Supply Chain Disruption and Reorganization: Theory and Evidence from Ukraine's War *

Vasily Korovkin† Alexey Makarin‡ Yuhei Miyauchi§

February 2024

Abstract

Using firm-to-firm Ukrainian railway shipment data around the onset of the 2014 Russia-Ukraine conflict, we document that firms with prior production linkages to conflict areas experience a significant output decrease. Simultaneously, they reorganize supplier linkages toward peaceful areas. Based on this evidence, we develop a model of how disruption and reorganization of production networks affect production and welfare, not relying on the specific microfoundations of network formation. We show that our model accurately explains observed firm-level output reduction. We predict a 3 percentage point reduction of aggregate welfare strictly outside conflict areas, with almost two-fold overestimation if we shut down network reorganization.

JEL: D22, D74, F14, F51, H56

Keywords: Production Networks, Firm-to-Firm Trade, War, Conflict

*We thank comments from Daron Acemoglu, Francesco Amodio, David Atkin, Costas Arkolakis, Dave Donaldson, Banu Demir, Xiang Ding, Jonas Hjort, Amit Khandelwal, Sam Kortum, Ezra Oberfield, Michael Peters, Giacomo Romanini, Alireza Tahbaz-Salehi, Daniel Sturm, Daniel Xu, Ekaterina Zhuravskaya, and participants of various seminars and conferences for their helpful comments. We are grateful to Artyom Lipin, Aruzhan Nurlankul, Ella Sargsyan, Martin Strobl for their superb research assistance. This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No. 870245.

†Universitat Pompeu Fabra and CEPR (e-mail: vasily.korovkin@upf.edu).

‡MIT Sloan School of Management and CEPR (e-mail: makarin@mit.edu).

§Boston University (e-mail: miyauchi@bu.edu).

1 Introduction

The modern economy relies on intricate supply chains. These production networks are crucial to the regions' or countries' economic success. However, recent supply chain disruptions, such as those due to the COVID-19 pandemic, the Russia-Ukraine Conflict, and the Israel-Gaza Conflict and resulting insecurity in the Middle East, reveal a vulnerability of firms and regions that rely on these supply chains.

At the same time, intense and prolonged shocks may also affect the structure of supply chain networks. Such network reorganization may mitigate or amplify the negative effects of supply chain disruption on firm-level and aggregate production. On the one hand, firms may be able to find alternative suppliers and buyers to avoid the disruption. On the other hand, these firms may scale down production and stop sourcing from or selling to existing trading partners, generating cascading negative effects on the economy. In addition, a large and intense shock may induce a reallocation of economic activity across regions and change local factor prices. How the structure of the production networks responds to supply chain disruption and how such reorganization affects the firm-level and aggregate production and welfare remains an open empirical question.

In this paper, we analyze the impacts of large localized shocks on the economy in the context of the 2014 Russia-Ukraine conflict. This conflict began immediately following the Ukrainian Revolution in February 2014, when the Russian government annexed Crimea and started promoting separatist movements and militant groups in the Donetsk and Luhansk provinces (i.e., the Donbas region). While the prolonged conflict left a devastating toll on the Donbas region through bombing, infrastructure destruction, and loss of human lives, the rest of Ukraine was not exposed to violence directly.[1] This feature of this conflict allows us to trace the impacts of supply chain disruption and reorganization throughout the rest of Ukraine.

We start our analysis by providing reduced-form evidence of how the 2014 Russia-Ukraine conflict resulted in the disruption and reorganization of production networks. To accomplish this, we leverage a unique dataset of the universe of firm-to-firm railway shipments from 2012 through 2016 within Ukraine. The data records over 100 million transactions between over 8,500 firms,

[1] This situation rapidly changed on February 24, 2022, when Russia launched a full-scale invasion of Ukraine.

with information on sender and receiver firm IDs, dates, shipment weights, and origin and destination station codes. This data allows us to trace the patterns of Ukraine's production networks before the onset of the conflict and how they changed after the start of the conflict. We merge this dataset with firm-level accounting data for information about firm production, such as sales.

We first demonstrate that the conflict has resulted in a large disruption of firms' production outside the conflict areas. To do so, we use our railway shipment data to construct proxies for firms' exposure to conflict areas based on the preexisting supplier and buyer linkages with those areas. Using a difference-in-differences strategy, we document that firms located outside the directly affected areas but which traded with the conflict regions before the conflict's onset experienced a sudden 19% decline in sales compared to firms without trade connections to the conflict areas. These effects are present for both the supplier and buyer linkages with the conflict areas. They are also robust to a variety of checks, such as accounting for firms' distance to the conflict areas and its possible time-varying effects, as well as the industry-specific shocks. A dynamic difference-in-differences model confirms the absence of pretrends and reveals that the negative effect persists until the end of our data span in 2018.

We next show that the conflict shock has also led to the reorganization of production networks. We show that firms with a higher pre-conflict shipment share from conflict areas saw an increase in shipment from non-conflict areas after the start of the conflict. This evidence supports the interpretation that the loss of suppliers in the conflict areas is partially substituted by the suppliers in non-conflict areas. We also show that firms with a higher pre-conflict shipment share to conflict areas observed decreased shipments to non-conflict areas. This evidence is consistent with the interpretation that it is more difficult to find new buyers than new suppliers or there are general equilibrium reorganizations of the production process.

Based on the reduced-form evidence, we develop a theoretical framework to analyze how the disruption and reorganization of production networks affect firm production and aggregate welfare. Firms engage in production using intermediate inputs, which are produced by other firms in the economy in various locations and sectors. Firms can trade these intermediate inputs if they are connected through production linkages. We also assume that the structure of production linkages may endogenously change as a response to shocks, which is consistent with our empirical findings.

We derive a sufficient statistics expression for each firm's output changes upon supply chain disruption and reorganization. In particular, we derive "supplier and buyer accesses" as summary statistics for the influences of supplier-side and buyer-side production network structure on the firm's equilibrium output. These supplier and buyer accesses extend the ones in the gravity trade literature (i.e., Redding and Venables, 2004; Donaldson and Hornbeck, 2016) to accommodate the changes in production linkages. Importantly, we derive these expressions as direct functions of equilibrium production linkages. Therefore, our sufficient statistics expression holds across a broad class of models that takes alternative microfoundations for production network formation.

In the final part of the paper, we use our model to assess the aggregate effects of supply chain disruption and reorganization due to the 2014 Russia-Ukraine conflict. To do so, we first calibrate our model to Ukraine's economy using our railway firm-to-firm shipment data. We next validate our model by showing that our sufficient statistic for changes in firms' output, estimated using trade and production linkage patterns before and after the conflict, aligns with their *observed* changes. We find that the estimated regression coefficients (instrumented by direct supplier and buyer exposures to conflict areas) are close to one, indicating that our model accurately summarizes the channel in which supply chain disruption and reorganization affect firm output.

Having validated our model, we finally use it to quantify the aggregate effects of the 2014 Russia-Ukraine conflict. To do so, we calibrate our model using the pre-conflict period and undertake the simulation to shut down trade linkages from and to the conflict areas. To highlight the role of the reorganization of production linkages, we undertake this simulation under two scenarios: by fixing the production linkages before the onset of the conflict and by changing the production linkages consistent with our difference-in-differences estimates for their changes. We find that the workers' welfare strictly outside conflict areas decreases on average by around 3 log points in this simulation with production linkage changes. At the same time, we find that shutting down the changes in production linkage leads to a reduction of workers' welfare by around 5 log points, thereby overestimating the welfare loss. This evidence suggests that, in this context, production linkages are reorganized in a way to mitigate the aggregate welfare loss and not amplify it.

Our results suggest that localized conflicts can have far-reaching and detrimental economic consequences through production networks disruption. At the same time, the reorganization of

production networks could mitigate the adverse propagation effects.

This paper contributes to several strands of literature. First, we contribute to the existing literature on supply chain disruptions, augmenting it with a more careful approach to network reorganization. Existing literature has documented that negative transient shocks, particularly natural disasters, transmit through production networks. Our paper is most closely related to Carvalho, Nirei, Saito, and Tahbaz-Salehi (2021), who provide evidence that localized transient earthquake shock has disrupted output of indirectly connected firms in Japan and quantified their aggregate implications.[2] In contrast to their paper, we provide evidence that firms also reorganize production networks in response to a large and prolonged conflict shock. We also show that this reorganization crucially affects aggregate welfare. Our paper is also related to Khanna, Morales, and Pandalai-Nayar (2022), who provide evidence that firms reorganize supplier linkages depending on the intensity of lockdowns that varies across existing suppliers' locations during the COVID-19 pandemic using Indian firm-to-firm trade data. Our paper instead focuses on the context where the conflict shock hits only a particular region of the country. Using this context, we show how firms reorganize supplier and buyer linkages in response to shocks to both their suppliers and buyers and quantify the aggregate effects outside the direct conflict regions.[3]

We also contribute to the theoretical literature on modeling the endogenous formation of production networks. This literature has sought various microfoundations for the formation of supply chain linkages and production networks, such as market- or relationship-specific fixed costs, search and matching, and optimal supplier choice.[4] Our theoretical framework is distinct from this literature in its scope. Instead of taking a specific microfoundation of production network formation, we develop a sufficient statistics result for firm-level and aggregate welfare changes given *observed*

[2]Barrot and Sauvagnat (2016) and Boehm, Flaaen, and Pandalai-Nayar (2019) also provide empirical evidence that natural disaster shocks to suppliers transmit to buyers.

[3]Other recent papers documenting the impacts of firm-level shocks on reorganization of production networks include Huneeus (2018) and Demir, Fieler, Xu, and Yang (2021), who study international trade shocks, Alfaro-Urena, Manelici, and Vasquez (2022), who study the impacts of the entry of multinational corporations, and Miyauchi (2023) that study unanticipated supplier bankruptcy shocks.

[4]For example, Antras, Fort, and Tintelnot (2014) and Melitz and Redding (2014) consider supplier-market and buyer-market entry costs; Bernard, Moxnes, and Ulltveit-Moe (2018); Lim (2018); Dhyne, Kikkawa, Kong, Mogstad, and Tintelnot (2022) consider relationship-specific fixed costs; Demir et al. (2021); Arkolakis, Huneeus, and Miyauchi (2023); Eaton, Kortum, and Kramarz (2022); Miyauchi (2023) consider search and matching; and Oberfield (2018); Antràs and De Gortari (2020); Acemoglu and Azar (2020); Taschereau-Dumouchel (2020) consider optimal supplier choice.

changes in production networks. The benefit of our approach is that, as long as we observe the changes in production networks, our result applies to a general class of models with common production function assumptions. This approach comes at the cost of not allowing for counterfactual simulation where changes in production networks are not observed; in such a case, researchers need to impose more structure to predict the counterfactual changes in production networks.

Our framework is also related to sufficient statistics approaches in international trade. Our approach of using supplier and buyer accesses extends those in the gravity trade literature (i.e., Redding and Venables, 2004; Donaldson and Hornbeck, 2016) to accommodate the changes in production linkages. Our approach is also related to Arkolakis, Costinot, and Rodríguez-Clare (2012) and Blaum, Lelarge, and Peters (2018), who develop sufficient statistics for welfare gains from trade in the presence of input trade. Our approach is also closely related to Baqaee, Burstein, Duprez, and Farhi (2023), who analyze the role of supplier churning on firm production and aggregate welfare under a nonparametric production function. Instead, we focus on the parametric production function common in the existing literature and derive succinct and intuitive analytical sufficient statistics. We also apply our approach to analyze the supply chain disruption in the 2014 Russia-Ukraine conflict.

Finally, we build on the literature on the economic effects of conflict. Existing papers mostly focus on the economic consequences of conflict for directly affected firms and regions.[5] Our focus instead is the economic spillovers to firms and localities outside the conflict areas through supply chain disruption and reorganizations. We provide direct evidence of how firms respond to shocks using transaction-level data on actual firm-to-firm linkages, rarely available in a conflict setting. Our empirical evidence resonates with recent findings by Couttenier, Monnet, and Piemontese (2022) that the Maoist conflict in India negatively affects firm production depending on how their input and output bundles are related to the insurgent areas. Beyond confirming a similar negative

[5]See Guidolin and La Ferrara (2007); Amodio and Di Maio (2018); Utar (2018); Ksoll, Macchiavello, and Morjaria (2022); Del Prete, Di Maio, and Rahman (2023) for the empirical evidence that conflict affects firms in immediate conflict areas using micro data and Blattman and Miguel (2010) and Rohner and Thoenig (2021) for the in-depth overviews of the literature. Hjort (2014) and Korovkin and Makarin (2023) explore alternative channels of spillover effects of conflicts, where conflict-induced intergroup tensions adversely affect firm productivity and inter-firm trade, respectively. Finally, researchers have documented the direct effects of violence on the Donbas economy by using nightlight data and other indirect approaches, e.g., see Coupé, Myck, and Najsztub (2016); Mirimanova (2017); Kochnev (2019).

effect by directly utilizing data on actual trade between firms, we show that the reorganization of firm-level production networks is relevant for firm production and aggregate welfare.

The rest of this paper is organized as follows. Section 2 describes the background of the 2014 Ukraine-Russia conflict and discusses our main data. Section 3 presents our reduced-form results on the war's effects on the disruption and reorganization of production networks. Section 4 develops our theoretical framework. Section 5 provides the results of our quantitative analysis. Section 6 concludes.

