entry rate is the ratio of the number of entrants at time t to the number of firms at time t and the exit rate is the ratio of number of firms exiting between $t-1$ and t to the number of firms in time $t-1$. We use annual data from 2011 to 2018. We present estimates for the average treatment effect decomposed across three groups of high-risk destinations: (1) those with a risk weight of 0.5, (2) those with a risk weight of 1, and (3) those with a risk weight of 1.5. We include product-year and destination fixed effects. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. We also present the average entry and exit rates for 2013. Errors are clustered by destination.$\star$,$\star\star$ and $\star\star\star$ denote significance at the 10%, 5% and 1% levels, respectively.

	Entry			Exit		
	(1)	(2)	(3)	(4)	(5)	(6)
Risk weight = 0.5 × Post 2014	-0.056**	-0.060*	–0.025**	-0.005	-0.008	-0.026
	(0.018)	(0.017)	(0.015)	(0.012)	(0.013)	(0.019)
Risk weight = 1 × Post 2014	-0.010	-0.008	-0.011	0.026**	0.021*	0.013
	(0.010)	(0.009)	(0.011)	(0.011)	(0.011)	(0.011)
Risk weight = 1.5 × Post 2014	-0.025*	-0.022	-0.023*	0.053***	0.048***	0.020*
	(0.015)	(0.015)	(0.013)	(0.014)	(0.014)	(0.011)
Mean in 2013	.484	.484	.484	.273	.273	.273
Destination FE	✓	✓	✓	✓	✓	✓
Year FE	✓			✓		
Product FE	✓			✓		
Product × Year FE		✓	✓		✓	✓
Destination controls				✓		✓
Observations	202,950	202,494	198,192	176,184	175,617	172,103

TABLE A.V: Effect on entry - estimator robust to heterogeneous treatment effects

This table presents the results of estimating the average treatment effect on entry into high-risk destinations. We use annual data from 2011 to 2018. We include time fixed effects as well as product-destination fixed effects. We present two estimators. The first one is the two-way fixed effects estimator in which we use OLS with the fixed effect structure we described to compute the average treatment effect. For this estimator, we also report the sum of the positive weights assigned to each of the individual treatment effects. As shown in De Chaisemartin and d'Haultfoeuille (2020), the OLS estimator is a weighted average of the individual treatment effects but the weights are not all positive, even though they must add up to one. The second estimator is the estimator developed by De Chaisemartin and d'Haultfoeuille (2020), which is robust to the presence of heterogeneous treatment effects in our sample. For this second estimator, we also report the number of switchers, i.e. the number of observations which observe a change from untreated to treated (the treatment group). Errors are clustered by firm.*,** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	TWFE	Robust estimator
High-risk × Post 2014	-0.041***	-0.041***
	(0.010)	(0.011)
Year FE	✓	✓
Firm × Product × Destination FE	✓	✓
Observations	188,257	21,737
Number of switchers		11,604
Sum of positive weights	1.002	

TABLE A.VI: Effect on exit - estimator robust to heterogeneous treatment effects

This table presents the results of estimating the average treatment effect on exit into high-risk destinations. We use annual data from 2011 to 2018. We include time fixed effects as well as product-destination fixed effects. We present two estimators. The first one is the two-way fixed effects estimator in which we use OLS with the fixed effect structure we described to compute the average treatment effect. For this estimator, we also report the sum of the positive weights assigned to each of the individual treatment effects. As shown in De Chaisemartin and d'Haultfoeuille (2020), the OLS estimator is a weighted average of the individual treatment effects but the weights are not all positive, even though they must add up to one. The second estimator is the estimator developed by De Chaisemartin and d'Haultfoeuille (2020), which is robust to the presence of heterogeneous treatment effects in our sample. For this second estimator, we also report the number of switchers, i.e. the number of observations which observe a change from untreated to treated (the treatment group). Errors are clustered by firm.*,** and *** denote significance at the 10%, 5% and 1% levels, respectively.

toprule	TWFE	Robust estimator
High-risk × Post 2014	0.042***	0.027***
	(0.011)	(0.007)
Year FE	✓	✓
Firm × Product × Destination FE	✓	✓
Observations	168,616	19,805
Number of switchers		10,299
Sum of positive weights	1.002	

TABLE A.VII: Effect on entry - estimator robust to multiple treatments

This table presents the results of estimating the average treatment effect on entry into high-risk destinations. We use annual data from 2013 to 2018. We include time fixed effects as well as firm-product-destination fixed effects. We estimate the average treatment effect for each of the risk weight groups, using countries with low sovereign risk as the control group. We present two estimators. The first one is the two-way fixed effects estimator in which we use OLS with the fixed effect structure we described to compute the average treatment effect. The second estimator is the one proposed by De Chaisemartin and d'Haultfoeuille (2022), which is robust to the presence of multiple treatments and to heterogeneous treatment effects. This estimator uses the method developed in De Chaisemartin and d'Haultfoeuille (2022). Errors are clustered by firm.*,** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	OLS	Robust estimator
Medium risk × Post 2014	-0.076***	0.036***
	(0.019)	(0.017)
High risk × Post 2014	-0.018*	0.033**
	(0.010)	(0.023)
Very high risk × Post 2014	-0.048***	-0.036***
	(0.013)	(0.017)
Year FE	✓	✓
Firm × Product × Destination FE	✓	✓
Observations	188,257	11,604

TABLE A.VIII: Effect on exit - estimator robust to multiple treatments

This table presents the results of estimating the average treatment effect on exit into high-risk destinations. We use annual data from 2013 to 2018. We include time fixed effects as well as firm-product-destination fixed effects. We estimate the average treatment effect for each of the risk weight groups, using countries with low sovereign risk as the control group. We present two estimators. The first one is the two-way fixed effects estimator in which we use OLS with the fixed effect structure we described to compute the average treatment effect. The second estimator is the one proposed by De Chaisemartin and d'Haultfoeuille (2022), which is robust to the presence of multiple treatments and to heterogeneous treatment effects. This estimator uses the method developed in De Chaisemartin and d'Haultfoeuille (2022). Errors are clustered by firm.*,** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	OLS	Robust estimator
Medium risk × Post 2014	-0.010	-0.005
	(0.010)	(0.019)
High risk × Post 2014	0.028**	0.006
	(0.012)	(0.018)
Very high risk × Post 2014	0.055***	0.005
	(0.014)	(0.019)
Year FE	✓	✓
Firm × Product × Destination FE	✓	✓
Observations	168,614	10,299

TABLE A.IX: Effects on trade credit

We use firm-year data in the 2011–2018 period. We consider four outcome variables: (1) the logarithm of accounts payable, (2) the logarithm of accounts receivables, (3) the logarithm of inventories, and (4) the logarithm of the cash conversion cycle. We split firms into two groups according to the share of exports in 2014 that are directed to high-risk countries, excluding firms for which the share is either zero or one. We define firms with a share above the median as the treated group and use firms with a share below the median as the control group. We present estimates for the average treatment effect. We include firm and year fixed effects. The firm controls include: log of capital (where capital is defined as PP&E), leverage (total liabilities as a share of total assets), the EBITDA-to-assets ratio, sales growth, the sales-to-assets ratio, labor productivity (defined as total sales over the number of workers), the ratio of current liabilities to total liabilities, the age of the firm squared, exports as a share of total sales, and exports as a share of total sales squared. Errors are clustered by firm. *,** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Payables	Receivables	Inventories	Cash conversion cycle
High exposure × Post 2014	-0.018	-0.036*	-0.050*	-0.040
	(0.022)	(0.020)	(0.027)	(0.030)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓
Number of firms	3,416	3,414	3,076	2,644
Observations	23,929	23,796	21,398	16,841

B Appendix to Section 5

TABLE B.I: Effects on number of loans

We use firm-year data in the 2011–2018 period and use the logarithm of the number of loans as the outcome variable. We split firms into two groups according to the share of exports in 2014 that are directed to high-risk countries, excluding firms for which the share is either zero or one. We define firms with a share above the median as the treated group and use firms with a share below the median as the control group. We present estimates for the average treatment effect. We include firm and year fixed effects. The time-varying firm controls include: log of total sales, the sales-to-asset ratio, the leverage ratio, the EBITDA-to-assets ratio, the growth rate of total sales, labor productivity, the ratio of current-to-total liabilities, the ratio of current-to-total assets, as well as the firm's age and its age squared. Errors are clustered by firm. *,** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)
High exposure × Post 2014	-0.014	-0.012	-0.028	-0.027
	(0.026)	(0.023)	(0.026)	(0.024)
Firm FE		✓		✓
Year FE		✓		✓
Controls			✓	✓
Number of firms	10,008	8,394	9,969	8,340
Observations	38,090	36,476	37,843	36,214

FIGURE B.1: Dynamic average treatment effect on loan conditions

This figure presents the results of estimating regression (9), where the dependent variable is the interest rate or the loan amount for loan k obtained by firm i from bank b in year t, and where we allow the average treatment effect over time. We use individual loan data for exporting firms from 2013 to 2018, and consider only loans with maturities under 180 days. We present estimates for the average treatment effects. The time-varying loan controls include: the loan maturity, the log of the loan amount and a dummy variable that takes the value of 1 if the loan is collateralized and 0 if otherwise. The time-varying firm controls include: log of total sales, the sales-to-asset ratio, the leverage ratio, the EBITDA-to-assets ratio, the growth rate of total sales, labor productivity, the ratio of current-to-total liabilities, the ratio of current-to-total assets, as well as the firm's age and its age squared. We include firm and bank-year fixed effects. Errors are clustered by firm and we present 95 percent confidence intervals.

(a) Loan amounts (b) Interest rates

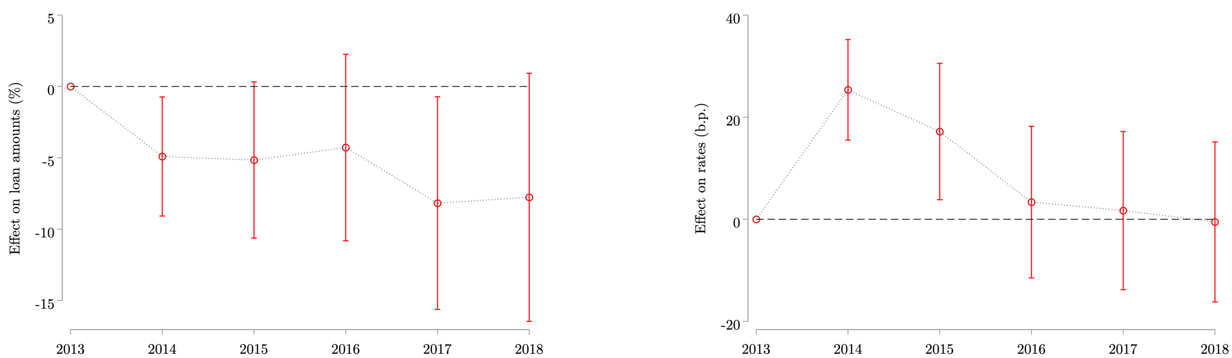
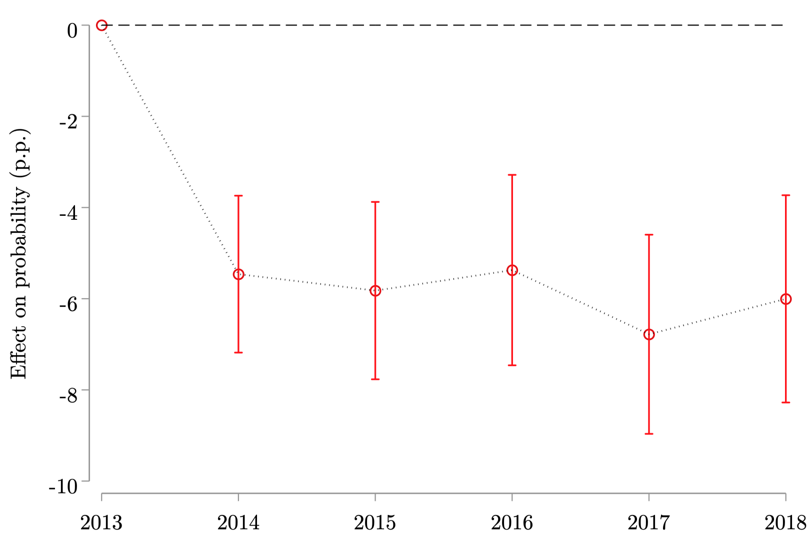


FIGURE B.2: Dynamic average treatment effects on probability of obtaining a loan

This figure presents the results of estimating regression (11), where the dependent variable is an indicator variable which takes the value of 1 if firm i receives at least one bank loan in year t and zero if otherwise. We use individual loan data for exporters from 2013 to 2018, and consider only loans with maturities under 180 days. We present estimates for the average treatment effect over time. The time-varying firm controls include: log of total sales, the sales-to-asset ratio, the leverage ratio, the EBITDA-to-assets ratio, the growth rate of total sales, labor productivity, the ratio of current-to-total liabilities, the ratio of current-to-total assets, as well as the firm's age and its age squared. Errors are clustered by firm and we present 95 percent confidence intervals.

