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

Vasily Korovkin† Alexey Makarin‡ Yuhei Miyauchi§

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Abstract

Using firm-to-firm Ukrainian railway shipment data around the onset of the 2014 Russia-Ukraine conflict, we document that firms with prior supplier and buyer linkages to conflict areas experience a significant output decrease. Simultaneously, the former firms increase supplier linkages in peaceful areas, while the latter firms decrease them. We develop a model of production network disruption and show that it accurately explains the observed firm-level output change once we account for the network reorganization. Our model predicts around nine percent reduction in aggregate welfare strictly outside conflict areas through production network disruption and reorganization.

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†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 supply chains or production networks are crucial to firms', regions', and countries' economic activity. For example, existing empirical evidence suggests that a country is more than 20 percent richer on a per capita basis within three years of joining a manufacturing global production network (World Bank, 2019).

At the same time, recent events of supply chain disruptions, such as those caused by the COVID-19 pandemic, the Russia-Ukraine war, and the Israel-Gaza conflict, reveal a vulnerability of firms and regions that rely on these production networks. For one thing, negative shocks may be transmitted to firms that are connected through production networks. For another, the structure of supply chain networks may change as a response to shocks, especially if the shocks are intense and persist for a prolonged period.

The effects of such network reorganization on the propagation of shocks are theoretically ambiguous. On the one hand, firms may be able to find alternative suppliers and buyers to mitigate the disruption. On the other hand, shocks may induce firms to scale down production and stop sourcing from or selling to existing trading partners, generating cascading negative effects on the economy. 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 examine 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

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

We first demonstrate that the conflict has resulted in a major disruption of firms' production outside the conflict areas. To do so, we use our railway shipment data to construct proxies for firms' supplier and buyer conflict exposures—the share of transactions with suppliers and buyers in the conflict areas before the onset of the conflict. Using a difference-in-differences strategy, we document that firms with a positive supplier or buyer exposure experienced a sudden 18% decline in sales compared to firms without any trade connections to the conflict areas. These effects are present for both the supplier and buyer conflict exposures separately. They are also robust to various checks, such as flexibly accounting for firms' distance to the conflict areas or controlling for the region-year or the industry-year fixed effects. 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 led to a systematic reorganization of the production network structure even outside conflict areas. To do so, we use our railway shipment data to define the changes in supplier and buyer linkages before and after the onset of the conflict. We then implement the difference-in-differences strategy to study how these linkages change depending on firms' supplier and buyer conflict exposures.

Our findings are summarized threefold. First, firms with a higher supplier conflict exposure *increased* supplier linkages strictly outside conflict areas. This evidence suggests that the loss of suppliers in the conflict areas is partially substituted by the suppliers in peaceful areas. Second, firms with a higher buyer conflict exposure *decreased* supplier linkages strictly outside conflict areas. This evidence is consistent with an interpretation that firms scaled down supplier portfolios as a response to demand reduction. Third, firms with higher conflict exposures, both for the supplier and buyer-sides, *decreased* buyer linkages strictly outside conflict areas. This evidence is consistent with an interpretation that the conflict shocks have resulted in production disruption, which led to the loss of buyer linkages even outside conflict areas. Overall, our evidence suggests that the localized conflict shocks have caused a mix of positive and negative responses in production linkages even outside the conflict areas, depending on whether firms are exposed to the conflicts through their suppliers or through their buyers.

Our results so far provide evidence for the supply chain disruption and how the production networks reorganize as a response to conflict shocks. However, there are at least two limitations in translating these reduced-form estimates to the economy-wide effect. First, our reduced-form evidence is based on the differences-in-differences strategy, comparing firms with different levels of direct supplier and buyer conflict exposures. However, firms without direct production linkages with conflict areas may also be affected by the shock, e.g., through their higher-order connections in production networks (suppliers' suppliers, buyers' buyers, and so on). This leads to a violation of the Stable Unit Treatment Value Assumption (SUTVA) and we cannot interpret the difference-in-differences results as the overall effect of the localized conflict on nonconflict areas. Second, the reduced-form evidence alone does not inform us about how the pattern of the reorganization of production networks is related to the changes in firm-level output and aggregate welfare.

To overcome these limitations, we develop a multi-sector and location general equilibrium trade model to analyze how the disruption and reorganization of production networks affect firm production and aggregate welfare. Firms produce differentiated varieties of intermediate inputs. Production requires labor and intermediate inputs, which are sourced from other firms connected through production networks in various locations and sectors. Having a larger number of suppliers benefits production through a love of variety in intermediate inputs. We also allow for the possibility that supplier and buyer connections may change as a response to shocks. Productivity or trade cost shocks to a particular segment of the economy affect firms' output not only through their direct supplier and buyer connections but also through their indirect production linkages and their reorganization as a response to shock.

Our model illustrates how and why disruption and reorganization of production networks affect firm-level output and aggregate welfare. In particular, we show that "supplier and buyer accesses" serve as sufficient statistics for a firm's output under general equilibrium. The supplier access summarizes the cost linkages of the firm, capturing direct and indirect supplier linkages as well as how these linkages change as a response to the shock. Buyer access summarizes the demand linkages of the firm, capturing direct and indirect buyer linkages as well as how these linkages change as a response to the shock. 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 observed changes in production linkages. Therefore, our sufficient statistics expression holds across a broad class of models that take alternative microfoundations for production network formation.

A key benefit of these sufficient statistics is that we can explicitly test our model prediction using observed firm-level output changes and the observed patterns of production network disruption and reorganization. To execute this idea, we estimate supplier and buyer accesses using our railway shipment data from Ukraine before and after the onset of the conflict. We then regress the model-predicted changes in firm-level output based on estimated supplier and buyer accesses using the observed changes in firm-level output. To deal with the endogeneity of the firm output, we use the supplier and buyer conflict exposures interacted with post-conflict dummies as instrumental variables (IV), following the empirical strategy in the reduced-form section. We find that the IV regression coefficients are close to one, indicating that our model-predicted output changes move one-for-one with the observed counterpart. Importantly, even with tight standard errors, we cannot reject the null hypothesis that the regression coefficient is one. In contrast, when we abstract from the changes in supplier and buyer linkages when estimating supplier and buyer accesses, the regression coefficients tend to be significantly below one. These findings suggest that, without taking into account the reorganization of production network reorganization, one may underestimate the variation in firm-level effects of supply chain disruption.

Having validated our model, we use it to assess the aggregate welfare effects of supply chain disruption and reorganization due to the 2014 Russia-Ukraine conflict. To do so, we calibrate our model using the pre-conflict period. We then 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 several alternate scenarios of production network reorganization. In our baseline scenario, we change the production linkages consistent with our difference-in-differences estimates depending on the firms' supplier and buyer conflict exposures. We compare this baseline scenario to a version where we fix the production linkages before the onset of the conflict.

We find that the aggregate welfare strictly outside conflict areas decreases on average by 9.1 percent in our baseline scenario. These large welfare losses are consistent with the economic importance of the conflict areas within Ukraine's economy before the onset of the conflict. We also find that, while the welfare loss is larger for regions that are geographically close to the conflict areas, regions that are geographically remote from the conflict areas (e.g., the western side of Ukraine) also face a substantial welfare loss. Therefore, the localized conflict has far-reaching and detrimental economic consequences through production network disruption.

We also find that the reorganization of production linkages plays a quantitatively important role in the aggregate welfare loss. If we shut down the increase in supplier linkages by firms with high supplier conflict exposures, the welfare loss will increase to 11.4 percent. This result indicates that the substitution of supplier linkages toward peaceful areas tends to mitigate the aggregate welfare effects of supply chain disruption. Alternatively, if we shut down the decrease in supplier linkages by firms with high buyer conflict exposures, the welfare loss decreases to 6.8 percent. This result indicates that scaling down supplier linkages by these firms amplifies the negative effects of supply chain disruption. Finally, if we shut down both channels, thereby fixing the production networks at the pre-conflict levels, we find a 9.0 percent reduction in aggregate welfare, similar in magnitude to our baseline scenario. Therefore, the disparate firm-level reorganization of production networks, as documented in our reduced-form section, have roughly offsetting effects in the aggregate welfare changes in this context.

