A Short Drop or a Sudden Stop? Sanctions, Trade Shocks, and Firms' Adjustment Margins

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Abstract

This paper examines firm-level responses to the large trade shock induced by the 2022 Russian invasion of Ukraine and the ensuing European Union sanctions. Using detailed administrative data from Latvia—a small, open economy with strong pre-war trade ties to Russia—I document the heterogeneous effects of the shock across firms with varying degrees of exposure. Employing a machine learning-based approach to determine a set of impacted firms and a difference-in-differences local projection method, the analysis shows firms with lower initial exposure to Russia are the most likely to sever trade ties. Only a small set of firms, the most exposed to Russian trade, suffered significant losses in turnover, employment, and profitability, despite some trade reorientation towards CIS countries. Mere exposure to Russia emerges as the primary determinant of these patterns, whereas sanctions targeting specific goods only play a secondary role. These findings contribute to the broader literature on economic sanctions and trade policy by providing micro-level evidence on the adjustment mechanisms of European firms in response to geopolitical disruptions.

Keywords: Sanctions, Trade shock, Adjustment margins

JEL: F14, F16, F61

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1 Introduction

On February 24, 2022, Russia launched a full-scale invasion of Ukraine. As a response, the European Union implemented a series of sanction packages targeting the Russian economy. Inside these packages, direct trade restrictions can be sorted into three categories. First, the successive sanction packages provide a continuously expanding list of goods under either export or import bans. This list includes various types of commodities and is not restricted to military or dual-use goods. Second, the EU initiated a list of Russian individuals and legal entities with which business links are banned. EU banks were tasked with conducting lengthy and costly compliance checks on their customers' transactions with Russian partners. Finally, the third sanction package, announced on March 2, 2022, imposed a ban preventing the largest Russian banks from using the SWIFT payment system, severely limiting their ability to obtain foreign currency and participate in international trade. As a consequence, European firms trading with Russia before the war experienced a *sudden* and *large* exogenous trade shock.

This paper studies firm-level responses to the trade shock caused by the 2022 Russian invasion of Ukraine and the subsequent trade restrictions imposed by the European Union from the perspective of the *sanctioning* side. It relies on a combination of Latvian administrative datasets, linking together customs data, firms' balance sheets, and monthly employer-employee data up to the end of 2022. In contrast with most of the related literature, which typically studies the effect of sanctions on trade flows (e.g., Crozet and Hinz, 2020; Crozet et al., 2021; Chupilkin et al., 2024; Corsetti et al., 2024; Fisman et al., 2024), this paper focuses on the adjustment margins that firms use to absorb large adverse shocks *in the short run*. Considering current geopolitical frictions and the ongoing trend towards more restrictive trade policies, such as tariffs and quotas, understanding how agents adapt to such shocks is primary importance.

Because of their geographical proximity, with the two countries sharing about 300 kilometers of border, Russia was in 2021 among Latvia's top five trading partners, both in terms of exports and imports. As such, Russia is a more important trading partner for Latvia than for any other EU country: nearly one in five exporting firms, and about one in six importing ones, traded with Russia before the war. At the same time, the relatively small size of the Latvian economy within the EU makes credible the assumption that the list of goods targeted by sanctions is exogenous for Latvian firms.

Examining firms' response to the trade shock requires two key elements: 1) a set of firms that experienced a shock and 2) a measure of the magnitude of the shock at the firm level. Regarding the set of firms, an intuitive approach would be to simply use all firms that traded with Russia in 2021, the last year before the full-scale war. This amounts to assuming that *all* firms that traded with Russia in 2021 experienced trade disruption in 2022. However, a large number of trade relationships naturally die out every year: had the war not started, many Latvian firms would have nevertheless stopped trading with Russia. During the 2010–2021 period, 30–40% of firms trading with Russia in any given year terminated their trade relationships the following year. Failing to account for this fact would result in an overestimation of trade disruption, since all LV-RU trade relationships terminating in 2022 would be attributed to the war. In parallel, including firms that would have stopped trading with Russia in the analysis would result in an underestimation of firms' responses. Filtering out these firms would allow to focus on the *excess* trade stops caused by the war. Whether or not a firm would have stopped trading with Russia in 2022 anyway is, however, not observable. To overcome this issue, I implement a machine learning approach. Exploiting precise information on firms' characteristics (e.g., sector, age) and the nature of their trade (e.g., trade history, types of products, number of shipments), I train a model to predict which firms that traded with Russia in 2021 would have maintained these trade relationships in 2022 in the absence of the war.

To characterize the extent of the trade shock at the firm level, I decompose the trade shock into two components: *exposure* and *bite*. First, the degree of mere exposure to the Russian market is likely to have an impact on firms. The ban on business with specific individuals and legal entities, together with the exclusion of Russian banks from SWIFT, imposed a sudden increase in the cost of trading with Russia.[1] Public pressure and ethical concerns also possibly raised this cost (Lu et al., 2022; Hart et al., 2024). As a consequence, the larger the exposure to Russia, the

[1]EU companies are required to ensure that the beneficial owner of their Russian trading partners is not on the sanctions list. The breach of sanctions may have a significant impact, as it is subject to criminal liabilities (Section 84 of the Criminal Law of the Republic of Latvia).

larger the shock. Second, for a given level of exposure, the intensity of the shock varies depending on the bite of the trade sanctions targeting specific goods. Whereas the former type of sanctions essentially increased the cost of trading with Russia, bans on specific goods simply halt (part of) trade.

To account for this dual nature of sanctions, I measure the intensity of the firm-level shock via the exposure, the bite, and the interaction between the two. I define exposure to Russia as the share of turnover accounted for by trade with Russia in 2021, the last year before the beginning of the full-scale war. This ratio varies greatly across firms, from nearly 0 to 1 (e.g., firms generating their entire turnover in the Russian market). The bite is captured by the share of "soon-to-be-sanctioned" goods traded with Russia in a firm's total value of trade with Russia (both measured in 2021). A share of 1 implies that 100% of the revenues earned trading with Russia in 2021 were generated by goods subsequently falling under sanction over the course of 2022. To construct this ratio, I extract from EU legal documents the list of products under sanctions across successive packages. For each adopted article, an appendix provides the list of affected goods together with their Harmonized System codes (up to 6 digits), allowing linkage with administrative customs data. Finally, the third component consists of the interaction between these two ratios, which amounts to the share of goods traded with Russia subsequently falling under sanction in a firm's turnover. Taken together, these variables allow me not only to precisely capture two different dimensions of sanctions, but also to compare their relative importance for firms. In other words, I investigate whether, for a given level of exposure to the Russian market, firms spared by targeted sanctions react differently than firms directly hit.

To study firms' responses to the trade shock, I implement a difference-in-differences local projection approach (Dube et al., 2023). I focus on firms that would have been likely to maintain trade with Russia if the war had not started and exploit the heterogeneity of the shock intensity across these firms. The identification of the impact of sanctions thus stems from comparing firms exposed to shocks of different severity and observing their behavior before and after the beginning of the war and the implementation of sanctions. Entering (and staying in) foreign markets is an endogenous choice. In particular, several papers document that some firms stopped trading with Russia in the wake of the invasion of Crimea in 2014 (Gullstrand, 2020; Crozet et al., 2021; Görg et al., 2024). Firms trading with Russia in 2021 may have specific characteristics (observable or not) that differentiate them from other firms active in international trade. Using variation across firms trading with Russia in 2021 alleviates this issue.

The analysis begins with an estimation of the impact of sanctions on trade with Russia to illustrate the magnitude of the shock. Following Crozet and Hinz (2020) and Crozet et al. (2021), I consider both the intensive and extensive margins of trade. I document that more than 50% of exporters and importers actively trading with Russia in 2021 stopped doing so in 2022, which is more than 10 p.p. larger than in any pre-war year. The probability of exiting is much larger for firms with a *small* exposure to Russia (both for importers and exporters), while this probability is essentially the same for firms affected by sanctions on specific goods and for firms that are not. This suggests that the increase in trade costs was large enough to scare away firms marginally connected to Russia and played a larger role than good-specific sanctions in firms' decisions to withdraw from Russia. Overall, firms remaining connected to the Russian market experienced a sharp decrease in their trade flow with Russia. A very small set of firms, however, experienced a boom in trade with Russia.

Having established that firms trading with Russia did indeed experience a serious adverse trade shock, I then examine different potential adjustment margins that firms may have used to absorb this shock. I first study the employment response at the extensive (firm closure) and intensive (% change in the number of employees) margins. I show that only a small number of firms, the most impacted ones, experienced a negative employment response. Highly Russian-exposed exporters are about 5 p.p. more likely to close by the end of 2022 than barely exposed firms. Being highly impacted by trade sanctions increases this probability by another 4 p.p. At the same time, employment in highly impacted exporters surviving the shock experienced on average a decrease of about 10% in their number of employees. Results are broadly similar for importers, though of smaller magnitude. To gain a better understanding of the timing of events, I further exploit the monthly frequency of the labor market data. The employment response was extremely swift: a significant negative effect appears as early as June 2022.

I then study how firms adapted their overall international trade in the aftermath of the shock. I begin by showing that only exporters with a relatively high exposure to Russia saw a decrease in their total exports in 2022 (compared to 2021). On the other hand, total imports decreased for all importers, even those with a relatively low exposure to Russia. To understand these results, I then examine the probability that a firm experienced a decrease in the total number of foreign markets with which it trades. Given that about half of the firms in the sample simply stopped trading with Russia, did they redirect their trade to other markets? If about 65% of exporters with low exposure to Russia exited the Russian market, only 40% exhibited activity in fewer foreign markets after the beginning of the war, implying that a large share of these firms found new foreign partners. This share is even larger for firms with greater exposure to Russia and for importers: the larger the exposure to Russia, the larger the probability of trade redirection.

Do firms reroute their trade to Russia via "entrepôt" countries? (Bove et al., 2023; Chupilkin et al., 2024; Fisman et al., 2024) provide evidence of sanction avoidance by rerouting trade via "neutral" third-party countries. Thus, I study the probability of a firm *starting* trade with CIS countries.[2] I provide evidence that the probability of exporting to Belarus increases with exposure to the Russian market, with highly exposed exporters having nearly a 30% probability of starting exports to CIS countries. Nearly half of these new trade relationships are cover goods on the sanction list. These results indicate that firms reorienting their iexports to "Russia-friendly" countries are those most dependent on Russian trade.On the other hand, importers exhibit a different reaction. The probability of starting imports from CIS countries is fairly low and does not depend much on exposure to Russia, although importers facing good-specific sanctions are more likely to start trading with CIS.

Finally, I also explore other margins through which firms may have absorbed the trade shock. I first study how firms' turnover changed between 2021 and 2022 depending on their exposure to Russia. Studying turnover can shed light on the possibility that firms compensated for lost trade with Russia by increasing domestic

[2]The Commonwealth of Independent States (CIS) is an intergovernmental organization created following the dissolution of the Soviet Union. As of 2021, it includes Armenia, Azerbaijan, Belarus, Kazakhstan, Kyrgyzstan, Moldova, Russia, Tajikistan, and Uzbekistan. Member countries participate in the CIS Free Trade Area.

sales. For exporters, the results indicate that only firms generating more than 25% of their turnover in Russia in 2021 experienced a decrease in turnover. For importers, however, the decrease in turnover is visible even at low levels of exposure. Finally, to complement the analysis of turnover changes, I study the change in profitability. Although exporters only mildly impacted by the trade shock managed to maintain their turnover, profitability nevertheless experienced a hit. Profitability dropped substantially for heavily impacted exporters. Regarding importers, virtually all of them saw a decrease in profitability.

This paper contributes to the vast literature on the economic effects of sanctions (see Morgan et al., 2023 for a recent review). Understanding the impact of sanctions is of particular importance, since the use of sanctions has been steadily growing over the past two decades (Felbermayr et al., 2020). A central focus of this literature is to evaluate the consequences of sanctions on cross-border trade flows (e.g., Glick and Taylor, 2010; Oja, 2015; Gullstrand, 2020; Crozet and Hinz, 2020; Crozet et al., 2021; Bove et al., 2023; Jäkel et al., 2024; Kohl et al., 2024; Chupilkin et al., 2024; Corsetti et al., 2024; Tyazhelnikov and Romalis, 2024). Evidence of the impact on firms affected by trade disruption is, however, scarcer. Ahn and Ludema (2020), Nigmatulina (2023), and Huynh et al. (2023) study the effect of the 2014 sanctions on targeted firms' performance in Russia. Closer to this paper, Lastauskas et al. (2023) studies Lithuanian exporters' response to the 2014 Russian counter-sanctions along various dimensions. Similarly, Aytun et al. (2024) examines how Turkish exporters adapted to the Russian embargo (and its removal) following the downing of a Russian military jet in Syria in 2015. In particular, these two papers document a negative employment effect for the most affected firms, suggesting that sanctions impact firms in ways that have broader implications beyond trade.

More generally, this paper contributes to the large literature studying how firms respond to shocks, such as currency shocks (e.g., Nucci and Pozzolo, 2010; Ekholm et al., 2012; Dai and Xu, 2017; Branstetter and Laverde-Cubillos, 2024), minimum wage shocks (e.g., Harasztosi and Lindner, 2019; Clemens, 2021; Gavoille and Zasova, 2023), supply chain disruptions (e.g., Boehm et al., 2019; Carvalho et al., 2021), and exposure to import competition (e.g., Bernard et al., 2006; Iacovone et al., 2013; Bloom et al., 2016; De Lyon and Pessoa, 2021; Aghion et al., 2021). Whereas the latter group of papers examines the consequences of trade liberalization, this paper studies the consequences of a sudden increase in trade barriers.

The findings of this paper have clear implications for EU trade and industrial policy. Only a small set of firms, the most exposed to Russian trade, suffered significant losses in turnover, employment, and profitability. This shows that sanctions impose real economic costs on EU businesses, but this cost is highly concentrated within a relatively small set of firms. For these firms, the difficulty of reorienting trade (besides re-routing to nearby markets like Belarus and other CIS countries) highlights structural barriers that limit firms' ability to adapt quickly. This provides evidence that abrupt restrictions disrupt firms beyond direct trade losses. Policymakers should focus on strengthening supply chain diversification, supporting affected firms - or providing incentives to reduce exposure ex ante, and improving enforcement to prevent sanction evasion (Bove et al., 2023; Fisman et al., 2024). As the EU continues using sanctions as a policy tool, balancing economic pressure on target countries with support for domestic firms will be crucial.

