

Conflict and Inter-Group Trade: Evidence from the 2014 Russia-Ukraine Crisis*

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November 2019

Abstract

Does armed conflict reduce trade even in non-combat areas through the destruction of inter-group social capital? We analyze Ukrainian trade transactions before and after the 2014 Russia-Ukraine conflict. In a difference-in-differences framework, we find that Ukrainian firms from districts with fewer ethnic Russians experienced a deeper decline in trade with Russia. This decline is economically significant, persistent, and explained by erosion of trust and the rise of local nationalism. Affected Ukrainian firms suffered a decrease in performance and diverted trade to other countries. Our results suggest that, through social effects, conflict can be economically damaging even away from combat areas.

JEL: D22, D74, F14, F51, H56

Keywords: Conflict, Inter-Group Tensions, Trade, Firms

*We are indebted to Nancy Qian, Lori Beaman, Georgy Egorov, Nicola Persico, and Chris Udry for the extremely helpful advice and encouragement. We would also like to thank Costas Arkolakis, Sandeep Baliga, Michal Bauer, Chris Blattman, Joshua Blumenstock, Julie Chytilová, Christian Dippel, Paul Dower, Konstantin Egorov, Scott Gehlbach, James Fearon, Tim Feddersen, Eliana La Ferrara, Stefano Fiorin, Raymond Fisman, Renata Gaineddenova, Luigi Guiso, Hanwei Huang, Seema Jayachandran, Dean Karlan, Cynthia Kinnan, Martí Mestieri, Joel Mokyr, Ameet Morjaria, Melanie Morten, Natalya Naumenko, Jordan Norris, Sam Norris, Michael Poyker, Ken Shotts, Egor Starkov, Vladimir Tyazhelnikov, and Romain Wacziarg for useful comments. We are grateful to the seminar participants at the CERGE-EI, Collegio Carlo Alberto, Compass Lexecon Chicago, EIEF, Higher School of Economics, IOS Regensburg, New Economic School, Northwestern University, Queen Mary University of London, Stockholm School of Economics SITE, Toulouse School of Economics, and to the conference participants at PacDev 2018, Ph.D. Conference at the University of Leicester, Strategy and Business Environment Conference at Wharton School of Business, DEVPEC 2018, ICSID Political Economy Conference, Wisconsin Russia Project Young Scholars Conference, NEUDC 2018, University of Chicago Development Day, MPSA 2019, and SIOE 2019 for helpful discussions. Artem Ilyin, Eugene Kosovan, Olga Tokariuk, and Serhij Vasylenko provided invaluable insights regarding the context. We are grateful to the Harriman Institute at Columbia University, Czech Science Foundation (GACR), and the UCLA Anderson Center for Global Management for financial support.

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1 Introduction

Assessing the economic consequences of conflict is a central problem in development economics and political economy. Past studies have thoroughly examined the multifaceted effects of direct exposure of individuals to violence (Blattman and Miguel, 2010). Potential ramifications of conflict, however, may also extend to areas not directly experiencing combat. This points to a considerable gap in the literature, given that at least 2.66 billion people live outside the warzones of their own conflict-ridden countries.¹ Moreover, if non-combat areas are affected, the traditional estimates obtained by comparing regions with and without violent events within the same country (e.g., Abadie and Gardeazabal, 2003) may differ from the total economic costs of conflict.

We focus on one important indirect consequence of conflict: namely, its impact on inter-group trade. Recent theoretical research hypothesizes that wars may reduce trade not only by destroying physical capital but also by elevating out-group hostility and eroding inter-group trust (Rohner, Thoenig, and Zilibotti, 2013b).² And yet, finding evidence of the latter effect has been challenging. This is partly because conflict-ridden countries do not possess high-quality micro-level data on trade, and partly due to a lack of credible identification strategies that would allow one to disentangle the rise of inter-group tensions from the physical effects of violence. Using transaction-level trade data and focusing on non-combat areas, this paper is the first to document the breakdown of trade through the erosion of inter-group relations. Furthermore, we explore whether such disruption is lasting and economically meaningful and study the underlying mechanisms.³

The 2014 Russia-Ukraine conflict provides a natural laboratory for this study. First, armed combat in this context has been isolated to a few locations; most Ukrainian territory and a large part of the Russia-Ukraine border have not been affected by violence. This feature allows us to focus on non-combat areas and abstract from such direct effects as the destruction of physical capital. Second, since it has been a proxy conflict as opposed to a full-fledged war, trade has

¹As of 2016, conflict-ridden countries contain 50% of the world's population (Bahgat, Dupuy, Østby, Rustad, Strand, and Wig, 2018, p.19). At the same time, the number of people living within a 50-kilometer radius of conflict events is estimated to be 840 million, or 12% of the world's population (Bahgat et al., 2018, p.21). This means that at least 2.66 billion people live in countries with an ongoing conflict but are not affected by violence directly.

²For the purposes of this paper, we unify these two objects—i.e., accumulated stock of affinity and trust between social groups—under the label of “inter-group social capital.” This definition of social capital closely follows the original definition by Hanifan (1916) “those tangible assets [that] count for most in the daily lives of people: namely goodwill, fellowship, sympathy [...] among the individuals and families who make up a social unit.” Our concept of inter-group social capital is also close to the “bridging” social capital by Putnam (2000), which is defined as social capital between groups in contrast to the “bonding” or intra-group social capital.

³Most closely related research has documented the importance of conflict-induced inter-group frictions for team productivity (Hjort, 2014), lending (Fisman, Sarkar, Skrastins, and Vig, 2019), and court decisions (Shayo and Zussman, 2011).

not ceased and the tariff environment has not changed.⁴ In fact, Russia has remained Ukraine's largest trading partner. This allows us to analyze Russia-Ukraine trade transactions even after the start of the conflict. Finally, given the ethnically charged nature of the conflict, the presence of a large, spatially dispersed Russian minority within Ukraine allows us to isolate the impact on trade between ethnic groups. We complement these features with new data on the universe of international trade transactions of all Ukrainian firms from 2013 through 2016 in tandem with firms' balance sheets and census characteristics of their home districts.

To causally establish whether trade was disrupted along ethnic lines after the start of the conflict, we employ a difference-in-differences identification strategy. We compare outcomes before and after the onset of conflict in February 2014 across Ukrainian districts (*raiony*) with a higher versus lower percentage of ethnic Russians. In this specification, firm fixed effects control for time-invariant differences across regions, such as geographic characteristics, or slow-moving features, such as culture. Time-period fixed effects control for changes that affect all regions similarly, such as macroeconomic changes in Ukraine or trade restrictions that affect Russia-Ukraine trade as a whole.⁵ Our identification strategy assumes that, absent the conflict, firm trade patterns in areas with varying presence of ethnic Russians would have evolved along parallel trends. Later in the paper, we present evidence supporting this parallel-trends assumption.

The key finding of the present study is that a decline in trade between Ukrainian firms and Russia was differential depending on the ethnic composition of the firms' home areas. That is, we find that firms located in less ethnically Russian districts of Ukraine decreased their trade with Russia by a larger margin. According to our estimates, moving an average firm from a district comprised of 17.7% ethnic Russians (75th percentile) to a district comprised of 9.6% ethnic Russians (25th percentile) would deepen the decline in monthly probability of trade with Russia by 12% and the monthly volume of trade with Russia by 15%.⁶ Month-by-month estimates report no evidence of pre-trends and indicate that the effect remains large and significant long after the start of the conflict. Our back-of-the-envelope calculations suggest that this indirect effect may have accounted for a total loss of up to US\$1 billion in mutual trade, equivalent to 2.5% of the

⁴As members of the Commonwealth of Independent States Free Trade Agreement (CISFTA), Russia and Ukraine continued to have zero tariffs on a vast majority of goods. Tariffs went up only in January 2016, when Russia and Ukraine ceased to respect CISFTA regulations regarding trade with each other. Our results are robust to excluding the 2016 data.

⁵Overall, the conflict has had a detrimental effect on trade between Russia and Ukraine. The percentage of Ukrainian exports to Russia plummeted after the start of the conflict from 25.7% in 2012 to 9.9% in 2016. Likewise, the share of Russian goods among all Ukrainian imports fell from 32.4% in 2012 to 13.1% in 2016. Still, the countries remained important trading partners.

⁶Similar results are observed among the share of the district population that considers Russian its mother tongue.

pre-conflict Russia-Ukraine trade volume, or 0.5% of the pre-conflict GDP of Ukraine.

Next, we examine the mechanisms through which conflict reduces inter-group trade in non-combat areas. Our central claim is that conflict damages inter-group social capital—i.e., goodwill between social groups accumulated over the course of history, —which may then disrupt inter-group trade. Deterioration of inter-group social capital manifests itself through the following channels. First, conflict may lead to animosity and erosion of trust between trading partners. Second, it may also affect the attitudes of the general population, leading to a decline in consumer demand for the other group’s products and reputational damage to firms trading with the enemy. Finally, conflict may further induce bias on the part of government bureaucrats at the border. While Rohner et al. (2013b) present a theory for how conflict may disrupt inter-group trade via reduced trust, supporting empirical evidence is lacking. Neither has the importance of bureaucratic bias and animosity between firms’ key decision makers for firm-level trade been addressed. Overall, we find strong support for erosion of trust and consumer boycotts, and some evidence in favor of reputational pressure on Ukrainian firms. We find no evidence of individual-level animosity and discrimination based on ethnicity at the border.

To investigate the trust channel, we highlight variation in contracts used by firms and corresponding timings of payments. There are two major types of contracts in international trade: open account (OA) contracts, in which exporters are paid after goods are delivered, and cash-in-advance (CIA) contracts, in which exporters are paid before goods are shipped. To circumvent the lack of information on contracts in our dataset, we use product-level data on trade contracts between Russian, Ukrainian, and Turkish firms from 2004 through 2011. These data allow us to measure predicted types of contracts used by firms based on the products they trade. We show that the differential effect of conflict across ethnicity is larger for Ukrainian exporters with a higher likelihood of using OA contracts, which leave them exposed to the risk of nonpayment. Conversely, the differential drop in trade is more pronounced for importers with a higher likelihood of using CIA contracts, leaving them vulnerable to the risk of never receiving the product in question. The above suggests that a differential decline in trust indeed plays a role in our results, providing incentives for Ukrainian firms from less ethnically Russian areas to stop trading with Russian firms.

Next, using survey data on social attitudes of the general population, we show that conflict led to a dramatic rise of nationalism along ethnic lines. That is, within Ukraine and outside of the combat areas, antipathy toward Russia skyrocketed immediately after the occupation of Crimea, but significantly more so among ethnic Ukrainians than ethnic Russians. Moreover, the differences in attitudes across ethnicity remained wide throughout the period of our analytical interest.

We argue that the rise of local ethnic nationalism reduces trade through consumer action and reputational pressure. As evidence for consumer action, we show that the differential effect is more pronounced for firms trading consumer goods than for those trading intermediate goods. Furthermore, using Google Trends data, we show that the word *boycott* was significantly more popular in online searches in regions with fewer ethnic Russians and that the differential effect of conflict is stronger in regions where *boycott* searches were more prevalent. These findings are consistent with the qualitative evidence documenting that 40–50% of Ukrainians reported taking part in a boycott campaign against Russian products. Albeit more suggestive, we also document an ample body of anecdotal evidence consistent with the reputational pressure faced by large Ukrainian firms. We also present indirect evidence supporting this hypothesis, showing that the differential effect for intermediate products comes almost entirely from large firms, which are traditionally viewed in the literature as more susceptible to activism and which can afford corporate social responsibility (CSR) initiatives (Perrini, Russo, and Tencati, 2007; Smith, 2013).

We find no support for other mechanisms that could might *a priori* be at work. For example, the rise in individual-level animosity between firms' key decision makers might have led to disruptions of trade ties. To address this possibility, we classify the surnames of Ukrainian firm managers into traditionally Russian and non-Russian categories. Our results indicate that firms with different shares of Russian-surnamed managers do not differ in their reaction to the conflict. Instead, the share of ethnic Russians in the district itself plays a critical role. In addition, we find no evidence of discrimination at the border, as there is no differential effect for trade between Ukrainian firms and Kazakhstan, which must pass through the Russia-Ukraine border.

The final part of this paper takes full advantage of the granularity and richness of our data to investigate how firms respond to the reduction of trade with Russia. First, we show that the breakdown of trade along ethnic lines has indeed been costly for Ukrainian firms. In a triple-difference specification with *all* Ukrainian firms, not only those engaged in international trade, we show that firms trading with Russia before the start of the conflict yet located in less ethnically Russian areas of Ukraine experienced a greater loss of sales, profits, and productivity relative to their counterparts. In addition, we document that firms accommodated this shock by trading with other countries. For instance, we find that firms from less Russian areas differentially increased their trade with Turkey and Poland. Furthermore, the baseline effect is strongest for Ukrainian firms with the lowest switching costs. Overall, these results suggest that conflict-induced decline in inter-group trade has serious economic implications for firms and their trade network.

We consider and rule out the most self-evident alternative explanations for our baseline results.

The first concern is that less ethnically Russian areas of Ukraine may be affected by the conflict differently because they are farther from the Russia-Ukraine border. We account for this possibility by including highly flexible controls for firms' distance to the Russian border. The second concern is that areas with a smaller Russian minority could have specialized in products that have been disproportionately affected by the conflict and subsequent events. We address this concern by including the product-post fixed effects in a granular firm-product-month-level specification. Finally, one may also conjecture that firms in more Russian areas took a smaller overall economic hit as a result of the conflict. For instance, it could be that these areas hosted more refugees, which may have generated positive labor supply and demand shocks. We show that this is not the case in a triple-difference multi-country specification in which trade with other countries allows us to include the district-post fixed effects.⁷

We add to the literature on the microeconomic consequences of inter-group frictions induced by armed conflict. Rohner et al. (2013b) theoretically argue that violent conflict may lead to a reduction in trust and, as a result, reduce inter-group trade even in non-combat areas.⁸ This paper is the first to empirically test and find support for this prediction at the micro-level, as well as examine other possible mechanisms through which inter-group trade may decline. Previous studies document that conflict reduces generalized trust (Rohner, Thoenig, and Zilibotti, 2013a) and strengthens group identity at a cost of elevated outgroup bias (Campante and Yanagizawa-Drott, 2015; Bauer, Blattman, Chytilová, Henrich, Miguel, and Mitts, 2016; Dell and Querubin, 2018). In turn, these biases curtail the productivity of inter-ethnic teams (Hjort, 2014) and lead to inter-group discrimination in institutions crucial for economic activity, such as courts (Shayo and Zussman, 2011), stock exchanges (Moser, 2012), and banks (Fisman et al., 2019).

We also contribute to the literature on armed conflict and firms, which remains sparse. Our paper is the first to document a negative impact of conflict on business transactions and firm per-

⁷In all the examples given above, the robustness checks were meant to account for omitted variables correlated with the ethnic composition of Ukraine. Some of those same robustness checks, however, may also address the issue of omitted events—simultaneous with but not directly related to the Russia-Ukraine conflict. For instance, the product-post fixed effects address any contemporaneous industry-specific shocks unrelated to armed conflict, such as the unilateral elimination of the E.U. import tariffs for Ukrainian products in April 2014. Similarly, the district-post fixed effects in a multi-country specification take care of any simultaneous local shocks that may occur due to the Ukrainian revolution (e.g., à la Earle and Gehlbach (2015)). Additional robustness checks rule out a few other explanations. For instance, our results are not due to redirection of contracts by the Ukrainian government after the revolution in the spirit of Berger, Easterly, Nunn, and Satyanath (2013) and Fisman, Hamao, and Wang (2014), as we show that state-owned firms are not driving our results.

⁸Previous research has shown that, in addition to formal rules, trade relies on trust and informal norms (Nunn, 2007; Guiso, Sapienza, and Zingales, 2009; Jha, 2013), which are, in turn, easier to sustain within groups of similar ethnicity (Greif, 1993; Fershtman and Gneezy, 2001; Rauch and Trindade, 2002). This paper provides the first causal micro-level evidence for what happens to economic exchange when inter-group relations are disrupted.

formance in non-combat areas. Previous studies on the economic effects of conflict on firms focused almost entirely on the direct effects of violence. Guidolin and La Ferrara (2007) provide time-series evidence that a breakout of civil war in Angola decreased the stock market value of firms operating in the country. Ksoll, Macchiavello, and Morjaria (2014) analyze the effect of violence on nearby exporters in Kenya that resulted, among other things, in a sharp increase in worker absence. Amodio and Di Maio (2017) show that Palestinian firms in violent areas substituted domestically produced materials for imported ones during the Second Intifada.⁹

The rest of this paper is organized as follows. Section 2 gives the historical background on ethnic divisions in Ukraine and on Russia-Ukraine trade. Section 3 describes the empirical strategy and the data. Section 4 displays our baseline difference-in-differences results, rules out some of the alternative explanations, and offers additional robustness checks. Section 5 studies the mechanisms behind our baseline results. Section 6 explores the consequences of this indirect effect for firms' overall sales, profits, and productivity. Section 7 concludes.

2 Background

2.1 Ethnic, Cultural, and Political Divisions Within Ukraine

Historically, many regions of Ukraine have had a sizable Russian minority. The number of Russians in Ukraine substantially increased during the Soviet era, reaching its peak, 11.3 million or 22.1% of the total population, in 1989. This share decreased after the fall of the Soviet Union, down to 17.2% by 2001, but the country's ethnic and cultural divide is still pronounced, spilling over into the political sphere.

Figure 1 displays the geographical variation in the share of ethnic Russians across Ukrainian districts (*raions*).¹⁰ In Western Ukraine, many districts have very few ethnic Russians, often less than 1%. Central and Southern Ukraine have a sizable Russian population, varying from 1% to 20%. Finally, the eastern part of the country has the highest percentage of ethnic Russians; while Crimea and some other areas actually have a Russian majority. Use of the Russian language exhibits a similar geographic divide: in 2001, 29.6% of Ukrainian citizens considered Russian their mother tongue and approximately 60% used it at home on a daily basis, with substantial

⁹Although this paper is focused on armed conflict, it adds to the literature on political disputes and consumer boycotts (Pandya and Venkatesan, 2016; Fouka and Voth, 2016), as well as the resulting breakdown of business-to-business trade (Michaels and Zhi, 2010; Fisman et al., 2014). It is first to bring micro-level data on trade transactions to this literature, which allows for a more granular analysis of the mechanisms.

¹⁰These data come from the latest census of the Ukrainian population concluded in 2001. The Ukrainian government has not conducted a census since then, due to financial issues.

Figure 1: Shares of Ethnic Russians



Notes: This figure maps the distribution of the share of ethnic Russians across Ukrainian districts (raions). Data are from the latest census of Ukrainian population, conducted in 2001. The thick black line represents the border between Ukraine and Russia.

heterogeneity across regions.¹¹

The ethnic and cultural divide manifested itself in a constant political battle between the Ukrainian west and the “Russian” east prior to 2014. The western part of the country traditionally supported pro-European and nationalistic political candidates, while Eastern Ukraine generally supported pro-Russian candidates. Figures A2 and A3 in the Online Appendix illustrate this political polarization, showing strikingly segregated voting patterns in the 2004 presidential elections (second round) and the 2012 parliamentary elections. This political divide, fueled by the interference of the Russian government, has been one of the reasons for the political instability in the country. During the Orange Revolution of 2004, the pro-European Victor Yushchenko beat the pro-Russian candidate, Victor Yanukovich, to become the president of Ukraine from 2005 to 2010. However, Yanukovich won in 2010 and was the president until the revolution in February 2014, when he lost power and was replaced first by an interim president Oleksandr Turchynov, and ultimately by the current president, Petro Poroshenko, who was elected on 25 May 2014.¹²

2.2 The Russia-Ukraine Conflict (2014–)

The transition of power to President Petro Poroshenko was a result of the 2014 Ukrainian revolution. In November 2013, the president of Ukraine, Victor Yanukovich, walked back his promise to enter a political and economic association with the European Union. This step led to

¹¹See Figure A1 in the Online Appendix for the geographic distribution across Ukrainian districts of the percentage of people who consider Russian language their mother tongue.

¹²This pattern is highly consistent with the conflict literature that would predict that ethnic and linguistic divisions coupled with the centralized structure of the Ukrainian state would lead to a tug-of-war and, eventually, social conflict (Esteban and Ray, 2008, 2011; Esteban, Mayoral, and Ray, 2012).

massive protests in Kyiv and their violent suppression by Yanukovich’s police forces, on November 29, 2013. Protests spread across the country over the next several months. After several deadly clashes between protesters and the police, Victor Yanukovich fled to Russia on February 22, 2014, and, at that point, the revolution had succeeded.

In response, the Russian government decided to occupy Crimea and started promoting separatist movements in Eastern Ukraine, justifying its actions by the need to protect the ethnic Russian minority. The decision to occupy Crimea was made secretly by Vladimir Putin and a handful of senior security advisors, and took everyone else by surprise (Treisman, 2018). Although it was widely understood that the military units in Crimea bearing no identifying markings were Russian, the occupation of Crimea was a covert operation and did not lead to a formal war. Vladimir Putin did not admit Russian involvement until April 2014. The annexation of Crimea in late February 2014–early March 2014 occurred without direct military conflict.

After the revolution and the occupation of Crimea, pro-Russian protests ensued in the Donetsk and Luhansk provinces (i.e., Donbass region). Eventually, these areas proclaimed their independence from Ukraine, forming the Donetsk People’s Republic (DPR) on April 7, 2014, and the Luhansk People’s Republic (LPR) on April 27. In response, the new acting Ukrainian president launched an “antiterror” operation against these separatist movements. Russia started supporting the DPR and LPR, providing military power among other things. A long-lasting civil conflict ensued, leading to more than 13,000 casualties (as of December 2018) and the displacement of hundreds of thousands of people.