Related 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, and quantify its implication for firm production and aggregate welfare. Our paper is also related to Khanna, Morales, and Pandalai-Nayar (2022), who provide empirical evidence on how firms' production and supplier retention and acquisition patterns are affected if their existing suppliers are exposed to lockdowns during the COVID-19 pandemic in India. Besides an obvious difference in the contexts, our paper differs in two key dimensions. First, we show how firms reorganize both supplier and buyer linkages as a response to both supplier and buyer exposures to conflict areas, thereby capturing comprehensive patterns of the reorganization of production networks. Second, we provide a theory and quantification for how these reorganizations affect firm-level output and aggregate welfare.[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* 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

[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), who studies 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 bilateral search and matching; and Oberfield (2018); Acemoglu and Azar (2020); Taschereau-Dumouchel (2020) consider optimal supplier choice.

need to impose more structure to predict the counterfactual changes in production networks.[5]

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.[6] Instead, our focus is on 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 effect on firm sales by directly utilizing data on actual trade between firms, we also provide evidence for the reorganization of firm-level production networks, and how this reorganization affects 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 model-based 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

[5] Our approach is related to Baqaee, Burstein, Duprez, and Farhi (2023), who analyze the role of supplier churning on firm production and aggregate welfare. In contrast to their nonparametric approach, we focus on the parametric production function common in the existing literature to derive succinct sufficient statistics and apply it to the context of the 2014 Russia-Ukraine conflict.

[6] 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 interfirm 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). See also Behrens (2024) for the conflict's impact on the Russian firms located near Ukraine.

provinces (i.e., the Donbas region).[7] The annexation was complete by early March 2014; it occurred without direct military conflict. Later, pro-Russian protests ensued in Donbas. Groups of protesters captured security service buildings and main administrative buildings and 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 acting Ukrainian president launched an "Anti-Terrorist 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.[8] The conflict has been in a rather "frozen" state after the Minsk agreements and especially following the election of President Zelensky until 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.

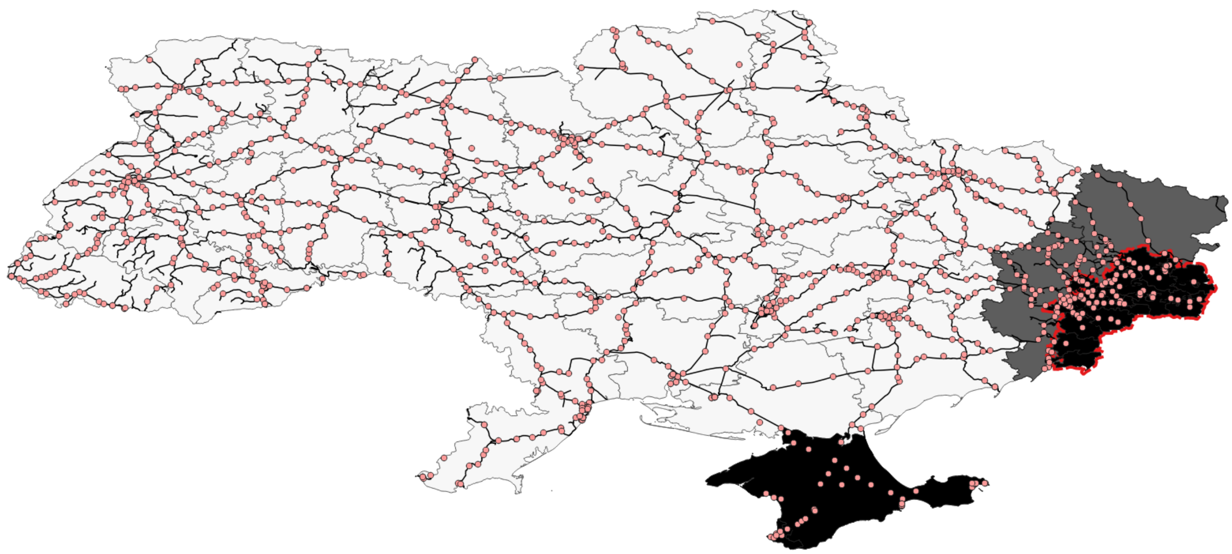
Economic Activity in Donbas and Crimea. Before the conflict, Donbas and Crimea accounted for a sizeable share of Ukraine's economy. Together, they were responsible for about 17.5% of Ukraine's 2013 GDP. The Donbas region has always been prominent for its extractive industries, especially coal, metallurgy, 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 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 annexation,

[7]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).

[8]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.

hosting 2.2 million people and being the center of several industries, such as shipbuilding.[9]

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 two years, manufacturing production fell by 50% in Donetsk oblast and by more than 80% in Luhansk oblast (Amosha, Buleev, and Zaloznova, 2017, pp.132–133; see also Appendix A.5).

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,

[9] Appendix Figure A.1 shows the distribution of the shares of manufacturing, mining, and other sectors across regions within Ukraine.

as of 2018, railroads were responsible for 80% of ton-km of all freight transport.[10] 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).[11] 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.[12] The dataset contains around 100 million transactions between around 8,500 firms. It includes shipment dates, weights (in kg), freight charges, product codes (ETSNV codes with around 4,600 unique classifications), 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. We use the railway shipments data both for the purpose of defining firms' preexisting supplier and buyer linkages before the onset of the conflict (i.e., supplier and buyer conflict exposures) and as outcome variables for the changes in production linkages before and after the onset of the conflict.[13]

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 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 first use separate customs data from Ukraine to obtain the geometric mean of the value per weight of imported and exported product codes at the HS-8-digit code level. We then use the correspondence between HS-8-digit code and ETSNV codes (the product code classification in our railway shipment data) to impute the value of each transaction. Appendix B describes further details of

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

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

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

[13] To focus our analysis on trade between firms, we discard intra-firm trade, which constitutes 6.5 % of all transactions in weight shares in 2013.

this procedure.

One limitation of this data set is that we only observe the shipment over railways but not through other transportation modes. We believe that our results are not substantially biased by this limitation for two reasons. First, as noted earlier, railroads were responsible for 80% of ton-km of all freight transport, due to a relatively high-quality railway network system compared to other modes of shipment. Second, by focusing on the changes in firm-level trade patterns in our difference-in-differences strategy, any time-invariant factors that affect the coverage rates of railway shipment out of overall shipment is absorbed through firm-level fixed effects. Therefore, the only identification concern is the presence of systematic time-varying factors in the coverage rates of railway shipments. We argue that assuming away such time-varying factors is plausible especially when we study the reorganization of production networks *strictly outside conflict areas* in Section 3.3, as there were no systematic disruption specific to railway networks relative to road networks within peaceful areas of Ukraine.[14]

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.[15] We combine these two data sets for their complementary coverage 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.

[14]See Appendix C.4 for a more detailed discussion of this identification concern using a formal model where firms choose shipment modes.

[15]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).

Customs Data. For our value-imputation exercise and for some of the robustness checks, we also use the transaction-level customs data for Ukraine from 2012 through 2016. For each international shipment, we observe its date, weight, value (in Ukrainian hryvnia), product code, direction (export or import), tax ID of the Ukrainian firm, and the country of the firm's counterpart.

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.

2.3 Conflict Exposures and Summary Statistics

Our main reduced-form empirical design is to study how firms' preexisting supplier and buyer linkages with conflict areas affect the changes in firms' output and reorganization of production networks after the onset of the conflict. To do so, we define "conflict areas" as the combination of Crimea and the part of the Donbas area where the separatists were active (DPR and LPR regions). Although Crimea was not directly affected by violence, the trade linkages to both areas were substantially disrupted after the onset of the conflict as we document below.

Table A.1 displays the summary statistics for our datasets, including the pattern of the preexisting trade linkages with conflict areas. 55% of firms in our data have traded with the conflict areas in 2012–2013, i.e., before the conflict started. An average firm received 11% of their 2012–2013 incoming shipments from the conflict areas and sent 10% of their 2012–2013 outgoing shipments to the conflict areas. The median revenue of the firms 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 are in manufacturing.

Besides the disruption of trade linkages within Ukraine, the conflict has also resulted in a disruption of international trade, in particular to and from Russia. In this paper, we primarily focus on the disruption of production networks from/to conflict areas within Ukraine. We make this choice because, for Ukrainian firms outside conflict areas, trade exposures with conflict areas within the Ukrainian border are substantially larger than those with Russia: according to Table A.1, 55% of the firms in our sample have traded with the conflict areas in 2012–13 but only 23% traded with Russia in 2012–13. Furthermore, while the trade with conflict areas fell to almost zero as we show below, the trade with Russia declined only about a half. At the same time, to deal with a concern that our primary exposure proxies with conflict areas are confounded by preexisting trade with Russia, we present robustness by controlling for the trade exposure to Russia using our separate customs data.

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 of a substantial decline in transactions between firms in and outside direct conflict areas. Section 3.2 presents evidence that firms outside conflict areas with prior supplier and buyer linkages to those areas experience a significant output decrease. Section 3.3 presents evidence that firms with prior supplier and buyer linkages with conflict areas change their supplier and buyer linkages outside conflict areas.