The rest of the paper is organized as follows. Section 2 provides an overview of the context and describes the data. In Section 3, I introduce the empirical approach, detailing the creation of the sample and the measurement of the trade shock. Section 4 displays the results. Section 5 concludes.

2 Context and data

2.1 Timing of the events

The Russian full-scale aggression against Ukraine, which began on February 24, 2022, marked a significant turning point in the geopolitical landscape of Europe. This conflict has had profound implications not only for the security and stability of the region but also for trade relations between Russia and the European Union. This subsection provides an overview of the context and timeline of the war, as well as the sanctions imposed by the EU in response to Russia's actions.

The conflict between Russia and Ukraine has deep historical roots, with tensions escalating in 2014 following the annexation of Crimea by Russia and the subsequent support for and creation of separatist movements in eastern Ukraine. Despite international condemnation and initial sanctions, Russia continued to exert influence in the region, resulting in a protracted conflict that persisted until the full-scale invasion in 2022. The EU responded to Russia's aggression with a series of comprehensive sanctions aimed at isolating Russia economically and diplomatically. The sanctions were implemented in several packages, each targeting different sectors of the Russian economy and political elite.

The first package of sanctions was imposed on February 23, 2022, one day before the invasion began. This package targeted key Russian individuals and entities, including freezing assets and imposing travel bans. The second, third, fourth, and fifth packages were all adopted between February 25 and April 8, 2022. While the third package focused on sanctions targeting the Russian financial sector, the second, fourth, and fifth packages contained measures restricting Russian access to EU markets and aimed at further isolating Russia from the global economy, with additional restrictions on trade, including a ban on the import of Russian coal and other raw materials.

Each package of sanctions consists of several articles, each defining a specific sanction.[3] These articles describe the nature of the sanctions (essentially their object, enforcement date, and possible exceptions). The precise timing of trade sanctions (i.e., bans on exports or imports of specific types of goods) is not straightforward to measure. Most articles explicitly specify the final date by which a given product can be shipped to or received from Russia, conditional on the contract having been signed before the enforcement date. For instance, Article 3k in the fifth package (announced on April 8, 2022) imposes a ban on exports to Russia for a list of 1,388 products. It states that this ban does not apply to the "execution until 10 July 2022 of contracts concluded before 9 April 2022." Nevertheless, as shown in the next subsection, the vast majority of goods traded by Latvian firms in 2021 that subsequently entered the sanction list in 2022 fell under sanctions by mid-July 2022. This suggests that even under the extreme scenario where the final possible date for trade is considered the binding date, there is still about half a year until the end of 2022. Since balance sheets and other firm-level data reflect a company's situation at the end of the year,

[3] Legal documents related to sanctions are available there: https://eur-lex.europa.eu.

this provides a reasonable timeframe for expecting the materialization of the shock in the administrative data.

2.2 Data

This paper relies on a combination of anonymized administrative datasetsm which I combine thanks to a unique firm ID.[4] First, I use customs data, which includes information on exports and imports of goods at the transaction level. For each transaction, I observe the anonymized ID of the Latvian firm, the month in which the transaction is registered by customs, the type of transaction (import/export), the 8-digit HS code of the product, the value of the transaction, the weight (in kilograms), and the country of origin for imports or the country of destination for exports. This allows me to observe whether a firm trades with Russia and, if so, to what extent. I use this information to assess the magnitude and impact of the war and sanctions at the firm level, as described in the next subsection.

Second, I am able to link this data with yearly information on administrative firms' balance sheet and income statement, also provided by the Latvian State Revenue Service. This provides a great amount of information (turnover, profit, etc.), depicting a precise situation of the firm *at the end of the year*. Third, I complement this data set with firm-level general characteristics coming from the Latvian Business Registry (NACE code, registration year, etc.). Finally, I also use a matched employer-employee dataset at a monthly frequency, collected by the Latvian State Revenue Service. It covers almost the entire population of firms, with a few exceptions, such as firms in the banking and financial sectors. It includes approximately 800,000 unique employees per month on average, capturing nearly the entire population of firms and employees. This dataset enables me to calculate the number of employees working in a given firm in each month, and to precisely observe whether a firm stops its activities. These administrative datasets generally cover the period from 2007 to 2022, but in the main part of the analysis, I focus on the period from 2020 to 2022, as I will describe in the next section. All variables expressed in nominal terms are deflated using 2015 as the base year.

In addition, I gather information on the sanctions on goods imposed by the Eu-

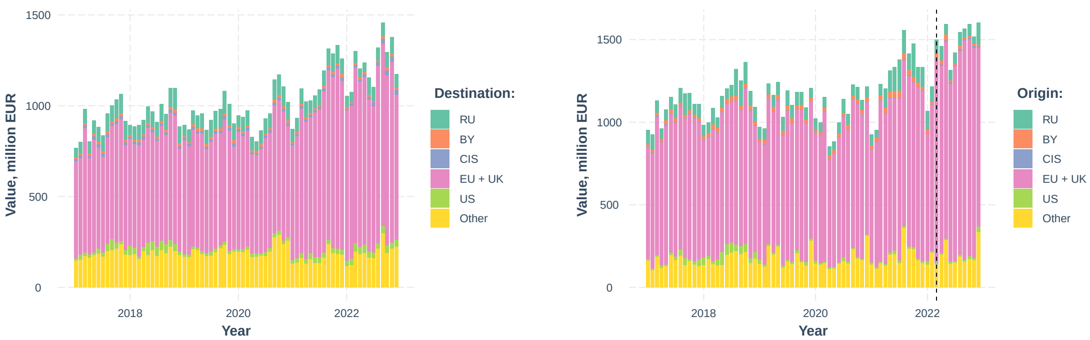
[4] I access the data via a secured server provided by the Latvian Central Statistical Bureau.

ropean Union since February 2022. As described above, each package of sanctions consists of several articles, each outlining a specific measure. Sanctions related to trade are usually accompanied by a list of products subject to restrictions. I collect this information for all sanction packages announced throughout 2022. Using HS codes, it is possible to link this information to customs data, allowing the identification of firms trading goods that were subsequently sanctioned. Figure A.1 in Appendix A presents an excerpt from EU legal documents.

2.3 Latvian trade with Russia

Prior to the escalation of geopolitical tensions and the imposition of sanctions, trade between Latvia and Russia played a significant role in Latvia's economy. Before 2022, Russia was one of Latvia's major trading partners, ranking among the top five trading partners in terms of both imports and exports. In 2021, exports to Russia accounted for 7% of all exports, while imports from Russia represented 9% of all imports. Key export sectors included food products, machinery, and chemical products. However, this trade relationship slowly evolved over the past decade, particularly following Russia's annexation of Crimea in 2014 and the subsequent imposition of EU sanctions and counter-sanctions. The full-scale invasion of Ukraine in 2022 and the resulting expanded sanctions disrupted this trade. Figure 1 shows Latvian monthly trade, disaggregated by groups of trading partners. Although the vast majority of trade occurs with other EU countries, the share of trade with Russia remains significant. Despite the war and sanctions, the overall value of trade with Russia remained largely unchanged.

Figure 1: Trading partners of Latvia



(a) Exports **(b)** Imports

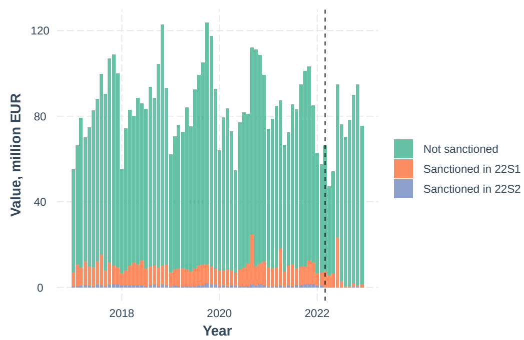
NOTE: These figures display the overall *monthly* exports and imports of Latvia, disaggregated by groups of trading partners (in constant Euro, base 2015). The vertical dashed line indicates February 2022.

Figure 2 focuses on monthly trade with Russia, disaggregating exports and imports into three categories: 1) goods that are not subject to sanctions in 2022, 2) goods that become subject to sanctions in the first half of 2022, and 3) goods that become subject to sanctions in the second half of 2022.[5] These figures highlight several aspects of sanctions. First, trade restrictions on imports affect a large portion of total imports. This share is larger than the equivalent for exports, though exports also experience a significant impact. Second, sanctions implemented in the first half of 2022 cover a much larger share of trade between Latvia and Russia. Goods subject to sanctions taking effect in the second half of 2022 constitute a negligible share of bilateral trade. Third, the effect of sanctions on specifically targeted goods is clearly visible. For exports, trade in goods sanctioned during the first half of 2022 almost completely ceases in the second half of the year. For imports, though trade in sanctioned goods does not fall to zero, it declines by more than half relative to the first half of the year.[6]

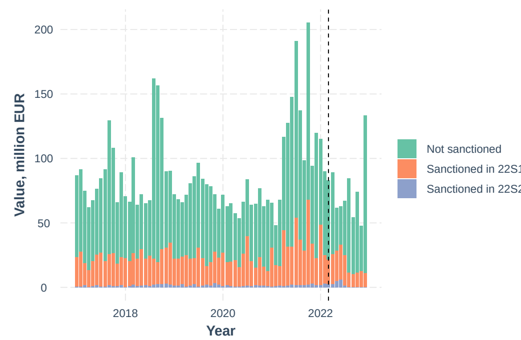
[5] This classification is based on the latest possible date allowing trade, as indicated in EU legal texts. I classify goods for which the trade deadline is July 15 as falling under sanctions in the first half of the year.

[6] Two main reasons explain why trade in sanctioned goods does not completely stop. First, as described above, some categories of sanctioned goods include exceptions described only in textual form, making them difficult to capture in the data. Second, national governments have the authority to grant certain exemptions under specific conditions.

Figure 2: Trade with Russia



(a) Exports

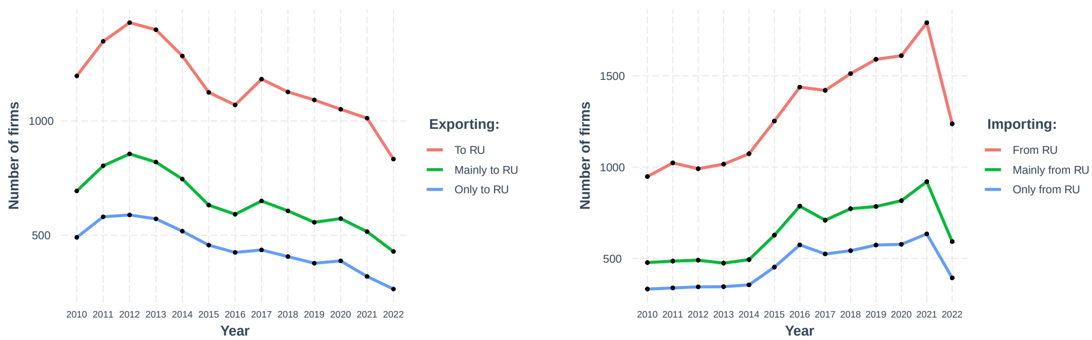


(b) Imports

NOTE: These figures display overall *monthly* trade with Russia (in constant Euro, base 2015). The green, orange, and blue bars respectively indicate trade in goods not affected by sanctions in 2022, trade in goods subject to sanctions imposed in the first half of 2022, and trade in goods subject to sanctions imposed in the second half of 2022.

The previous figures describe trade between Latvia and Russia at the aggregate level, in terms of value. At the firm level, how significant is trade with Russia? Figure 3 displays the number of firms trading with Russia over the years. The number of Latvian firms exporting to Russia declines gradually but consistently over time, with a visible drop in 2022. The trend for importing firms differs, as an increasing number of firms engage in trade with Russia. However, the decline in 2022 is significantly larger for importers than for exporters. In addition to the total number of firms, these figures illustrate the importance of Russia for these firms in terms of international trade. Specifically, I present the number of firms that 1) primarily export to or import from Russia (i.e., Russia accounts for more than 50% of their total exports or imports in value), and 2) firms that exclusively export to or import from Russia. This underscores that for nearly half of the firms engaged in trade with Russia, Russia serves as their primary trading partner.

Figure 3: Evolution of # of Latvian firms trading with Russia

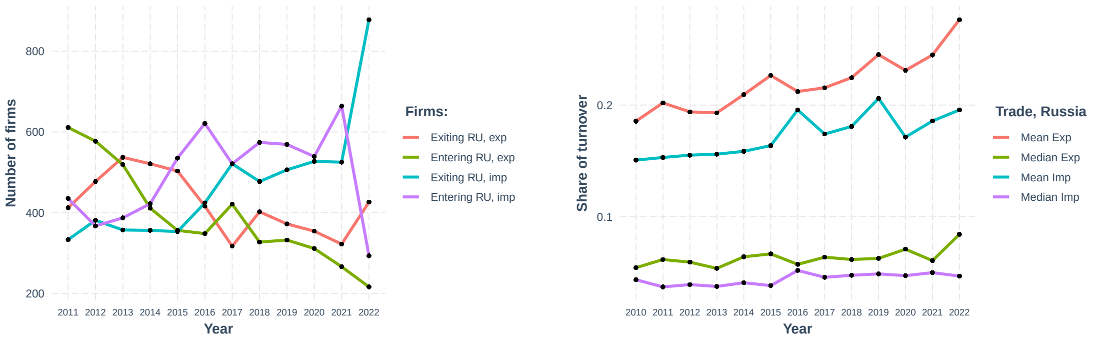


(a) Exports **(b)** Imports

NOTE: These figures display the annual number of firms trading with Russia. The red, green, and blue lines respectively indicate i) the number of firms that export to or import from Russia in a given year, ii) firms that export or import more than 50% of their total trade (in value) with Russia, and iii) firms that exclusively export to or import from Russia.

Panel a) in Figure 4 illustrates the entry and exit flows of firms in the Russian market, distinguishing between exporters and importers. While the number of firms beginning to import goods from Russia sharply declines in 2022, the decrease is milder for exporters. The dynamics also differ: the number of new exporters entering the Russian market had been declining since 2019, whereas the number of firms importing goods from Russia was on an upward trend. On the exit side, after a relatively stable number of exits since 2016, the number of firms exiting the Russian market sharply increased for importers, though to a lesser extent for exporters. These flows highlight that, despite relatively stable aggregate trade figures, the firm-level composition of trade with Russia varies significantly from year to year.

Figure 4: Firm-level statistics



(a) Entry and exit in the Russian market **(b)** Firm-level trade intensity with Russia

Note: This Figure displays the annual number of firms that begin and cease trading with Russia in panel (a), and the evolution of the mean and median ratios of trade with Russia to total turnover for firms engaged in trade with Russia in panel (b).

