Trading with the Enemy: The Impact of Conflict on Trade in Non-Conflict Areas*

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Abstract

This study presents novel evidence on the effects of conflict on trade in non-conflict areas. We examine the context of the ongoing Russian military intervention in Ukraine. In a difference-in-differences framework, we leverage a newly compiled firm-level panel with the universe of Ukrainian trade transactions from 2013 through 2016 and exploit substantial spatial variation in the ethnic composition of Ukrainian counties. The estimates suggest that Ukrainian firms from counties with fewer ethnic Russians experienced a deeper decline in trade with Russia. We argue that this result stems from increased ethnic tensions and a differential rise in negative attitudes and beliefs about Russia. Possible mechanisms include consumer boycotts of Russian products, reputational concerns of Ukrainian firms, and a breakdown of trust in contract enforcement. In contrast, we find no evidence for individual-level animosity between firms' key decision makers or discrimination at the border. We also rule out that the differential decline in trade arises only from economic spillovers, such as refugee flows and destruction of supply chains with conflict areas.

JEL: D22, D74, F14, F51, H56
Keywords: Conflict, International Trade, Firms, Firm Linkages

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1 Introduction

Assessing the economic consequences of conflict is a central problem in political economy and development economics. An extensive empirical literature finds that conflict, besides its tragic humanitarian effects, can adversely affect aggregate economic outcomes such as GDP and stock market indices (e.g., Abadie and Gardeazabal, 2003; Glick and Taylor, 2010). Past studies have also thoroughly examined the multifaceted effects of direct exposure to violence on firms and individuals.[1] However, potential ramifications of conflict can also extend to areas that are not directly experiencing combat. This is a considerable gap in the literature, given that at least 2.66 billion people live in conflict-ridden countries but outside of the war zones.[2] Moreover, if non-conflict areas are affected, the traditional estimates of the effects of violence obtained by comparing regions with and without violent events within the same country may differ from the total economic costs of conflict (e.g., Ksoll, Macchiavello, and Morjaria, 2014; Amodio and Di Maio, 2017).

We focus on one particular indirect consequence of conflict—the impact of conflict-induced ethnic tensions on trade. In environments with imperfect contract enforcement, trade relies on other mechanisms to support cooperation, such as trust and informal norms (Nunn, 2007; Guiso, Sapienza, and Zingales, 2009; Jha, 2013). Common social identity of trade participants, such as their ethnicity, a cast, or a tribe, helps create these mechanisms (Greif, 1993) and alleviate information frictions (Rauch and Trindade, 2002). It follows from this logic that, when ethnic tensions arise after the start of the conflict, this could break down these informal mechanisms of sustaining cooperation and lead to a reduction in trade (Rohner, Thoenig, and Zilibotti, 2013). In this project, we examine a setting in which there were very few changes in formal rules of trade, but there was a dramatic increase in ethnic tensions and nationalistic attitudes, which spilled over onto non-conflict areas. This setting allows us to study whether trade is indeed disrupted along ethnic lines, and what are the mechanisms behind this effect.

Specifically, we study this question in the context of the ongoing Russian military intervention in Ukraine. The Russia-Ukraine conflict, which began in February 2014 with the annexation of Crimea and continued with the War in Donbass, provides a natural laboratory for examining these effects. First, armed combat 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. Second, since it has

[1] See our detailed discussion of the literature later in the Introduction.

[2] As of 2016, conflict-ridden countries contain 50% of the world 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 at 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.

been a proxy conflict as opposed to a full-fledged war, trade at the border has not ceased. In fact, Russia has remained Ukraine's largest trading partner since the start of the conflict. As members of the CIS Free Trade Agreement (CISFTA), Russia and Ukraine continued to have zero tariffs on the vast majority of goods.[3] Finally, given the ethnically charged nature of the conflict,[4] the presence of a large, spatially dispersed Russian minority within Ukraine allows us to isolate the impact of ethnic tensions and nationalistic attitudes after the start of the conflict. We exploit these advantageous features of the Russia-Ukraine conflict with new data on the universe of international trade transactions of all Ukrainian firms from 2013 through 2016, merged with firms' balance sheets and the census characteristics of their home counties.

To causally establish whether trade is disrupted along ethnic lines after the start of the conflict, even without violence and formal trade restrictions, we employ a difference-in-differences strategy. We compare outcomes before and after the onset of conflict in February 2014 across Ukrainian counties containing 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 language. Time-period fixed effects control for changes that affect all regions similarly, such as macroeconomic changes in Ukraine or trade sanctions that may be imposed on the country as a whole due to the conflict. Our identification strategy assumes that absent the conflict, firm trade patterns in areas with different percentages of ethnic Russians would have evolved along parallel trends. Later in the paper, we provide several pieces of evidence supporting this parallel-trends assumption.

The key finding of this paper is that a decline in trade between Ukrainian firms and Russia was differential and depended on the ethnic composition of the firms' home areas. That is, we find that firms located in more ethnically Russian counties (raions) of Ukraine decreased their trade with Russia by a smaller margin. According to our estimates, moving an average firm from a county at the 75th percentile of share of Russians (17.7%) to a county at the 25th percentile of share of Russians (9.6%) would deepen the decline in monthly incidence of trade with Russia by 12% and would deepen the decline in the monthly volume of trade with Russia by 15%.[5] The month-by-month estimates show no evidence of pre-trends and indicates that the effect stays large

[3]Tariffs went up only in January 2016, when Russia and Ukraine stopped respecting CISFTA regulations regarding trade with each other. Our results are robust to excluding the 2016 data.

[4]Ethnically Russian regions of Ukraine, such as Crimea and Donbass, to secede away from Ukraine, and Russia was helping them accomplish this goal.

[5]Overall, the conflict has had a detrimental effect on trade between Russia and Ukraine. The percentage of Ukrainian exports that go 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.

and significant long after the start of the conflict. Our back-of-the-envelope calculations suggest that this indirect effect may account for a total loss of up to US$1 billion in mutual trade, which is equivalent to 2.5% of the pre-conflict Russia-Ukraine trade volume or 0.5% of the pre-conflict GDP of Ukraine.

We show that other simultaneous events not directly related to Russia-Ukraine conflict are unlikely to drive our results. For example, a unilateral elimination of E.U. import tariffs for Ukrainian products in April 2014 could have led to a differential shock due to different product specialization across Ukrainian areas.[6] We address this concern by accommodating any product-specific shocks in a granular firm-product-month-level specification with product-post fixed effects. Using this estimation strategy, we obtain similar results with similar magnitudes, suggesting that ethnicity matters even after accounting for any simultaneous product-specific shocks. Second, the Ukrainian revolution itself, even without the conflict, may have caused a shift of resources within Ukraine to help areas that supported the new leaders (Earle and Gehlbach, 2015).[7] We document that state-owned firms, which would likely receive such transfers, are not driving our results. Furthermore, to mitigate the concern of local economic shocks due to revolution, we accommodate any county-specific shocks in a triple-difference "gravity-style" specification, where trade with other countries allows us to include county-post (i.e., raion-post) fixed effects. We find our baseline results are preserved in this exercise, with even larger magnitude.

We also provide evidence in favor of our preferred interpretation that conflict intensifies inter-ethnic tensions and nationalistic attitudes, and this leads to a differential decline in trade. We do this in two steps.

First, we provide "negative evidence" by ruling out alternative explanations not related to ethnicity. That is, we take the causal reduced-form estimates as given and ask whether counties with fewer Russians differ in ways other than ethnicity and culture that would also cause trade with Russia to decline. Amongst other exercises, we consider and rule out three of the arguably most self-evident possible concerns: differences in distance to the Russian border, confounding product-specific shocks that arise due to conflict, and confounding conflict-induced local economic shocks. The first big concern is that areas of Ukraine with a smaller share of Russians may be affected by conflict differently merely because they are farther from the Russia-Ukraine border. To account

[6] For instance, agricultural products were subject to higher E.U. tariffs beforehand and were primarily produced in rural areas of Ukraine, where the share of ethnic Russians is typically low.

[7] This would likely go against our findings since, in this case, areas with a smaller Russian minority would receive more resources. However, if these resources are then used to cover the fixed cost of entering the European market, this could generate a pattern similar to our baseline results.

for this possibility, we show that our results are robust to highly flexible controls for firms' distance to the Russian border. The second concern is that areas with a smaller Russian minority could specialize in the types of products that have been disproportionately affected by the conflict and subsequent events. Similar to the E.U.-tariff explanation mentioned above, we address this concern in a product-firm-level specification with product-post fixed effects. Finally, one may also conjecture that firms in more Russian areas of Ukraine, for one reason or another, 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 generate positive labor supply and demand shocks, and in turn improve firms' overall performance. We argue that the triple-difference "gravity-style" specification mentioned above, in which trade with other countries allows us to include county-post (i.e., raion-post) fixed effects, accounts for these potential explanations not related to ethnicity.

Second, using survey data on attitudes, we provide positive evidence that the conflict intensified ethnic tensions and nationalistic attitudes. We document that Ukrainian antipathy toward Russia skyrocketed immediately after the start of the conflict, and significantly more so for ethnic Ukrainians than ethnic Russians within Ukraine. Moreover, the difference across ethnicity in attitudes toward Russia remained large throughout the period of our analysis.

Finally, we investigate the mechanisms of how exactly inter-ethnic tensions and nationalistic attitudes affect trade. Motivated by the existing literature and anecdotal evidence, we investigated the following mechanisms: (i) consumer boycotts of Russian products, (ii) corporate social responsibility (CSR) activity by large Ukrainian firms,[8] (iii) erosion of trust in the willingness of Russian institutions to enforce contracts, (iv) individual-level animosity between managers and owners, and (v) discrimination at the border. We found evidence consistent with (i)-(iii), and no evidence for (iv)-(v).

As evidence for consumer boycotts, we show first that the differential effect is more pronounced for firms importing consumer goods than for firms importing intermediate goods, suggesting that consumer action indeed played a role. 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 the *boycott* search was more prevalent. These findings are consistent with the qualitative evidence documenting that 40-50% of Ukrainians

[8] We define CSR as costly actions to reach out to stakeholders, such as consumers, activists, workers, and investors (Smith, 2003). Throughout the paper, we are agnostic about whether CSR activity arises from profit maximization, activism, public pressure (Egorov and Harstad, 2017), or altruistic moral preferences (Baron, 2010). While CSR is a broad concept associated with many causes, it can also refer to issues of international relations and trade—e.g., not buying minerals from conflict-ridden areas with the goal of discouraging violence (Bennett, 2002).

reported taking part in a boycott campaign against Russia products.

Consumer reaction cannot be the only explanation of our baseline results, since there is a significant, albeit smaller, effect for a subset of firms that import only intermediate products. To investigate further, we show that the differential effect for intermediate products comes almost entirely from large firms, which are traditionally viewed in the literature as more vulnerable to activism and which can afford CSR activity (Perrini, Russo, and Tencati, 2007; Smith, 2013). To complement these quantitative findings, we document an ample body of anecdotal evidence that is consistent with CSR activity by large Ukrainian firms.

Finally, we argue that Ukrainian firms' eroding trust in the willingness of Russian institutions to enforce trade contracts, fuelling their fear of nonpayment, is an additional mechanism that helps explain our results. To investigate this explanation, we use variation in contracts used by firms and the corresponding timing of the payment. There are three major types of international contracts in trade — *open account* (OA) countracts, in which exporter is paid after the good is delivered, *cash-in-advance* (CIA) contracts, in which exporter is paid before the good is shipped, and *letters of credit* (LC), in which a bank takes on the risk for a certain fee. To circumvent the lack of information on contract types in our dataset, we use product-level data on the typical trade contracts between Russian, Ukrainian, and Turkish firms from 2004 through 2011. These data allow us to construct a measure of predicted types of contracts used by firms in our sample based on the products they trade. We show that the differential effect of conflict by ethnicity is higher for Ukrainian exporters with a high likelihood of using OA contracts. Moreover, we find no differential effect for exporters that are likely to use CIA or LC contracts. These results suggest that a differential decline in trust in Russian institutions indeed plays a role in our results, providing additional incentives for exporters to stop trading with the firms on the other side of the conflict.[9]

As we mentioned earlier, we investigated, and did not find support for, several other mechanisms that could *a priori* be at work. For example, the rise in individual-level animosity between managers and owners could have led to a disruption of trade ties—in other words, it could be the individual-level, not the locality-level, animosity that mattered. To address this possibility, we rely on research on the origin and history of Russian last names, which helps us classify the last names of managers, directors, and owners into groups comprising traditionally Russian names (and others). Our results indicate that firms with different shares of managers with Russian last names do not differ in their reaction to the conflict—rather, it is the share of ethnic Russians in the county

[9]These results echo a finding in the trade literature that cash-in-advance contracts are used more frequently by US exporters when their partners are in located in countries with weak institutions (Antras and Foley, 2015).

of the firm that plays the critical role. In addition, we do not find evidence of discrimination at the border, since there is no differential effect for trade between Ukrainian firms and Kazakhstan, which has to pass through the Russia-Ukraine border.

The final part of the paper takes full advantage of the granularity and richness of the data to investigate how firms respond to the reduction of trade with Russia and whether their overall financial standing worsened as a result. First, we document that one of the ways in which firms accommodated this shock was switching to trading with other countries. For instance, we find that firms from areas with fewer Russians *increased* their trade with Turkey and Poland relative to firms from more Russian areas. Moreover, the effect is largest for Ukrainian firms that traded with at least one country other than Russia before the start of the conflict, strongly suggesting that switching was happening. However, we also show that, despite such switching, the indirect effect of conflict documented in the paper have 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, net of the broad economic shocks that affected all firms due to their location, firms trading with Russia before the start of the conflict but located in less Russian areas of Ukraine experienced a greater loss of sales, profits, and productivity relative to their counterparts from areas with more ethnic Russians. These results suggest that the breakdown of trade due to increased inter-ethnic tensions indeed led to a loss of welfare, at least on the side of the firms.

We make several contributions to the literature. Our paper is the first to document a negative impact of armed conflict on business operations of firms in non-conflict areas. Previous studies on the economic effects of conflict on firms focused almost fully 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 et al. (2014) analyze the effect of violence on nearby exporters in Kenya that resulted, among other things, in a sharp increase in worker absence. Montoya (2016) documents a negative impact of drug violence in Mexico on firms' revenue and employment. Amodio and Di Maio (2017) show that Palestinian firms in violent areas substituted the domestically produced materials for the imported ones during the Second Intifada. Most recently, Blumenstock, Ghani, Herskowitz, Kapstein, Scherer, and Toomet (2018) use mobile phone metadata to study the reaction of firms to violence in Afghanistan.[10]

[10]These studies are part of the broader literature on economic effects of wars and violence. Several studies document a large negative impact of wars and political instability on trade at the cross-country level (Nitsch and Schumacher, 2004; Blomberg and Hess, 2006; Martin, Mayer, and Thoenig, 2008; Glick and Taylor, 2010). However, such aggregate estimates combine both direct and indirect effects of conflict, which we attempt to disentangle. Among other work on the economic effects of wars, see Davis and Weinstein (2002); Brakman, Garretsen, and Schramm (2004); Miguel and Roland (2011), and Feigenbaum, Lee, and Mezzanotti (2017) for the long-run effects of armed conflict on

Our work naturally complements the literature on ethnicity, culture, and trade. This paper provides the first causal micro-level evidence on what happens when ethnic relations are disrupted, and explores the mechanisms in great detail. Previous research has documented that trade relies on trust and other informal mechanisms (Nunn, 2007; Guiso et al., 2009; Jha, 2013), which are, in turn, easier sustained within groups of similar ethnicity (Greif, 1993; Fershtman and Gneezy, 2001). Common ethnicity and culture alleviate information frictions more generally (Rauch and Trindade, 2002). Rohner et al. (2013) theoretically argue that conflict-induced ethnic tensions may lead to a reduction in trust and, as a result, reduce inter-ethnic trade in non-conflict areas. This paper is the first to empirically test this prediction and examine other possible mechanisms through which inter-ethnic trade may decline after the start of the conflict. We find partial support for the trust channel: we see no evidence of reduced trust between key firms decisionmakers of different ethnicity; however, using variation in contract types, we observe that firms from areas with fewer ethnic Russians are fearful of not getting paid.

We also contribute to the literature on international relations and trade. By using transaction-level trade data and a uniquely suitable context, we are able to fully utilize the geographic and firm-level variation and, as a result, improve upon the existing literature in terms of identification and mechanisms. Specifically, spatial variation in the share of ethnic Russians allows us to move beyond the time-series estimates and use a difference-in-differences strategy to rule out confounding time-specific shocks. Moreover, extensive firm-level characteristics enable us to study mechanisms in greater detail, such as animosity between firm owners and managers of different ethnicity, and study the consequences of the trade shock to firms' sales, profits, and productivity. The existing literature has shown that political disputes produce consumer boycott campaigns

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economic development.

The literature also documents a strong negative impact of conflict exposure on individuals' overall well-being (Kesternich, Siflinger, Smith, and Winter, 2014); human-capital accumulation and labor-market outcomes (Blattman and Annan, 2010; Shemyakina, 2011; Chamarbagwala and Morán, 2011; Leon, 2012), and fundamental economic preferences, such as increased risk aversion (Callen, Isaqzadeh, Long, and Sprenger, 2014) and intensified present-bias (Imas, Kuhn, and Mironova, 2015). Evidence also shows that individuals from conflict areas are more likely to cause violence, even after migrating to a peaceful country (Couttenier, Preotu, Rohner, and Thoenig, 2016). Conversely, exposure to war can lead to higher social capital and better ability to overcome the collective-action problem (Campante and Yanagizawa-Drott, 2015; Bauer, Blattman, Chytilová, Henrich, Miguel, and Mitts, 2016).

While most of the literature focuses on the impact of direct exposure to violence, notable exceptions include the literature on the impact of refugees and displacement on destination communities (Calderón-Mejía and Ibáñez, 2015; Morales, 2018) and the spillovers of wars for frontier scientific activity (Iaria, Schwarz, and Waldinger, 2018). Most closely to our work, studies have shown that conflict may induce ethnic tensions which then reduces the productivity of inter-ethnic teams (Hjort, 2014) and increases discrimination in various critical economic institutions, such as stock exchange (Moser, 2012). We take this literature a step further and document that ethnic tensions also hurt trade.

which can, in turn, result in a temporary negative shock to trade between countries.[11] Beyond consumer action, political tensions may matter even for firms that trade only intermediate products (Edwards, Gut, and Mavondo, 2007; Michaels and Zhi, 2010; Fisman, Hamao, and Wang, 2014).

Finally, in examining environments with no open combat between countries, we contribute to the nascent literature on the economic effects of covert interventions by foreign nations. In contrast to our estimates, Berger, Easterly, Nunn, and Satyanath (2013) find that CIA interventions had a *positive* effect on trade between the United States and the affected countries, partly because the latter allocated more government contracts to U.S. firms.[12] Furthermore, Dube, Kaplan, and Naidu (2011) document an overall positive impact of CIA interventions on multinational firms operating in the area by strengthening property rights in the affected nations. We add to these studies by showing that covert interventions can have a negative economic impact on the meddling country by causing local firms to stop trading with it, even absent formal trade barriers. We also add evidence on the mechanisms by exploring whether consumer demand drives the results and by studying the erosion of trust between the hostile areas.[13]

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 strategies. Section 4 discusses the data used in the analysis and provides descriptive statistics. Section 5 displays our baseline difference-in-differences results, rules out some of the alternative explanations, and offers additional robustness checks. Section 6 studies the mechanisms behind our baseline results. Section 7 explores the consequences of this indirect effect for firms' overall sales, profits, and productivity. Section 8 concludes.