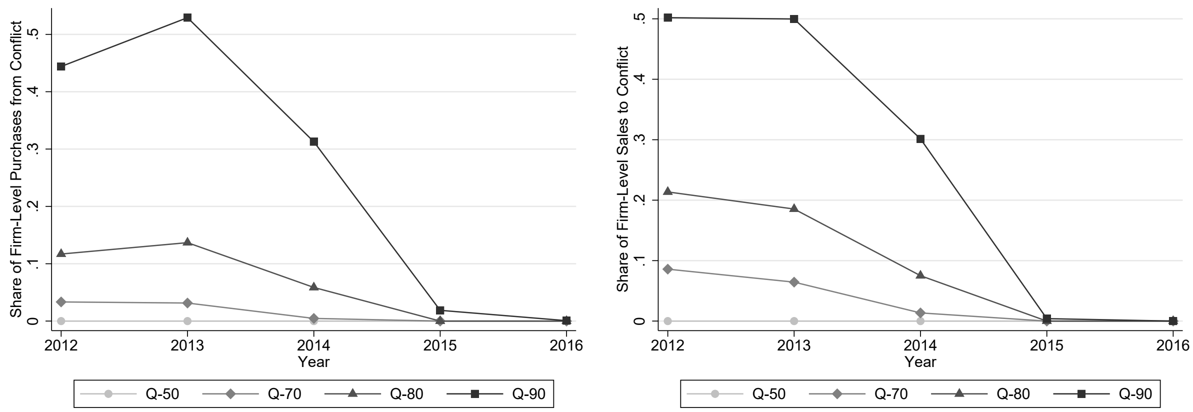
3.1 Impacts on Trade with Conflict Areas

We first 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 firms that received any shipments from the conflict areas in 2012–2013. We present the median and the upper percentiles (70th, 80th, and 90th) of the distribution of the yearly value of shipments received by a firm from the conflict areas normalized by the total value of the firm's incoming shipments. The right-hand-side panel of Figure 2 performs the same analysis, focusing on firms sending their goods to Crimea and the occupied parts of Donbas. In both instances, the receiving and sending loading percentiles plummet to zero at a rapid rate, become close to zero by 2015 and precisely zero by 2016.

These sharp declining patterns are confirmed in event-study graphs displayed in Figure A.2, which show that an average firm reduced the share of its trade with the conflict areas by 8–10 percentage points by 2015–2016, with negligible pretrends prior to the conflict. Figures A.3 and A.4 based on shipment weight as opposed to value present identical results.

Overall, these estimates suggest that trade between the conflict areas and the rest of Ukraine was severely disrupted as a result of the Annexation of Crimea and the war in Donbas. In the

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



Notes: This figure displays the evolution of the distribution of firm trade share with DPR, LPR, and Crimea. Q-50 refers to the median, Q-70 refers to the 70th percentile, Q-80 refers to the 80th percentile, and Q-90 refers to the 90th percentile of the distribution. The figure on the left (right) describes the distribution for the share of firm sales that went to (purchases that came from) conflict areas, measured as the value of the shipments sent to (received from) the conflict areas divided by the total value of the shipments sent out (received) by a given firm that year. Value is imputed based on the weight and product type of a given shipment based on the customs data, as described in Appendix B.

immediate conflict areas in Donbas region, this disruption of transactions is likely driven by the severe disruption of firm operation in those areas, coupled with the disruption of transportation and boycotts.[16] In what follows, we analyze how these disruptions in trade linkages to conflict areas relate to firms' output and reorganization of production linkages strictly outside conflict areas.

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. We estimate the following equation:

$$Y_{it} = \alpha_i + \delta_t + \beta \times \text{Post}_t \times \text{ConflictExposure}_{i,2012-13} + \varepsilon_{it}, \tag{1}$$

[16]Figure A.7 shows a large and sharp decline in firms' reported output in the conflict areas in the Donbas region. The official trade blockade of Donbas came into effect only after our study period, in March 2017 (Fisman, Marcolongo, and Wu, 2024), and the official trade blockade of Crimea started only in mid-December 2015 (see, e.g., https://tass.com/world/844510), so the decline in trade with the conflict areas is not mechanical, with the possible exception of trade with Crimea in 2016.

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.

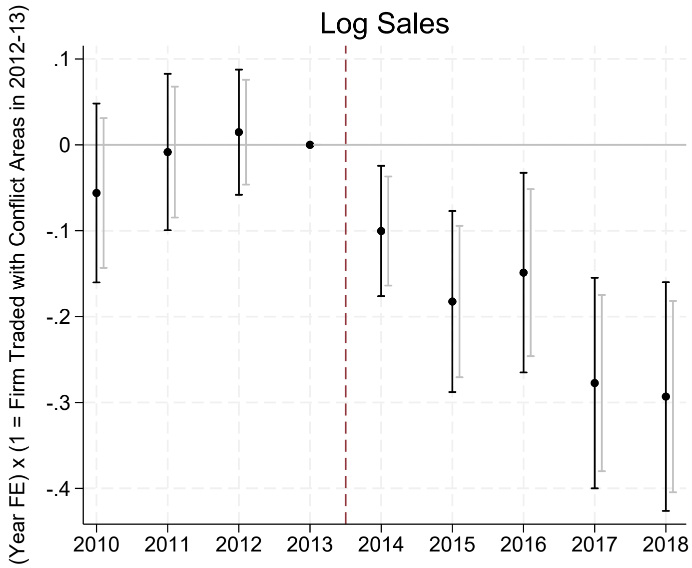
The specification raises two main concerns. First, one may worry about the plausibility of the parallel trends assumption. Specifically, for β to accurately estimate the causal effect of conflict on firms through production linkages, it's crucial that the outcomes of firms with varying degrees of trade engagement with conflict areas would have evolved similarly in a counterfactual scenario absent the conflict. Second, the measure of firms' exposure to conflict through trade could be confounded with other conflict-induced shocks that affect either demand (for instance, due to military demand) or supply (such as through refugee resettlement). To address the first issue, we present the dynamic difference-in-differences estimates and examine them for potential pretrends. To address the second issue, we provide a battery of robustness checks, including controlling for the region-year and industry-year fixed effects as well as testing whether the flows of internally-displaced persons were correlated with trade conflict exposures.

Baseline Results. Figure 3 presents our baseline estimates of the conflict's impact on firm sales, slightly modifying Equation (1) by interacting the year fixed effects with the conflict exposure indicator. The results show no pretrends, reinforcing the validity of the parallel trends assumption introduced above, followed by a sharp and persistent differential drop in firm sales of 10–30 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 areas through production linkages.

Encouraged by the patterns in Figure 3, we now estimate Equation (1) focusing not only on the annual accounting sales but also on an indicator of whether accounting sales data is missing, which we interpret as an alternative proxy for production disruption.

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 18.3% decline in sales compared to firms without such connections. Column (2) shows that these firms are also 8.8 percentage points more likely to cease reporting sales data in a given year. Importantly, the sales impact is not driven by differential attrition, as our analysis presented later confirms that the effect holds even restricting the sample to firms that reported sales every year. These estimates

Figure 3: Conflict Exposures and Sales of Firms in Non-Conflict Areas



Notes: This figure displays the results of estimating Equation (1) 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.

are large compared to existing studies. For instance, Carvalho et al. (2021) find that firms who had at least one supplier or buyer directly exposed to the Great East Japan Earthquake saw a reduction in their sales by 3–4% the year after. We interpret this difference in magnitudes as being due to the size and persistence of the conflict shock in our context.

Next, we disaggregate firm connections to the conflict areas into those coming from the supplier side and those coming from the buyer side and estimate the following specification:

$$Y_{it} = \alpha_i + \delta_t + \beta \times \text{Post}_t \times \text{BuyerExposure}_{i,2012-13} + \gamma \times \text{Post}_t \times \text{SupplierExposure}_{i,2012-13} + \varepsilon_{it}, \quad (2)$$

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.[17] The estimates, presented in Columns (3)–(6) of Table 1, demonstrate that connections to conflict areas, regardless of direction, affect firm performance

[17]Table A.4 shows that the results remain similar if we use weight-based exposures instead.

Table 1: Conflict Exposures and 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 × 𝟙[Firm traded with conflict areas, 2012–13]	-0.183***	0.088***				
	(0.046)	(0.010)				
Post-2014 × Firm's buyer conflict exposure, 2012–13			-0.265**	0.074***		
			(0.109)	(0.025)		
Post-2014 × Firm's supplier conflict exposure, 2012–13			-0.316***	0.106***		
			(0.103)	(0.022)		
Post-2014 × 𝟙[High firm's buyer conflict exposure, 2012–13]					-0.197***	0.051***
					(0.069)	(0.014)
Post-2014 × 𝟙[High firm's supplier conflict exposure, 2012–13]					-0.167**	0.069***
					(0.066)	(0.014)
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Mean	16.890	0.327	16.890	0.327	16.890	0.327
SD	2.484	0.469	2.484	0.469	2.484	0.469
Observations	35,029	52,272	35,029	52,272	35,029	52,272
Number of Firms	4,802	6,071	4,802	6,071	4,802	6,071

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

negatively and with broadly similar magnitudes.