Figure 2 shows the areas directly affected by the conflict. These include Crimea (in light red at the bottom) and two quasi-independent states of the Donetsk and Luhansk People’s Republics (in dark red). We exclude the firms located in these regions from our analysis. We also do not consider firms located in the rest of the Donbass region (in light red to the right). We do this because these areas were located next to the war zones and could have been facing some violence or experiencing severe uncertainty about whether they will face violence in the future. While the conflict was intense in some of the DPR and LPR territories, the rest of the country and of the Russia-Ukraine border was not exposed to violence directly.

2.3 Russia-Ukraine Trade

Ever since the fall of the Soviet Union, Russia and Ukraine have been major trading partners. In September 2012, together with eight other post-Soviet nations, the two countries formed the Commonwealth of Independent States Free Trade Area (CISFTA). Under CISFTA, all export and

Figure 2: Conflict Areas



Notes: The figure highlights the areas directly affected by the Russia-Ukraine conflict. The Crimean Peninsula, in light red at the bottom, was occupied by Russia in early 2014. The Donetsk People's Republic (DPR) and Luhansk People's Republic (LPR) territories, in dark red, have been the areas of armed conflict since April 2014. The Donbass area, in light red on the right side of the graph, consists of the Donetsk and Luhansk provinces. Our analysis in this paper focuses on the rest of the country, in white, excluding the areas mentioned above. The thick black line represents the border between Ukraine and Russia.

import tariffs were set to zero, with very few exceptions.¹³ The tariffs went up only in January 2016, two years after the start of the conflict, when Russia and Ukraine stopped respecting the CISFTA regulations regarding trade with each other.¹⁴

The conflict led to a massive shock to Russia-Ukraine trade. The percentage of Ukrainian exports going to Russia plummeted after the start of the conflict, from 25.7% in 2012 to 9.9% in 2016. Likewise, the share of Russian goods among all Ukrainian imports fell from 32.4% in 2012 to 13.1% in 2016. Despite such a severe decline, Russia remained Ukraine's largest trading partner. The role of Ukraine in Russian international trade also remained significant.¹⁵ Notably, the volume of Russia-Ukraine trade increased in 2017 relative to 2016, marking the first annual increase since the start of the conflict.

¹³White sugar was the only product for which Russia and Ukraine had nonzero import tariffs.

¹⁴In January 2016, Ukraine formally entered the economic association with the E.U., which lowered tariffs for both parties. However, earlier in late April 2014, the European Union had unilaterally eliminated import tariffs for Ukrainian goods as an act of diplomatic and economic support. Note, however, that this would not affect our main results because we account for product-specific post-conflict shocks, which would absorb any changes in tariffs. See Section 4.2 for details.

¹⁵Ukraine was the fifth-largest exporter to Russia in 2011, with 5.8% of all goods imported to Russia coming from Ukraine. This share dropped to 2.3% after the start of the conflict; by 2014, Ukraine had become the eleventh-largest exporter to Russia. Russia has traditionally imported a wide variety of products from Ukraine, including machines and engines, chemicals, paper, agriculture, processed food, iron, and steel.

3 Empirical Strategy and Data

3.1 Baseline Specification

The general goal of our empirical strategy is to identify the consequences of the Russia-Ukraine conflict for inter-group trade. To identify the effect of interest, we employ a difference-in-differences approach. That is, we compare firms' trade intensity with Russia before and after the start of the conflict, for firms located in more versus less ethnically Russian districts within Ukraine (but outside the conflict areas).¹⁶ Specifically, we estimate the following equation:

$$Y_{idt} = \alpha_i + \delta_t + \beta \times \text{Rus}_d \times \text{Post}_t + \epsilon_{idt}, \quad (1)$$

where the outcome variable Y_{idt} is the trade intensity of firm i from district d with Russia, at year-month t ; α_i and δ_t are the firm and year-month fixed effects, respectively; Rus_d is the share of ethnic Russian or native Russian-speaking population in the district d of firm i ; and Post_t is the post-February 2014 indicator.¹⁷ To the extent that trade patterns for firms in more and less Russian areas would follow the same time trend absent the conflict, the coefficient β identifies the differential impact of conflict on inter-group trade.

In our baseline results, since we are interested in firm's overall trade intensity with Russia, we study the firm's export and import transactions summed together, i.e., $Y_{idt} = Y_{idt}^{\text{exp}} + Y_{idt}^{\text{imp}}$. However, we present the results for exports and imports separately when we study the mechanisms.

Since our main right-hand-side variable, the share of ethnic Russians, is measured at the level of Ukrainian districts (raions), we cluster the standard errors at the district level. Note, however, that our results are robust to the spatial HAC standard errors (Conley, 1999).¹⁸

3.2 Data Sources

Our empirical analysis combines administrative data on Ukrainian trade transactions with demographic census and firm-level accounting information. In addition, we examine a repeated nationally representative survey to track changes in popular opinion before and after the start of the conflict.

¹⁶This analysis treats Russia as homogeneous. While Russia is home to many ethnic minorities, as of 2010, 80.9% of its population was of Russian ethnicity, with ethnic Tatars at 3.9%, and all other minorities not exceeding 2% each. We also note that, at the start of the conflict, there were relatively few ethnic Ukrainians in Russia (1.4% as of 2010), with only 0.82% of the Russian population speaking Ukrainian.

¹⁷Note that the stand-alone coefficients on Rus_d and Post_t are absorbed by the firm and year-month fixed effects, respectively.

¹⁸See Table A2 for the baseline estimates with Conley spatial HAC standard errors.

The customs dataset includes the universe of Ukrainian trade transactions with dates, weights, values (in Ukrainian hryvnia), and product codes of each export and import transaction, as well as the tax IDs of the Ukrainian trading firms. Both export and import data are from January 2013 through December 2016. Unfortunately, the information on exports is missing for five months from February through June 2014. However, our findings are robust to excluding these five months from the analysis and to imputing exports data in various ways (see Table A3). Moreover, our baseline results hold for export and import transactions separately (see Table A4).¹⁹ In total, the trade dataset contains 21.6 million transactions, 2.2 million of which are with Russia. For most of our results, we focus on trade with Russia and collapse the data at the firm-month level.

Crucially, our trade dataset contains the addresses of the Ukrainian trading firms. This feature, rarely available for similar customs datasets, allows us to merge trade transactions with various characteristics of the firm’s home district, including its ethnolinguistic composition. Data on the ethnolinguistic composition of the districts (*raions*) come from the latest Ukrainian Census, conducted in 2001. From this census, we obtain district-level data on the share of ethnic Russians and the share of local population who consider Russian their mother tongue.

Using tax IDs of Ukrainian firms, another feature infrequently available in analogous datasets, we merge trade transactions with the ORBIS/AMADEUS database. Available for 2011–2016, this dataset contains the accounting information, including total sales, profits, inputs, number of employees, etc. It also includes names of the firms’ managers, which we merge and use to calculate a proxy for the prevailing ethnicity of the firms’ key decision-makers. We introduce our name classification methods in Section 5.2. In total, the ORBIS/AMADEUS dataset contains information on more than 460,000 Ukrainian firms, i.e., the near universe of firms that are obliged to hand their accounting information over to the Ukrainian government based on their organizational form.²⁰

Based on the ten-digit HS product code available for every trade transaction, we categorize each transaction based on the type of product traded. For instance, using the correspondence tables between the HS and BEC codes, we classify each entry as an intermediate good or consumer good transaction.²¹ Similarly, using the methodology in Rauch (1999), we categorize each transaction as

¹⁹Note that, although the coefficients for imports are smaller in magnitude, the baseline decline in trade was also bigger for exports than for imports (see Table 1). Thus, in the end, the relative magnitudes are similar.

²⁰As one can see from Table A.1 in Kalemli-Ozcan, Sorensen, Villegas-Sanchez, Volosovych, and Yesiltas (2015), Ukrainian filing requirements are one of the most demanding in the world. Similar to other countries, individual entrepreneurs are not subject to these requirements and are absent from the database. Although we are unaware of any estimates of the ORBIS/AMADEUS coverage for Ukraine, in a neighboring country with similar, if not more lenient, filing requirements, as well as similar culture and institutions — Romania —, ORBIS/AMADEUS database was found to cover 92% of gross output and 93% of total employment in the manufacturing sector (Kalemli-Ozcan et al., 2015).

²¹We use the official conversion table between HS 2012 and BEC 4 product codes, available

involving differentiated or homogeneous products.²² Furthermore, to study heterogeneous effects by contract types (open account and cash-in-advance), we merge data from Demir, Michalski, and Ors (2017) and Demir and Javorcik (2018) on the frequency of different trade contracts used in trade between Russia, Ukraine, and Turkey in 2004—2011 at the four-digit HS level.

Finally, to trace the changes in attitudes toward Russia, we use a series of nationally representative surveys of Ukrainian citizens conducted by the Kyiv International Institute of Sociology (KIIS). These track the opinions of the Ukrainian people on societal and political issues four to five times per year using a repeated cross-section sampling design. We use 15 survey waves conducted on a nearly quarterly basis from January 2013 to December 2016. For each wave, the sample of the KIIS survey includes two thousand adults in 110 localities across all 25 Ukrainian provinces (*oblast*). Importantly, the data include information on the respondent’s self-reported ethnic identity and home province, which we use to track the changes in attitudes across ethnicity and provinces of different ethnic composition.

3.3 Descriptive Statistics

Before turning to our main analysis, Table A1 presents the basic summary statistics of the data used in this study. In this study, we analyze trade transactions of 12,872 Ukrainian firms located in 394 Ukrainian raions over the period of 48 months, from January 2013 to December 2016. As presented in Panel A, an average firm in our sample traded with Russia every fifth month and, overall, engaged in roughly three trade transactions per month. As for the quantity of trade, an average firm traded 230 tons and UAH 1.3 million worth of product per month.²³ Notably, the distributions of the total net weight and the total value traded have long right tails, which motivates the use of logarithm transformations in our analysis. Per Panel B, an average firm traded intermediate goods in 76% of its transactions, stressing the prevalence of the B2B sector transactions in our dataset. Similarly, only 22% of average firms’ transactions involved

at <https://unstats.un.org/unsd/trade/classifications/correspondence-tables.asp>. We then use the official COM-TRADE classification of BEC codes into capital, intermediate, and consumption goods (see details at <https://unstats.un.org/unsd/trade/knowledgebase/50090/Intermediate-Goods-in-Trade-Statistics>). For simplicity, we combine intermediate and capital goods into a single category under the name “intermediate goods.”

²²First, we use the official conversion table between the HS 2012 and SITC 2 product codes available at <https://unstats.un.org/unsd/trade/classifications/correspondence-tables.asp>. We then use data from Rauch (1999), available at <https://www.maclester.edu/research/economics/PAGE/HAVEMAN/Trade.Resources/TradeData.html>, to categorize SITC 2 product codes into differentiated, reference-priced, or homogeneous goods. For the rest of the paper, we combine reference-priced products and the goods traded on an organized exchange into a single category we call “homogeneous goods.” We use the more conservative classification from Rauch (1999) in our analysis, although our results are robust to using a less conservative (“liberal”) classification.

²³230 tons is equivalent to 11–12 fully loaded trucks. As of August 2014, UAH 1.3 million was equivalent to \$108,000 worth of product.

homogeneous goods.

As suggested by Panel C of Table A1, Ukrainian firms that trade with Russia are located in highly ethnically and linguistically diverse areas. An average firm trading with Russia is based in a district with 15% ethnic Russians and 26% native Russian speakers. However, even after excluding the conflict areas, which historically have had a sizable Russian presence, some firms in our sample are located in districts with 53% ethnic Russians or 75% native Russian speakers. In contrast, many firms in our sample are also based in areas with less than 1% ethnic Russians or native Russian speakers. As displayed in Panel D, depending on the classification method, 10% to 30% of the managers in an average Ukrainian firm trading with Russia have a traditionally Russian last name. Notably, these numbers are in line with the summary statistics of the ethnolinguistic composition of the firm's districts in Panel C, which validates our classification methods.²⁴

According to Panel E of Table A1, an average Ukrainian firm trading with Russia is located about 250 km away from the Russia-Ukraine border. Note that the closure of some part of the border due to the conflict somewhat increased the average distance, but the magnitude of that increase is rather small (6.5 km, or 4% of the standard deviation). Finally, Panel F of Table A1 presents accounting data for all Ukrainian firms in the ORBIS/AMADEUS database.²⁵

3.4 Descriptive Time-Series Analysis

To complement the static description of the data in Table A1, this section examines the overall decline in trade between Ukrainian and Russian firms after the start of the conflict.

First, we document a large decline in firms' monthly trade activity. Figure A4 in the Online Appendix traces the change in the monthly number of Ukrainian firms trading with Russia. As one can see, before the start of the conflict, the number of firms trading with Russia was relatively stable at around 3,500 per month. However, after the start of the conflict, this number substantially declined and remained rather stable at about 2,500 firms per month.²⁶

Second, we show that firms not only decreased their monthly trade frequency, but also their monthly volume of trade. To document this fact, we compare firms' trade intensity before and

²⁴For details on the classification methods, see Section 5.2.

²⁵Accounting data is available for 9,954 out of 12,872 firms in our main sample. Selection is due to individual entrepreneurs not being required to report the data to the government. See Kalemlı-Ozcan et al. (2015) for details on ORBIS/AMADEUS filing requirements by country.

²⁶Note that the number of firms trading with Russia in January is consistently lower than in other months. January is a short business month in Russia because of the New Year and Christmas holidays. However, after explicitly controlling for the monthly indicators in a regression form, we still estimate the effect of conflict on the number of firms as a loss of 1,000 firms trading with Russia per month.

after the conflict started in a simple time-series specification.²⁷ Columns (1) to (3) of Table 1 display the results for the entire sample of firms that ever traded with Russia from 2013 through 2016. Column (1) shows that, with the start of the conflict, the probability of monthly trade with Russia by an average firm declined by 8 percentage points, or 0.2 standard deviations. Columns (2) and (3) suggest that an average Ukrainian firm experienced a substantial decline in monthly trade volume with Russia. The estimates correspond to a dramatic 58.9% to 63.7% decline in firm-level trade volume with the start of the conflict (interpreting the coefficients following Halvorsen and Palmquist, 1980).

Finally, both exports to and imports from Russia suffered as a result of the conflict, although the exports fell by a somewhat larger margin. According to Columns (4) and (7) of Table 1, the average monthly frequency of trade fell by 9.1 percentage points for exporters and by 5.9 percentage points for importers. This is despite a similar pre-conflict base of 25.4 and 22.6 percentage points, respectively. A similar pattern is observed for the drop in weight and value of the exported and imported products.²⁸

Figure 3 offers a preview to our main results by splitting the firm-level trade before and after the start of the conflict into firms located in districts above and below the median in terms of the share of ethnic Russians.²⁹ As one can see, in 2013, i.e., before the conflict, the two groups of firms behaved very similarly. However, after the start of the conflict, firms from the districts with fewer Russians decreased their trade by a bigger margin relative to the firms from more Russian areas of Ukraine. Moreover, the gap between the two subsets of firms is always of the same sign and is increasing over time.

Overall, the time-series results in Section 3.4 suggest that, with the start of the conflict: (i) an average Ukrainian firm substantially decreased both the frequency and the volume of trade with

²⁷Specifically, we estimate:

$$Y_{it} = \alpha_i + \delta_m + \gamma \times Post_t + \epsilon_{it}, \quad (2)$$

where the outcome variable Y_{it} is the trade activity of firm i at year-month t ; $Post_t$ is an indicator for whether a given time period falls before or after the start of the conflict; α_i and δ_m present the firm and month fixed effects, respectively, and ϵ_{it} are the unobserved firm-time-specific shocks. Under the assumptions that the conflict was unexpected, that there were no other simultaneous shocks of similar magnitude, and that the fixed-effects model describes the data-generating process correctly, this regression model (2) provides consistent estimates for the overall effect of conflict on trade in non-combat areas.

²⁸We hypothesize that the exports could have declined more due to the unilateral elimination of import tariffs by the European Union with respect to Ukrainian products in April 2014. However, in Section 4.2.2, we argue why this institutional change cannot explain our main findings.

²⁹To construct this graph, we first regress the log of total weight traded with Russia by a firm in a given month on the firm fixed effects. We then calculate the median residuals for two subsets of firms, depending on whether they are located in a district with more or fewer ethnic Russians.

Table 1: Reduction in Trade After the Start of the Conflict

Dependent variable:	(1) Any Trade Activity	(2) Log Total Weight Traded	(3) Log Total Value Traded	(4) Any Export Activity	(5) Log Total Weight Exported	(6) Log Total Value Exported	(7) Any Import Activity	(8) Log Total Weight Imported	(9) Log Total Value Imported
	<i>All Trade</i>			<i>Export Transactions</i>			<i>Import Transactions</i>		
Post Feb 2014	-0.080*** (0.003)	-0.809*** (0.038)	-1.014*** (0.041)	-0.091*** (0.007)	-0.931*** (0.081)	-1.139*** (0.087)	-0.059*** (0.005)	-0.570*** (0.050)	-0.738*** (0.073)
Firms FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.200	1.968	2.723	0.194	1.886	2.637	0.189	1.859	2.565
Dep. Var. SD	0.400	4.139	5.504	0.396	4.028	5.421	0.392	4.061	5.377
R ²	0.41	0.49	0.46	0.41	0.48	0.46	0.41	0.48	0.45
Observations	591,541	591,541	591,541	305,472	305,472	305,472	366,432	366,432	366,432
Firms	12,872	12,872	12,872	7,104	7,104	7,104	7,634	7,634	7,634
Districts	394	394	394	342	342	342	314	314	314

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table presents the time-series estimates of the average decline in trade between Ukrainian firms and Russia after the start of the conflict. Columns (1)–(3) focus on the sum of export and import transactions, columns (4)–(6) only on export transactions, and columns (7)–(9) only on import transactions. Columns (1), (4), and (7) use an indicator for a firm trading with, exporting to, or importing from Russia in a given month. The logs of total value and net weight of shipped goods are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. Standard errors in parentheses are clustered at the district level.

Russia, (ii) both exports to and imports from Russia have suffered, and (iii) a simple split of trade patterns along districts’ ethnicity already reveals that conflict had a differential impact on firms along ethnic lines. In the next section, we introduce our formal difference-in-differences estimates which examine this divergent reaction in greater detail.

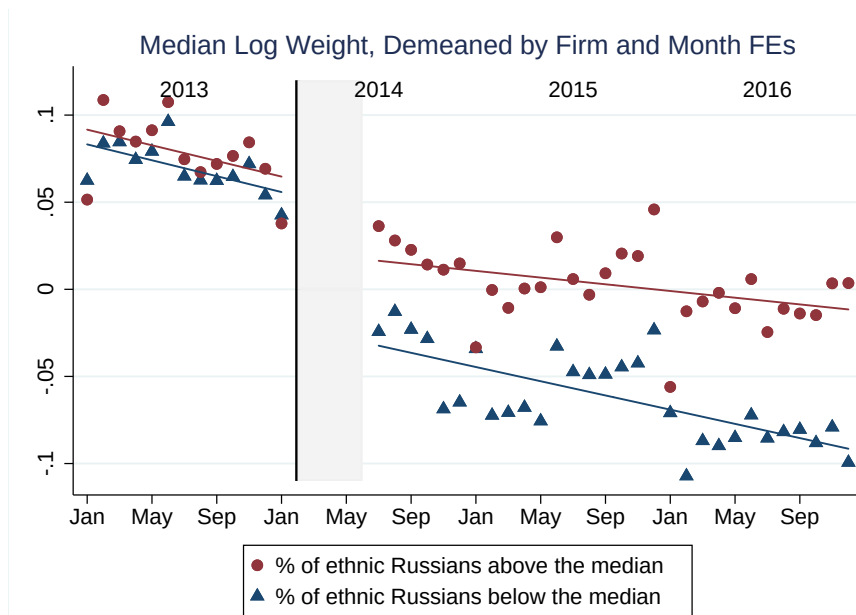
4 Results

4.1 Main Results

We start by estimating our baseline difference-in-differences equation (1), which seeks to establish whether trade between Russian and Ukrainian firms broke down along ethnic and cultural lines after the start of the 2014 Russia-Ukraine conflict. Table 2 presents the baseline estimates. Similar to Table 1, we estimate the effect using three outcome variables: (i) an indicator for any trade activity (export or import) with Russia by a firm in a given month, (ii) a logarithm of the total net weight traded by a firm in a given month, and (iii) a logarithm of the total value traded by a firm in a given month.

Columns (1) to (3) of Table 2 display the results for the share of ethnic Russians as a measure of cultural distance from Russia. The interaction coefficient β is positive and significant at the 1% level across all three specifications. The estimates suggest that moving a firm from a Ukrainian district at the 75th percentile of ethnic Russians (17.7%) to a district at the 25th percentile of ethnic Russians (9.6%) would have decreased the monthly incidence of trade by 0.8 percentage points and

Figure 3: Firm-Level Trade with Russia by Ethnic Composition of Firms' Districts



Notes: The data plotted are the monthly median residuals from a firm-level regression of the logarithm of the total weight traded (export+import) on firm fixed effects. Data are then broken down by the share of Russian population in firms' districts and are cleaned of seasonality with month fixed effects and an interaction between the January indicator and the share of ethnic Russians to account for January as a seasonal outlier. (January is a short business month in Russia, with a full holiday week from January 1 to 7.) Export data are missing for February to June 2014 (colored in gray). These months are removed for the purpose of this graph. All calculations exclude firms located in the areas affected by the conflict (see Figure 2). Lines represent the linear fit to the scatter plots with the corresponding color separately before and after the start of the conflict in February 2014.

firm's volume of trade by 9.4–10.5%. When compared to the results in Table 1, such a move would have deepened the decline in firm's monthly incidence of trade by about 9.3% for the incidence of trade and by 10.3–11.6% for trade volume. Moreover, these estimates suggest that a hypothetical firm located in an all-Russian district would not have decreased its trade with Russia at all, with a caveat that this is an out-of-sample prediction.