To further assess the importance of the Russian market for these firms, panel b) in Figure 3 presents the average and median share of turnover accounted for by trade with Russia, distinguishing between importers and exporters. The fact that the mean is significantly higher than the median indicates substantial heterogeneity in trade intensity with Russia. While Russia serves as the primary trading partner for some firms, trade with Russia remains marginal for many others. Second, although the number of firms has changed over time, the depth of firms' trade connections with Russia has remained relatively stable. The slight increase in mean exposure in 2015–2016 suggests that firms with low trade intensity with Russia withdrew, while the median remained stable.

3 Empirical strategy

3.1 Detecting impacted firms

Studying firms' responses to a trade shock requires identifying a set of firms that actually experienced trade disruption. A natural definition of impacted firms includes all firms that traded with Russia in 2021, the last year before the full-scale war. This approach is, for instance, employed by Aytun et al. (2024). However, as shown in

Figure 4, a large share of firms trading with Russia in year t ceases to do so in year $t + 1$. Beņkovskis et al. (2024) document that nearly 40% of Latvian firms entering a foreign market exit after just one year, while the export survival rate five years after entry is below 25%.[7] Figure 4 indicates that each year, about 30–40% of firms trading with Russia terminate their trade relationships. Failing to account for this would result in an overestimation of trade disruption, as all Latvia-Russia trade terminations in 2022 would be attributed to the war. Conversely, including non-impacted firms in the sample would lead to an underestimation of firms' responses. Excluding these firms from the analysis allows to focus on the *excess* trade disruptions caused by the war. However, whether a firm would have ceased trading with Russia in 2022 regardless of the war is unobservable.

To determine the set of firms that actually experienced a trade shock, I use machine learning techniques to predict which firms would have continued trading with Russia in 2022 had the war not occurred.[8] These tools are particularly relevant when the objective is purely predictive accuracy (Varian, 2014). I conduct a supervised classification task, analyzing exporters and importers separately. This approach involves three key components: 1) a set of predictor variables, 2) an algorithm that learns from these variables to classify firms, and 3) a set of firms for which the actual outcome (i.e., whether the trade relationship with Russia was terminated) is known for training purposes.

The set of predictor variables is based on the literature on export survival (see Beņkovskis et al., 2024 for a recent review). These variables fall into two broad categories: firms' general characteristics (e.g., age, sector, number of employees, turnover) and trade-specific characteristics (e.g., total trade volume, trade with Russia, number of products exported, number of shipments, types of products traded, and the quarter in which trade occurred). The full list of variables is provided in Appendix B.

[7] This low survival rate is not specific to Latvia; see, for instance, Albornoz et al. (2016).

[8] An alternative approach is to restrict the sample to firms that traded with Russia for two consecutive years, in 2020 and 2021. While this mitigates the issue by eliminating short-lived trade relationships, it does not account for the continuous decline in survival rates over time or the possibility that new trade relationships might persist. Results using this alternative, naïve approach are nevertheless consistent with those presented in the next section.

For the algorithm, I implement gradient boosting (Friedman, 2001), an ensemble machine learning technique used for predictive modeling, particularly in regression and classification tasks.[9] It sequentially builds predictive models by combining multiple weak learners—typically decision trees—into a stronger model that improves accuracy. Each new model focuses on correcting the errors of the previous models by training on the gradient of the loss function. By iteratively minimizing the loss function, gradient boosting reduces both bias and variance, potentially leading to highly accurate predictions (Hastie et al., 2009). A drawback of this method is that it does not provide explicit information about the functional form linking outcomes and predictors. However, feature importance can be extracted to gain insights into the key determinants of the predictions.

To train the algorithm, I use data on all firms that traded with Russia between 2012 and 2021. For each firm-year observation involving trade with Russia (considering exporters and importers separately), I determine whether the firm continues exporting to or importing from Russia in the following year. I use this information to construct a binary variable that equals 1 if a firm continues trading with Russia in the next period.

With these three components, the general procedure is as follows. The sample of firms with known outcomes is randomly split into a training sample (80%) and a test sample (20%). The ensemble consists of 500 trees, and I fine-tune four hyperparameters: maximum tree depth, minimum node size for further splitting, learning rate, and the loss function reduction threshold that triggers additional splits. I conduct 10-fold cross-validation, using the Precision-Recall AUC as the performance metric. This choice is motivated by two considerations. First, the Precision-Recall AUC prioritizes accurate prediction of the positive class, reducing the likelihood of false positives. Second, this metric is particularly well-suited for handling class imbalance (Saito and Rehmsmeier, 2015).

The optimized model is then applied to the observations in the test sample, which the algorithm has not previously encountered, to evaluate out-of-sample per-

[9]In economics, gradient boosting has been applied to predict labor market outcomes (Cengiz et al., 2022), labor tax evasion (Gavoille and Zasova, 2023), judicial decisions (Kleinberg et al., 2018), and macroeconomic forecasting (Goulet Coulombe et al., 2022).

Table 1: OUT-OF-SAMPLE PERFORMANCE

		Export		Import	
		Actual			
		0	1	0	1
Prediction	0	400	296	449	349
	1	146	1059	133	1218
ROC-AUC		0.835		0.848	
PR-AUC		0.652		0.642	
F_1		0.644		0.651	
Accuracy		0.767		0.776	

NOTE: This table displays classification performance metrics evaluated on the test sample for exporters and importers. Prediction = 0 indicates a firm classified as terminating trade with Russia in the following year, while Prediction = 1 indicates a firm classified as continuing trade with Russia. See Appendix B for technical details.

formance. A straightforward way to assess performance is to compare predicted class labels with actual class labels in the test set. Gradient boosting produces an output score between 0 and 1, representing the probability that a firm is classified as exiting (i.e., terminating trade in our context). To derive a binary classification, a threshold is applied to this score. In the baseline analysis, I select the threshold that maximizes the F_1 score, which represents the harmonic mean of precision and recall, ranging from 0 to 1, with higher values indicating better performance. This choice is consistent with the emphasis on the Precision-Recall curve. The classification results corresponding to this threshold are presented in Table 1.

For both exporters and importers, the model is, as expected, relatively conservative, misclassifying only a few exiting firms as stayers. The table also includes several standard performance metrics in its lower section. Although accuracy is relatively high, it is important to acknowledge that the base rate—i.e., the accuracy obtained by simply classifying all firms as stayers—is already high due to class imbalance. Further details on performance evaluation are provided in Appendix A.2. Finally, I evaluate the relative importance of the input variables using the permutation method (Greenwell et al., 2020), with results presented in Figure B.2 in Appendix B.

The final step involves predicting outcomes for all firms that traded with Russia in 2021. Overall, I estimate that 70% of firms exporting to Russia in 2021 would have continued exporting in 2022 had the war not occurred. For importers, this share is 65%. These shares are similar to those observed during the 2015–2020 period.

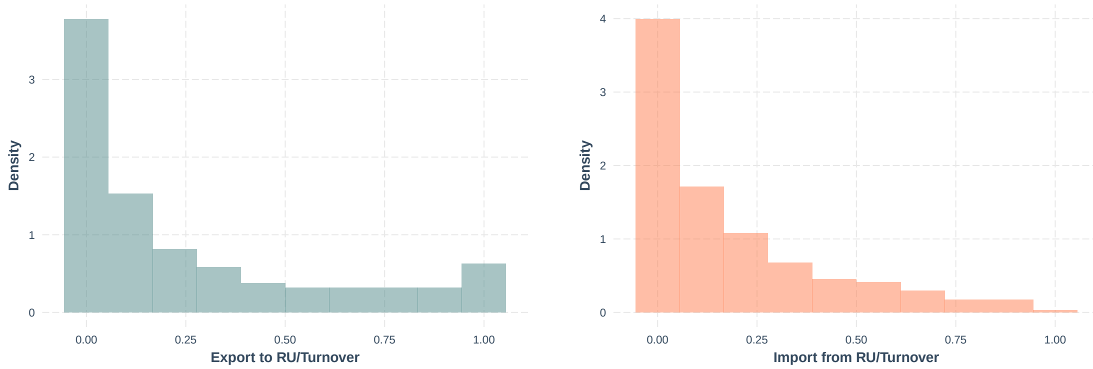
3.2 Measuring the magnitude of the shock

To analyze how firms absorb the trade shock induced by the war and sanctions, I decompose the trade shock into three components: *exposure*, *bite*, and their interaction. First, all firms engaged in trade with Russia may have been affected by the shock, even those not trading goods targeted by specific sanctions. The first sanction package introduced broad restrictions on trade with specific individuals and Russian legal entities. EU firms trading with Russian partners must legally verify that the ultimate beneficiary of their counterpart is not on the sanctions list, leading to additional costs and potential risks. Compliance with these restrictions also required extensive checks by banks, delaying the processing and execution of payment transactions. In cases of uncertainty, banks may refuse to process payments. Consequently, these sanctions directly increase the costs associated with trade with Russia for *all* firms engaged in business there. Beyond legal sanctions, firms may also face pressure to cease trading with Russia or choose to withdraw due to ethical concerns.

The first component of the overall shock measure captures firms' exposure to Russia. To capture this effect, I calculate the share of turnover derived from trade with Russia in 2021, the last year before the full-scale war. This measure is defined separately for exporters and importers as follows:

$$\frac{Exports\ RU_{2021}}{Turnover_{2021}}, \text{ and } \frac{Imports\ RU_{2021}}{Turnover_{2021}}$$

Figure 5: Exposure to Russia



(a) Exports **(b)** Imports

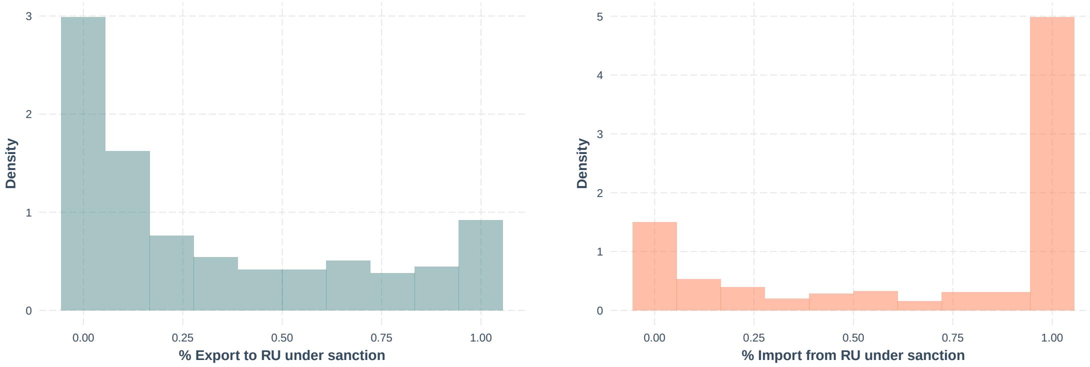
NOTE: These figures display the distribution of the exposure to Russia, measured as the share of exports to/import from Russia in turnover in 2021.

Figure 5 illustrates the distribution of this continuous measure among firms trading with Russia in 2021. This indicates that for most firms, trade with Russia constitutes only a small share of their turnover, whereas for some firms, it accounts for nearly all of their business activity.

The second component of the shock measure captures the *bite* of sanctions targeting specific goods. For a given level of exposure to Russia, firms affected by trade sanctions may experience a greater impact than those unaffected. To capture this dimension, I use data from EU legal texts to compute, for all firms trading with Russia in 2021, the share of their trade that would become subject to sanctions in 2022. This measure is separately defined for exporters and importers as follows:

$$\frac{Exports\ to\ RU\ under\ sanction_{2021}}{Exports\ to\ RU_{2021}}, \text{ and } \frac{Imports\ from\ RU\ under\ sanction_{2021}}{Imports\ from\ RU_{2021}}.$$

Figure 6: Exposure to trade sanctions



(a) Exports

(b) Imports

NOTE: These figures illustrate the distribution of exposure to trade sanctions, measured as the share of exports to or imports from Russia in 2021 that were subsequently banned in 2022.

Figure 6 shows the distribution of this measure. Importers are much more affected by specific trade restrictions than exporters, as a large number of importers face a ban on *all* their imports from Russia. For exporters, though more homogeneously distributed, the impact remains substantial for many firms.

The third component of the shock measurement is the interaction between exposure and bite. This captures the idea that the impact of a stronger sanction bite may vary depending on a firm's exposure. In other words, a firm exporting to Russia only goods subsequently falling under sanctions, but for which the Russian market represents only a minor share of its revenue, is likely to experience a lower trade disruption than a firm having 50% of its exports to Russia included in the sanctions list but generating 100% of its turnover in Russia.

Finally, in the existing literature, trade disruption is typically measured as the share of a firm's revenue derived from exports of banned products relative to its total revenue during the last pre-sanction period (e.g., Lastauskas et al., 2023). However, note that this ratio can be decomposed as follows:

$$\frac{Exports\ under\ sanction\ to\ RU}{Turnover} = \frac{Exports\ to\ RU}{Turnover} \times \frac{Exports\ under\ sanction\ to\ RU}{Exports\ to\ RU}$$

Measuring the shock as the share of embargoed products in total turnover effectively introduces an interaction term without accounting for the main effects. This can be problematic if mere exposure to Russia constitutes a shock in itself, as the interaction term would conflate both effects. Given the payment constraints and additional costs associated with trading with Russia, this is a likely concern. Decomposing the shock into three components helps disentangle the effect of trade sanctions on specific goods from the broader effect of exposure to Russia.