2 Background and Data

2.1 Annexation of Crimea and the Donbas War (2014–2022)

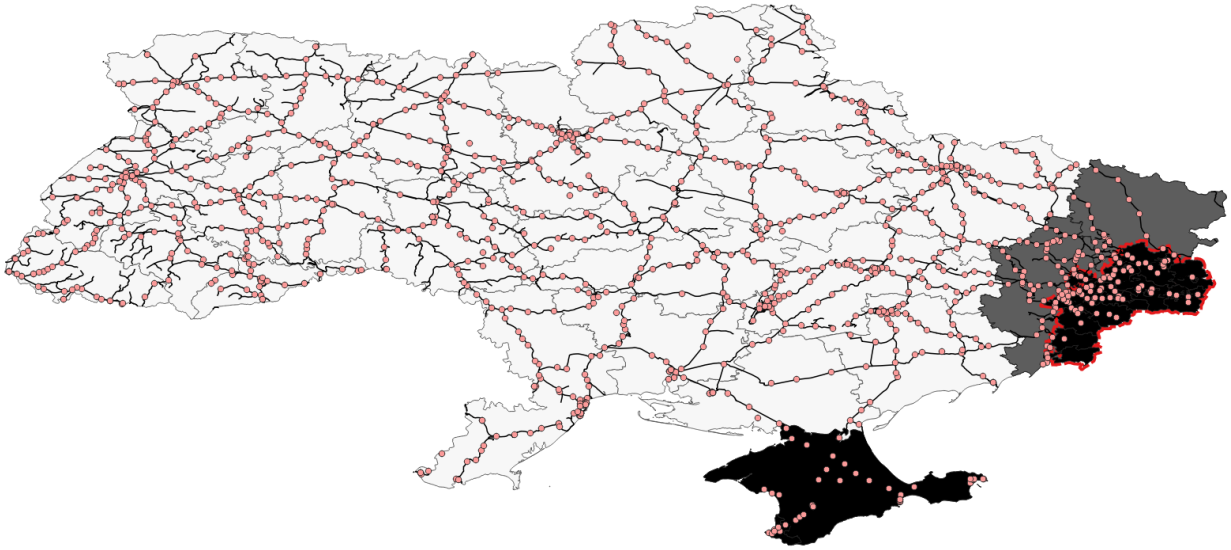
Immediately after the Ukrainian revolution of February 2014, the Russian government decided to occupy Crimea and started promoting separatist movements in the Donetsk and Luhansk provinces (i.e., the Donbas region).[6] The annexation was complete by early March 2014; it occurred without direct military conflict. Later, pro-Russian protests ensued in Donbas. Parts of these areas proclaimed independence from Ukraine, forming the Donetsk People's Republic (DPR) on April 7, 2014, and the Luhansk People's Republic (LPR) on April 27, 2014. In response, the new acting Ukrainian president launched an "Anti-Terrorist Operation" operation to suppress these separatist movements. Russia supported the DPR and LPR and, among other things, provided them with military power. A long-lasting conflict ensued, leading to more than 13,000 casualties, 30,000 wounded, and the displacement of hundreds of thousands of people.[7] The conflict has been in a rather "frozen" state ever since the election of President Zelensky. That abruptly changed on February 24, 2022, when Russia launched a full-scale invasion of Ukraine.

Figure 1 shows the areas directly affected by the 2014 Russia-Ukraine conflict. These include Crimea (in black at the bottom) and the two quasi-independent states of the Donetsk and Luhansk People's Republics (in black with a red rim, on the right side of the map). While the conflict was intense in certain DPR and LPR territories, especially at their respective borders, the rest of the country was not exposed to violence directly.

[6]The decision on Crimea was made secretly by Vladimir Putin and a handful of senior security advisors. It took everyone else by surprise (Treisman, 2018).

[7]E.g., see https://neweasterneurope.eu/2019/09/24/the-cost-of-five-years-of-war-in-donbas/

Figure 1: Conflict Areas (2014–2022) and Railroads in Ukraine



Notes: The map highlights the areas directly affected by the 2014 Russia-Ukraine conflict and displays the geographic location of the railroads and the railway stations. The Crimean Peninsula, in black at the bottom of the map, was occupied by Russia in early 2014. The Donetsk People's Republic (DPR) and Luhansk People's Republic (LPR) territories are in black with a red rim to the right. Together with the rest of Donestk and Luhansk provinces, in light gray, they form the Donbas region. Black lines indicate the Ukrainian railroads. Red dots represent the railway stations in our railway-shipments data.

Economic Activity in Donbas and Crimea Before the conflict, Donbas and Crimea accounted for a sizeable share of Ukraine's economy. Together, they were responsible for about 17.5% of Ukraine's 2013 GDP. The Donbas region has always been prominent for its extractive industries, especially coal, metallurgy, and manufacturing. Being the most populous province in Ukraine, with 4.4 million people, or 10% of Ukraine's population, Donetsk oblast (province) has been responsible for more than 20% of all Ukrainian manufacturing and 20% of all Ukraine's exports as of 2013.

Though less economically important than Donetsk, Luhansk oblast (province) has also been essential for Ukraine; it was the sixth-most-populous Ukrainian province, with 2.16 million people producing 6% of Ukraine's exports. In contrast to Donbas, Crimea is particularly well-known for its agriculture and tourism. However, it was also a vital part of Ukraine's economy before the conflict, hosting 2.2 million people and being the center of several industries, such as shipbuilding.

The consequences of conflict for these regions were devastating. Crimea became almost entirely cut off from the Ukrainian transportation network, leading to a sudden disruption of supply-chain

links. The DPR and LPR were overtaken by violence, bombing, destruction of infrastructure and physical capital, and the loss of labor force. In the course of a year, manufacturing production fell by 60% in Donetsk oblast and by 80% in Luhansk oblast. Due to the complexity of the conflict treatment, we will not separately estimate the impacts of each of its components and instead focus on the aggregate consequences of the conflict shock. Furthermore, we will provide quantitative confirmation of the adverse direct effects of conflict in Section 3.1.

Ukrainian Railroad System Railway transportation is critical for Ukraine's economy. Ukraine has the 13th-most-extended railroad network and is the world's seventh-largest railway freight transporter. Railroads are the main way of transporting products in Ukraine: according to UkrStat, as of 2018, railroads were responsible for 80% of ton-km of all freight transport.[8] Meanwhile, other modes of transportation were not particularly well maintained. According to the WEF Global Competitiveness Report, the Ukrainian railroad infrastructure was among the best in the world (25th in 2013–2014).[9] In contrast, regular roads and airway transportation ranked poorly relative to those in other countries (144th and 105th in the world in 2013–2014, respectively).

2.2 Data

Firm-to-firm Railway Shipment Data Our main data set is the universe of railway shipments within Ukraine from 2012 through 2016. The data originate from the records of *Ukrainian Railways*, a state-owned monopoly company on the market of railway transportation services. The dataset contains 100 million transactions between around 8,500 firms. It includes shipment dates, weights (in kg), freight charges, product codes, and station codes filled out by railway clerks. Importantly, the dataset contains unique IDs of the Ukrainian firms-senders and firms-receivers, which enables us to merge the dataset with other firm-level data.[10]

We use the railway shipments data both for the reduced-form analysis in Section 3 and for the model-based analysis in Section 5. For some parts of the analysis, we use information about the value of transactions between firm pairs, in addition to the presence of transaction linkages and

[8] http://www.ukrstat.gov.ua/operativ/operativ2018/tr/vtk/xls/vtk_2018_e.xlsx.

[9] https://www.weforum.org/reports/global-competitiveness-report-2013-2014.

[10] This data has been purchased by CERGE-EI from Statanalys LLC, a marketing company collecting and selling the data on export and import transactions and domestic shipments for the post-Soviet states.

the shipment weights. Given that the value of transactions is not reported in our data, we impute transaction value using the detailed product codes and the shipment weights associated with each transaction. More specifically, we leverage separate customs data from Ukraine obtained from the same source, which allows us to infer the value per weight of imported and exported product codes at the HS-8-digit code level. Appendix B describes further details of this procedure.

Figure 1 depicts the Ukrainian railway network, as well as the 1,200 railway stations in our dataset. The stations cover the entire territory of Ukraine, indirectly confirming the universal nature of our data on railway shipments. As one can see, the railway network is especially dense in the Donbas region. This pattern is consistent with the Donbas' heavy reliance on railway transportation, given its focus on coal and mineral extraction, metallurgy, and other heavy industries.

Firm Accounting Data We complement our firm-to-firm railway shipment data with firm-level accounting data from ORBIS/AMADEUS and SPARK-Interfax (2017). Both ORBIS/AMADEUS and SPARK-Interfax are based on official government statistics, the provision of which is mandatory for all Ukrainian firms except individual entrepreneurs.[11] We combine ORBIS/AMADEUS and SPARK-Interfax data for their complementary coverages in available variables. Hereinafter, we call the combined data as SPARK-Interfax data for brevity. The datasets contain information on firm IDs, sales, profits, total costs, capital, and other variables for more than 370,000 Ukrainian firms from 2010 through 2018.

Input-Output Tables We use the official input-output tables produced by the State Statistics Service of Ukraine published on their website (State Statistics Service of Ukraine, 2021). We use the 2013 version for our model calibration in Section 5.

Summary Statistics Table A.1 displays the summary statistics for these datasets. 55% of firms in our data have traded with the conflict areas in 2012–2013, i.e., before the conflict has started. An average firm received 11% of their 2012–2013 incoming shipments from the conflict areas and sent 9% of their 2012–2013 outgoing shipments to the conflict areas. The median revenue of the firms

[11] As noted in Kalemli-Ozcan et al. (2015), Ukrainian filing requirements are among the most demanding in the world. We are unaware of any estimates of the SPARK-Interfax or ORBIS/AMADEUS coverage for Ukraine, but in Romania, a neighboring country with similar filing requirements, ORBIS/AMADEUS was found to cover 92% of gross output and 93% of total employment in the manufacturing sector (Kalemli-Ozcan et al., 2015).

over the 2010–2018 period was 23.5 million Ukrainian hryvnias (around US$864,800 applying the average exchange rate for 2019). 20% of the firms' main sector is manufacturing.

3 Reduced-Form Evidence

In this section, we provide reduced-form evidence on the impact of the 2014 Russia-Ukraine conflict on firm activity and production networks in Ukraine. Section 3.1 presents evidence that firms in direct conflict zones face a significant loss in output and transactions with other firms. Section 3.2 presents evidence that firms outside conflict areas with prior production linkages to those areas experience a significant output decrease. Section 3.3 presents evidence on how these firms reorganize supplier and buyer linkages outside conflict areas.

3.1 Impacts on Firms in Conflict Areas

First, we establish that the conflict had a profound negative effect on the economic activity of directly affected territories of the self-proclaimed Donetsk and Luhansk People's Republics (DPR and LPR). To demonstrate this quantitatively, we utilize data for the near-universe of Ukrainian firms from the ORBIS/AMADEUS database for the years 2011–2016, aggregate it at the rayon level, and estimate a fully-dynamic difference-in-differences specification comparing sales of firms inside the conflict-affected areas relative to firms outside, before and after the start of the conflict.[12]

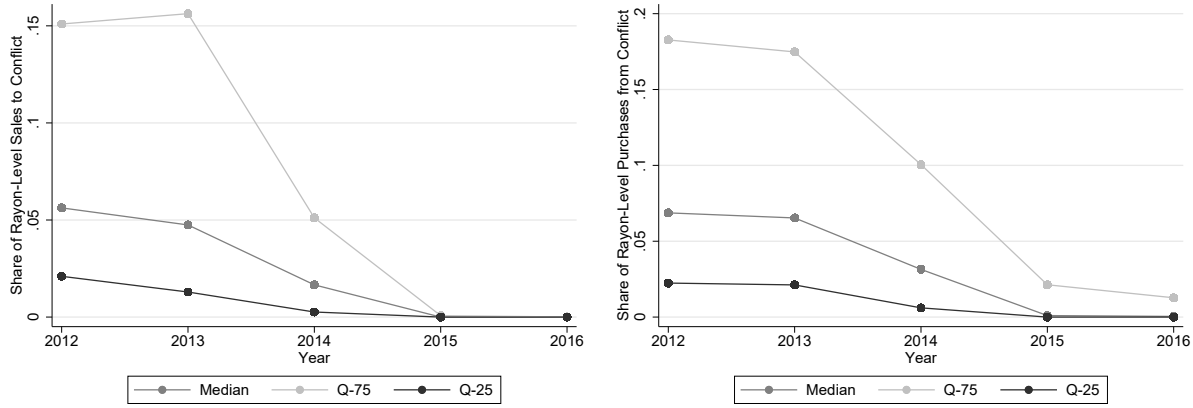
Figure A.1 presents the results. It reveals that the aggregate sales of Ukrainian firms located in the self-proclaimed Donetsk and Luhansk People's Republics—i.e., the direct conflict territories—decreased by two to four log points after the conflict began, with no pretrends preceding the conflict events. While these estimates could partly be due to data reporting issues caused by conflict, they are in line with the previous findings in Kochnev (2019), documenting a sharp 0.8-1.1 log-points decline in nighttime luminosity in the Donetsk and Luhansk People's Republics post-2014.

[12] Specifically, we estimate:

$$Y_{rt} = \alpha_r + \kappa_t + \beta_t^{LPR} \times \text{LPR}_r + \beta_t^{DPR} \times \text{DPR}_r + \beta_t^{DON} \times \text{Donetsk}_r + \beta_t^{LUH} \times \text{Luhansk}_r + \varepsilon_{rt} \quad (1)$$

where Y_{rt} represents the aggregate firm sales in rayon r at year t, LPR_r is an indicator for whether rayon r is in LPR; DPR_r is an indicator for whether rayon r is in DPR; Donetsk_r is an indicator for whether rayon r is in Donetsk province; and Luhansk_r is an indicator for whether rayon r is in Luhansk province. We cluster standard errors at the rayon level. We leave out Crimea due to reporting inconsistencies in firm accounting data following the annexation.

Figure 2: Quartiles of Production Network Weights Distribution for Trade with Conflict Areas



Notes: This figure displays the quartiles of the distribution of inter-rayon trade with DPR, LPR, and Crimea. Q-25 refers to the first quartile or the 25th percentile and Q-75 refers to the third quartile or the 75th percentile of the distribution. The figure on the left (right) presents the distribution quartiles for the share of rayon-level sales that went to (purchases that came from) conflict areas, measured as the weight of the shipments sent to (received from) the conflict areas divided by the total weight of the shipments sent out (received) by a given rayon that year.

Figure A.1 also reports a reduction in sales of firms situated in the rest of Donetsk and Luhansk provinces outside direct conflict areas, potentially driven by the spillover violence but also possibly by the reorganization of the production linkages, as we investigate further below.

Next, we document how conflict led to the disruption of trade between the conflict-affected areas and the rest of Ukraine. The left-hand-side panel of Figure 2 illustrates the evolution of input loadings distribution for rayons that received any shipments from the conflict areas in 2013. We present the median and the quartiles of the distribution, which represent the weight of shipments received from the conflict areas normalized by the total weight of the shipments received by a rayon in a given year. The right-hand-side panel of Figure 2 performs the same analysis, focusing on rayons sending their goods to Donbas or Crimea. In both instances, the receiving and sending loading percentiles plummet to zero at a rapid rate. These patterns are confirmed in event-study graphs displayed in Figure A.2, which show that an average rayon reduced the share of its trade with the conflict areas by 10 percentage points by 2015–2016, with no pretrend prior to the conflict. These effects arise partially due to a decline in firm activity and partially due to transportation in conflict areas is associated with a sharp reduction in transactions with the rest of Ukraine.