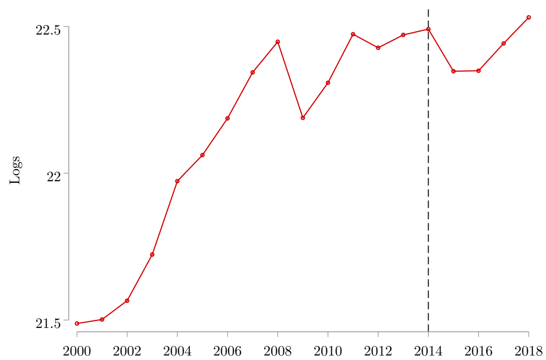


C Appendix to Section 6

FIGURE C.1: Evolution of E.U. exports

This Figure presents the evolution of E.U. exports from 2000 to 2018, using data from CEPII. In Panel (a), we show the evolution of total E.U. exports of goods at current prices. In Panel (b), we present the share of E.U. exports going to high-risk countries.

(a) Total Exports



(b) Share of exports to high-risk destinations

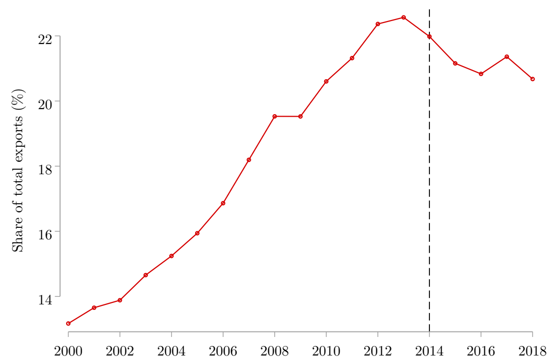
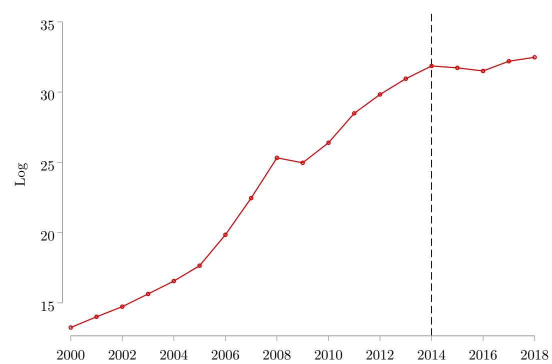


FIGURE C.2: Evolution of share of exports to high-risk destinations

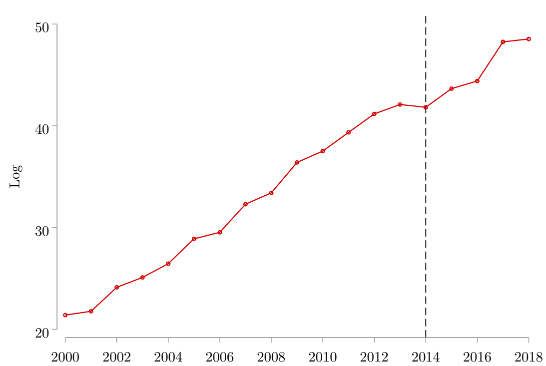
This Figure presents the evolution of the share of exports to high-risk destinations from 2000 to 2018, using data from CEPII. In Panel (a), we present this share for Germany. In panel (b), we present it for China. We present it for Indonesia in panel (c) and for Russia in panel (d).

(a) Germany

(b) China



(c) Indonesia



(d) Russia

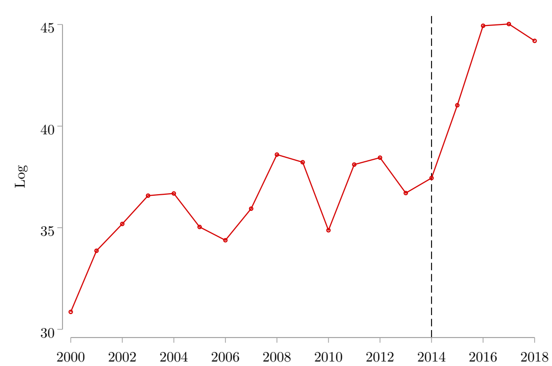


FIGURE C.3: Effect on exports from E.U. countries to high-risk destinations

This Figure presents the results of estimating regression (12), where the dependent variable is the log of exports of country s of product p to destination d at time t, and where we allow the average treatment effect to vary over time. We use annual data from 2008 to 2018. We present estimates for the average treatment effect. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. We also include destination and source-product-year fixed effects. Errors are clustered by destination. We present 90 percent confidence intervals.

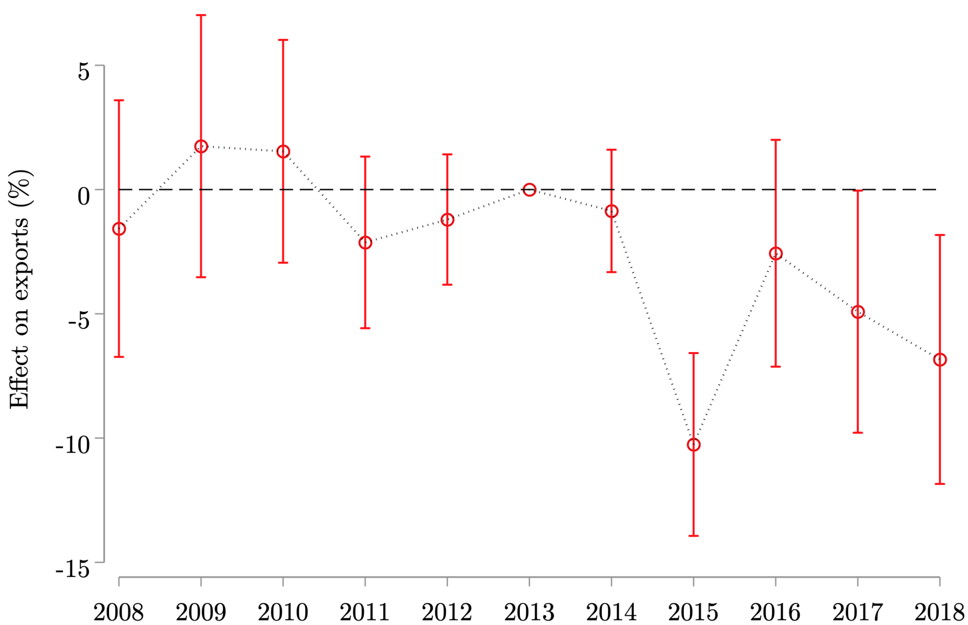


FIGURE C.4: Effect on exports from E.U. countries to high-risk destinations

This Figure presents the results of estimating regression (12), where the dependent variable is the log of exports of country s of product p to destination d at time t, and where we allow the average treatment effect to vary over time. We also allow the average treatment effect to vary across three groups of high-risk countries: (1) countries with an OECD sovereign rating of 2 (medium risk), (2) countries with an OECD sovereign rating of 3 (high risk), and (3) countries with an OECD sovereign rating between 4 and 7 (very high risk). We use low-risk countries as the control group. We use annual data from 2008 to 2018. We present estimates for the average treatment effect. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. We also include destination and source-product-year fixed effects. Errors are clustered by destination. We present 90 percent confidence intervals.

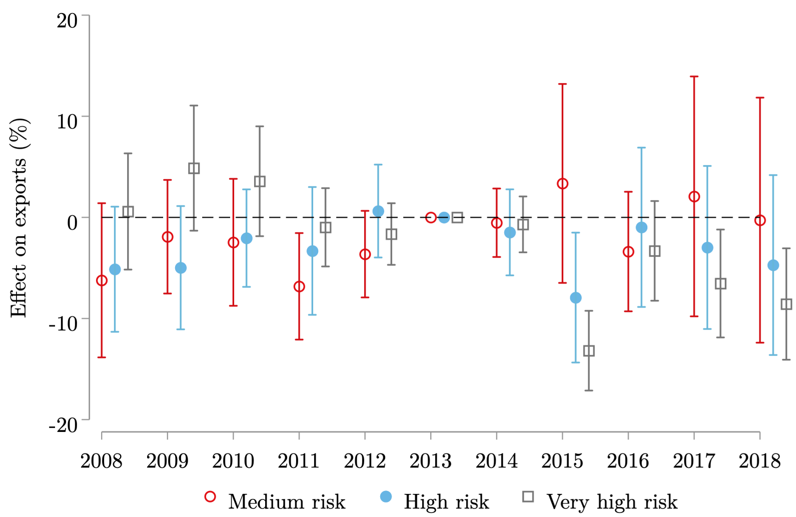


FIGURE C.5: Effect on exports from E.U. countries to high-risk destinations - decomposition across products

This Figure presents the results of estimating regression (12), where the dependent variable is the log of exports of country s of product p to destination d at time t, and where we allow the average treatment effect to vary across groups of products. In panel (a), we present the average treatment effect on products with a low dependence on credit. In panel (b) we present the difference in the average treatment effect between products with a high dependence on credit and products with a low dependence on credit. We use annual data from 2008 to 2018. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. We also include destination and source-product-year fixed effects. Errors are clustered by destination. We present 90 percent confidence intervals.