We observe similar patterns with a different proxy for cultural distance from Russia—the share of residents who consider Russian language their mother tongue across Ukrainian districts. For simplicity, throughout the paper, we call this measure the 'share of native Russian speakers.' Columns (4) to (6) of Table 2 present the estimates. The results are strikingly similar to columns (1) to (3), in terms of both statistical significance and magnitude. As before, all else held equal, moving an average firm from a district at the 75th percentile of native Russian speakers (25.8%) to a district at the 25th percentile (12.1%) would have led to a 0.6 percentage points drop in firm's monthly incidence of trade and a 7.8–8.4% decline in firm's trade volume.

To allow for the visual exploration of our results, we present our estimates in a month-by-

Table 2: Baseline Results

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded
Post Feb 2014 × Share of Ethnic Russians	0.092*** (0.030)	1.163*** (0.360)	1.297*** (0.401)			
Post Feb 2014 × Share of Native Russian Speakers				0.044*** (0.014)	0.570*** (0.170)	0.615*** (0.191)
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.200	1.968	2.723	0.200	1.968	2.723
Dep. Var. SD	0.400	4.139	5.504	0.400	4.139	5.504
R ²	0.41	0.49	0.46	0.41	0.49	0.46
Observations	591,541	591,541	591,541	591,541	591,541	591,541
Firms	12,872	12,872	12,872	12,872	12,872	12,872
Districts	394	394	394	394	394	394

Notes: * p<0.1, ** p<0.05, *** p<0.01. This table presents the baseline difference-in-differences estimates of the impact of the Russia-Ukraine conflict on trade between Russia and Ukrainian firms in areas with different presence of ethnic Russians and native Russian speakers. Columns (1) and (4) use an indicator for a firm trading with Russia in a given month (export+import). The logs of total value and net weight of shipped goods (export+import) are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. Data on ethnolinguistic composition are at the district level and come from the 2001 Ukrainian Census. The share of native Russian speakers is the percentage of people who named Russian their mother tongue (“rodnoi yazik”). Standard errors in parentheses are clustered at the district level.

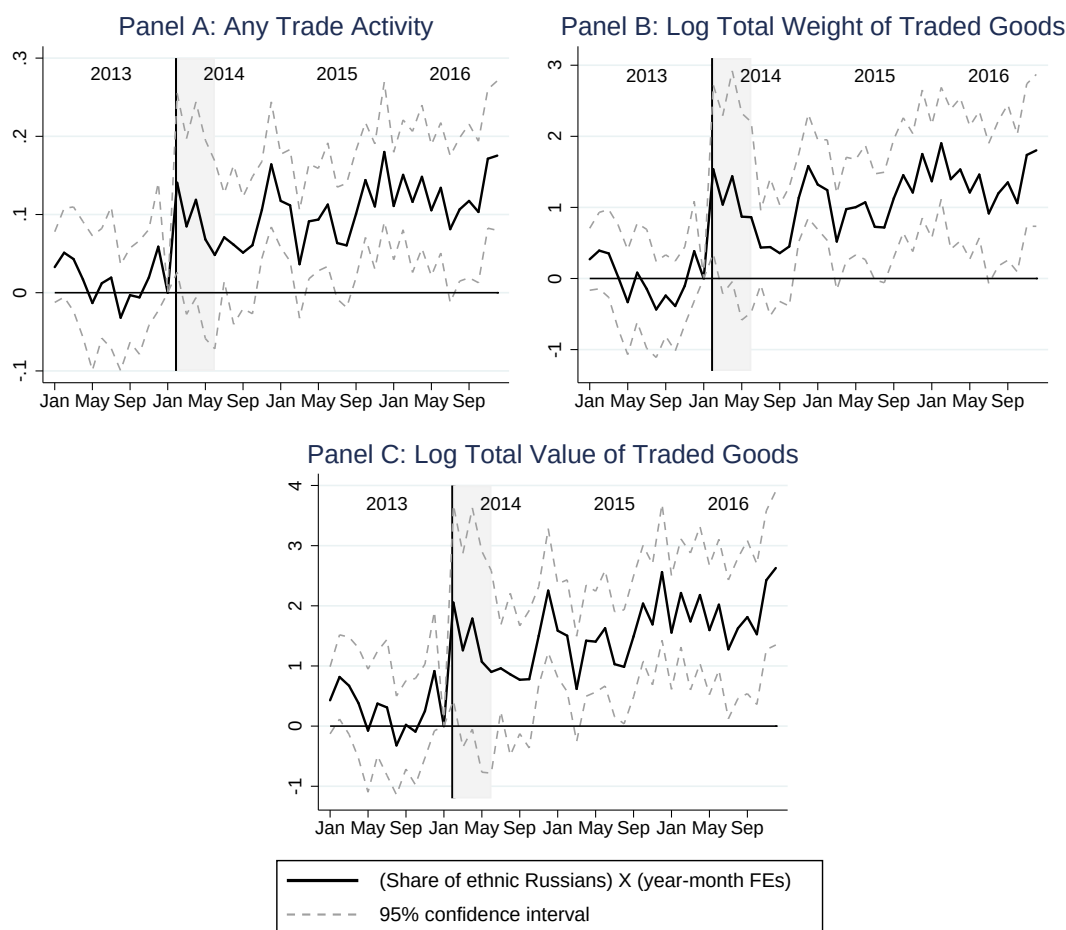
month form. That is, instead of the interaction with the post-February 2014 indicator, we interact the districts’ ethnic composition with a full set of year-month dummy variables.³⁰ Figure 4 displays the results. First, we find no evidence of pre-trends, as the share of ethnic Russians in the firm’s district consistently does not matter for its trade with Russia before the conflict. Thus, we find support for the central assumption of our difference-in-differences strategy, i.e., parallel trends. Second, the differential impact of conflict on trade between Russian and Ukrainian firms stayed positive and significant until the end of our time series, in December 2016, i.e., long after the start of the conflict. This long-lasting effect stands in stark contrast with the short-lived response observed in the literature on political disputes and consumer boycotts, suggesting that a more severe armed conflict can have a much more profound influence on trade between nations. Finally, we note that the timing of the spike in the interaction term in December 2014–February 2015

³⁰That is, we estimate the following equation:

$$Y_{idt} = \alpha_i + \gamma_t + \sum_t \beta_t \times \text{Rus}_d \times \gamma_t + \epsilon_{idt}, \quad (3)$$

where the outcome variable Y_{idt} is the trade intensity of firm i at district d with Russia (export+import), at year-month t ; α_i and γ_t are the firm and year-month fixed effects; and Rus_d is the share of ethnic Russians in the district d of firm i .

Figure 4: Dynamics of the Importance of Local Ethnic Composition for Firms' Trade with Russia



Notes: This graph displays the results of estimating equation (3), which modifies the baseline equation (1) by interacting year-month fixed effects with the ethnic composition of the firms' districts. For February through June 2014, only import data are present (colored in gray). Removing these five months from our analysis does not change the baseline results. Panel A displays the results for any trade activity with Russia in a given month (export+import) as the dependent variable, Panel B displays the results for the logarithm of total weight of the goods traded with Russia (export+import), and Panel C displays the results for the log of total value traded (export+import). 95% confidence intervals are constructed for standard errors clustered at the district level.

coincides with the spike in violence and negative attitudes toward Russia in Figure 5, consistent with our preferred interpretation.

Overall, the baseline difference-in-differences estimates point to a sizable and a highly statistically significant differential decline in trade across Ukrainian districts—firms from areas with fewer preexisting ethnic and cultural ties with Russia decreased trade with Russia by a larger margin relative to the firms from more ethnically Russian regions of Ukraine. More generally, these results provide the first evidence that armed conflict has a substantial indirect effect on inter-

group trade. In the next section, we provide evidence that these results survive multiple rigorous robustness checks and are not due to various mechanical explanations unrelated to ethnicity or anti-Russian sentiments. After that, we attempt to tease out whether our main results are due to out-group animosity between firm managers, decline in trust, or local pressure from consumers and activists.

4.2 Alternative Explanations and Robustness Checks

In this section, we rule out the three main alternative explanations for our findings: differences in distance to the Russian border, confounding product-specific shocks, and contemporaneous local economic shocks. We also discuss other potential explanations and test the overall robustness of our estimates.

4.2.1 *Geographical Distance to Russia*

The first concern that we address is that the baseline results may be driven by the geographical distance to Russia, rather than the preexisting ethnic and cultural heterogeneity per se. As can be observed in Figure 1, the areas with the fewest ethnic Russians are, relatively speaking, located far from the Russia-Ukraine border. Therefore, a distance-related shock due to conflict—for instance, if it substantially raised transportation costs—could mechanically have a bigger impact on firms in the areas of Ukraine with fewer ethnic Russians.

To rule out this explanation, we calculate the shortest linear path to Russia for each firm and include its interaction with the post-February 2014 indicator as a covariate. We also account for the change in the border after the start of the conflict by recalculating the shortest path without taking into account the boundary between Russia and the Donetsk and Luhansk provinces.³¹

Table A5 present the results. Column (1) through (4) add the flexible distance controls, starting with a simple linear measure and ending with the fifth polynomial of the log of distance. Columns (5) through (8) interact these distance measures with the post-conflict indicator, thus, allowing for the conflict-induced shocks that correlated with distance, such as increased transportation costs. For brevity, we focus on the specification with firms' monthly incidence of trade as the outcome. Across all specifications, the interaction between the post-February 2014 indicator and the share of ethnic Russians remains positive, highly statistically significant, and of a similar magnitude to column (1) of Table 2. Therefore, it is highly unlikely that the presence of ethnic Russians matters for our estimates only as a proxy for distance to Russia.

³¹To deal with the potential relocation of firms from the conflict areas, whenever possible, we use pre-conflict addresses for these calculations. Fewer than 1% of the firms in our sample changed their host district from 2013 to 2016, and excluding these firms from our sample does not affect the results.

4.2.2 *Confounding Product- and Industry-Specific Shocks*

Another important alternative explanation concerns product- and industry-specific shocks that may arise due to the Russia-Ukraine conflict. Note that all shocks that applied uniformly to all products would be absorbed by time fixed effects. However, one example for why industry differences may matter in this context is that, immediately after the start of the conflict, all military cooperation between the two countries ceased, which naturally affected trade in the related sectors.³² Thus, hypothetically, if areas with fewer preexisting ties with Russia were more involved in the production of products in military-related sectors, this may have biased our baseline difference-in-differences estimates upward, without ethnicity playing any role.³³

To address this issue, first, we estimate a difference-in-differences specification at the product-firm-month level with product-post fixed effects.³⁴ Similar to equation (1), this specification compares firm-product pairs' reaction to the start of the conflict depending on the ethnic composition of the firm's district. However, in addition, it accounts for the product-specific shocks contemporaneous with the start of the conflict. Identification still relies on the parallel trends assumption. That is, one needs to assume that firm-product trade would have evolved along similar trends in districts with different ethnic composition absent the conflict. To the extent that this assumption holds and there are no other events simultaneous with the conflict that could generate a similar pattern, the interaction coefficient estimates a causal impact of conflict on inter-group trade.³⁵

Table A6 presents the results. Columns (1) through (3) contain the firm-product-level version of the baseline estimates, and columns (4) through (6) add the interaction of distance with the post

³²Trade of arms, weapons, and other military products is classified information and, as such, is not present in our data. However, our data could still theoretically contain military-related procurement (e.g., airplane engines), trade of which may have stopped for political reasons.

³³Other examples of product-specific shocks that may not be uniform across Ukrainian regions and may potentially confound our estimates are (i) bans of certain agricultural Ukrainian products by the Russian Federal Consumer Protection Agency, with rural areas of Ukraine being predominantly ethnically and culturally Ukrainian, and (ii) unilateral removal of all import tariffs for Ukrainian goods by the European Union in late April 2014 (albeit with some restrictions and quotas still in place), with greatest tariff cuts for agricultural products.

³⁴Specifically, we estimate the following equation:

$$Y_{ijdt} = \alpha_i + \gamma_t + [\delta_j + \kappa_j \text{Post}_t] + \beta \times \text{Post}_t \times \text{Rus}_d + \varepsilon_{ijdt}, \quad (4)$$

where Y_{ijdt} is trade intensity of firm i from district d of product j with Russia (export+import) at year-month t ; α_i , γ_t , δ_j , and κ_j are, respectively, the firm, year-month, product, and product-post fixed effects; Rus_d is the share of ethnic Russian in the district d of firm i ; and Post_t is the post-February 2014 indicator.

³⁵To detect whether the parallel-trends assumption holds in this specification for the pre-conflict period, we estimate the month-by-month version of equation (4), interacting the share of ethnic Russians in firm's district with a full set of year-month indicators. Figure A5 visually displays the estimates. As one can see, the coefficients for periods before the start of the conflict are not statistically significant and are close to zero in magnitude. This result lends support for the parallel-trends assumption that underlies specification (4).

indicator as a control variable. The main coefficient stays positive and statistically significant, with magnitudes decreasing but remaining relatively large (16%–19% of a standard deviation compared to 23–28% of a standard deviation in Table 2). Hence, our baseline results cannot be explained by the product-specific shocks that appear contemporaneously with the start of the conflict.³⁶

We also estimate a version of our baseline specification controlling for the industry-post fixed effects. Table A7 displays the results and, as one can see, the baseline estimates remain virtually unchanged. This further confirms that industry differences cannot fully explain our estimates.

4.2.3 *Confounding Local Economic Shocks*

Another set of potential explanations relates to district-level economic shocks arising simultaneously with the start of the conflict and which are correlated with the districts’ ethnic composition. For instance, areas close to the armed conflict may have hosted more refugees, which could have generated positive demand and labor-supply shocks. Similarly, areas with fewer ties with Russia may have produced more activists and soldiers, possibly leading to an adverse labor-supply shock. Finally, political turnover after the Ukrainian revolution may have led to productivity shocks depending on the local electoral support for the new leader (Earle and Gehlbach, 2015).

If negative district-specific shocks drive our results, then we should observe that areas with lower shares of ethnic Russians decreased their trade with all countries, not only Russia. We test this intuitive prediction in a triple-difference multi-country specification with district-post fixed effects.³⁷ In this strategy, outcomes are changing across space, time, and foreign country. The coefficient of interest on the triple interaction measures how much trade intensity with Russia changes with the start of the conflict for firms in districts with higher versus lower share of ethnic Russians, relative to such differential change in trade with other countries. With the help of cross-country variation, this strategy allows us to account for any contemporaneous district-specific economic shocks.

Table A8 presents the results for the ten top trading partners of Ukraine, with all other countries

³⁶See Figure A6 for firm-product-level coefficients estimated by product type, i.e., on subsamples of transactions that involve certain product codes. Note that neither military-related production, such as metals and machinery, nor agricultural products are the main drivers of the differential effect across ethnicity. Instead, the coefficients are positive and close to the baseline coefficient (horizontal dashed line) across all types of products.

³⁷Specifically, we estimate the following equation:

$$Y_{idct} = \alpha_i + \gamma_t + [\mu + \beta \text{Post}_t] \times \text{Rus}_d \times \text{Russia}_c + [\delta_c + \kappa_c \text{Post}_t] + \nu_d \text{Post}_t + \varepsilon_{idct}. \quad (5)$$

Here, Y_{idct} is trade intensity (export+import) of firm i of district d with country c at time t , Post_t is an indicator for whether time period t is after the start of the conflict, Russia_c is an indicator for whether the trading country c is Russia or not, and Rus_d is the share of ethnic Russians in district d of firm i . Furthermore, α_i , γ_t , and δ_c are firm, time, and country fixed effects; κ_c and ν_d are country-post and district-post fixed effects, respectively.

counted as the eleventh country. First, consistent with the literature on ethnic networks and trade (Rauch and Trindade, 2002), we document that trade with Russia, on average, is higher in areas with a higher share of ethnic Russians. However, the triple-difference coefficient is positive and significant, which means that, with the start of the conflict, firms in districts with fewer ethnic Russians decreased trade with Russia by a *disproportionately* larger margin relative to the change in their trade with other countries, and relative to their counterparts in other parts of Ukraine. That is, when a firm is moved from an area with 17.7% (75th percentile) to an area with 9.6% (25th percentile) of ethnic Russians, its chance of having any monthly trade activity with Russia after the start of the conflict, as opposed to with other countries, drops by 1 percentage point. The magnitude of the triple-difference coefficient is not reduced and, if anything, is bigger than the baseline effect (32–41% compared to 23–28% of a standard deviation). Overall, these estimates back our assertion that our baseline results are not driven by negative locality-specific shocks.³⁸

4.2.4 *Additional Alternative Explanations and Robustness Checks*

In addition to accounting for distance as well as product- and district-specific shocks, we are able to rule out four other explanations. First, in contrast to Berger et al. (2013), we document that our baseline results are not due to the relocation of government contracts by Ukrainian state-owned firms.³⁹ Second, our difference-in-differences estimates are not due to an increase in tariffs between Russia and Ukraine in 2016, since we can exclude 2016 altogether without any qualitative change in our results.⁴⁰ Third, we can show that our baseline results are not driven by any one specific area, thus ruling out the possibility that the effect is driven by regions-outliers.⁴¹ Finally, it is unlikely that our effects are due to some other event happening before or after the start of the conflict, as our baseline difference-in-differences estimate is larger than 44 out of 45 placebo estimates obtained by creating fake starting months of the conflict.⁴²

³⁸Figure A7 displays the month-by-month coefficients across top-10 trading partners. As one can see, the coefficients for Russia turn from being in the middle of the pack to being consistently bigger relative to the coefficients for the other countries. These figures further confirm that ethnic heterogeneity mattered in a unique way for trade with Russia as opposed to other countries.

³⁹Table A9 shows that removing state-owned firms from the analysis does not change our results.

⁴⁰See Table A10 for these results.

⁴¹Table A11 shows that the baseline results hold without the capital of Ukraine (Kyiv), without the regions close to conflict areas, and without Western Ukraine. Moreover, Figure A8 illustrates that the baseline coefficient remains stable when we remove Ukrainian provinces one by one from our sample.

⁴²See Figure A9. The only placebo estimate larger than the baseline assumes November 2016 as the start of the conflict and, thus, is estimated using only one month of data.

5 Mechanisms

In this section, we seek to explain why conflict leads to a reduction in inter-group trade in non-combat areas. First, using variation in contract types, we argue that trade went down at least in part due to a differential decline in trust. Second, classifying the last names of firm managers, we show that our baseline estimates are driven not by managers' ethnicity but by the ethnic composition of a district. This suggests that trust breaks down between antagonistic localities as opposed to individual managers and that individual-level animosity does not play a role. Next, using survey data, we document a rise of nationalism in less Russian areas of Ukraine, which causes a disruption of inter-group trade through consumer boycotts and reputational pressure on Ukrainian firms. Finally, we show that discrimination at the border does not drive our baseline estimates.

5.1 Erosion of Trust

First, we explore whether our results are due to a decline in trust between Ukrainian firms and their Russian counterparts. The existing theoretical literature suggests that conflict may cause a decline in confidence between trade partners from antagonistic groups, resulting in a breakdown of trade (Rohner et al., 2013b). Moreover, even if there is no decline in trust between managers from different ethnic groups, a breakdown of trust could occur between the areas with different ethnic composition, such that firms from less Russian areas of Ukraine are fearful that the opposite side of the conflict would discriminate based on their location.

To test for the general importance of trust in our results, we explore variation in trade contracts. There are two major standard types of contracts in international trade: open account (OA) and cash-in-advance (CIA) contracts. In a CIA contract, the importer pays before the good is shipped. In contrast, an OA contract refers to a sale where the goods are shipped and delivered before payment is due. Thus, if the breakdown of trust is indeed driving our results, we would expect a greater effect for *exporters* that primarily used OA contracts before the start of the conflict, as these types of contracts placed a bigger risk on exporters. On the contrary, if Ukrainian *importers* were fearful of the contract not being honored, we would expect a bigger effect if they relied on CIA contracts.

The closest available micro-level data on the types of trade contracts are between Ukraine, Russia, and Turkey over the 2004–2011 period.⁴³ Due to privacy concerns, these data are available only as averages at the HS4 product-code level. For each firm in our sample, we use information on the products they trade to calculate the predicted shares of transactions conducted in one of the

⁴³These data, kindly shared with us by Banu Demir Pakel, were previously used in Demir et al. (2017) and Demir and Javorcik (2018).

three types of standard trade contracts mentioned above.⁴⁴ Using the predicted contract usage, we test the hypothesis of weakened trust and problems in contract enforcement.

Table 3 presents the results. To disentangle the risks levied on exporters and importers by different types of contracts, Panel A and Panel B display the results for export and import activity respectively. As one can see from columns (1) and (2) of Panel A, the differential effect of conflict is more pronounced for exporters with a higher predicted use of OA contracts, which put the burden of potential nonpayment on exporters. In contrast, no differential effect of conflict exists among exporters with a higher predicted use of CIA contracts, in which the risk is placed on the importer. Notably, the picture is reversed for Ukrainian importers. Panel B of Table 3 suggests that the baseline effect was higher for importers with a higher predicted usage of CIA contracts and lower predicted usage of OA contracts—again, consistent with a decline in trust.⁴⁵

Overall, these results strongly suggest that the breakdown of trust along ethnic lines played a significant role in explaining the reaction of Ukrainian firms to the Russia-Ukraine conflict.

5.2 Individual-Level Animosity by Key Decision Makers

In the previous subsection, we established that erosion of trust is one mechanism behind the decline in inter-group trade. However, it remains unclear whether it is interpersonal trust that declined or is it that firms fear being cheated on based on their location. Furthermore, another possible mechanism is individual-level taste-based discrimination between firms' key decisionmakers. Specifically, it could be that severe conflict causes managers of different backgrounds to discontinue their business ties voluntarily due to sharp political disagreements. To test these hypotheses, we bring in data from ORBIS/AMADEUS about firms' managers and infer whether their surnames have Russian roots.