3.2 Impacts on Firms outside Conflict Areas

Having established that the conflict disrupted firm activity and trade to and from the conflict areas, we now investigate how firms outside conflict areas are affected depending on the trade linkages with direct conflict areas. We combine the data on firms' yearly sales from SPARK-Interfax, data on firms' railway shipments, and measures of pre-conflict exposure through railway linkages and estimate the following equation:

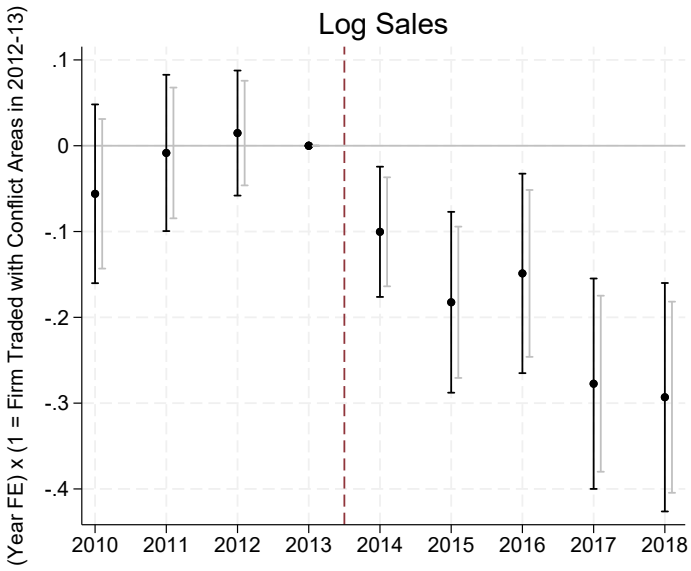
$$Y_{it} = \alpha_i + \delta_t + \beta \times \text{Post}_t \times \text{ConflictExposure}_{i,2012-13} + \varepsilon_{it}, \tag{2}$$

where Y_{it} is an outcome of firm i at year t; α_i and δ_t are the firm and year fixed effects; and $\text{ConflictExposure}_{i,2012-13}$ is an indicator for whether i traded with the conflict areas in 2012–2013. We cluster the standard errors at the firm level.

Baseline Estimates. Figure 3 presents our baseline estimates of the conflict's impact on firm sales, slightly modifying equation (2) by interacting the year fixed effects with the conflict exposure indicator. The results show no pretrends, reinforcing the validity of the difference-in-differences approach in this setting, followed by a sharp and persistent differential drop in firm sales of 0.1–0.3 log points. This result confirms that conflict adversely impacts not only firms in close proximity to violence but also those indirectly connected to the conflict regions through trade networks.

Encouraged by the patterns in Figure 3, we now estimate equation (2) focusing not only on the annual accounting sales but also on an indicator of whether accounting sales data is missing, which we interpret as a proxy for firm exit. Columns (1) and (2) of Table 1 present the results. Column (1) shows that firms outside the directly affected conflict areas, but with prior trade links to these regions, experienced an 18.4% decline in sales compared to firms without such connections. Column (2) shows that these firms are also 8.7 percentage points more likely to cease reporting sales data in a given year, suggesting an increased likelihood of exit. Importantly, the sales impact is not driven by differential attrition, as our analysis presented later in this section confirms that the effect holds even in a strongly balanced sample. Taken together, these results strongly reject a null hypothesis that firms with greater exposure to conflict are able to perfectly compensate for the conflict shock by finding new buyers or suppliers outside the conflict areas.

Figure 3: The Indirect Impact of Conflict on Sales of Firms in Non-Conflict Areas



Notes: This figure displays the results of estimating equation (2) and explores the impact of conflict on firm sales by whether a firm had prior trade ties with the conflict areas. Black bars represent 95% confidence intervals, gray bars represent 90% confidence intervals. Standard errors are clustered at the firm level.

Estimates by Direction of Exposure. Next, we disaggregate firm connections to the conflict areas into whether those coming from the supplier side and those coming from the buyer side and estimate the following specification:

$$Y_{it} = \alpha_i + \delta_t + \beta \times \text{Post}_t \times \text{BuyerExposure}_{i,2012-13} + \gamma \times \text{Post}_t \times \text{SupplierExposure}_{i,2012-13} + \varepsilon_{it}, \quad (3)$$

where $\text{BuyerExposure}_{i,2012-13}$ is measured as the share of firm's out-shipments being to the conflict areas and $\text{SupplierExposure}_{i,2012-13}$ is the share of firm's in-shipments being from the conflict areas, both calculated as value shares. The estimates, presented in columns (3)–(6) of Table 1, demonstrate that connections to conflict areas, regardless of direction, affect firm performance negatively and with broadly similar magnitudes.

Robustness. Tables 2 and A.4 probe the robustness of the estimates in Table 1. First, we show that the estimates remain similar for both outcomes when we focus on a strictly balanced sample of firms (column 2 in each table). This restriction addresses the concern of sample composition

Table 1: The Impact of Conflict on Sales of Firms Trading With Conflict Areas

	(1) Log Sales	(2) No Sales Reported	(3) Log Sales	(4) No Sales Reported	(5) Log Sales	(6) No Sales Reported
Post-2014 × Firm traded with conflict areas, 2012–13	-0.184***	0.087***				
	(0.046)	(0.010)				
Post-2014 × Firm's buyer conflict exposure, 2012–13			-0.249**	0.077***		
			(0.117)	(0.028)		
Post-2014 × Firm's supplier conflict exposure, 2012–13			-0.328***	0.118***		
			(0.114)	(0.025)		
Post-2014 × High firm's buyer conflict exposure, 2012–13					-0.144***	0.055***
					(0.050)	(0.011)
Post-2014 × High firm's supplier conflict exposure, 2012–13					-0.137***	0.062***
					(0.046)	(0.010)
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Mean	16.889	0.327	16.889	0.327	16.889	0.327
SD	2.484	0.469	2.484	0.469	2.484	0.469
R^2	0.81	0.66	0.81	0.66	0.81	0.66
Observations	35,000	52,212	35,000	52,212	35,000	52,212
Number of Firms	4,799	6,057	4,799	6,057	4,799	6,057

Notes: The table presents the estimates for the conflict's impact on firm sales and an indicator for sales data missing by firms' preexisting connectedness with the conflict areas. High exposure refers to exposure greater than the 85th percentile in the sample. The sample is restricted to firms outside the conflict areas (i.e., DPR, LPR, and Crimea). The firm accounting data comes from SPARK/Interfax in 2010–2018. Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

changes, which may be especially salient given our earlier results suggestive of firm exit. Second, the results remain unchanged after we flexibly control for firms' geolocation (columns 3–4) and their distance to the conflict areas (columns 5–6). These checks assuage the concerns of concurrent conflict-induced spatially-correlated common shocks, such as those related to future threat of military expansion or negative demand shocks. Third, the results survive controls for firm's 2-digit industry code interacted with the post-2014 indicator absorbing any time-varying industry-specific shocks (column 7). This addresses an issue of possible simultaneous industry-specific shocks, such as increased demand for military-related products. Fourth, we control for the total number of trade partners before the conflict interacted with post-2014 indicator (column 8) thus assuaging the concern in Borusyak and Hull (2020). Finally, our results are not driven by outlier regions, as they survive omitting firms near the conflict areas, i.e., Donetsk and Luhansk oblasts (columns 9 and 10, respectively), and removing firms in the capital city of Kyiv (column 11).

Table 2: Robustness Checks: Impact on Sales of Firms Trading With Conflict Areas

	(1) Baseline	(2) Strictly balanced panel	(3) Latitude & longitude	(4) Latitude & longitude	(5) Distance to conflict areas	(6) Distance to conflict areas	(7) 2-digit industry × post	(8) Pre-conflict trade partners	(9) Removing Donetsk oblast	(10) Removing Luhansk oblast	(11) Removing Kyiv
Post-2014 ×	-0.184***	-0.114**	-0.153***	-0.139***	-0.156***	-0.162***	-0.134***	-0.167***	-0.150***	-0.177***	-0.153***
Traded with conflict areas in 2012-13	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.048)	(0.047)	(0.047)	(0.047)	(0.048)
Post-2014 ×			0.074***	-1.408							
Latitude			(0.016)	(0.944)							
Post-2014 ×			-0.024***	-1.016***							
Longitude			(0.006)	(0.293)							
Post-2014 ×				0.007							
Latitude^2				(0.010)							
Post-2014 ×				-0.003**							
Longitude^2				(0.001)							
Post-2014 ×				0.024***							
Latitude × longitude				(0.006)							
Post-2014 ×					0.613***						
Distance to conflict area					(0.101)						
Post-2014 ×						0.463***					
Distance to LPR or DPR						(0.082)					
Post-2014 ×								-0.000**			
# of pre-conflict trade partners								(0.000)			
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean	16.889	17.232	16.889	16.889	16.889	16.889	16.919	16.889	16.853	16.893	16.834
SD	2.484	2.288	2.482	2.482	2.482	2.482	2.475	2.484	2.458	2.477	2.438
R^2	0.81	0.86	0.81	0.81	0.81	0.81	0.82	0.81	0.81	0.81	0.82
Observations	35,000	23,598	34,893	34,893	34,893	34,893	33,495	35,000	32,902	34,282	30,148
Number of Firms	4,799	2,622	4,776	4,776	4,776	4,776	4,597	4,799	4,484	4,679	4,062

Notes: The table presents the robustness checks of the estimates for the conflict's impact on yearly sales of firms located outside the conflict areas but that traded with the conflict areas before the start of the conflict. The baseline results (column 1) are robust to focusing on a strictly balanced sample of firms (column 2), controlling for firm's latitude and longitude and their powers interacted with Post_{it} (column 3), controlling for firm's distance (in 1,000 km) to conflict areas (DPR, LPR, and Crimea) and distance to LPR and DPR interacted with Post_{it} (columns 4 and 5), controlling for firm's 2-digit industry SIC code interacted with Post_{it} (columns 6 and 7), controlling for the total number of trade partners before the conflict (2012 and 2013) interacted with Post_{it} (column 8), omitting firms near the conflict areas, i.e., Donetsk and Luhansk oblast (columns 9 and 10, respectively), and removing firms in Kyiv (column 11). The outcome variable is the logarithm of the firm's yearly sales. Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

Overall, the results in this section offer novel evidence indicating that conflict severely affects firms even outside the areas directly exposed to violence, if firms are connected to those areas via production networks. Specifically, we find such firms experience a substantial and lasting reduction in total revenue and see an increased probability of exit.

3.3 Evidence of Reorganization of Production Networks

Finally, we make full use of the granular railway shipment data and present evidence that conflict affects not only firm production but also the patterns of production linkages.

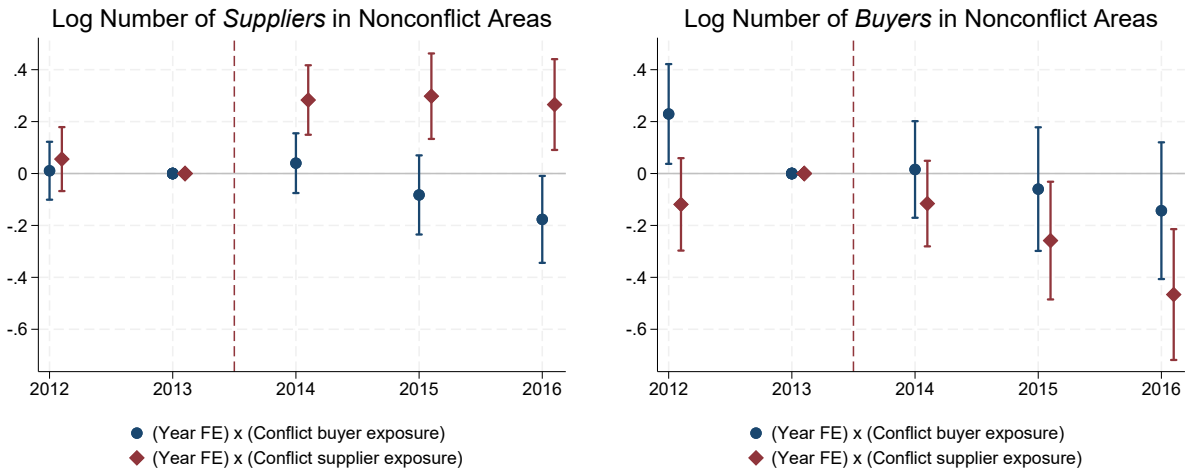
To examine whether firms reallocate their trade to nonconflict areas, we estimate equation (3) but with total volume of trade overall and with the nonconflict areas as outcome variables. Furthermore, to study pretrends and the effect dynamics, we estimate an event-study-like version of the equation whereby we interact the measures of conflict exposure with the year fixed effects.

Figure 4 presents the resulting estimates. Firms with greater conflict supplier exposure saw an increase in the number of their suppliers in nonconflict areas and a decline in the number of buyers in those areas. In contrast, firms with higher conflict buyer exposure did not change the number of buyers located in nonconflict areas and reduced the number of suppliers from those areas. Figure A.3 examines the impact on the total volume of outgoing and incoming shipments into and from nonconflict areas and shows that these effects generally mirror the findings in Figure 4, suggesting that trade was affected at both the extensive and the intensive margins.

Tables A.5 and A.6 display the non-dynamic estimates of equation (3) for the incoming and outgoing shipments, respectively. The results in columns (1), (3), (5), and (7) confirm the patterns documented in Figures 4 and A.3. In addition, the results in columns (2), (4), (6), and (8) show that, despite the presence of substitution patterns on the supplier side, the conflict's impact on the total trade volume is negative and large in magnitude. These results further highlight the detrimental effects of conflict on firms indirectly connected to the conflict areas through trade networks.

Overall, these results above suggest that firms indeed reorganize their production linkages, particularly in terms of their supplier relationships, in response to conflict.

Figure 4: The Impact of Conflict on Firm's Linkages with Non-Conflict Areas



Notes: This figure displays the results of estimating equation (3) evaluating whether a firm's number of partners in nonconflict areas changes with the start of the conflict and how it depends on the aggregate rayon-level buyer and supplier conflict exposure. Bars represent 95% confidence intervals. Standard errors are clustered at the firm level.

4 Theoretical Framework

In this section, we build a theoretical framework to analyze how the disruption and reorganization of production networks affect firm production and aggregate welfare.

The economy is segmented by a finite number of locations denoted by $u, i, d \in \mathcal{L}$. In each location, there are L_i measure of households. Each household supplies one unit of labor and earns a competitive wage w_i.

There is a fixed mass of firms in each location producing goods that can be used both for intermediate and final use. The goods are further divided into sectors denoted by $k, m, l \in K$. Each firm belongs to a distinct sector and engages in production using labor and intermediate goods. Intermediate goods can be traded across firms in different locations and sectors subject to trade costs as long as there are production linkages between them. Goods produced for final use are sold to local competitive retailers, and the retailers sell the combined composites to local consumers.

4.1 Production

There is a continuum of firms producing a distinct variety in each location and sector. To account for a flexible form of firm heterogeneity, we assume that each firm in location i and sector k belongs to a distinct firm type indexed by $\upsilon, \omega, \psi \in \Omega_{i,k}$. These firm types capture the heterogeneity of firm productivity, trade costs, and production linkages. While our model accommodates an arbitrary number of firm heterogeneity dimensions, in our quantification in Section 5, we particularly focus on firm heterogeneity with respect to preexisting supplier and buyer linkages to conflict areas.[13] We denote the measure of type ω firms in location i and sector k by $N_{i,k}(\omega)$.