3.3 Identification

Equipped with this firm-level measure of the shock and a set of firms that experienced trade disruption, I turn to estimating the causal response of firms along various margins. I exploit heterogeneity in the size of the shock: firms that are heavily exposed to Russia and primarily trade goods subject to sanctions experience a greater impact than firms that only marginally trade with Russia in goods not included in the sanctions list. This allows me to implement a difference-in-differences analysis, using the shock size as a continuous treatment variable. More specifically, I implement a difference-in-differences local projection approach in the spirit of Dube et al. (2023). This approach consists of cross-sectional regressions using the percentage change in a given outcome between a period t and a reference period, which, in this case, is 2021—the last full pre-war year.[10] I estimate the following regression models, allowing time effects and the impact of firm characteristics to vary over time:

$$\frac{y_{i,t} - y_{i,2021}}{y_{i,t}} = \alpha_t + \beta_t Exposure_i + \gamma_t Bite_i + \delta_t Exposure_i \times Bite_i + \lambda_t X_i + \epsilon_{it},$$

The left-hand side of the equation represents the percentage change in outcome y for firm i between period t and 2021, the reference year. *Exposure* and *Bite* are, respectively, the share of turnover represented by trade with Russia (in 2021) and the share of trade with Russia in 2021 that would have fallen under sanctions in 2022, as described in the previous section. For ease of interpretation, both variables are mean-centered in all regressions, so that γ represents the effect of an increase

[10] This empirical framework is identical to many studies examining the firm-level impact of minimum wage increases, where the shock is measured as the share of affected workers (Machin et al., 2003; Draca et al., 2011; Harasztosi and Lindner, 2019; Gavoille and Zasova, 2023).

in trade restrictions for a firm with average exposure to Russia. The set of control variables, X, includes firm age, NACE macro-sector, average labor share, and average profitability, with the latter calculated over the 2020–2021 period. All regressions are weighted by firm size, proxied by the logarithm of average turnover over the 2020–2021 period (as in Harasztosi and Lindner, 2019). This specification assumes a linear relationship between the covariates and the dependent variable. Alternatively, I also estimate a model splitting the exposure measure in three categories (low, medium and high exposure) and the bite measure in two categories (impacted by targeted sanctions or not). The results obtained with this alternative specification, provided in Appendix C, are overall qualitatively similar to those obtained with the main specifications. For some outcomes, however, the response of the most impacted firms drives the results.

I estimate these regressions using the sample of firms that would have continued trading with Russia in 2022, analyzing exporters and importers separately. In principle, I could use a broader set of firms, at least for outcomes that are not exclusive to firms trading with Russia. However, this group of firms may exhibit specific (and possibly unobservable) characteristics, as firms may self-select into foreign markets. If this is the case, exporters and importers that do not trade with Russia may not serve as an appropriate benchmark. Restricting the analysis to firms that traded with Russia in the pre-war period enables a comparison among firms operating in a similar trade environment. Additionally, I retain only firms that had existed for at least two years before the war. I include all firms that ceased operations between the reference period and the final period of the sample. For instance, a firm that closed in 2022 remains in the sample, with its number of employees recorded as zero. Descriptive statistics are provided in Table 2, contrasting the characteristics of firms trading with Russia with (1) the overall population of firms and (2) the set of exporting/importing firms.

The identification relies on three key assumptions. The first assumption is that firms did not anticipate the shock. This assumption is debatable in the long run, as some exporting firms gradually reduced trade with Russia over the years, particularly after the invasion of Crimea. However, in the short run, the full-scale invasion was still considered unlikely just days before it began. The second assumption is the

Table 2: SUMMARY STATISTICS

	All firms N = 137,400	All exporters N = 5,399	Exporters to RU N = 889	Predicted Exp. to RU N = 617	All importers N = 9,817	Importers from RU N = 1,480	Predicted Imp. from RU N = 969
Turnover (million EUR)	0.044	0.969	1.416	1.871	0.544	1.091	1.425
Profitability	0.025	0.045	0.043	0.047	0.043	0.044	0.045
Labor share	0.470	0.432	0.422	0.432	0.443	0.425	0.410
Firm age	8.000	13.000	15.000	15.000	12.000	15.000	15.000
# Employees	2.000	9.000	10.000	13.000	6.000	10.000	11.000
Employment, % change	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Exit	1,397 (2.8%)	71 (1.5%)	19 (2.1%)	13 (2.1%)	125 (1.5%)	23 (1.6%)	15 (1.5%)
Sector							
Manufacturing	12,331 (9.0%)	1,683 (31%)	260 (29%)	205 (33%)	1,928 (20%)	322 (22%)	207 (21%)
Other	76,716 (56%)	863 (16%)	80 (9.0%)	45 (7.3%)	2,654 (27%)	238 (16%)	101 (10%)
Transportation	9,361 (6.8%)	318 (5.9%)	110 (12%)	67 (11%)	429 (4.4%)	109 (7.4%)	39 (4.0%)
Wholesale and Retail	38,992 (28%)	2,535 (47%)	439 (49%)	300 (49%)	4,806 (49%)	811 (55%)	622 (64%)
Export (million Eur)		0.238	0.493	0.952			
Export, % change		-0.039	0.020	0.042			
Export to RU (million EUR)			0.061	0.152			
Export to RU, % change			-0.870	-0.774			
Export to RU/Turnover			0.046	0.095			
Import (million Eur)					0.056	0.263	0.581
Import, % change					-0.191	-0.128	-0.052
Import from RU (million EUR)						0.028	0.091
Import from RU, % change						-0.906	-0.730
Import from RU/Turnover						0.033	0.077

NOTE: This table displays summary statistics for different groups of firms. It provides the median for continuous variables and the count (along with the respective share) for categorical variables. Variables expressed as changes represent differences between 2021 and 2022. All monetary values are expressed in constant Euros (base year 2015).

parallel trend assumption: in a counterfactual scenario where no sanctions were implemented and Russia did not invade Ukraine in 2022, firms' exposure to the Russian market would not have been correlated with their outcomes in 2022. Third, I assume that a firm's response depends only on the shock it experiences, independent of the shocks affecting other firms. In other words, firms experiencing a mild shock do not suffer indirect effects from firms that were more severely affected. Given the relatively small number of firms trading with Russia compared to the overall size of the Latvian economy, this assumption appears reasonable.

4 Results

4.1 Magnitude of trade disruption

To better understand how sanctions disrupted firm-level trade with Russia, I begin by estimating the impact of sanctions on firm-level trade with Russia. For this purpose, I use two alternative dependent variables. First, a binary variable indicating whether a firm continued trading with Russia after the start of the war. This measure captures the extensive trade margin, following Crozet et al. (2021). I calculate this measure in two different ways: (i) whether firms traded *at all* with Russia in 2022, and (ii) whether a firm traded with Russia *after* March 2022. Since firms may not trade with Russia every month and some trade flows exhibit seasonality, these two alternative definitions thus provide upper and lower bounds for the share of firms that ceased trading with Russia due to sanctions. Second, I focus on the intensive margin of trade with Russia and use the percentage change in trade with Russia between 2021 and 2022, in the spirit of Crozet and Hinz (2020).

The results are presented in Table 3. In Column (1), the dependent variable is a binary indicator that equals 1 if a firm did not trade at all with Russia in 2022, whereas in Column (2), it takes the value of 1 if a firm did not trade with Russia after March 2022. In other words, these two specifications amount to estimating respectively a lower and an upper bound of trade disruption. The results are nearly identical across these two specifications, and the signs of the coefficients of interest are similar for exporters and importers. For a firm with the average level of exposure to Russia and *Bite*, an increase in exposure to Russia *decreases* the probability of exiting the Russian market. To better understand this interaction, the upper panel of Figure 8 displays the estimated probability for a firm to exit the Russian market, conditional on *Exposure* and *Bite*.[11] These results suggest that firms with a small stake in Russia prefer to forgo their trade relationships and exit the Russian market. On the other hand, targeted sanctions appear to play a secondary role.

Turning now to the evolution of trade intensity, as a preliminary step, Figure 8

[11] For some firms, the predicted probability of exit is negative. Using a Probit model instead of a linear specification yields similar results, as shown in Appendix D. For other binary outcomes, the results using a probit model are near-identical as well.

Table 3: Trade with Russia - regression results

Dependent variable:	P(Exit RU)		Trade with RU, % change
Exporters			
RU Exposure	-0.336 ***	-0.445 ***	-0.079
	(0.050)	(0.064)	(0.164)
Share sanction	-0.026	0.033	-0.289 ***
	(0.062)	(0.072)	(0.109)
RU exposure * Share sanction	0.033	0.302	-0.037
	(0.173)	(0.246)	(0.334)
N	617	617	429
R2	0.063	0.100	0.052
Importers			
RU exposure	-0.423 ***	-0.725 ***	0.285 **
	(0.062)	(0.070)	(0.115)
Share sanction	-0.100 ***	-0.098 ***	0.000
	(0.032)	(0.037)	(0.058)
RU exposure * Share sanction	0.202 *	0.155	-0.538 ***
	(0.117)	(0.139)	(0.205)
N	969	969	645
R2	0.074	0.121	0.026

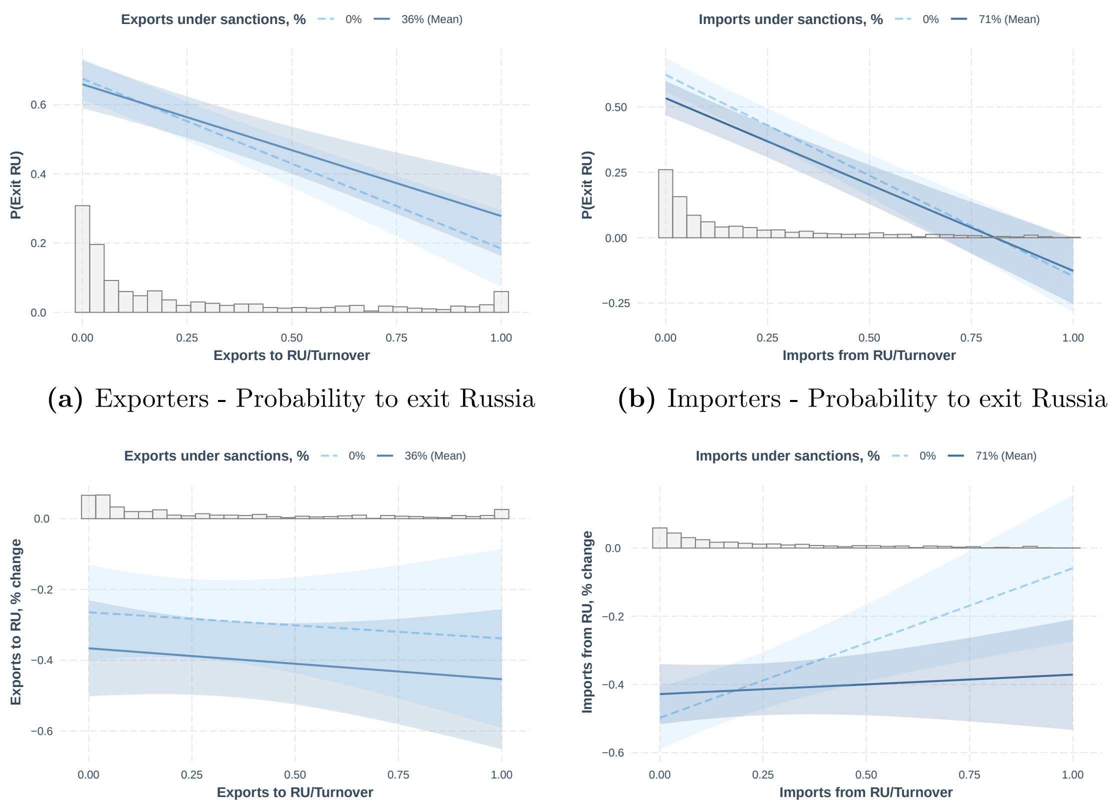
Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. All regressions are weighted by firm's average turnover 2020-2021 and include the following set of controls: firm age, sector, labor share, and profitability. The interacted variables are centered. The dependent variables are, respectively: a binary variable indicating whether a firm trading with Russia in 2021 still traded with Russia in 2022 (Column 1); a binary variable indicating whether a firm trading with Russia in 2021 still traded with Russia after Q1 2022 (Column 2); and the percentage change in import/export value between 2021 and 2022, conditional on not exiting the Russian market (Column 3).

displays the distribution of the percentage change in trade with Russia between 2021 and 2022. A negative value indicates that a firm reduced its trade with Russia, which is the case for the vast majority of firms. However, a very small number of firms experienced a substantial increase in their trade with Russia, with some seeing growth as high as 6000%. This suggests that a small number of firms have specialized in trading with Russia and are thriving despite the sanctions. For the remainder of the paper, I use the full sample for binary regressions and a trimmed sample—excluding the top 5% of the dependent variable's distribution—for continuous regressions.

Turning to the regression results, firms that maintained trade relations with Russia nevertheless experienced a significant decline in trade intensity. However, the effects differ for exporters and importers. In particular, for importers, targeted sanctions play a significant role: an importer largely affected by targeted sanctions is estimated to reduce its import value from Russia by approximately 40%, regardless of its exposure to Russia. On the other hand, for firms unaffected by targeted sanctions, greater exposure is associated with a smaller decline in imports: firms that are highly dependent on Russia but were spared by targeted sanctions did not reduce their trade with Russia by the end of 2022.

Overall, firms with low exposure to Russia are highly likely to exit the Russian market, regardless of targeted sanctions, while those that continue trading experience a significant decline in trade intensity. Exposure to Russia emerges as the primary determinant of these patterns, whereas targeted sanctions play a secondary role—except in shaping the trade intensity of importers that remain active in the Russian market.

Figure 7: Change in trade with Russia



(a) Exporters - Probability to exit Russia

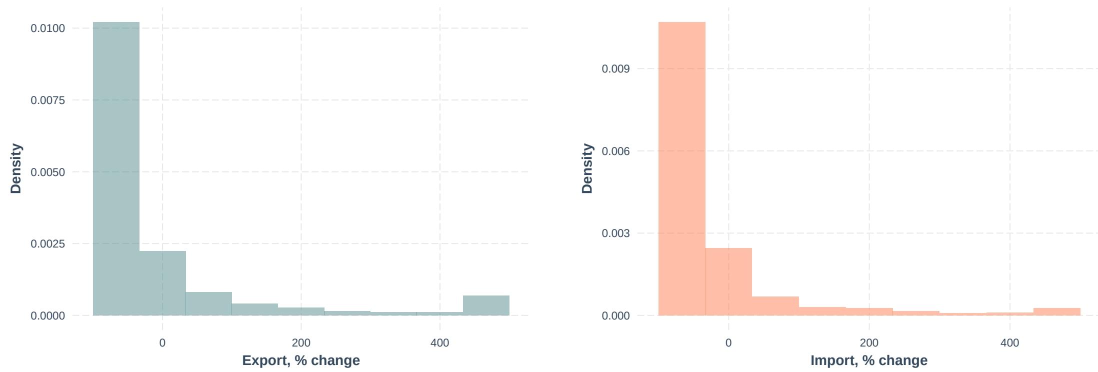
(b) Importers - Probability to exit Russia

(c) Exporters - % change in export value

(d) Importers - % change in import value

NOTE: These figures display the predicted probability of exiting the Russian market (upper panels) and the predicted change in trade intensity with Russia, conditional on remaining in the market (lower panels), holding the control variables at their mean values. In each panel, the predicted outcome is shown for two different levels of trade sanction exposure: 0% (the firm did not trade soon-to-be sanctioned goods with Russia in 2021) and the average sanction exposure (conditional on being affected). The shaded areas represent the 90% confidence intervals. The histograms in the background represent the distribution of the variable shown on the y-axis.