[11] At the cross-country level, Heilmann (2016) estimates a sizable negative impact of several prominent boycott instances on trade. Similarly, it has been documented that sales of Japanese products dropped after the anti-Japanese demonstrations in China in 2012 (Luo and Zhou, 2016; Tanaka, Ito, and Wakasugi, 2017; Chen, Senga, Sun, and Zhang, 2017); also, the demand for French-sounding brands in the United States declined after the 2003 U.S.-France political dispute (Pandya and Venkatesan, 2016). Our approach of using preexisting geographic heterogeneity during political disputes is closest to Fouka and Voth (2016), who show that the sales of German cars in Greece heterogeneously dropped during the Greece-Germany feud in 2010, depending on the intensity of German atrocities during World War II.

[12] In one of our robustness exercises, we show that state-owned firms and government organizations constitute less than 5% of our sample and that removing this part of the sample does not change our results. For more details, see Section 5.2.

[13] This paper also brings new evidence to a long-standing debate on the effectiveness of hard-power interventions. We contribute by highlighting a novel economic "blowback" effect that operates via increased antipathy and decreased trade activity with the opposite side of the conflict. Most closely related is Dell and Querubin (2018) finding that U.S. bombing of Vietnam intensified communist insurgency.

2 Background

2.1 Ethnic, Cultural, and Political Divisions Within Ukraine

Historically, many regions of Ukraine have had a large minority Russian population. The number of Russians in Ukraine substantially increased during the Soviet era, reaching its peak, 11.3 million, in 1989, or 22.1% of the total population. 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 as well.

Figure 1 displays the geographical variation in the share of ethnic Russians across Ukrainian counties ("raions").[14] In Western Ukraine, many counties 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 heterogeneity across regions.[15]

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 A4 and A5 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 Yanukovych, to become the president of Ukraine from 2005 to 2010. However, Yanukovych 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.

[14] These 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.

[15] See Figure A1 in the Online Appendix for the geographic distribution of native Russian speakers across Ukrainian counties. Figure A2 in the Online Appendix presents the survey data on the daily usage of Russian language across Ukrainian macro-regions, and Figure A3 in the Online Appendix displays the language of social media accounts on VK, a social-media platform akin to Facebook that is popular in the CIS region.

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 Yanukovych, walked back his promise to enter a political and economic association with the European Union. This step led to massive protests in Kiev and their violent suppression by Yanukovych'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 Yanukovych 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 asserting its need to protect the 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 regions. 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 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 11,000 casualties 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), the two quasi-independent states of the Donetsk and Luhansk People's Republics (in dark red), and other counties of the Donetsk and Luhansk regions that are not part of the separatist territory (in light red to the right). Since all of these areas have been directly affected by foreign intervention, we focus on the rest of the country. While the conflict was intense in some of the affected provinces, especially in the DPR and LPR territories, the rest of the country was not influenced by 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 import tariffs were set to zero, with very few exceptions.[16] 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.[17]

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.[18] Notably, the volume of Russia-Ukraine trade increased in 2017 relative to 2016, marking the first annual increase since the start of the conflict.

2.4 Changes in Attitudes After the Conflict

The Russia-Ukraine conflict abruptly changed the relationship between the two nations. To show this quantitatively, we use poll data to track the change in attitudes of Ukrainian citizens toward Russia. Figures 3a and 3b display these data plotted over time by ethnicity of the respondents.

Before the start of the conflict, Ukrainian citizens of all stripes had overwhelmingly friendly attitudes toward their eastern neighbour. Per Figure 3a, the share of ethnic Ukrainians favorable toward Russia before the conflict was 80% to 90% (blue triangles), while the same share for ethnic Russians was very close to 100% (red circles).[19] Such camaraderie reflects a long history of being part of the same country (the USSR and the Russian Empire), a formal relationship that ended with

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

[17] In 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 5.2 for details.

[18] Ukraine 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.

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

the fall of the Soviet Union in 1991. However, in the immediate aftermath of the conflict, the share of ethnic Ukrainians favorable toward Russia declined dramatically—in a matter of two months it was down to around 50%, falling further to 30% by the end of 2015. As shown by the red line with triangles, although the attitudes of ethnic Russians toward Russia also worsened somewhat, they still 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.[20]

One may wonder whether this change in attitudes is due to respondents becoming very antagonistic toward Russia, becoming mildly unfavorable, or simply turning indifferent. Figure 3b shows that the former is the case. Specifically, the share of ethnic Ukrainians with extreme negative views toward Russia (blue triangles) jumped from close to zero (3%) to more than a quarter of all respondents (26%) immediately after the start of the conflict. This number rose to a peak of 40% by May 2015. The share of ethnic Russians with extremely poor views of Russia (red circles) also slightly increased (to 8% in April 2014), but not as dramatically. Moreover, it always stayed 20 percentage points lower than that for ethnic Ukrainians through 2016.

Figure 3 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 (i.e., post-February 2014) and its interaction with the share of ethnic Russians or native Russian speakers in the region of the respondent.[21] Table A1 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. The estimates suggest that, depending on the outcome, an average respondent from a region with 30% to 50% of ethnic Russians or 70% to 90% of native Russian speakers would not have changed their opinion of Russia at all after the start of the conflict. Moreover, according to these results, the increase in anti-Russian sentiments has been higher in regions with zero share of ethnic Russians (35.7 percentage points, according to column (3) of Table A1) than for ethnic Ukrainians individually (23 percentage points, according to Figure 3). Thus, if anything, spatial variation in ethnic heterogeneity is a better predictor of anti-Russian sentiments than individual ethnicity.

[20]Our findings are consistent with large conflict-induced shocks to public opinion in other contexts. For instance, Ananyev and Poyker (2018) document that the Tuareg-led insurgency in Mali brought about an enormous decline in national identification among other ethnic groups living outside of the conflict areas.

[21]Unfortunately, due to privacy restrictions, a region is the highest level of geographic analysis available for these survey data.

Overall, the results in Figure 3 and Table A1 present a consistent pattern in which ethnic and cultural divisions within Ukraine translated into massively heterogeneous attitudes toward the opposite side of the conflict. These results show that, even after the occupation of Crimea and the breakout of the armed conflict in the East, there are vast disagreements across regions about whether Russia and Ukraine are at war with each other.

3 Empirical Strategy

The general goal of our empirical strategy is to identify the effect of increased antagonism toward the opposite side of the conflict on firm-level trade with that side. More specifically to our context, we want to study how local animosity or allegiance toward Russia, as measured by the local ethnolinguistic composition of the firm's county, affects trade between Ukrainian firms and their Russian counterparts after the start of the Russia-Ukraine conflict.

To identify the effect of interest, we employ a difference-in-differences approach. That is, we compare trade intensity (export+import) with Russia before and after the start of the conflict for firms located in more versus less ethnically Russian counties within Ukraine. Specifically, we estimate the following specification:

$$Y_{imy} = \alpha_i + \delta_m + \kappa_y + \beta \times \text{Rus}_i \times \text{Post}_{my} + \gamma \times \text{Post}_{my} + \epsilon_{imy}, \tag{1}$$

where the outcome variable Y_{imy} is the trade intensity of firm i with Russia (export+import), at month m of year y; α_i, δ_m, and κ_y are, respectively, the firm, month, and year fixed effects; Rus_i is the share of ethnic Russian or native Russian-speaking population in the county of firm i in 2001, or any other measure of alignment with Russia; and Post_{my} is the post-February 2014 indicator.[22] 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 firm-level trade between opposing sides in the conflict depending on local antipathy toward the enemy.[23]

Since our main right-hand-side variables, the share of ethnic Russians and native Russian speakers, are measured at the level of Ukrainian counties (raions), we cluster the standard errors at the county level. Note, however, that our results are robust to spatial HAC standard errors

[22]Note that, because we included year and month fixed effects separately, the coefficient γ is not omitted. This will allow us to compare the magnitude of our differential effect with an overall change in firm-level trade after the start of the conflict. Moreover, note that, per Table A2, the estimates of the β coefficient in a model with year-month fixed effects are identical to the ones obtained in model (1).

[23]We address potential alternative explanations in Section 5.2.

(Conley, 1999).[24]

4 Data and Descriptive Analysis

4.1 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.

Our unique dataset on the universe of Ukrainian trade transactions includes dates, weights, values (in Ukrainian hryvnia), and product codes of each export and import transaction, as well as the tax ID of the Ukrainian trading firm. The data are from 2013 through 2016 and include not only trade with Russia but also trade with other countries. Crucially, our trade dataset also includes addresses of the Ukrainian firms, which allows us to merge trade transactions with various characteristics of the firm's locality, including its ethnolinguistic composition.

Data on ethnolinguistic composition of the counties (raions) come from the latest Ukrainian Census, conducted in 2001.[25] From this census, we obtain county-level data on the share of ethnic Russians and the share of native Russian speakers among the local population.

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.[26] Similarly, we use the methodology in Rauch (1999) to categorize each transaction as involving differentiated or homogeneous products.[27]

[24]See Table A3 for the baseline estimates with Conley spatial HAC standard errors.

[25]As a robustness check, we can show that our results hold when using later measures of cultural and political divisions, such as the voting shares for pro-Russian presidential candidates in 2004 and 2010. These results are available upon request.

[26]We use the official conversion table between HS 2012 and BEC 4 product codes, available at https:/unstats.un.org/unsd/trade/classifications/correspondence-tables.asp. We then use the official COMTRADE classification of BEC codes into capital, intermediate, and consumption goods (see details at https://unstats.un.org/unsd/tradekb/Knowledgebase/50090/Intermediate-Goods-in-Trade-Statistics). For simplicity, we combine intermediate and capital goods into a single category under the name "intermediate goods."

[27]First, 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.macalester.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.

Using tax IDs of Ukrainian firms, we merge trade transactions with the ORBIS/AMADEUS and SPARK databases. These datasets, available for the 2011–2016 period, contain the accounting information on total sales, profits, and inputs of individual firms. These datasets also include names of the managers, directors, and owners, which we merge and use to calculate a proxy for the prevailing ethnicity of the firms' key decision makers. The ORBIS/AMADEUS dataset contains information on more than 460,000 firms, i.e., the universe of all firms that are obliged to hand their accounting information over to the Ukrainian government based on their organizational form.[28] The SPARK and ORBIS/AMADEUS datasets contain similar information from similar sources, but SPARK has more variables.

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). The surveys 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 the surveys conducted from January 2013 to December 2016. For each wave, the sample of the KIIS survey includes two thousand adults in 110 localities across all Ukrainian regions and is representative at the national level.

4.2 Descriptive Statistics

Before turning to our main analysis, we present the summary statistics of the data used in this study. In addition, we provide the descriptive analysis of the overall decline in trading activity between Ukrainian and Russian firms after the start of the conflict.

Table 1 presents the basic summary statistics. In this study, we analyze trade transactions of 12,848 Ukrainian firms located in 393 Ukrainian raions over the period of 48 months, from January 2013 to December 2016.[29] 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.[30] Notably, the distributions of the total net weight and the total value traded have long

[28] As 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).

[29] Note that, unfortunately, we do not have data for export transactions from February to June 2014. Thus, for the firms that engage in export activity only, we observe their behavior over 43 instead of 48 months. All our results are robust to excluding these five months from our analysis.

[30] 230 tons is equivalent to 11–12 fully loaded trucks. As of August 2014, UAH 1.3 million was equivalent to

right tails, which motivates the use of logarithm transformations in our analysis. Per Panel B, an average firm traded intermediate goods in 77% of its transactions, stressing the prevalence of the B2B sector transactions in our dataset. Similarly, only 22% of average firms' transactions involved homogeneous goods.

As suggested by Panel C of Table 1, 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 county 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 counties 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 counties in Panel C, which validates our classification methods.[31]

According to Panel E of Table 1, 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 (7 km, or 4% of the standard deviation). Finally, Panel F of Table 1 presents accounting data for all Ukrainian firms in the ORBIS/AMADEUS database.[32]

4.3 Descriptive Time-Series Analysis

To complement the static description of the data in Table 1, 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 A6 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.[33]

$108,000 worth of product.

[31] For details on the classification methods, see Section 6.4.

[32] Accounting data is available for 8,206 out of 12,848 firms in our main sample. Selection is due to individual entrepreneurs not being required to report the data to the government. See Kalemli-Ozcan et al. (2015) for details on ORBIS/AMADEUS filing requirements by country.

[33] Note 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. After explicitly controlling for the January indicator in a regression form, we still estimate the effect of conflict on the number of firms as a loss of

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 after the conflict started in a simple time-series specification:

$$Y_{it} = \alpha_i + \gamma \times Post_t + \epsilon_{it}, \tag{2}$$

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 presents the firm-level fixed effects, 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-conflict areas.[34]

Table 2 presents the estimates of equation (2). Columns (1) to (3) display the results for the entire sample of firms that ever traded with Russia from 2013 through 2016. First, as a firm-level equivalent of Figure A6, column (1) of Table 2 shows that, with the start of the conflict, the probability of monthly trade with Russia by an average firm declined by 7.2 percentage points, or 0.18 standard deviations. Columns (2) and (3) of Table 2 examine the time-series effect of conflict on the monthly volume of trade measured by log-total weight and log-total value of the traded goods.[35] The obtained estimates are highly statistically significant—they suggest that an average Ukrainian firm experienced a substantial decline in monthly trade volume with Russia. The estimates correspond to a dramatic 52.05% to 59.75% decline in firm-level trade volume with the start of the conflict (interpreting the coefficients following Halvorsen and Palmquist, 1980). Therefore, an average Ukrainian firm trading with Russia decreased both the frequency of its monthly shipments and their volume.

To assess the intensive-margin effect of conflict on trade in greater detail, we estimate equation (2) on a subsample of firms that have been trading with Russia both before and after February 2014. Columns (4) to (6) of Table 2 display the results. Evidently, firms that continued trading have substantially decreased their trade intensity. They considerably reduced the monthly frequency of their shipments—the probability that an average remaining firm trades with Russia in a given month fell by 17.5 percentage points, off the base of a 53% pre-conflict probability. Moreover, the

1,000 firms trading with Russia per month.

[34]The latter assumption is potentially restrictive since it implies that firm's trade cannot exhibit any time trends. However, graphic evidence presented in Figure A6 suggests that it may hold in this context.

[35]We use a $\log(1 + x)$ transformation to accommodate zero trade flows.

average volume of their monthly shipments fell by a staggering amount — by 84.4% and 89.87% for total weight and total value traded, respectively. Thus, our findings in columns (1) to (3) of Table 2 are not driven exclusively by firms exiting trade with Russia, but also, to a large extent, by firms that continued trading with Russia but with decreased trade volumes.

The overall impact of conflict on trade between Russia and Ukrainian firms in non-conflict areas is sizable, especially given that Russia and Ukraine were major trading partners before the conflict. In Section 5, in a difference-in-differences framework, we will identify the extent to which this decline can be attributed to the rise of anti-Russian sentiments in Ukraine. However, Figure 4 offers a preview to our results by splitting the firm-level trade dynamics into firms located in counties with the share of ethnic Russians above and below the median. To construct this graph, we first regress the log of total weight traded with Russia by a firm in a given month on firm fixed effects. We then calculate the median residuals for two subsets of firms, depending on whether they are located in a county with more or fewer ethnic Russians.[36] 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 counties 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 4.3 suggest that (i) an average Ukrainian firm substantially decreased both the frequency and the volume of trade with Russia, (ii) a large part of this effect is on the intensive margin, meaning that many firms did not quit trade with Russia right away but rather decreased their trade intensity instead, and (iii) a simple split of trade patterns along ethnic and cultural ties with Russia already reveals that conflict had a differential impact on firms along this dimension. In the next section, we examine this divergent reaction in greater detail.

5 Results

5.1 Main Results

In the previous sections, we established that the Russia-Ukraine conflict led to a dramatic decrease in trade between the two countries and the rise of anti-Russian sentiments within Ukraine. In this section, we combine these two observations and identify the causal impact of conflict on trade via variation in initial pro-Russian leanings.

Table 3 presents the baseline estimates of the difference-in-differences equation (1), building

[36] We use median residuals instead of averages to obtain a cleaner graph which will not be influenced by outliers.

on the intuition offered by Figure 4. Similar to Table 2, we estimate the effect on trade using three different 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.

We start with the share of ethnic Russians across Ukrainian counties (raions) as our main proxy for a smaller increase of anti-Russian attitudes after the start of the conflict.[37] Columns (1) to (3) of Table 3 show the results for the three outcomes described above. The interaction coefficient β for the monthly probability of trade with Russia (column 1) is 0.091 (or 22.75% of a standard deviation). Together with the coefficient on the post-February 2014 indicator, these estimates suggest that moving a firm from a Ukrainian county with an average share of ethnic Russians (15%) to a county with the highest share of Russians among the counties in our sample (53%) would mitigate the adverse effect of conflict on the monthly probability of trade by 46%. Moreover, these estimates suggest that a hypothetical firm located in an all-Russian county would not have decreased its trade with Russia at all, with a caveat that this is an out-of-sample prediction. We obtain very similar results when we use the log-volumes of trade as outcomes in columns (2) and (3). Across all three specifications, the coefficient of interest is highly statistically significant at the 1% level.

We observe similar patterns with a different proxy for cultural ties with Russia. Columns (4) to (6) of Table 3 present the estimates using the share of native Russian speakers across Ukrainian counties instead. 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 county with an average share of Russian speakers (26%) to a 75% Russian-speaking county (highest in our sample) would mitigate the negative effect of conflict on the monthly probability of trade by 31%.

To allow for the visual exploration of our results, we present our estimates in an month-by-month form. That is, instead of the post-February 2014 indicator equal to one for all months after the start of the conflict, we interact the counties' ethnic composition with a full set of monthly dummy variables.[38] Figure 5 displays the results. First, we find no evidence of pre-trends, as

[37] Note that our results are robust to using share of ethnic Ukrainians and share of native Ukrainian speakers instead. However, the results are more pronounced for ethnic Russians and native Russian speakers, confirming our intuition that local ethnic and cultural ties to Russia serve as a better proxy for lower levels of animosity during the conflict and that other ethnicities are politically closer to the ethnic Ukrainians.

[38] That is, we estimate the following equation:

$$Y_{it} = \alpha_i + \gamma_t + \sum_t \beta_t \times \text{Rus}_i \times \gamma_t + \epsilon_{it}, \tag{3}$$

the share of ethnic Russians in the firm's raion 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.

One may wonder if our baseline difference-in-differences results are due to the breakdown of existing trade relationships or due to a differential creation of new trade ties after the start of the conflict. Anti-Russian sentiments at the local level can affect trade along both of these dimensions. To provide evidence for whether existing trade relationships are discontinued at a differential rate, or at least substantially decreased the frequency of trade, we study the survival rates of trade firm-pairs before and after the start of the conflict. For this, we take pairs of firms that traded with each other at any point in 2013 and identify the month of their last trade. We then look for a systematic difference in survival rates across Ukrainian counties with different ethnic composition.