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, such firms experience a substantial and lasting reduction in total revenue and see an increased probability of missing reported sales. These estimates add to the conflict literature that thus far has mostly focused on the impact on firms directly exposed to the violence (e.g., Amodio and Di Maio, 2018; Del Prete et al., 2023).

Robustness. In Appendix A.3, we demonstrate that the findings above are robust to a battery of checks. Specifically, the results are invariant to restricting the sample to firms that reported revenue every year. Furthermore, the estimates remain similar when we flexibly account for the proximity of firms to conflict areas, control for firms' prewar trade with Russia, and include industry-year and region-year fixed effects in the specification. Finally, our results remain unchanged if we exclude firms located close to the conflict areas or in Kyiv.

3.3 Evidence of Reorganization of Production Networks

We next show that the conflict shock has led to a systematic reorganization of the production network structure strictly outside conflict areas. To do so, we use our railway shipment data to define the changes in supplier and buyer linkages before and after the onset of the conflict. We then implement the difference-in-differences strategy to study how these linkages change depending on firms' supplier and buyer conflict exposures.

To examine whether firms reorganize their production linkages strictly outside conflict areas, we estimate Equation (2) but with the total number of trade linkages with the nonconflict areas as outcomes. Furthermore, to study pretrends and the effect dynamics, we estimate an event-study version of the equation whereby we interact firm conflict exposures with the year fixed effects.

Figure 4 presents the resulting estimates for the number of suppliers and buyers in the nonconflict areas. In the left figure, we present the results where the dependent variable is the log number of the firms' *suppliers* strictly outside conflict areas. In the right figure, we present the results where the dependent variable is the log number of the firms' *buyers* strictly outside conflict areas. In both figures, we present the estimated regression coefficients and their 95 percent confidence intervals for the interaction between supplier and buyer conflict exposures and the year dummies.

In the left panel of Figure 4, we find that firms with a higher supplier conflict exposure increased supplier linkages strictly outside conflict areas. There are no pretrends, and the effects occur immediately after the onset of the conflict in 2014. This evidence suggests that the loss of suppliers in the conflict areas is partially substituted by the suppliers in peaceful areas. We also find that, firms with a higher buyer exposure decreased supplier linkages strictly outside conflict areas. In contrast to the responses in supplier linkages, this effect occurs relatively gradually over time and becomes significant in 2016. This evidence is consistent with an interpretation that firms scaled down supplier portfolios as a response to demand reduction.

In the right panel of Figure 4, we find that firms with a higher supplier conflict exposure decreased buyer linkages strictly outside conflict areas. There are no pretrends, and the effects increase gradually as time goes by. This evidence is consistent with an interpretation that both supplier and buyer conflict exposures translated in production disruption, which resulted in the loss of buyer linkages even in peaceful areas. We also find that firms with a higher buyer conflict exposure decreased buyer linkages strictly outside conflict areas, although we find significant pretrends for this outcome variable.

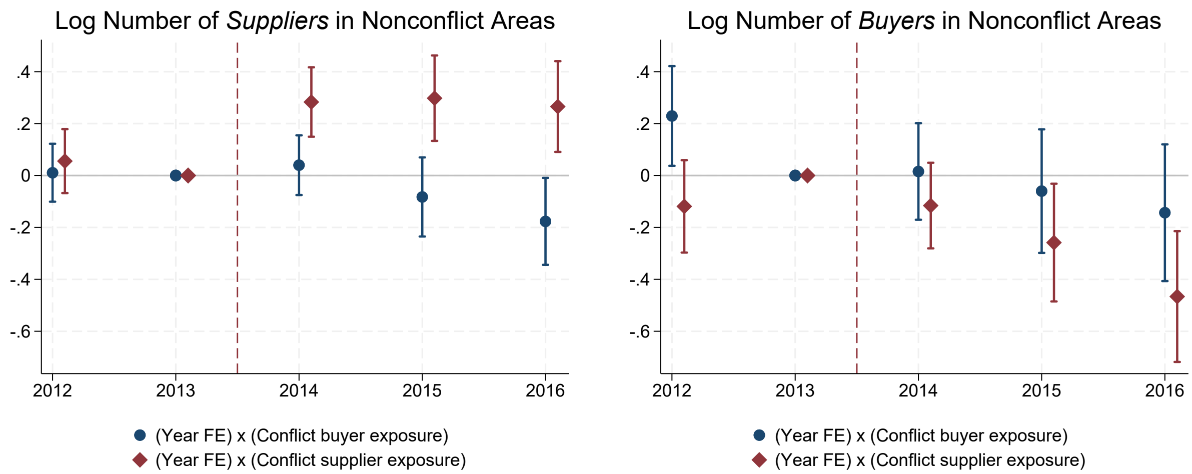
Table 2 displays the non-dynamic estimates for the number of linkages. The results confirm the patterns displayed earlier in Figures 4. Column (3) of Table 2 suggests that firms with high supplier conflict exposure increased the number of suppliers in nonconflict areas by 10%, suggesting substitution. In turm, firms with high buyer conflict exposure decreased the number of buyers in the nonconflict areas by 6%, suggesting scaling-down effects. Albeit the latter effect is marginally statistically insignificant, Figure 4 shows that it becomes large and statistically different from zero over time. Column (4) of Table 2 implies that both firms with high buyer exposure and firms with high supplier exposure reduced the number of buyers in nonconflict areas by 10.6–13.2%.[18]

Finally, Table A.6 displays the estimates for the total number of linkages and the total volume of shipments, respectively (instead of only within non-conflict areas). We find negative effects across the board, including the impacts of conflict supplier exposure on the number of suppliers (Column 1). This pattern indicates that the substitution of supplier linkages induced by a higher supplier conflict exposure only imperfectly recovers the number of suppliers.

Overall, our evidence suggests that the localized conflict shocks have led to a mix of positive and negative responses in production linkages outside the conflict areas, depending on whether firms are exposed to the conflicts through their suppliers or their buyers.

[18]Figure A.6 and Table A.5 examine the impact on the total *volume* of outgoing and incoming shipments into and from nonconflict areas (instead of the number of linkages) and show that these effects generally mirror the findings in Figure 4, suggesting that the changes in linkages crucially drive the trade patterns.

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



Notes: This figure displays the results of estimating Equation (2) 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.

Table 2: The Impact of Conflict Exposures on Firm's Linkages with Non-Conflict Areas

	(1) Log # of Suppliers in Nonconflict Areas	(2) Log # of Buyers in Nonconflict Areas	(3) Log # of Suppliers in Nonconflict Areas	(4) Log # of Buyers in Nonconflict Areas
Post-2014 × Firm's buyer conflict exposure, 2012–13	-0.099	-0.192**		
	(0.062)	(0.097)		
Post-2014 × Firm's supplier conflict exposure, 2012–13	0.245***	-0.199**		
	(0.066)	(0.095)		
Post-2014 × $\mathbb{1}$[High firm's buyer conflict exposure, 2012–13]			-0.060	-0.132***
			(0.037)	(0.046)
Post-2014 × $\mathbb{1}$[High firm's supplier conflict exposure, 2012–13]			0.103***	-0.106**
			(0.037)	(0.051)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean	1.755	1.916	1.755	1.916
SD	1.247	1.488	1.247	1.488
Observations	20,628	13,410	20,628	13,410
Number of Firms	4,983	3,600	4,983	3,600

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.

4 Model

In the previous section, we provide reduced-form evidence for the supply chain disruption and reorganization based on difference-in-differences method. These estimates, however, do not provide economy-wide effect as firms without direct production linkages with conflict areas may also be affected by the shock, for instance, through their higher-order connections in production networks. Furthermore, the reduced-form evidence does not inform us about how the pattern of the reorganization of production networks is related to firm-level output and aggregate welfare. In this section, we build a multi-location and sector general equilibrium trade model of production network disruption and reorganization to overcome these challenges.

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. Each firm also belongs to a sector denoted by $k, m, l \in K$. Firms produce goods that can be used both for intermediate and final use using labor and intermediate goods. Intermediate goods can be traded across firms in different locations and sectors subject to iceberg 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 $v, \omega, \psi \in \Omega_{i,k}$. These firm types capture the heterogeneity of firm productivity, trade costs, and production linkages. While our model accommodates an arbitrary dimension of firm heterogeneity, in our quantification in Section 5, we particularly focus on firm heterogeneity with respect to preexisting supplier and buyer linkages to conflict areas.[19] 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

[19] 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.