(a) Low credit products

(b) High credit vs. low credit products

TABLE C.I: Effect on exports to high-risk destinations from non-E.U. countries

This table presents the results of estimating regression (12) for non-E.U. countries and where the dependent variable is the log of exports of country s of product p to destination d at time t. We use annual data from 2010 to 2018 for the exports of non-E.U. countries. We present estimates for the average treatment effect. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. We also include destination and source-product-year fixed effects. Errors are clustered by destination.*,** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
High-risk × Post 2014	0.136**	0.120**	0.082	0.093	0.078	0.034
	(0.063)	(0.060)	(0.050)	(0.064)	(0.061)	(0.050)
Share of high-risk (%)	48	48	48	48	48	48
Destination FE	✓	✓	✓	✓	✓	✓
Year FE	✓			✓		
Exporter FE	✓			✓		
Product FE	✓	✓		✓	✓	
Source × Year FE		✓			✓	
Source × Product × Year FE			✓			✓
Destination controls				✓	✓	✓
Observations	26,925,468	26,925,468	26,604,900	26,132,221	26,132,221	25,810,296

TABLE C.II: Effect on exports to high-risk destinations around the Great Recession

This table presents the results of estimating regression (12) for E.U. countries and where the dependent variable is the log of exports of country s of product p to destination d at time t. We use annual data from 2003 to 2013. We present estimates for the average treatment effect: we compare exports to high-risk vs. exports to low-risk countries, before and after 2008. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. We also include destination and source-product-year fixed effects. Errors are clustered by destination.*,** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
High-risk × Post 2008	0.143***	0.155***	0.142***	-0.027	-0.020	-0.042
	(0.042)	(0.041)	(0.043)	(0.037)	(0.036)	(0.037)
Share of high-risk (%)	24	24	24	24	24	24
Destination FE	✓	✓	✓	✓	✓	✓
Year FE	✓			✓		
Exporter FE	✓			✓		
Product FE	✓	✓		✓	✓	
Source × Year FE		✓			✓	
Source × Product × Year FE			✓			✓
Destination controls				✓	✓	✓
Observations	15,052,396	15,052,396	15,041,476	14,546,122	14,546,122	14,534,976

TABLE C.III: Effect across destinations and products for E.U. countries

This table presents the results of estimating regression (12) where the dependent variable is the log of exports of country s of product p to destination d at time t. We use annual data from 2010 to 2018. We present estimates for the average treatment effect for products with low credit dependence and for the difference in average treatment effects between high and low credit dependence products. We define high credit dependence products as products in the top third of the distribution of the cash conversion cycle and we define low credit dependence products as products in the bottom third of the distribution of the cash conversion cycle. We exclude products in the middle third of the distribution. The time-varying destination controls include the log of GDP, the logarithm of total exports, the share of imports to GDP, the nominal exchange rate, the real exchange rate, the share of the current account to GDP and the sovereign risk rating, as well as region-year fixed effects. We also include destination and source-product-year fixed effects. We also present the exports that go to high-credit products within exports to high-risk countries. Errors are clustered by destination.*,** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)
High-risk × Post 2014	0.032	-0.013	0.026	-0.019
	(0.031)	(0.031)	(0.030)	(0.030)
High-risk × High-credit × Post 2014	-0.044***	-0.039***	-0.048***	-0.042***
	(0.016)	(0.014)	(0.017)	(0.015)
Share of high-credit (%)	28	28	28	28
Destination FE	✓	✓	✓	✓
Year FE	✓		✓	
Source FE	✓		✓	
Product FE	✓		✓	
Source × Product × Year FE		✓		✓
Destination controls			✓	✓
Observations	11,088,552	11,081,607	10,723,838	10,716,703

D Effect on Labor Demand

We have shown that, as the cost of financing for exports to high-risk destinations, firms reduce their exports to these countries. However, we have not discussed the impact of this shock on input demand. As the marginal cost of exporting increases, demand for inputs should decrease as the marginal productivity of inputs becomes smaller than the marginal cost. For instance, we expect that labor demand should decline. As labor demand declines, both wages and the number of workers should decrease at the firm level.[50]

D.1 Effect on number of workers

We begin by investigating the impact of Basel III on the number of full-time employees. We aggregate the data at the firm-year level and split firms according to the median share of exports to high-risk destinations in 2013: firms with a share above or equal to the median are the treated firms and firms with a share below the median are the control firms.[51] To understand the impact of Basel III on the number of full-time employees, we estimate the following regression:

$$\log N_{it} = \alpha_i + \lambda_t + \beta X_{it} + \sum_{m=-3, m\neq -1}^{4} \gamma_m \times \mathbf{1}\{i \in \text{Treated}\} \times \mathbf{1}\{m = t - 2014\} + \varepsilon_{it} \tag{D.1}$$

where the outcome variable is the logarithm of the number of full-time employees employed by firm i in year t. We include firm fixed effects, year fixed effects, and a vector of firm controls including firm leverage (total liabilities divided by total assets), the ratio of EBITDA to assets, the ratio of EBITDA to sales, the logarithm of total sales, the ratio of cash and equivalents to total assets, and the ratio of total bank debt to total assets. We also include a vector of firm-level destination controls, including the logarithm of GDP, the logarithm of total exports, the share of imports to GDP, the nominal and real exchange rates, the logarithm of the current account surplus, and the share of the current account to GDP. For each of these variables, we aggregate them to the firm-year level by taking the average across all destinations to which the firm exports using the share of exports to each destination as the weight. The coefficients of interest are the γ_m which represent the effect of Basel III on the number of full-time employees m periods after 2014. We cluster standard errors at the firm level.

There may be substantial heterogeneity in the response of firms to the increase in the cost of credit induced by Basel III. We focus on one dimension - firm size, which we measure using the number of workers in 2013. We split firms according to the median number of workers in 2013. We then estimate equation (D.1) for three samples: (1) using all firms, (2) using firms with a number of workers above the median (large firms), and (3) using firms with a number of workers below the median (small firms). We present the results of this analysis in Figure D.1.

We find that there is no statistically significant effect on the average number of workers employed by exporters following the implementation of Basel III. All of the coefficients following 2014 are negative but are not statistically significant. However, there is heterogeneity across firms. We find that, if we focus on large firms (firms with a large number of workers), there is no evidence that treated firms reduce the number of employees. In contrast, smaller treated firms sharply reduce the number of employees. In 2018,

[50] Another possibility is that firms decrease the number of hours. However, decreasing the number of hours is very difficult under Portuguese labor legislation and so firms will either decrease the number of workers or lower wages.

[51] As before, we exclude firms that only export to high-risk destinations and firms that only export to low-risk destinations. Therefore, we end up with 4,673 firms.

treated firms reduce the number of employees by 5.4 percent which represents a decrease of approximately one worker relative to the average number of workers in 2013.

D.2 Effect on wages

We now turn to the analysis of the effect of Basel III on monthly wages. Using our worker-level labor data and splitting firms into treated and control groups as before, we estimate the following regression:

$$\log w_{ijt} = \alpha_i + \lambda_t + \theta_{\text{occ}} + \beta X_{it} + \delta W_{jt} + \sum_{m=-3, m\neq -1}^{4} \gamma_m \times \mathbf{1}\{i \in \text{Treated}\} \times \mathbf{1}\{m = t - 2014\} + \varepsilon_{it} \quad \text{(D.2)}$$

where the outcome variable is the logarithm of the monthly wage of worker j in firm i in year t. We include firm fixed effects, year fixed effects, and occupation fixed effects.[52] We also include a vector of firm-level controls as in equation (12). We include a vector of worker controls, which contains a gender fixed effect, the logarithm of the worker's age, and the logarithm of the worker's tenure at the current firm. The coefficients of interest are the γ_m which represent the effect of Basel III on the wage m periods after 2014. We cluster standard errors at the firm level. As before, we estimate (D.2) for three samples: (1) using all firms, (2) using firms with a number of workers above the median (large firms), and (3) using firms with a number of workers below the median (small firms). We present the results in Figure Figure D.2.

We find that, in response to Basel III, treated firms decrease their wages. However, this decrease only starts in 2016 unlike the decline in number of employees which starts earlier (around 2015). The delay in the wage decline is likely driven by the fact that firms either need time to negotiate wages with incumbent workers, or need time to replace incumbent workers with similar workers with lower wages. In 2016, workers in treated firms observe a decline of 2.2 percent in their monthly wage. The wage seems to recover slightly towards the end of our sample as the decline in 2018 is only 1.4 percent. Therefore, for the average treated firm, there seems to be a decline in wages paid to workers as well as a decline in the number of workers. We find that most of the decline in wages we observe for the average treated firm is driven by large firms, with the exception of an outlier in 2015. For example, in 2016, workers in large treated firms experience a decline of 2.4 percent in their wage, which is basically the same decline we observe for the average treated firm. This decline is also somewhat persistent following 2016, with a slight recovery in 2018. Therefore, the response of firms to an increase in the cost of credit depends on the size of the firm: large firms reduce wages while small firms reduce the number of workers.

D.2.1 Heterogeneity across workers

We have documented that, in response to the increase in the cost of credit introduced by Basel III, treated firms decrease wages. However, this decrease masks some heterogeneity across workers. In particular, we are interested in understanding which workers bear the brunt of this decline. To understand this, we start by comparing the evolution of wages of managers with that of other workers. In our data, firms report the hierarchical position of each worker within the firm.[53] We therefore estimate equation (D.2) in

[52] In our worker-level labor data, we can identify the occupation of each worker for every observation. We observe 398 different occupations in our data. The inclusion of these fixed effects allows us to account for possible differences in the skill level across workers.

[53] Firms must assign each worker to one of seven levels: top manager, medium-level manager, low-level manager, highly qualified worker, qualified worker, semi-qualified worker, unqualified worker, and intern. We define managers as workers assigned to any of the first three levels. This classification is identical to the one used in Caliendo et al. (2020).

three samples: (1) using all observations, (2) using observations for managers, and (3) using observations for non-managers. We are also interesting in understanding which occupations face a larger decline in wages. For each occupation, we compute the average wage in 2013. We then classify occupation in two groups: occupations with an average wage above or equal to the median in 2013 are classified as high-wage occupations, and the remaining occupations are classified as low-wage occupations. We then estimate equation (13) in three samples: (1) using all observations, (2) using observations for workers in low-wage occupations, and (3) using observations for workers in high-wage occupations. We present the result of this analysis in Figure D.3.

In panel (a), we find that all of the decline in wages is driven by workers who do not occupy managerial positions. In 2018, non-managers in treated firms experience a decline of 1.5 percent in their wage, while managers in treated firms do not exhibit any change in their wage relative to 2013. There are two possible causes for this asymmetry. One possibility is that, in response to the Basel III shock, treated firms wish to decrease labor costs for unskilled workers but not for skilled workers. Another possibility is related to renegotiation costs. Firms may wish to lower wages for all workers, but it might be costlier to lower wages for managers (either because renegotiating with managers is harder or because replacing incumbent managers with new managers with lower wages is harder). In panel (b), we find that workers in occupations that have lower wages in 2013 exhibit a larger decline in wages following the implementation of Basel III. This finding is consistent with the idea that treated firms want to reduce by more the wages of unskilled workers, when compared to more skilled workers.

FIGURE D.1: Effect on number of full-time employees

This figure presents the results of estimating equation (D.1) on a sample of 4,673 firms between 2011 and 2018. The outcome variable is the logarithm of the number of full-time employees for each firm and year. We compare two groups of firms based on the share of exports to high-risk destinations in 2013: firms with a share above or equal to the median are the treated firms and firms with a share below the median are the control firms. We include firm fixed effects, year fixed effects, and a vector of firm controls including firm leverage (total liabilities divided by total assets), the ratio of EBITDA to assets, the ratio of EBITDA to sales, the logarithm of total sales, the ratio of cash and equivalents to total assets, and the ratio of total bank debt to total assets. We also include a vector of firm-level destination controls, including the logarithm of GDP, the logarithm of total exports, the share of imports to GDP, the nominal and real exchange rates, the logarithm of the current account surplus, and the share of the current account to GDP. For each of these variables, we aggregate them to the firm-year level by taking the average across all destinations to which the firm exports using the share of exports to each destination as the weight. We use the year 2013 as the base year and present average treatment effects for treated firms relative to 2013. We further divide firms according to the number of workers in 2013, using the median in 2013. We estimate equation (12) for three samples: (1) using all firms, (2) using firms with a number of workers above the median, and (3) using firms with number of workers below the median. We cluster errors at the firm-level and present 95 percent confidence intervals.