Figure 6 presents the graphic illustration of the results. Most of the firm-pairs that appear in 2013 data are short-term arrangements, with 70% of all firm pairs never trading again after December 2013. Moreover, before the start of the conflict, firm-pairs with the Ukrainian firms located in areas with few ethnic Russians (below the 25th percentile in our sample, or less than 3.3%) have almost identical survival rates compared to the firm-pairs with the Ukrainian firms located in areas with a high share of ethnic Russians (above the 75th percentile, or more than 15.6%). However, after the start of the conflict, the survival rates start to diverge, reaching their greatest difference of 7 percentage points in October 2015.[39] Thus, it is clear that a significant portion of our difference-in-differences estimates comes from the existing trade relationships being discontinued or, at least, substantially reducing their trade frequency.

Overall, the baseline difference-in-differences estimates point to a sizable and a highly statistically significant differential decline in trade across Ukrainian counties—firms from areas with fewer preexisting ethnic and cultural ties with Russia decreased trade with Russia by a larger mar-

where the outcome variable Y_{it} is trade intensity of firm i with Russia (export+import), at year-month t; α_i and γ_t are firm and year-month fixed effects; and Rus_i is the share of ethnic Russians in the county of firm i in 2001. Note that we obtain identical results when we use the share of native Russian speakers instead of the share of ethnic Russians as a measure of preexisting ties to Russia.

[39] According to the regression estimates (available upon request), the difference in survival rates across areas with different shares of ethnic Russians is highly statistically significant.

gin relative to the firms from more ethnically Russian regions of Ukraine. Moreover, at least in part, these results come from the breakdown of existing trade relationships. More generally, these results provide the first evidence that armed conflict can have a substantial indirect effect on trade between the conflicting sides, an effect that operates via increased antipathy toward the opposite side of the conflict. In the next section, we provide evidence that these results survive multiple rigorous robustness checks and are not due to various mechanical explanations not related to ethnicity or anti-Russian sentiments.

5.2 Alternative Explanations and Robustness Checks

The results in the previous section suggest that armed conflict has a negative impact on trade that operates through rising antipathy between the opposite sides of the conflict. Before we proceed to exploring the mechanisms, however, we rule out the three main alternative explanations for our findings: differences in distance to the Russian border, confounding product-specific shocks, and local economic shocks that arise due to the conflict. We then discuss other potential explanations and test the overall robustness of our estimates.

5.2.1 Geographical Distance to Russia

First, it is possible that the geographical distance to Russia drives our baseline results, rather than the preexisting ethnic and cultural ties with Russia 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 the conflict substantially increased transportation costs—could mechanically have a bigger impact on firms in the areas of Ukraine with fewer ethnic Russians. To address this alternative explanation, we calculate the shortest path to Russia for each firm and include its interaction with the post-February 2014 indicator as a covariate in our regressions.[40] Table 4 shows that, after accounting for distance to the border, the results are almost identical to those in Table 3. Arguably, a linear control for distance may not be enough to account for distance-related shocks. Table A4 shows that including higher-order polynomials of distance does not change the results. Therefore, it is unlikely that the presence of ethnic Russians or native Russian speakers matters for our estimates only as a proxy for distance to Russia.

[40] 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 regions. To 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 county from 2013 to 2016, and excluding these firms from our sample does not affect the results.

5.2.2 *Confounding Product-Specific Shocks*

Another important alternative explanation concerns product-specific shocks that may arise due to the conflict. Immediately after the start of the conflict, all military cooperation between the two countries ceased, which naturally affected export and import transactions in the related sectors.[41] Thus, hypothetically, if areas with fewer preexisting ties with Russia have been more involved in the production of products in military-related sectors, this may have biased our baseline difference-in-differences estimates upward, without mutual antipathy playing any role.[42] To address this issue, we estimate a difference-in-differences specification at the product-firm-month level with product-post fixed effects:

$$Y_{ijt} = \alpha_i + \gamma_t + \underbrace{[\delta_j + \kappa_j \text{Post}_t]}_{\text{Product-Post FEs}} + \beta \times \text{Post}_t \times \text{Rus}_i + \varepsilon_{ijt}, \tag{4}$$

where the outcome variable Y_{ijt} is the trade intensity of firm i with Russia (export+import) with product j 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_i is the share of ethnic Russian or native-Russian-speaking population in the county of firm i in 2001, or any other measure of alignment with Russia; and Post_t is the post-February 2014 indicator.[43]

Similar to equation (1), specification (4) compares firm-product pairs' reaction to the start of the conflict depending on the ethnic composition of the firm's county. However, in addition, it also nets out all conflict-induced product-specific shocks, confounding or not. The identification of the β coefficient still relies on the parallel trends assumption. That is, one needs to assume that firm-product trade would have evolved along similar trends in counties 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 β coefficient estimates a causal impact of local animosity toward the opposite side of the conflict on firm-level trade with

[41] Trade 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.

[42] Note that all shocks that applied uniformly to all products would be absorbed by time fixed effects. Other 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.

[43] Since the coefficient on Post_t would be consumed by product-post fixed effects, we switch from a specification with year and month fixed effects to one with year-month fixed effects.

that side.[44]

Table 5 presents the results of estimating equation (4): Panel A contains the baseline product-level estimates, and Panel B adds the distance controls. The main coefficient stays positive and statistically significant, with magnitudes remaining at 16% to 19% of a standard deviation. Hence, our baseline results cannot be explained by any type of product-specific shocks that appear due to the start of the conflict.[45]

5.2.3 *Local Economic Shocks Due to Conflict*

Another set of potential explanations is related to county-specific economic shocks arising after the start of the conflict. These may include any demand or supply shocks that vary across Ukrainian counties, whenever they happen to be correlated with the ethnic composition of these counties. For instance, areas close to the armed conflict may have hosted more refugees, which could have generated a positive demand and labor-supply shocks.[46] Similarly, areas with fewer ties with Russia may have produced more protesters, activists, and soldiers, possibly leading to an adverse labor-supply shock. Finally, political turnover in a weak institutional context may lead to productivity shocks across Ukrainian areas, depending on their electoral support for the new leader (Earle and Gehlbach, 2015). Using trade between Ukrainian firms and other countries, we can see whether areas with lower shares of ethnic Russians decreased trade with everyone, not just Russia, and whether these negative county-specific shocks drive our results. This intuition leads to a triple-difference specification with county-post fixed effects (not to be confuses with *country*-post fixed effects) in the spirit of gravity equations estimated in the trade literature (Allen, Arkolakis, and

[44]To detect whether the parallel-trends assumption holds in this specification for the pre-conflict period, we estimate the following equation:

$$Y_{ijt} = \alpha_i + \gamma_t + [\delta_j + \kappa_j \text{Post}_t] + \sum_t \beta_t \times \text{Rus}_i \times \gamma_t + \varepsilon_{ijt}, \tag{5}$$

where the outcome variable Y_{ijt} is the trade intensity of firm i in 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_i is the share of ethnic Russians in the county of firm i in 2001, or any other measure of preexisting ties to Russia; and Post_t is an indicator for the post-conflict period.

Figure A7 visually presents the estimates of equation (5). As one can see, coefficients β_t 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).

[45]See Figure A8 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.

[46]In Table A5, we explicitly show that the influx of refugees cannot explain our results. Specifically, our estimates stay the same when we control for the number of refugees across Ukrainian regions interacted with the post-February 2014 indicator.

Takahashi, 2018):

$$Y_{ict} = \alpha_i + \gamma_t + [\mu + \beta \text{Post}_t] \times \text{Rus}_i \times \text{Russia}_c + \underbrace{[\delta_c + \kappa_c \text{Post}_t]}_{\text{Country-Post FEs}} + \underbrace{\nu_{\{r:i \in r\}} \text{Post}_t}_{\text{County-Post FEs}} + \varepsilon_{ict}. \quad (6)$$

Here, Y_{ict} is trade intensity (export+import) of firm i 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_i is the share of ethnic Russians or native Russian speakers in county r (for *raion*) to which firm i belongs. Furthermore, α_i, γ_t, and δ_c are firm, time, and country fixed effects; κ_c and $\nu_{\{r:i \in r\}}$ are country-post and county-post fixed effects, respectively.

This equation is akin to a difference-in-difference-in-differences strategy in which an outcome is changing across space, across time, and across countries. In this specification, the coefficient of interest, β, measures how much trade intensity with Russia changes with the start of the conflict for firms in counties with higher versus lower share of ethnic Russians, relative to the differential change in trade with other countries. With the help of cross-country variation, this strategy allows us to account for any county-specific economic shocks, whether these are demand shocks, such as differential declines in income after the start of the conflict, or supply shocks, such as an increase in labor supply due to an inflow of refugees from the conflict areas.

Table 6 presents the results of estimating equation (6) for the ten top trading partners of Ukraine, with all other countries counted as the eleventh country. First, consistent with the literature on ethnic networks and trade (Rauch and Trindade, 2002), we document that pre-conflict trade with Russia was higher in areas with a higher share of ethnic Russians. However, the triple-difference coefficient is positive and significant, meaning that, with the start of the conflict, firms in counties with fewer ethnic Russians decreased trade with Russia by a *disproportionately* large 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 15% to an area with 53% ethnic Russians, its chance of having any monthly trade activity with Russia after the start of the conflict, as opposed to with other countries, rises 4.6 percentage points. The magnitude of the triple-difference coefficient is not reduced and, if anything, is bigger than the baseline effect (32.2% versus 22.5% of a standard deviation). Since such shocks as a refugee influx would most likely affect trade with all countries, not just with Russia, the estimates in Table 6 back our assertion that our baseline results are not driven by any type of locality-specific shocks.[47]

[47] See Figure A9 for the β coefficients from equation (1) estimated for each of these countries individually. Note that

5.2.4 Additional Alternative Explanations and Robustness Checks

In addition to accounting for product- and county-specific shocks and distance, 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.[48] Second, we show that our findings unlikely result from ethnic discrimination at the border, since there is no differential effect for trade with Kazakhstan, which has to go through the Russia-Ukraine border.[49] Third, 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.[50] Finally, 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.[51]

6 Mechanisms

Previous sections documented a robust result that firms in areas with fewer preexisting ethnic and cultural ties with Russia decreased trade with Russia by a larger margin after the start of the conflict. Moreover, we show that this result is unlikely to be explained by some omitted variable that happens to be correlated with the ethnic composition of the firms' counties. Instead, we argue that it stems from a dramatic rise of anti-Russian sentiments in localities with fewer ethnic Russians. In this section, we look into specific mechanisms of how antipathy between areas translates into a decline in trade. First, we show that consumer action and CSR activity by Ukrainian firms play a role in driving our results. Furthermore, we find that a differential decline in trust in Russian contract enforcement is another mechanism by which anti-Russian sentiments translate into breakdown of trade. Specifically, inferring types of trade contracts used by Ukrainian firms based

no other top-10 trading partner of Ukraine had a positive and significant coefficient at the 5% confidence level on the interaction between share of ethnic Russians and the post–February 2014 indicator. Moreover, see Figure A10 for the month-by-month coefficients across top-10 trading partners. As one can see, coefficients for Russia turn from being in the middle of the pack to being consistently bigger relative to the coefficients for the other countries. Together, these figures further confirm that it is highly unlikely that firms in areas with fewer Russians just happened to experience a negative economic shock and that this is the chief reason they stopped trading with Russia.

[48] See Table A6 in the Online Appendix for the results. As there is no difference in coefficients between state-owned and other firms, government firms either did not experience pressure from the top and acted as regular firms, or the pressure was also differential across regions.

[49] See Figure A9 in the Online Appendix for this result. Negative difference-in-differences coefficients for Poland, Turkey, and other countries suggest that firms could be switching from trading with Russia to trading with other countries. See Section 7.1 for a detailed discussion of this hypothesis.

[50] See Table A7 in the Online Appendix for the results.

[51] Per Table A8 in the Online Appendix, the results hold without the capital of Ukraine (Kyiv), without the regions close to conflict areas, and without Western Ukraine. Moreover, Figure A11 in the Online Appendix displays that the baseline coefficient remains stable when we remove Ukrainian regions one by one from our sample.

on the products they trade, we show that the effect is larger for firms that are predicted to use trade contracts that leave them vulnerable to the risk of non-payment. We conclude by showing that individual-level ethnicity of firms' key decision makers does not appear to matter for our results, suggesting that our effect does not come from inter-ethnic conflict at the personal level. While we argue that a combination of consumer boycotts, CSR by Ukrainian firms, and a breakdown of trust in contract enforcement can potentially explain all of our results, we acknowledge that there may be other mechanisms which we cannot rule out.

6.1 Consumer Action

One of the natural mechanisms via which local-level animosity may affect trade with the opposing side is consumer action. Specifically, our results could potentially arise from Ukrainian consumers refusing to buy Russian brands, refusing to shop at Russian-owned stores, and, possibly, refusing to support Ukrainian firms that trade with Russia.

There 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.[52] 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.[53] 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.[54] By March 2015, the latter number had grown to 45%.[55] Thus, as opposed to the typical short-lived boycott campaign studied in the literature, the anti-Russian boycott in Ukraine lasted a long time. Consumer reaction is thought to have had a severe impact on Russian imports in Ukraine. Some estimates show that sales of Russian products decreased by up to 40%.[56] That said, no rigorous estimates exist that would separate the effect of consumer action from other economic shocks happening in Ukraine at the time.

Despite this qualitative evidence of consumer boycotts taking place, it is still possible that these activities were either not effective enough or not as heterogeneously spread across Ukrainian counties to contribute to our estimates. We use two methods to check whether consumer boycotts

[52] https://korrespondent.net/ukraine/3442493-sdelano-v-rossyy-kak-mahazyny-markyruuit-tovary-yz-rf

[53] https://www.gazeta.ru/tech/2014/03/31_a_5971313.shtml

[54] https://www.pravda.com.ua/rus/news/2014/05/15/7025437/

[55] https://tsn.ua/ukrayina/bilshist-ukrayinciv-pidtrimuyut-boykot-tovariv-iz-rosiyi-doslidzhennya-420268.html

[56] https://tsn.ua/groshi/rosiyski-virobniki-maskuyut-shtrih-kodi-na-svoyih-tovarah-schob-naduriti-ukrayinciv-341901.html

indeed mattered for our results: first, we test whether the differential effect of animosity is more pronounced for traders of consumer goods, especially for imports from Russia, and second, we examine whether our results are stronger in regions with a higher relative incidence of online searches regarding boycotts.

Table 7 presents the results of the consumer-intermediate goods breakdown; for simplicity, we use "any trade activity" as the only dependent variable. As a benchmark for the rest of the table, columns (1) and (4) present the baseline estimates for all trade transactions (export+import) and import transactions separately. Columns (2) and (3) display the breakdown of the baseline results in column (1) 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 differential effect of conflict across areas with different ethnic and cultural ties with Russia. To ascertain whether consumer boycotts indeed drive these differences, we study import transactions separately from exports in column (4) and further break down the results by firm type in columns (5) through (8). 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.[57] This pattern is highly consistent with the consumer boycotts explanation, in which boycotts have been more widespread in areas with greater anti-Russian sentiments.

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. Unfortunately, we were not able to locate data on actual boycott activity at a geographically disaggregated level. To approximate the intensity of boycotts in Ukrainian regions, we rely on relative popularity of online searches for *boycott*, which we obtain from Google Trends.[58] Figure A12 shows, unsurprisingly, a strong negative association between the standardized *boycott* search intensity and the share of ethnic Russians in a region.[59] Table A9 further tests whether boycott intensity matters for our estimates. Columns (2) and (3) illustrate that the differential ef-

[57] Since 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.

[58] Specificallly, 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.

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

fect of local ethnic composition is higher especially in regions with higher boycott intensity; and, conversely, ethnicity does not matter as much in regions where boycotts appear less widespread. Columns (4) and (5) show that, in principle, we could use our measure of boycott intensity instead of the local ethnic composition and obtain similar results. Taken together, these results strongly suggest that local anti-Russian sentiments documented in Section 2.4 translate into higher boycott intensity, and that consumer and activist action likely explains at least part of our results.

6.2 CSR Activity by Ukrainian Firms

The previous section indicates that consumer boycotts of Russian products constitute one of the mechanisms behind our baseline results. However, consumer action cannot be the only explanation, since the differential effect is present even for import transactions of the firms that imported only intermediate products from Russia (as suggested by column (8) of Table 7). We argue that this empirical evidence is consistent with CSR activity, i.e., voluntary compliance with local social norms, on the part of firms involved in B2B trade transactions.

While obtaining hard evidence of CSR is difficult, we document an additional pattern that confirms this conjecture indirectly. In a typical model of CSR activity, activists are rational agents maximizing the impact they can make, given their limited resources. Since large firms are more visible and can more easily accommodate activists' demands, these firms know that they have a higher chance of being targeted by activists. As a result, to prevent this from happening, they voluntarily self-regulate and spend more resources on CSR activity. This model generates a prediction that, if CSR activity is the mechanism behind the differential effect for intermediate-goods traders, we would expect larger firms to drive the results.

Table 8 shows that large firms indeed drive our estimates for the intermediate-goods traders. 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 larger relative to their smaller counterparts. This pattern is consistent with local animosity putting pressure on firms to discontinue trade with Russia, even in the B2B sector, and with large firms accommodating this pressure by ceasing business relationships with their Russian partners.

These quantitative findings are in line with the anecdotal evidence of CSR activity on behalf of Ukrainian firms under the risk of suffering reputational damage. We have factual records that

Ukrainian firms trading with Russian firms were under relentless public pressure to discontinue those relationships, even if they traded only intermediate goods, such as automobile parts.[60] The pressure was in place even for firms that were exporting products to Russia, especially if buyers were somehow tied to Russian army providers.[61] Naturally, many Ukrainian companies 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.[62] 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.[63]

6.3 The Erosion of Trust in Russian Institutions

In the previous two subsections, we documented that our baseline results can be explained, at least in part, by consumer action and CSR activity by firms. However, while this explanation is likely to suffice for imports of Russian goods to Ukraine, it remains unclear whether CSR activity and consumer pressure can affect exports to Russia as strongly, even though exporters to Russia also suffered from some media backlash. We consider another potential mechanism—a decrease in trust of Ukrainian firms in Russian institutions. The existing theoretical literature suggests that a decline in confidence between trade partners can result in a breakdown of existing trade ties and increased importance of informal contract enforcement via intra-ethnic ties (Dixit, 2003; Rohner et al., 2013). In contrast, we argue that erosion of trust in enemy's institutions can be equally

[60] For example, the bus corporation Bogdan got heavily criticized for importing Russian inputs (https://www.volyn24.com/news/97774-bogdan-maie-vidmovytysia-vid-zakupivli-rosijskyh-detalej-gunchyk and https://www.volyn24.com/news/96598-luckyj-zavod-kupuie-avtomobilni-detali-v-rosii-deputat). Another company faced pressure for producing buses with 95% of all inputs coming from Russia (https://tsn.ua/groshi/tenderniy-skandal-ukrayina-zakupila-shkilni-avtobusi-u-virobnika-tehniki-dlya-armiyi-rf-713165.html).

[61] E.g., a firm faced severe public pressure for allegedly exporting engines to Russia that may have then been used to create military products (https://interfax.com.ua/news/economic/404613.html).