Figure 8: Firm-level change in trade with Russia, 2021-2022



(a) Exporters

(b) Importers

NOTE: These figures display the distribution of firm-level changes in trade with Russia between 2021 and 2022 (in %). Firms with trade increases exceeding 500% between 2021 and 2022 are top-coded at 500% in these figures.

4.2 Employment response

How do firms respond to a severe trade shock? To address this question, I study both the extensive and the intensive margins. First, I estimate a model where the dependent variable is a binary variable indicating whether a firm remained active in December 2022. To observe whether a firm is still active at this point in time, I exploit the matched employer-employee data, which is available at the monthly frequency. The results are provided in Table 4, and the interaction between *Exposure* and *Bite* is illustrated in Figure 9. The results indicate that the probability for a firm to close increases with both greater exposure to Russia and a stronger sanction bite. Among exporters not impacted by targeted sanctions, highly exposed firms exhibit a 5 p.p. higher probability to close than barely exposed firms. The probability to close is even increased by another 4 p.p. for highly exposed firms seriously hit by sanctions. Using a discrete version of the exposure and bite measures, Figure C.2 in Appendix C shows that this positive effect on the probability to close is primarily driven by the most exposed *sanctioned* firms. The impact of exposure and bite is, however, much milder for importers. For the remainder of the paper, the analysis is restricted to the set of surviving firms.

In a second step, I investigate changes in employment among surviving firms.

Table 4: Employment response - regression results

	Exporters		Importers	
Dependent variable:	P(Exit RU)	Employment, % change	P(Exit RU)	Employment, % change
RU Exposure	0.062 **	-0.160 ***	0.027	-0.071 *
	(0.027)	(0.042)	(0.023)	(0.038)
Share sanction	0.002	0.019	0.011	-0.000
	(0.017)	(0.034)	(0.010)	(0.016)
RU exposure * Share sanction	0.134	-0.202	0.047	-0.072
	(0.125)	(0.167)	(0.059)	(0.077)
N	617	438	969	649
R2	0.047	0.060	0.022	0.023

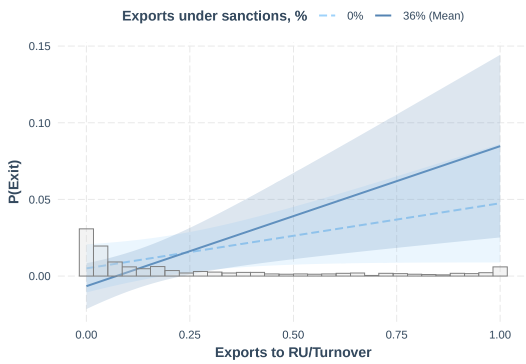
*** p < 0.01; ** p < 0.05; * p < 0.1.

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. All regressions are weighted by firm's average turnover in 2020–2021 and include the following set of controls: firm age, sector, labor share, and profitability. The interacted variables are centered. The dependent variables are: (i) a binary indicator of firm closure (Columns 1 and 3) and (ii) the percentage change in import/export value to/from Russia between 2021 and 2022, conditional on firm survival (Columns 2 and 4).

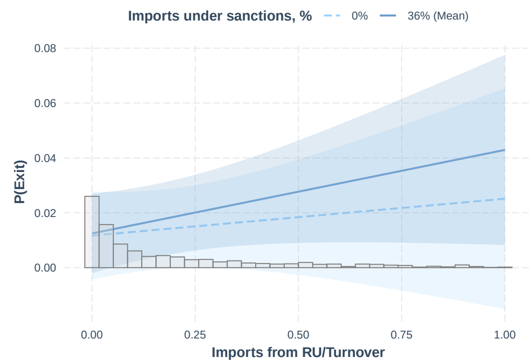
Once again, greater exposure to Russia is associated with a larger decline in employment. Moreover, exporters that are only marginally affected do not experience a decline in employment. This can be clearly seen in Figure C.2 in Appendix C, which shows that only highly exposed firms experienced a decline employment. However, among importers, even firms with minimal involvement in trade with Russia exhibit some job losses. A possible explanation is that importers may rely on specific inputs that, despite their low monetary value, are difficult to substitute in the production process. For importers, most of the employment adjustment is made through the intensive margin rather than the extensive margin.

Finally, to shed more light on the timing of the employment response, I leverage monthly matched employer-employee data. In Table E.3 and Table E.4 in Appendix E, I present regression results for (i) the probability of firm closure at any given month in 2022 and (ii) the percentage change in employment between January 2022 and subsequent months. These results indicate that firms responded rapidly, both at the extensive and intensive margins. The effects of the shock became statistically significant as early as June 2022.

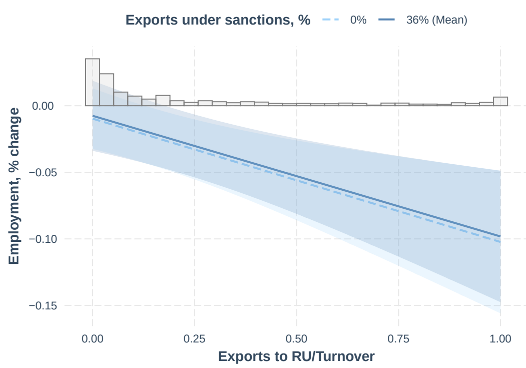
Figure 9: Employment response



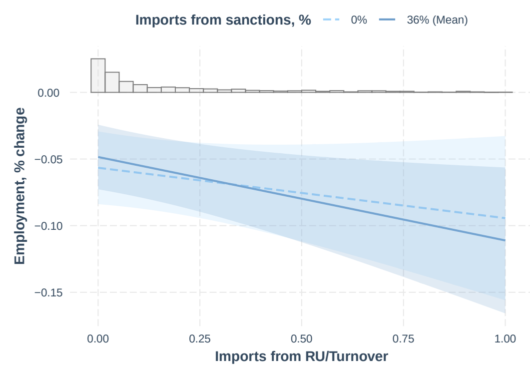
(a) Exporters - Probability to close



(b) Importers - Probability to close



(c) Exporters - % change in employment



(d) Importers - % change in employment

NOTE: These figures display the predicted probability of firm closure (upper panels) and the predicted employment response conditional on firm survival (lower panels), holding the control variables at their mean values. In each panel, the predicted outcome is shown for two different levels of trade sanction exposure: 0% (the firm did not trade soon-to-be sanctioned goods with Russia in 2021) and the average exposure (conditional on being affected). The shaded areas represent the 90% confidence intervals. The histograms in the background represent the distribution of the variable shown on the y-axis.

4.3 Trade response

After studying the probability of survival and the employment response, I now turn to the trade response, which has received the most attention in the literature. Do

Table 5: Trade response - regression results

Dependent variable:	Total trade,	P(decrease #markets)	P(CIS)	P(Sanction CIS)
Dependent variable:	% change			
Exporters				
RU Exposure	-0.412 ***	-0.197 ***	0.181 ***	-0.015
	(0.111)	(0.065)	(0.064)	(0.021)
Share sanction	-0.087	0.063	-0.030	0.094 ***
	(0.099)	(0.073)	(0.058)	(0.021)
RU exposure * Share sanction	-0.423	-0.052	-0.188	-0.042
	(0.289)	(0.264)	(0.202)	(0.066)
N	573	604	442	940
R2	0.054	0.021	0.036	0.057
Importers				
RU exposure	-0.385 ***	0.297 **	-0.047	-0.015
	(0.110)	(0.140)	(0.032)	(0.021)
Share sanction	-0.008	0.095	0.060 ***	0.094 ***
	(0.054)	(0.076)	(0.023)	(0.021)
RU exposure * Share sanction	-0.326	-0.428	-0.014	-0.042
	(0.227)	(0.300)	(0.073)	(0.066)
N	905	954	899	940
R2	0.047	0.022	0.028	0.057

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses. All regressions are weighted by firm's average turnover 2020-2021 and include the following set of controls: firm age, sector, labor share, and profitability. The interacted variables are centered. The dependent variables are, respectively: the percentage change in total export/import value between 20221 and 2022 (Column 1); a binary variable indicating whether the number of destinations/origins decreased between 2021 and 2022 (Column 2); a binary variable indicating whether a firm started trading with CIS countries in 2022 (Column 3); a binary variable indicating whether a firm started trading *sanctioned goods* with CIS countries in 2022 (Column 4)

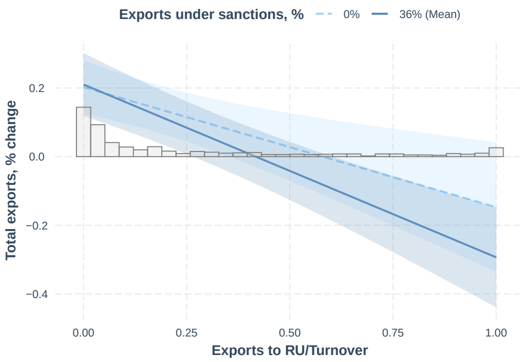
affected firms successfully reorient their trade away from Russia? To address this question, I examine four key outcomes.

I begin with the percentage change in overall international trade. If highly affected firms experienced no decline in trade, this would indicate successful rerouting.

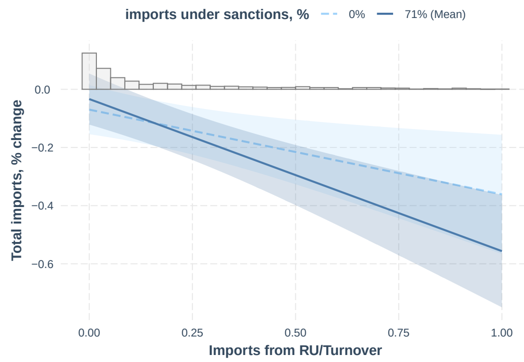
However, as shown in the first column of Table 5 and in Figure 10, this is not the case. While exporters with marginal to moderate exposure to Russia saw an increase in total exports, greater exposure to Russia is associated with a large decline in total exports, with targeted sanctions amplifying this effect. For importers, even minor exposure to Russia leads to a decline in total imports. This could indicate that importers with low involvement in Russian trade are nevertheless likely to import exclusively from Russia. In parallel, consistent with findings from previous subsections, it may suggest that certain Russian imports are difficult to substitute.

Another way to assess the overall change in exports and imports of affected firms is to examine the change in the number of international markets in which firms operate. However, since some firms operate in numerous countries while others rely on Russia as their sole international trade partner, simply examining the absolute change in the number of markets may not be very informative. Instead, I construct a binary variable that equals 1 if a firm experienced a *decrease* in the number of international trade partners and 0 otherwise. As shown in Column 2 of Table 5 and in Figure C.3a, firms with low exposure to Russia are more likely to experiencing a reduction in the number of international trade partners, suggesting a failure to replace Russia by other markets. However, this reduction is smaller in magnitude than the probability of exiting the Russian market, indicating that at least some trade is successfully exported to new destinations.

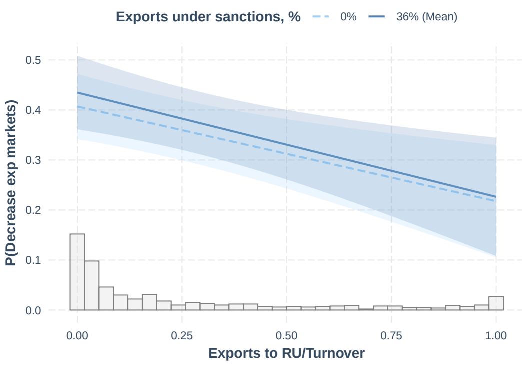
Figure 10: Trade response - Change in overall trade



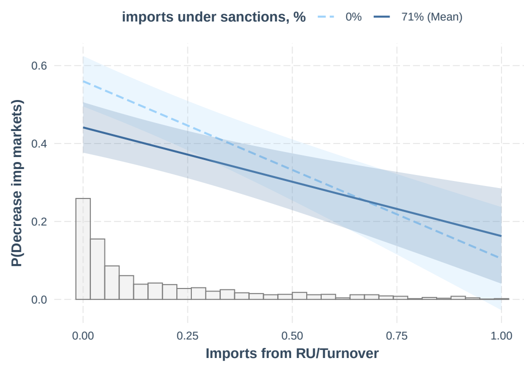
(a) Exporters - % change in total exports



(b) Importers - % change in total imports



(c) Exporters - Probability of fewer # markets



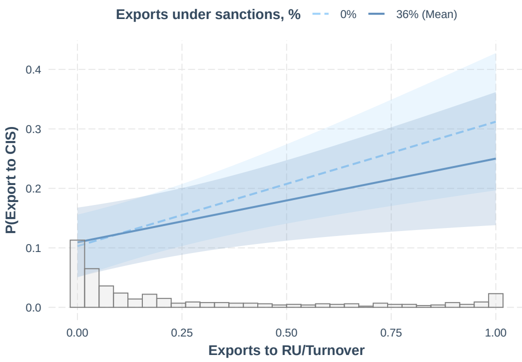
(d) Importers - Probability of fewer # markets

NOTE: These figures display the predicted change in total trade (conditional on remaining in activity), holding the control variables at the mean. In each panel, the predicted outcome is represented for two different trade sanction bites: at 0% (the firm did not trade soon-to-be sanctioned goods with Russia in 2021) and at the average bite (conditional on being impacted). The shaded areas represent the 90% confidence bands. The histograms in the background represent the distribution of the variable represented on the y-axis.

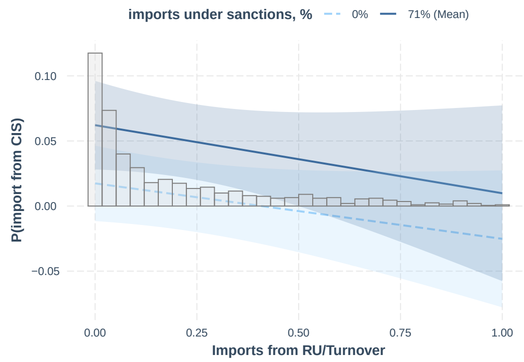
An important concern related to sanction is the possibility to re-route trade with Russia via "neutral" third-party countries (Bove et al., 2023; Chupilkin et al., 2024; Fisman et al., 2024). Are firms that are severely impacted more likely to *start* trading with these partners? To address this question, I restrict the sample to firms that did not trade with CIS countries in 2021 and construct binary variables that equal 1 if a firm began trading with CIS countries in 2022. In addition, I replicate this exercise but only considering firms starting to export goods on the sanction list to this set of countries.