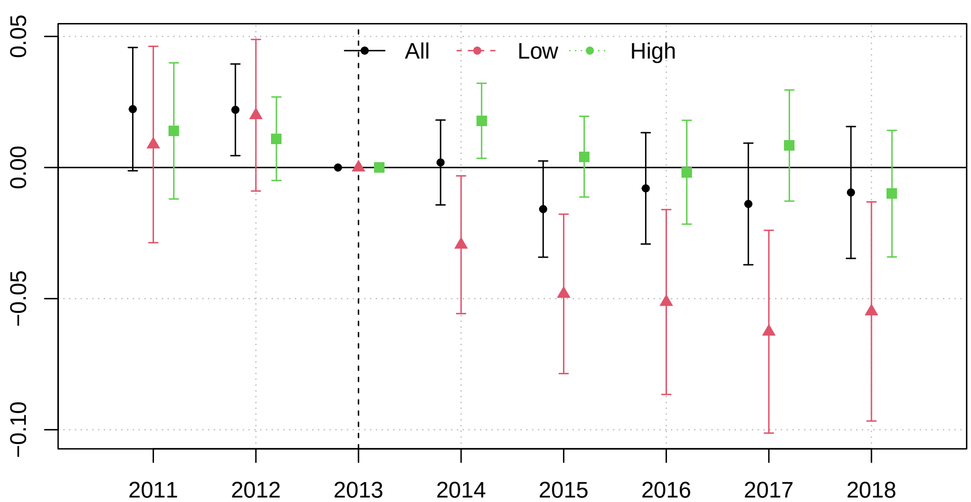


FIGURE D.2: Effect on wages

This figure presents the results of estimating equation (D.2) on a sample of 600,308 workers and 4,673 firms between 2011 and 2018. The outcome variable is the logarithm of the monthly wage for each worker, firm, and year. We compare two groups of firms based on the share of exports to high-risk destinations in 2013: firms with a share above or equal to the median are the treated firms and firms with a share below the median are the control firms. We include firm fixed effects, year fixed effects, occupation fixed effects, and a vector of firm controls including firm leverage (total liabilities divided by total assets), the ratio of EBITDA to assets, the ratio of EBITDA to sales, the logarithm of total sales, the ratio of cash and equivalents to total assets, and the ratio of total bank debt to total assets. We also include a vector of firm-level destination controls, including the logarithm of GDP, the logarithm of total exports, the share of imports to GDP, the nominal and real exchange rates, the logarithm of the current account surplus, and the share of the current account to GDP. For each of these variables, we aggregate them to the firm-year level by taking the average across all destinations to which the firm exports using the share of exports to each destination as the weight. We also include worker controls: a gender fixed effect, the logarithm of the worker's age, and the logarithm of the worker's tenure. We use the year 2013 as the base year and present average treatment effects for treated firms relative to 2013. We further divide firms according to the number of workers in 2013, using the median in 2013. We estimate equation (12) for three samples: (1) using all firms, (2) using firms with a number of workers above the median, and (3) using firms with number of workers below the median. We cluster errors at the firm-level and present 95 percent confidence intervals.

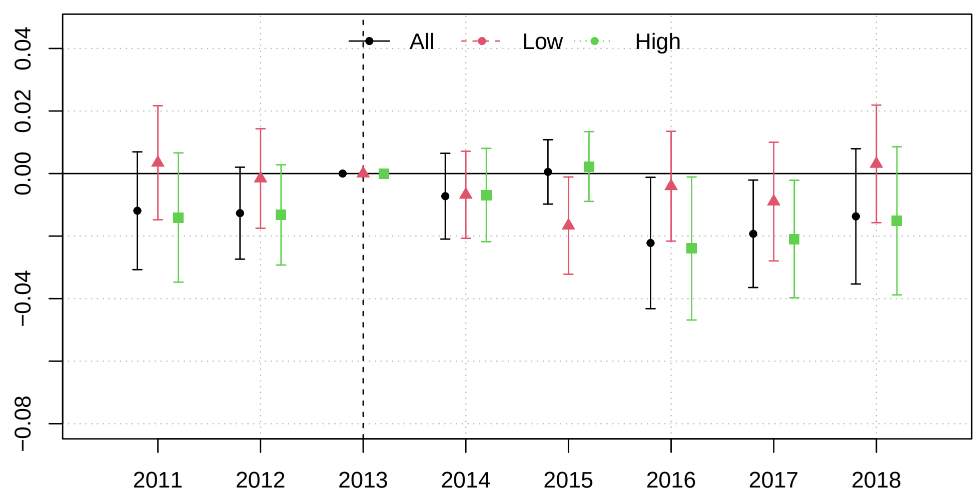
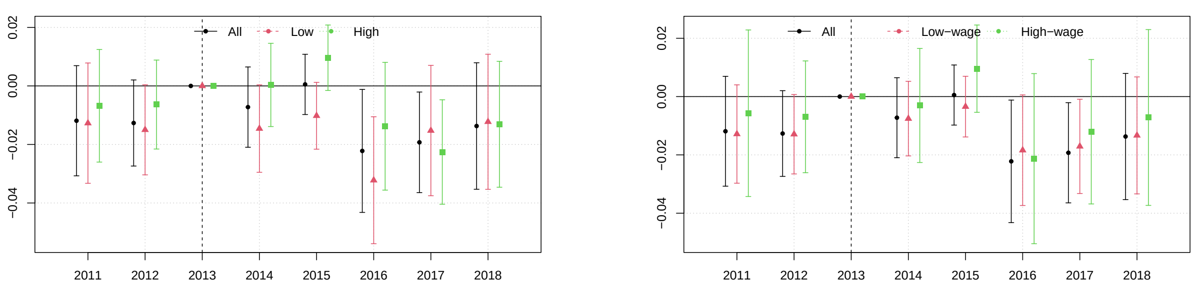


FIGURE D.3: Effect on wages - heterogeneity across workers

This figure presents the results of estimating equation (D.2) on a sample of 600,308 workers and 4,673 firms between 2011 and 2018. The outcome variable is the logarithm of the monthly wage for each worker, firm, and year. We compare two groups of firms based on the share of exports to high-risk destinations in 2013: firms with a share above or equal to the median are the treated firms and firms with a share below the median are the control firms. We include firm fixed effects, year fixed effects, occupation fixed effects, and a vector of firm controls including firm leverage (total liabilities divided by total assets), the ratio of EBITDA to assets, the ratio of EBITDA to sales, the logarithm of total sales, the ratio of cash and equivalents to total assets, and the ratio of total bank debt to total assets. We also include a vector of firm-level destination controls, including the logarithm of GDP, the logarithm of total exports, the share of imports to GDP, the nominal and real exchange rates, the logarithm of the current account surplus, and the share of the current account to GDP. For each of these variables, we aggregate them to the firm-year level by taking the average across all destinations to which the firm exports using the share of exports to each destination as the weight. We also include worker controls: a gender fixed effect, the logarithm of the worker's age, and the logarithm of the worker's tenure. We use the year 2013 as the base year and present average treatment effects for treated firms relative to 2013. We divide workers into two groups according to their hierarchical position: managers vs. non-managers. In panel (a), we estimate equation (13) for three samples: (1) using all observations, (2) using observations for managers, and (3) using observations for non-managers. For each occupation, we compute the average wage in 2013 and then sort occupations into two groups: occupations with an average wage above or equal to the median are classified as high-wage occupations, and occupations with an average wage below the median are classified as low-wage occupations. In panel (b), we estimate equation (13) for three samples: (1) using all observations, (2) using all observations for workers in low-wage occupations, and (3) using all observations for workers in high-wage occupations. We cluster errors at the firm-level and present 95 percent confidence intervals.

(a) Hierarchical position (b) Occupation wage



E Appendix to Section 7

E.1 Model setup

We consider a multi-country multi-sector Ricardian model of international trade as in Caliendo and Parro (2015). The model is static. There are N countries indexed by either n or i and, within each country, there are J sectors indexed by j or k. Throughout the description of the model, subscripts will always denote countries and superscripts will always denote sectors. In this model, trade exists because firms want to purchase the cheapest inputs for production. Households will not consume foreign goods. There are two types of goods within each sector: composite goods and intermediate goods. Composite goods use intermediates from their sector in their production and are non-tradable. Producers of composite goods may import intermediates. Intermediate goods use domestic composite goods from all sectors and labor in production and may be tradable.

E.1.1 Households and preferences

In each country, there is a representative household with preferences

$$U\left(C_n\right) = C_n = \prod_{j=1}^{J} \left(C_n^j\right)^{\alpha_n^j}, \quad \sum_{j=1}^{J} \alpha_n^j = 1,$$

where C_n^j is the consumption of sector j composite goods by the representative household and C_n is aggregate consumption. The share parameters $\alpha_n^j \geq 0$ may vary by country and capture the share of expenditure by the representative household one each sector. The household only consumes domestic goods, i.e. C_n^j is produced domestically. Given this structure, the domestic CPI is given by

$$P_n = \prod_{j=1}^{J} \left(\frac{P_n^j}{\alpha_n^j}\right)^{\alpha_n^j},$$

where P_n^j is the price of the composite good j in country n.

The household has two sources of income. First, the representative household is endowed with L_n units of labor which it supplies inelastically at a wage w_n.[54] Second, the household receives a lump-sum transfer from the government with the proceeds from tariffs imposed on imports.

E.1.2 Production

Intermediate goods: in each sector-country (j, n) there is a continuum of intermediate goods $\omega^j \in [0, 1]$, where each variety ω^j exists in all countries. Production requires two types of factors: labor and materials. Materials are composite goods from all sectors in the country. Therefore, an intermediate producer in country n and sector j may use composite goods from all sectors in country n. Each intermediate producer

[54] We are therefore assuming that there is free labor mobility across sectors within a particular country but that there is no labor mobility across countries.

has a productivity $z_n^j(\omega^j)$. Production takes the form

$$q_n^j\left(\omega^j\right)=z_n^j\left(\omega^j\right)\left(l_n^j\left(\omega^j\right)\right)^{\gamma_n^j}\prod_{k=1}^{J}\left(m_n^{kj}\left(\omega^j\right)\right)^{\gamma_n^{kj}},\quad \gamma_n^j+\sum_{k=1}^{J}\gamma_n^{kj}=1$$

where l_n^j is labor and m_n^{kj} are materials from sector k used in production. The parameter $\gamma_n^j \geq 0$ represents the share of value added in production and γ_n^{kj} represents the share of production that is allocated to inputs from sector k. The factors shares and the share of value added may vary across sectors and countries.

Markets are perfectly competitive and so producers of intermediate goods will price their goods at the marginal cost which is $c_n^j/z_n^j(\omega^j)$ where

$$c_n^j=\Upsilon_n^j w_n^{\gamma_n^j}\prod_{k=1}^{J}\left(P_n^k\right)^{\gamma_n^{kj}},\tag{E.1}$$

and where $\Upsilon_n^j=\left(\gamma_n^j\right)^{-\gamma_n^j}\prod_{k=1}^{J}\left(\gamma_n^{kj}\right)^{-\gamma_n^{kj}}$ is a constant that varies across sectors and countries. We will interpret c_n^j as the unit cost of the production bundle.

Composite goods: producers of composite goods in sector j and country n supply a quantity Q_n^j according to the production function

$$Q_n^j=\left[\int_0^1\left(h_n^j\left(\omega^j\right)\right)^{1-1/\sigma^j}d\omega^j\right]^{\sigma^j/\left(\sigma^j-1\right)},\quad \sigma>0$$

where $\sigma>0$ is the elasticity of substitution across intermediate goods and $h_n^j(\omega^j)$ is the demand for intermediate good ω^j by composite good producer j in country n. Cost minimization yields the following demand for intermediates

$$h_n^j\left(\omega^j\right)=\left(\frac{p_n^j\left(\omega^j\right)}{P_n^j}\right)^{-\sigma^j}Q_n^j,$$

where $p_n^j(\omega^j)$ is the price of the intermediate good and P_n^j is the unit price of the composite good which is given by

$$P_n^j=\left[\int_0^1\left(p_n^j\left(\omega^j\right)\right)^{1-\sigma^j}d\omega^j\right]^{\frac{1}{1-\sigma^j}}.$$

Producers of composite goods may purchase intermediate ω^j from any country and they choose the lowest cost supplier.