[62] "Under conditions where Russia is leading an unparged 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 (https://kmb.ua/ua/news/kievgorstroj-otkazyvaetsya-ot-produktsii-rossijskogo-proizvodstva/).

[63] https://ukr.segodnya.ua/economics/avto/ukrainskiy-avtogigant-polnostyu-otkazalsya-ot-rossiyskih-komplektuyushchih-609274.html. Yet another example is Ukrainian aircraft manufacturers, which have abandoned Russian components by early 2015 (https://ukr.lb.ua/economics/2015/06/16/308464_ukrainski_virobniki_litakiv.html). 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 (https://lb.ua/economics/2014/03/19/259929_ukrainskaya_kompaniya_ubrala.html).

important—even if there is no decline in inter-ethnic trust, firms may become fearful that the opposite side of the conflict will stop enforcing trade contracts.

To test the importance of trust in Russian institutions, we explore variation in trade contracts used by firms. There are three standard types of contracts in international trade: open account (OA), cash-in-advance (CIA), and letters of credit (LC). In a CIA contract, the importer pays before the good is shipped. An OA contract refers to a sale where the goods are shipped and delivered before payment is due, which is typically in 30, 60, or 90 days. An LC contract allows importers to guarantee the payment via a bank, thus alleviating the risk levied on both exporters and importers. Thus, if the breakdown of trust to Russia is indeed driving our results, we would expect a greater effect for exporters (importers) if they primarily used OA (CIA) contracts before the start of the conflict, as these types of contracts place a bigger risk of non-payment on exporters (importers). On the contrary, we would expect the breakdown of trust to have little or no impact on firms which use letters of credit.

Ideally, we would want to test these predictions by exploiting the types of contracts used by firms for each of their transactions. Unfortunately, our customs data do not contain such information. The closest available analog is data on the types of contracts used in trade between Ukraine, Russia, and Turkey over the 2004–2011 period.[64] 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 three types of standard trade contracts mentioned above. In line with anecdotal evidence, the summary statistics on these shares show that OA contracts, in which importer pays only after receiving the product, dominate the Russia-Ukraine trade relations—the median predicted probability that a Ukrainian firm is using an OA contract in a given transaction is 86.7%, with 95% of all firms predicted to use OA contracts for at least 50% of its transactions. The median probabilities for CIA and LC contracts are 11.6% and 0.28%, respectively.

Using the predicted contract usage, we test the hypothesis of weakened trust and problems in contract enforcement. Given the predominance of OA contracts in the region, it is especially interesting to check whether the effect of conflict on exports comes from a breakdown of trust. Table 9 presents the results of estimating the baseline specification (1) for subsets of firms depending on

[64]These data, kindly shared with us by Banu Demir, were previously used in Demir, Michalski, and Ors (2017) and Demir and Javorcik (2018). The implicit assumptions here are that (i) Russian and Ukrainian firms use similar types of contracts for similar products when they trade with each other as they do when they trade with Turkey, and (ii) there have been no substantial changes between the 2004–2011 and 2013–2016 periods in terms of typical use of different types of contracts.

their predicted use of different types of contracts. To disentangle the risks levied on exporters and importers by different types of contracts, Panel A and Panel B display, respectively, the results for export and import activity only.

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 than the median predicted use of OA contracts, which place the burden of potential nonpayment on exporters. Moreover, the estimate is significantly different from the effect on exporters among whom OA contracts are likely not as widespread. In contrast, no differential effect of conflict exists among exporters with a high predicted use of CIA contracts, in which the risk is placed on the importer, again with a statistically significant difference between the two groups of firms. Similarly, there is also no differential impact on exporters with a high predicted usage of LC contracts, in which there is little risk of nonpayment in the first place.[65] Notably, estimates in Panel B of Table 9 suggest that the breakdown of trust was not present for importers—across all specifications, little difference exists between firms with different predicted contract use.

Overall, the results in Table 9 indeed suggest that the breakdown of trust to Russian institutions played a role in explaining the reaction of Ukrainian exporters to Russia. Given the widespread use of OA contracts in the CIS region, Ukrainian exporters from areas with fewer Russians likely feared nonpayment from the Russian buyers after the start of the conflict.

6.4 Individual-Level Animosity by Key Decision Makers

In the previous subsections, we explored the primary mechanisms behind our findings—consumer boycotts, CSR activity by Ukrainian firms, and breakdown of trust in Russian institutions. However, another potential mechanism exists: a rise in individual-level animosity between firms' key decision makers. While this mechanism is typically ignored by the economics literature, which views firms as purely rational profit-seeking agents, it is not impossible to imagine that a severe conflict would cause some firm owners and managers to voluntarily discontinue their relationships with a partner from a hostile area due to sharp political disagreements.

To address this possibility, we infer whether the firms' top-level managers have surnames with Russian roots. Russian and Ukrainian surnames traditionally had different endings and, in gen-

[65] In a comprehensive study of the consequences of Russian sanctions, Crozet and Hinz (2016) find that trade between French firms and Russia declined more for products with a high predicted usage of LC contracts, suggesting that financial sanctions against Russian banks adversely affected products that required bank guarantees. Since we find either no heterogeneity by LC contract use (for imports), or that the differential effect of preexisting ties to Russia is actually reduced for firms with high predicted use of LC contracts (for exports), no evidence exists that financial sanctions played any significant role in our context.

eral, 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" or "in."[66] 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.[67] Based on these two methods, we produce two measures of the share of managers with Russian roots, which we use in a difference-in-differences equation (1) to discern whether personal identity can explain some part of our results.

Table A11 in the Online Appendix displays the corresponding estimates. Evidently, the share of managers with Russian roots does not produce the same results as the share of ethnic Russians in the area the firm resides.[68] In a horse-race exercise in Panel A of Table A11, where the "Russianness" of the managers is included together with that of the firm's county, the effect of the managers' Russian roots stays close to zero and statistically insignificant; meanwhile the effect of the share of ethnic Russians in a county 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.

Although individual-level animosity is unlikely to explain our results on its own, some evidence suggests that it can interact with local ethnic composition. Panel B of Table A11 displays the results of a triple-difference specification in which our measures of the Russian origin of the firm's managers is interacted with the share of ethnic Russians in the firm's county. As one can see, although insignificant for the share of native Russian speakers, these results suggest that the effect of increased local animosity on trade is much more pronounced for firms with fewer managers of Russian origin. Moreover, firms with no managers of Russian origin did not alter their trade with Russia with the start of the conflict, no matter where they are located, suggesting that local animosity toward Russia starts to play a role only when the key decision makers within the firm do

[66] See Zhuravlev (2005) for a detailed discussion of this approach.

[67] The 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 over the 1970–2000 period to calculate the frequency of last names with tranditional 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.

[68] For robustness, we also calculate the share of Russian-sounding last names of firm owners and directors, and we obtain identical results. These results are available upon request.

not themselves have cultural or ethnic ties with Russia.

7 Implications for Firms

7.1 Switching Patterns

Our main result in this paper is documenting a novel indirect effect of conflict on firm-level trade via increased antipathy toward the opposite side of the conflict. We also detailed several mechanisms through which this indirect effect is operating. However, it remains to be explored what are the implications of this effect for firms. For instance, how do firms accommodate this effect? Do firms increase trade with other countries, or do they assume the losses?

So far, we have evidence that (i) Ukrainian firms that traded with Russia before the start of the conflict discontinued their trade relationships with Russian firms at a higher rate if they were located in a county with a lower Russian minority (Figure 6); (ii) Ukrainian firms in the areas with fewer Russians increased their trade with countries such as Poland and Turkey by a larger margin relative to firms in other regions (see Figure A9 in the Online Appendix; note that these results include firms that never traded with Russia in 2013 through 2016). However, to what extent do these two results coincide? Do *individual* firms switch from trading with Russia to trading with other countries? In this section, we investigate the firm-level switching patterns.

If switching is indeed one of the primary ways of accommodating the indirect effect of conflict of shifts in public opinion, one would expect firms with lower costs of switching to be more responsive to this effect. To determine whether this is indeed the case, for each Ukrainian firm, we document whether it traded with other countries, excluding Russia, before the start of the conflict. We then estimate the baseline difference-in-differences specification to compare the results across two groups of firms: firms that traded with Russia and at least one other country before the start of the conflict, and those that traded with Russia only. Table A12 in the Online Appendix presents the estimates. We find that, highly consistent with the switching response, firms with already established connections in other countries are responsible for the entire differential effect on trade with Russia (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.

Although previous results indeed indicate that firms switch from trading with Russia to trading with other countries, the magnitude of this effect remains unclear. Did exporters lose part of their sales? Similarly, were importers able to find substitutes for all of the products they were importing from Russia? To examine these issues, we look at the consequences of the indirect effect of conflict on the firms *total* trade with *all* countries. That is, for each Ukrainian firm that traded with Russia before the start of the conflict, we calculate monthly trade intensity with all countries, including Russia. We then estimate a baseline difference-in-differences equation with total trade as the primary outcome. To zero in on the firms that are likely to switch, we look at the firms that traded with Russia before the start of the conflict and at least one other country after the start of the conflict. Table A13 in the Online Appendix reports the results. Columns (4) through (6) illustrate that there is an indication that switching exporters were able to switch fully to trading with other countries, as there is no indication that *total* trade for these firms changed differentially depending on their location. In contrast, columns (7) through (9) indicate that switching importers did not switch completely, as total import activity declined more for firms in areas with fewer ethnic Russians after the start of the conflict.

We conclude that part of the differential effect of conflict is explained by Ukrainian firms shifting their trade activity to other countries. Moreover, the magnitude of this switching activity is large and, at least in the case of exports, switching firms were able to fully transfer their trading activity to other countries.

7.2 Sales, Profits, and Productivity

In the previous section, we documented that part of the indirect effect of conflict via shifts in public opinion is absorbed by firms switching to trade with other countries. However, does this mean that it leads to no negative consequences and, as such, is a costless signalling device for firms? In this section, we explore whether, empirically, the differential effect on trade documented in Section 5.1 has any negative implications for trading firms' sales, profits, and productivity.

Due to the possible county-specific economic shocks, it may be misleading to directly compare balance-sheet characteristics of firms trading with Russia that are located in areas with high and low shares of ethnic Russians. As Table A14 shows, Ukrainian areas with a higher Russian presence, in fact, experienced a deeper economic decline in the immediate aftermath of the conflict. Specifically, when we look at all firms, not only those trading with Russia, we find that firms located in areas with more ethnic and linguistic ties to Russia, on average, experienced a more substantial decline in their sales, profits, and even productivity, although the latter results are less statistically significant.[69] It is beyond the scope of this paper to rationalize this pattern, but we

[69] See Section 5.2.4 for a robustness check that accounts for any county-specific shocks in a gravity-style framework. Furthermore, see Table A15 for the baseline results conditioning on firms' overall change in sales. Clearly, the interaction coefficient goes up relative to Table A15, which goes against our baseline results on trade with Russia and suggests that firms trading with Russia from more Russian areas of Ukraine were overall hurt more by local economic shocks than their counterparts in areas with fewer ethnic Russians.

speculate that it may be due to either the disruption of input-output linkages with the areas of armed conflict (Carvalho, Nirei, Saito, and Tahbaz-Salehi, 2016) or a differential effect of political turnover (Earle and Gehlbach, 2015).

In light of county-specific shocks to the overall economic performance of firms, one needs to compare firms from more Russian areas trading with Russia not only to their counterparts from areas with fewer ethnic Russians but also to the overall change in performance in their locality for other firms. This intuition leads to the following triple-difference specification:

$$Y_{ist} = \alpha_i + \gamma_t + [\mu + \beta \text{Post}_t] \times \text{Rus}_i \times \text{Traded}_s + \text{Post}_t \times [\delta \text{Rus}_i + \kappa \text{Traded}_s] + \varepsilon_{ict}. \quad (7)$$

Here, Y_{ist} is a balance-sheet variable (sales, profits, etc.) of firm i 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_i is the share of ethnic Russians in a county of firm i; and α_i and γ_t are firm and year fixed effects, respectively.[70] Under the standard triple-difference assumptions, β identifies the negative consequences of conflict on a firm's overall performance among trading firms from areas of Ukraine with different preexisting cultural and ethnic ties to Russia, net of the changes that are due to broad economic shocks that affect all firms.

Table 10 presents the estimates of equation (7) for all Ukrainian firms excluding individual entrepreneurs.[71] 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 that affected all firms due to their location in areas with more or fewer ethnic Russians, firms that were trading with Russia before the start of the conflict and were located in areas with fewer Russians suffered a larger decline in sales, profits, and productivity relative to their counterparts from more Russian areas of Ukraine. The magnitude of this differential decline is economically meaningful. For instance, according to column (1) of Table 10, moving a firm that traded with Russia before the conflict from a county with 50% to a county with 15% of ethnic Russians would decrease its sales by 0.074 standard deviations relative to other firms in the area.

Overall, the results in this section suggest that the differential effect of conflict on trade via

[70] Note that the coefficients on Traded_s, Rus_i, and Post_t are absorbed by firm and year fixed effects.

[71] These data come from the ORBIS/AMADEUS dataset and include the universe of firms that are obliged to hand their accounting information over to the Ukrainian government (Kalemli-Ozcan et al., 2015). This requirement encompasses all firms that are not individual entrepreneurs.

increased antipathy to the opposite side of the conflict adversely affects firms that traded with Russia, not only via decreased sales but also via decreased profits and productivity, at least over the time period of our study. Thus, the effects documented in this study can indeed have far-reaching consequences for individual firms.

8 Conclusion

Conflicts have vast and multifaceted effects on the economy. They can impact economic agents directly, through violence and damage to property, or indirectly, for example, by disrupting business relationships. While the existing literature offers evidence on the direct effects of conflict, the indirect effects are still largely understudied. This paper provides evidence on one such type of indirect effect—the disruption of trade relations due to increased animosity toward the opposing side of the conflict—by studying the recent, ongoing Russia-Ukraine conflict, which is unique for its near absence of newly imposed trade restrictions and is accompanied by a dramatic but heterogeneous increase in antipathy toward Russia across Ukrainian counties. Using rich, transaction-level data on Ukrainian trade, we show that firms located in counties with higher preexisting ties with Russia, measured by their ethnic composition, experienced a smaller drop in trade with Russia relative to firms in other counties. Using survey evidence, we show that these were precisely the counties with the lowest increase in anti-Russian sentiments. We interpret our findings as arising partly from local-level animosity, which translates into consumer boycotts against Russian products and public pressure on firms to discontinue their business relationships with the enemy, and partly from erosion of trust in Russian institutions of contract enforcement.

Our study highlights the importance of analyzing economic activity in non-conflict areas. Given the context, the effects that we document may be especially applicable to conflicts in which countries are large trading partners and were part of the same country historically. These effects may be even more important in the context of civil conflicts, in which trade embargoes are often not enacted or not strictly enforced (e.g., see Leigh (2012) on trade between the North and the South in the American Civil War). This paper may also shed light on why economic exchange between mutually antagonistic areas may stay suppressed even after trade embargoes are lifted. That said, more research is needed to see whether our results can be replicated in other contexts. Generally speaking, the economic impact of conflict on non-conflict areas remains an understudied topic that would benefit from more scholarly work.

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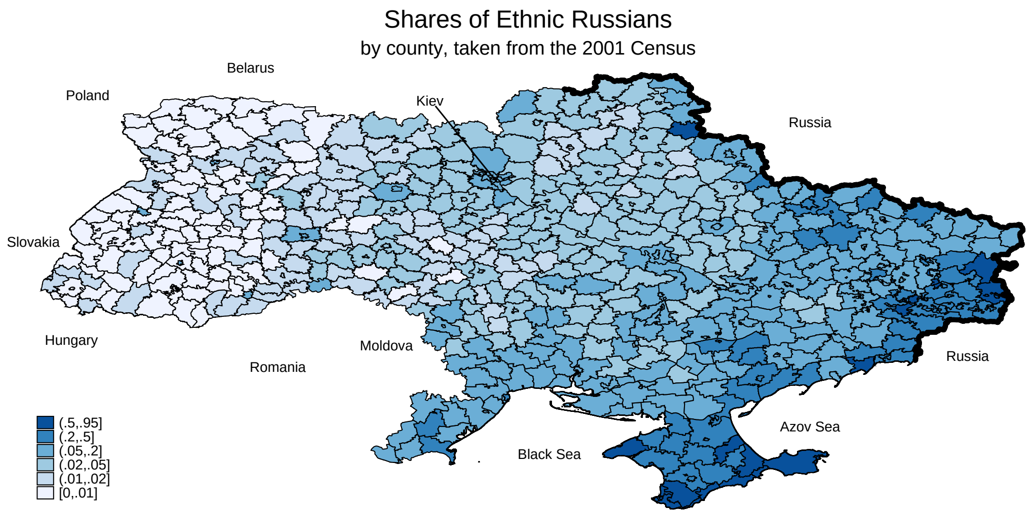
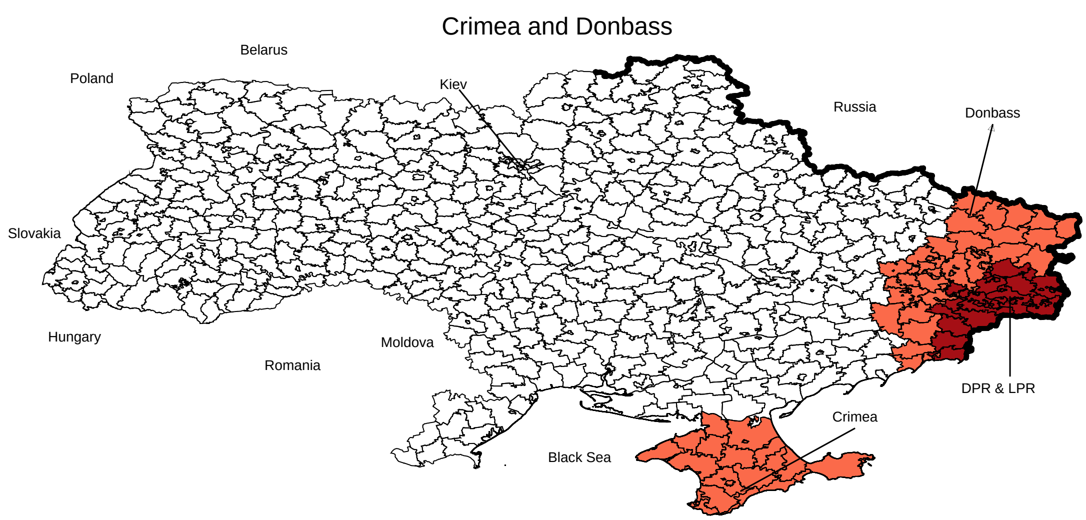
FIGURES