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

$$Y_{i,m}(\omega) = Z_{i,m}(\omega) \left(\frac{L_{i,m}(\omega)}{\beta_{m,L}}\right)^{\beta_{m,L}} \prod_{k \in K} \left(\frac{Q_{i,km}(\omega)}{\beta_{km}}\right)^{\beta_{km}}, \tag{3}$$

where $Z_{i,m}(\omega)$ is the total factor productivity (TFP), $L_{i,m}(\omega)$ 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 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 $M_{ui,km}(\upsilon, \omega)$. Therefore, the input composite $Q_{i,km}(\omega)$ is given by

$$Q_{i,km}(\omega) = \left(\sum_{u \in \mathcal{L}} \sum_{\upsilon \in \Omega_{u,k}} M_{ui,km}(\upsilon, \omega) q_{ui,km}(\upsilon, \omega)^{\frac{\sigma_k - 1}{\sigma_k}}\right)^{\frac{\sigma_k}{\sigma_k - 1}}, \tag{4}$$

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 a firm type, firms are identical in terms of the measure of supplier and buyer connections. Therefore, without a risk of confusion, we may 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.[20] However, unlike these existing approaches, we do not take a specific microfoundation of these production linkages. Instead, we develop sufficient statistics for firm-level and aggregate welfare given *observed* patterns in production linkages, without specifying the rules that determine $\{M_{ui,km}(\upsilon, \omega)\}$ in the equilibrium.

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

[20] 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.

following technology

$$Y_i^F = \prod_{k\in K} \left(\frac{Q_{i,k}^F}{\alpha_k}\right)^{\alpha_k}, \qquad Q_{i,k}^F = \left(\sum_{\omega\in\Omega_{i,k}} N_{i,k}(\omega) q_{i,k}^F(\omega)^{\frac{\sigma_k-1}{\sigma_k}}\right)^{\frac{\sigma_k}{\sigma_k-1}}, \tag{5}$$

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 $\omega \in \Omega_{i,m}$ to 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 (4), and the fact that there are continuum of suppliers connected to each buyer, 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 type $\psi \in \Omega_{d,l}$ is given by

$$p_{id,ml}(\omega,\psi) = \frac{\sigma_m}{\sigma_m - 1} C_{i,m}(\omega)\, \tau_{id,ml}(\omega,\psi), \tag{6}$$

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 (3) and (4) as

$$C_{i,m}(\omega) = \frac{1}{Z_{i,m}(\omega)} w_i^{\beta_{m,L}} \prod_{k\in K} P_{i,km}(\omega)^{\beta_{km}}, \tag{7}$$

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

$$P_{i,km}(\omega) = \left(\sum_{u\in\mathcal{L}} \sum_{\upsilon\in\Omega_{u,k}} M_{ui,km}(\upsilon,\omega) p_{ui,km}(\upsilon,\omega)^{1-\sigma_k}\right)^{\frac{1}{1-\sigma_k}}. \tag{8}$$

Given the vector of wages $\{w_i\}$ and the production linkages $\{M_{ui,km}(\upsilon,\omega)\}$, Equations (6), (7), and (8) uniquely determine the set of prices $\{p_{id,ml}(\omega,\psi), C_{i,m}(\omega), P_{i,km}(\omega)\}$.

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 $D^*_{i,km}(\omega)$.[21] Then, from the CES input demand (Equation 8), 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

$$X_{ui,km}(\upsilon,\omega) = \varsigma_k M_{ui,km}(\upsilon,\omega)\tau_{ui,km}(\upsilon,\omega)^{1-\sigma_k} C_{u,k}(\upsilon)^{1-\sigma_k} D_{i,km}(\omega), \tag{10}$$

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 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*

$$R_{i,m}(\omega) = \tilde{\varsigma}_m Z_{i,m}(\omega)^{\sigma_m-1} w_i^{\beta_{m,L}(1-\sigma_m)} \mathcal{A}^S_{i,m}(\omega)\mathcal{A}^B_{i,m}(\omega), \tag{11}$$

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

$$\mathcal{A}^S_{i,m}(\omega) \equiv \prod_{k\in K}\left(\sum_{u\in\mathcal{L}}\sum_{\upsilon\in\Omega_{u,k}} M_{ui,km}(\upsilon,\omega)\tau_{ui,km}(\upsilon,\omega)^{1-\sigma_k} C_{u,k}(\upsilon)^{1-\sigma_k}\right)^{\frac{1-\sigma_m}{1-\sigma_k}\beta_{km}}, \tag{12}$$

$$\mathcal{A}^B_{i,m}(\omega) \equiv \sum_{l\in K}\sum_{d\in\mathcal{L}}\sum_{\psi\in\Omega_{d,l}} M_{id,ml}(\omega,\psi)\tau_{id,ml}(\omega,\psi)^{1-\sigma_m} D_{d,ml}(\psi). \tag{13}$$

[21] Specifically, from intermediate goods market clearing,

$$D^*_{i,km}(\omega) = \beta_{km}\frac{\sigma_m-1}{\sigma_m}\left(R_{i,m}(\omega) + R^F_{i,m}(\omega)\right), \tag{9}$$

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

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 $Z_{i,m}(\omega)$ is higher. 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., $\mathcal{A}^S_{i,m}(\omega) \propto \left[\prod_{k\in K} P_{i,km}(\omega)^{\beta_{km}}\right]^{1-\sigma_m}$. 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, locations, and sectors. Buyer access represents the potential of making sales to other firms. It is a sum of demand shifter $D_{d,ml}(\psi)$, weighted by the iceberg trade costs $\tau_{id,ml}(\omega,\psi)^{1-\sigma_m}$ and the measure of buyer 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). We extend their insights by allowing for the effects of the 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 with direct supplier and buyer linkages to those areas experience a relative sales decline. However, firms may be indirectly affected through production networks even if they are not directly connected to the conflict areas. Furthermore, changes in production linkages $\{M_{ui,km}(\upsilon,\omega)\}$ also affect these accesses. Proposition 1 provides 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 5), and assuming that there are no iceberg trade costs between firms and retailers, the final goods sales of firm type $\omega \in \Omega_{i,m}$ is given by

$$R^F_{i,m}(\omega) = \frac{\varsigma_m N_{i,m}(\omega)\, C_{i,m}(\omega)^{1-\sigma_k}}{\left(P^F_{i,m}\right)^{1-\sigma_m}} \alpha_m E_i L_i, \tag{14}$$

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

$$P^F_{i,m} = \left(\varsigma_m \sum_{\omega \in \Omega_{i,m}} N_{i,m}\left(\omega\right) C_{i,m}\left(\omega\right)^{1-\sigma_m} \right)^{\frac{1}{1-\sigma_m}}. \tag{15}$$

The labor market clearing at each location is given by

$$w_i L_i = \sum_{m \in K} \beta_{L,m} \frac{\sigma_m - 1}{\sigma_m} \sum_{d \in \mathcal{L}} \sum_{\psi \in \Omega_{d,l}} \left(R_{i,m}(\omega) + R^F_{i,m}(\omega) \right), \tag{16}$$

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

We assume that representative workers in each location own local firms. Therefore, per-capita income is given by

$$E_i = w_i + \frac{1}{L_i} \sum_{m \in K} \sum_{\omega \in \Omega_{i,m}} \pi_{i,m}(\omega), \tag{17}$$

where $\pi_{i,m}(\omega)$ is the profit by firm type $\omega \in \Omega_{i,m}$, given by[22]

$$\pi_{i,m}(\omega) = \sum_{m \in K} \frac{1}{\sigma_m} \sum_{d \in \mathcal{L}} \sum_{\psi \in \Omega_{d,l}} \left(R_{i,m}(\omega) + R^F_{i,m}(\omega) \right). \tag{18}$$

Together, given TFP $\{Z_{i,m}(\omega)\}$, trade costs $\{\tau_{id,ml}(\omega, \psi)\}$, measure of firms $\{N_{i,m}\}$, and the rules for production linkages $\{M_{id,ml}(\omega, \psi)\}$, the equilibrium is defined by the set of prices $\{p_{id,ml}(\omega, \psi), C_{i,m}\left(\omega\right), P_{i,km}(\omega), P^F_i, w_i\}$, 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 (6), (7), (8), (10), (11), (15), (16), (17), and (18).

[22]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. Alternatively, our formulation is also isomorphic to models satisfying the macro restriction that the aggregate profit is a constant fraction of aggregate labor compensation (i.e., Macro Restriction 2 in Arkolakis, Costinot, and Rodríguez-Clare, 2012). This assumption is satisfied, for example, in a single sector version of Arkolakis et al. (2023) using labor and intermediate inputs for search costs.

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

$$\mathcal{W}_i = \frac{E_i}{P_i^F}, \tag{19}$$

where $P_i^F = \prod_{m \in K} \left(P_{i,m}^F\right)^{\alpha_m}$.