Production of intermediate goods requires labor and intermediate inputs. Intermediate inputs are sourced from firms that are directly connected by production networks. The production function of firm type $\omega \in \Omega_{i,m}$ is given by

$$Y_{i,m}(\omega) = Z_{i,m}(\omega) \left(\frac{L_{i,m}(\omega)}{\beta_{m,L}} \right)^{\beta_{m,L}} \prod_{k \in K} \left(\frac{Q_{i,km}(\omega)}{\beta_{km}} \right)^{\beta_{km}}, \tag{4}$$

where $Z_{i,m}(\omega)$ is Hicks-neutral productivity, $L_{i,m}(\omega)$ is labor inputs, $Q_{i,km}(\omega)$ is the composite of intermediate inputs, $\beta_{m,L}$ and β_{km} are the parameters proxying sector m's input share for labor and intermediate inputs from sector k, respectively.

The composite of intermediate inputs from sector k is a constant elasticity of substitution (CES) aggregator of the input varieties sourced from their connected suppliers. We assume that all firms of type $\omega \in \Omega_{i,m}$ are connected with identical measure of suppliers of type $\upsilon \in \Omega_{u,k}$, denoted by $M_{ui,km}(\upsilon, \omega)$. Under these assumptions, the input composite $Q_{i,km}(\omega)$ is given by

$$Q_{i,km}(\omega) = \left(\sum_{u \in \mathcal{L}} \sum_{\upsilon \in \Omega_{u,k}} M_{ui,km}(\upsilon, \omega) q_{ui,km}(\upsilon, \omega)^{\frac{\sigma_k - 1}{\sigma_k}} \right)^{\frac{\sigma_k}{\sigma_k - 1}}, \tag{5}$$

where $q_{ui,km}(\upsilon, \omega)$ is the quantity of input for each variety, and σ_k is the elasticity of substitution of sector k goods. We also assume that, within firm type pairs, links are formed randomly; therefore

[13] While we assume a discrete number of firm types for expositional purposes, our framework can be extended with continuum of firm types by replacing summation with integrals.

all suppliers of type $\upsilon \in \Omega_{u,k}$ has an identical measure of buyer linkages and expected demand from buyers of type $\omega \in \Omega_{i,m}$. This assumption ensures that firms are *ex-post* identical within a type. Therefore, without a risk of confusion, we sometimes use firm type $\omega \in \Omega_{i,m}$ to index each firm.

The Cobb-Douglas and CES production function specification follows and nests many existing models of endogeneous production network formation.[14] However, unlike these existing approaches, we do not take a specific microfoundation of these production linkages $\{M_{ui,km}(\upsilon, \omega)\}$. Instead, we develop sufficient statistics for firm-level and aggregate welfare changes given *observed* changes in production linkages.

Final goods are produced by firms and sold to competitive retailers within the same location. Retailers have access to all firms within the region and produce final goods aggregator using the following technology

$$Y_i^F = \prod_{k \in K} \left(\frac{Q_{i,k}^F}{\alpha_k} \right)^{\alpha_k}, \qquad Q_{i,k}^F = \left(\sum_{\omega \in \Omega_{i,k}} N_{i,k}(\omega) q_{i,k}^F(\omega)^{\frac{\sigma_k - 1}{\sigma_k}} \right)^{\frac{\sigma_k}{\sigma_k - 1}} \tag{6}$$

where α_k is the final consumption share of sector k, $Q_{i,k}^F$ is the aggregator of goods from sector k, $q_{i,k}^F(\omega)$ is the quantity of final consumption of a variety from firm type $\omega \in \Omega_{i,k}$, and $N_{i,k}(\omega)$ is the measure of type $\omega \in \Omega_{i,k}$ firms.

4.2 Trade Costs, Market Structure, and Prices

The shipment of goods from suppliers of type $\omega \in \Omega_{i,m}$ for buyers of type $\psi \in \Omega_{d,l}$ incurs an iceberg trade cost $\tau_{id,ml}(\omega, \psi)$. From the CES input demand in Equation (5), and the fact that there are continuum of suppliers, suppliers charge a constant markup $\sigma_m / (\sigma_m - 1)$ on top of their production and shipment cost. The unit price charged by suppliers of type $\omega \in \Omega_{i,m}$ for buyers of

[14] For example, Melitz and Redding (2014) microfound $\{M_{ui,km}(\upsilon, \omega)\}$ by suppliers' decision to enter a buyer market by paying a fixed cost; Antras et al. (2014) model buyers' decision to enter a supplier market by paying a fixed cost; Bernard et al. (2018); Lim (2018) model suppliers' decision to acquire a buyer by paying a relationship-specific fixed cost; and Arkolakis et al. (2023) model production network formation under search and matching frictions. Oberfield (2018); Eaton et al. (2022) instead assume homogeneous inputs with random shocks under Fréchet distribution, which is isomorphic to CES production above.

type $\psi \in \Omega_{d,l}$ is given by

$$p_{id,ml}(\omega, \psi) = \frac{\sigma_m}{\sigma_m - 1} C_{i,m}(\omega)\, \tau_{id,ml}(\omega, \psi), \tag{7}$$

where $C_{i,m}(\omega)$ is the marginal cost of production by suppliers in sector m. The marginal cost of production, $C_{i,m}(\omega)$, is in turn derived from Production Functions (4) and (5) as

$$C_{i,m}(\omega) = \frac{1}{Z_{i,m}(\omega)} w_i^{\beta_{m,L}} \prod_{k \in K} P_{i,km}(\omega)^{\beta_{km}}, \tag{8}$$

where $P_{i,km}(\omega)$ is the price index of bundle given by

$$P_{i,km}(\omega) = \left(\sum_{u \in \mathcal{L}} \sum_{\upsilon \in \Omega_{u,k}} M_{ui,km}(\upsilon, \omega) p_{ui,km}(\upsilon, \omega)^{1-\sigma_k} \right)^{\frac{1}{1-\sigma_k}}. \tag{9}$$

Given the vector of wages $\{w_i\}$ and the production linkages $\{M_{ui,km}(\upsilon, \omega)\}$, Equations (7), (8), and (9) uniquely determine the set of prices $\{p_{id,ml}(\omega, \psi), C_{i,m}(\omega), P_{i,km}(\omega)\}$ up to scale.

4.3 Trade Flows and Firm Sales

We now derive the trade flows between firm type pairs. Denote the aggregate input demand by firms of type $\omega \in \Omega_{i,m}$ for input k by $D^*_{i,km}(\omega)$.[15] Then, from the CES input demand (Equation 9), the nominal trade flow of intermediate goods from suppliers of type $\upsilon \in \Omega_{u,k}$ to buyers of type $\omega \in \Omega_{i,m}$ is given by

$$X_{ui,km}(\upsilon, \omega) = \varsigma_k M_{ui,km}(\upsilon, \omega) \tau_{ui,km}(\upsilon, \omega)^{1-\sigma_k} C_{u,k}(\upsilon)^{1-\sigma_k} D_{i,km}(\omega), \tag{11}$$

where $\varsigma_k \equiv \left(\frac{\sigma_k}{\sigma_k - 1} \right)^{1-\sigma_k}$, and $D_{i,km}(\omega) \equiv D^*_{i,km}(\omega) / P_{i,km}(\omega)^{1-\sigma_k}$ is the buyers' aggregate demand adjusted by the input price index. This equation is analogous to the gravity equations in trade

[15] Specifically, from intermediate goods market clearing,

$$D^*_{i,km}(\omega) = \beta_{km} \frac{\sigma_m - 1}{\sigma_m} \left(R_{i,m}(\omega) + R^F_{i,m}(\omega) \right), \tag{10}$$

where $R_{i,m}(\omega)$ and $R^F_{i,m}(\omega)$ are aggregate intermediate goods and final goods sales by firm type $\omega \in \Omega_{i,m}$.

literature, except that the measure of production linkages $M_{ui,km}(\upsilon,\omega)$ additionally enters in the expression.

Denote the aggregate intermediate goods sales by firms of type $\omega \in \Omega_{i,m}$ by $R_{i,m}(\omega) = \sum_{l\in K}\sum_{d\in\mathcal{L}}\sum_{\psi\in\Omega_{d,l}} X_{id,ml}(\omega,\psi)$. The following proposition shows a convenient analytical expression for $R_{i,m}(\omega)$.

Proposition 1. *The aggregate intermediate goods sales by firms of type $\omega \in \Omega_{i,m}$ is given by*

$$R_{i,m}(\omega) = \tilde{\varsigma}_m Z_{i,m}(\omega)^{\sigma_m - 1} w_i^{\beta_{m,L}(1-\sigma_m)} \mathcal{A}^S_{i,m}(\omega)\mathcal{A}^B_{i,m}(\omega), \tag{12}$$

where $\tilde{\varsigma}_m \equiv \varsigma_m \prod_{k\in K} \varsigma_k^{\beta_{km}(1-\sigma_m)}$, and $\mathcal{A}^S_{i,m}(\omega)$ and $\mathcal{A}^B_{i,m}(\omega)$ correspond to supplier and buyer access, defined by

$$\mathcal{A}^S_{i,m}(\omega) \equiv \prod_{k\in K}\left(\sum_{u\in\mathcal{L}}\sum_{\upsilon\in\Omega_{u,k}} M_{ui,km}(\upsilon,\omega)\tau_{ui,km}(\upsilon,\omega)^{1-\sigma_k} C_{u,k}(\upsilon)^{1-\sigma_k}\right)^{\frac{1-\sigma_m}{1-\sigma_k}\beta_{km}}, \tag{13}$$

$$\mathcal{A}^B_{i,m}(\omega) \equiv \sum_{l\in K}\sum_{d\in\mathcal{L}}\sum_{\psi\in\Omega_{d,l}} M_{id,ml}(\omega,\psi)\tau_{id,ml}(\omega,\psi)^{1-\sigma_m} D_{d,ml}(\psi). \tag{14}$$

See Appendix C.1 for the derivation. The proposition states that, aside from the constant term $\tilde{\varsigma}_m$, firm sales are exactly decomposed into four terms. First, firm revenue is higher if the firm's productivity $Z_{i,m}(\omega)$. Second, firm revenue is lower if local wages are higher.

The third and fourth terms are supplier and buyer access, and they summarize the contribution of upstream and downstream production linkages to firm sales. Supplier access represents the influence of intermediate inputs cost on firm sales, i.e., $\mathcal{A}^S_{i,m}(\omega) = \left[\prod_{k\in K} P_{i,km}(\omega)^{\beta_{km}}\right]^{1-\sigma_m}$. It is a CES aggregate of the marginal cost of potential suppliers $C_{u,k}(\upsilon)^{1-\sigma_k}$ weighted by iceberg trade costs $\tau_{ui,km}(\upsilon,\omega)^{1-\sigma_k}$ and the measure of supplier linkages $M_{ui,km}(\upsilon,\omega)$ across all supplier types. Buyer access represents the potential of making sales to other firms. It is a sum of demand per firm $D_{d,ml}(\psi)$, weighted by the iceberg trade costs $\tau_{id,ml}(\omega,\psi)^{1-\sigma_m}$ and the measure of linkages $M_{id,ml}(\omega,\psi)$.

The observation that the supplier and buyer access serve as key summary statistics for firm sales under general equilibrium is reminiscent of the observations in the gravity trade literature (Redding

and Venables 2004; Donaldson and Hornbeck 2016). The main departure from this literature is that we allow for the changes in production linkages $\{M_{ui,km}(\upsilon,\omega)\}$.

Proposition 1 provides a useful structural interpretation of the reduced-form results in Section 3. In Section 3.2, we present evidence that firms outside conflict areas but have supplier and buyer linkages to those areas experience a relative sales decline. However, as already discussed, firms may be indirectly affected through production networks even if they are not directly connected to the conflict areas. Proposition 1 provide sufficient statistics that summarize these indirect effects. We use these sufficient statistics results to assess the validation of our model in the next section.

4.4 General Equilibrium and Aggregate Welfare

We finally close the model under general equilibrium. First, from the assumption of production function of competitive retailers (Equation 6), and assuming that there are no iceberg trade costs between firms and retailers, the final goods expenditure of firm type $\omega \in \Omega_{i,m}$ is given by

$$R_{i,m}^{F}(\omega) = \frac{\varsigma_m N_{i,m}(\omega) C_{i,m}(\omega)^{1-\sigma_k}}{\left(P_{i,m}^{F}\right)^{1-\sigma_m}} \alpha_m E_i L_i, \tag{15}$$

where E_i is per-capita income of residents in location i arising from labor income and firm profit as discussed further below, and $P_{i,m}^{F}$ is final price index of sector m in location i, given by

$$P_{i,m}^{F} = \left(\varsigma_m \sum_{\omega \in \Omega_{i,m}} N_{i,m}(\omega) C_{i,m}(\omega)^{1-\sigma_m} \right)^{\frac{1}{1-\sigma_m}}. \tag{16}$$

The labor market clearing at each location is given by

$$w_i L_i = \sum_{m \in K} \beta_{L,m} \frac{\sigma_m - 1}{\sigma_m} \sum_{d \in \mathcal{L}} \sum_{\psi \in \Omega_{d,l}} \left(R_{i,m}(\omega) + R_{i,m}^{F}(\omega) \right), \tag{17}$$

where $\beta_{L,m}\frac{\sigma_m - 1}{\sigma_m}$ corresponds to the fraction of labor in firm sales for sector m.

We assume that workers in each location have an equal share of firms producing in those

regions. Therefore, per-capita income is given by

$$E_i = w_i + \frac{1}{L_i} \sum_{m \in K} \sum_{\omega \in \Omega_{i,m}} \pi_{i,m}(\omega), \tag{18}$$

where $\pi_{i,m}(\omega)$ is the profit by firm type $\omega \in \Omega_{i,m}$, given by[16]

$$\pi_{i,m}(\omega) = \sum_{m \in K} \frac{1}{\sigma_m} \sum_{d \in \mathcal{L}} \sum_{\psi \in \Omega_{d,l}} \left(R_{i,m}(\omega) + R^F_{i,m}(\omega) \right). \tag{19}$$

Together, given the fundamentals $\{Z_{i,m}(\omega), \tau_{id,ml}(\omega, \psi), N_{i,m}\}$ and production linkages $\{M_{id,ml}(\omega, \psi)\}$, the equilibrium is defined by the set of prices $\{p_{id,ml}(\omega, \psi), C_{i,m}(\omega), P_{i,km}(\omega), P^F_i, w_i\}$, trade flows $\{X_{id,ml}(\omega, \psi)\}$, firm sales $\{R_{i,m}(\omega), R^F_{i,m}(\omega)\}$, profit $\{\pi_{i,m}(\omega)\}$, residents income $\{E_i\}$, that satisfy Equations (7), (8), (9), (11), (12), (16), (17), (17), (18), (19).

We also define location i's aggregate welfare by real income, given by

$$\mathcal{W}_i = \frac{E_i}{P^F_i}, \tag{20}$$

where $P^F_i = \prod_{m \in K} \left(P^F_{i,m} \right)^{\alpha_m}$.

5 Quantitative Analysis

In this section, we combine our theoretical framework in Section 4 with our production network data to quantitatively assess how the localized conflict in Ukraine has affected firm production and aggregate welfare outside direct conflict areas.