Figure 1: Shares of Ethnic Russians



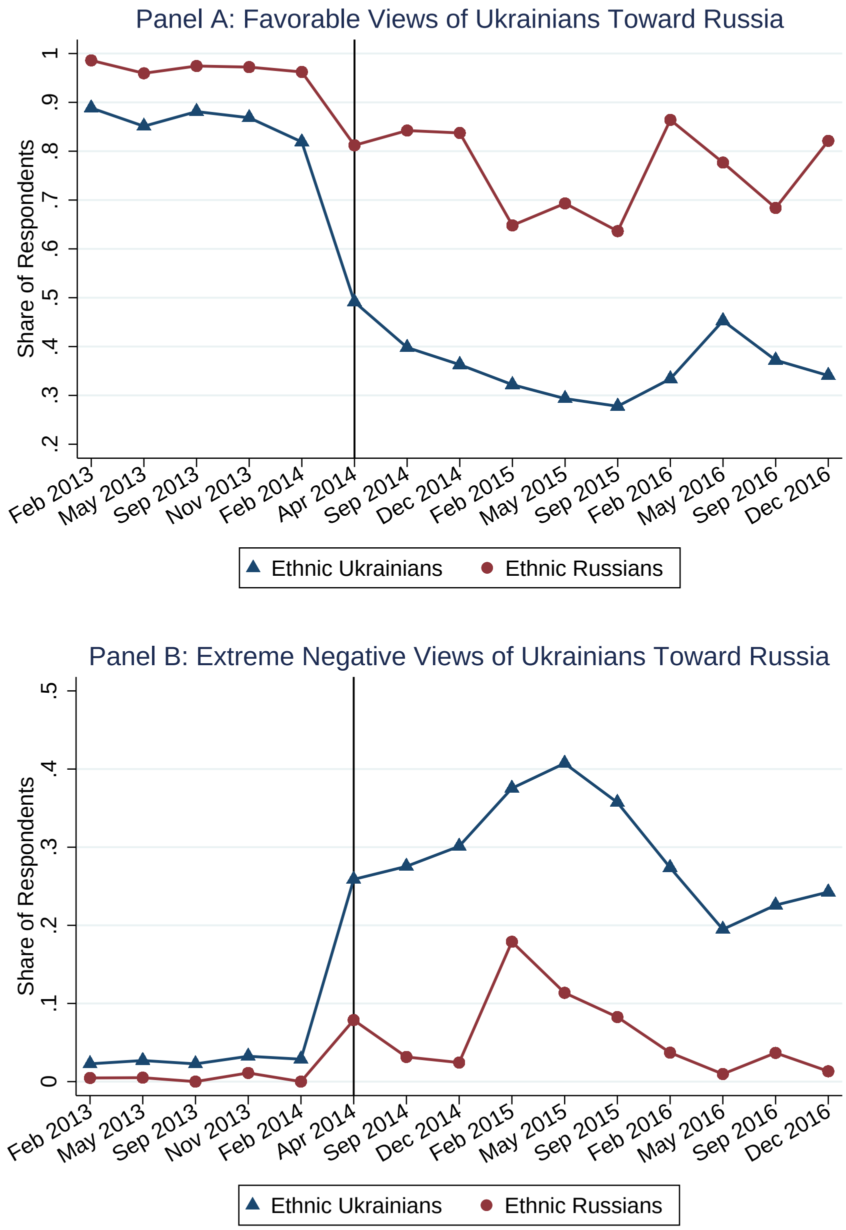
Notes: This figure maps the distribution of the share of ethnic Russians across Ukrainian counties (raions). Data are from the latest census of Ukrainian population, conducted in 2001. The thick black line represents the border between Ukraine and Russia.

Figure 2: Conflict Areas



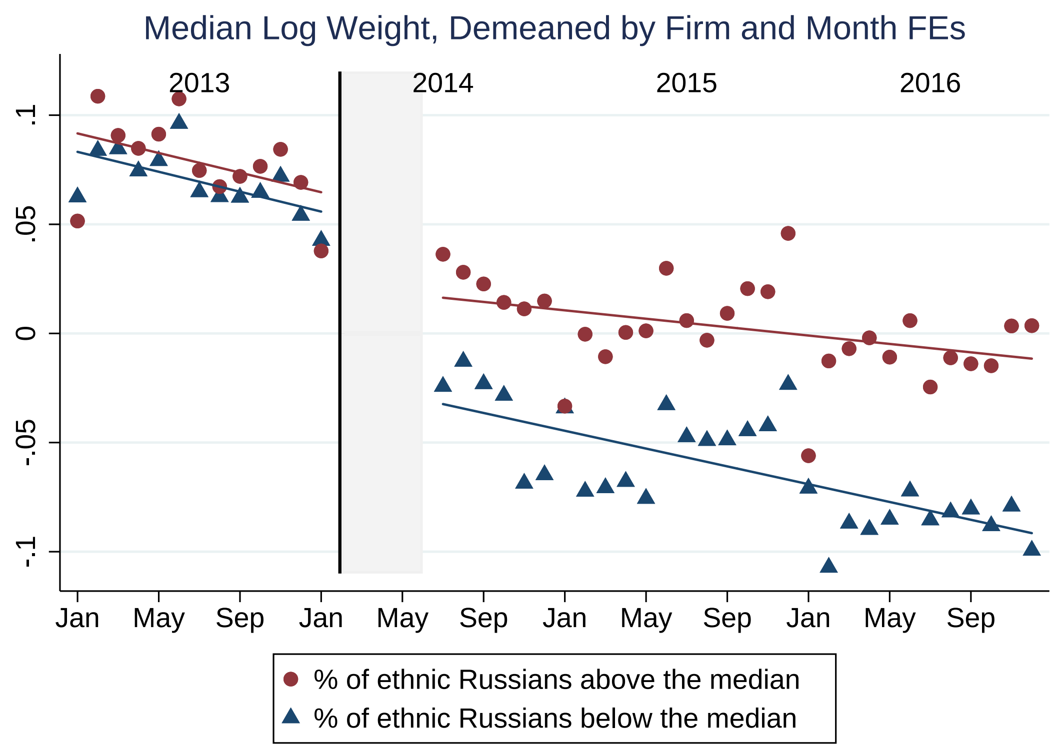
Notes: This figure displays the location of the areas directly affected by the Russia-Ukraine conflict. The Crimean Peninsula, in light red at the bottom, was occupied by Russia in early 2014. The Donetsk People's Republic (DPR) and Luhansk People's Republic (LPR) territories, in dark red, have been 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 administrative regions. 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.

Figure 3: Dynamics of Ukrainians' Attitudes Toward Russia



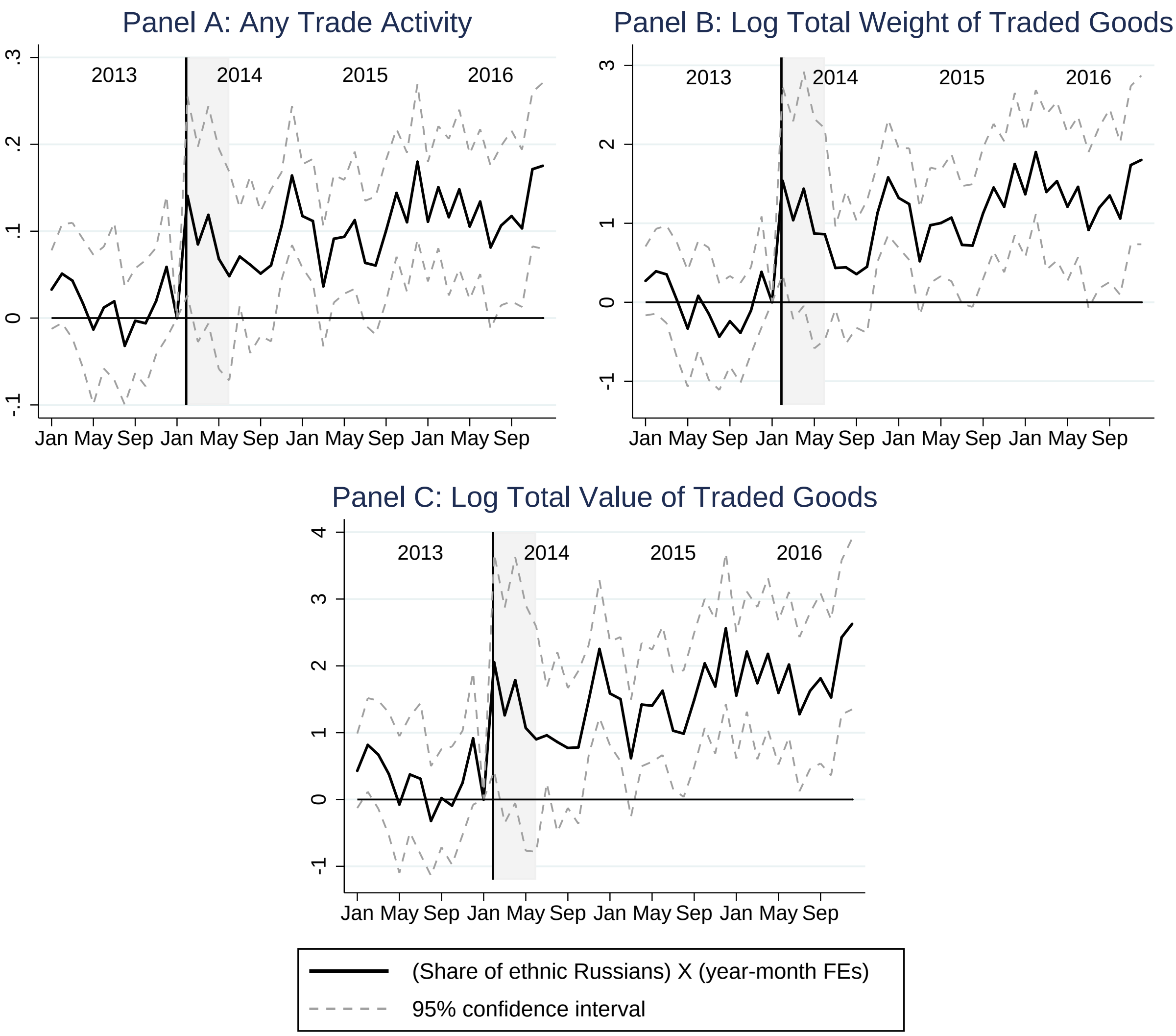
Notes: The figures illustrate the effect of the Russia-Ukraine conflict on attitudes of Ukrainian citizens toward Russia. Panel A displays the share of respondents who answer the question "What Is Your Overall Attitude Toward Russia?" as "very good" and "good" plotted over time. Panel B displays the 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.

Figure 4: Firm-Level Trade with Russia by Ethnic Composition of Firms' Counties



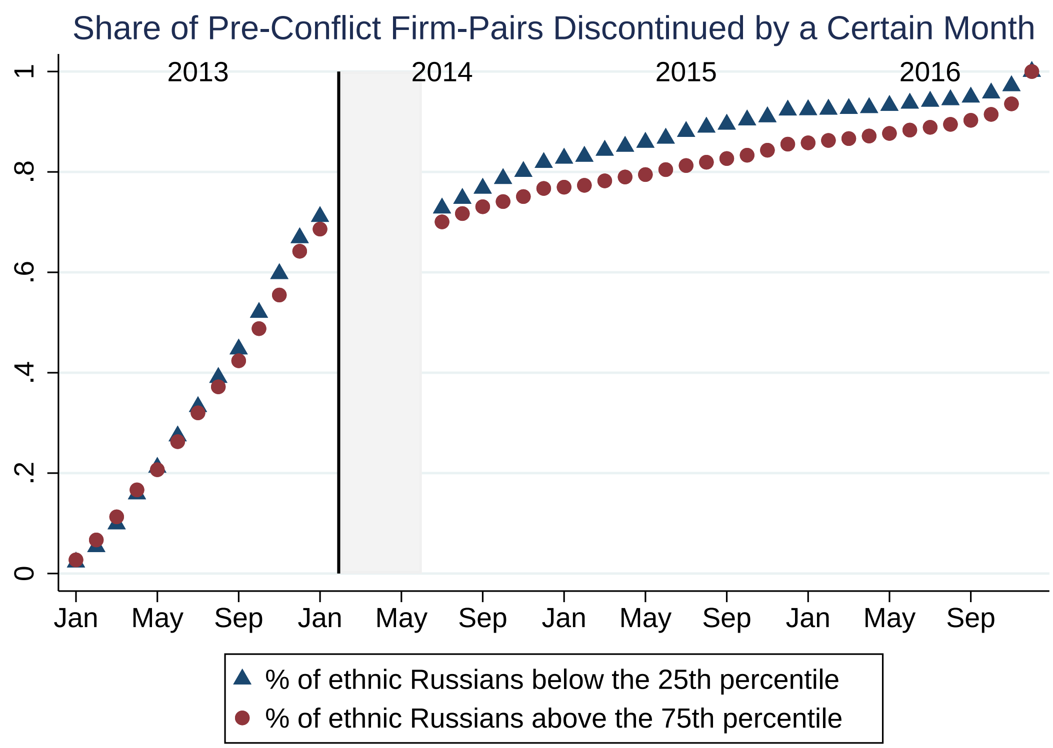
Notes: The data plotted are the monthly median residuals from a firm-level regression of the logarithm of the total weight traded (export+import) on firm fixed effects. Data are then broken down by the share of Russian population in firms' counties and are cleaned of seasonality with month fixed effects 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 until we are able to include a more flexible set of controls. 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.

Figure 5: 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 ethnolinguistic composition of the firms' counties. 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 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 county level.

Figure 6: Differential Effect of Conflict on Breakup of Trade Links



Notes: This graph displays the shares of pre-conflict trading firm-pairs discontinued by a certain date, separately for firms located in areas with a very low share of ethnic Russians (first quartile, or below 3.3%) and areas with a very high share of ethnic Russians (fourth quartile, or above 15.7%). A firm-pair is considered "discontinued" by a certain date if we do not observe any trade transactions between these two firms beyond this date. Export data are missing for February through June 2014 (colored in gray). These five months are removed for the purpose of this graph.

TABLES

Table 1: Summary Statistics

	Observations	Mean	SD	Min	Max
	Panel A: Trade Transaction Data				
Any Trade Activity	590,462	.201	.4	0	1
Log of Total Weight Traded	590,462	1.97	4.14	0	21
Log of Total Value Traded	590,462	2.73	5.51	0	23
Number of Trade Transactions	590,462	3.16	32.2	0	5,420
Total Net Weight Traded in a Given Month, in Tons	590,462	230	6,823	0	1,709,763
Total Value Traded in a Given Month, in UAH (1,000s)	590,462	1,283	31,492	0	8,045,764
	Panel B: Types of Goods Traded				
Share of Intermediate Goods Traded by a Firm, 2013–2016	12,848	.765	.362	0	1
Share of Consumer Goods Traded by a Firm, 2013–2016	12,848	.171	.334	0	1
Share of Homogeneous Goods Traded by a Firm, 2013–2016	12,843	.219	.387	0	1
	Panel C: Ethnic Composition of Counties				
Share of Russian Speakers, 2001 Census	12,848	.26	.2	0.001	.75
Share of Ethnic Russians, 2001 Census	12,848	.15	.097	0.002	.53
	Panel D: Ethnic Composition of Management				
Share of Managers with Russian Last Names, Method #1	10,302	.29	.42	0.000	1
Share of Managers with Russian Last Names, Method #2	10,302	.1	.28	0.000	1
	Panel E: Distance to the Border				
Shortest Path to the Russian Border, Post-Conflict, km	11,756	254	165	1.505	794
Shortest Path to the Russian Border, Pre-Conflict, km	11,756	247	164	1.505	794
	Panel F: Accounting Data				
IHS Transformation of Sales, Traders, 2013–2015	27,863	16.78	2.90	0.00	25.92
IHS Transformation of Profits, Traders, 2013–2015	27,863	14.93	4.64	-19.41	24.07
Total Factor Productivity, Traders, 2013–2015	27,863	15.56	2.14	8.94	25.24

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 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 $L(X) = \log(X + \text{sqrt}(X^2 + 1))$ 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 2: Reduction in Trade After the Start of the Conflict

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded
Subsample:	*All Firms*			*Firms Trading Before and After*		
Post Feb 2014	-0.072***	-0.735***	-0.910***	-0.175***	-1.856***	-2.290***
	(0.003)	(0.037)	(0.041)	(0.004)	(0.066)	(0.062)
Firms FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.201	1.970	2.726	0.403	4.014	5.551
Dep. Var. SD	0.400	4.141	5.506	0.490	5.220	6.857
R^2	0.41	0.48	0.45	0.39	0.50	0.45
Observations	590,462	590,462	590,462	225,005	225,005	225,005
Firms	12,848	12,848	12,848	4,844	4,844	4,844
Counties	393	393	393	297	297	297

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. The logs of total value and net weight of shipped goods (export+import) are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. Columns (1) and (4) use an indicator for a firm trading with Russia in a given month (export+import). Columns (4) through (6) restrict the sample to firms that were trading with Russia both before and after February 2014.

Table 3: Baseline Results

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	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	0.091***	1.142***	1.269***			
	(0.031)	(0.365)	(0.409)			
Post Feb 2014 × Share of Russian Speakers				0.043***	0.559***	0.600***
				(0.015)	(0.173)	(0.194)
Post Feb 2014	-0.076***	-0.809***	-1.048***	-0.074***	-0.783***	-1.014***
	(0.007)	(0.076)	(0.088)	(0.006)	(0.066)	(0.079)
Firm FE	✓	✓	✓	✓	✓	✓
Year and 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
R^2	0.41	0.49	0.46	0.41	0.49	0.46
Observations	590,462	590,462	590,462	590,462	590,462	590,462
Firms	12,848	12,848	12,848	12,848	12,848	12,848
Counties	393	393	393	393	393	393

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. The logs of total value and net weight of shipped goods (export+import) are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. Columns (1) and (4) use an indicator for a firm trading with Russia in a given month (export+import). Data on ethnolinguistic composition are at the county level and come from the 2001 Ukrainian Census. The share of Russian speakers is measured as the percentages of people who named Russian as their mother tongue ("rodnoi yazik").

Table 4: Baseline Results with Controls for Distance to Russian Border

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	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	0.086**	1.237***	1.247**			
	(0.038)	(0.434)	(0.496)			
Post Feb 2014 × Share of Russian Speakers				0.042**	0.605***	0.595**
				(0.018)	(0.201)	(0.232)
Post Feb 2014 × Shortest Path to Russia, km	-0.032*	-0.192	-0.360*	-0.035**	-0.229	-0.403*
	(0.017)	(0.182)	(0.217)	(0.016)	(0.176)	(0.211)
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.213	2.095	2.899	0.213	2.095	2.899
Dep. Var. SD	0.409	4.242	5.638	0.409	4.242	5.638
R^2	0.41	0.49	0.46	0.41	0.49	0.46
Observations	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
Counties	388	388	388	388	388	388

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. The logs of total value and net weight of shipped goods (export+import) are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. Columns (1) and (4) use an indicator for a firm trading with Russia in a given month (export+import). Data on ethnolinguistic composition are at the county level and 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"). All specifications control for the distance to the Russian border (in km), accounting for changes due to conflict in the Luhansk and Donetsk regions, interacted with the post–February 2014 indicator.