E.1.3 Trade costs and prices

Prices of intermediate goods: producers of composite goods may purchase intermediate goods from any country, and they choose the lowest cost supplier. In the presence of trade costs, a unit of an intermediate good ω^j produced in country i is available in country n at a price $c_i^j\kappa_{in}^j/z_i^j(\omega^j)$. Therefore, the cost to the composite good producer of purchasing the lowest price intermediate ω^j is

$$p_n^j\left(\omega^j\right) = \min_i \left\{ \frac{c_i^j \kappa_{in}^j}{z_i^j\left(\omega^j\right)} \right\}.$$

If sector j is a non-tradable sector, we set $\kappa_{in}^j = \infty$ for all $i \neq n$ and this implies that $p_n^j\left(\omega^j\right) = c_n^j / z_n^j\left(\omega^j\right)$ as the lowest cost supplier is the domestic producer.

We adopt a probabilistic representation of productivities. In particular, we assume that the productivity of producing an intermediate good ω^j in country n is the realization of a Fréchet distribution with a location parameter $\lambda_n^j \geq 0$ and a shape parameter $\theta^j \geq 0$. We also assume that the distribution of productivities is independent across goods, sector and countries and that $1 + \theta^j \geq \sigma^j$. This representation allows to independently vary absolute and comparative advantages. The location parameter λ_n^j represents absolute advantage, as a higher λ_n^j increases average productivity. The shape parameter θ^j represents comparative advantage as a smaller θ^j implies a higher dispersion of productivities. With this distributional assumption, we can then compute the sectoral price index as

$$P_n^j = A^j \left[\sum_{i=1}^{N} \lambda_i^j \left(c_i^j \kappa_{in}^j \right)^{-\theta^j} \right]^{-1/\theta^j}, \tag{E.2}$$

where A^j is a constant. For a non-tradable sector where $\kappa_{in}^j = \infty$ for all $i \neq n$, $P_n^j = A^j \left(\lambda_n^j\right)^{-1/\theta^j} c_n^j$.

E.1.4 Expenditure shares and market clearing

We can define total expenditure on sector j goods in country n as X_n^j. Define X_{in}^j as the expenditure in country n of goods from sector j coming from country i. Using these two terms, we can write the share of country i in country n's expenditure of sector j goods as $\pi_{in}^j = X_{in}^j / X_n^j$. Using the properties of the Fréchet distribution, we can then express this share as a function of unit costs, trade costs and exogenous parameters as

$$\pi_{in}^j = \frac{\lambda_i^j \left[c_i^j \kappa_{in} \right]^{-\theta^j}}{\sum_{h=1}^{N} \lambda_h^j \left[c_h^j \kappa_{hn}^j \right]^{-\theta^j}}, \tag{E.3}$$

and for a non-tradable sector where $\kappa_{in}^j = \infty$ for all $i \neq n$, $\pi_{nn}^j = 1$. With this result, we can now write the gravity equation of this model:

$$X_{in}^j = \frac{\lambda_i^j \left[c_i^j \kappa_{in} \right]^{-\theta^j}}{\sum_{h=1}^{N} \lambda_h^j \left[c_h^j \kappa_{hn}^j \right]^{-\theta^j}} X_n^j, \tag{E.4}$$

where trade flows depend on demand in the destination country X_n^j as well as productivity across all possible countries (λ_h^j), marginal costs across all countries (c_h^j), trade costs κ_{hn}^j and the dispersion of the distribution of productivities θ^j. This term appears in the same fashion as trade elasticities appear in Armington models. We will therefore often refer to the dispersion of the distribution of productivity as the trade elasticity.

We now turn to market clearing. Consider sector j in country n with a value of production X_n^j. This production is used both for final consumption of households in country n and as materials by intermediate producers in country n. Given the Cobb-Douglas assumption we made for the utility function of the representative household, production used for household consumption is $\alpha_n^j I_n$, where I_n is the income of the representative household. From the Cobb-Douglas assumption in the production function, each intermediate good producer in sector k will use a share γ_n^{jk} of its production to purchase composite goods from sector j. In turn, total production of these intermediate goods will be sold to all sectors k in all countries. Therefore, we can write the market clearing condition as

$$X_n^j = \alpha_n^j I_n + \sum_{k=1}^{J} \gamma_n^{jk} \sum_{i=1}^{N} X_i^k \frac{\pi_{ni}^k}{1+\tau_{ni}^k}, \tag{E.5}$$

where $\sum_{i=1}^{N} X_i^k \pi_{ni}^k / (1+\tau_{ni}^k)$ represents total production of intermediates in sector k in country n. Note that in equation (E.5), we are removing tariffs from total expenditure. We do this because firms only receive the unit costs, not the tariffs. We don't do this for iceberg costs or interest rates because the value of these frictions is a loss of resources and is not distributed to households.

Households derive income from two sources: (1) labor income $w_n L_n$, where w_n is the wage and L_n is the exogenous labor endowment in country n and (2) tariff revenue R_n. Therefore, household income is given by $I_n = w_n L_n + R_n$. As tariffs are imposed on all tariffs, tariff revenue can be written as

$$R_n = \sum_{j=1}^{J} \sum_{i=1}^{N} \tau_{in}^j X_n^j \frac{\pi_{in}^j}{1+\tau_{in}^j},$$

which is jus the sum of the value of the ad-valorem flat rate tariffs imposed on unit costs (which is why we need to divide the shares π_{in}^j by the tariffs). We assume national trade deficits are zero but sectoral trade deficits are endogenous. National trade deficits are given by $D_n = \sum_{j=1}^{J} D_n^j$, where D_n is exogenous but D_n^j is an equilibrium object. Sectoral deficits are given by

$$D_n^j = \sum_{i=1}^{N} X_n^j \frac{\pi_{in}^j}{1+\tau_{in}^j} - \sum_{i=1}^{N} X_i^j \frac{\pi_{ni}^j}{1+\tau_{ni}^j}, \tag{E.6}$$

which is the difference between imports and exports. We can use the definition of national deficits together with (E.6) to write the balanced trade equation

$$\sum_{j=1}^{J} \sum_{i=1}^{N} X_n^j \frac{\pi_{in}^j}{1+\tau_{in}^j} = \sum_{j=1}^{J} \sum_{i=1}^{N} X_i^j \frac{\pi_{ni}^j}{1+\tau_{ni}^j}, \tag{E.7}$$

in which the left hand side is the value of exports and the right hand side is the value of imports.[55]

[55] We have not specified market clearing for the labor market. We don't need to do this because market clearing in each sector-country together with the balanced trade equation yields market clearing for the labor market in each country. In order to see this, we can add equation (E.5) across all sectors, use the expression for household income and then substitute into the balanced trade equation (E.6) to obtain

$$w_n L_n = \sum_{j=1}^{J} \gamma_n^j \sum_{i=1}^{N} X_i^j \frac{\pi_{ni}^j}{1+\tau_{ni}^j}.$$

E.1.5 Equilibrium

We can now define an equilibrium under policies $\left\{r_{ni}^{j}, \tau_{ni}^{j}\right\}$.

Definition 1 *Given $L_n, D_n, \lambda_n^j, \theta^j$ and d_{ni}^j, and equilibrium under policy $\{r, \tau\}$ is a wage vector $\boldsymbol{w} \in \mathbb{R}_{++}^{N}$ and prices $\left\{P_n^j\right\}_{j=1,n=1}^{J,N}$ that satisfy equilibrium conditions (E.1), (E.2), (E.3), (E.5) and (E.7) for all j, n.*

Instead of solving for an equilibrium under a policy $\{r, \tau\}$ and then solving for another equilibrium under a new policy $\{r', \tau\}$, we will use the exact hat algebra method of Dekle et al. (2008) to solve for the equilibrium in relative changes.[56] In this method, instead of computing two equilibria and then computing the changes, we can compute the changes directly. This method is appealing for two reasons. First, we can identify the effect on equilibrium outcomes from a pure change in the cost of credit. Second, we can solve the model without needing to estimate parameters which may be difficult to identify. For example, this method implies that we do not need to specify the interest rates before Basel III and we can instead focus on the change in interest rates.

Therefore, if we have a change in interest rates we can then compute the equilibrium changes without relying on estimates of productivity or transport costs. We only need data on bilateral trade shares π_{in}^{j}, the share of value added in production γ_n^j, value added $w_n L_n$, the share of intermediate consumption γ_n^{kj} and the sectoral dispersion of productivity θ^j. We will obtain the share of each sector in final demand α_n^j from these data.

E.1.6 Aggregation

In this model, we can write a sectoral production function as a function of factor usage in the sector. Total production in sector j in country n can be written as

$$\frac{Y_n^j}{P_n^j} = \frac{c_n^j}{P_n^j} \left(L_n^j\right)^{\gamma_n^j} \prod_{k=1}^{J} \left(M_n^{kj}\right)^{\gamma_n^{kj}},$$

where $Y_n^j = \int \left(c_n^j / z_n^j\left(\omega^j\right)\right) q_n^j\left(\omega^j\right) d\omega^j$ is the value of production in sector j and country n, L_n^j is total labor used in the sector and M_n^{kj} is total usage of materials from sector k in sector n. According to this representation, we can think of the ratio c_n^j / P_n^j as a multiplicative TFP factor. In fact, this term captures gains from trade in this model. To see this, note that in autarky, $d \log P_n^j = d \log c_n^j$ and so changes in marginal costs of domestic production move one-to-one with changes in price of the good j in country n. With trade, an increase in marginal costs no longer causes the same increase in the price, as this term will be dampened by the change in the share of own consumption π_{nn}^j. Therefore, in the presence of trade, increases in the cost of domestic production do not fully pass-through into the cost of the good in country n. Therefore, we shall call this ratio $A_n^j = c_n^j / P_n^j$ and will interpret it as productivity in sector j in country n. We can further use equation (E.3) to write changes in productivity as

$$d \log A_n^j = -\frac{1}{\theta^j} d \log \pi_{nn}^j, \tag{E.8}$$

[56] We present a formal definition of the equilibrium in changes in Appendix E.

which implies that we only need to know two quantities to identify changes in productivity: (1) the trade elasticity and (2) the share of own consumption.[57] Suppose that there is a shock that increases the share of own consumption. In that case, marginal costs increase because firms are no longer importing cheap intermediates from abroad and are instead relying on the more expensive domestically produced intermediates. Therefore, production becomes more expensive and productivity decreases. This representation of gains from trade as a function of these two quantities is very general. In fact, Arkolakis et al. (2012) show that in most trade models gains from trade can be summarized by the elasticity of imports with respect to variable trade costs (which in this model is the trade elasticity) and the share of expenditure on domestic goods. In their seminal paper, the Ricardian model written by Eaton and Kortum (2002) displays this characterization, as does the Caliendo and Parro (2015) model.

E.2 Calibration and solution

Before describing the data sources we employ to calibrate the model, we need to specify the number of countries and sectors. We have 31 countries: 30 countries and one constructed rest of the world. We consider $J = 40$ sectors of which 20 are tradable. We follow the list of countries and sectors in Caliendo and Parro (2015). These choices maximize the number of countries and sectors covered in our sample conditional to obtaining reliable data. We will use 2013, the year before Basel III is implemented, as the base year. We now briefly describe the data sources.[58]

The main advantage from solving the model in changes is that we can avoid calibrating certain parameters of the model like iceberg costs. In fact, in order to calibrate the model we only need four sources of data: (1) bilateral trade flows X_{in}^j, (2) value added by sector and country V_n^j, (3) gross production by sector Y_n^j, and (4) I-O tables to identify the coefficients of the production function of intermediates. Using these data we can then calculate the data counterparts of π_{in}^j, γ_n^j,γ_n^{kj} and α_n^j.

We begin by obtaining bilateral trade flows from Comtrade for all countries. We obtain gross output and value added from three different sources: (1) the OECD STAN database for industrial analysis, (2) the Industrial Statistics Database INDSTAT2 and (3) the OECD Input-Output database. We use I-O tables from the World Input-Output Database (WIOD) and the OECD Input-Output Database. We obtain data on tariffs for the year 2013 from the United Nations Statistical Division, Trade Analysis and Information System. Finally, we use the estimated trade elasticities from Caliendo and Parro (2015).