The results are presented in Column 2 and 3 of Table 5 and in Figure 11. This exercise reveals that exporters with greater exposure to Russia are more likely to begin trading with CIS countries, regardless of the severity of targeted sanctions. This increase is to a large extend driven by firms exporting sanctioned goods. Moreover, using a categorized version of the shock variables, Figure C.4 shows that this result is largely driven by firms that are highly exposed to Russia and directly affected by targeted sanctions. However, for importers, exposure to Russia does not significantly influence the probability of starting trade with CIS countries, which remains close to zero. Only the bite of targeted sanctions plays a role, as can be seen in Figure C.4.

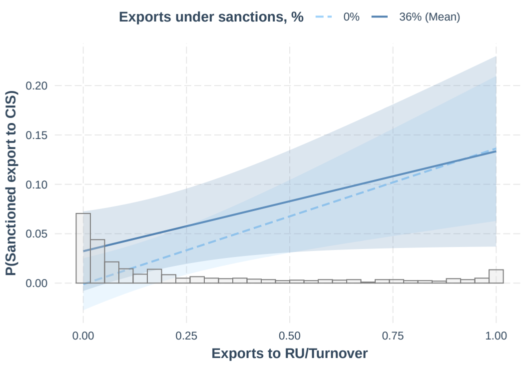
Figure 11: Trade response - Trade partners



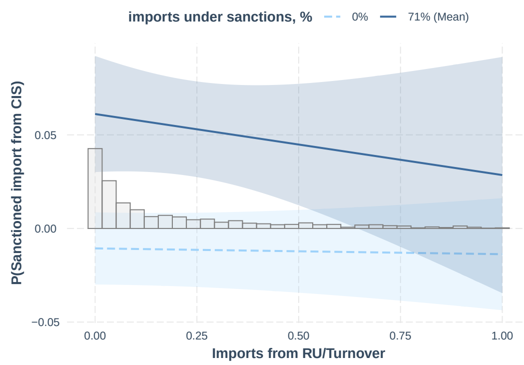
(a) Probability to start exporting to CIS



(b) Probability to start importing from CIS



(c) Probability to start exporting sanctioned goods to CIS



(d) Probability to start importing sanctioned goods from CIS

NOTE: These figures display the predicted probability of beginning trade with CIS countries (upper panel) and the predicted probability of beginning trade of sanctioned goods with CIS countries (lower panel), holding the control variables at the mean. In each panel, the predicted outcome is shown for two different levels of trade sanction exposure: 0% (the firm did not trade soon-to-be sanctioned goods with Russia in 2021) and the average exposure (conditional on being affected). The shaded areas represent the 90% confidence intervals. The histograms in the background represent the distribution of the variable shown on the y-axis.

4.4 Other margins

Finally, I examine two additional margins through which firms may have absorbed the trade shock: turnover and profitability. The results are displayed in Table 6 and in Figure 12. I first analyze how firms' turnover changed between 2021 and 2022 based on their exposure to Russia. Although domestic sales are not directly observed, analyzing turnover provides insights into whether firms offset lost trade with Russia

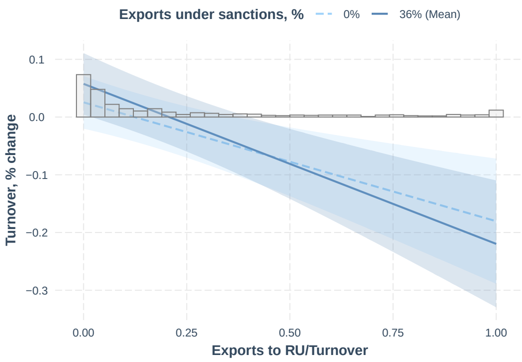
Table 6: Other margins - regression results

Dependent variable:	Turnover	Profitability	Debt
Exporters			
RU Exposure	-0.235 ***	-0.076	-0.079
	(0.062)	(0.048)	(0.076)
Share sanction	0.038	0.026	0.082
	(0.062)	(0.049)	(0.076)
RU exposure * Share sanction	-0.196	-0.045	0.190
	(0.226)	(0.151)	(0.352)
N	573	573	573
R2	0.055	0.027	0.018
Importers			
RU exposure	-0.201 ***	-0.025	-0.052
	(0.068)	(0.019)	(0.090)
Share sanction	-0.019	0.008	-0.078 **
	(0.028)	(0.010)	(0.034)
RU exposure * Share sanction	-0.277 **	0.026	-0.043
	(0.134)	(0.044)	(0.179)
N	905	906	905
R2	0.041	0.020	0.019

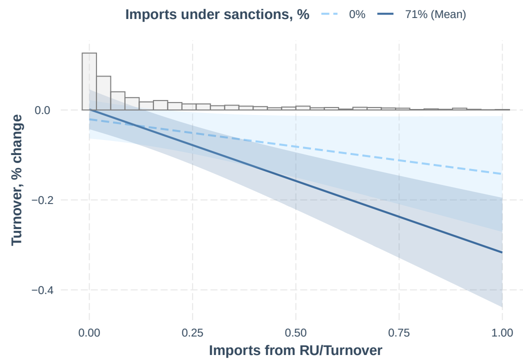
Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. All regressions are weighted by firm's average turnover 2020-2021 and include the following set of controls: firm age, sector, labor share, and profitability. The interacted variables are centered.

through increased domestic sales. For exporters, the results suggest that only firms deriving more than 25% of their turnover from Russia in 2021 experienced a decline in turnover. This is confirmed by Figure C.5, which shows that the most exposed firms drive this result. For importers, turnover declines even at lower levels of exposure, with only firms having a near-zero exposure to Russia not exhibiting a decline in turnover. Next, I examine changes in profitability to complement the turnover analysis. Profitability is measured as $(Turnover_{2022} - Turnover_{2021})/Turnover_{2021}$, as in e.g., Harasztosi and Lindner (2019). The results show a negative impact of exposure on profitability for exporters. Figure C.5 reveals that profitability declined substantially for exporters that were heavily affected (with large variation), but remained stable for others. This suggests that part of the cost of sanctions is paid by the owners of these firms. On the other hand, among importers, the profitability response is almost flat along exposure to Russia and exposure to targeted sanctions, suggesting that for importers, a large part of the cost of sanctions was passed on consumers.

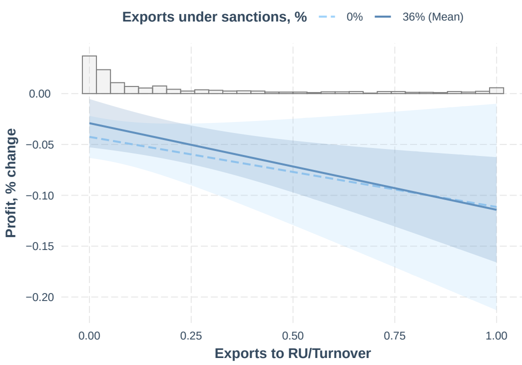
Figure 12: Firms' response - Other margins



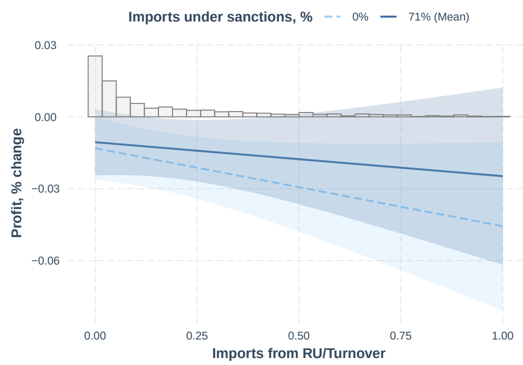
(a) Exporters - % change in turnover



(b) Importers - % change in turnover



(c) Exporters - % change in profitability



(d) Importers - % change in profitability

NOTE: These figures display the predicted percentage change in turnover (upper panel) and in profitability (profit/turnover, lower panel), holding the control variables at their mean values. In each panel, the predicted outcome is shown for two different levels of trade sanction exposure: 0% (the firm did not trade soon-to-be sanctioned goods with Russia in 2021) and the average exposure (conditional on being affected). The shaded areas represent the 90% confidence intervals. The histograms in the background represent the distribution of the variable shown on the y-axis.

5 Conclusion

This paper investigates the response of Latvian firms to the trade shock induced by the 2022 Russian invasion of Ukraine and the ensuing EU sanctions. Using rich administrative data, I document the extent to which firms adjusted their trade relationships, employment, and financial outcomes in response to the disruption. I use for this purpose a set of firms that would have been likely to maintain trade relationship with Russia in the absence of the war.

The results show that firms with low exposure to Russia were the most likely to terminate trade. For firms continuing to trade with Russia, the intensity of trade decreased substantially, especially among importers. This shock also had significant consequences for the labor market. Firms with high exposure and a strong bite of sanctions were more likely to shut down, Among them, surviving firms significantly reduced employment. These employment effects materialized swiftly, with significant impacts observed as early as mid-2022.

The analysis also provides insights into firms' trade adjustment strategies. While some firms successfully diversified trade away from Russia, others redirected exports toward CIS countries, raising concerns about potential sanction circumvention. However, the scale of trade redirection was insufficient to fully offset the loss of Russian market access, as reflected in the observed declines in turnover and profitability. Overall, this implies that the cost of the trade shock was essentially split between employees and firms' owners.

Overall, sanctions on targeted goods only played a second order role. For most outcomes, firms' reaction is primarily driven by the exposure to Russia, both for exporters and importers. It also appears that the magnitude of firms' response is larger for exporters than for importers. This paper, however, only documents *direct short-term effects*. Further research should examine the long-term effects of this trade shock.

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A Appendix: EU legislation

Figure A.1: Trade restrictions - Example

ANNEX XXIII

LIST OF GOODS AND TECHNOLOGY AS REFERRED TO IN ARTICLE 3k

CN code	Name of the good
0601 10	Bulbs, tubers, tuberous roots, corms, crowns and rhizomes, dormant
0601 20	Bulbs, tubers, tuberous roots, corms, crowns and rhizomes, in growth or in flower; chicory plants and roots
0602 30	Rhododendrons and azaleas, grafted or not
0602 40	Roses, grafted or not
0602 90	Other live plants (including their roots), cuttings and slips; mushroom spawn - Other
0604 20	Foliage, branches and other parts of plants, without flowers or flower buds, and grasses, mosses and lichens, being goods of a kind suitable for bouquets or for ornamental purposes, fresh, dried, dyed, bleached, impregnated or otherwise prepared - Fresh
2508 40	Other clays
2508 70	Chamotte or dinas earths
2509 00	Chalk

Note: This is an excerpt of a legal text adopted by the European Union imposing trade restrictions with Russia. It indicates the list of goods subject to a specific article - here, article 3k, banning exports to Russia.

B Appendix: Classification details

This appendix provides additional details on the machine learning procedure. The objective of this classification is to determine the set of firms would have been trading with Russia in 2022 in the absence of the Russian full-scale offensive in Ukraine. For this purpose, I use all the firm/year observations trading with Russia over the 2012-2020 period (the data series starts earlier, but the time span is reduced due to lagged variables). Over this period, I observe for each observation whether the firm traded again with Russia in the following year. I also observe many firm and trade characteristics that I use to predict this outcome. The overall procedure is implemented for exporters and importers separately. For exporters, the list of variables used in the classification task is the following (the list of variables for importers is similar, swapping export and import):

1. **Firm characteristics**: sector (two-digit NACE sector), legal entity types (e.g., private company limited by shares), foreign-owned firm, Russia owned-firm, number of employees, turnover, value added.

2. **Trade characteristics**: total value exported, total value exported to Russia, binary variable indicating whether the firm also imports from Russia, a binary variable indicating whether the firm exported in year $t-1$, a binary variable indicating whether the firm exported in year $t-2$, a binary variable indicating whether the firm exported to Russia in year $t-1$, a binary variable indicating whether the firm exported to Russia in year $t-2$, year of the first international export, year of the first trade with Russia, number of export destinations, number of products exported, number of product exported to Russia, total weight exported, total weight exported to Russia, a series of binary variables indicating whether the firm exported to Russia at each quarter of the previous year, and a series of 21 binary variables indicating whether the types of goods exported by the firm (representing the 21 major sections of the HS nomenclature).

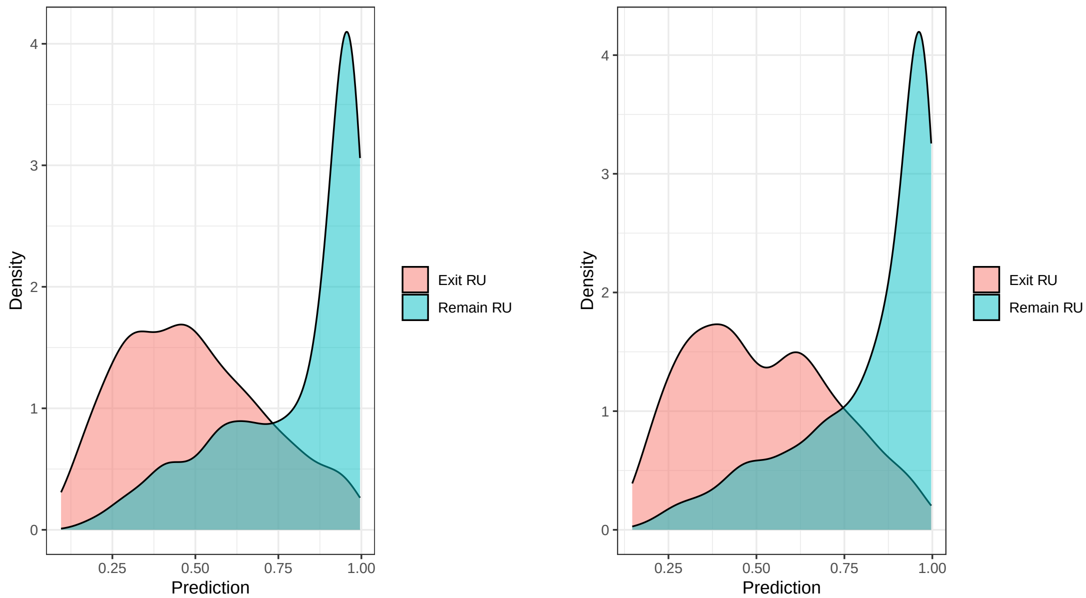
I randomly split this sample into two subsets: 80% of the observations are assigned to the training set, and the remaining 20% to the test set. Gradient boosting is implemented using the R package XGBoost via the Tidymodels interface. All numeric inputs (as detailed in the previous subsection) are standardized by centering and rescaling, while variables with absolute correlations exceeding 0.9 are automatically excluded. The ensemble contains 500 trees, and the model is tuned across four hyperparameters using a grid of 100 parameter combinations. The tuned hyperparameters are: (i) maximum tree depth, (ii) the minimum number of data points required in a node for further splitting, (iii) the learning rate, and (iv) the minimum reduction in the loss function needed to allow a split.