Russian and Ukrainian surnames traditionally had different endings and, in general, had a different origin (Slavutych, 1962; Unbegaun, 1972). Based on the scholarly work by Zhuravlev (2005) and Balanovskaya, Solov'eva, Balanovskii, et al. (2005), we use two classification methods to categorize last names into traditionally Russian and others. In the first method, a last name is considered Russian if it contains traditional Russian endings, such as “ov,” “ova,” “ev,” “eva,” “in,”

⁴⁴We make several implicit assumptions in this analysis: (i) Russian and Ukrainian firms use similar contracts for similar products when they trade with each other as they do when they trade with Turkey, (ii) there have only been limited changes in the typical use of different types of contracts between the 2004–2011 and 2013–2016 periods, and (iii) the erosion of trust is asymmetric—ethnic Russians and ethnic Ukrainians vary in their trust in Russia or their trade counterparts, while Russian citizens do not differentiate between Ukrainians of different ethnicity.

⁴⁵Note that the fact that the heterogeneity pattern is different for exporters and importers makes it highly unlikely that these results are due to some omitted product-level heterogeneity.

Table 3: Heterogeneity Analysis by Types of Trade Contracts

Subsample:	(1)	(2)	(3)	(4)
	High Predicted OA Usage	Low Predicted OA Usage	High Predicted CIA Usage	Low Predicted CIA Usage
<i>Panel A: Any Export Activity</i>				
	<i>Difference p-value: 0.034</i>		<i>Difference p-value: 0.036</i>	
Post Feb 2014 × Share of Ethnic Russians	0.218*** (0.043)	0.005 (0.090)	0.001 (0.092)	0.216*** (0.043)
Firm FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Dep. Var. Mean	0.208	0.178	0.178	0.208
Dep. Var. SD	0.406	0.383	0.383	0.406
R ²	0.44	0.38	0.38	0.43
Observations	176,343	121,948	117,648	180,643
Firms	4,101	2,836	2,736	4,201
Districts	279	271	270	277
<i>Panel B: Any Import Activity</i>				
	<i>Difference p-value: 0.006</i>		<i>Difference p-value: 0.100</i>	
Post Feb 2014 × Share of Ethnic Russians	0.014 (0.024)	0.124*** (0.034)	0.096*** (0.034)	0.030 (0.023)
Firm FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Dep. Var. Mean	0.187	0.187	0.184	0.188
Dep. Var. SD	0.390	0.390	0.388	0.391
R ²	0.40	0.42	0.42	0.40
Observations	231,936	139,728	127,920	243,744
Firms	4,832	2,911	2,665	5,078
Districts	275	229	220	279

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table explores the importance of trust by breaking down the baseline results along the direction of trade (exports to vs. imports from Russia) and along the type of contract a firm is predicted to use. “OA” refers to an open account contract in which a good is delivered before the payment is due. “CIA” refers to a cash-in-advance contract in which an importer pays before the good is shipped. Predicted contract usage is calculated based on the types of products traded by a firm weighted by the amount of trade. We consider contract usage high (low) if the predicted share is above (below) the mean among the firms in the sample. For each HS4 product code, we use data from Demir et al. (2017) and Demir and Javorcik (2018) on average contract types used in trade between Ukraine, Russia, and Turkey from 2004 to 2011. The dependent variable in Panel A (Panel B) is an indicator of any exports to (imports from) Russia by a firm in a given month. Inference across regression models is conducted using a similarly unrelated regressions framework with standard errors clustered at the district level. Standard errors in parentheses are clustered at the district level.

or “ina.”⁴⁶ In the second, more conservative approach, we see whether a last name is present in a database of 622 traditionally Russian last names that we compiled for this purpose.⁴⁷ Based on

⁴⁶See Zhuravlev (2005) for a detailed discussion of this approach.

⁴⁷The database combines the 500 most popular Russian last names from Zhuravlev (2005) and the 250 most widespread Russian last names from Balanovskaya et al. (2005), net of all duplicates. The difference between the two lists comes from differences in methodology. While Zhuravlev (2005) uses phonebooks from several Russian cities

these two methods, we produce two measures of the share of managers with Russian roots, which we then use in a difference-in-differences equation (1) to discern whether personal identity can explain part of our results.⁴⁸

Panel A of Table 4 in the Online Appendix displays the difference-in-differences estimates in which we interact the post-conflict indicator with the firm’s share of Russian managers *instead of* the share of ethnic Russians in the firm’s home district. We observe positive and, for measure #2, statistically significant coefficients, although the results are weaker than for the share of ethnic Russians in the firm’s district. Panel B of Table 4 presents a horse-race exercise where the “Russian-ness” of the managers is included together with that of the firm’s district. The effect of the managers’ Russian roots stays close to zero and is statistically insignificant, while the effect of the share of ethnic Russians in a district remains large and positive. These results suggest that conflict did not affect trade through individual-level animosity of firm owners and instead operates through the culture and attitudes in the surrounding area.⁴⁹

5.3 The Rise of Local Nationalism

Results in the previous subsection suggest that it is the district-level, not the individual-level ethnicity that drives our estimates. Here, we document the rise of nationalistic attitudes within Ukraine and show that they affected our difference-in-differences estimates via consumer action and reputational pressure.

over the 1970–2000 period to calculate the frequency of last names with traditional Russian endings, Balanovskaya et al. (2005) use a bank of more than 50,000 last names in Russian rural areas and consider a last name Russian only if there lived at least five people with this family name for three generations across all five macroregions of Russia.

⁴⁸We validate our classification methods by aggregating the share of Russian managers at the province level and comparing the resulting percentages with the actual share of ethnic Russians from the Ukrainian Census. Figure A10 displays the results. As one can see, the share of Russian managers calculated with our measures is strongly and positively correlated with the share of ethnic Russians in the region. A 1% increase in the share of ethnic Russians in a province is associated with a 1.02% and a 0.38% increase in the share of Russian managers measured according to the surname endings and the bank of surnames, respectively. Figure A11 displays the relationship between the two measures of managers’ ethnicity, confirming that (i) they are tightly related and are measuring the same underlying factor, and (ii) the bank-of-surnames measure is more conservative, as for any given value of this measure, the average share of Russian managers according to the alternative surname-endings measure is higher.

⁴⁹One concern with these results is that both measures of the share of Russian managers may be plagued with measurement error, which would bias the corresponding estimates toward zero. To reduce the measurement error bias, we follow Ashenfelter and Krueger (1994) and use one measure of the share of Russian managers as an instrument for the other. Panel B of Table A12 shows that the association between the two measures is very robust, thus forming a very strong first stage relationship (see Figure A11 for the illustration). Panel A of Table A12 displays the second stage estimates with measure #2 used as an instrument for measure #1. As one can see from Panel A.1., the IV estimates are indeed larger and more precise. However, according to Panel A.2., this correction for measurement error does not change our overall conclusion that it is the ethnic composition of the area that matters and not the one of the firm. Similar results are obtained when measure #1 is used as an instrument for measure #2.

Table 4: Share of Russian Managers vs. Russian Ethnicity in a District

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded
<i>Panel A: Difference-in-Differences</i>						
	<i>Measure #1: Surname Endings</i>			<i>Measure #2: Bank of Surnames</i>		
Post Feb 2014 × Managers with Russian Last Names	0.003 (0.005)	0.063 (0.057)	0.047 (0.073)	0.015** (0.007)	0.153* (0.080)	0.199* (0.105)
<i>Panel B: Horse-Race Specification</i>						
	<i>Measure #1: Surname Endings</i>			<i>Measure #2: Bank of Surnames</i>		
Post Feb 2014 × Managers with Russian Last Names	-0.001 (0.006)	0.011 (0.067)	-0.013 (0.082)	0.011 (0.007)	0.111 (0.080)	0.151 (0.108)
Post Feb 2014 × Share of Ethnic Russians	0.136*** (0.031)	1.639*** (0.394)	1.851*** (0.432)	0.132*** (0.032)	1.617*** (0.406)	1.801*** (0.447)
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.223	2.197	3.046	0.223	2.197	3.046
Dep. Var. SD	0.416	4.322	5.751	0.416	4.322	5.751
R ²	0.42	0.50	0.47	0.42	0.50	0.47
Observations	497,762	497,762	497,762	497,762	497,762	497,762
Firms	10,794	10,794	10,794	10,794	10,794	10,794
Districts	376	376	376	376	376	376

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table explores whether the fact that firm managers are of Russian descent drive the baseline results. In columns (1) through (3), managers' last names are treated as Russian if they end in "ov," "ova," "ev," "eva," "in," or "ina" (for a detailed discussion of this approach, see Zhuravlev (2005) (in Russian)). In columns (4) through (6), we use a bank of 622 traditionally Russian last names, combined from the lists of 250 traditional Russian last names from Balanovskaya et al. (2005) and 500 most frequent Russian last names from Zhuravlev (2005), net of all duplicates. Columns (1) and (4) use an indicator for a firm trading with Russia in a given month (export+import). The logs of total value and net weight of shipped goods are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. Standard errors in parentheses are clustered at the district level.

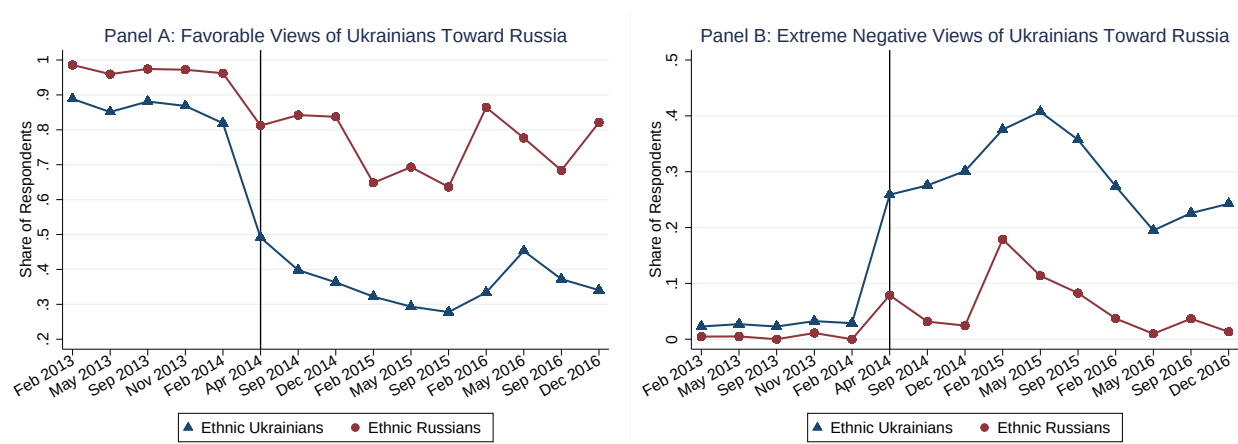
5.3.1 Changes in Attitudes of the General Population

Figures 5a and 5b track the change in attitudes of Ukrainian citizens toward Russia over time by ethnicity of the respondents. Before the start of the conflict, all Ukrainian citizens had overwhelmingly friendly attitudes toward the Russian Federation. Figure 5a shows that the share of favorable respondents was stable around 80–100% depending on respondent's ethnicity. Similarly, Figure 5b shows no extreme negative views toward Russia at the time.⁵⁰

In the immediate aftermath of the conflict, however, the attitudes of ethnic Ukrainians changed dramatically—in a matter of two months, favorability was down to around 50%, falling further to 30% by the end of 2015 (blue triangles on Figure 5a). Moreover, the share of ethnic Ukrainians with extreme negative views toward Russia jumped from close to zero (3%) to more than a quarter

⁵⁰For brevity, we only present the numbers starting in February 2013. However, earlier data show that these favorable attitudes persisted over time.

Figure 5: Dynamics of Ukrainians' Attitudes Toward Russia



Notes: The figures illustrate the effect of the Russia-Ukraine conflict on attitudes of Ukrainian citizens toward Russia. Panel A displays the share of respondents who answer the question “What Is Your Overall Attitude Toward Russia?” as “very good” and “good” plotted over time. Panel B displays the share of respondents who answer the same question as “very bad.” Data come from 15 nationally representative surveys conducted by Kyiv International Institute of Sociology between 2013 and 2016. The February 2014 survey was conducted February 7 to 17, 2014, i.e., before the occupation of Crimea and the start of the conflict. The December 2015 survey did not contain the survey question of interest and, as a result, is omitted from the figures. Conflict regions are excluded from the analysis.

of all respondents (26%) immediately after the start of the conflict (blue triangles on Figure 5b). This number rose to a peak of 40% by May 2015.

Although the attitudes of ethnic Russians toward Russia also worsened, as shown by the red line with circles on both figures, they remained predominantly positive. The share of respondents with favorable views stayed above 80% throughout 2014 and always remained at least 30 percentage points higher relative to ethnic Ukrainians through 2016. The share of ethnic Russians with extremely poor views of Russia slightly increased (to 8% in April 2014), but not as dramatically as for ethnic Ukrainians.⁵¹ Moreover, it always stayed 20 percentage points lower than that for ethnic Ukrainians through 2016.⁵²

5.3.2 Consumer Action

One of the natural mechanisms via which the rise of nationalism may affect trade is consumer action. Specifically, our results could potentially arise from consumers in less Russian areas of Ukraine refusing to buy Russian brands, refusing to shop at Russian-owned stores, and, possibly,

⁵¹The spike in Dec 2014–Feb 2015 is likely due to a contemporaneous surge in violence in the Donbass region.

⁵²Figure 5 documents the differential change of attitudes toward Russia by individual ethnicity. One might wonder whether these individual differences translate into similar patterns across regions with different ethnic characteristics. To shed light on this issue, we regress individual attitudes toward Russia on the post-conflict indicator and its interaction with the share of ethnic Russians or native Russian speakers in the province (*oblast*) of the respondent, the lowest level of geographic analysis available. Table A13 presents the results. In all specifications, it is evident that anti-Russian sentiments grew especially high in regions with low shares of ethnic Russians or native Russian speakers.

refusing to support Ukrainian firms that trade with Russia.⁵³

To check whether consumer action matters for our results, first, we test whether the reduction in trade across ethnic lines is more pronounced for traders of consumer goods. Columns (1) and (2) of Table 5 display the breakdown of the baseline results by the share of operations conducted by a firm with consumer or intermediate goods from 2013 through 2016. It is evident that traders doing business mostly with consumer goods experienced a larger decline in trade across areas with different ethnic composition. To ascertain whether consumer boycotts play a role, we study import transactions separately from exports and further break down the results by firm type in columns (3) through (6) of Table 5. The results show that the differential effect is significantly more pronounced for the frequency of import activity of consumer-goods traders relative to that of intermediate-goods traders.⁵⁴ This pattern is highly consistent with the consumer boycotts explanation, in which boycotts have been more widespread in areas with fewer ethnic and cultural ties to Russia.

Although comparing consumer- and intermediate-goods traders strongly suggests consumer action, ideally, we would want to obtain more direct evidence that boycott intensity matters for our estimates. To approximate the intensity of boycotts in Ukrainian provinces, we rely on relative popularity of online searches for *boycott*, which we obtain from Google Trends.⁵⁵ Figure A12 shows, unsurprisingly, a strong negative association between the standardized *boycott* search intensity and the share of ethnic Russians in a region.⁵⁶ Columns (2) and (3) of Table A14 illustrate that the differential effect of local ethnic composition is higher especially in provinces with higher

⁵³There is plenty of qualitative and anecdotal evidence of a widespread consumer boycott campaign erupting with the start of the conflict. In many parts of Ukraine, supermarkets began to put a special label on Russian products that marked them as Russian, to make them easier for consumers to identify (korrespondent.net/ukraine/3442493-sdelano-v-rossyy-kak-mahazny-markyruiit-tovary-yz-rf). Activists held rallies at supermarkets to persuade their compatriots not to buy Russian goods. As Russian producers started to hide the origin of their products, activists developed a popular phone application that would detect them based on the barcode (www.gazeta.ru/tech/2014/03/31_a_5971313). In March and April 2014, 52% of Ukrainian consumers viewed these boycott campaigns as favorable and 39% stated that they had boycotted Russian products themselves (www.pravda.com.ua/rus/news/2014/05/15/7025437/). By March 2015, the latter number had grown to 45% (tsn.ua/ukrayina/bilshist-ukrayinciv-pidtrimuyut-boykot-tovariv-iz-rosiyi-doslidzhennya-420268). Thus, as opposed to the typical short-lived boycott campaign studied in the literature, the anti-Russian boycott in Ukraine lasted a long time.

⁵⁴Since the number of firms importing only consumer goods is not high, to increase power, we study them together with firms that spend some of their time trading intermediate goods as well.

⁵⁵Specifically, these data cover February 1 to May 1, 2014, from <https://trends.google.com/trends/explore?date=2014-02-01%202014-05-01&geo=UA&q=%D0%B1%D0%BE%D0%B9%D0%BA%D0%BE%D1%82>. We restrict our attention to this time period so that the word *boycott* definitely refers to the boycott of Russian goods by Ukrainian consumers or to the boycott of companies affiliated with Russia in one way or another. It is possible that *boycott* may take other meanings in other months, which would then dilute our measure.

⁵⁶Note that this relationship is not confounded by differences in usage of Google search across Ukrainian provinces, as Google Trends calculate *relative* popularity of a search in each province, dividing the number of searches for a particular word by the total number of searches in a province.

Table 5: Consumer-Goods and Intermediate-Goods Traders

Specification:	(1)	(2)	(3)	(4)	(5)	(6)
	Firms with > 50% of Transactions in Consumer Goods	Firms with > 50% of Transactions in Intermediate Goods	Import by Firms with > 50% of Transactions in Consumer Goods	Import by Firms with > 50% of Transactions in Intermediate Goods	Import by Firms with > 0% of Transactions in Consumer Goods	Import by Firms with 100% of Transactions in Intermediate Goods
	<i>Diff p-value: 0.029</i>		<i>Diff p-value: 0.084</i>		<i>Diff p-value: 0.065</i>	
Post Feb 2014 × × Share of Ethnic Russians	0.236*** (0.078)	0.065** (0.032)	0.204** (0.092)	0.036 (0.026)	0.154*** (0.052)	0.057** (0.026)
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.182	0.204	0.188	0.190	0.268	0.119
Dep. Var. SD	0.386	0.403	0.391	0.392	0.443	0.324
Observations	88,054	450,231	41,040	277,392	84,432	206,592
Firms	1,972	9,910	855	5,779	1,759	4,304
Districts	216	365	91	288	149	260

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table presents the heterogeneity analysis of the baseline results by the percentage of trade transactions a firm makes in consumer or intermediate goods. Intermediate goods and consumer goods are identified by the transaction's HS6 product code using the BEC classification. The dependent variables are the indicator of any trade activity (export+import) with Russia by a firm in a given month in columns (1) through (3), and the indicator of any imports from Russia by a firm in a given month in columns (4) through (8). Inference across regression models is conducted using a similarly unrelated regressions framework with standard errors clustered at the district level. Standard errors in parentheses are clustered at the district level.

boycott intensity; and, conversely, ethnicity does not matter as much in provinces where boycotts appear less widespread. Column (4) of Table A14 shows that, after the start of the conflict, trade declined more in areas with higher boycott intensity.

Taken together, these results strongly suggest that consumer action is one of the mechanisms through which armed conflict disrupts inter-group trade.

5.3.3 CSR Activity by Ukrainian Firms

In addition to consumer boycotts, activists may also create reputational pressure on firms that do business with the enemy, even if they do not deal with consumer products. As a result, firms may self-regulate and decrease their trade with Russia voluntarily, thus, by definition, engaging in corporate social responsibility (CSR) activity.

There is rich anecdotal evidence of Ukrainian firms trading with Russia being under relentless public pressure to discontinue such relationships. The pressure was in place even for firms trading only intermediate goods, such as automobile parts,⁵⁷ as well as exporting products, especially if buyers were somehow tied to Russian army providers.⁵⁸ Naturally, many Ukrainian companies

⁵⁷E.g., a large bus corporation was criticized for importing Russian inputs [www.volyn24.com/news/97774-bogdanmaie-vidmovytysia-vid-zakupivli-rosijskyh-detalej-gunchyk (in Ukrainian)], and another company faced pressure for producing buses with 95% of inputs coming from Russia [tsn.ua/groshi/tenderniy-skandal-ukrayina-zakupila-shkilni-avtobusi-u-virobnika-tehniki-dlya-armiyi-rf-713165.html (in Ukrainian)].

⁵⁸E.g., a firm faced severe public pressure for allegedly exporting engines to Russia that may have then been used

reacted to the pressure by decreasing their trade with Russia. Case studies abound coming from the construction, automobile, and aircraft manufacturing industries, in which firms declared that they would stop buying parts from Russia and selling the final product. For instance, an association of more than 700 companies in the construction sector pledged to abandon the use of Russian materials.⁵⁹ Another example is from the Ukrainian automobile producer AvtoKrAZ, which started to decrease its dependence on Russian products in 2014 and completely abandoned Russian components by early 2015, publicizing this process in the media.⁶⁰

While obtaining hard evidence of CSR is difficult, we document a pattern that is indirectly consistent with this conjecture. Specifically, we check whether our results are driven by large firms, which are traditionally viewed in the literature as more likely to be targeted by activists and to engage in CSR activity (Perrini et al., 2007; Smith, 2013). Table A15 breaks down our main results by the size of the firm. For the purposes of this exercise, we call a firm large if it employs more than 19 people, which is the median for our sample. Columns (2) and (3) present the difference-in-differences results for large and small intermediate-goods traders separately for all transactions (export+import); columns (4) and (5) display this breakdown for import transactions only, and columns (6) and (7) for export transactions only. As one can see, across all these specifications, the effect for large intermediate-goods traders is always significantly higher in magnitude relative to their smaller counterparts. Albeit indirectly, this pattern is consistent with higher reputational pressure on larger firms in areas with lower share of ethnic Russians to discontinue trade with Russia. Note that, according to these results, the pressure may be in place even for firms in the B2B sector and for exporters to Russia.