5.1 Calibration

We start by specifying the location and sector in our model. We set the location $\mathcal{L}$ as regions (Oblasts) within Ukraine. As of 2012, there are 27 regions in total (including cities of regional significance). We treat all of Crimea region and a part of Donetsk and Luhansk regions with intense conflict as one single location in our model. We treat the remaining part of Donetsk and Luhansk

[16] In some existing models of production network formation, firms use some resource to establish linkages, such as relationship-specific fixed cost (e.g., Bernard et al., 2018) or search cost (e.g., Arkolakis et al., 2023). Our formulation above is isomorphic as long as these resources are fixed factors owned by local households.

regions as two independent locations. Altogether, our location $\mathcal{L}$ consists of 27 locations, with 26 locations strictly outside conflict areas. We segment firms into three sectors: Mining, Manufacturing, and Other. We take this definition to reflect the dominance of mining and manufacturing sectors in direct conflict and surrounding areas.

A crucial aspect of firm heterogeneity in our context is the firms' preexisting trade linkages with conflict areas. We divide the set of firms within a location into four types based on the production linkages at the point of 2013: (1) positive suppliers and buyers in conflict areas, (2) positive suppliers and zero buyers in conflict areas, (3) zero suppliers and positive buyers with conflict areas, (4) zero suppliers and buyers in conflict areas. These four types of firms correspond to firm types $\Omega_{i.k}$ in our model.

We next calibrate structural parameters $\{\beta_{L,m}, \beta_{km}, \alpha_k, \sigma_k\}$. Table 3 summarizes our parameter choice. We calibrate $\{\beta_{L,m}, \beta_{km}, \alpha_k\}$ from the input-output table produced by the State Statistics Service of Ukraine as described in Section 2.2. We calibrate $\{\sigma_k\}$ from Fontagné, Guimbard, and Orefice (2022), who estimate product-level trade elasticity using international trade data.

Table 3: Calibrated Parameters

	Sectors		
	Mining	Manufacturing	Other
(A) β_{km}			
k =Mining	0.09	0.10	0.05
k =Manufacturing	0.14	0.29	0.14
k =Other	0.30	0.39	0.30
(B) $\beta_{k,L}$	0.47	0.22	0.51
(C) α_k	0.01	0.6	0.39
(D) σ_k	4.4	7.2	3.9

For our quantitative analysis below, we also use trade flows across firm types and locations $\{X_{ui,km,t}(\upsilon, \omega)\}$, production linkages $\{M_{ui,km,t}(\upsilon, \omega)\}$, and wages $\{w_{i,t}\}$, where t indexes year ($t \in [2012, 2016]$). We construct these proxies using our railway shipment data. To obtain nominal trade flows $\{X_{ui,km,t}(\upsilon, \omega)\}$, we use the value-imputed transaction volumes of our railway shipment data as described in Section 2.2. The measure of production linkages $\{M_{ui,km,t}(\upsilon, \omega)\}$

is simply defined by the unique count of the number of linkages between suppliers and buyers across firm types and locations. Finally, we calibrate the wages $\{w_{i,t}\}$ using the model's labor market clearing condition (Equation 17), given the lack of reliable data on wages at the rayon-year-level. Namely, using the calibrated trade flows $\{X_{ui,km,t}(\upsilon,\omega)\}$, the set of structural parameters $\{\beta_{L,m}, \beta_{km}, \alpha_k, \sigma_k\}$, and population size $\{L_i\}$, we look for the set of wages $\{w_{i,t}\}$ that satisfy the set of Equations (17) for each year.

5.2 Model Validation: Can Model Explain Observed Changes in Firm Output?

This section shows that our model can explain the observed patterns of firm output changes before and after the onset of the 2014 Russia-Ukraine War as documented in Section 3.

Empirical Strategy. We validate our model using our sufficient statistics expression of firm-level output in Proposition 1. The proposition shows that the logarithm of the aggregate intermediate goods sales by firms of type ω in sector m in location i in year t is expressed as

$$\log R_{i,m,t}(\omega) = \log\left[w_{i,t}^{\beta_{m,L}(1-\sigma_m)}\mathcal{A}^S_{i,m,t}(\omega)\mathcal{A}^B_{i,m,t}(\omega)\right] + \log Z_{i,m,t}(\omega)^{\sigma_m-1}. \tag{21}$$

As we discuss below, we can directly estimate supplier and buyer accesses $\mathcal{A}^S_{i,m,t}(\omega)$ and $\mathcal{A}^B_{i,m,t}(\omega)$ using observed trade flows and production networks for each year t. Denoting these estimates of supplier and buyer accesses by $\tilde{\mathcal{A}}^S_{i,m,t}(\omega)$ and $\tilde{\mathcal{A}}^B_{i,m,t}(\omega)$, we test our model prediction by running the following regression:

$$\log R_{i,m,t}(\omega) = \gamma \log\left[w_{i,t}^{\beta_{m,L}(1-\sigma_m)}\tilde{\mathcal{A}}^S_{i,m,t}(\omega)\tilde{\mathcal{A}}^B_{i,m,t}(\omega)\right] + \eta_{i,m}(\omega) + \nu_{i,t} + \delta_{m,t} + \epsilon_{i,m,t}(\omega), \tag{22}$$

where $\eta_{i,m}(\omega)$ is firm-type-location-sector fixed effects, $\nu_{i,t}$ is location-time fixed effects, $\delta_{m,t}$ is sector-time fixed effects, and $\epsilon_{i,m,t}(\omega)$ is the residual. These last four terms in Equation (22) capture time-varying productivity $\log Z_{i,m,t}(\omega)^{\sigma_m-1}$ in Equation (21). We test $\gamma = 1$, i.e., whether changes in firm revenue move one-for-one with the changes in our sufficient statistics for firm revenue ($w_{i,t}^{\beta_{m,L}(1-\sigma_m)}\tilde{\mathcal{A}}^S_{i,m,t}(\omega)\tilde{\mathcal{A}}^B_{i,m,t}(\omega)$) after controlling for the changes in firm productivity.

However, estimating this regression using the ordinary least squares (OLS) estimator is problematic for at least two reasons. First, the unobserved changes in TFP, $\epsilon_{i,m,t}(\omega)$, may be correlated

with the first term, $\log\left[w_{i,t}^{\beta_{m,L}(1-\sigma_m)}\tilde{\mathcal{A}}_{i,m,t}^{S}(\omega)\tilde{\mathcal{A}}_{i,m,t}^{B}(\omega)\right]$. This may happen even if we focus solely on changes in TFP (by controlling for firm-type-location-sector fixed effects), as supplier and buyer accesses are endogenous in our model. Second, our proxies for supplier and buyer accesses $\tilde{\mathcal{A}}_{i,m,t}^{S}(\omega)$ and $\tilde{\mathcal{A}}_{i,m,t}^{B}(\omega)$ necessarily involve measurement and estimation errors, leading to an underestimation of γ.

To deal with these issues, we instead estimate Equation (22) using an instrumental variable (IV) approach. In particular, we use the interaction term between the dummy variable indicating positive prior supplier (or buyer) exposure to conflict areas and the post-period (2014) dummy as IVs for the first term in Equation (22). If the TFP changes are uncorrelated with the prior exposures to conflict areas, we would expect an estimate of $\gamma = 1$.[17]

Estimation of Supplier and Buyer Accesses. To execute this idea, we first need to estimate supplier and buyer access. We do so by using our model prediction of trade flows in Equation (11). By adding the time subscript t and manipulating the equation, the logarithms of trade flow normalized by the measure of linkages are expressed as

$$\log X_{ui,km,t}(\upsilon,\omega) - \log M_{ui,km,t}(\upsilon,\omega) = \xi_{u,km,t}(\upsilon) + \zeta_{i,km,t}(\omega) + \eta_{ui,km}(\upsilon,\omega) + \epsilon_{ui,km,t}(\upsilon,\omega), \tag{23}$$

where $\xi_{u,km,t}(\upsilon) \equiv \log \varsigma_k C_{u,k,t}(\upsilon)^{1-\sigma_k}$, $\zeta_{i,km,t}(\omega) \equiv \log D_{i,km,t}(\omega)$, $\eta_{ui,km}(\upsilon,\omega) \equiv \mathbb{E}_t[\log \tau_{ui,km,t}(\upsilon,\omega)^{1-\sigma_k}]$ where $\mathbb{E}_t$ indicates the expectation over time, and $\epsilon_{ui,km,t}(\upsilon,\omega) \equiv \log \tau_{ui,km,t}(\upsilon,\omega)^{1-\sigma_k} - \mathbb{E}_t\left[\log \tau_{ui,km,t}(\upsilon,\omega)^{1-\sigma_k}\right]$ captures the idiosyncratic changes in trade costs and measurement error. We estimate Equation (11) by three-way fixed effects model the fixed effects $\tilde{\xi}_{u,km,t}(\upsilon)$, $\tilde{\zeta}_{i,km,t}(\omega)$, and $\tilde{\eta}_{ui,km}(\upsilon,\omega)$, where tilde $\tilde{x}$ denotes the estimates of parameter x. Once we estimate Equation (23), we can use the expression for supplier and buyer market access up to scale using the empirical analogs of

[17] This idea of testing model prediction using orthogonality conditions closely follows Adão, Costinot, and Donaldson (2023).

Equations (13) and (14) so that

$$\tilde{\mathcal{A}}^{S}_{i,m,t}(\omega) = \prod_{k\in K}\left(\sum_{u\in\mathcal{L}}\sum_{\upsilon\in\Omega_{u,k}} M_{ui,km,t}(\upsilon,\omega)\exp\left(\tilde{\eta}_{ui,km}(\upsilon,\omega)\tilde{\xi}_{u,km,t}(\upsilon)\right)\right)^{\frac{1-\sigma_m}{1-\sigma_k}\beta_{km}}, \tag{24}$$

$$\tilde{\mathcal{A}}^{B}_{i,m,t}(\omega) = \sum_{l\in K}\sum_{d\in\mathcal{L}}\sum_{\psi\in\Omega_{d,l}} M_{id,ml,t}(\omega,\psi)\exp\left(\tilde{\eta}_{ui,km}(\omega,\psi)\tilde{\zeta}_{i,km,t}(\psi)\right). \tag{25}$$

Results. Table 4 presents our results. In our baseline results, we use two years 2013 (pre-period) and 2016 (post-period) to focus on long differences. We come back to the robustness to using all years later. Panel (A) reports the first-stage. Column (1) reports the results with only firm-type-region fixed effects and year-fixed effects. The coefficients on supplier and buyer exposures are negative, while they are not statistically significantly different from zero. Column (2) further controls for sector-year fixed effects. The coefficients are both significantly negative and precisely estimated. Column (3) shows that the results are similar by further controlling for region-year fixed effects.

Panel (B) reports the estimation results of Equation (22). Column (1) stars with the OLS with only firm-type-region fixed effects and year-fixed effects. The estimated coefficient γ is 0.05, which is statistically significant, yet far below one. In Column (2), we estimate the same specification using supplier and buyer exposures times post-period dummies as IV. We find that the coefficient increases to 0.91. We cannot reject that the coefficient is equal to one, while the standard error is somewhat large (0.50). In Columns (3) and (4), we further control for sector-year fixed effects and region-year fixed effects. The coefficients remain close to one (0.97 and 0.89, respectively), with more precise standard errors (0.14 and 0.10). In Columns (5) and (6), we use each of supplier exposure and buyer exposure as IVs (interracted with post-period dummy) instead of using both of them simultaneously. We find coefficients of 0.86 and 0.93 (with standard errors of 0.15 and 0.16), which are close to one. Across the board, the IV regression results are close to one and precisely estimated, providing a strong support for our model validation.

In Appendix D, we report further robustness and sensitivity of these model validation results. In Table D.1, we assess the validity of the model abstracting the changes in production linkages $\{M_{ui,km}(\upsilon,\omega)\}$. In particular, we undertake the same model validation exercise assuming that the

Table 4: Model Validation

(A) First-Stage

	Dependent variable:		
	$\log w_i^{\beta_{m,L}(1-\sigma_m)} \tilde{A}^S_{i,m}(\omega)\tilde{A}^B_{i,m}(\omega)$		
	OLS	OLS	OLS
	(1)	(2)	(3)
Sup Exp × Post	−0.49	−0.76***	−0.87***
	(0.67)	(0.20)	(0.18)
Buy Exp × Post	−1.05	−0.82***	−0.85***
	(0.67)	(0.21)	(0.19)
Firm-Type-Region-Sector Fixed Effects	X	X	X
Year Fixed Effects	X	X	X
Sector × Year Fixed Effects		X	X
Region × Year Fixed Effects			X
Observations	502	502	502
Adjusted R^2	0.78	0.98	0.98

(B) Second-Stage

	Dependent variable:					
	log Firm Out-Shipment (Value): $\log R_{i,m}(\omega)$					
	OLS	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
$\log w_i^{\beta_{m,L}(1-\sigma_m)} \tilde{A}^S_{i,m}(\omega)\tilde{A}^B_{i,m}(\omega)$	0.05**	0.91*	0.97***	0.90***	0.86***	0.93***
	(0.02)	(0.51)	(0.14)	(0.10)	(0.15)	(0.16)
Firm-Type-Region-Sector Fixed Effects	X	X	X	X	X	X
Year Fixed Effects	X	X	X	X	X	X
Sector × Year Fixed Effects			X	X	X	X
Region × Year Fixed Effects				X	X	X
IVs		Supplier & Buyer Exp × Post	Supplier & Buyer Exp × Post	Supplier & Buyer Exp × Post	Supplier Exp × Post	Buyer Exp × Post
Observations	502	502	502	502	502	502
Adjusted R^2	0.83	−0.66	0.85	0.88	0.88	0.88

Notes: The sample of the regression is type-region-sector-year using 2013 and 2016. Standard errors are clustered at type-region-sector level. Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

production linkages $\{M_{ui,km}(\upsilon,\omega)\}$ remains constant at the level of $t = 2013$. We find that the supplier and buyer accesses as constructed under this scenario are not statistically significantly related to our IVs. As a consequence, the IV coefficients are highly volatile across specifications with large standard errors. While the lack of first stage prevents us for a formal test of our model against the model abstracting production network linkages, the lack of first stage ignoring the production link changes implies that the this alternative model cannot capture intuitive effects of supply chain disruptions. In Table D.2, we show that our results are virtually unchanged if we assume that $w_{i,t}$ is unchanged over time. Therefore, our results are driven by the supplier and buyer accesses. Finally, in Table D.3, we use all years (2012-2016) to estimate Equation (22), instead of focusing only on 2013 and 2016. We find that the IV coefficients ranges around 0.6-0.7 and significantly below one. One plausible explanation is that our model is suited to capture the long-run changes in firm output, but less so for the output changes during the period of transition.