To identify the optimal hyperparameter configuration, I employ 10-fold cross-validation, aiming to maximize the Precision-Recall Area Under the Curve (AUC). Precision is defined as the ratio of true positives to the total number of predicted positives, while recall is the ratio of true positives to the total number of actual positives (true positives plus false negatives). Typically, there is a trade-off between precision and recall: raising the classification threshold increases precision but often reduces recall. The Precision-Recall curve illustrates this trade-off by plotting precision against recall across varying classification thresholds. The Precision-Recall AUC, representing the area under this curve, provides a single metric to evaluate classifier performance.

I focus on Precision-Recall AUC for two key reasons. First, it emphasizes accurate prediction of the positive class, promoting caution in positive classifications and thereby reducing false positives. This ensures that the set of firms used in the econometrics analysis is composed of firms that actually experienced a trade shock. Second, it is well-suited for addressing class imbalance (Saito and Rehmsmeier, 2015).

After tuning the model on the training set, I evaluate its out-of-sample performance using the test set. A correctly functioning model should assign a higher average probability of sustaining trade with Russia to observation that indeed sustained trading with Russia in the following year than to firms that stopped. Conversely, it should give a lower score to firms that exited the following year. Figure B.1 illustrates the density of scores for firms in the test set. In the case of a perfect classifier, the two groups would have no overlap, while a no-skill classifier (one unable to differentiate between the two classes) would produce complete overlap. The results show that the majority of staying firms receive very high scores. This is the case both for exporters and importers. Detecting observations that will stop trade is more difficult, but overall, the density weakly overlap.

Figure B.1: Classification score - Densities



(a) Exporters

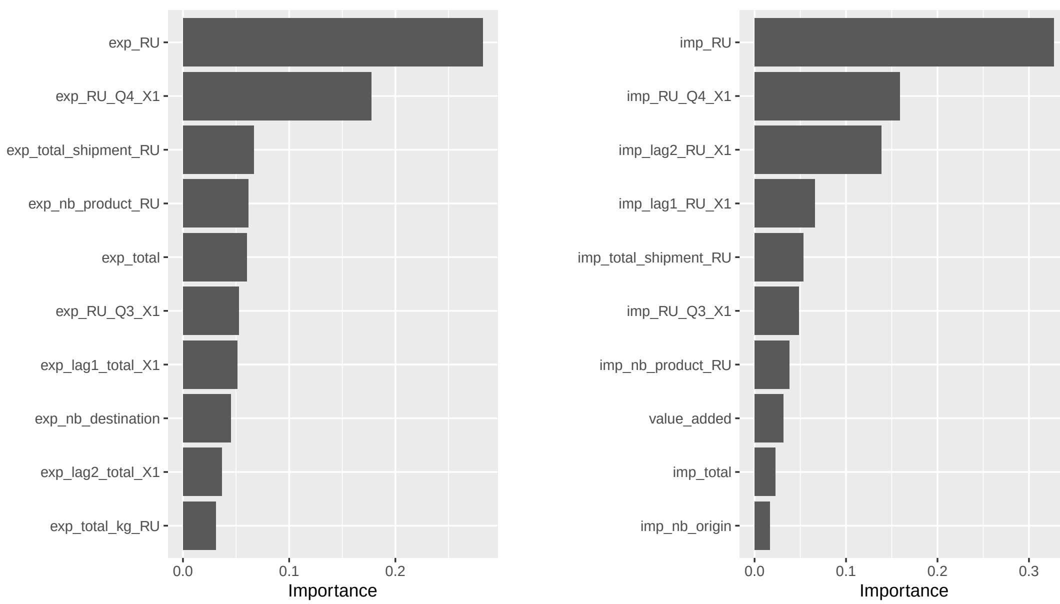
(b) Importers

NOTE: These Figures display the density of the scores obtained for each observation in the test set, for firms that exited and remained in Russia the following year.

A notable limitation of gradient boosting is its inability to reveal the functional relationship between inputs and outputs. To assess the importance of each variable in the classification, I use the permutation procedure described by Greenwell et al. (2020). The approach works as follows: after training the model and calculating the performance metrics of interest, the values of a single explanatory variable are randomly permuted. The performance metrics are then recalculated and compared to their original values. The greater the decline in performance, the more important the variable is for classification. This process is repeated for each explanatory variable.

Figure B.2 presents the 10 variables that contribute most to the classification outcome. For both exporters and importers, the two most important variables for classifications are the value exported/imported and whether any trade with Russia occurred in the last quarter. Most of the other variables are common to exporters and importers: the total number of shipments to/from Russia, the number of product traded, the number of foreign markets with which the firm trade, and the overall value traded (i.e., with any foreign country).

Figure B.2: Variable Importance Plots



(a) Exporters **(b)** Importers

Note: These Figures display variable importance plots, using the permutation method. It represents the 10 variables contributing the most to the classification outcome, for exporters and importers separately.

C Appendix: Categorical specification

This Appendix reports results from a model using exposure and bite as categorical variables. Low, Medium and High exposure to Russia respectively indicate a share of trade with Russia in turnover lower than 5%, between 5 and 25%, and larger than 25% in 2021. The bite of targeted sanctions is represented via a binary variable taking the value 1 if a firm exported/imported goods in 2021 that subsequently came under sanction in 2022, and 0 otherwise. The cross-distribution of these two categorical variables is provided in Table C.1.

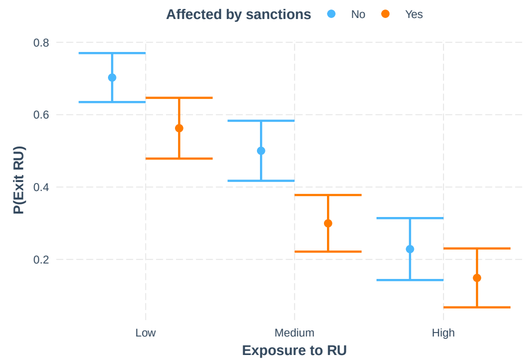
Table C.1: Exposure and Bite, categorical

	Exporters		Importers	
Exposure	Sanction	No sanction	Sanction	No sanction
Low	80	168	129	278
Medium	76	86	139	166
High	127	80	140	117

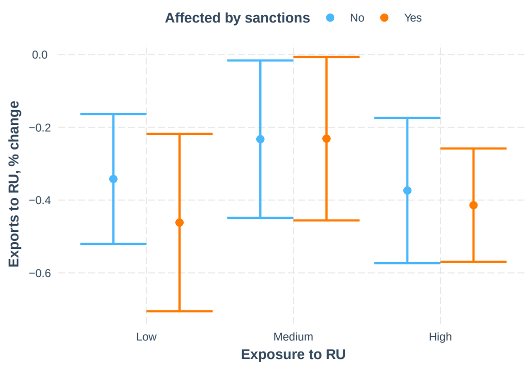
Note: This table provides the cross-distribution of the categorized exposure and bite measures.

Figure C.1: Change in trade with Russia - Categorical

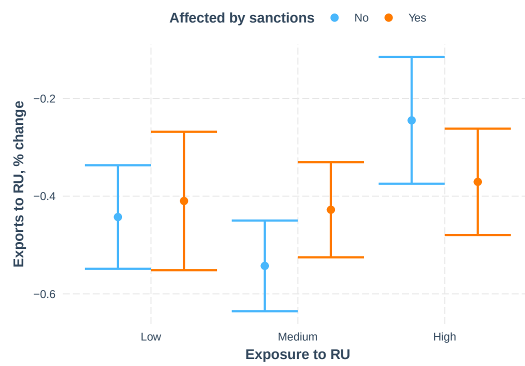
(a) Exporters - Probability to exit Russia



(b) Importers - Probability to exit Russia



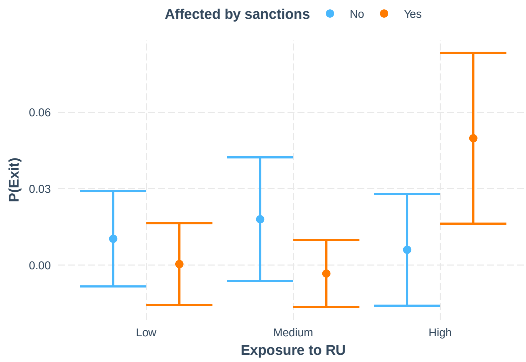
(c) Exporters - % change in export value



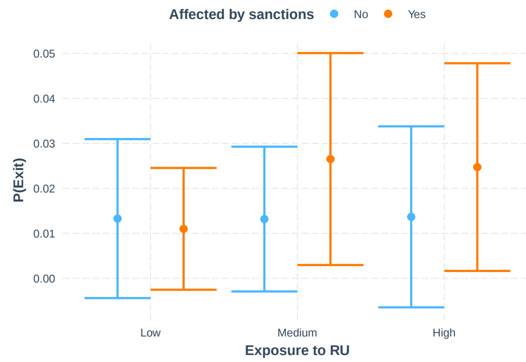
(d) Importers - % change in import value

NOTE: These figures display the predicted probability of exiting the Russian market (upper panels) and the predicted change in trade intensity with Russia, conditional on remaining in the market (lower panels), holding the control variables at their mean values. In each panel, the predicted outcome is shown for three different levels of exposure to Russia. Low, Medium and High exposure to Russia respectively indicate a share of trade with Russia in turnover lower than 5%, between 5 and 25%, and larger than 25% in 2021. "Affected by sanctions" indicates whether a firm traded in 2021 goods subsequently on the sanction list. The vertical bars represent the 90% confidence intervals.

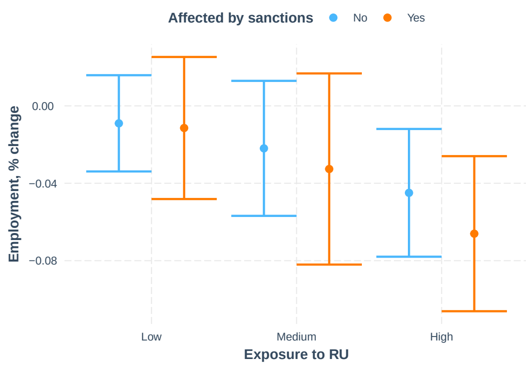
Figure C.2: Employment response - Categorical



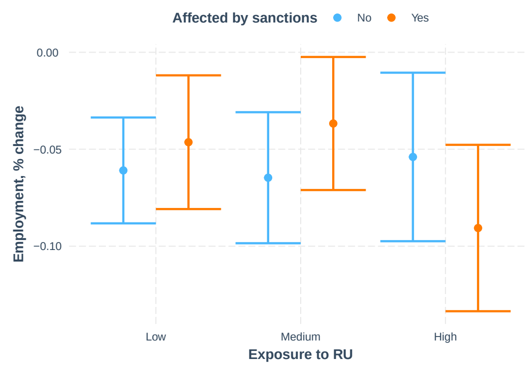
(a) Exporters - Probability to close



(b) Importers - Probability to close



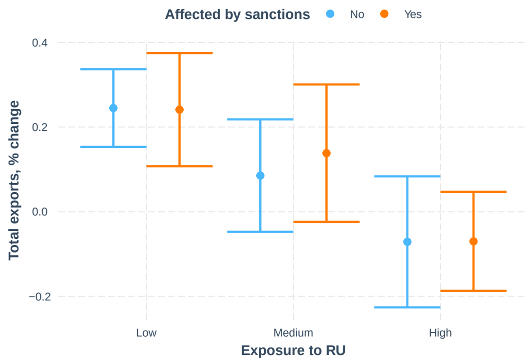
(c) Exporters - % change in employment



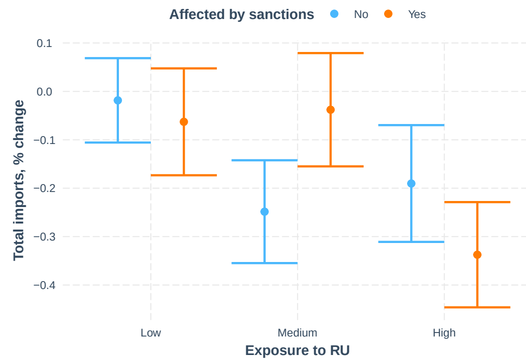
(d) Importers - % change in employment

Note: These figures display the predicted probability of firm closure (upper panels) and the predicted employment response conditional on firm survival (lower panels), holding the control variables at their mean values. In each panel, the predicted outcome is shown for three different levels of exposure to Russia. Low, Medium and High exposure to Russia respectively indicate a share of trade with Russia in turnover lower than 5%, between 5 and 25%, and larger than 25% in 2021. "Affected by sanctions" indicates whether a firm traded in 2021 goods subsequently on the sanction list. The vertical bars represent the 90% confidence intervals.