5.4 Discrimination at the Border

The final hypothesis we test is discrimination at the border. That is, it could be that Ukrainian firms from less Russian areas faced greater hostility from the Russian customs officials.

We test this hypothesis by focusing on trade between Ukraine and Kazakhstan. Nearly all trade

to create military products [interfax.com.ua/news/economic/404613.html (in Russian)].

⁵⁹“Under conditions where Russia is leading an unpargued war against our country, the whole civilized world introduces sanctions against the aggressor, we must take a firm stand and abandon the use of building materials and equipment produced by the Russian Federation,” said the President of the Confederation of Builders of Ukraine, Lev Partskhaladze [kmb.ua/ua/news/kiygorstroj-otkazvaetsya-ot-produktsii-rossijskogo-proizvodstva/ (in Ukrainian)].

⁶⁰ukr.segodnya.ua/economics/avto/ukrainskiy-avtogigant-polnostyu-otkazalsya-ot-rossiyskih-komplektuyushchih-609274.html (in Ukrainian). Another example are Ukrainian aircraft manufacturers, which have abandoned Russian components by early 2015 [ukr.lb.ua/economics/2015/06/16/308464_ukrainski_virobniki_litakiv.html (in Ukrainian)]. An indicator of how severe the pressure was, some companies, even in the B2B sector, changed their names so as not to be associated with Russia [lb.ua/economics/2014/03/19/259929_ukrainskaya_kompaniya_ubrala.html (in Russian)].

between these two countries uses ground transportation and, as a result, has to pass through the Russia-Ukraine border.⁶¹ Thus, if Russian customs officials discriminate against Ukrainian firms from less Russian areas, we would expect it to appear in transactions between Ukrainian firms and Kazakhstan too. Columns (1) through (3) of Table A16 display the baseline results for trade between Ukrainian firms and Kazakhstan. As one can see, the Russian-ethnicity-post interaction coefficient is statistically insignificant and has the opposite sign relative to Table 2. This speaks against the discrimination hypothesis, suggesting that, if anything, trade with Kazakhstan declined more for Ukrainian firms in *more* Russian areas. One may object that, if the goal of the customs officials was to hurt Ukrainian firms from certain regions, discrimination would have been more pronounced for Ukrainian exporters, not importers. However, the results for the exports from Ukraine to Kazakhstan in columns (4) through (6) of Table A16 suggest that this is not the case.

Overall, these empirical findings suggest that our baseline results are not due to discrimination at the border by Russian customs officials.

6 Implications for Firms

6.1 Sales, Profits, and Productivity

In this section, we explore whether the negative shock to inter-group trade, documented in the preceding parts of this paper, had any implications for the trading firms' sales, profits, and productivity. A simple difference-in-differences framework with firm performance on the left-hand side of the equation may conflate the effect of a trade shock with the negative effects of being close to the conflict zone. This may lead to a puzzling result that firms from more Russian areas lost *more* sales after the start of the conflict.⁶² To isolate the consequences of a trade shock from other contemporaneous shocks, we compare firms from more Russian areas *trading* with Russia not only to their counterparts in less Russian areas, but also to all other firms in the economy that *did not trade* with Russia. We do this in a triple-difference specification, with the outcome varying across

⁶¹ See the map on Figure A13. For the breakdown of trade between Ukraine and Kazakhstan by mode of transportation, see p.4 at www.beratergruppe-ukraine.de/wordpress/wp-content/uploads/2016/04/PB_04_2016_en.pdf.

⁶² Analyzing the census of Ukrainian firms from the ORBIS/AMADEUS database shows that firms in areas with a higher Russian presence experienced a deeper overall economic decline in the immediate aftermath of the conflict (see Table A17). It is beyond the scope of this paper to rationalize this pattern, but we speculate that it may be due to the disruption of input-output linkages with the areas of armed conflict (Carvalho, Nirei, Saito, and Tahbaz-Salehi, 2016).

Note that, although this pattern can affect our results for sales and profits, it does not drive our estimates for trade. In Section 4.2.4, in a multi-country-trade specification, we have already shown that our results are robust to the inclusion of the district-post fixed effects. Furthermore, Table A18 shows that our main estimates survive conditioning on firm's yearly sales—if anything, the interaction coefficient on the share of ethnic Russians goes up relative to the baseline.

time, ethnic composition, and an indicator for whether a firm traded with Russia or not.⁶³ Under the standard triple-difference assumptions of parallel trends across multiple groups, and assuming that non-trade shocks affect traders and non-traders in the same manner, the triple interaction coefficient identifies the negative consequences of conflict on a firm’s overall performance via the shock to trade with Russia, net of the changes that are due to broad economic shocks that affect all firms.⁶⁴

Table 6 presents the triple difference estimates. Across all three measures of firm performance—sales, profits, and productivity,—the coefficient on the triple interaction is positive and highly statistically significant. Therefore, net of broad economic shocks, firms from less Russian areas that traded with Russia before the conflict suffered a larger decline in sales, profits, and productivity relative to their counterparts. This indicates that a negative trade shock across ethnicity indeed led to worse firm performance. The magnitude of this differential decline is economically meaningful. For instance, according to column (1) of Table 6, moving a firm that traded with Russia before the conflict from a district with 17.7% (75th percentile) to a district with 9.6% (25th percentile) of ethnic Russians would have decreased its sales by 7.2% relative to other firms in the area after the start of the conflict.

Overall, this section suggests that the differential effect of conflict on inter-group trade adversely affects firms, not only via decreased sales but also via decreased profits and productivity. Thus, the baseline results of this study have far-reaching implications for individual firms.

6.2 Switching Patterns

This section presents evidence that one of the ways in which Ukrainian firms accommodated the trade shock is by switching to trading with other countries. First, according to Figure A15,

⁶³Specifically, we estimate the following equation:

$$Y_{isdt} = \alpha_i + \gamma_t + [\mu + \beta\text{Post}_t] \times \text{Rus}_d \times \text{Traded}_s + \text{Post}_t \times [\delta\text{Rus}_d + \kappa\text{Traded}_s] + \varepsilon_{isdt}. \quad (6)$$

Here, Y_{isdt} is a balance-sheet variable (sales, profits, etc.) of firm i in district d at year t of status s , where $s = 1$ if a firm traded with Russia in 2013; Post_t is an indicator for whether time period t is after the start of the conflict in February 2014; Traded_s is an indicator for whether a firm traded with Russia in 2013; Rus_d is the share of ethnic Russians in a district d of firm i ; and α_i and γ_t are firm and year fixed effects, respectively.

⁶⁴Figure A14 illustrates this strategy. As one can see, a simple difference-in-differences exercise among the firms trading with Russia (solid line) suggests that, if anything, firms from more Russian areas suffered a *bigger* loss of sales. However, this is not true in comparison with all firms in Ukrainian economy, as the differential drop in sales across areas of different ethnicity was even larger for firms not trading with Russia (dashed line). Thus, the former result likely combines both trade and broad economic shocks, which the latter helps to disentangle. It is also important to note that there has been no differential trend in firms’ sales before the start of the conflict neither across ethnicity, nor across the status of firms’ trade activity with Russia. Thus, the identifying assumption of the triple-difference specification likely holds.

Table 6: Consequences for Firms: Sales, Profits, and TFP

Dependent variable:	(1) Log Sales	(2) Log Profit	(3) Log TFP
Post Feb 2014 × Traded with Russia × Share of Ethnic Russians	0.893*** (0.285)	1.037** (0.494)	0.190** (0.074)
Post Feb 2014 × Share of Ethnic Russians	-1.323*** (0.256)	-1.757*** (0.341)	-0.168*** (0.054)
Post Feb 2014 × Traded with Russia	-0.046 (0.052)	-0.062 (0.092)	0.039** (0.016)
Firm FE	✓	✓	✓
Year FE	✓	✓	✓
Dep. Var. Mean	13.169	10.761	13.560
Dep. Var. SD	4.216	6.673	1.870
R ²	0.75	0.51	0.93
Observations	1,107,520	1,107,215	1,026,585
Firms	190,515	190,470	176,352
Districts	491	491	495

Notes: * p<0.1, ** p<0.05, *** p<0.01. This table estimates the consequences of the differential shock to trade in a triple-difference specification comparing firm performance before and after the start of the conflict, for firms in areas with more versus fewer ethnic Russians, and for firms that traded with Russia at least once in 2013 and not. The analysis includes all Ukrainian firms, not only those that traded with Russia, but excludes firms from conflict areas and firms with missing accounting data for more than one year from 2011 to 2016. Dependent variables in Columns (1) and (2) are total sales and gross profit, respectively, transformed using the inverse hyperbolic sine function $L(X)$, such that $L(X) = \log(X + \sqrt{X^2 + 1})$ as in MacKinnon and Magee (1990). Total factor productivity in column (3) is derived from a Cobb-Douglas specification regressing turnover on capital and labor (all in logs) with two-digit industry fixed effects. Data on ethnic composition are at the district level and come from the 2001 Ukrainian Census. Standard errors in parentheses are clustered at the district level.

Ukrainian firms in less Russian areas increased their trade, relative to their counterparts, with countries such as Poland and Turkey (note that these results include firms that never traded with Russia from 2013 through 2016). This pattern is highly indicative of switching. Second, if switching is indeed one of the primary ways of accommodating the reduction in trade with Russia, one would expect firms with lower costs of switching to be driving our baseline estimates. We indeed find this to be the case. Highly consistent with the switching response, Table A19 shows that firms with already established connections in other countries before the conflict drive our baseline estimates (columns 1–2). Moreover, this pattern holds for both exporters and importers separately (columns 3–4 and 5–6, respectively), suggesting that the fixed costs of entering a new market are binding for both exporters and importers. Finally, Table A20 shows that the baseline effect is driven by firms that traded homogeneous products, as opposed to differentiated ones, further suggesting that lower switching costs indeed mattered for our results. Overall, these findings strongly suggest that one of the ways in which Ukrainian firms accommodated the conflict-induced shock to inter-group trade is by shifting their trade away from Russia to other countries.

7 Conclusion

Armed conflict has vast and multifaceted effects on the economy. It can impact economic agents directly, through violence and property damage, or indirectly—e.g., by disrupting business relationships. While the existing literature offers plenty of evidence on the direct effects of conflict, such effects remain largely understudied. This paper provides evidence on one such type of indirect consequence: the disruption of inter-group trade outside of the conflict areas. We study the ongoing Russia-Ukraine conflict, which is unique for its near absence of newly imposed trade restrictions. Using rich, transaction-level data on Ukrainian trade, we show that firms located in districts with a higher share of ethnic Russians experienced a smaller drop in trade with Russia relative to firms in other districts. We interpret our findings as arising partly from a decline in inter-group trust, and partly from the rise of local nationalism, which translates into consumer boycotts against Russian products and public pressure on firms to discontinue their business relationships with the enemy.

Our findings may have far-reaching implications for the economic development of fragile states. Ethnic heterogeneity has been associated at the macro level with lower economic growth, lower public good provision, more frequent conflict, and lower trust (Alesina and Ferrara, 2005). It has also been suggested that ethnic divisions, created by arbitrary colonial borders, have contributed greatly to Africa’s underdevelopment (Easterly and Levine, 1997). Our results indicate that ethnic heterogeneity may lead to lower economic performance in part because of reduced inter-group economic exchange resulting from frequent conflicts.

We hypothesize that our estimates may be especially applicable to conflicts in which the two sides are crucial trading partners or have been part of the same entity historically. One broad category of such conflicts is civil wars, in which trade embargoes are often not enacted or not strictly enforced.⁶⁵ As such, our results may be highly informative with regard to the numerous civil wars with an ethnic component (Ray and Esteban, 2017). Still, more research is needed to determine whether our results will replicate in other contexts.

Our study also highlights the importance of analyzing economic activity in non-combat areas. Modern empirical studies of conflict tend to focus on comparing areas with violence to those without, leaving potential spillovers unexplored and unaccounted for. In contrast, we focus only on areas unaffected by violence directly and find that, even there, conflict hurts inter-group trade. In a companion project, we explore how the shocks from the war in Donbass impact the rest of Ukraine through the supply chain network (Korovkin and Makarin, 2019). It also remains unclear

⁶⁵See, e.g., Leigh (2012) on the continued trade between the North and the South during the American Civil War.

to what extent conflict affects other types of voluntary interactions besides economic exchange, such as formation of business partnerships, collaborative innovation, etc., and what the overall welfare implications of these effects might be. In summary, the economic impact of conflict on non-combat areas remains an understudied topic that would benefit from further scholarly work.

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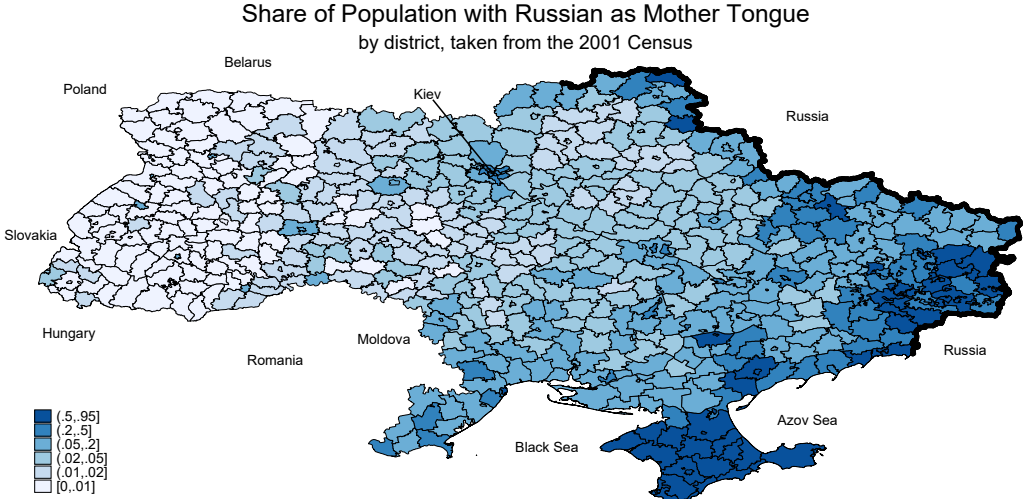
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ONLINE APPENDIX

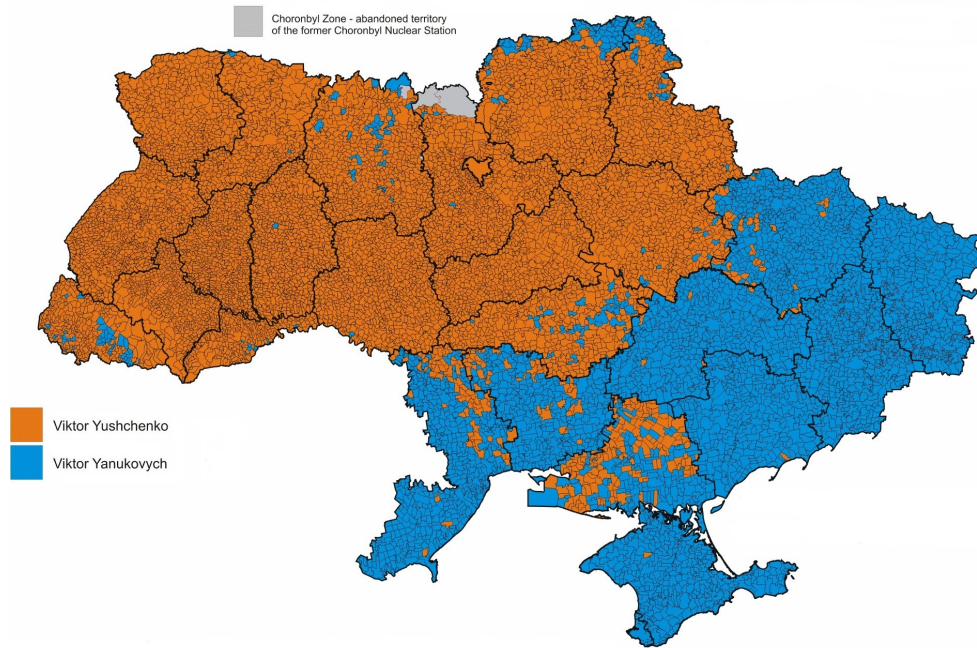
A1 FIGURES

Figure A1: Shares of Native Russian Speakers



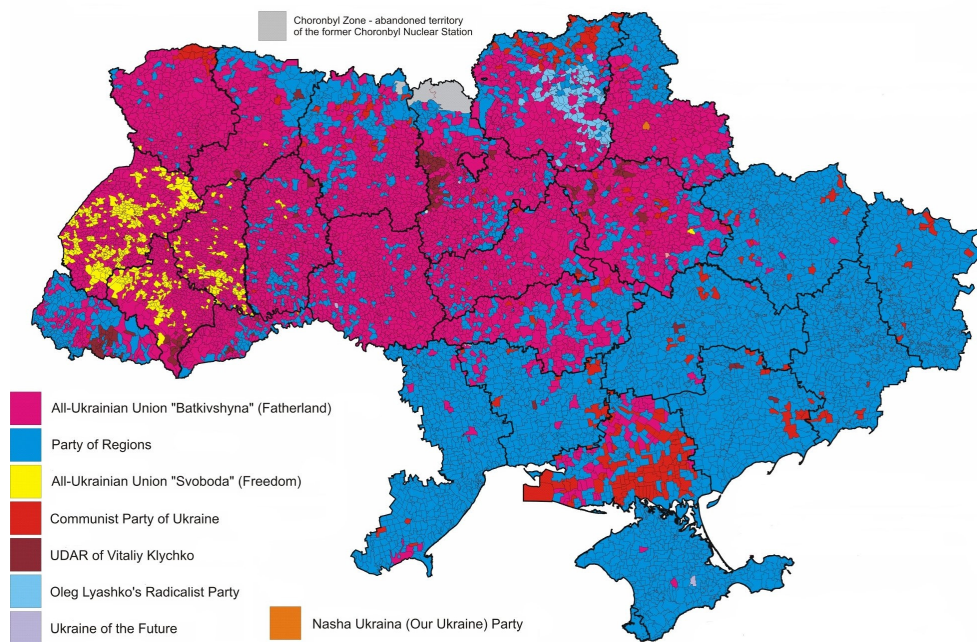
Notes: This figure maps the distribution of the share of native Russian speakers across Ukrainian districts (raions). Data come from the 2001 Ukrainian Census. The thick black line represents the border between Ukraine and Russia.

Figure A2: Results of the 2004 Presidential Elections (Second Round) at the Polling-Station Level



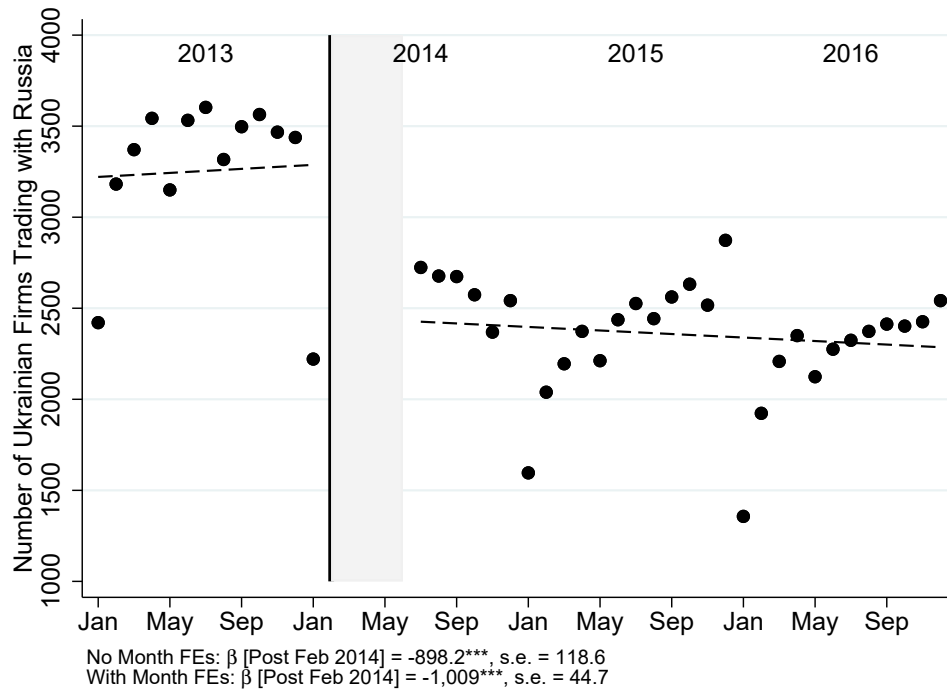
Source: This electoral map is the intellectual property of Serhij Vasylchenko.