5.3 Aggregate Welfare outside Conflict Areas

Having validated our calibrated model, we now use it to analyze how the conflict affect aggregate welfare strictly outside conflict areas. To do so, we use our model to simulate the effect of localized conflicts. We first calibrate our model using the trade and production linkage patterns in 2013 (right before the conflict). We then assume that the conflict makes the trade with firms in conflict areas prohibitively large, i.e., $\tau_{ui,km}(\upsilon,\omega) \to \infty$ if u or i are in the conflict areas.[18] We assume that trade costs $\{\tau_{ui,km}(\upsilon,\omega)\}$ and firm productivity $\{Z_{i,m}(\omega)\}$ outside the conflict areas are unchanged in this simulation.

To highlight the role of the reorganization of production linkages $\{M_{ui,km}(\upsilon,\omega)\}$, we undertake this simulation in two scenarios. In our first scenario, we assume that the patterns of production linkages $\{M_{ui,km}(\upsilon,\omega)\}$ are unchanged by the shock. We call this scenario "without link adjustment." In the second scenario, we assume that production linkages systematically change as a response to shock $\{M_{ui,km}(\upsilon,\omega)\}$ based on our reduced-form estimates. We call this scenario "with link adjustment." In particular, based on Table A.5, if firm type ω has a positive supplier conflict exposure, we assume that the firm increases the measure of supplier linkages by 0.11 log

[18] From the perspective of regions outside the conflict areas, this simulation is equivalent to taking the productivity $Z_{i,m}(\omega)$ to zero for conflict areas.

points outside conflict areas. Similarly, if firm type ω has a positive buyer conflict exposure, we assume that the firm increases the measure of supplier linkages by -0.01 log points outside conflict areas.

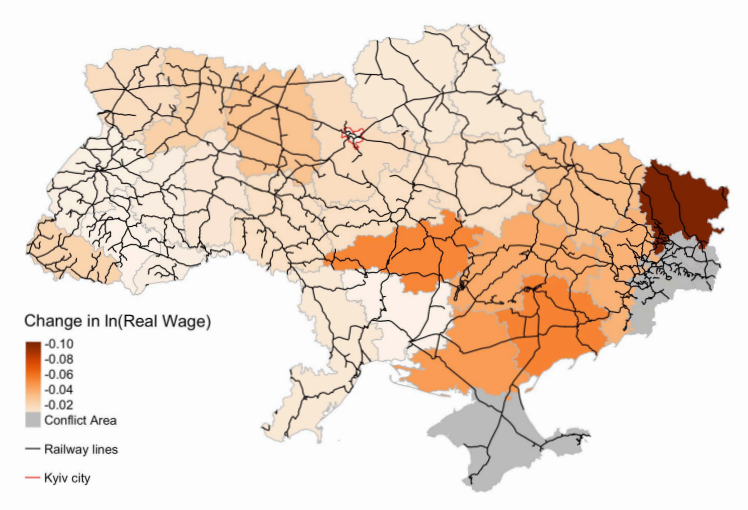
Table 5 reports the aggregate welfare changes of these simulations, defined by the population-weighted welfare changes across regions strictly outside conflict areas. In our baseline specification ("with link adjustment"), we find the welfare loss of 2.6% strictly outside conflict areas. In contrast, if we abstract the link adjustment ("without link adjustment"), we find 4.8% welfare loss. These findings suggest that the changes in production linkages, in particular the substitution of supplier linkages toward non-conflict areas, mitigate the negative propagation effects.

Table 5: Aggregate Welfare Changes outside Conflict Areas

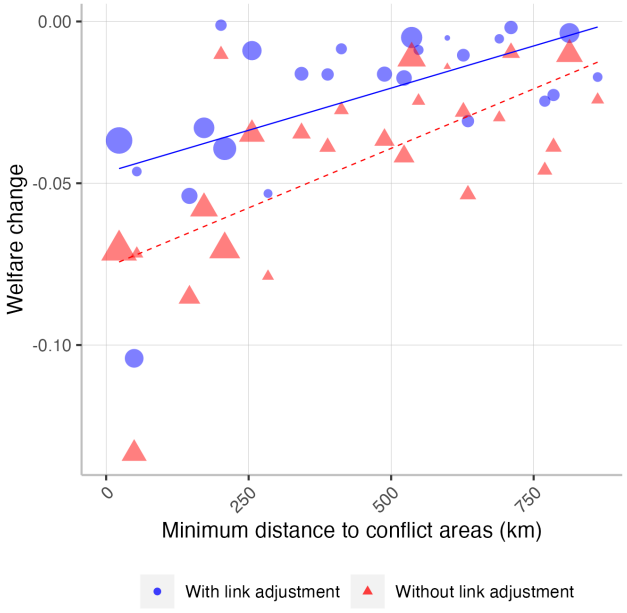
	Aggregate Welfare Changes outside Conflict Areas (%)
With Link Adjustment	2.6
Without Link Adjustment	4.8

These average effects, however, mask substantial heterogeneity of welfare changes across regions. In Figure 5, we show the geographic patterns of these welfare losses. In Panel (A), we plot the simulated welfare loss of each region on a map. We find that there is a large variation of welfare loss across regions in Ukraine, ranging from 0% to 10%. Overall, the welfare loss tend to be greater if the regions are geographically closer to the conflict areas. To further emphasize this point, in Panel (B), we project the welfare changes as a function of the distance to conflict areas. We find strong upward-sloping relationships, confirming that regions close to conflict areas are particularly affected by the conflict. At the same time, some regions that are more than 750 kilometers away face 2-3 % of welfare loss. These results indicate that localized conflicts can have far-reaching and detrimental economic consequences through production networks.

Figure 5: Real Wage Changes outside Conflict Areas



(a) Welfare changes across oblasts (with link adjustment)



(b) Oblast-level changes in welfare by distance to conflict areas

6 Conclusion

How does an intense localized conflict leads to disruption and reorganization of production networks? What are the consequences of firm production and aggregate welfare? This paper answer these questions in the context of the 2014 Russia-Ukraine conflict. Using firm-to-firm Ukrainian railway shipment data around the onset of the 2014 Russia-Ukraine conflict, we document that firms with prior production linkages to conflict areas experience a significant output decrease. Simultaneously, they reorganize supplier linkages toward peaceful areas. Based on the evidence, we develop a model of how disruption and reorganization of production networks affect production and welfare. We predict a 3 percentage point reduction of aggregate welfare strictly outside conflict areas, with almost two-fold overestimation if we abstract network reorganization.

Our results indicate that localized conflicts can have far-reaching and detrimental economic consequences through production networks. At the same time, we find accounting for the reorganization of production networks is also crucial for accurately assessing these propagation effects.

References

Acemoglu, D. and P. D. Azar (2020). Endogenous production networks. *Econometrica 88*(1), 33–82.

Adão, R., A. Costinot, and D. Donaldson (2023). Putting quantitative models to the test: An application to trump's trade war. Technical report, National Bureau of Economic Research.

Alfaro-Urena, A., I. Manelici, and J. P. Vasquez (2022). The effects of joining multinational supply chains: New evidence from firm-to-firm linkages. *The Quarterly Journal of Economics 137*(3), 1495–1552.

Amodio, F. and M. Di Maio (2018). Making do with what you have: Conflict, input misallocation and firm performance. *The Economic Journal 128*(615), 2559–2612.

Antràs, P. and A. De Gortari (2020). On the geography of global value chains. *Econometrica 88*(4), 1553–1598.

Antras, P., T. C. Fort, and F. Tintelnot (2014). The margins of global sourcing: theory and evidence from us firms. Technical report, National Bureau of Economic Research.

Arkolakis, C., A. Costinot, and A. Rodríguez-Clare (2012). New trade models, same old gains? *American Economic Review 102*(1), 94–130.

Arkolakis, C., F. Huneeus, and Y. Miyauchi (2023). Spatial production networks. *Unpublished, Yale University*.

Baqaee, D. R., A. Burstein, C. Duprez, and E. Farhi (2023). Supplier churn and growth: A micro-to-macro analysis.

Barrot, J.-N. and J. Sauvagnat (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics 131*(3), 1543–1592.

Bernard, A. B., A. Moxnes, and K. H. Ulltveit-Moe (2018). Two-sided heterogeneity and trade. *Review of Economics and Statistics 100*(3), 424–439.

Blattman, C. and E. Miguel (2010). Civil War. *Journal of Economic Literature*, 3–57.

Blaum, J., C. Lelarge, and M. Peters (2018). The gains from input trade with heterogeneous

importers. *American Economic Journal: Macroeconomics 10*(4), 77–127.

Boehm, C. E., A. Flaaen, and N. Pandalai-Nayar (2019). Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake. *Review of Economics and Statistics 101*(1), 60–75.

Borusyak, K. and P. Hull (2020). Non-random exposure to natural experiments: Theory and applications. *NBER Working Paper 27845*.

Carvalho, V. M., M. Nirei, Y. U. Saito, and A. Tahbaz-Salehi (2021). Supply Chain Disruptions: Evidence from the Great East Japan Earthquake. *The Quarterly Journal of Economics 136*(2), 1255–1321.

Chalendard, C., A. M. Fernandes, G. Raballand, and B. Rijkers (2023). Corruption in customs. *The Quarterly Journal of Economics 138*(1), 575–636.

Coupé, T., M. Myck, and M. Najsztub (2016). And the Lights Went Out—Measuring the Economic Situation in Eastern Ukraine. *Vox Ukraine 18*.

Couttenier, M., N. Monnet, and L. Piemontese (2022). The economic costs of conflict: A production network approach.

Del Prete, D., M. Di Maio, and A. Rahman (2023). Firms amid conflict: Performance, production inputs, and market competition. *Journal of Development Economics*.

Demir, B., A. C. Fieler, D. Y. Xu, and K. K. Yang (2021). O-Ring Production Networks. *Working Paper*.

Dhyne, E., A. K. Kikkawa, X. Kong, M. Mogstad, and F. Tintelnot (2022). Endogenous production networks with fixed costs. *Working Paper*.

Donaldson, D. and R. Hornbeck (2016). Railroads and American Economic Growth: A "Market Access" Approach. *The Quarterly Journal of Economics 131*(2), 799–858.

Eaton, J., S. Kortum, and F. Kramarz (2022). Firm-to-Firm Trade: Imports, exports, and the labor market. *Working Paper*.

Fisman, R. and S.-J. Wei (2004). Tax rates and tax evasion: evidence from "missing imports" in

china. *Journal of political Economy 112*(2), 471–496.

Fontagné, L., H. Guimbard, and G. Orefice (2022). Tariff-based product-level trade elasticities. *Journal of International Economics 137*, 103593.

Guidolin, M. and E. La Ferrara (2007). Diamonds are Forever, Wars are Not: Is Conflict Bad for Private Firms? *American Economic Review 97*(5), 1978–1993.

Hjort, J. (2014). Ethnic Divisions and Production in Firms. *The Quarterly Journal of Economics 129*(4), 1899–1946.

Huneeus, F. (2018). Production Network Dynamics and the Propagation of Shocks. *Working Paper*.

Kalemli-Ozcan, S., B. Sorensen, C. Villegas-Sanchez, V. Volosovych, and S. Yesiltas (2015). How to Construct Nationally Representative Firm Level Data from the ORBIS Global Database. Technical report, National Bureau of Economic Research.

Khanna, G., N. Morales, and N. Pandalai-Nayar (2022). Supply chain resilience: Evidence from indian firms. Technical report, National Bureau of Economic Research.

Kochnev, A. (2019). Dying light: War and trade of the separatist-controlled areas of Ukraine. *Available at SSRN 3579099*.

Korovkin, V. and A. Makarin (2023). Conflict and Intergroup Trade: Evidence from the 2014 Russia-Ukraine Crisis. *American Economic Review 113*(1), 34–70.

Ksoll, C., R. Macchiavello, and A. Morjaria (2022). Electoral violence and supply chain disruptions in kenya's floriculture industry. *Review of Economics and Statistics*, 1–45.

Lim, K. (2018). Endogenous Production Networks and the Business Cycle. *Working Paper*.

Melitz, M. J. and S. J. Redding (2014). Missing gains from trade? *The American Economic Review 104*(5), 317–321.

Mirimanova, N. (2017). Economic connectivity across the line of contact in Donbas, Ukraine. *Centre for Humanitarian Dialogue*.

Miyauchi, Y. (2023). Matching and Agglomeration: Theory and Evidence from Japanese Firm-to-

Firm Trade. *Working Paper*.

Oberfield, E. (2018, mar). A Theory of Input-Output Architecture. *Econometrica 86*(2), 559–589.

Redding, S. and A. J. Venables (2004). Economic geography and international inequality. *Journal of international Economics 62*(1), 53–82.

Rohner, D. and M. Thoenig (2021). The Elusive Peace Dividend of Development Policy: From War Traps to Macro Complementarities. *Annual Review of Economics 13*(1), 111–131.

SPARK-Interfax (2010–2017). Spark-interfax database. https://spark-interfax.com/.

State Statistics Service of Ukraine (2003–2021). Input-output tables (at consumer prices). https://ukrstat.gov.ua/. Accessed: 2024-01-11.

Taschereau-Dumouchel, M. (2020). Cascades and fluctuations in an economy with an endogenous production network. *Available at SSRN 3115854*.

Treisman, D. (2018). *The New Autocracy: Information, Politics, and Policy in Putin's Russia*. Brookings Institution Press.

Utar, H. (2018). Firms and Labor in Times of Violence: Evidence from the Mexican Drug War.

Online Appendix for "Production Networks and War: Theory and Evidence from Ukraine" (Not for Publication)

Vasily Korovkin, Alexey Makarin, Yuhei Miyauchi

A Additional Tables and Figures

Table A.1: Summary Statistics

	Observations	Mean	SD	Min	Max
	Panel A: Conflict Exposures				
Firm traded with conflict areas in 2012–2013	52,642	0.55	0.50	0	1
Firm's buyer conflict exposure, 2012–2013	52,642	0.09	0.23	0	1
Firm's supplier conflict exposure, 2012–2013	52,642	0.11	0.24	0	1
High firm's buyer conflict exposure, 2012–2013	52,642	0.14	0.35	0	1
High firm's supplier conflict exposure, 2012–2013	52,642	0.14	0.35	0	1
	Panel B: Sales and Trade				
Log of firm sales, 2010–2018	35,162	16.88	2.49	4.61	25.13
No sales reported, 2010–2018	52,642	0.33	0.47	0	1
Log weight sent total, 2012–2016	15,091	15.35	3.06	1.61	24.86
Log weight sent to nonconflict areas, 2012–2016	14,734	15.31	3.03	1.61	24.72
Log weight received total, 2012–2016	22,052	15.65	2.39	3	24.57
Log weight received from nonconflict areas, 2012–2016	21,610	15.57	2.37	3	24.56
Log number of buyers total, 2012–2016	15,091	1.85	1.51	0	7.64
Log number of buyers in nonconflict areas, 2012–2016	14,734	1.81	1.49	0	7.64
Log number of suppliers total, 2012–2016	22,052	1.77	1.27	0	7.80
Log number of suppliers from nonconflict areas, 2012–2016	21,610	1.71	1.25	0	7.79
	Panel C: Industry				
Agriculture, forestry, fishing	52,642	0.11	0.32	0	1
Mining	52,642	0.04	0.21	0	1
Construction	52,642	0.05	0.21	0	1
Manufacturing	52,642	0.20	0.40	0	1
Transportation, communications, utilities	52,642	0.14	0.35	0	1
Wholesale trade	52,642	0.29	0.45	0	1
Retail trade	52,642	0.02	0.13	0	1
Services	52,642	0.02	0.15	0	1

Notes: This table presents the summary statistics for the firm-year trade and accounting data. The (natural) logarithms do not adjust for zero trade volume and, as such, are only defined for firm-year observations with positive trade volume. The industry indicators are based on the firms' SIC codes from SPARK & Interfax. We leave out the industries for which the share of firms in our sample is below 2%.