Table 5: Results with Firm, Year-Month, and Four-Digit Product-Code Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded
	Panel A: Product-Post Fixed Effects					
Post Feb 2014 × Share of Ethnic Russians	0.055***	0.541***	0.725***			
	(0.019)	(0.167)	(0.215)			
Post Feb 2014 × Share of Russian Speakers				0.029***	0.304***	0.388***
				(0.009)	(0.095)	(0.112)
	Panel B: Product-Post Fixed Effects and Distance Controls					
Post Feb 2014 × Share of Ethnic Russians	0.048*	0.576***	0.679**			
	(0.025)	(0.197)	(0.274)			
Post Feb 2014 × Share of Russian Speakers				0.026**	0.318***	0.366***
				(0.012)	(0.102)	(0.133)
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
4-Digit Product-Code-Post Fixed Effects	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.139	1.029	1.626	0.139	1.029	1.626
Dep. Var. SD	0.346	2.895	4.175	0.346	2.895	4.175
Observations	2,170,379	2,170,379	2,170,379	2,170,379	2,170,379	2,170,379
Firms	11,722	11,722	11,722	11,722	11,722	11,722
Counties	381	381	381	381	381	381

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. The logs of total value and net weight of shipped goods (export+import) are calculated by transforming the initial variable X with $L(X) = \log(X+1)$. Columns (1) and (4) use an indicator for a firm trading with Russia in a given month (export+import). Data on ethnolinguistic composition are at the county level and 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"). The 4-digit product code refers to the first four digits of the harmonized system code (HS4). One observation is a firm-month four-digit product.

Table 6: Gravity-Style Difference-in-Difference-in-Differences Specification

	(1)	(2)	(3)
Dependent variable:	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded
Post Feb 2014 × Share of Ethnic Russians × Russia	0.123***	1.457***	1.649***
	(0.038)	(0.449)	(0.495)
Share of Ethnic Russians × Russia	0.262***	1.994**	3.556***
	(0.097)	(0.977)	(1.321)
Year-Month FE	✓	✓	✓
Firm FE	✓	✓	✓
Raion-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
Counties	473	473	473
Months	48	48	48
Countries	11	11	11

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. This table presents the results of a triple-difference specification (6) 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 ethnolinguistic composition are at the county level and come from the 2001 Ukrainian Census. One observation is a firm-country-month.

Table 7: Consumer-Goods and Intermediate-Goods Traders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specification:	Baseline	Firms with $> 50\%$ of Transactions in Consumer Goods	Firms with $> 50\%$ of Transactions in Intermediate Goods	Baseline with Import Transactions Only	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
		Diff p-value: 0.029			*Diff p-value: 0.084*		*Diff p-value: 0.065*	
Post Feb 2014 × Share of Ethnic Russians	0.092***	0.232***	0.065**	0.048**	0.204**	0.036	0.154***	0.057**
	(0.031)	(0.081)	(0.032)	(0.022)	(0.092)	(0.026)	(0.052)	(0.026)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.201	0.183	0.204	0.189	0.188	0.190	0.268	0.119
Dep. Var. SD	0.400	0.387	0.403	0.392	0.391	0.392	0.443	0.324
Observations	590,462	87,738	449,564	366,432	41,040	277,392	84,432	206,592
Firms	12,848	1,965	9,896	7,634	855	5,779	1,759	4,304
Counties	393	216	365	314	91	288	149	260

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. 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). Intermediate goods and consumer goods are identified by the HS6 product code using the BEC classification. Inference across regression models is conducted using a similarly unrelated regressions framework with standard errors clustered at the county level.

Table 8: Heterogeneity Analysis By the Size of the Trading Firm

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Specification:	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
		Diff p-value: 0.004		*Diff p-value: 0.033*		*Diff p-value: 0.000*	
Post Feb 2014 × Share of Ethnic Russians	0.092***	0.153***	-0.036	0.079**	-0.082	0.240***	0.063*
	(0.031)	(0.043)	(0.044)	(0.039)	(0.057)	(0.048)	(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
Counties	393	302	226	231	153	290	197

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. 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. 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. Inference across regression models is conducted using a similarly unrelated regressions framework with standard errors clustered at the county level.

Table 9: Heterogeneity Analysis by Types of Trade Contracts

	(1)	(2)	(3)	(4)	(5)	(6)
Subsample:	Predicted OA Usage Above Median	Predicted OA Usage Below Median	Predicted CIA Usage Above Median	Predicted CIA Usage Below Median	Predicted LC Usage Above Median	Predicted LC Usage Below Median
	Panel A: Any Export Activity					
	Difference p-value: 0.066		*Difference p-value: 0.039*		*Difference p-value: 0.272*	
Post Feb 2014 × Share of Ethnic Russians	0.215***	0.041	0.041	0.220***	0.059	0.190***
	(0.048)	(0.081)	(0.077)	(0.045)	(0.088)	(0.060)
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.213	0.178	0.179	0.213	0.189	0.203
Dep. Var. SD	0.410	0.383	0.383	0.409	0.391	0.402
R^2	0.44	0.38	0.38	0.44	0.41	0.42
Observations	153,682	144,609	147,705	150,586	148,737	149,554
Firms	3,574	3,363	3,435	3,502	3,459	3,478
Counties	268	284	287	266	250	296
	Panel B: Any Import Activity					
	Difference p-value: 0.456		*Difference p-value: 0.509*		*Difference p-value: 0.920*	
Post Feb 2014 × Share of Ethnic Russians	0.042*	0.070**	0.065**	0.040*	0.053**	0.057
	(0.025)	(0.029)	(0.030)	(0.024)	(0.022)	(0.035)
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.192	0.182	0.182	0.192	0.191	0.183
Dep. Var. SD	0.394	0.385	0.386	0.394	0.393	0.386
R^2	0.40	0.41	0.41	0.41	0.42	0.40
Observations	189,504	181,824	191,520	180,144	184,704	186,960
Firms	3,948	3,788	3,990	3,753	3,848	3,895
Counties	250	256	254	255	254	249

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. 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. "OA" refers to an open account contract in which a good is delivered before the payment is due, which is typically in 30, 60, or 90 days. "CIA" refers to a cash-in-advance contract in which an importer pays before the good is shipped. "LC" refers to letters of credit, which allow importers to guarantee the payment through a bank, thus alleviating the risk levied on both exporters and importers. Predicted contract usage is calculated based on the types of products traded by a firm (weighted by the amount of trade). For each HS4 product code, we use data from Demir et al. (2017) and Demir and Javorcik (2018) on contract types used in trade between Ukraine, Russia, and Turkey from 2004 to 2011. Inference across regression models is conducted using a similarly unrelated regressions framework with standard errors clustered at the county level.

Table 10: Consequences for Firms: Sales, Profits, and TFP

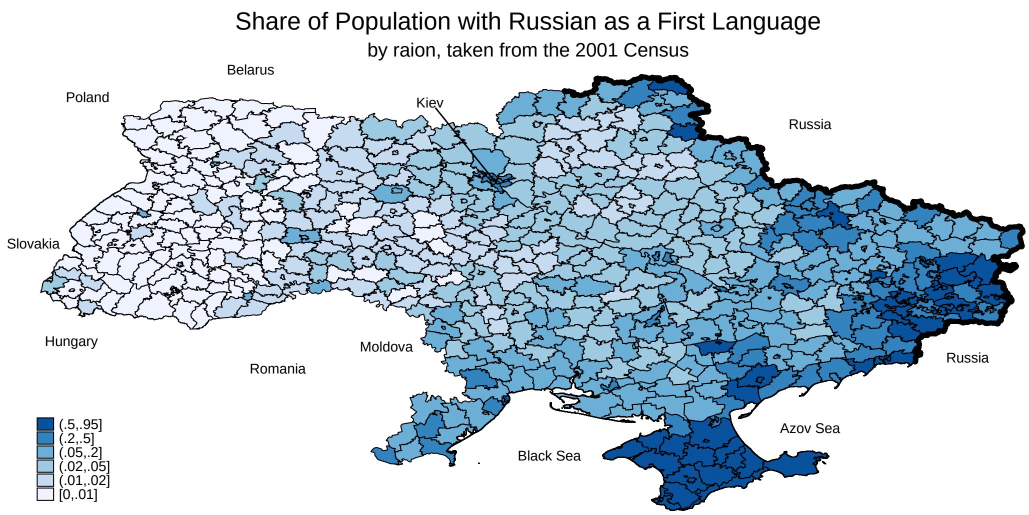
	(1)	(2)	(3)
Dependent variable:	Log Sales	Log Profit	Log TFP
Post Feb 2014 × Traded with Russia × Share of Ethnic Russians	0.893***	1.037**	0.190**
	(0.285)	(0.494)	(0.074)
Post Feb 2014 × Share of Ethnic Russians	-1.323***	-1.757***	-0.168***
	(0.256)	(0.341)	(0.054)
Post Feb 2014 × Traded with Russia	-0.046	-0.062	0.039**
	(0.052)	(0.092)	(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
Counties	491	491	495

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. 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. Data on ethnolinguistic composition are at the county level and come from the 2001 Ukrainian Census. Dependent variables in Columns (1) and (3) are total sales and gross profit, respectively, transformed using the inverse hyperbolic sine function $L(X)$, such that $L(X) = \log(X + \text{sqrt}(X^2 + 1))$ as in MacKinnon and Magee (1990). Total factor productivity in column (2) is derived from a Cobb-Douglas specification regressing turnover on capital and labor (all in logs) with two-digit industry fixed effects. The "Traded with Russia" indicator is equal to one for firms that traded with Russia at least once in 2013, and is zero otherwise.

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 counties (raions). Data come from the 2001 Ukrainian Census. The thick black line represents the border between Ukraine and Russia.

Figure A2: Usage of Russian Language Across Ukrainian Regions

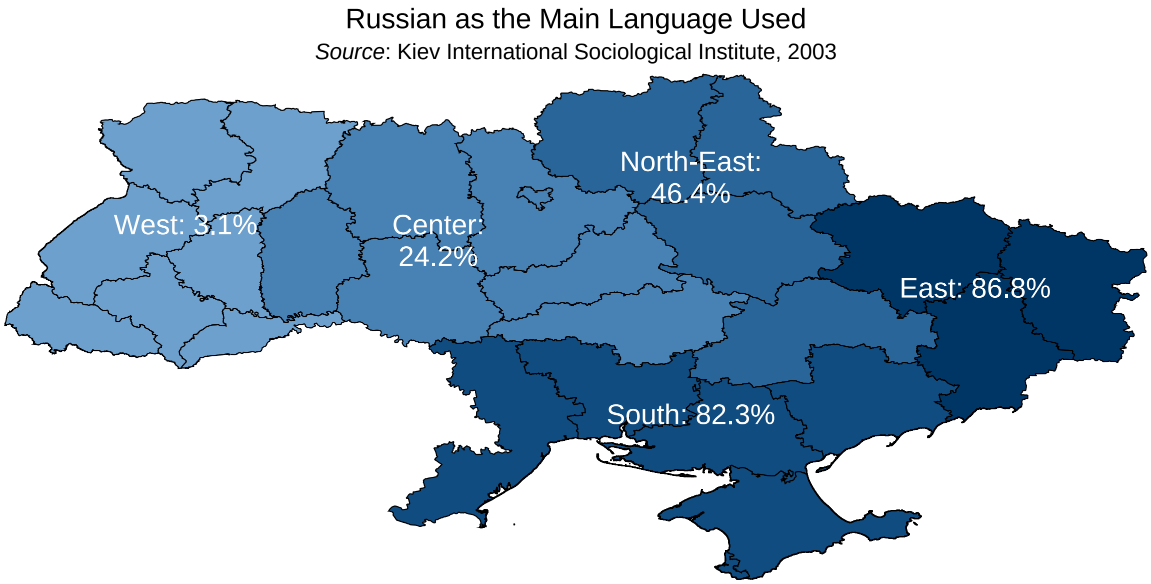
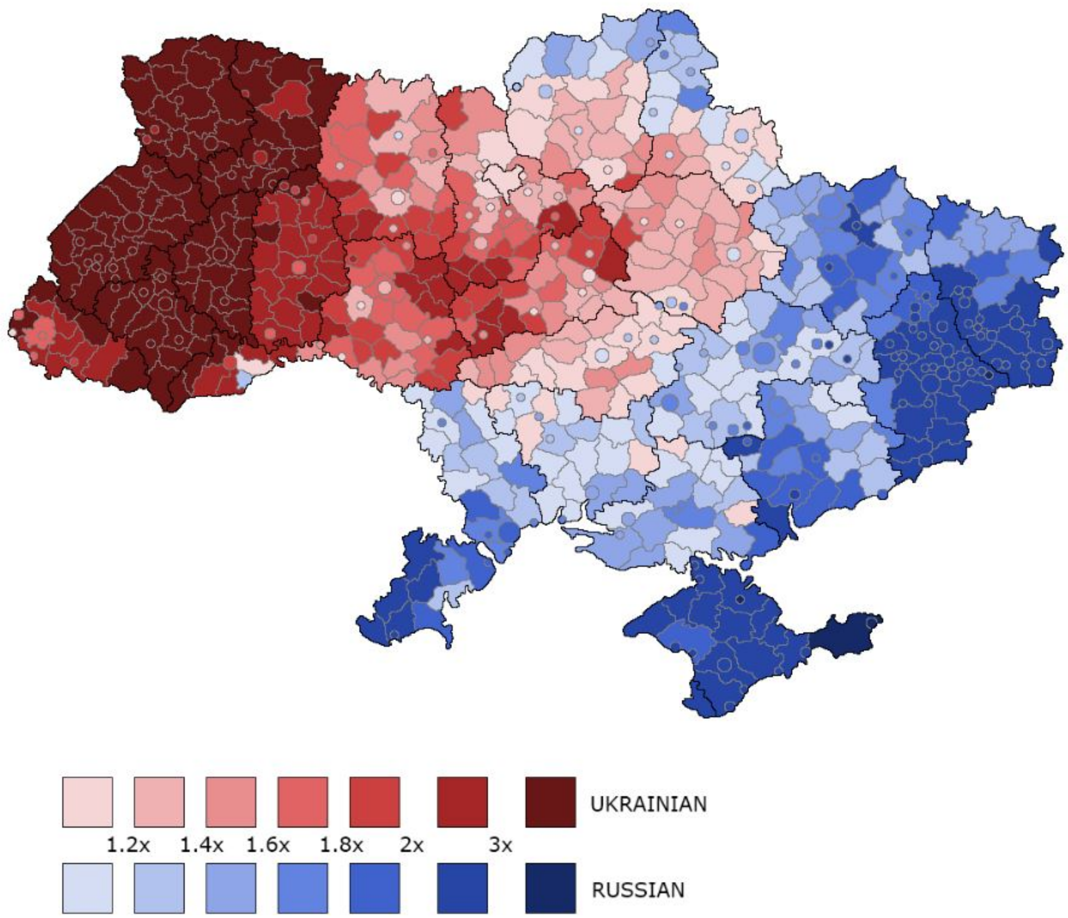
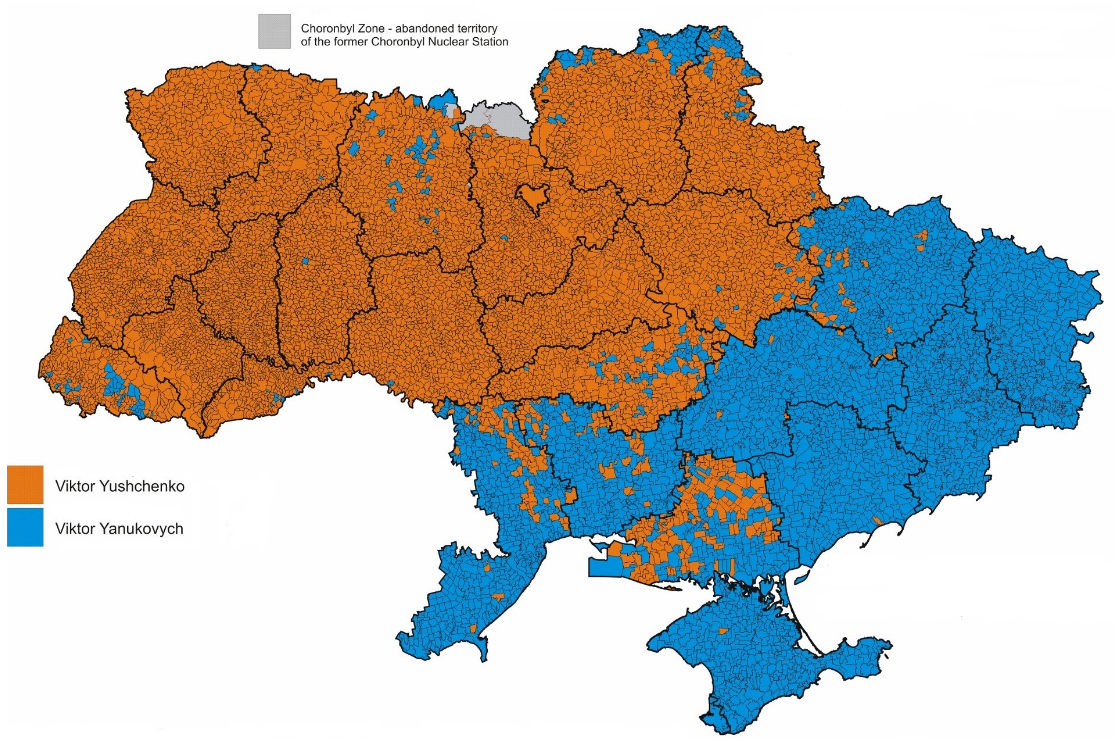


Figure A3: Language of Social Media Accounts on VK.com



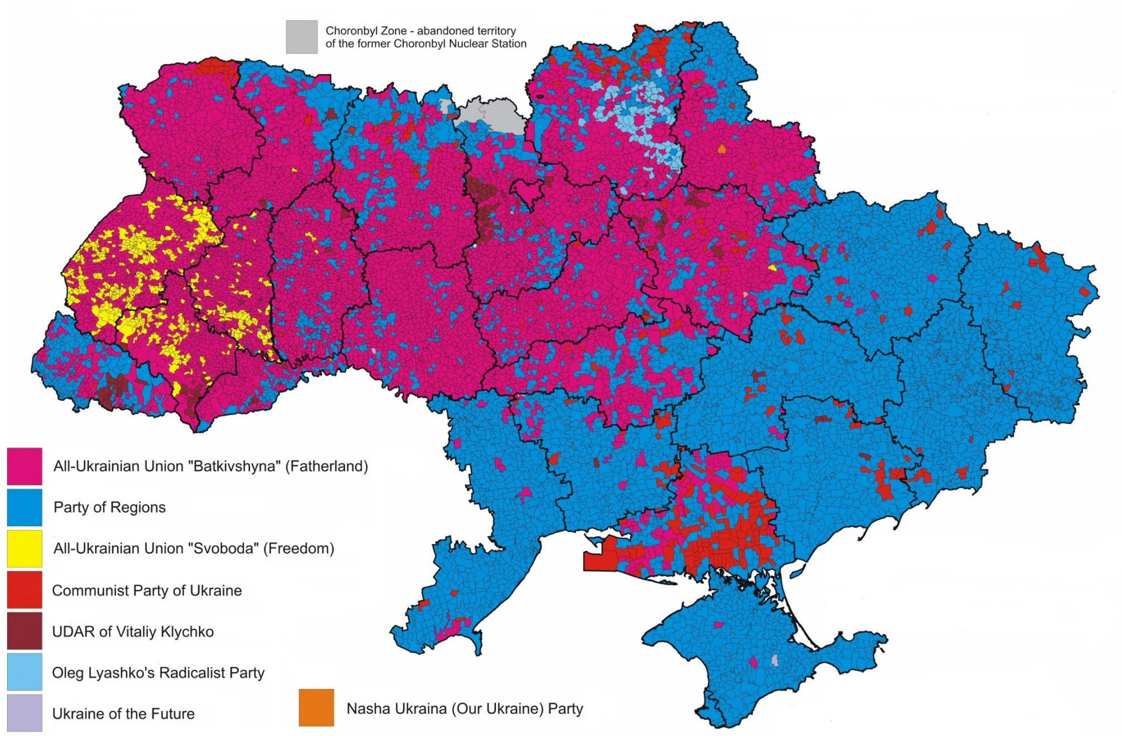
Source: https://andriy-lopata.livejournal.com/46386.html