In order to compute the bilateral trade shares π_{in}^j we begin by calculating domestic sales in each country as the difference between gross production and total exports: $X_{nn}^j = Y_n^j - \sum_{i \neq n}^N X_{ni}^j$. Define M_{in}^j as the trade flows we obtain from Comtrade, which exclude tariffs. We compute the expenditure of country n in sector j goods from country i as $X_{in}^j = M_{in}^j \left(1 + \tau_{in}^j\right)$. We then obtain the shares by computing $\pi_{in}^j = X_{in}^j / \sum_{h=1}^N X_{ih}^j$. The share of sector j's spending on sector k goods, γ_n^{kj}, is directly computed from the I-O matrix as the share of intermediate consumption of sector k in sector j over the total intermediate consumption of sector j minus the share of value-added. We compute the share of value added by dividing value added by gross production and so $\gamma_n^j = V_n^j / Y_n^j$. We calculate the final consumption share by taking the total expenditure of sector j goods and subtracting the intermediate goods expenditure and dividing the result by income and so $\alpha_n^j = \left(Y_n^j + D_n^j - \sum_{k=1}^J \gamma_n^{jk} Y_n^k\right) / I_n$, which just follows from the market clearing condition (E.5). We compute trade deficits in each sector j and country n as $D_n^j = \sum_{i=1}^N M_{in}^j - \sum_{i=1}^N M_{ni}^j$.

[57] Note that, for non-tradable goods, $\pi_{nn}^j = 1$ and so productivity is fixed at $A_n^j = \left(A^j\right)^{-1} \left(\lambda_n^j\right)^{1/\theta^j}$.

[58] We present these sources in greater detail in Appendix E, along with some summary statistics.

We solve the model following the algorithm in Caliendo and Parro (2015). We begin by guessing a vector of wage changes $\hat{w}$. Given this vector we can solve for obtain the changes in unit costs and sectoral prices which are consistent with our guess. We can then use the changes in unit costs, the changes in sectoral prices and the shares in the base year to solve for the new shares $\pi_{in}^{j\prime}$. We then use the market clearing condition to compute total expenditure which is consistent with our initial guess for the change in wages. Substituting all of these terms in the balanced trade equation we can check if this equilibrium condition holds. If it does not, we adjust our guess for the wage changes and iterate until convergence.[59]

E.3 Definitions

Definition 2 *Let (w, P) be an equilibrium under policy $\{r, \tau\}$ and let (w', P') be an equilibrium under policy $\{r', \tau\}$. Define $(\hat{w}, \hat{P})$ as an equilibrium under policy $\{r', \tau\}$ relative to $\{r, \tau\}$, where for a variable x $\hat{x} = x'/x$.*[60] *Using equations (E.1), (E.2), (E.3), (E.5) and (E.7) the equilibrium conditions in relative changes satisfy:*

Cost of the input bundles:

$$\hat{c}_n^j = (\hat{w}_n)^{\gamma_n^j} \prod_{k=1}^{J} \left(\hat{P}_n^k\right)^{\gamma_n^{kj}}. \tag{E.9}$$

Price index:

$$\hat{P}_n^j = \left[\sum_{i=1}^{N} \pi_{in}^j \left(\hat{\kappa}_{in}^j \hat{c}_i^j\right)^{-\theta^j}\right]^{-1/\theta^j}. \tag{E.10}$$

Bilateral trade shares:

$$\hat{\pi}_{in}^j = \left(\frac{\hat{c}_i^j \hat{\kappa}_{in}^j}{\hat{P}_n^j}\right)^{-\theta^j}. \tag{E.11}$$

Total expenditure in each country n and sector j:

$$X_n^{j\prime} = \alpha_n^j I_n' + \sum_{k=1}^{J} \gamma_n^{jk} \sum_{i=1}^{N} X_i^{k\prime} \frac{\pi_{ni}^{k\prime}}{1+\tau_{ni}^k}. \tag{E.12}$$

Trade balance:

$$\sum_{j=1}^{J}\sum_{i=1}^{N} X_n^{j\prime} \frac{\pi_{in}^{j\prime}}{1+\tau_{in}^j} - D_n = \sum_{j=1}^{J}\sum_{i=1}^{N} X_i^{j\prime} \frac{\pi_{ni}^{j\prime}}{1+\tau_{ni}^j}, \tag{E.13}$$

where $\hat{k}_{in}^j = \left(1 + r_{in}^{j\prime}\right) / \left(1 + r_{in}^j\right)$ *and* $I_n' = \hat{w}_n w_n L_n + D_n + \sum_{j=1}^{J} \sum_{i=1}^{N} \tau_{in}^j X_n^{j\prime} \frac{\pi_{in}^{j\prime}}{1+\tau_{in}^j}$.

E.4 Proofs

E.4.1 Proof of Proposition 1

The change in welfare is given by

$$d\log W_n = \frac{w_n L_n}{I_n} d\log w_n + \frac{R_n}{I_n} d\log R_n - d\log P_n.$$

[59] The Appendix of Caliendo and Parro (2015) describes the algorithm in greater detail.

[60] Note that this definition can be easily extended to include changes in tariffs as well as changes in interest rates. We do not do so for the interest of simplicity.

From equation (E.9), the change in marginal costs for a given sector j in country n is given by

$$d\log c_n^j = \gamma_n^j d\log w_n + \sum_{k=1}^{J} \gamma_n^{kj} d\log P_n^k$$

and so the change in the wage is given by

$$d\log w_n = \frac{1}{\gamma_n^j} d\log c_n^j - \sum_{k=1}^{J} \frac{\gamma_n^{kj}}{\gamma_n^j} d\log P_n^k.$$

Using the market clearing condition for labor, it also follows that

$$\begin{aligned}
\frac{w_n L_n}{I_n} d\log w_n &= \frac{1}{I_n} \sum_{j=1}^{N} \gamma_n^j \sum_{i=1}^{N} E_{ni}^j d\log w_n \\
&= \frac{1}{I_n} \sum_{j=1}^{N} \gamma_n^j \sum_{i=1}^{N} E_{ni}^j \left\{ \frac{1}{\gamma_n^j} d\log c_n^j - \sum_{k=1}^{J} \frac{\gamma_n^{kj}}{\gamma_n^j} d\log P_n^k \right\} \\
&= \frac{1}{I_n} \sum_{j=1}^{N} \sum_{i=1}^{N} E_{ni}^j d\log c_n^j - \frac{1}{I_n} \sum_{j=1}^{N} \sum_{i=1}^{N} E_{ni}^j \sum_{k=1}^{J} \gamma_n^{kj} d\log P_n^k \\
&= \underbrace{\frac{1}{I_n} \sum_{j=1}^{N} \sum_{i=1}^{N} E_{ni}^j d\log c_n^j}_{A_1} - \underbrace{\frac{1}{I_n} \sum_{j=1}^{N} \sum_{k=1}^{J} \gamma_n^{kj} d\log P_n^k \sum_{i=1}^{N} E_{ni}^j}_{A_2}
\end{aligned}$$

where $E_{ni}^j \equiv X_i^j \pi_{ni}^j / \left(1+\tau_{ni}^j\right)$ are the exports of sector j goods from country n to country i.

The change in tariff revenue is given by

$$\begin{aligned}
d\log R_n &= \frac{\sum_{j=1}^{J} \sum_{i=1}^{N} \tau_{in}^j M_{in}^j \left(d\log X_n^j + d\log \pi_{in}^j\right)}{R_n} \\
&= \frac{\sum_{j=1}^{J} \sum_{i=1}^{N} \tau_{in}^j M_{in}^j d\log M_{in}^j}{R_n}
\end{aligned}$$

where $M_{in}^j \equiv X_n^j \pi_{in}^j / \left(1+\tau_{in}^j\right)$ are country n's imports of sector j goods from country i. Therefore, it follows that

$$\frac{R_n}{I_n} d\log R_n = \underbrace{\frac{1}{I_n} \sum_{j=1}^{J} \sum_{i=1}^{N} \tau_{in}^j M_{in}^j d\log M_{in}^j}_{A_3}.$$

From equation (E.10), we can write the change in the domestic CPI as

$$d\log P_n = \sum_{j=1}^{J} \alpha_n^j \sum_{i=1}^{N} \pi_{in}^j \left(d\log c_i^j + d\log \kappa_{in}^j\right)$$

and then, using the market clearing condition for sector j, we can write

$$\alpha_n^j = \frac{X_n^j}{I_n} - \frac{1}{I_n} \sum_{k=1}^{J} \gamma_n^{jk} \sum_{i=1}^{N} E_{ni}^k$$

and so the change in the domestic CPI is given by

$$
\begin{aligned}
d\log P_n &= \sum_{j=1}^{J}\left\{\frac{X_n^j}{I_n} - \frac{1}{I_n}\sum_{k=1}^{J}\gamma_n^{jk}\sum_{i=1}^{N}E_{ni}^k\right\}\sum_{i=1}^{N}\pi_{in}^j\left(d\log c_i^j + d\log\kappa_{in}^j\right) \\
&= \underbrace{\sum_{j=1}^{J}\frac{X_n^j}{I_n}\sum_{i=1}^{N}\pi_{in}^j\left(d\log c_i^j + d\log\kappa_{in}^j\right)}_{B_1} \\
&\quad \underbrace{-\frac{1}{I_n}\sum_{j=1}^{J}\sum_{k=1}^{J}\gamma_n^{jk}\sum_{i=1}^{N}E_{ni}^k\sum_{i=1}^{N}\pi_{in}^j\left(d\log c_i^j + d\log\kappa_{in}^j\right)}_{A_4}
\end{aligned}
$$

and we can write the first term as

$$
\begin{aligned}
B_1 &= \frac{1}{I_n}\sum_{j=1}^{J}\sum_{i=1}^{N}\pi_{in}^j X_n^j\left(d\log c_i^j + d\log\kappa_{in}^j\right) \\
&= \frac{1}{I_n}\sum_{j=1}^{J}\sum_{i=1}^{N}\left(1+\tau_{in}^j\right)M_{in}^j\left(d\log c_i^j + d\log\kappa_{in}^j\right) \\
&= A_5 + A_6 + A_7
\end{aligned}
$$

where

$$
A_5 = \frac{1}{I_n}\sum_{j=1}^{J}\sum_{i=1}^{N}M_{in}^j d\log c_i^j,
$$

$$
A_6 = \frac{1}{I_n}\sum_{j=1}^{J}\sum_{i=1}^{N}\left(1+\tau_{in}^j\right)M_{in}^j d\log\kappa_{in}^j,
$$

$$
A_7 = \frac{1}{I_n}\sum_{j=1}^{J}\sum_{i=1}^{N}\tau_{in}^j M_{in}^j d\log c_i^j.
$$

Therefore, the change in the real wage can be written as

$$
d\log W_n = A_1 - A_2 + A_3 + A_4 - A_5 - A_6 - A_7.
$$

Gathering terms, note that

$$
A_1 - A_5 = \frac{1}{I_n}\sum_{j=1}^{N}\sum_{i=1}^{N}\left(E_{ni}^j d\log c_n^j - M_{in}^j d\log c_i^j\right)
$$

$$
A_3 - A_7 = \frac{1}{I_n}\sum_{j=1}^{J}\sum_{i=1}^{N}\tau_{in}^j M_{in}^j\left(d\log M_{in}^j - d\log c_i^j\right)
$$

$$
A_4 - A_2 = 0
$$

$$
-A_6 = -\frac{1}{I_n}\sum_{j=1}^{J}\sum_{i=1}^{N}\left(1+\tau_{in}^j\right)M_{in}^j d\log\kappa_{in}^j
$$

and so the change in welfare is given by

$$d \log W_n = \frac{1}{I_n} \sum_{j=1}^{N} \sum_{i=1}^{N} \left(E_{ni}^j d \log c_n^j - M_{in}^j d \log c_i^j \right) + \frac{1}{I_n} \sum_{j=1}^{J} \sum_{i=1}^{N} \tau_{in}^j M_{in}^j \left(d \log M_{in}^j - d \log c_i^j \right)$$
$$- \frac{1}{I_n} \sum_{j=1}^{J} \sum_{i=1}^{N} \left(1 + \tau_{in}^j \right) M_{in}^j d \log \kappa_{in}^j$$

as we wanted to show.