Table A.2: Robustness Checks: Impact on Log Total Weight of Incoming Shipments Firms Trading With Conflict Areas

	(1) Baseline	(2) Strictly balanced panel	(3) Latitude & longitude	(4) Latitude & longitude	(5) Distance to conflict areas	(6) Distance to conflict areas	(7) 2-digit industry × post	(8) Pre-conflict trade partners	(9) Removing Donetsk oblast	(10) Removing Luhansk oblast	(11) Removing Kyiv
Post-2014 ×	-0.366***	-0.247***	-0.329***	-0.273***	-0.333***	-0.337***	-0.324***	-0.333***	-0.372***	-0.328***	-0.358***
Traded with conflict areas in 2012-13	(0.052)	(0.056)	(0.054)	(0.054)	(0.054)	(0.054)	(0.057)	(0.054)	(0.054)	(0.053)	(0.054)
Post-2014 ×			0.028	1.578							
Latitude			(0.017)	(0.991)							
Post-2014 ×			-0.013**	-0.692**							
Longitude			(0.006)	(0.330)							
Post-2014 ×				-0.022**							
Latitude^2				(0.010)							
Post-2014 ×				-0.004***							
Longitude^2				(0.001)							
Post-2014 ×				0.019***							
Latitude × longitude				(0.006)							
Post-2014 ×					0.272***						
Distance to conflict area					(0.103)						
Post-2014 ×						0.215**					
Distance to LPR or DPR						(0.085)					
Post-2014 ×								-0.000***			
# of pre-conflict trade partners								(0.000)			
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean	15.738	16.304	15.770	15.770	15.770	15.770	15.786	15.738	15.685	15.737	15.711
SD	2.357	2.171	2.364	2.364	2.364	2.364	2.366	2.357	2.323	2.359	2.344
R^2	0.78	0.79	0.78	0.78	0.78	0.78	0.78	0.78	0.77	0.78	0.78
Observations	21,053	14,025	19,608	19,608	19,608	19,608	19,017	21,053	19,601	20,529	18,563
Number of Firms	5,073	2,805	4,669	4,669	4,669	4,669	4,525	5,073	4,745	4,950	4,444

Notes: The table presents the robustness checks for the estimates of the conflict's indirect impact on firms' log total weight of incoming shipments. The baseline results (column 1) are robust to focusing on a strictly balanced sample of firms (column 2), controlling for firm's latitude and longitude and their powers interacted with Post_{it} (column 3), controlling for firm's distance (in 1,000 km) to conflict areas (DPR, LPR, and Crimea) and distance to LPR and DPR interacted with Post_{it} (columns 4 and 5), controlling for firm's 2-digit industry SIC code interacted with Post_{it} (columns 6 and 7), controlling for the total number of trade partners before the conflict (2012 and 2013) interacted with Post_{it} (column 8), omitting firms near the conflict areas, i.e., Donetsk and Luhansk oblast (columns 9 and 10, respectively), and removing firms in Kyiv (column 11). The outcome variable is the logarithm of the firm's yearly sales. Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.3: Robustness Checks: Impact on Log Total Weight of Outgoing Shipments Firms Trading With Conflict Areas

	(1) Baseline	(2) Strictly balanced panel	(3) Latitude & longitude	(4) Latitude & longitude	(5) Distance to conflict areas	(6) Distance to conflict areas	(7) 2-digit industry × post	(8) Pre-conflict trade partners	(9) Removing Donetsk oblast	(10) Removing Luhansk oblast	(11) Removing Kyiv
Post-2014 ×	-0.517***	-0.509***	-0.497***	-0.476***	-0.495***	-0.498***	-0.417***	-0.471***	-0.486***	-0.500***	-0.544***
Traded with conflict areas in 2012-13	(0.079)	(0.088)	(0.083)	(0.084)	(0.082)	(0.082)	(0.086)	(0.083)	(0.084)	(0.081)	(0.083)
Post-2014 ×			-0.006	3.780**							
Latitude			(0.029)	(1.642)							
Post-2014 ×			-0.010	1.110**							
Longitude			(0.010)	(0.523)							
Post-2014 ×				-0.034**							
Latitude^2				(0.016)							
Post-2014 ×				-0.007***							
Longitude^2				(0.002)							
Post-2014 ×				-0.014							
Latitude × longitude				(0.010)							
Post-2014 ×					0.140						
Distance to conflict area					(0.159)						
Post-2014 ×						0.097					
Distance to LPR or DPR						(0.130)					
Post-2014 ×								-0.000***			
# of pre-conflict trade partners								(0.000)			
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean	15.571	16.697	15.617	15.617	15.617	15.617	15.598	15.571	15.458	15.559	15.601
SD	3.006	2.737	3.006	3.006	3.006	3.006	3.025	3.006	2.961	3.007	3.007
R^2	0.78	0.80	0.78	0.78	0.78	0.78	0.79	0.78	0.78	0.78	0.79
Observations	13,776	7,460	13,176	13,176	13,176	13,176	12,559	13,776	12,598	13,362	11,928
Number of Firms	3,697	1,492	3,492	3,492	3,492	3,492	3,343	3,697	3,406	3,588	3,197

Notes: The table presents the robustness checks for the estimates of the conflict's indirect impact on firms' log total weight of outgoing shipments. The baseline results (column 1) are robust to focusing on a strictly balanced sample of firms (column 2), controlling for firm's latitude and longitude and their powers interacted with Post_{it} (column 3), controlling for firm's distance (in 1,000 km) to conflict areas (DPR, LPR, and Crimea) and distance to LPR and DPR interacted with Post_{it} (columns 4 and 5), controlling for firm's 2-digit industry SIC code interacted with Post_{it} (columns 6 and 7), controlling for the total number of trade partners before the conflict (2012 and 2013) interacted with Post_{it} (column 8), omitting firms near the conflict areas, i.e., Donetsk and Luhansk oblast (columns 9 and 10, respectively), and removing firms in Kyiv (column 11). The outcome variable is the logarithm of the firm's yearly sales. Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.4: Robustness Checks: Impact on Exit of Firms Trading With Conflict Areas

	(1) Baseline	(2) Strictly balanced panel	(3) Latitude & longitude	(4) Latitude & longitude	(5) Distance to conflict areas	(6) Distance to conflict areas	(7) 2-digit industry × post	(8) Pre-conflict trade partners	(9) Removing Donetsk oblast	(10) Removing Luhansk oblast	(11) Removing Kyiv
Post-2014 ×	0.147***	0.150***	0.125***	0.097***	0.127***	0.134***	0.142***	0.153***	0.116***	0.125***	0.155***
Traded with conflict areas in 2012-13	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)
Post-2014 ×			-0.026***	-1.097***							
Latitude			(0.004)	(0.195)							
Post-2014 ×			0.011***	0.318***							
Longitude			(0.001)	(0.065)							
Post-2014 ×				0.014***							
Latitude^2				(0.002)							
Post-2014 ×				0.002***							
Longitude^2				(0.000)							
Post-2014 ×				-0.009***							
Latitude × longitude				(0.001)							
Post-2014 ×					-0.267***						
Distance to conflict area					(0.022)						
Post-2014 ×						-0.187***					
Distance to LPR or DPR						(0.017)					
Post-2014 ×								-0.000***			
# of pre-conflict trade partners								(0.000)			
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean	0.326	0.305	0.304	0.304	0.304	0.304	0.308	0.326	0.325	0.324	0.321
SD	0.469	0.461	0.460	0.460	0.460	0.460	0.462	0.469	0.468	0.468	0.467
R^2	0.67	0.64	0.65	0.65	0.65	0.65	0.65	0.67	0.67	0.67	0.69
Observations	52,281	50,733	50,472	50,472	50,472	50,472	48,771	52,281	49,041	51,084	44,667
Number of Firms	6,064	5,637	5,608	5,608	5,608	5,608	5,419	6,064	5,704	5,931	5,218

Notes: The table presents the robustness checks for the estimates of the conflict's indirect impact on firms' exit as proxied by them not submitting revenue data to the government. The baseline results (column 1) are robust to focusing on a strictly balanced sample of firms (column 2), controlling for firm's latitude and longitude and their powers interacted with Post_{it} (column 3), controlling for firm's distance (in 1,000 km) to conflict areas (DPR, LPR, and Crimea) and distance to LPR and DPR interacted with Post_{it} (columns 4 and 5), controlling for firm's 2-digit industry SIC code interacted with Post_{it} (columns 6 and 7), controlling for the total number of trade partners before the conflict (2012 and 2013) interacted with Post_{it} (column 8), omitting firms near the conflict areas, i.e., Donetsk and Luhansk oblast (columns 9 and 10, respectively), and removing firms in Kyiv (column 11). The outcome variable is the logarithm of the firm's yearly sales. Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.5: Log number of supplier and buyer links with non-conflict areas

	(1) Log # of Suppliers in Nonconflict Areas	(2) Log # of Suppliers Total	(3) Log # of Suppliers in Nonconflict Areas	(4) Log # of Suppliers Total	(5) Log Weight Received From Nonconflict Areas	(6) Log Weight Received Total	(7) Log Weight Received From Nonconflict Areas	(8) Log Weight Received Total
Post-2014 × Firm's buyer conflict exposure, 2012–13	-0.076	-0.079			-0.280**	-0.245**		
	(0.062)	(0.060)			(0.119)	(0.113)		
Post-2014 × Firm's supplier conflict exposure, 2012–13	0.255***	-0.149***			0.560***	-0.514***		
	(0.067)	(0.056)			(0.136)	(0.107)		
Post-2014 × High firm's buyer conflict exposure, 2012–13			-0.068*	-0.074**			-0.166**	-0.147**
			(0.038)	(0.037)			(0.071)	(0.069)
Post-2014 × High firm's supplier conflict exposure, 2012–13			0.114***	-0.108***			0.211***	-0.297***
			(0.038)	(0.035)			(0.072)	(0.065)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean	1.755	1.813	1.755	1.813	15.665	15.740	15.665	15.740
SD	1.247	1.261	1.247	1.261	2.338	2.358	2.338	2.358
R^2	0.78	0.79	0.78	0.79	0.77	0.78	0.77	0.78
Observations	20,597	21,045	20,597	21,045	20,597	21,045	20,597	21,045
Number of Firms	4,974	5,072	4,974	5,072	4,974	5,072	4,974	5,072

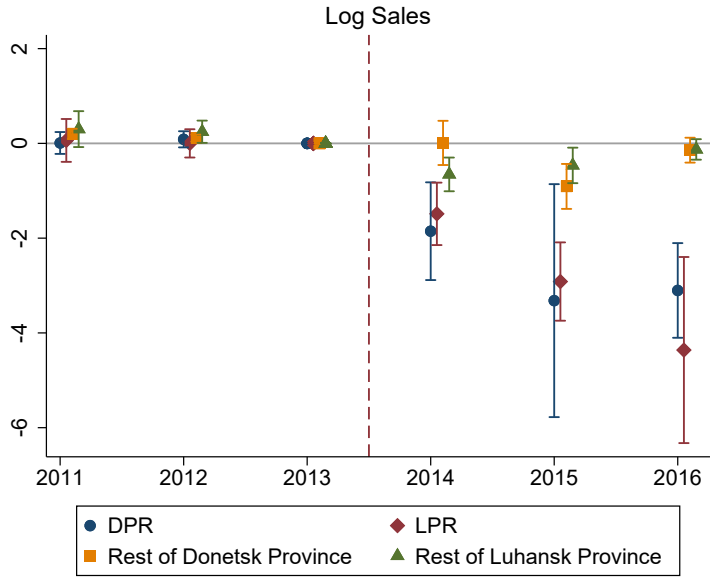
Notes: The table presents the estimates for the conflict's impact on firm total outgoing and incoming trade with nonconflict areas by firms' preexisting connectedness with the conflict areas. High exposure refers to exposure greater than the 85th percentile in the sample. The sample is restricted to firms outside the conflict areas (i.e., DPR, LPR, and Crimea). The firm accounting data comes from SPARK/Interfax in 2010–2018. Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01. * p<0.1, ** p<0.05, *** p<0.01.

Table A.6: Log number of supplier and buyer links with non-conflict areas

	(1) Log # of Buyers in Nonconflict Areas	(2) Log # of Buyers Total	(3) Log # of Buyers in Nonconflict Areas	(4) Log # of Buyers Total	(5) Log Weight Sent to Nonconflict Areas	(6) Log Weight Sent Total	(7) Log Weight Sent to Nonconflict Areas	(8) Log Weight Sent Total
Post-2014 × Firm's buyer conflict exposure, 2012–13	-0.175*	-0.240***			0.161	-0.509***		
	(0.096)	(0.087)			(0.213)	(0.191)		
Post-2014 × Firm's supplier conflict exposure, 2012–13	-0.211**	-0.197**			-0.469**	-0.424**		
	(0.095)	(0.093)			(0.194)	(0.193)		
Post-2014 × High firm's buyer conflict exposure, 2012–13			-0.142***	-0.245***			-0.083	-0.414***
			(0.048)	(0.046)			(0.096)	(0.092)
Post-2014 × High firm's supplier conflict exposure, 2012–13			-0.094*	-0.085			-0.268**	-0.253**
			(0.052)	(0.053)			(0.106)	(0.108)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean	1.917	1.952	1.917	1.952	15.532	15.574	15.532	15.574
SD	1.488	1.507	1.488	1.507	2.979	3.006	2.979	3.006
R^2	0.79	0.79	0.79	0.79	0.78	0.78	0.78	0.78
Observations	13,389	13,770	13,389	13,770	13,389	13,770	13,389	13,770
Number of Firms	3,593	3,693	3,593	3,693	3,593	3,693	3,593	3,693

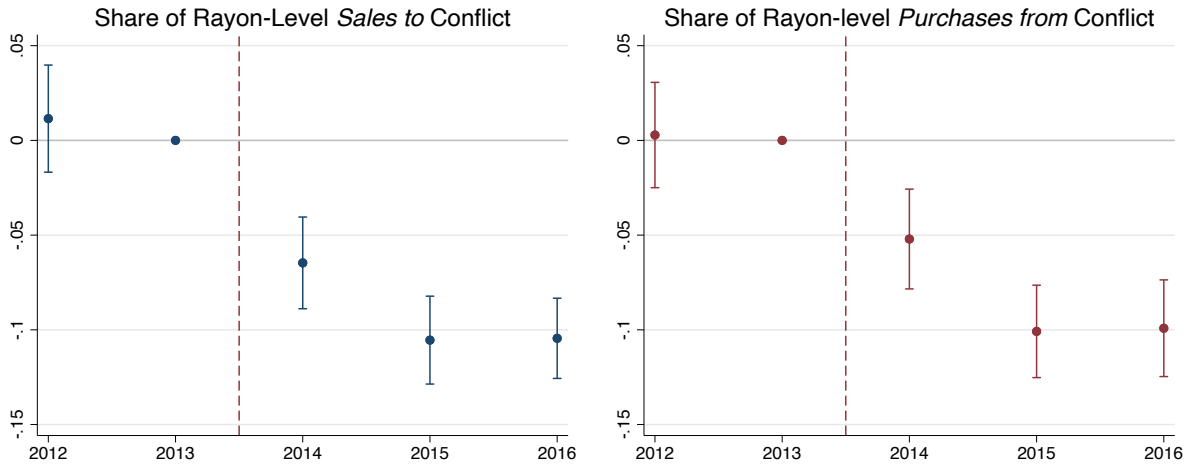
Notes: The table presents the estimates for the conflict's impact on firm total outgoing and incoming trade with nonconflict areas by firms' preexisting connectedness with the conflict areas. High exposure refers to exposure greater than the 85th percentile in the sample. The sample is restricted to firms outside the conflict areas (i.e., DPR, LPR, and Crimea). The firm accounting data comes from SPARK/Interfax in 2010–2018. Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01. * p<0.1, ** p<0.05, *** p<0.01.