Figure A4: Results of the 2004 Presidential Elections (Second Round) at the Polling-Station Level



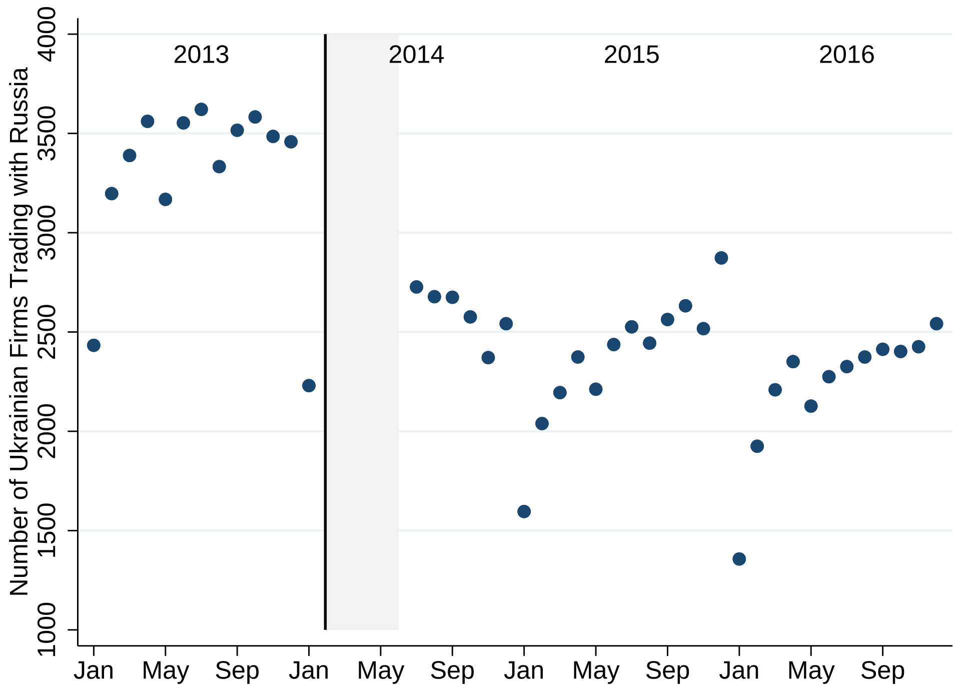
Source: This electoral map is the intellectual property of Serhij Vasylchenko.

Figure A5: Results of the 2012 Parliamentary Elections at the Polling-Station Level



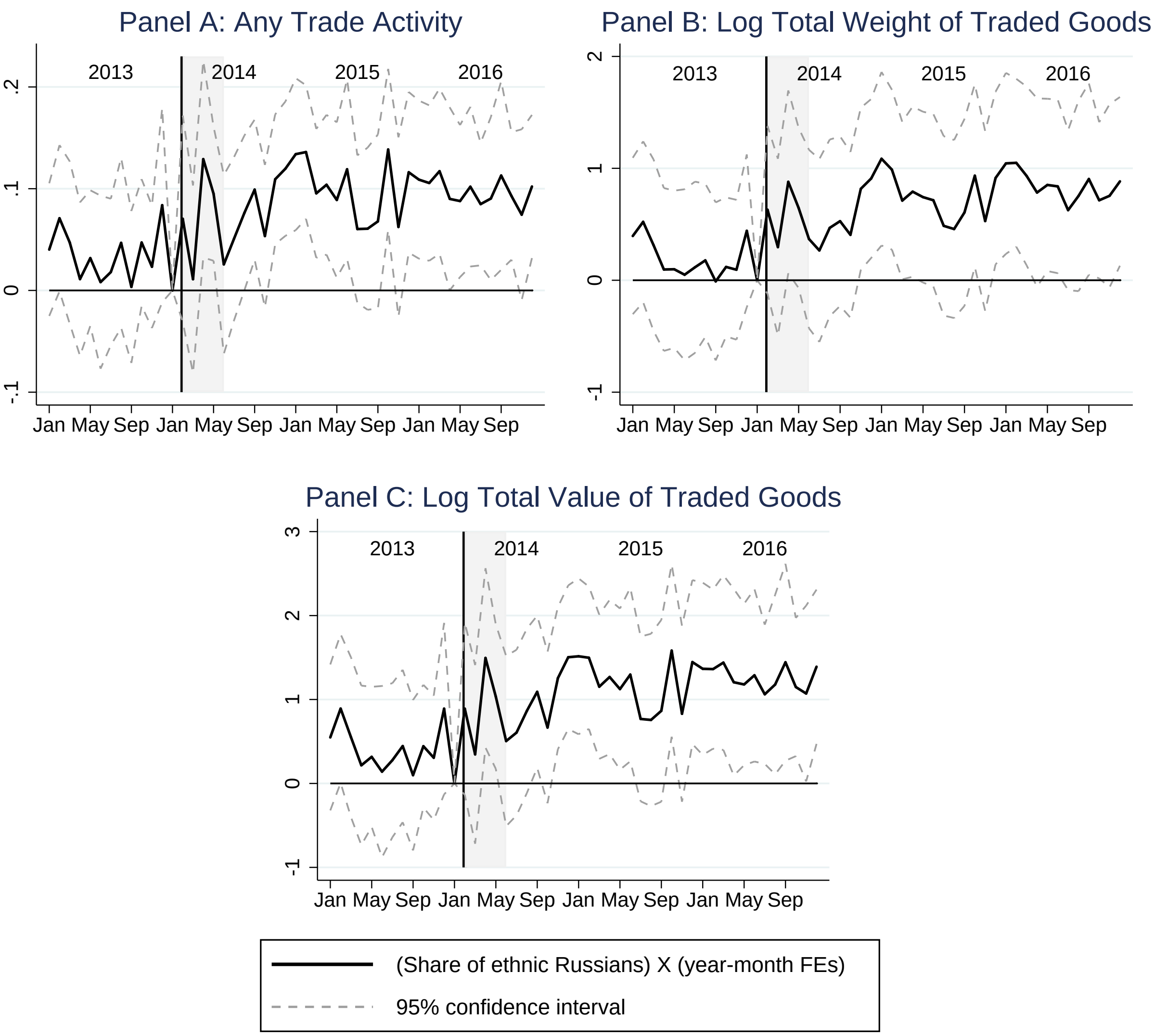
Source: This electoral map is the intellectual property of Serhij Vasylchenko.

Figure A6: Number of Ukrainian Firms Trading with Russia



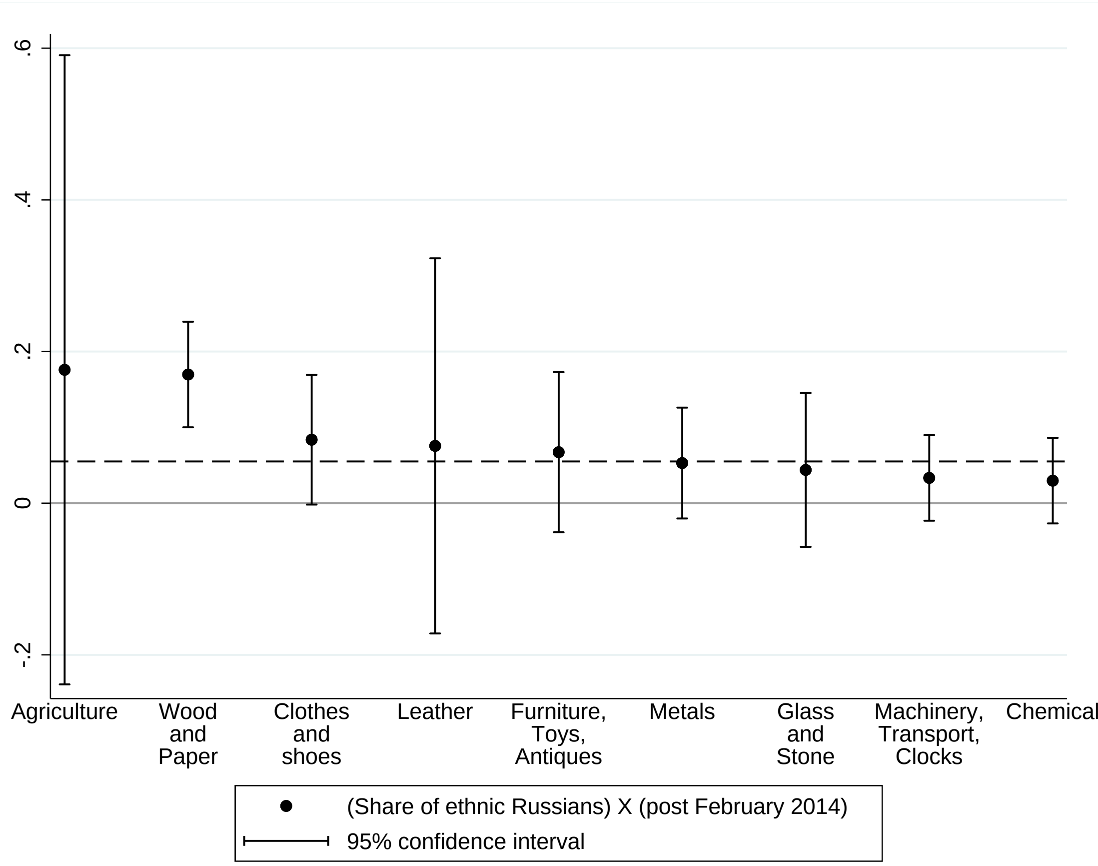
Notes: This figure displays the number of firms trading with Russia; it includes exporters and importers. These calculations exclude all firms located in the areas affected by conflict. Export data are missing for February through June 2014 (colored in gray). These five months are removed for the aggregate 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, one should view January data as seasonal outliers.

Figure A7: Month-by-Month Analysis at the Firm-Product Level with Product-Post FEs.



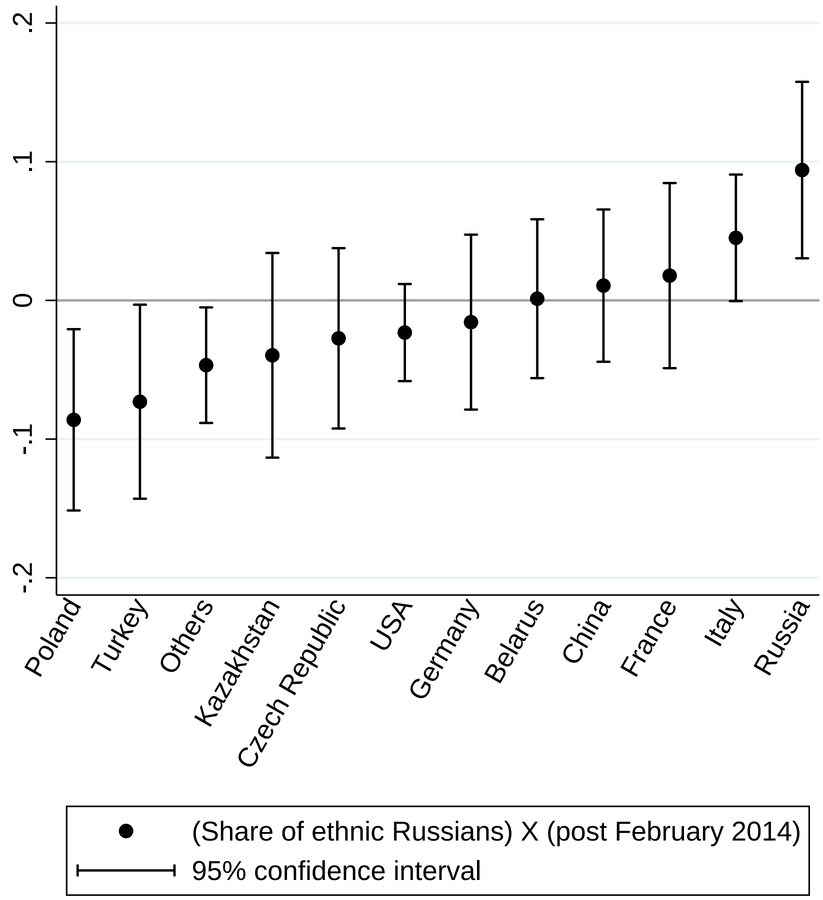
Notes: This graph displays the results of estimating equation (5), which modifies the baseline equation (4) by interacting year-month fixed effects with the ethnolinguistic composition of the firms' counties. The unit of observation is a firm's trade of a given product (HS4) with Russia. For February 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 county level.

Figure A8: Difference-in-Differences Coefficients for Various Types of Products



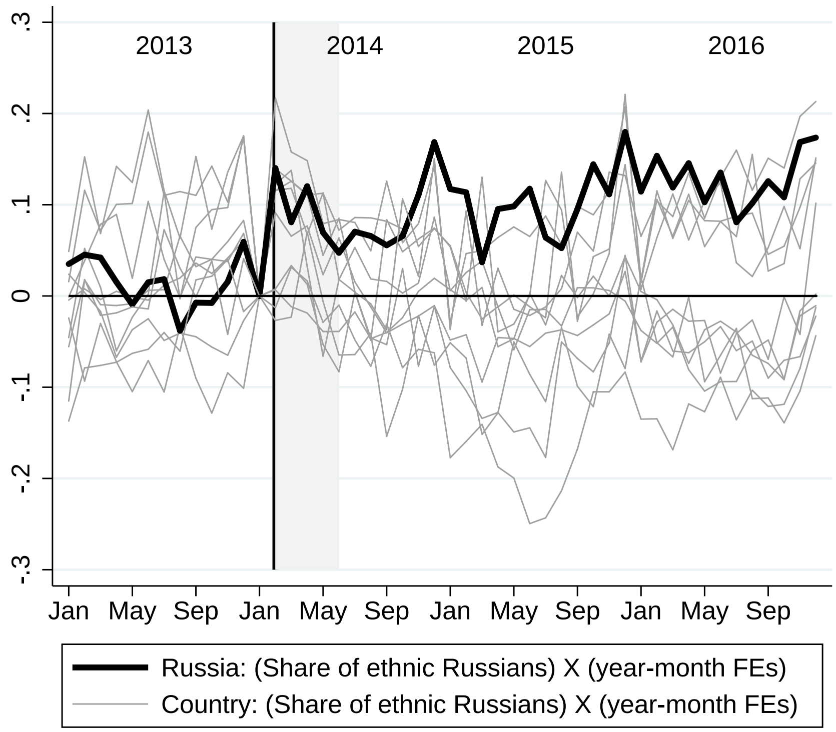
Notes: This figure presents the estimation results of equation (4) for firm-product-level trade for different types of products. The dependent variable is an indicator of any trade activity by a firm in a given month with a given HS2 product-type (export+import). The horizontal dashed line represents the baseline coefficient for trade with Russia at a firm-product level taken from column (1) of Table 5 Panel A. 95% confidence intervals are constructed for the standard errors clustered at the county (raion) level. 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.

Figure A9: Difference-in-Differences Coefficients Across Countries



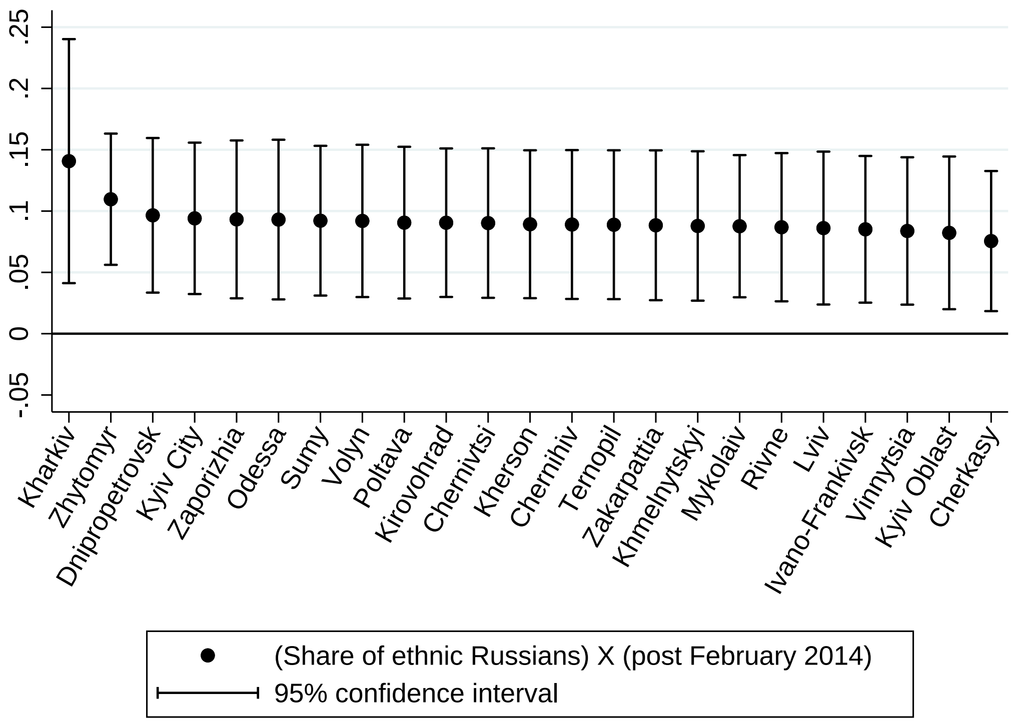
Notes: This figure presents the estimation results of equation (1) for firm-level trade with the top-10 trading partners of Ukraine, Kazakhstan (which is included to provide a robustness check for potential border effects, such as discrimination at the border), and all other countries pooled together. 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 3. 95% confidence intervals are constructed for the standard errors clustered at the county (raion) level.