E.5 Effect of interest rates on real household income

If the revenue from interest rates is distributed back to households, then the change in real household income is given by

$$d \log W_n = \frac{w_n L_n}{I_n} d \log w_n + \frac{R_n}{I_n} d \log R_n + \frac{B_n}{I_n} d \log B_n - d \log P_n,$$

where we define B_n as the revenue from interest rates and

$$B_n = \sum_{j=1}^{J} \sum_{i=1}^{N} r_{ni}^j X_i^j \frac{\pi_{ni}^j}{\left(1 + \tau_{ni}^j \right) \left(1 + r_{ni}^j \right)}.$$

Therefore, to understand the impact of the additional channel, we will look at $\frac{B_n}{I_n} d \log B_n$. We know that R_n / I_n is very small for all countries in our sample (and usually below 1 percent). As the average tariff is around 4 percent, we can assume that interest rates should be around the same value. Therefore, B_n / I_n will also be very small. Therefore, for the additional channel to be important, it must be that $d \log B_n$ is large. We can write this change as

$$\begin{aligned} d \log B_n &= \frac{1}{B_n} \sum_{j=1}^{J} \sum_{i=1}^{N} \frac{1}{1 + \tau_{ni}^j} \left[dr_{ni}^j \frac{X_{ni}^j}{\left(1 + r_{ni}^j \right)} + dX_{ni}^j \frac{r_{ni}^j}{\left(1 + r_{ni}^j \right)} - \frac{r_{ni}^j X_{ni}^j}{\left(1 + r_{ni}^j \right)^2} dr_{ni}^j \right] \\ &= \frac{1}{B_n} \sum_{j=1}^{J} \sum_{i=1}^{N} \frac{r_{ni}^j X_{ni}^j}{\left(1 + \tau_{ni}^j \right) \left(1 + r_{ni}^j \right)} \left[d \log r_{ni}^j + d \log X_{ni}^j - \frac{r_{ni}^j}{1 + r_{ni}^j} d \log r_{ni}^j \right] \\ &= \sum_{j=1}^{J} \sum_{i=1}^{N} s_{ni}^j \left[\frac{1}{1 + r_{ni}^j} d \log r_{ni}^j + d \log X_{ni}^j \right] \end{aligned}$$

where $s_{ni}^j \equiv B_n^{-1} \frac{r_{ni}^j X_{ni}^j}{\left(1+\tau_{ni}^j\right)\left(1+r_{ni}^j\right)}$ and $\sum_{j=1}^{J} \sum_{i=1}^{N} s_{ni}^j = 1$. Using the gravity equation (E.4) we can then write the change in the value of exports as

$$d \log X_{ni}^j = d \log X_i^j - \theta^j d \log c_n^j - \theta^j dr_{ni}^j + \theta^j d \log \Psi_i^j$$

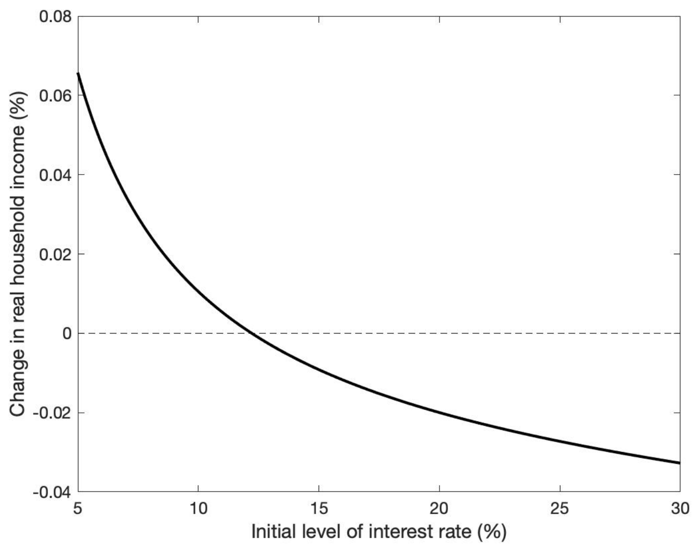
and we will focus on the third term $-\theta^j dr_{ni}^j$. We are assuming then that the changes in demand in the foreign country, changes in domestic marginal costs and changes in marginal costs and trade costs in other countries are negligible. Therefore, we can write

$$
\begin{aligned}
d\log B_n &\approx \sum_{j=1}^{J}\sum_{i=1}^{N} s_{ni}^{j}\left[\frac{1}{1+r_{ni}^{j}}d\log r_{ni}^{j} - \theta^{j} dr_{ni}^{j}\right] \\
&= \sum_{j=1}^{J}\sum_{i=1}^{N} s_{ni}^{j} d\log r_{ni}^{j}\left[\frac{1}{1+r_{ni}^{j}} - \theta^{j} r_{ni}^{j}\right].
\end{aligned}
$$

We now wish to plot $d\log B_n$ for different levels of initial interest rates and for the same shock dr_{ni}^{j} as in our main results. For simplicity, we will assume that interest rates are identical for all tradable products, sources and destinations. We present the results in Figure E.1.

FIGURE E.1: Effect of interest rate revenue on real household income

This Figure change in real household income arising from an increase in interest rates, through the change in interest rate revenue.



E.6 Data

This appendix describes the data sources we use in solving the model. We consider 31 countries: Argentina, Australia, Austria, Brazil, Canada, Chile, China, Denmark, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Korea, Mexico, Netherlands, New Zealand, Norway, Portugal, South Africa, Spain, Sweden, Turkey, U.K., U.S., and a constructed rest of the world. We consider 40 sectors, which we report in Table E.I.

In Figure E.2 we plot the share of exports which we can attribute the the thirty countries we include in our model. In 2013, which is our year of interest, these countries account for two thirds of world exports. This representativeness is larger for E.U. countries than it is for high-risk countries. However, even for high-risk countries we are able to include half of world exports. The share is smaller for high-risk countries because there are many more of these countries and, for most of them, there is not enough data on input-output tables to include them in the quantitative model. In Figure E.3, we do the same exercise but with imports. The results are very similar. In Figure E.4, we plot the share of exports and imports we attribute

TABLE E.I: Tradable and non-tradable sectors

Tradable			Nontradable		
Number	Description	ISIC Rev. 4	Number	Description	ISIC Rev. 4
1	Agriculture	1–3	21	Electricity	35–39
2	Mining	5–9	22	Construction	41–43
3	Food	10–12	23	Retail	45–47
4	Textile	13–15	24	Hotels	55–56
5	Wood	16	25	Land transport	49
6	Paper	17–18	26	Water transport	50
7	Petroleum	19	27	Air transport	51
8	Chemicals	20–21	28	Auxiliary transport	52, 79
9	Plastic	22	29	Post and telecom	53, 61
10	Minerals	23	30	Finance	64–66
11	Basic Metals	24	31	Real estate	68
12	Metal products	25	32	Renting	77
13	Machinery n.e.c.	28	33	Computers	62–63, 95
14	Office	26	34	R&D	72
15	Electrical	27	35	Other business	69–71, 73–74, 80–82
16	Communication	58–60	36	Public admin	84
17	Medical	325, 266	37	Education	85
18	Auto	29	38	Health	75, 86–88
19	Other transport	30	39	Other services	78, 90–96
20	Other	31–33	40	Private households	97–98

to the "Rest of the World" country which come from high-risk countries. As more than half of exports and imports in this fictional country come from high-risk countries, we will assign this fictional country to the group of high-risk countries.

E.6.1 Bilateral trade shares

We use bilateral trade flows for 2013 for our sample of countries and the first 20 sectors (which are the tradable sectors) in Table D.I. Bilateral trade data come from CEPII, which collects bilateral trade from the United Nations Statistical Division Commodity Trade database. Value are in thousands of dollars at current prices and exclude cost, insurance and freight (CIF). We define commodities using the Harmonized Commodity Description and Coding System (HS) 12. We match each commodity to a 2-digit ISIC Rev. 4 industry code using the OECD's concordance table. To compute imports from the rest of the world we, for each country in our sample, subtract total imports from all other countries in the sample from total imports of that country. To compute exports to the rest of the world we, for each country in our sample, subtract export to all other countries in the sample from total exports of that country.

E.6.2 Tariffs

We obtain bilateral trade tariffs at the sectoral level for the year 2013 from World Integrated Trade Solutions (WITS). We extract the effectively applied tariffs for all reporting countries and partner countries and for all 3 digit ISIC Rev. 3 sectors. We then map the 3 digit ISIC Rev. 3 sectors to ISIC Rev. 4 sectors and then

TABLE E.II: Sectors according to dependence on credit

Number	Sector	Credit Group
1	Agriculture	Low credit
2	Mining	Low credit
3	Food	Low credit
4	Textile	High credit
5	Wood	Low credit
6	Paper	Low credit
7	Petroleum	Low credit
8	Chemicals	High credit
9	Plastic	Low credit
10	Minerals	Low credit
11	Basic Metals	High credit
12	Metal products	High credit
13	Machinery n.e.c.	High credit
14	Office	Low credit
15	Electrical	High credit
16	Communication	Low credit
17	Medical	High credit
18	Auto	High credit
19	Other transport	High credit
20	Other	High credit

to our sectoral classification. We also use data from years 2011, 2012, 2014 and 2015 to fill some missing values for tariff data. At the end of this process, close to 20 percent of the observations still contain missing data. In order to address this we will use two sequential algorithms. First, we replace the missing value with the median tariff applied by the same country to the same source country (across all sectors). Second, we replace the missing values that are not replace by the first manual input with the median tariff applied by the same country to the same sector products (across all source countries). This allows us to fill all of the missing values.

E.6.3 Value added and gross production

Following Caliendo and Parro (2015), we obtain data on gross output and value added at the sectoral level for the year 2013 from three different data sets. We list these data sets in order of preference. For example, if we have data for the same variable for the same sector-country pair from data set 1 and from data set 2, we will use the value from data set 1.

OECD STAN: our first data set is the OECD STAN database for industrial analysis. This data set contains information on gross output and value added for OECD countries at the sectoral level using the ISIC Rev. 4 classification at current prices and in national currency. We convert these values to U.S. dollars using the exchange rates available at the OECD STAN database. This database allows us to fill around 75 percent of the information on value added per sector.

FIGURE E.2: Model coverage - exports

This Figure presents the share of world exports attributable to the countries in our quantitative model. In panel (a), we present the share of world exports that is attributable to the countries in our quantitative model. In panel (b) we present the same share for E.U. countries. In panel (c), we present the same share for high-risk countries. In panel (d), we present the same share for non-E.U. low-risk countries.

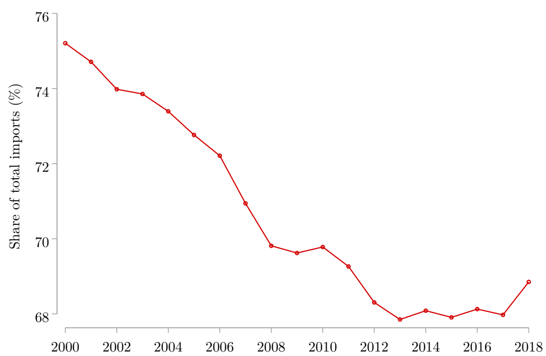
INDSTAT: our second data set is the Industrial Statistics Database INDSTAT2. This data set contains information at current prices in U.S. dollars for 71 3-digit manufacturing sectors. We aggregate these sectors at the 2-digit level and then use the allocation in Table D.I to compute value added and gross output for each sector-country. Using these two data sets allows us to fill most of the data for all countries in our sample.