Figure A.1: Impact of Conflict on Sales of Firms Located in the Conflict Areas, Rayon-Level



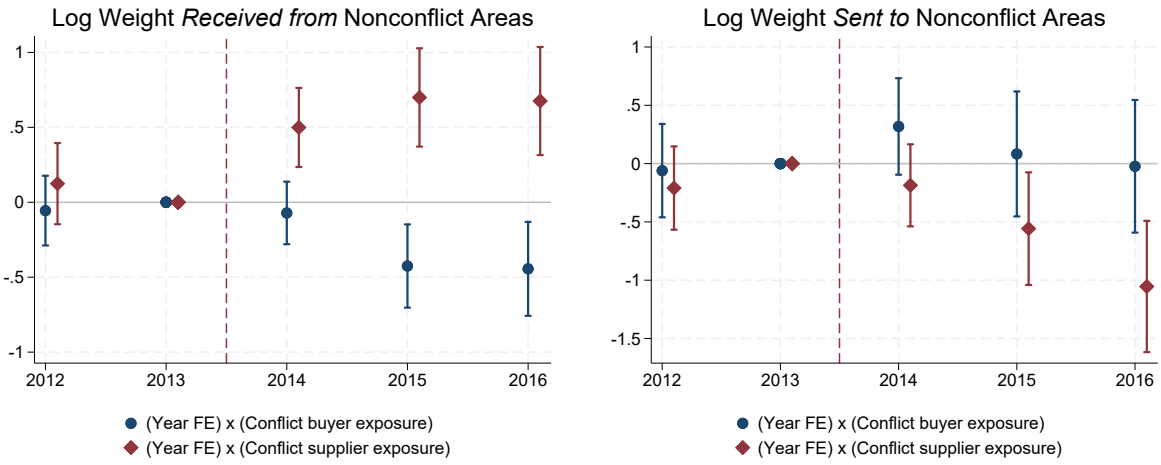
Notes: This figure displays the impact of conflict on the immediately affected areas in terms of their aggregate firm sales. The outcome is the sales of all Ukrainian firms in the ORBIS/AMADEUS dataset located outside of Crimea, aggregated to the rayon level. Firms located in Crimea are removed from the sample due to inconsistencies in reporting after the annexation. Blue dot estimates are the estimates for rayons in the so-called Donetsk People's Republic, red diamonds are for rayons in the so-called Luhansk People's Republic, orange squares are for rayons in the rest of Donetsk province, and green triangles are for rayons in the rest of Luhansk province. Bars represent 95% confidence intervals. Standard errors are clustered at the rayon level.

Figure A.2: Share of Trade with Conflict Areas



Notes This figure represents how the aggregate rayon-level buyer and supplier exposures to conflict areas changed over time. Specifically, the figure presents the estimates of the yearly fixed effect coefficients from the following specification: $Y_{rt} = \alpha_r + \beta_t + \varepsilon_{rt}$, where Y_{rt} is the share of rayon r's sales to or purchases from the conflict areas in year t and α_r and β_t are rayon and year fixed effects respectively. We take 2013 as the baseline year. Bars represent 95% confidence intervals. Standard errors are clustered at the firm level.

Figure A.3: The Impact of Conflict on Firm's Trade with Non-Conflict Areas



Notes: This figure displays the results of estimating equation (3) evaluating whether a firm's trade activity with non-conflict areas changes with the start of the conflict and how it depends on the aggregate rayon-level buyer and supplier conflict exposure. Bars represent 95% confidence intervals. Standard errors are clustered at the firm level.

B Value Imputation of Railway Shipment Data

We start by creating a correspondence between the railway cargo codes (ETSNV codes) and the product codes available in the customs data (HS codes).

The crosswalks for different periods are available from the national railways website. The links are provided below, with the two most relevant codebooks—the first ten months of 2012 and the rest of the period.

The codebooks do not always provide the match on the most granular—HS8-level, but if there is no match from the ETSNV to HS code on the most granular level, there usually is a match on the higher level of aggregation—either HS6 or HS5 or HS4.[1] Overall we have 6,019 unique HS8 codes and 2,697 unique ETSNV (cargo) codes in the cross-walk.

For the value prediction, we use an approach similar to (Chalendard, Fernandes, Raballand, and Rijkers, 2023, page 589) where at each level of aggregation we extract value-to-weight ratio for HS8 (HS6 if there is no match on HS8, then HS5, and HS4) code from the custom data, and this number serves as a unit price for this code. We then use this unit price and the codebook correspondence to get the unit price for each transaction in the railway data. Then we multiple the unit price by weight and it gives us an imputed value for each transaction.

If a ETSNV-cargo code has more than one corresponding HS code, which does happen sometimes in our data, we compute a weighted average unit price, weighted by the number of transactions in each respective HS code of the custom data.

To probe robustness of value imputation we do it in four different ways. We use either all of the custom transactions or only the export ones, as one can imagine that imports has a higher chance of being misreported (Fisman and Wei (2004); Chalendard et al. (2023)), and export reporting would be more precise.

We also use two different ways of averaging individual custom transaction to the HS8 (HS6, HS5, HS4) code: either based on the total value for the HS code, divided by total weight or by using a log-transformation first and then exponentiating after averaging, to smooth out the outliers.[2]

[1] The HS levels determine how generic or broad the product category is: for instance, fodder vs. horse fodder.

[2] Specifically, for transaction i in good category j we use $\widehat{unit\ value}_j = \exp((1/N_j)\sum_i(\log(value_{ij}/weight_{ij})))$, N_j is the number of observations in the j-th HS code.

There are several reasons why we think our algorithm delivers an accurate value prediction. Firstly, depending on the codebook year (2012 or 2013) and on using export transactions or all transactions, the adjusted R-squared of log-unit-transaction value on the HS8-code fixed effects is always between 0.70 and 0.87. In other words, HS codes predict unit value reasonably well.

Secondly, the log-per-unit values on the HS-code level for the four approaches we tried have correlations between 0.85 and 0.98. We proceed with using export-based approach using the exp-log transformation.

Codebooks:

01.07.2011 http://uz.gov.ua/files/file/cargo_transportation/smgs/G_142_izm_2011.rar

01.07.2012 http://uz.gov.ua/files/file/cargo_transportation/smgs/G_142_03_07_2012.xls

10.10.2012 http://uz.gov.ua/files/file/cargo_transportation/smgs/G_142_2012.xls

01.07.2013 http://uz.gov.ua/files/file/cargo_transportation/smgs/G_142_01.07.2013.xls

https://web.archive.org/web/20121014063056/http://uz.gov.ua/cargo_transportation/legal_documents/nomenklatura/table_gnv_snd/

https://web.archive.org/web/20130816101734/http://uz.gov.ua/cargo_transportation/legal_documents/nomenklatura/table_gnv_snd/

(Links within the archives are non-clickable, but if one copies and pastes them, they will start the download process).

C Appendix for Model

C.1 Proof of Proposition 1

From Equation (11),

$$\begin{aligned} R_{i,m}(\omega) &= \sum_{l\in K}\sum_{d\in\mathcal{L}}\sum_{\psi\in\Omega_{d,l}} X_{id,ml}(\omega,\psi) \\ &= \sum_{l\in K}\sum_{d\in\mathcal{L}}\sum_{\psi\in\Omega_{d,l}} \varsigma_m M_{id,ml}(\omega,\psi)\tau_{id,ml}(\omega,\psi)^{1-\sigma_m} C_{i,m}(\omega)^{1-\sigma_m} D_{d,ml}(\psi) \\ &= \varsigma_m C_{i,m}(\omega)^{1-\sigma_m} \mathcal{A}^B_{i,m}(\omega). \end{aligned}$$

Furthermore, from Equations (7), (8) and (9),

$$\begin{aligned} C_{i,m}(\omega)^{1-\sigma_m} &= Z_{i,m}(\omega)^{\sigma_m-1} w_i^{\beta_{m,L}(1-\sigma_m)} \prod_{k\in K} P_{i,km}(\omega)^{\beta_{km}(1-\sigma_m)} \\ &= Z_{i,m}(\omega)^{\sigma_m-1} w_i^{\beta_{m,L}(1-\sigma_m)} \prod_{k\in K} \left[\left(\sum_{u\in\mathcal{L}}\sum_{\upsilon\in\Omega_{u,k}} M_{ui,km}(\upsilon,\omega) p_{ui,km}(\upsilon,\omega)^{1-\sigma_k} \right)^{\frac{1}{1-\sigma_k}} \right]^{\beta_{km}(1-\sigma_m)} \\ &= Z_{i,m}(\omega)^{\sigma_m-1} w_i^{\beta_{m,L}(1-\sigma_m)} \mathcal{A}^S_{i,m}(\omega) \prod_{k\in K} \varsigma_k^{\beta_{km}(1-\sigma_m)}. \end{aligned}$$

Combining, we obtain the desired results.

D Additional Exhibits for Model Validation

Table D.1: Model Validation: Abstracting Production Network Reorganization

(A) First-Stage

	Dependent variable:		
	$\log w_i^{\beta_{m,L}(1-\sigma_m)} \tilde{\mathcal{A}}^S_{i,m}(\omega) \tilde{\mathcal{A}}^B_{i,m}(\omega)$		
	OLS	OLS	OLS
	(1)	(2)	(3)
Sup Exp × Post	0.23	−0.02	−0.12
	(0.68)	(0.32)	(0.29)
Buy Exp × Post	−0.56	−0.39	−0.48
	(0.67)	(0.33)	(0.31)
Firm-Type-Region-Sector Fixed Effects	X	X	X
Year Fixed Effects	X	X	X
Sector × Year Fixed Effects		X	X
Region × Year Fixed Effects			X
Observations	485	485	485
Adjusted R^2	0.81	0.96	0.96

(B) Second-Stage

	Dependent variable:					
	log Firm Out-Shipment (Value): $\log R_{i,m}(\omega)$					
	OLS	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
$\log w_i^{\beta_{m,L}(1-\sigma_m)} \tilde{\mathcal{A}}^S_{i,m}(\omega) \tilde{\mathcal{A}}^B_{i,m}(\omega)$	0.01	0.91	2.25	1.93*	4.51	1.71*
	(0.02)	(1.10)	(1.77)	(1.07)	(7.64)	(1.02)
Firm-Type-Region-Sector Fixed Effects	X	X	X	X	X	X
Year Fixed Effects	X	X	X	X	X	X
Sector × Year Fixed Effects			X	X	X	X
Region × Year Fixed Effects				X	X	X
IVs		Supplier & Buyer Exp × Post	Supplier & Buyer Exp × Post	Supplier & Buyer Exp × Post	Supplier Exp × Post	Buyer Exp × Post
Observations	485	485	485	485	485	485
Adjusted R^2	0.82	−0.77	−1.01	−0.60	−7.50	−0.28

Notes: The sample of the regression is type-region-sector-year using 2013 and 2016. Standard errors are clustered at type-region-sector level. Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table D.2: Model Validation: Omitting Wages

	Dependent variable:					
	log Firm Out-Shipment (Value): $\log R_{i,m}(\omega)$					
	OLS	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
$\log \tilde{\mathcal{A}}^S_{i,m}(\omega)\tilde{\mathcal{A}}^B_{i,m}(\omega)$	0.05**	0.91*	0.93***	0.89***	0.86***	0.93***
	(0.02)	(0.49)	(0.11)	(0.10)	(0.15)	(0.16)
Firm-Type-Region-Sector Fixed Effects	X	X	X	X	X	X
Year Fixed Effects	X	X	X	X	X	X
Sector × Year Fixed Effects			X	X	X	X
Region × Year Fixed Effects				X	X	X
IVs		Supplier & Buyer Exp × Post	Supplier & Buyer Exp × Post	Supplier & Buyer Exp × Post	Supplier Exp × Post	Buyer Exp × Post
Observations	502	502	502	502	502	502
Adjusted R^2	0.83	−0.61	0.89	0.88	0.89	0.88

Notes: The sample of the regression is type-region-sector-year using 2013 and 2016. Standard errors are clustered at type-region-sector level. Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table D.3: Model Validation: Use All Years

	Dependent variable:					
	log Firm Out-Shipment (Value): $\log R_{i,m}(\omega)$					
	OLS	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
$\log w_i^{\beta_{m,L}(1-\sigma_m)}\tilde{\mathcal{A}}^S_{i,m}(\omega)\tilde{\mathcal{A}}^B_{i,m}(\omega)$	0.06***	0.70***	0.67***	0.62***	0.64***	0.60***
	(0.01)	(0.15)	(0.12)	(0.09)	(0.15)	(0.14)
Firm-Type-Region-Sector Fixed Effects	X	X	X	X	X	X
Year Fixed Effects	X	X	X	X	X	X
Sector × Year Fixed Effects			X	X	X	X
Region × Year Fixed Effects				X	X	X
IVs		Supplier & Buyer Exp × Post	Supplier & Buyer Exp × Post	Supplier & Buyer Exp × Post	Supplier Exp × Post	Buyer Exp × Post
Observations	1,257	1,257	1,257	1,257	1,257	1,257
Adjusted R^2	0.88	0.38	0.86	0.88	0.88	0.88

Notes: The sample of the regression is type-region-sector-year using 2013 and 2016. Standard errors are clustered at type-region-sector level. Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.