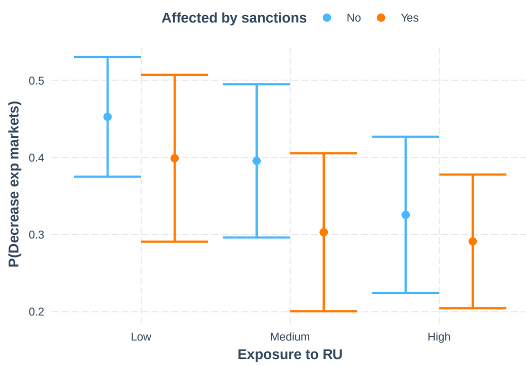
Figure C.3: Change in overall trade - Categorical



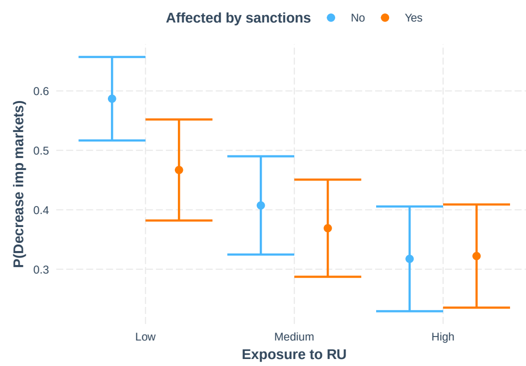
(a) Exporters - % change in total exports



(b) Importers - % change in total imports



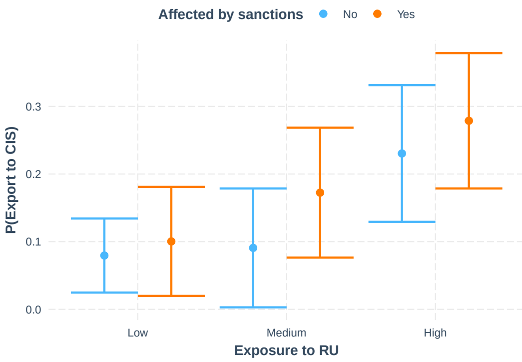
(c) Exporters - Probability of fewer # markets



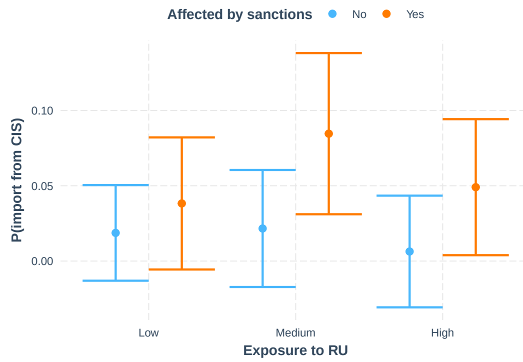
(d) Importers - Probability of fewer # markets

Note: These figures display the predicted change in total export/import (upper panels) and the predicted probability to experience a decrease in total number of foreign market served, holding the control variables at their mean values. In each panel, the predicted outcome is shown for three different levels of exposure to Russia. Low, Medium and High exposure to Russia respectively indicate a share of trade with Russia in turnover lower than 5%, between 5 and 25%, and larger than 25% in 2021. "Affected by sanctions" indicates whether a firm traded in 2021 goods subsequently on the sanction list. The vertical bars represent the 90% confidence intervals.

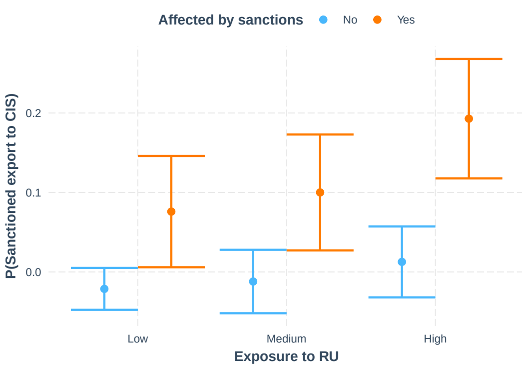
Figure C.4: Trade partners - Categorical



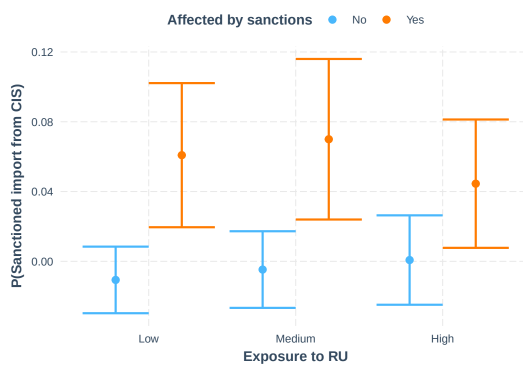
(a) Probability to start exporting to CIS



(b) Probability to start importing from CIS



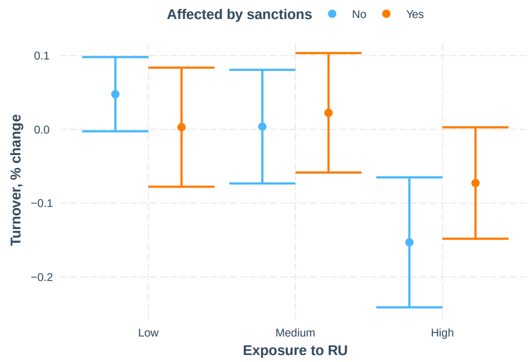
(c) Probability to start exporting sanctioned goods to CIS



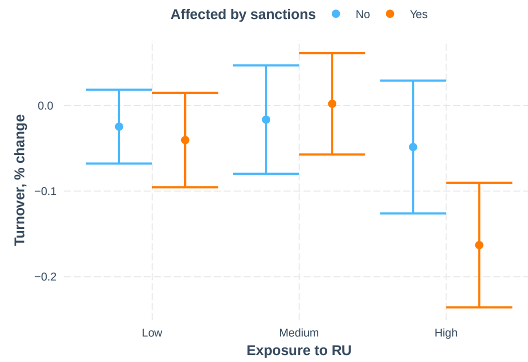
(d) Probability to start importing sanctioned goods from CIS

Note: These figures display the predicted probability of beginning trade with CIS countries (upper panel) and the predicted probability of beginning trade of sanctioned goods with CIS countries (lower panel), holding the control variables at their mean values. In each panel, the predicted outcome is shown for three different levels of exposure to Russia. Low, Medium and High exposure to Russia respectively indicate a share of trade with Russia in turnover lower than 5%, between 5 and 25%, and larger than 25% in 2021. "Affected by sanctions" indicates whether a firm traded in 2021 goods subsequently on the sanction list. The vertical bars represent the 90% confidence intervals.

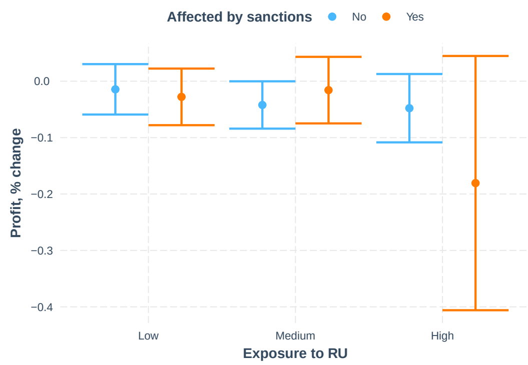
Figure C.5: Firms' response - Other margins



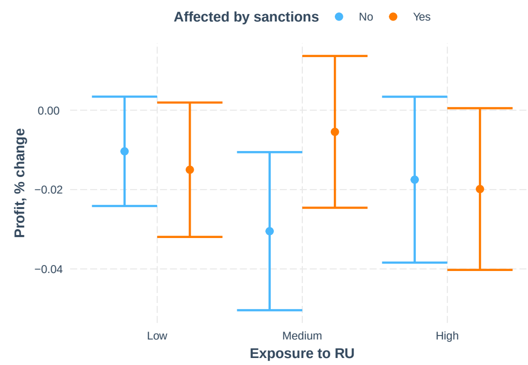
(a) Exporters - % change in turnover



(b) Importers - % change in turnover



(c) Exporters - % change in profitability

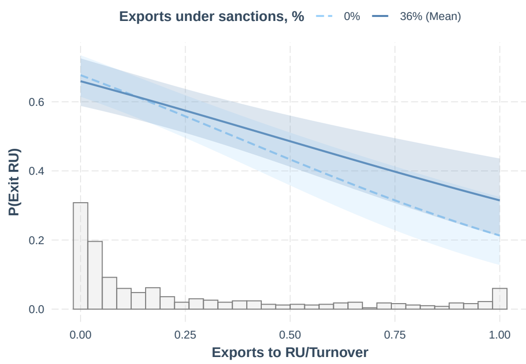


(d) Importers - % change in profitability

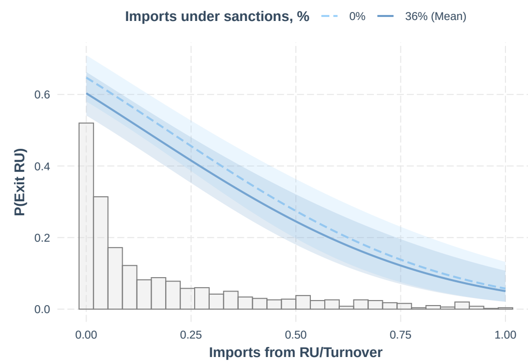
Note: These figures display the predicted percentage change in turnover (upper panel) and in profitability (profit/turnover, lower panel), holding the control variables at their mean values. In each panel, the predicted outcome is shown for three different levels of exposure to Russia. Low, Medium and High exposure to Russia respectively indicate a share of trade with Russia in turnover lower than 5%, between 5 and 25%, and larger than 25% in 2021. "Affected by sanctions" indicates whether a firm traded in 2021 goods subsequently on the sanction list. The vertical bars represent the 90% confidence intervals.

D Appendix: Probit specification

Figure D.1: Exiting Russia



(a) Exporters - Probability to exit Russia



(b) Importers - Probability to exit Russia

Note: These figures display the predicted probability of exiting the Russian market estimated from a probit model, holding the control variables at their mean values. In each panel, the predicted outcome is shown for three different levels of exposure to Russia. Low, Medium and High exposure to Russia respectively indicate a share of trade with Russia in turnover lower than 5%, between 5 and 25%, and larger than 25% in 2021. "Affected by sanctions" indicates whether a firm traded in 2021 goods subsequently on the sanction list. The vertical bars represent the 90% confidence intervals.

E Appendix: Monthly level regressions

Table E.1: Probability to close - Exporters

Employment, % change Jan-	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
RU Exposure	0.009	0.009	0.003	0.014	0.030 **	0.030 **	0.038 **	0.045 **	0.062 ***	0.062 ***
	(0.005)	(0.005)	(0.010)	(0.011)	(0.013)	(0.013)	(0.017)	(0.017)	(0.019)	(0.019)
Share sanction	-0.003	-0.003	-0.008	-0.008	-0.009	-0.009	-0.009	0.002	-0.001	-0.001
	(0.005)	(0.005)	(0.010)	(0.011)	(0.014)	(0.014)	(0.017)	(0.018)	(0.019)	(0.019)
RU exposure * Share sanction	-0.019	-0.019	-0.008	-0.004	-0.002	-0.002	0.043	0.127 **	0.108 *	0.108 *
	(0.017)	(0.017)	(0.032)	(0.037)	(0.044)	(0.044)	(0.055)	(0.057)	(0.061)	(0.061)
N	614	614	614	614	614	614	614	614	614	614
R2	0.013	0.013	0.010	0.022	0.027	0.027	0.030	0.038	0.046	0.046

*** p < 0.01; ** p < 0.05; * p < 0.1.

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. All regressions are weighted by firm's average turnover 2020-2021 and include the following set of controls: firm age, sector, labor share, and profitability. The interacted variables are centered.

Table E.2: EMPLOYMENT CHANGE - EXPORTERS

Employment, % change Jan-	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
RU Exposure	-0.002	-0.018	-0.073 ***	-0.098 ***	-0.124 ***	-0.131 ***	-0.126 ***	-0.114 ***	-0.127 ***	-0.132 ***	-0.144 ***
	(0.009)	(0.015)	(0.019)	(0.022)	(0.026)	(0.030)	(0.033)	(0.032)	(0.034)	(0.036)	(0.038)
Share sanction	0.008	0.016	0.015	0.046 **	0.043 *	0.050 *	0.045	0.031	0.012	0.011	0.007
	(0.009)	(0.015)	(0.019)	(0.022)	(0.026)	(0.030)	(0.033)	(0.032)	(0.034)	(0.036)	(0.038)
RU exposure * Share sanction	0.003	0.001	0.026	0.024	0.021	0.014	0.001	0.001	0.007	-0.036	-0.009
	(0.030)	(0.050)	(0.062)	(0.072)	(0.086)	(0.099)	(0.108)	(0.105)	(0.113)	(0.119)	(0.125)
N	601	601	601	601	601	601	601	601	601	601	601
R2	0.004	0.007	0.032	0.044	0.048	0.046	0.035	0.034	0.041	0.044	0.047

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

NOTE: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. All regressions are weighted by firm's average turnover 2020-2021 and include the following set of controls: firm age, sector, labor share, and profitability. The interacted variables are centered.

Table E.3: Probability to close - Importers

Employment, % change Jan-	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
RU imposure	0.005	0.005	0.014	0.016	0.014	0.024 *	0.037 **	0.032 *	0.027	0.027
	(0.007)	(0.007)	(0.010)	(0.011)	(0.013)	(0.013)	(0.016)	(0.017)	(0.018)	(0.018)
Share sanction	0.007 **	0.007 **	0.004	0.007	0.014 **	0.016 **	0.013 *	0.014 *	0.011	0.011
	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)	(0.007)	(0.008)	(0.008)	(0.009)	(0.009)
RU imposure * Share sanction	0.017	0.017	0.002	0.017	0.023	0.063 **	0.037	0.040	0.046	0.046
	(0.014)	(0.014)	(0.020)	(0.022)	(0.026)	(0.027)	(0.032)	(0.035)	(0.037)	(0.037)
N	957	957	957	957	957	957	957	957	957	957
R2	0.009	0.009	0.005	0.009	0.014	0.025	0.025	0.023	0.022	0.022

*** p < 0.01; ** p < 0.05; * p < 0.1.

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. All regressions are weighted by firm's average turnover 2020-2021 and include the following set of controls: firm age, sector, labor share, and profitability. The interacted variables are centered.

Table E.4: Employment change - Importers

Employment, % change Jan-	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
RU Exposure	-0.012	-0.008	0.014	0.019	0.011	0.045	0.021	0.025	0.020	-0.001	0.026
	(0.011)	(0.020)	(0.024)	(0.028)	(0.034)	(0.039)	(0.042)	(0.044)	(0.046)	(0.048)	(0.049)
Share sanction	-0.001	-0.008	-0.010	-0.013	-0.003	0.001	-0.003	-0.010	-0.006	0.004	-0.001
	(0.005)	(0.010)	(0.012)	(0.014)	(0.016)	(0.019)	(0.020)	(0.022)	(0.023)	(0.023)	(0.024)
RU exposure * Share sanction	0.009	-0.018	-0.065	-0.065	-0.147 **	-0.243 ***	-0.230 ***	-0.234 **	-0.223 **	-0.191 *	-0.206 **
	(0.023)	(0.041)	(0.050)	(0.058)	(0.069)	(0.080)	(0.086)	(0.091)	(0.095)	(0.098)	(0.102)
N	942	942	942	942	942	942	942	942	942	942	942
R2	0.005	0.006	0.008	0.008	0.010	0.017	0.019	0.021	0.021	0.018	0.023

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. All regressions are weighted by firm's average turnover 2020-2021 and include the following set of controls: firm age, sector, labor share, and profitability. The interacted variables are centered.