Figure A10: Baseline Month-by-Month Coefficients for Russia Compared to Other Countries



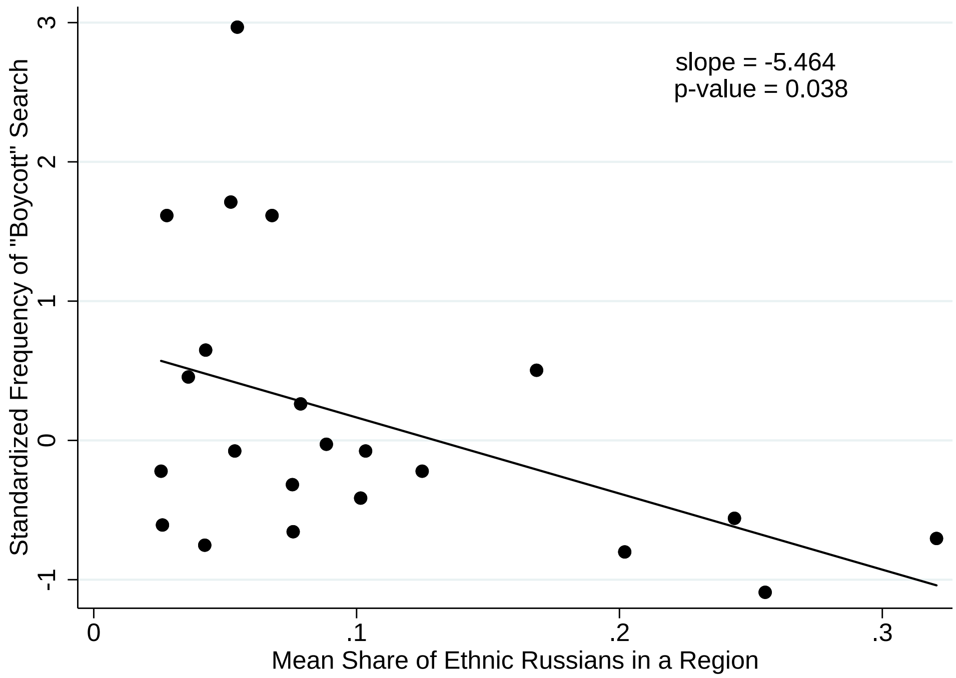
Notes: This figure presents the estimation results of equation (3) for firm-level trade with the top-10 trading partners of Ukraine and all other countries pooled together. The dependent variable is an indicator of any trade activity by a firm in a given month (export+import). The coefficients for trade with Russia (in bold) are identical to the ones in Panel A of Figure 5.

Figure A11: Baseline Results Excluding Ukrainian Regions One-by-One



Notes: This figure presents the baseline results in column (1) of Table 3 for 23 different subsamples. Those exclude Ukrainian regions, i.e., all firms located in those regions, from the sample one by one. 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 county (raion) level.

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



Notes: This figure displays the association between (1) the standardized frequency of online searches for the word “boycott” from February 1 to May 1, 2014, across Ukrainian regions, obtained from Google Trends, and (2) the average share of ethnic Russians in Ukrainian regions, obtained by collapsing county-level data on ethnic composition to account for the placement of trading firms within the regions.

A2 TABLES

Table A1: Differential Effect of Conflict on Attitudes of Ukrainian Citizens Toward Russia

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	% with Positive Attitude Toward Russia		% with Extreme Negative Views Toward Russia		% Yes to Closed Borders and Visas with Russia	
Post Conflict	-0.604***	-0.586***	0.357***	0.337***	0.489***	0.466***
	(0.027)	(0.024)	(0.028)	(0.028)	(0.027)	(0.028)
% of Russian Ethnicity	0.724***		-0.158**		-0.779***	
	(0.176)		(0.057)		(0.199)	
Post Conflict × % of Russian Ethnicity	1.263***		-1.093***		-1.192***	
	(0.167)		(0.176)		(0.175)	
% of Russian Language		0.338***		-0.072**		-0.366***
		(0.087)		(0.027)		(0.108)
Post Conflict × % of Russian Language		0.632***		-0.527***		-0.562***
		(0.078)		(0.087)		(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. Standard errors in parentheses are clustered at the region level. 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 3. The February 2014 survey was conducted February 7 to 17, 2014, i.e., before the occupation of Crimea. Conflict regions are excluded from the analysis. The regional-level data on ethnolinguistic composition come from the 2001 Ukrainian Census.

Table A2: Baseline Results with Firm and Year-Month Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	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***	1.155***	1.286***			
	(0.031)	(0.367)	(0.410)			
Post Feb 2014 × Share of Russian Speakers				0.043***	0.566***	0.609***
				(0.015)	(0.173)	(0.194)
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
R^2	0.41	0.49	0.46	0.41	0.49	0.46
Observations	590,462	590,462	590,462	590,462	590,462	590,462
Firms	12,848	12,848	12,848	12,848	12,848	12,848
Counties	393	393	393	393	393	393

Notes: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Standard errors in parentheses are clustered at the county (raion) level. The logs of total value and net weight of shipped goods (export+import) are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. Columns (1) and (4) use an indicator for a firm trading with Russia in a given month (export+import). The county-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: Baseline Results with Conley Spatial HAC Standard Errors

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	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***	1.356***	1.490***			
	(0.009)	(0.102)	(0.116)			
Post Feb 2014 × Share of Russian Speakers				0.051***	0.666***	0.712***
				(0.004)	(0.048)	(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
Counties	388	388	388	388	388	388

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are Conley spatial HAC standard errors calculated using STATA routine by Fetzer (2014), with the distance cutoff of 1,000 km and the time lag cutoff of 20 months. The logs of total value and net weight of shipped goods (export+import) are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. Columns (1) and (4) use an indicator for a firm trading with Russia in a given month (export+import). County-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 A4: 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 X Distance	Post Feb 2014 X Log of Distance	Post Feb 2014 X Fifth Polynomial of Distance	Post Feb 2014 X Fifth Polynomial of Log of Distance
Post Feb 2014 × Share of Ethnic Russians	0.109***	0.109***	0.110***	0.110***	0.087**	0.090**	0.108***	0.116***
	(0.033)	(0.032)	(0.033)	(0.033)	(0.038)	(0.036)	(0.039)	(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
Counties	388	388	388	388	388	388	388	388

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. The dependent variable is the indicator of any trade activity (export+import) by a firm in a given month. County-level data on ethnolinguistic composition come from the 2001 Ukrainian Census. Distance controls listed in column headers indicate the controls included in the specification. 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 regions. As a result, the distance measures in columns (1) and (2) are not absorbed by firm fixed effects.

Table A5: Inflow of Refugees to Ukrainian Regions

Dependent variable:	(1) Any Trade Activity	(2) Log Total Weight Traded	(3) Log Total Value Traded	(4) Any Trade Activity	(5) Log Total Weight Traded	(6) Log Total Value Traded
	August 2014			*October 2017*		
Post Feb 2014 × Share of Ethnic Russians	0.097***	1.295***	1.345***	0.088***	1.147***	1.306***
	(0.033)	(0.372)	(0.440)	(0.030)	(0.378)	(0.413)
Post Feb 2014 × Log Number of Refugees	-0.001	-0.015***	-0.007	0.000	-0.001	-0.007
	(0.001)	(0.006)	(0.007)	(0.004)	(0.043)	(0.049)
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
R^2	0.41	0.49	0.46	0.41	0.49	0.46
Observations	590,462	590,462	590,462	590,462	590,462	590,462
Firms	12,848	12,848	12,848	12,848	12,848	12,848
Counties	393	393	393	393	393	393

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. This table tests whether inflow of refugees to Ukrainian regions affects our baseline results. The number of refugees is measured as of August 2014 in columns (1) to (3) and as of October 2017 in columns (4) to (6). Data on the number of refugees come from the Ministry of Social Policy of Ukraine. The logs of total value and net weight of shipped goods (export+import) are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. Columns (1) and (4) use an indicator for a firm trading with Russia in a given month (export+import). Country-level data on ethnolinguistic composition come from the 2001 Ukrainian Census.

Table A6: Ukrainian State-Owned Firms

Dependent variable:	(1) Any Trade Activity	(2) Log Total Weight Traded	(3) Log Total Value Traded	(4) Any Trade Activity	(5) Log Total Weight Traded	(6) Log Total Value Traded
	State-Owned			*Not State-Owned*		
Post Feb 2014 × Share of Ethnic Russians	0.123	1.005	0.673	0.126***	1.574***	1.751***
	(0.152)	(1.888)	(2.193)	(0.039)	(0.449)	(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
Counties	91	91	91	405	405	405

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

Table A7: Baseline Results Without 2016 Data

Dependent variable:	(1) Any Trade Activity	(2) Log Total Weight Traded	(3) Log Total Value Traded	(4) Any Trade Activity	(5) Log Total Weight Traded	(6) Log Total Value Traded
Post Feb 2014 × Share of Ethnic Russians	0.073***	0.920***	1.009***			
	(0.025)	(0.289)	(0.332)			
Post Feb 2014 × Share of Russian Speakers				0.034***	0.448***	0.474***
				(0.012)	(0.143)	(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
Counties	401	401	401	401	401	401

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. This table replicates Table 3 but excluding data for 2016, after Russia and Ukraine imposed tariffs on each other's products. The logs of total value and net weight of shipped goods (export+import) are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. Columns (1) and (4) use an indicator for a firm trading with Russia in a given month (export+import). County-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 A8: Heterogeneity Across Regions

Dependent variable:	(1) Any Trade Activity	(2) Log Total Weight Traded	(3) Log Total Value Traded	(4) Any Trade Activity	(5) Log Total Weight Traded	(6) Log Total Value Traded	(7) Any Trade Activity	(8) Log Total Weight Traded	(9) Log Total Value Traded
	Without Kyiv			*No Regions Close to Conflict*			*No Western Ukraine*		
Post Feb 2014 × Share of Ethnic Russians	0.090***	1.163***	1.252***	0.167**	2.173**	2.180**	0.067**	0.937**	1.013**
	(0.031)	(0.345)	(0.407)	(0.067)	(0.856)	(0.918)	(0.033)	(0.388)	(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
Counties	397	397	397	341	341	341	301	301	301

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. The logs of total value and net weight of shipped goods are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. Country-level data on ethnolinguistic composition come from the 2001 Ukrainian Census. This table tests whether our results are robust to 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), regions 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.

Table A9: Baseline Results Depending on Frequency of Google Search for "Boycott"

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Any Trade Activity with Russia				
Specification:	Baseline with Google Trends Data Present	Regions with $>$ 75pct Frequency of Google Search "Boycott"	Regions with $<$ 75pct Frequency of Google Search "Boycott"	Baseline with Google Trends Data Instead	Horserace Google Trends Data vs. Ethnicity
		Diff p-value: 0.076			
Post Feb 2014 × Share of Ethnic Russians	0.096***	0.249**	0.055		0.054
	(0.031)	(0.100)	(0.041)		(0.041)
Post Feb 2014 × "Boycott" Search				-0.012***	-0.009**
				(0.003)	(0.004)
Firm FE	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓
Dep. Var. Mean	0.206	0.205	0.206	0.206	0.206
Dep. Var. SD	0.404	0.404	0.405	0.404	0.404
R^2	0.41	0.42	0.41	0.41	0.41
Observations	425,281	100,416	324,865	425,286	425,281
Firms	9,307	2,207	7,107	9,307	9,307
Counties	389	148	253	389	389

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. The logs of total value and net weight of shipped goods are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. The dependent variable is an indicator for a firm trading with Russia in a given month (export+import). 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 rather low (below 75th 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. Column (5) presents a 'horse race' exercise with both share of ethnic Russians and the frequency of Google searches for "boycott" from February 1 to May 1, 2014, included in the same regression.

Table A10: Export of Consumer Goods and Intermediate Goods

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Any Exports to Russia				
Specification:	Baseline with Export Transactions Only	Export by Traders with $> 50\%$ of Transactions in Consumer Goods	Export by Traders with $> 50\%$ of Transactions in Intermediate Goods	Export by Traders with $> 0\%$ of Transactions in Consumer Goods	Export by Traders with 100% of Transactions in Intermediate Goods
		Difference p-value: 0.178		*Difference p-value: 0.046*	
Post Feb 2014 × Share of Ethnic Russians	0.136***	0.247***	0.106**	0.266***	0.100
	(0.047)	(0.090)	(0.053)	(0.058)	(0.063)
Firm FE	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓
Dep. Var. Mean	0.194	0.162	0.199	0.226	0.161
Dep. Var. SD	0.396	0.369	0.399	0.418	0.368
Observations	305,472	72,027	245,053	113,768	170,565
Firms	7,104	5,332	6,902	5,926	4,609
Counties	342	328	341	334	308

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. The dependent variable is the indicator of any exports to Russia by a firm in a given month. Intermediate goods and consumer goods are identified by their HS6 product code using the BEC classification. Inference across regression models is conducted using a similarly unrelated regressions framework with standard errors clustered at the county level.

Table A11: Share of Russian Managers vs. Russian Ethnicity in a County

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded	Any Trade Activity	Log Total Weight Traded	Log Total Value Traded
	Panel A: Difference-in-Differences					
	Measure #1: Surname Endings			*Measure #2: Bank of Surnames*		
Post Feb 2014 × Managers w/ Russian Last Names	-0.008	-0.085	-0.117	0.003	0.016	0.038
	(0.007)	(0.091)	(0.114)	(0.008)	(0.093)	(0.121)
Post Feb 2014 × Share of Ethnic Russians	0.131***	1.638***	1.819***	0.125***	1.573***	1.726***
	(0.035)	(0.435)	(0.480)	(0.036)	(0.441)	(0.495)
	Panel B: Triple Difference					
	Measure #1: Surname Endings			*Measure #2: Bank of Surnames*		
Post Feb 2014 × Managers w/ Russian Last Names	0.021*	0.192	0.263	0.029	0.281	0.367
	(0.011)	(0.148)	(0.170)	(0.020)	(0.214)	(0.276)
Post Feb 2014 × Share of Ethnic Russians	0.188***	2.188***	2.573***	0.142***	1.752***	1.948***
	(0.036)	(0.432)	(0.479)	(0.045)	(0.505)	(0.594)
Post Feb 2014 × Managers × Share of Ethnic Russians	-0.182***	-1.748***	-2.392***	-0.154	-1.609	-1.997
	(0.054)	(0.669)	(0.801)	(0.111)	(0.996)	(1.361)
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.227	2.234	3.096	0.227	2.234	3.096
Dep. Var. SD	0.419	4.354	5.789	0.419	4.354	5.789
R^2	0.43	0.51	0.48	0.43	0.51	0.48
Observations	480,286	480,286	480,286	480,286	480,286	480,286
Firms	10,402	10,402	10,402	10,402	10,402	10,402
Counties	367	367	367	367	367	367

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. The logs of total value and net weight of shipped goods are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. Columns (1) and (4) use an indicator for a firm trading with Russia in a given month (export+import). Last names in columns (1) through (3) are treated as Russian if they end in "ov," "ova," "ev," "eva," "in," "ina," "yov," or "yova" (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.

Table A12: Heterogeneity Analysis By Pre-Existing Trade Ties with Other Countries

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	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
	Difference p-value: 0.000		*Difference p-value: 0.048*		*Difference p-value: 0.006*	
Post Feb 2014 × Share of Ethnic Russians	0.144***	-0.022	0.190***	0.071	0.113***	-0.039
	(0.037)	(0.048)	(0.053)	(0.057)	(0.038)	(0.039)
Post Feb 2014	-0.135***	-0.068***	-0.106***	-0.089***	-0.068***	-0.045***
	(0.011)	(0.011)	(0.012)	(0.013)	(0.007)	(0.009)
Firm FE	✓	✓	✓	✓	✓	✓
Year and 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
Counties	321	225	286	211	236	149

Notes: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Standard errors in parentheses are clustered at the county (raion) level. 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 firms 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 county level.

Table A13: Changes in Total Trade of Ukrainian Firms that Traded with Russia Before the Conflict

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	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
	Total Trade with All Countries			*Total Exports to All Countries*			*Total Imports from All Countries*		
Post Feb 2014 × Share of Ethnic Russians	0.017	0.991***	0.519	-0.009	0.661	0.074	0.080*	1.418***	1.505**
	(0.025)	(0.334)	(0.373)	(0.042)	(0.543)	(0.614)	(0.048)	(0.511)	(0.669)
Post Feb 2014	-0.131***	-1.648***	-1.909***	-0.010	-0.236*	0.100	-0.050***	-0.730***	-0.744***
	(0.011)	(0.132)	(0.151)	(0.011)	(0.126)	(0.162)	(0.011)	(0.118)	(0.152)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year and Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.616	6.346	8.830	0.588	5.982	8.287	0.612	6.327	8.860
Dep. Var. SD	0.486	5.572	7.148	0.492	5.568	7.106	0.487	5.570	7.218
R^2	0.44	0.60	0.53	0.45	0.62	0.54	0.46	0.62	0.55
Observations	266,468	266,468	266,468	123,281	123,281	123,281	146,496	146,496	146,496
Firms	5,621	5,621	5,621	2,867	2,867	2,867	3,052	3,052	3,052
Counties	321	321	321	279	279	279	224	224	224

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. The logs of total value and of net weight of shipped goods are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. County-level data on ethnolinguistic composition come from the 2001 Ukrainian Census. To zero in on the switching firms, this table focuses on firms that traded with Russia from January 1, 2013 to January 31, 2014, and traded with at least one other country from February 1, 2014 to December 31, 2016. All dependent variables are calculated by aggregating firms' trade with all countries, not only Russia.

Table A14: Conflict and Local Economic Shocks to Firms in Non-Conflict Areas

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Log Profit	Log Sales	TFP	Log Profit	Log Sales	TFP
	Ethnic Russians			*Native Russian Speakers*		
Share × 2012	0.025	-0.069	0.110***	0.159	0.004	0.051**
	(0.312)	(0.101)	(0.042)	(0.116)	(0.047)	(0.026)
Share × 2013	0.340	-0.178	0.140***	0.259*	-0.066	0.066**
	(0.287)	(0.125)	(0.053)	(0.134)	(0.059)	(0.033)
Share × 2014	-0.748**	-0.864***	0.035	-0.334*	-0.418***	0.011
	(0.324)	(0.190)	(0.064)	(0.175)	(0.098)	(0.036)
Share × 2015	-1.850***	-1.604***	-0.107	-0.948***	-0.778***	-0.061
	(0.400)	(0.364)	(0.077)	(0.245)	(0.188)	(0.039)
Share × 2016	-2.212***	-1.665***	-0.137	-1.084***	-0.851***	-0.079*
	(0.515)	(0.363)	(0.089)	(0.306)	(0.200)	(0.045)
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	10.761	13.169	13.560	10.761	13.169	13.560
Dep. Var. SD	6.673	4.216	1.870	6.673	4.216	1.870
R^2	0.51	0.75	0.93	0.51	0.75	0.93
Observations	1,107,215	1,107,520	1,026,585	1,107,215	1,107,520	1,026,585
Firms	190,470	190,515	176,352	190,470	190,515	176,352
Counties	491	491	495	491	491	495

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. Excludes firms from conflict areas. County-level data on ethnolinguistic composition come from the 2001 Ukrainian Census. Russian language is measured as the share of people who named Russian as their mother tongue ("rodnoi yazik"). Dependent variables in columns (1), (2), (4), and (5) are gross profit and total sales transformed using the inverse hyperbolic sine function $L(X)$, such that $L(X) = \log(X + \text{sqrt}(X^2 + 1))$, as in MacKinnon and Magee (1990). Total factor productivity in columns (3) and (6) is derived from a Cobb-Douglas specification regressing turnover on capital and labor (all in logs) with two-digit industry fixed effects.

Table A15: Difference-in-Differences Results Accounting for Firm Sales

	(1)	(2)	(3)	(4)
Dependent variable:	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***	4.572***		
	(0.684)	(0.709)		
Post Feb 2014 × Share of Native Russian Speakers			1.833***	2.081***
			(0.306)	(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
Counties	345	345	345	345

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses are clustered at the county (raion) level. The logs of total value, of net weight of shipped goods, and of sales are calculated by transforming the initial variable X with $L(X) = \log(X + 1)$. Log-sales are included as a covariate. County-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"). Data are aggregated to the yearly level, rather than being split on the monthly level.