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 the 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 were 27 regions in total (including 2 cities of regional significance). We treat all of Crimea, Sevastopol, and the occupied parts of Donetsk and Luhansk oblasts as one single "conflict" location in our model. We treat the parts of Donetsk and Luhansk oblasts under the control of the Ukrainian government as two independent locations. Altogether, our location set $\mathcal{L}$ consists of 26 locations, with 25 locations strictly outside the conflict areas. We segment firms into three sectors: Mining, Manufacturing, and Other. We take this definition to reflect the importance of mining and manufacturing sectors in direct conflict and surrounding areas (see Figure A.1 for the spatial distribution of these industries). We take the unit of "firms" in our model as a combination of firm ID and the region in our data.

In our context, a crucial aspect of firm heterogeneity is the firms' preexisting trade linkages with conflict areas. We divide the set of firms within a location into four types based on the supplier and buyer exposures with conflict areas before the onset of the war. Specifically, we define high supplier conflict exposure firms where the value share of in-shipment from conflict areas in our railway shipment data is above the 85th percentile of the entire firms in our sample before 2013, following the definition of high/low exposures in Section 3. Similarly, we define high buyer conflict exposure as those where the value share of out-shipment to conflict areas in our railway shipment data is above the 85th percentile of the entire firms in our sample. We then divide firms in each region and sector into four types: (1) high supplier and buyer exposures, (2) high supplier exposure and low buyer exposure, (3) low supplier exposure and high buyer exposures, (4) low suppliers and buyer exposures. These four types of firms correspond to firm types $\Omega_{i.k}$ in our model.

We calibrate structural parameters $\{\beta_{L,m}, \beta_{km}, \alpha_k, \sigma_k\}$ using the aggregate input-output table as described in Section 2.2. Specifically, for each sector m, we obtain $\{\beta_{L,m}, \beta_{km}\}$ as the share of labor compensation and the input expenditure from sector k. We obtain $\{\alpha_k\}$ from the household expenditure share for each sector k. Finally, we calibrate the elasticity of substitution $\{\sigma_k\}$ from the ratio between pre-tax operation surplus and corporate income to nominal output, which corresponds to $1/\sigma_k$ in our model.

Table 3 summarizes these parameter choices. The calibrated parameters follow intuitive patterns. Labor share $\{\beta_{L,m}\}$ is 0.35 and 0.36 for mining and others, while it is lower at 0.10 for manufacturing. Final expenditure share $\{\alpha_m\}$ is almost zero for mining, and higher for manufacturing and others. Finally, the elasticity of substitution $\{\sigma_k\}$ hovers around 4.8 (mining) to 8.1 (manufacturing). These values are within the range of values found in the existing literature.[23]

Table 3: Calibrated Parameters

	Sectors (m)		
	Mining	Manufacturing	Other
(a) β_{km}			
k =Mining	0.11	0.12	0.06
k =Manufacturing	0.18	0.33	0.18
k =Other	0.36	0.45	0.40
(b) $\beta_{m,L}$	0.35	0.10	0.36
(c) α_m	0.01	0.6	0.39
(d) σ_m	4.8	8.1	5.0

Notes: Calibrated parameters based on the aggregate input-output table produced by the State Statistics Service of Ukraine as described in Section 2.2.

For our quantitative analysis below, we also use trade flows across firm types and locations

[23] For example, Broda and Weinstein (2006) show that the median estimate of the elasticity of substitution across imported varieties in the U.S. are 3.1, ranging from 1.2 to 22.1 across sectors.

$\{X_{ui,km,t}(\upsilon, \omega)\}$, production linkages $\{M_{ui,km,t}(\upsilon, \omega)\}$, for each year $t \in [2012{,}2016]$. We calibrate these values using our railway shipment data. To obtain the 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.

5.2 Model Validation: Can Production Network Disruption and Reorganization Explain Observed Changes in Firm Output?

In this section, we show that our model, together with the observed reorganization of production networks, can accurately account for the changes in firm output as a response to the conflict shocks. Specifically, we regress our model's prediction for firm-level output in Proposition 1 against the observed firm output, instrumented by the supplier and buyer exposures to conflict areas. We test the null hypothesis that this regression coefficient is one, indicating that the model's prediction for firm output changes based on production network changes moves one for one with the observed firm output changes.

Empirical Strategy. Reformulating Proposition 1, we have the following model-predicted relationship for the aggregate intermediate goods sales by firms type ω in sector m, location i, and year t:

$$\log\left[w_{i,t}^{\beta_{m,L}(1-\sigma_m)}\mathcal{A}^S_{i,m,t}(\omega)\mathcal{A}^B_{i,m,t}(\omega)\right] = \log R_{i,m,t}(\omega) - \log Z_{i,m,t}(\omega)^{\sigma_m - 1}. \tag{20}$$

The left-hand side of this equation summarizes our model prediction for aggregate intermediate goods sales except for the TFP term. 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 the corresponding estimates 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:

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

where the unit of observation of the regression is firm-type and year. $\eta_{i,m}(\omega)$ are the firm-type-location-sector fixed effects, $\nu_{i,t}$ are the location-time fixed effects, $\delta_{m,t}$ are the sector-time fixed effects, and $\epsilon_{i,m,t}(\omega)$ is the residual. These last four terms in Equation (21) capture time-varying TFP $-\log Z_{i,m,t}(\omega)^{\sigma_m-1}$ in Equation (20). $R_{i,m,t}(\omega)$ on the right-hand side is the observed intermediate goods sales obtained by aggregating the value of out-shipment in our railway shipment data. $w_{i,t}$ on the right-hand side is the wages in each region and time. Given the lack of reliable data on wages across regions throughout this period, we construct the proxies for wages using the model's labor market clearing condition (Equation 16).[24] Note also that the wages do not influence the regression coefficient γ once we control for the region-time fixed effects.

Using regression (21), we test for $\gamma = 1$, i.e., whether the changes in our sufficient statistics for TFP-adjusted firm intermediate goods sales ($w_{i,t}^{\beta_{m,L}(1-\sigma_m)}\tilde{\mathcal{A}}^S_{i,m,t}(\omega)\tilde{\mathcal{A}}^B_{i,m,t}(\omega)$) moves one-for-one with the observed counterpart. Importantly, by controlling for firm-type-location-sector fixed effects, we assess the model performance in terms of time changes beyond the cross-sectional variation.

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 firm revenue. Second, our measurement of firm revenue $R_{i,m,t}(\omega)$ may involve measurement error, leading to an underestimation of γ.

To deal with these issues, we instead estimate Equation (21) using an instrumental variable (IV) approach leveraging the variation induced by the localized conflict. Specifically, motivated by the difference-in-differences strategy in Section 3, we choose our IVs as the interaction between the post-period (2014) dummy and the supplier and buyer exposures to conflict areas. We expect an estimate of $\gamma = 1$ under the identification assumption that the unobserved changes in TFP are uncorrelated with the IVs. Through the lens of our model, this identification assumption implies that firms with supplier and buyer conflict exposures are differentially affected by the conflict shocks only through the disruption and reorganization of production networks but not in other channels that operate through TFP. Since we have only one endogenous variable, while we have multiple candidates for IVs based on either or both of the supplier and buyer conflict exposures,

[24] See Appendix D for further details of the calibration.

we execute this model validation using an alternate set of IVs to gauge robustness.[25]

Estimation of Supplier and Buyer Accesses. We first need to estimate supplier and buyer access to execute this idea. We do so by using our model prediction of trade flows in Equation (10). By adding the time subscript t and manipulating the equation, the trade flow normalized by the measure of linkages are expressed as

$$\frac{X_{ui,km,t}(\upsilon,\omega)}{M_{ui,km,t}(\upsilon,\omega)} = \xi_{u,km,t}(\upsilon)\zeta_{i,km,t}(\omega)\eta_{ui,km}(\upsilon,\omega)\epsilon_{ui,km,t}(\upsilon,\omega), \tag{22}$$

where $\xi_{u,km,t}(\upsilon) \equiv \varsigma_k C_{u,k,t}(\upsilon)^{1-\sigma_k}$, $\zeta_{i,km,t}(\omega) \equiv D_{i,km,t}(\omega)$, $\eta_{ui,km}(\upsilon,\omega) \equiv \mathbb{E}_t[\tau_{ui,km,t}(\upsilon,\omega)^{1-\sigma_k}]$ with $\mathbb{E}_t$ indicating expectation over time, and $\epsilon_{ui,km,t}(\upsilon,\omega) \equiv \tau_{ui,km,t}(\upsilon,\omega)^{1-\sigma_k}/\mathbb{E}_t\left[\tau_{ui,km,t}(\upsilon,\omega)^{1-\sigma_k}\right]$ captures the idiosyncratic changes in trade costs and measurement error. To account for the possibility of zero trade flows on the left-hand side, we estimate Equation (22) using a Pseudo-Poisson Maximum Likelihood (PPML) estimator (i.e., Silva and Tenreyro, 2006) with three-way 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 (22), we can use the expressions for the supplier and buyer market accesses up to scale using the empirical analogs of Equations (12) and (13), so that

$$\tilde{\mathcal{A}}^S_{i,m,t}(\omega) = \prod_{k\in K}\left(\sum_{u\in\mathcal{L}}\sum_{\upsilon\in\Omega_{u,k}} M_{ui,km,t}(\upsilon,\omega)\tilde{\eta}_{ui,km}(\upsilon,\omega)\tilde{\xi}_{u,km,t}(\upsilon)\right)^{\frac{1-\sigma_m}{1-\sigma_k}\beta_{km}}, \tag{23}$$

$$\tilde{\mathcal{A}}^B_{i,m,t}(\omega) = \sum_{l\in K}\sum_{d\in\mathcal{L}}\sum_{\psi\in\Omega_{d,l}} M_{id,ml,t}(\omega,\psi)\tilde{\eta}_{ui,km}(\omega,\psi)\tilde{\zeta}_{i,km,t}(\psi). \tag{24}$$