Figure A3: Results of the 2012 Parliamentary Elections at the Polling-Station Level



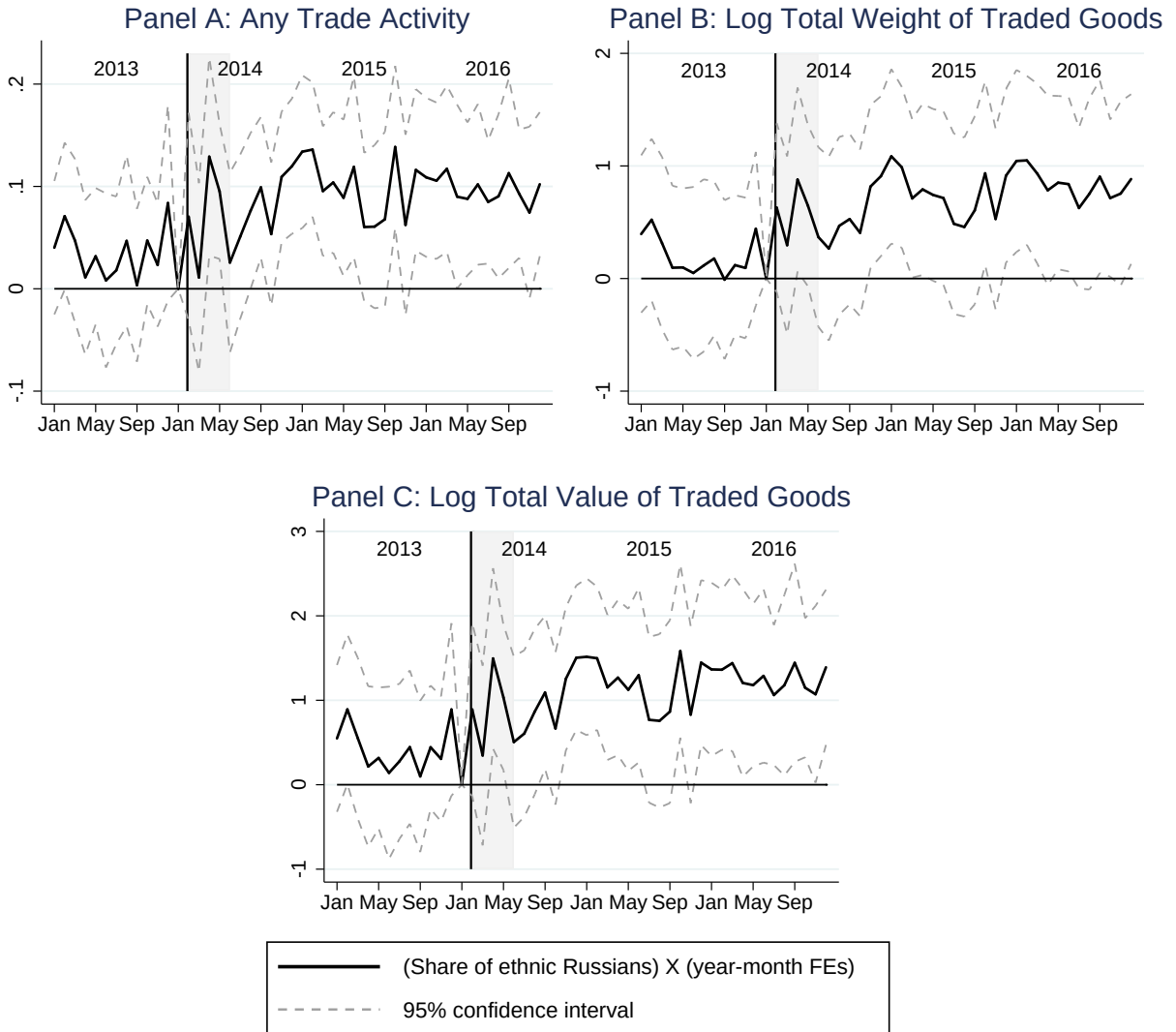
Source: This electoral map is the intellectual property of Serhij Vasylchenko.

Figure A4: Number of Ukrainian Firms Trading with Russia



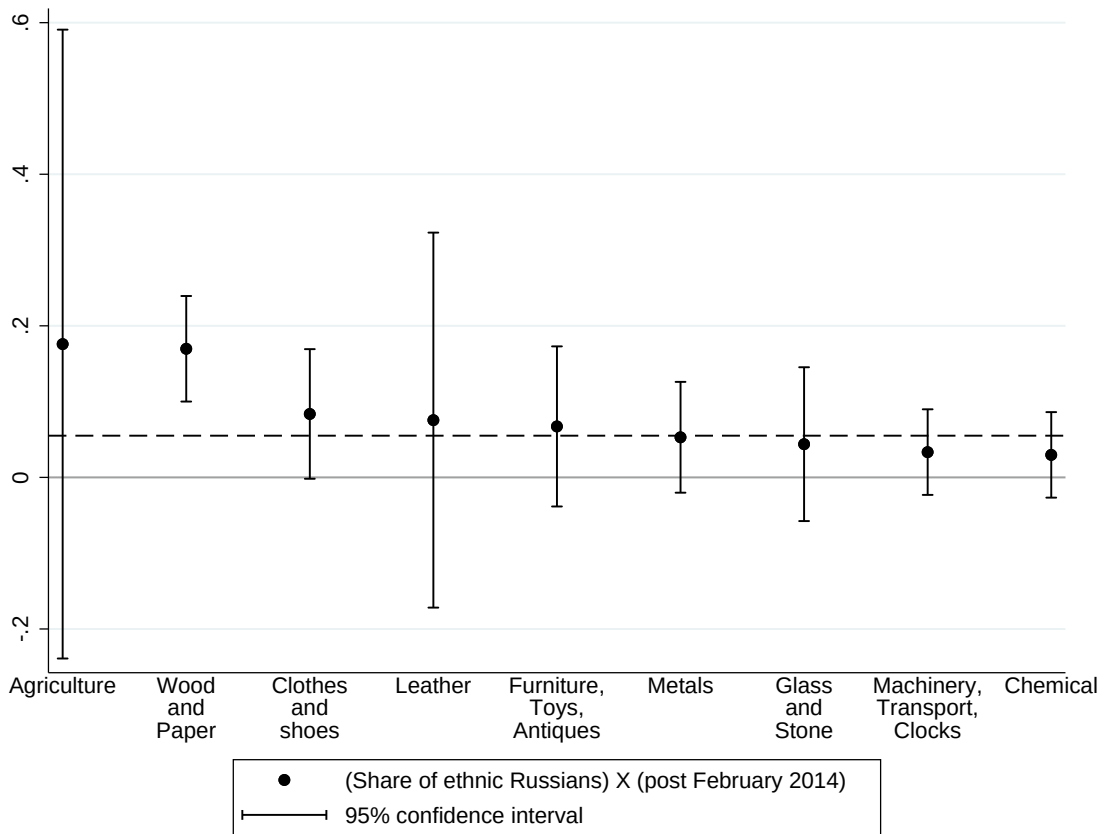
Notes: This figure displays the number of Ukrainian firms trading with Russia in a given month, including both exporters and importers. Firms located in the areas of conflict are excluded. Dashed lines represent the linear fit for the scattered data before and after the start of the conflict. Export data are missing for February through June 2014 (colored in gray). These five months are removed for the aggregate comparisons. January is a short business month in Russia because of a full holiday week, January 1 to 7. Similarly, Ukraine has two official holidays in January — New Year’s Eve (January 1) and Orthodox Christmas (January 7). As such, January data are seasonal outliers. As suggested by the text below the graph, the inclusion of monthly fixed effects deepens the conflict-induced drop in the monthly number of firms trading with Russia from about 900 to about 1,000.

Figure A5: Month-by-Month Analysis at the Firm-Product Level with Product-Post FEs.



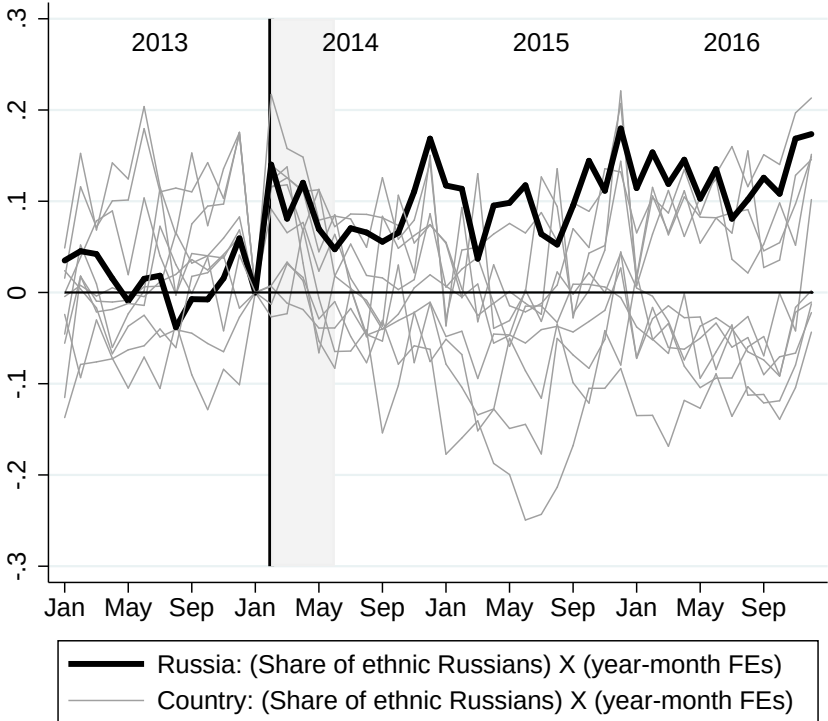
Notes: This graph displays the results of a month-by-month product-firm specification, which modifies the baseline equation (4) by interacting year-month fixed effects with the ethnic composition of the firms' districts. The unit of observation is firm's trade of a given product (HS4) with Russia. For February through June 2014, only import data are present (colored in gray). Removing these five months from our analysis does not change the results. Panel A displays the results for any trade activity with Russia by a firm with a given product in a given month (export+import) as the dependent variable, Panel B displays the results for the logarithm of total weight of the goods traded with Russia (export+import), and Panel C displays the results for the log of total value traded (export+import). 95% confidence intervals are constructed for standard errors clustered at the district level.

Figure A6: Difference-in-Differences Coefficients for Various Types of Products



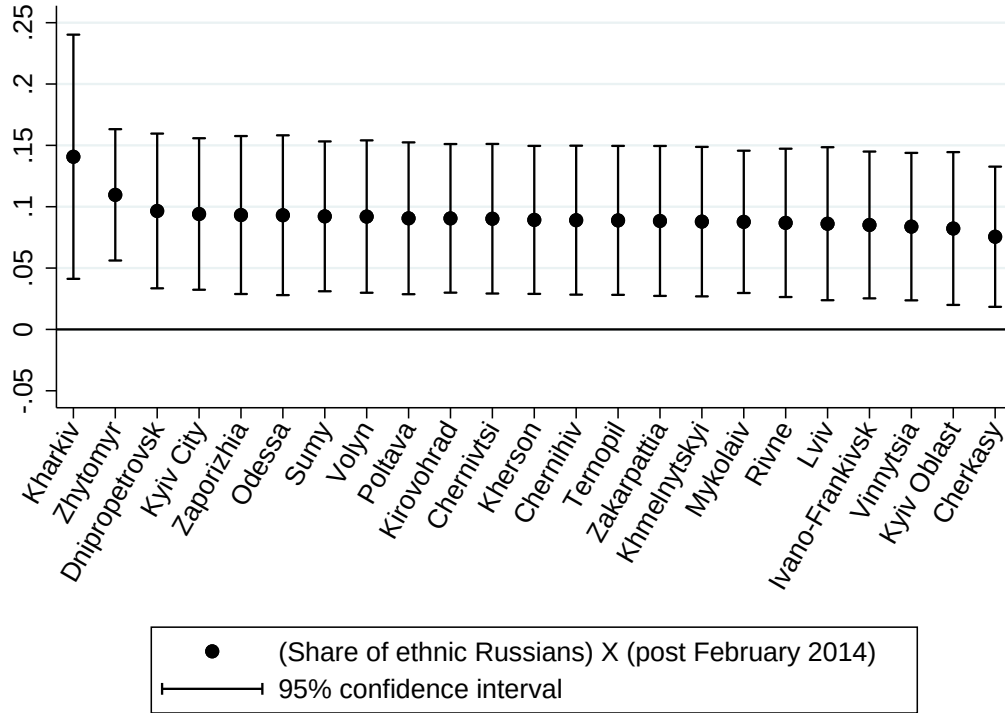
Notes: This figure presents the estimation results of equation (4) for firm-product-level trade for different types of products. The dependent variable is an indicator of any trade activity by a firm in a given month with a given HS2 product-type (export+import). The horizontal dashed line represents the baseline coefficient for trade with Russia at a firm-product level taken from column (1) of Table A6 Panel A. The correspondence between product types and HS2 codes is as follows: “agriculture” refers to HS2 01–24 codes, “chemical” to HS2 25–40, “leather” to HS2 41–43, “wood and paper” to HS2 44–49, “clothes and shoes” to HS2 50–67, “glass and stone” to HS2 68–71, “metals” to HS2 72–83, “machinery, transport, and clocks” to HS2 84–92, and “furniture, toys, and antiques” to HS2 94–97. 95% confidence intervals are constructed for the standard errors clustered at the district level.

Figure A7: Baseline Month-by-Month Coefficients for Russia Compared to Other Countries



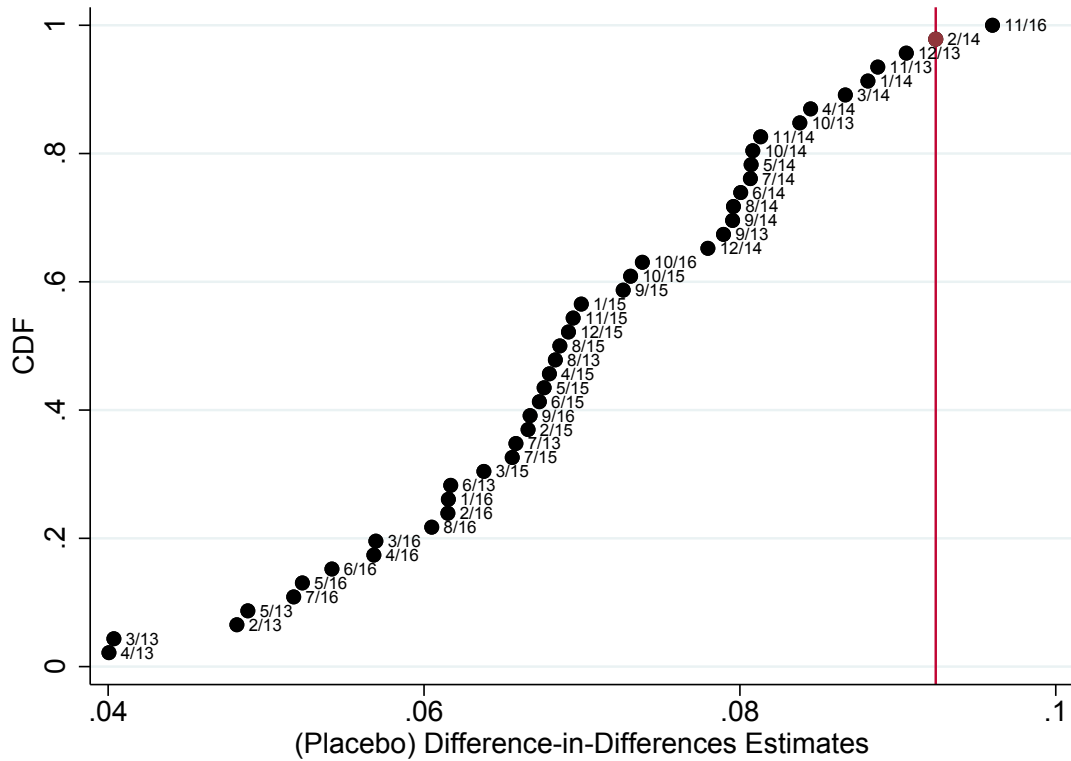
Notes: This figure presents the estimation results of the month-by-month equation (3) for firm-level trade with the top-10 trading partners of Ukraine and all other countries pooled together. The dependent variable is an indicator of any trade activity by a firm in a given month (export+import). The coefficients for trade with Russia (in bold) are identical to the ones in Panel A of Figure 4.

Figure A8: Baseline Results Excluding Ukrainian Provinces One at a Time



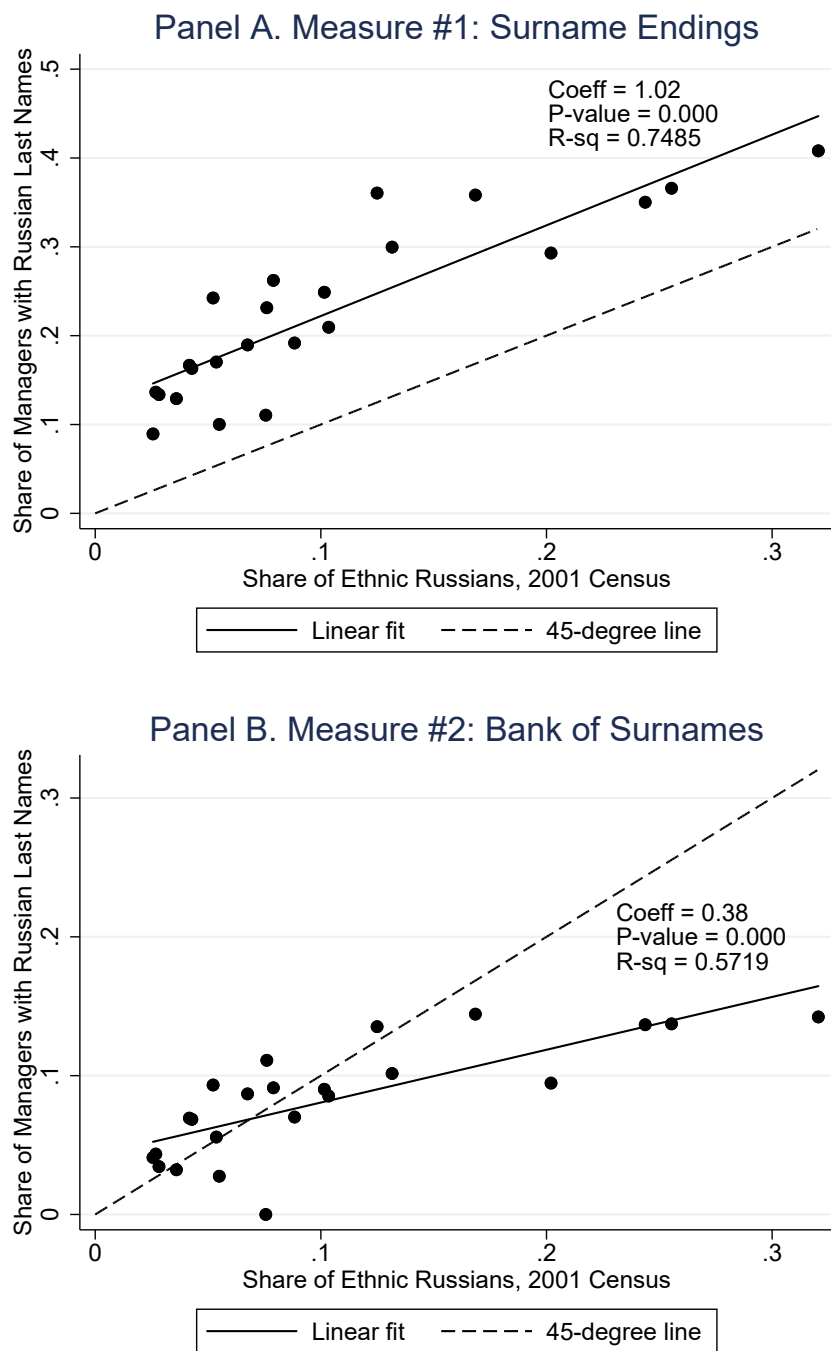
Notes: This figure presents the baseline results in column (1) of Table 2 for 23 different subsamples, excluding Ukrainian provinces (*oblasts*) from the sample one at a time. The dependent variable is an indicator of any trade activity by a firm in a given month (export+import). 95% confidence intervals are constructed for standard errors clustered at the district level.

Figure A9: Placebo Conflict Starting Times



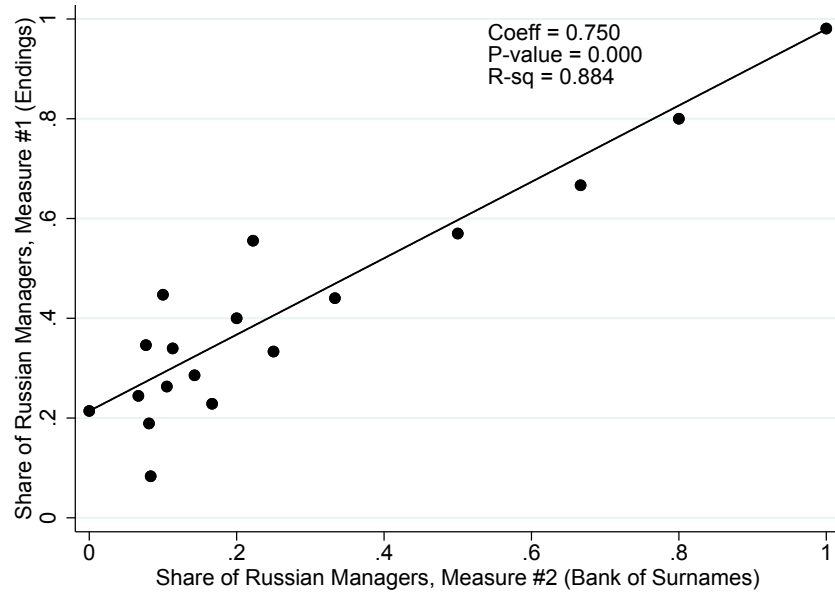
Notes: This figure presents the baseline difference-in-differences estimates from column (1) in Table 2 for the true starting month of the conflict, February 2014 (red dot), and for 45 placebo conflict starting months (black dots). Month and year of the (placebo) starting month is displayed next to the value of the coefficient. The dependent variable is an indicator for whether a firm traded with Russia in a given month (export+import).