OECD I-O and UNSTATS: we now need to compute the value added and gross production for the remaining sectors and countries. First, we use information from the OECD's Input-Output Tables to compute the value added and gross production for any sector and OECD country with missing data.Second, we use this data set to compute value added for the following large sectors: Agricultural, Hunting, Forestry and Fishing (sector 1), Mining and Utilities (sectors 2-12 and 21), Manufacturing (sectors 13-15 and 17-20), Construction (sector 22), Wholesale, retail trade, restaurants and hotels (sectors 23-24), Transport, storage and communication (sectors 16 and 25-29) and other activities (sectors 30-40). We add up value added across all countries. For each of these big sectors, we compute total value added and the share of each sector in value added of the big sector. We then obtain data on these big sectors from the United Nations National Accounts Database, which contains value added data for 200 countries. We decompose the value added of these big

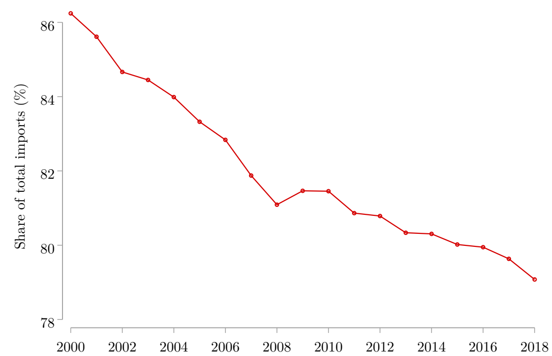
FIGURE E.3: Model coverage - imports

This Figure presents the share of world imports attributable to the countries in our quantitative model. In panel (a), we present the share of world imports that is attributable to the countries in our quantitative model. In panel (b) we present the same share for E.U. countries. In panel (c), we present the same share for high-risk countries. In panel (d), we present the same share for non-E.U. low-risk countries.

(a) Total imports

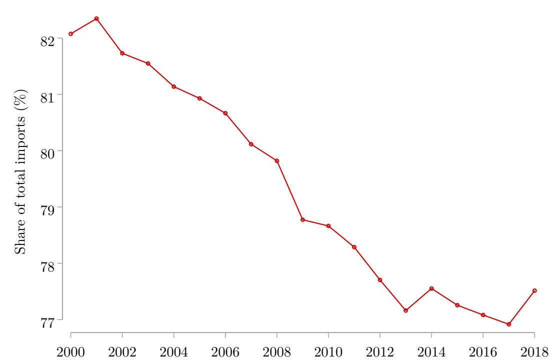


(b) E.U. countries



(c) High-risk countries

(d) Non-E.U. low-risk countries



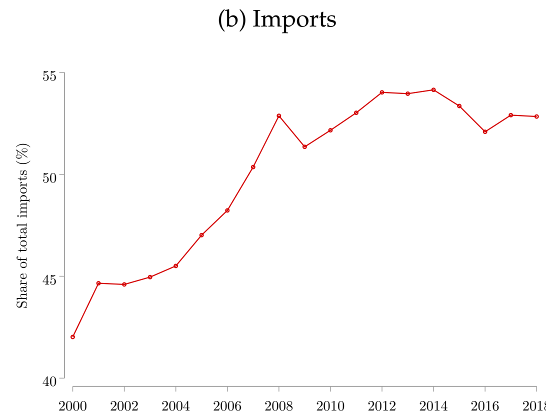
sectors into our sectoral classification using the shares we computed in the OECD I-O database. We then use the median sectoral share of value added in the OECD I-O database to compute gross production.

Rest of the world: we need to compute sectoral value added and gross output for the rest of the world. We begin by computing the world's value added for the big sectors using the United Nations Database, after excluding the countries in our sample. We then apply the sectoral shares of value added we obtained from the I-O database to split the value added in our 40 sectors and use the shares of value added in the OECD I-O database to compute gross production.

Filters: we also impose some filters in all stages of this process. We exclude observations where gross production or value added are negative. We also interpret observations where value added is larger than gross production as an error and therefore exclude them accordingly.

FIGURE E.4: Rest of the World

This Figure presents the relevance of high-risk countries to the "Rest of the World" country. In panel (a), we report the share of exports of this group of countries which are from high-risk countries. In panel (b), we report the share of imports of this group of countries which are from high-risk countries.



E.6.4 Input-Output tables and intermediate consumption

For each sector, we need information on the share of intermediate inputs per sector of origin. We obtain these data from the WIOD database, which contains I-O tables for 43 countries. We use information from 2013 and combine information on use of domestic intermediate inputs and imported intermediate inputs. This database allows us to compute the shares for most of the sector-countries in our sample. We fill missing values by taking the median share for that sector across countries.

E.6.5 Dispersion of productivity

We use the estimates for the dispersion of productivity from Caliendo and Parro (2015).

E.7 Additional results

E.7.1 Effect on exports

We start by looking at the direct effects of the shock on exports. In Table E.III we present the growth rate of the exports of E.U. exports, as well as the growth rates of exports to high-risk destinations and to low-risk destinations.

As expected, exports to high-risk countries decrease and the magnitudes are similar to our empirical analysis in Section 6. For example, exports from Germany to high-risk countries decrease by 4.2 percent in response to an increase in interest rates faced by firms exporting to high-risk countries. Furthermore, as we discussed before, the model predicts a modest increase in exports to low-risk countries. This increase is driven by the fact that exports from high-risk countries have now become more expensive. This increase in cost is driven by an increase in the price of imports which then leads to an increase in marginal costs. However, this increase is not enough to prevent overall exports from E.U. countries to decrease. It's also important to note that is significant heterogeneity across E.U. countries in terms of impact on exports. For example, Dutch exports to high-risk countries fall by only 2.04 percent while Greek exports to high-risk countries fall by 5.54 percent. There are two factors that explain this heterogeneity. First, as the increase in

TABLE E.III: Effect on E.U. exports

This table presents the effect of the increase in interest rates on exports of E.U. countries. We present the growth rate of total exports, as well as the growth rates of exports to high-risk destinations and to low-risk destinations. We focus on the E.U. countries we include in our model: Austria, Denmark, Germany, Finland, France, Greece, Hungary, Ireland, Italy, Netherlands, Portugal, Spain, Sweden and the U.K.

	To high-risk countries	To low-risk countries	Total
Austria	-4.04	0.83	-0.97
Denmark	-3.89	0.48	-0.69
Finland	-4.12	0.86	-1.25
France	-4.45	1.24	-1.18
Germany	-4.31	1.06	-1.29
Greece	-5.74	1.92	-2.67
Hungary	-4.00	0.89	-1.14
Ireland	-3.14	0.71	-0.46
Italy	-4.31	0.76	-1.44
Netherlands	-2.13	0.51	-0.88
Portugal	-4.55	0.95	-0.88
Spain	-4.15	0.72	-1.25
Sweden	-4.24	1.04	-0.88
U.K.	-4.38	1.54	-1.19

interest rates is larger for high-credit sectors, countries with an export mix skewed towards these sectors will face a larger effective increase in interest rates. The second factor is related to trade elasticities. From the gravity equation in (18) we see that the impact on exports will increase (in absolute value) with the value of trade elasticities, as more elastic products respond more to the same increase in interest rates. Therefore, E.U. countries that focus on sectors with higher trade elasticities will face a larger drop in exports to high-risk destinations. We can analyze the impact of these two forces on E.U. exports by plotting a binned scatter plot in Figure 14 of exports by sector and country against trade elasticities for high-credit and low-credit sectors.

For a given level for the trade elasticity, the impact on exports of high-credit products is larger than the impact on exports of low-credit sectors. This follows from the fact that the shock on interest rates for high-credit products is larger than the shock on exports of low-credit sectors. As the trade elasticity increases, so does the impact on exports, which means that countries that mostly exported less elastic products faced a smaller decrease in exports. For example, sectors like Petroleum, which has a trade elasticity of 65, observed very large drops in exports (close to 25 percent), whereas sectors like Machinery which has a trade elasticity of 1 face smaller drops in exports.

This heterogeneity suggests that the impact of this increase in interest rates has very different impacts on different sectors and countries. For example, for a low-credit sector with a low trade elasticity, the impact is very close to zero. For a high-credit sector with a high trade elasticity, the losses in terms of exports to high-risk destinations can be very large. At the country level, countries which had focused on exporting products with high trade elasticities and high credit demands will see a larger drop in exports.

E.7.2 Short-run vs. long-run effects

We have written a model in which there are no frictions in adjustment. In particular, in response to a shock to interest rates, firms immediately adjust both their input purchases to reflect the change in prices. Furthermore, prices are also fully flexible, which also removes another possible friction in adjustment. The predictions of the model are therefore only valid for the long-run, as is the case with most trade models. However, in the short-run firms are unable to fully adjust their intermediate purchases as well as the countries to which they sell. In this section, we will take advantage of the findings in Boehm et al. (2020) to compare the short-run vs. long run effects of this trade shock.

In order to motivate this analysis, we can take the gravity equation in equation (E.4) and, after log-linearizing it, we obtain

$$d\log X_{in}^{j} = d\log X_{n}^{j} - \theta^{j} d\log c_{i}^{j} - \theta^{j} d\log \kappa_{in}^{j} + \theta^{j} d\log \Psi_{n}^{j},$$

where the first term represents changes in demand at the destination level, the second term reflects changes in marginal costs in country i, the third term represents the direct effect of changes in trade costs and we can interpret the fourth and final term as a change in the competitive environment.[61] In our numerical exercise, the term that explains most of the variation (and that does not require general equilibrium forces) is $\theta^{j} d\log \kappa_{in}^{j}$. Therefore, conditional on a shock size, the reaction of trade flows will depend on the elasticity. Hence, in order to mimic a world with adjustment frictions, we will consider a sequence of economies with an increasing trade elasticity. This exercise also reflects the findings in Boehm et al. (2020), who find that in response to a variation in trade costs, trade elasticities increase over time.

In order to conduct this analysis, we will vary all trade elasticities for tradable costs by multiplying them by a constant inside the unit interval. We fix the size of the shock as in Table XI and solve the model for each vector of trade elasticities. We can also compute the changes in welfare, measured by the real wage, for different values of the trade elasticity. For each group of countries - E.U., high-risk and non-E.U. low-risk countries - we compute the average of the changes in the real wage for each value of the trade elasticity while keeping the size of the shock constant. We report the results of this exercise in Figure E.5.

We start with the evolution of welfare for high-risk countries. We saw in Table XIII that most of the variation in the change in welfare is driven by the first-round effect of credit costs. This effect does not depend on the trade elasticity as it does not vary with the ability of firms to adjust. Therefore, changes in welfare for high-risk countries are relatively invariant to the trade elasticity. This is not the case for E.U. countries. In the long-run, which is the last point in the red line in Figure E.5, we recover the effect we presented in Table XIII. In the short run, the welfare loss is much smaller and then it increases in absolute value over time as the trade elasticity increases. This evolution is driven by the change in the terms-of-trade effect. In the short run when elasticities are low, most of the welfare effect is driven by the volume-of-trade effect. As trade elasticities increase, global demand for E.U. exports decrease which will imply a larger fall in factor prices. Therefore, the terms-of-trade effect are increase in absolute value as trade elasticities increase.

[61] This term contains the changes in marginal costs for all other exporting countries as well as the change in trade costs for exports from all other countries to destination n.

FIGURE E.5: Change in welfare for different trade elasticities

This Figure presents the change in real household income, which is our measure of welfare, for different values of the trade elasticity. For each group of countries - E.U., high-risk and non-E.U. low-risk countries - we compute the average of the changes in real wage while keeping the size of the shock constant. We multiply all dispersions of productivity θ^j (which are also the trade elasticities) of tradable goods by a constant $\alpha \in (0, 1)$ and plot the average change in the real wage for each α.