Baseline Results. Table 4 presents our results of the IV regressions (21). In our baseline estimates, we use two years, 2013 (pre-period) and 2016 (post-period), to focus on long differences, while the results are similar using all years (Appendix Table E.3). In Panel (A), we present our baseline results using our baseline estimates of supplier and buyer accesses using Equations (23) and (24). To benchmark our results, in Panel (B), we present the results of the same IV regressions (21), where we abstract from the changes in production linkage reorganization when estimating the

[25]Our idea closely follows Adão, Costinot, and Donaldson (2023), who propose to test a model prediction using orthogonality conditions. See also Donaldson (2018) who uses model-predicted welfare sufficient statistics to test whether trade mechanism is the main driver of the welfare gains from railway networks in Colonial India.

supplier and buyer accesses. That is, when constructing $\{\tilde{\mathcal{A}}^S_{i,m,t}(\omega), \tilde{\mathcal{A}}^B_{i,m,t}(\omega)\}$ using Equations (23) and (24), we fix the measure of supplier and buyer linkages at the level of 2013 instead of the actual values for each year.[26] For each specification, we also report the p-value for the Wald test for the null hypothesis that the regression coefficient is equal to one. We also report the cluster-robust first-stage F-statistics in the bottom rows (Andrews, Stock, and Sun, 2019). Across the board, the F-statistics are above 10, with a somewhat lower value of 4.2 for Column (5) using solely the supplier exposure as an IV. The strong first stage is consistent with the reduced-form evidence in Section 3.2 that supplier and buyer conflict exposures are associated with a significant reduction in observed firm-level output.

Columns (1)-(3) of Panel (A) start with the specification where the IV corresponds to the interaction between the post-period dummy and the dummy variable that takes one if the firm type has high supplier *and* buyer conflict exposures and the post-conflict dummies. Column (1) starts with the specification where we only control for firm-type-region-sector fixed effects and year-fixed effects. The regression coefficient is 1.12, with a standard error of 0.17. Therefore, while the coefficients are tightly estimated, we cannot reject the null hypothesis that the regression coefficient is one (with a p-value of 0.50).

Column (2) further controls for the sector-year fixed effects, and Column (3) further controls for the region-year fixed effects. The regression coefficients are 1.13 and 1.16, respectively, with standard errors of 0.19 for both columns. Therefore, the results are similar to Column (1), and we cannot reject the null hypothesis that the regression coefficient is one (with p-values of 0.50 and 0.41, respectively).

In the remaining columns of Panel (A), we execute the same exercise with an alternative set of IVs. In Column (4), we only use the high buyer conflict exposure dummy (interacted with post-conflict dummies), instead of using high supplier *and* buyer conflict exposure dummies. We find a coefficient of 0.97 with a standard error of 0.25. Again, we cannot reject the null hypothesis that the coefficient is equal to one with a p-value of 0.92. In Column (5), we only use the high supplier

[26]Note that we use the same estimates of gravity equations (22) to construct supplier and buyer accesses between Panels (A) and (B). In Appendix Table E.4, we show that the model abstracting production link changes tend to be rejected even when we estimate gravity equations using aggregate trade flows, i.e., by eliminating $M_{ui,km,t}(\upsilon, \omega)$ from the denominator of the left-hand side in Equation (22).

Table 4: Model Validation

	$\log w_{i,t}^{\beta_{m,L}(1-\sigma_m)} \tilde{\mathcal{A}}_{i,m,t}^{S}(\omega)\tilde{\mathcal{A}}_{i,m,t}^{B}(\omega)$				
	(1)	(2)	(3)	(4)	(5)
Panel A: With Link Adjustment					
$\log R_{i,m,t}(\omega)$	1.12	1.13	1.16	0.97	1.44
	(0.17)	(0.19)	(0.19)	(0.25)	(0.51)
p-value (coefficient = 1)	0.50	0.50	0.41	0.92	0.39
Panel B: Without Link Adjustment					
$\log R_{i,m,t}(\omega)$	0.42	0.45	0.47	0.25	0.97
	(0.13)	(0.14)	(0.12)	(0.14)	(0.47)
p-value (coefficient = 1)	0.00	0.00	0.00	0.00	0.96
IV	High Buyer and Supplier Exposures	High Buyer and Supplier Exposures	High Buyer and Supplier Exposures	High Buyer Exposure	High Supplier Exposure
Cluster-Robust First-Stage F-Statistics	26.4	27.6	27.3	11.5	4.2
Observations	427	427	427	427	427
Firm-Type-Region-Sector Fixed Effects	X	X	X	X	X
Year Fixed Effects	X	X	X	X	X
Sector $\times$ Year Fixed Effects		X	X	X	X
Region $\times$ Year Fixed Effects			X	X	X

Notes: The sample of the regression is firm-type and year, for 2013 and 2016. Standard errors are clustered at the firm-type level. Cluster-robust first-stage F-statistics follow Andrews et al. (2019).

conflict exposure for the IV. We still cannot reject the regression coefficient at one (coefficient of 1.44 with standard error of 0.51), while the first-stage F-statistics is somewhat smaller at 4.2 than other specifications.

These patterns are in stark comparison with the specification in Panel (B), where we abstract from the changes in production linkages when estimating supplier and buyer accesses. In Columns (1)–(3), when using high supplier *and* buyer conflict exposures as IV, the regression coefficients range from 0.42–0.47, with tight standard errors of 0.12–0.14. Therefore, we can reject the null hypothesis that the regression coefficient is equal to one with p-values of zero. The fact that the coefficients are significantly below one indicates that the model tends to underpredict the variation of firm-level output changes as a response to conflict shocks. This pattern is primarily driven by the fact that both supplier and buyer conflict exposures lead to a reduction in buyer linkages in peaceful areas (Columns 3 and 4, Table 2), as we further discuss below. In Column (4), when we use high buyer conflict exposures for our IV, the coefficient is even smaller at 0.25, and we continue to reject the null hypothesis that the regression coefficient is one. The only exception where we cannot reject the null hypothesis that the regression coefficient is one is in Column (5) when we use high supplier conflict exposures for our IV. In this case, the regression coefficient is 0.97 with a standard error of 0.47.

Robustness and Additional Results. To further illustrate why the model without the production link adjustment fails to capture the observed changes in firm output, in Appendix Table E.1 and E.2, we report the results where we only shut down changes in buyer linkages and supplier linkages to compute buyer and supplier access, instead of shutting down both of them simultaneously as in Panel (B) of Table 4. We find that abstracting from changes in buyer linkages are mostly accountable for the reason behind the rejection of abstracting overall production link changes. Abstracting solely from buyer link changes (Appendix Table E.1) yields a similar pattern of results to Panel (B) of Table 4. When we only abstract from the changes in supplier linkages (Appendix Table E.1), the model instead overpredicts the variation of output changes, especially when using supplier exposure as IV (Column 5). This pattern is consistent with the observation that a higher supplier conflict exposure leads to an increase of suppliers in peaceful areas (Columns 1 and 2, Table 2).

In Appendix Table E.3, we report the results where we use all five years of data $t \in [2012, 2016]$ to run regression (21) instead of using only 2013 and 2016. We find a similar patterns as in Panel (A) of Table 4 with slightly larger coefficients (Columns (1)–(3) range from 1.24 to 1.33). In all specifications, we cannot reject that the regression coefficients equal to one with *p*-values of 0.15.