Figure A10: Surname-Based Measures of Ethnicity Aggregated to the Province Level vs. Census



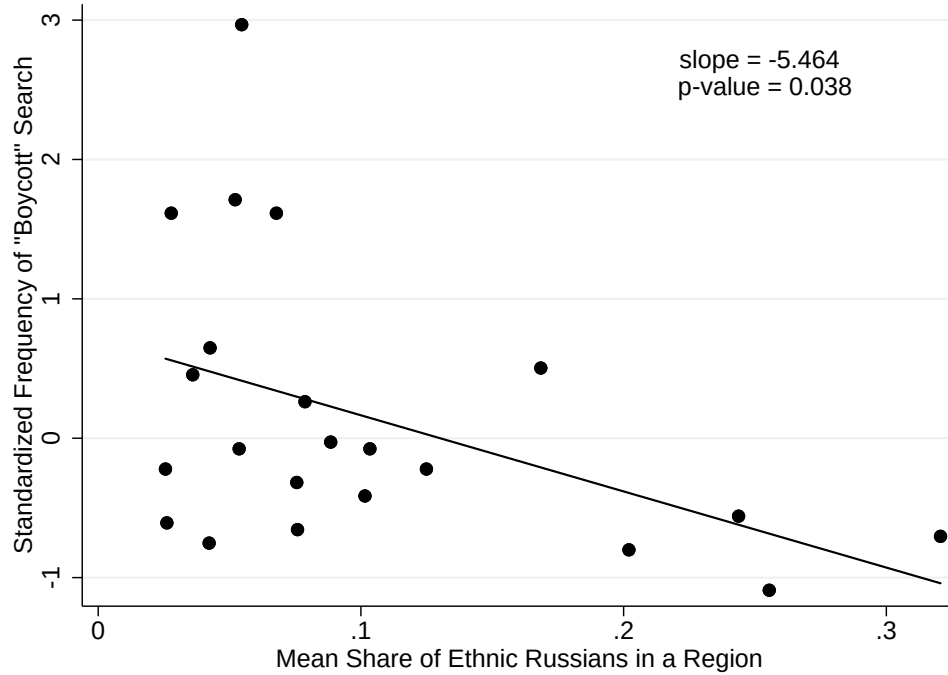
Notes: This figure illustrates the relationship between the share of ethnic Russians as measured by the 2001 Ukrainian Census and the share of firms' managers with Russian last names aggregated to the province level (*oblast*). The results of a corresponding regression are displayed in the top-right corner. The three conflict provinces — Crimea, Donetsk oblast, and Luhansk oblast — are excluded from the analysis. Measure #1 classifies last names as Russian if they end in “ov,” “ova,” “ev,” “eva,” “in,” or “ina” (for a detailed discussion of this approach, see Zhuravlev (2005) (in Russian)). Measure #2 relies on the bank of 622 traditionally Russian last names, combined from the lists of 250 traditional Russian last names from Balanovskaya et al. (2005) and 500 most frequent Russian last names from Zhuravlev (2005), net of all duplicates.

Figure A11: Relationship between the Two Surname-Based Measures of Ethnicity



Notes: This figure is a binned scatterplot of the relationship between the two measures of the share of Russian managers in a firm. Measure #1 classifies last names as Russian if they end in “ov,” “ova,” “ev,” “eva,” “in,” or “ina” (for a detailed discussion of this approach, see Zhuravlev (2005) (in Russian)). Measure #2 relies on the bank of 622 traditionally Russian last names, combined from the lists of 250 traditional Russian last names from Balanovskaya et al. (2005) and 500 most frequent Russian last names from Zhuravlev (2005), net of all duplicates. The results of a corresponding regression are displayed in the top-right corner. The conflict regions (Crimea, Donetsk Oblast, and Luhansk Oblast) are excluded from this analysis.

Figure A12: Frequency of Online Search for “Boycott” and Regional Ethnic Composition

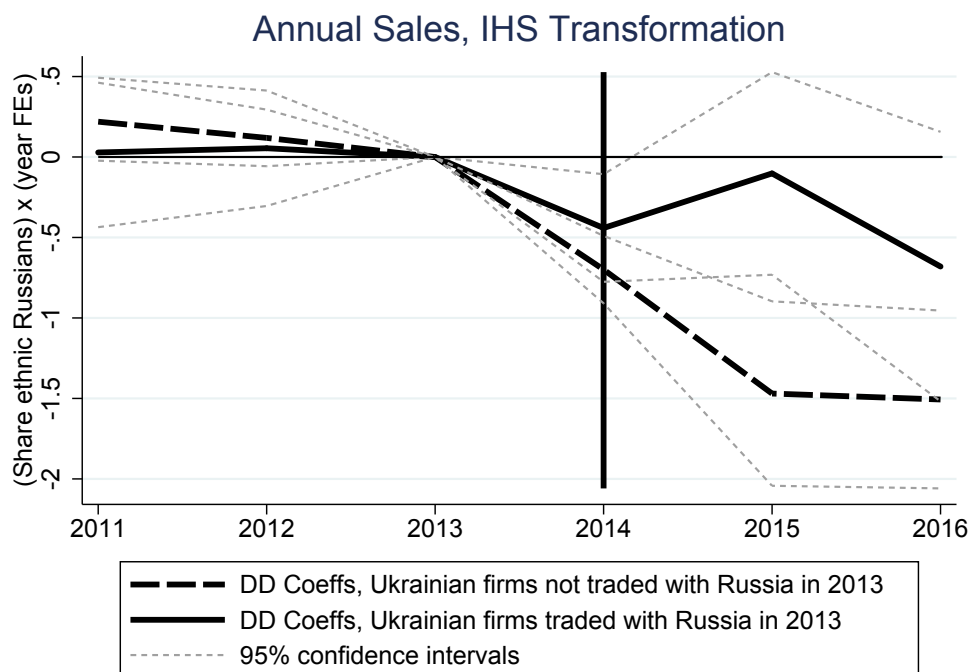


Notes: This figure displays the association between the standardized frequency of online searches for the word “boycott” from February 1 to May 1, 2014, across Ukrainian provinces, obtained from Google Trends, and the average share of ethnic Russians in Ukrainian provinces (*oblasts*). The results of a corresponding regression are displayed in the top-right corner.

Figure A13: Location of Ukraine, Kazakhstan, and Russia on the World Map

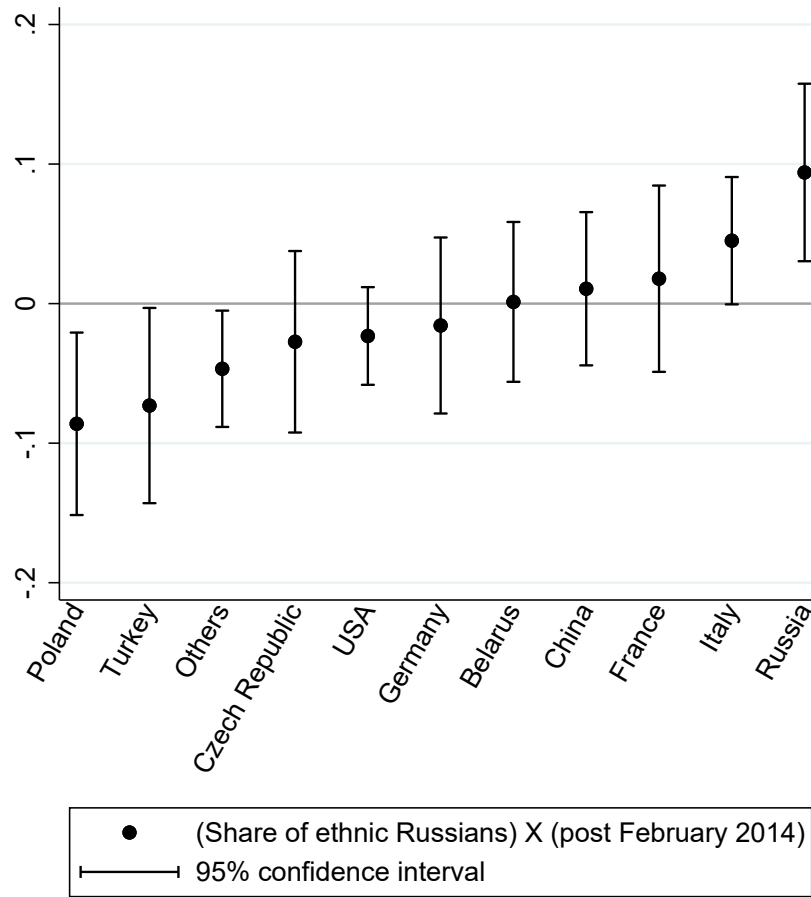


Figure A14: Differential Decline in Sales: Triple-Difference Specification



Notes: This figure presents an illustration of the triple-difference estimation results in Table 6. The solid black line represents the difference-in-differences coefficients coming from regressing the yearly sales of the firms that *did not* trade with Russia on the interaction between the yearly fixed effects and the share of ethnic Russians. The long-dash black line represents the difference-in-differences coefficients coming from regressing the yearly sales of the firms that *traded* with Russia before the start of the conflict on the interaction between the yearly fixed effects and the share of ethnic Russians in the home district of a given firm. As such, the triple-difference specification (6) estimates the divergence between these two sets of coefficients after the start of the conflict in 2014. The analysis excludes firms from the conflict areas and firms with missing accounting data for more than one year from 2011 through 2016. Data on ethnic composition are at the district level and come from the 2001 Ukrainian Census. The dependent variable is firm's total yearly sales transformed using the inverse hyperbolic sine function $L(X)$, such that $L(X) = \log(X + \sqrt{X^2 + 1})$ as in MacKinnon and Magee (1990). 95% confidence intervals are constructed for standard errors clustered at the district level.

Figure A15: Difference-in-Differences Coefficients Across Countries



Notes: This figure presents the estimation results of equation (1) for firm-level trade with the top-10 trading partners of Ukraine and all other countries pooled together. The dependent variable is an indicator of any trade activity by a firm in a given month (export+import). As such, the coefficient for trade with Russia is identical to column (1) of Table 2. 95% confidence intervals are constructed for the standard errors clustered at the district level.

A2 TABLES

Table A1: Summary Statistics

	Observations	Mean	SD	Min	Max
<i>Panel A: Trade Transaction Data</i>					
Any Trade Activity	591,541	.2	.4	0	1
Log of Total Weight Traded	591,541	1.97	4.14	0	21
Log of Total Value Traded	591,541	2.72	5.5	0	23
Number of Trade Transactions	591,541	3.16	32.2	0	5,420
Total Net Weight Traded in a Given Month, in Tons	591,541	230	6,817	0	1,709,763
Total Value Traded in a Given Month, in UAH (1,000s)	591,541	1,281	31,463	0	8,045,764
<i>Panel B: Types of Goods Traded</i>					
Share of Intermediate Goods Traded by a Firm in 2013-2016	12,872	.765	.363	0	1
Share of Consumer Goods Traded by a Firm in 2013-2016	12,872	.172	.335	0	1
Share of Homogeneous Goods Traded by a Firm in 2013-2016	12,867	.219	.387	0	1
<i>Panel C: Ethnic Composition of Districts</i>					
Share of Ethnic Russians, 2001 Census	12,872	.15	.097	0.002	.53
Share of Native Russian Speakers, 2001 Census	12,872	.26	.2	0.001	.75
<i>Panel D: Ethnic Composition of Management</i>					
Share of Managers with Russian Last Names, Method #1	10,794	.29	.45	0	1
Share of Managers with Russian Last Names, Method #2	10,794	.11	.3	0	1
<i>Panel E: Distance to the Border</i>					
Shortest Path to Russian Border, Post-Conflict, km	11,779	254	165	1.505	794
Shortest Path to Russian Border, Pre-Conflict, km	11,779	247	164	1.505	794
<i>Panel F: Accounting Data</i>					
IHS Transformation of Sales, Traders, 2013–2015	36,889	16.83	3.07	0	26.50
IHS Transformation of Profits, Traders, 2013–2015	36,889	15.03	4.64	-19.41	25.25
Total Factor Productivity, Traders, 2013–2015	36,889	15.68	2.14	8.88	27.16

Notes: Data on trade include export and import transactions. Homogeneous goods are defined as in Rauch (1999). The standardized BEC classification specifies intermediate goods. An individual is considered a native Russian speaker if Russian is his or her mother tongue. Method #1 of calculating the share of managers with Russian last names treats a last name as traditionally Russian if it ends in “ov,” “ova,” “ev,” “eva,” “in,” “ina,” “yov,” or “yova” (Zhuravlev, 2005). Method #2 uses a bank of 622 traditionally Russian last names, combined from the lists of 250 traditional Russian last names from Balanovskaya et al. (2005) and 500 most frequent Russian last names from Zhuravlev (2005), net of all duplicates. The shortest path to the Russian border for the periods after the conflict began excludes parts of the border that are located in conflict regions. IHS stands for inverse hyperbolic sine transformation $L(X) = \log(X + \sqrt{X^2 + 1})$ as in MacKinnon and Magee (1990). Total factor productivity is derived from a Cobb-Douglas specification regressing turnover on capital and labor (all in logs) with two-digit industry fixed effects.

Table A2: Baseline Results with Conley Spatial HAC Standard Errors

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded
Post Feb 2014 × Share of Ethnic Russians	0.107*** (0.009)	1.356*** (0.102)	1.490*** (0.116)			
Post Feb 2014 × Share of Russian Speakers				0.051*** (0.004)	0.666*** (0.048)	0.712*** (0.055)
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.201	1.970	2.726	0.201	1.970	2.726
Dep. Var. SD	0.400	4.141	5.506	0.400	4.141	5.506
Observations	542,831	542,831	542,831	542,831	542,831	542,831
Firms	11,756	11,756	11,756	11,756	11,756	11,756
Districts	388	388	388	388	388	388

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table examines the robustness of the baseline results to allowing spatial correlation among districts that fall within a certain distance of each other. Standard errors in parentheses are Conley spatial HAC standard errors calculated using STATA routine by Fetzer (2019), with the distance cutoff of 1,000 km and the time lag cutoff of 20 months. Columns (1) and (4) use an indicator for a firm trading with Russia in a given month (export+import). The logs of total value and net weight of shipped goods (export+import) are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. District-level data on ethnolinguistic composition come from the 2001 Ukrainian Census. The share of Russian speakers is measured as the percentage of people who named Russian as their mother tongue (“rodnoi yazik”).

Table A3: Robustness of Baseline Results to Missing Data

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded
	<i>Without Feb–Jun 2014</i>			<i>Zero Exports in Feb–Jun 2014</i>		
Post Feb 2014 × Share of Ethnic Russians	0.094*** (0.030)	1.163*** (0.348)	1.312*** (0.388)	0.099*** (0.032)	1.264*** (0.380)	1.371*** (0.422)
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.202	1.983	2.743	0.192	1.886	2.609
Dep. Var. SD	0.401	4.154	5.523	0.394	4.071	5.415
R ²	0.42	0.49	0.47	0.41	0.48	0.45
Observations	553,281	553,281	553,281	617,616	617,616	617,616
Firms	12,867	12,867	12,867	12,867	12,867	12,867
Districts	390	390	390	390	390	390
	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable:	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded
	<i>Imputed as in Feb–Jun 2013</i>			<i>Imputed as Average Trade in 2013</i>		
Post Feb 2014 × Share of Ethnic Russians	0.082*** (0.025)	1.011*** (0.299)	1.145*** (0.336)	0.064*** (0.024)	0.785*** (0.281)	0.963*** (0.321)
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.205	2.014	2.781	0.226	2.152	2.999
Dep. Var. SD	0.404	4.178	5.544	0.418	4.232	5.635
R ²	0.42	0.49	0.47	0.41	0.49	0.46
Observations	617,808	617,808	617,808	617,808	617,808	617,808
Firms	12,871	12,871	12,871	12,871	12,871	12,871
Districts	393	393	393	393	393	393

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table examines the robustness of the baseline results in Table 2 to four alternative ways of accommodating the missing exports data from February through June 2014. Columns (1) through (3) present the estimates without the February–June 2014 import data. Columns (4) through (6) display the baseline results when firms' export flows from February through June 2014 are assumed to be zero. Columns (7) through (9) assume that firm i 's exports at month m from February through June 2014 are the same as firm i 's exports at month m from February through June 2013. Finally, columns (10) through (12) assume that firm i 's exports at any month from February through June 2014 is the same as firm i 's average exports throughout 2013. Columns (1), (4), (7), and (10) use an indicator for a firm trading with Russia in a given month (export+import). The logs of total value and net weight of shipped goods (export+import) are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. District-level data on ethnolinguistic composition come from the 2001 Ukrainian Census. Standard errors in parentheses are clustered at the district level.

Table A4: Baseline Results for Exports and Imports Separately

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Any Export Activity	Log Total Weight Exported	Log Total Value Exported	Any Import Activity	Log Total Weight Imported	Log Total Value Imported
	<i>Exports to Russia</i>			<i>Imports from Russia</i>		
Post Feb 2014 × Share of Ethnic Russians	0.136*** (0.047)	1.718*** (0.525)	1.930*** (0.607)	0.048** (0.022)	0.467** (0.236)	0.592* (0.315)
Firms FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.194	1.886	2.637	0.189	1.859	2.565
Dep. Var. SD	0.396	4.028	5.421	0.392	4.061	5.377
R ²	0.41	0.48	0.46	0.41	0.48	0.45
Observations	305,472	305,472	305,472	366,432	366,432	366,432
Firms	7,104	7,104	7,104	7,634	7,634	7,634
Districts	342	342	342	314	314	314

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table presents the baseline results estimated separately for exports to and imports from Russia. Columns (1) through (3) focus on export transactions only, while columns (4) through (6) focus on import transactions. Columns (1) and (4) use an indicator for a firm exporting to or importing from Russia in a given month. The logs of total value and net weight of exported or imported goods are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. Data on ethnic composition are at the district level and come from the 2001 Ukrainian Census. Standard errors in parentheses are clustered at the district level.

Table A5: Baseline Results with Flexible Distance Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Any Trade Activity with Russia							
Distance controls:	Distance to the Border with Russia	Log of Distance	Fifth Polynomial of Distance	Fifth Polynomial of Log of Distance	Post Feb 2014 × Distance	Post Feb 2014 × Log of Distance	Post Feb 2014 × Fifth Polynomial of Distance	Post Feb 2014 × Fifth Polynomial of Log of Distance
Post Feb 2014 × Share of Ethnic Russians	0.109*** (0.033)	0.109*** (0.032)	0.110*** (0.033)	0.110*** (0.033)	0.087** (0.038)	0.090** (0.036)	0.108*** (0.039)	0.116*** (0.041)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓
Distance Controls	✓	✓	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.213	0.213	0.213	0.213	0.213	0.213	0.213	0.213
Dep. Var. SD	0.409	0.409	0.409	0.409	0.409	0.409	0.409	0.409
R ²	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41
Observations	542,676	542,676	542,676	542,676	542,676	542,676	542,676	542,676
Firms	11,756	11,756	11,756	11,756	11,756	11,756	11,756	11,756
Districts	388	388	388	388	388	388	388	388

Notes: * p<0.1, ** p<0.05, *** p<0.01. This table documents the robustness of the baseline results to various controls for firms' distance to Russia. Specific distance controls used in each column are listed in column headers. We recalculate the distance of each firm to the Russia-Ukraine border after the start of the conflict by taking out the part of the border located in the Donetsk and Luhansk provinces. As a result, the distance measures in columns (1) and (2) are not absorbed by firm fixed effects. The dependent variable is the indicator of any trade activity (export+import) by a firm in a given month. District-level data on ethnic composition come from the 2001 Ukrainian Census. Standard errors in parentheses are clustered at the district level.

Table A6: Results with Firm, Year-Month, and Four-Digit Product-Code Fixed Effects

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded
Post Feb 2014 × Share of Ethnic Russians	0.057*** (0.018)	0.527*** (0.156)	0.725*** (0.200)	0.048* (0.025)	0.575*** (0.196)	0.677** (0.274)
Post Feb 2014 × Distance to Russia ('000 km)				-0.014 (0.018)	0.068 (0.129)	-0.065 (0.188)
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
4-Digit Product Code FE	✓	✓	✓	✓	✓	✓
4-Digit Product Code-Post Fixed Effects	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.134	0.991	1.565	0.139	1.029	1.626
Dep. Var. SD	0.340	2.849	4.107	0.346	2.895	4.175
Observations	2,310,851	2,310,851	2,310,851	2,170,373	2,170,373	2,170,373
Firms	13,009	13,009	13,009	11,722	11,722	11,722
4-Digit Products Codes	1,070	1,070	1,070	1,064	1,064	1,064
Districts	395	395	395	381	381	381

Notes: * p<0.1, ** p<0.05, *** p<0.01. This table presents the firm-product-level analog of the baseline results with product-post fixed effects. Columns (4) through (6) also add controls for firms' distance toward Russia. The product codes used in this specification are the first four digits of the harmonized system code (HS4). Columns (1) and (4) use an indicator for a firm trading a given 4-digit product code with Russia in a given month (export+import). The logs of total value and net weight of shipped goods (export+import) are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. Data on ethnic composition are at the district level and come from the 2001 Ukrainian Census. Standard errors in parentheses are clustered at the district level.

Table A7: Baseline Results Controlling for Industry Codes

Dependent variable:	(1) Any Trade Activity	(2) Log Total Weight Traded	(3) Log Total Value Traded
Post Feb 2014 × Share of Ethnic Russians	0.077** (0.035)	0.767** (0.382)	1.083** (0.480)
Firm FE	✓	✓	✓
Year and Month FE	✓	✓	✓
Post Feb 2014 × NAICS FE	✓	✓	✓
Dep. Var. Mean	0.233	2.301	3.187
Dep. Var. SD	0.423	4.403	5.848
R ²	0.44	0.52	0.49
Observations	452,473	452,473	452,473
Firms	9,821	9,821	9,821
Districts	365	365	365

Notes: * p<0.1, ** p<0.05, *** p<0.01. This table replicates the baseline results from Table 2 controlling for the interaction between the industry code (NAICS) fixed effects and the post-February 2014 indicator. NAICS industry codes for each Ukrainian firm come from the ORBIS/AMADEUS dataset. The logs of total value and net weight of shipped goods (export+import) are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. In column (1), the outcome is an indicator for a firm trading with Russia in a given month (export+import). Data on ethnic composition are at the district level and come from the 2001 Ukrainian Census. Standard errors in parentheses are clustered at the district level.

Table A8: Multi-Country Triple-Difference Specification

Dependent variable:	(1)	(2)	(3)
	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded
Post Feb 2014 × Share of Ethnic Russians × Russia	0.123*** (0.038)	1.457*** (0.449)	1.649*** (0.495)
Share of Ethnic Russians × Russia	0.262*** (0.097)	1.994** (0.977)	3.556*** (1.321)
Year-Month FE	✓	✓	✓
Firm FE	✓	✓	✓
District-Post FE	✓	✓	✓
Country FE	✓	✓	✓
Country-Post FE	✓	✓	✓
Dep. Var. Mean	0.177	1.489	2.239
Dep. Var. SD	0.382	3.530	4.927
Observations	7,464,835	7,464,835	7,464,835
Firms	73,675	73,675	73,675
Districts	473	473	473
Months	48	48	48
Countries	11	11	11

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table presents the results of a triple-difference specification (5) comparing trade before and after the start of the conflict, for firms in areas with more versus fewer ethnic Russians, with Russia as opposed to other countries. The set of comparison countries consists of the 10 nations with which Ukraine had the most transactions from 2013 to 2016, including Russia. Trade with the rest of the world comprises the eleventh nation in this exercise. Column (1) uses an indicator for a firm trading with a given country in a given month (export+import) as the outcome variable. The logs of total value and net weight of shipped goods to a given country in a given month (export+import) are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. Data on ethnic composition are at the district level and come from the 2001 Ukrainian Census. One observation is a firm-country-month. Standard errors in parentheses are clustered at the district level.

Table A9: Ukrainian State-Owned Firms

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded
	<i>State-Owned</i>			<i>Not State-Owned</i>		
Post Feb 2014 × Share of Ethnic Russians	0.123 (0.152)	1.005 (1.888)	0.673 (2.193)	0.126*** (0.039)	1.574*** (0.449)	1.751*** (0.532)
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.200	1.555	2.859	0.213	2.106	2.905
Dep. Var. SD	0.400	3.540	5.795	0.409	4.263	5.649
R ²	0.47	0.52	0.54	0.42	0.49	0.46
Observations	9,779	9,779	9,779	529,934	529,934	529,934
Firms	213	213	213	11,484	11,484	11,484
Districts	91	91	91	405	405	405

Notes: * p<0.1, ** p<0.05, *** p<0.01. This table tests whether state-owned Ukrainian firms are responsible for our baseline results. We consider a firm state-owned if it is indicated so by its legal organizational form. Data on the organizational form of firms come from the SPARK dataset. Columns (1) and (4) use an indicator for a firm trading with Russia in a given month (export+import). The logs of total value and net weight of shipped goods (export+import) are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. District-level data on ethnolinguistic composition come from the 2001 Ukrainian Census. Standard errors in parentheses are clustered at the district level.

Table A10: Baseline Results Without 2016 Data

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded
Post Feb 2014 × Share of Ethnic Russians	0.073*** (0.025)	0.920*** (0.289)	1.009*** (0.332)			
Post Feb 2014 × Share of Russian Speakers				0.034*** (0.012)	0.448*** (0.143)	0.474*** (0.166)
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.210	2.064	2.836	0.210	2.064	2.836
Dep. Var. SD	0.407	4.226	5.574	0.407	4.226	5.574
R ²	0.44	0.52	0.49	0.44	0.52	0.49
Observations	442,470	442,470	442,470	442,470	442,470	442,470
Firms	13,009	13,009	13,009	13,009	13,009	13,009
Districts	401	401	401	401	401	401

Notes: * p<0.1, ** p<0.05, *** p<0.01. This table replicates Table 2 but excluding data for 2016, after Russia and Ukraine imposed tariffs on each other's products. Columns (1) and (4) use an indicator for a firm trading with Russia in a given month (export+import). The logs of total value and net weight of shipped goods (export+import) are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. District-level data on ethnolinguistic composition come from the 2001 Ukrainian Census. The share of Russian speakers is measured as the percentage of people who named Russian as their mother tongue ("rodnoi yazik"). Standard errors in parentheses are clustered at the district level.

Table A11: Heterogeneity Across Regions

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded
	<i>Without Kyiv</i>			<i>No Regions Close to Conflict</i>			<i>No Western Ukraine</i>		
Post Feb 2014 × Share of Ethnic Russians	0.090*** (0.031)	1.163*** (0.345)	1.252*** (0.407)	0.167** (0.067)	2.173** (0.856)	2.180** (0.918)	0.067** (0.033)	0.937** (0.388)	1.013** (0.434)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.204	2.049	2.783	0.191	1.880	2.595	0.199	1.949	2.706
Dep. Var. SD	0.403	4.233	5.552	0.393	4.078	5.398	0.399	4.121	5.493
R ²	0.41	0.49	0.46	0.41	0.48	0.45	0.41	0.49	0.46
Observations	431,074	431,074	431,074	404,951	404,951	404,951	544,606	544,606	544,606
Firms	9,424	9,424	9,424	8,814	8,814	8,814	11,822	11,822	11,822
Districts	397	397	397	341	341	341	301	301	301

Notes: * p<0.1, ** p<0.05, *** p<0.01. This table tests whether our results are robust to potential region-outliers. In columns (1) through (3), firms located in the capital of Ukraine, Kyiv, are omitted from the sample. In columns (4) through (6), provinces close to Donetsk and Luhansk are taken out omitted — the Dnipropetrovskaya, Zaporozhskaya, and Kharkovskaya oblasts. In columns (7) through (9), Western Ukraine — the Chernivtsi, Ivano-Frankivsk, Lviv, Rivne, Ternopil, Volyn, and Zakarpattia oblasts — is omitted from the sample. The logs of total value and net weight of shipped goods are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. District-level data on ethnic composition come from the 2001 Ukrainian Census. Standard errors in parentheses are clustered at the district level.

Table A12: Shares of Russian Managers, IV Results

<i>Panel A: Second Stage Estimates</i>			
Dependent variable:	(1)	(2)	(3)
	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded
<i>A.1. Difference-in-Differences</i>			
Post Feb 2014 × Share of Russian Managers (Measure #1, Predicted)	0.029*** (0.010)	0.329*** (0.114)	0.404*** (0.140)
<i>A.2. Horse-Race Specification</i>			
Post Feb 2014 × Share of Russian Managers (Measure #1, Predicted)	0.015 (0.010)	0.147 (0.107)	0.201 (0.143)
Post Feb 2014 × Share of Ethnic Russians	0.124*** (0.035)	1.539*** (0.434)	1.695*** (0.477)
Firm FE	✓	✓	✓
Year and Month FE	✓	✓	✓
Dep. Var. Mean	0.223	2.197	3.046
Dep. Var. SD	0.416	4.322	5.751
R ²	0.42	0.50	0.47
Observations	497,762	497,762	497,762
Firms	10,794	10,794	10,794
Districts	369	369	369
<i>Panel B: First Stage Estimates</i>			
Dependent variable:	(1)	(2)	(3)
	Share of Russian Managers, Measure #1 (Surname Endings)		
Share of Russian Managers, Measure #2 (Bank of Surnames)	0.752*** (0.016)	0.752*** (0.016)	0.752*** (0.016)
R ²	0.279	0.279	0.279
Observations	10,789	10,789	10,789
F-statistics	2,320	2,320	2,320

Notes: * p<0.1, ** p<0.05, *** p<0.01. This table reports the IV estimates for the specifications in Table 4. In this IV specification, following Ashenfelter and Krueger (1994), one of the measures of the share of Russian managers is instrumented with the second one to reduce the measurement error. The instrumented measure (Measure #1) classifies last names as Russian if they end in “ov,” “ova,” “ev,” “eva,” “in,” or “ina” (for a detailed discussion of this approach, see Zhuravlev (2005) (in Russian)). The second measure that serves as an instrument (Measure #2) relies on the bank of 622 traditionally Russian last names, combined from the lists of 250 traditional Russian last names from Balanovskaya et al. (2005) and 500 most frequent Russian last names from Zhuravlev (2005), net of all duplicates. The logs of total value and the net weight of shipped goods are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. District-level data on ethnic composition come from the 2001 Ukrainian Census. Conflict-affected regions are excluded. Standard errors in parentheses are clustered at the district level.

Table A13: Differential Effect of Conflict on Attitudes of Ukrainian Citizens Toward Russia

Dependent variable:	(1) % with Positive Attitude Toward Russia	(2) % with Positive Attitude Toward Russia	(3) % with Extreme Negative Views Toward Russia	(4) % with Extreme Negative Views Toward Russia	(5) % Yes to Closed Borders and Visas with Russia	(6) % Yes to Closed Borders and Visas with Russia
Post Conflict	-0.604*** (0.027)	-0.586*** (0.024)	0.357*** (0.028)	0.337*** (0.028)	0.489*** (0.027)	0.466*** (0.028)
% of Russian Ethnicity	0.724*** (0.176)		-0.158** (0.057)		-0.779*** (0.199)	
Post Conflict × % of Russian Ethnicity	1.263*** (0.167)		-1.093*** (0.176)		-1.192*** (0.175)	
% of Russian Language		0.338*** (0.087)		-0.072** (0.027)		-0.366*** (0.108)
Post Conflict × % of Russian Language		0.632*** (0.078)		-0.527*** (0.087)		-0.562*** (0.098)
Dep. Var. Mean	0.554	0.554	0.189	0.189	0.400	0.400
Dep. Var. SD	0.497	0.497	0.392	0.392	0.490	0.490
R ²	0.27	0.27	0.13	0.12	0.20	0.19
Observations	23,304	23,304	23,304	23,304	23,897	23,897
Regions	23	23	23	23	23	23

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table explores the heterogeneity of the effect of the Russia-Ukraine conflict on attitudes of Ukrainian citizens toward Russia depending on the share of ethnic Russians in the province of a respondent. In columns (1) and (2), the outcome is the share of respondents who answered the question “What Is Your Overall Attitude Toward Russia?” as “very good” or “good.” In columns (3) and (4), the outcome is the displays the share of respondents who answered the same question as “very bad.” In columns (5) and (6), the outcome is the share of respondents who answered the question “How would you like to see Ukraine’s relations with Russia?” as “They should be the same as with other states—with closed borders, visas, customs.” Data are from 15 nationally representative surveys conducted by Kyiv International Institute of Sociology from 2013 to 2016. Months of the surveys can be viewed on Figure 5. The February 2014 survey was conducted February 7 to 17, 2014, i.e., before the occupation of Crimea. The three conflict provinces—Crimea, Donetsk, and Luhansk oblasts—are excluded from the analysis. The province-level data on ethnolinguistic composition come from the 2001 Ukrainian Census. Standard errors in parentheses are clustered at the province level.

Table A14: Baseline Results Depending on Frequency of Google Search for “Boycott”

Dependent variable:	(1)	(2)	(3)	(4)
Specification:	Baseline with Google Trends Data Present	Regions with > 75pct Frequency of Google Search “Boycott”	Regions with < 25pct Frequency of Google Search “Boycott”	Baseline with Google Trends Data Instead
		<i>Diff p-value: 0.056</i>		
Post Feb 2014 × Share of Ethnic Russians	0.097*** (0.031)	0.250** (0.101)	0.040 (0.045)	
Post Feb 2014 × “Boycott” Search				-0.012*** (0.003)
Firm FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Dep. Var. Mean	0.206	0.205	0.204	0.206
Dep. Var. SD	0.404	0.404	0.403	0.404
R ²	0.41	0.42	0.41	0.41
Observations	426,269	100,866	126,180	426,274
Firms	9,328	2,217	2,750	9,328
Districts	389	148	78	389

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Column (1) shows the baseline results for a subsample of firms with a nonempty Google search variable. Columns (2) and (3) present the baseline results for firms in regions with, respectively, very high (above 75th percentile) and very low (below 25th percentile) frequency of Google searches for “boycott” from February 1 to May 1, 2014. Column (4) displays the baseline results where share of ethnic Russians is replaced by the frequency of Google searches for “boycott” from February 1 to May 1, 2014, across Ukrainian regions. The dependent variable is an indicator for a firm trading with Russia in a given month (export+import). Standard errors in parentheses are clustered at the district level.

Table A15: Heterogeneity Analysis By the Size of the Trading Firm

Specification:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	Large Firms with > 50% of Transactions in Intermediate Goods	Small Firms with > 50% of Transactions in Intermediate Goods	Import by Large Firms with > 50% of Transactions in Intermediate Goods	Import by Small Firms with > 50% of Transactions in Intermediate Goods	Export by Large Firms with > 50% of Transactions in Intermediate Goods	Export by Small Firms with > 50% of Transactions in Intermediate Goods
		<i>Diff p-value: 0.004</i>		<i>Diff p-value: 0.033</i>		<i>Diff p-value: 0.000</i>	
Post Feb 2014 × Share of Ethnic Russians	0.092*** (0.031)	0.153*** (0.043)	-0.036 (0.044)	0.079** (0.039)	-0.082 (0.057)	0.240*** (0.048)	0.063* (0.037)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.201	0.322	0.157	0.260	0.170	0.315	0.110
Dep. Var. SD	0.400	0.467	0.364	0.439	0.376	0.465	0.312
Observations	590,462	166,542	166,479	102,816	108,816	112,669	73,121
Firms	12,848	3,714	3,621	2,142	2,267	3,152	2,000
Districts	393	302	226	231	153	290	197

Notes: * p<0.1, ** p<0.05, *** p<0.01. This table presents the heterogeneity analysis of the baseline results by the size of a firm. Large firms are defined as having more than the median number of employees in our sample, i.e., 19 employees or more, as of 2013. Data on the number of employees are from the ORBIS/AMADEUS dataset. The dependent variables are the indicator of any trade activity (export+import) by a firm in a given month in columns (1) through (3), the indicator of any import activity by a firm in a given month in columns (4) and (5), and the indicator of any export activity by a firm in a given month in columns (6) and (7). Intermediate goods are identified by the HS6 product code using the standardized BEC classification. Inference across regression models is conducted using a similarly unrelated regressions framework with standard errors clustered at the district level. Standard errors in parentheses are clustered at the district level.

Table A16: Baseline Results for Ukrainian Trade with Kazakhstan

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded	Any Export Activity	Log Total Weight Exported	Log Total Value Exported
	<i>Total Trade with Kazakhstan</i>			<i>Exports to Kazakhstan</i>		
Post Feb 2014 × Share of Ethnic Russians	-0.040 (0.038)	-0.208 (0.417)	-0.485 (0.517)	-0.007 (0.038)	0.164 (0.410)	-0.027 (0.507)
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.144	1.376	1.962	0.143	1.329	1.935
Dep. Var. SD	0.351	3.521	4.831	0.350	3.408	4.783
R ²	0.33	0.41	0.37	0.33	0.41	0.37
Observations	110,410	110,410	110,410	97,868	97,868	97,868
Firms	2,530	2,530	2,530	2,276	2,276	2,276
Districts	240	240	240	227	227	227

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table presents the baseline difference-in-differences estimates but for Ukrainian trade with Kazakhstan. Columns (1) through (3) display the results for all trade with Kazakhstan, while columns (4) through (6) focus on the Ukrainian exports to Kazakhstan. Columns (1) and (4) use an indicator for a firm trading with or exporting to Russia in a given month. The logs of total value and net weight of shipped goods (export+import) are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. Data on ethnic composition are at the district level and come from the 2001 Ukrainian Census. Standard errors in parentheses are clustered at the district level.

Table A17: Conflict and Local Economic Shocks to Firms in Non-combat Areas

Dependent variable:	(1) Log Profit	(2) Log Sales	(3) TFP
Share of Ethnic Russians \times (Year == 2011)	-0.338 (0.287)	0.171 (0.121)	-0.138*** (0.053)
Share of Ethnic Russians \times (Year == 2012)	-0.313 (0.319)	0.102 (0.083)	-0.028 (0.023)
Share of Ethnic Russians \times (Year == 2014)	-1.086*** (0.240)	-0.693*** (0.104)	-0.103*** (0.026)
Share of Ethnic Russians \times (Year == 2015)	-2.188*** (0.356)	-1.432*** (0.290)	-0.245*** (0.055)
Share of Ethnic Russians \times (Year == 2016)	-2.549*** (0.444)	-1.496*** (0.280)	-0.274*** (0.070)
Firm FE	✓	✓	✓
Year FE	✓	✓	✓
Dep. Var. Mean	10.761	13.169	13.560
Dep. Var. SD	6.673	4.216	1.870
R ²	0.51	0.75	0.93
Observations	1,107,215	1,107,520	1,026,585
Firms	176,352	176,352	176,352
Districts	491	491	495

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table documents the differential drop in firm performance across areas with different ethnic composition. The sample includes all Ukrainian firms, not only those trading with Russia, but excludes firms from the conflict areas. Data on firms come from the AMADEUS/ORBIS database. District-level data on ethnic composition come from the 2001 Ukrainian Census. In columns (1) and (2), the dependent variables are gross profit and total sales transformed using the inverse hyperbolic sine function $L(X)$, such that $L(X) = \log(X + \sqrt{X^2 + 1})$, as in MacKinnon and Magee (1990). In column (3), the outcome is the total factor productivity of a firm derived from a Cobb-Douglas specification regressing turnover on capital and labor (all in logs) with two-digit industry fixed effects. Standard errors in parentheses are clustered at the district level.

Table A18: Difference-in-Differences Results Accounting for Firm Sales

Dependent variable:	(1)	(2)	(3)	(4)
	Log Total Weight Traded	Log Total Value Added	Log Total Weight Traded	Log Total Value Added
Post Feb 2014 × Share of Ethnic Russians	3.933*** (0.684)	4.572*** (0.709)		
Post Feb 2014 × Share of Native Russian Speakers			1.833*** (0.306)	2.081*** (0.361)
Firm-Level Yearly Revenue	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Dep. Var. Mean	5.764	8.097	5.764	8.097
Dep. Var. SD	5.651	7.317	5.651	7.317
R ²	0.60	0.54	0.60	0.54
Observations	31,372	31,372	31,372	31,372
Firms	7,843	7,843	7,843	7,843
Districts	345	345	345	345

Notes: * p<0.1, ** p<0.05, *** p<0.01. This table presents the firm-year-level version of the baseline results with log-sales included as a covariate. The logs of total value, of net weight of shipped goods, and of sales are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. District-level data on ethnolinguistic composition come from the 2001 Ukrainian Census. Russian language is measured as the percentage of people who named Russian as their mother tongue (“rodnoi yazik”). Standard errors in parentheses are clustered at the district level.

Table A19: Heterogeneity Analysis By Pre-Existing Trade Ties with Other Countries

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Any Trade with Russia		Any Exports to Russia		Any Imports from Russia	
Subsample:	Traded with Russia and Other Countries	Trade with Russia Only	Traded with Russia and Other Countries	Trade with Russia Only	Traded with Russia and Other Countries	Trade with Russia Only
	<i>Difference p-value: 0.000</i>		<i>Difference p-value: 0.048</i>		<i>Difference p-value: 0.006</i>	
Post Feb 2014 × Share of Ethnic Russians	0.144*** (0.037)	-0.022 (0.048)	0.190*** (0.053)	0.071 (0.057)	0.113*** (0.038)	-0.039 (0.039)
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.301	0.161	0.308	0.152	0.290	0.173
Dep. Var. SD	0.459	0.367	0.462	0.359	0.454	0.379
R ²	0.48	0.36	0.49	0.38	0.48	0.39
Observations	274,667	103,106	124,915	78,346	155,904	65,856
Firms	5,954	2,257	2,905	1,822	3,248	1,372
Districts	321	225	286	211	236	149

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table tests whether the baseline results are stronger for firms that had pre-existing trade connections with other countries. The dependent variables are, respectively, an indicator of any trade activity with Russia by a firm in a given month (columns (1) and (2)), an indicator of any exports to Russia by a firm in a given month (columns (3) and (4)), and an indicator of any imports from Russia by a firm in a given month (columns (5) and (6)). Columns (1), (3), and (5) focus on firms that traded with Russia and at least one other country at any point from January 1, 2013 to January 31, 2014. Columns (2), (4), and (6) focus on firms that traded only with Russia but not other countries from January 1, 2013 to January 31, 2014. Inference across regression models is conducted using a similarly unrelated regressions framework with standard errors clustered at the district level. Standard errors in parentheses are clustered at the district level.

Table A20: Homogeneous and Differentiated Goods

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded
	<i>Differentiated Goods Traders</i>			<i>Homogeneous Goods Traders</i>		
Post Feb 2014 × Share of Ethnic Russians	0.025 (0.037)	0.302 (0.392)	0.310 (0.471)	0.363*** (0.068)	4.745*** (1.011)	4.953*** (1.010)
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.144	1.240	1.855	0.146	1.777	2.072
Dep. Var. SD	0.351	3.187	4.577	0.354	4.425	5.053
R ²	0.33	0.38	0.36	0.30	0.36	0.33
Observations	395,381	395,381	395,381	75,842	75,842	75,842
Firms	8,658	8,658	8,658	1,644	1,644	1,644
Districts	362	362	362	223	223	223

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table tests whether the baseline results are stronger for firms trading homogeneous or differentiated products. Rauch (1999) defines homogeneous goods as those either traded on the organized exchange or having reference prices. We define homogeneous goods traders as firms that have only traded traded homogeneous goods with Russia under the classification of Rauch (1999) over the course of 2013–2016. We define differentiated goods traders as firms that have not traded homogeneous goods under the Rauch (1999) classification. Columns (1) and (4) use an indicator for a firm trading with Russia in a given month (export+import). The logs of total value and net weight of shipped goods are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. Standard errors in parentheses are clustered at the district level.