5.3 Aggregate Welfare Outside Conflict Areas

Having validated our model, we now use it to analyze how the localized conflict affects aggregate welfare strictly outside the 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, before the 2014 Russia-Ukraine conflict. We then assume that conflict makes trade with firms in the conflict areas prohibitively costly, i.e., $\tau_{ui,km}(\upsilon, \omega) \to \infty$ if u or i are in the conflict areas. We choose these simulations to reflect the fact that trade with conflict areas became virtually absent within a few years after the onset of the conflict, as we documented in Section 3.1. We assume that trade costs and firm productivity strictly outside conflict areas $\{\tau_{ui,km}(\upsilon, \omega)\}$ and firm productivity $\{Z_{i,m}(\omega)\}$ outside the conflict areas are unchanged in this simulation. To calibrate our model to the baseline economy, we also adjust the baseline trade flows to satisfy all the market clearing conditions (see Appendix D for details).

To quantify the role of the reorganization of production linkages $\{M_{ui,km}(\upsilon, \omega)\}$, we undertake this simulation in several alternate scenarios. In our baseline scenario, we change the production linkages consistent with our difference-in-differences estimates depending on the firms' supplier and buyer conflict exposures. In particular, based on Column (3) of Table 2, if firm type ω has a high supplier conflict exposure, we assume that the firm increases the measure of supplier linkages by 10.3 log points outside the conflict areas, equally across supplier types, locations and sectors. Similarly, if firm type ω has a high buyer conflict exposure, we assume that the firm changes the measure of supplier linkages by -6.0 log points outside the conflict areas. If firms have low supplier and buyer conflict exposures, we assume that the measure of supplier linkages does not change. To benchmark these results, we undertake this simulation with a version where we shut down either or both changes in supplier linkages by firms with high supplier or buyer conflict exposures. We also probe how the results differ by changing the measure of supplier linkages depending on whether the suppliers are directly exposed to shocks, thereby rationalizing the patterns of the changes in buyer linkages documented in Table 2 as robustness.

Before proceeding, we make several remarks on the nature of the simulation. First, we do not introduce any changes in TFP outside conflict areas. While we cannot reject the hypothesis that there are no differential changes in TFPs across firms with different supplier and buyer conflict exposures in Section 5.2 (i.e., the regression coefficient of model-predicted firm sales without incorporating TFP changes on observed firm sales is one), the localized conflict may equally affect TFP of all firms in the economy (e.g., through decline in investment). Second, we do not consider changes in international trade, particularly from/to Russia. While the decline in aggregate trade from/to Russia is likely smaller than from/to conflict areas, as discussed in Section 2.3, the decline in international trade may have additionally impacted Ukraine's economy in reality. For these reasons, the simulation and the resulting welfare effects should be interpreted solely as the effects of the quantification of the disruption and production network reorganization to and from conflict areas rather than the quantification of the overall cost of conflict.

Baseline Results. Table 5 reports our results. For each model specification in the row, we report the population-weighted welfare (real income) changes across regions strictly outside the conflict areas. We also report the 25th, 50th, and 75th percentiles of the welfare changes across regions.

Table 5: Aggregate Welfare Changes outside Conflict Areas

	Mean	25%-ile	50%-ile	75%-ile
(1) Baseline (With Supplier Link Adjustment)	-9.1	-11.8	-9.0	-4.9
(2) Shut Down Supplier Link Adjustment by High Supplier Exposure Firms	-11.4	-14.5	-12.4	-7.0
(3) Shut Down Supplier Link Adjustment by High Buyer Exposure Firms	-6.8	-9.1	-6.6	-3.2
(4) No Link Adjustment	-9.1	-11.9	-9.3	-5.1

Notes: For each scenario of the counterfactual simulation, we report the percent change in population-weighted welfare (real income) changes across regions strictly outside conflict areas. We also report the 25, 50, and 75 percentile of the welfare changes across regions.

Row (1) shows that, in our baseline specification, we observe a 9.1 percent decline in aggregate welfare loss strictly outside the conflict areas. This large magnitude of the propagation illustrates the intensity of the localized conflict in this context (i.e., the economic importance of the conflict areas and the reduction of trade with those regions) compared to the existing literature focusing on smaller, more transient shocks. For example, Carvalho and Tahbaz-Salehi (2019) quantifies that the Great Earth Tohoku Earthquake in Japan has resulted in a 0.47 percent decline in Japan's real GDP growth in the year following the disaster (using a model without changes in production networks). We also find a large regional disparity in the welfare loss: 11.8 percent at the 25th percentile and 4.9 percent at the 75th percentile. We revisit the pattern of spatial disparity in the welfare changes further below.

In Row (2), when we shut down the increase in supplier linkages by firms with high supplier conflict exposures, we find an 11.4 percent decline in aggregate welfare, which is substantially larger than our baseline specification. This result indicates that the substitution of supplier linkages toward peaceful areas, as documented in Section 3.3, has a sizable mitigation effect for the aggregate welfare loss from supply chain disruption.

In Row (3), where we shut down the decrease in supplier linkages by firms with high buyer conflict exposures, welfare decreases by a smaller 6.8 percent. This result indicates that the fact that firms who lost buyers in conflict areas tend to scale down supplier linkages, as also documented in Section 3.3, has a sizable amplification effect for the aggregate welfare loss.

Finally, in Row (4), if we completely shut down supplier linkages changes, thereby fixing the production networks at the pre-conflict levels, we find a 9.1 percent reduction in aggregate welfare, similar in magnitude to our baseline scenario. Therefore, the disparate firm-level responses in production linkages depending on the supplier and buyer conflict exposures, as documented in our reduced-form section, have roughly offsetting effects on the aggregate welfare changes.

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 25%. Overall, the welfare loss tends 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 the conflict areas. We find strong upward-sloping relationships, confirming that regions close to conflict areas are particularly facing welfare loss. At the same time, some regions that are more than 750 kilometers away face over 10 % of welfare loss. These results indicate that localized conflicts can have far-reaching and detrimental economic consequences through production networks.

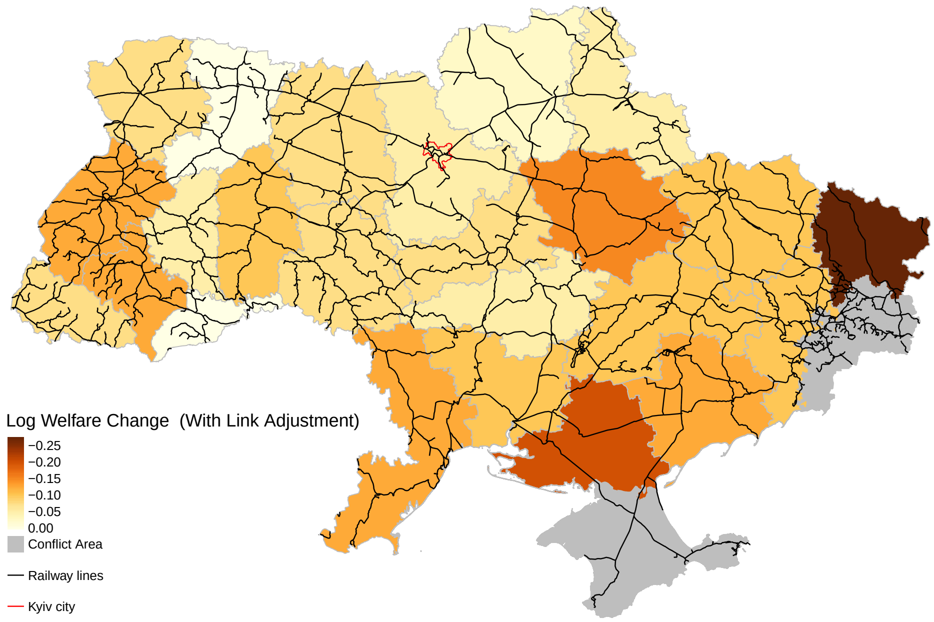
Robustness. In Appendix Table F.1, we report the robustness of our results to alternative specifications. First, we show that our results remain similar even if we change the measure of supplier linkages depending on suppliers' conflict exposures, thereby rationalizing the patterns of the changes in buyer linkages as well. More specifically, instead of assuming that supplier linkages change uniformly across supplier types conditional on the buyers' conflict exposures, as our main specification, we assume that this change also differs by whether the suppliers are directly exposed to shocks. We set the changes in the measure of production linkages to rationalize both the patterns of supplier and buyer linkages changes as a function of supplier and buyer exposures, as we find in Columns (3) and (4) of Table 2. See Appendix F.2 for the formal procedure of this version of the calibration. We find that this specification yields a 8.8 percent welfare loss (Row b), similar to our baseline specification (9.1 percent). The slightly smaller welfare loss than our baseline specification comes from the welfare benefit through reorganizing buyer linkages away from suppliers negatively hit by the shock, as we find in Column (4) of Table 2. However, this effect is quantitatively negligible compared to the average shift of supplier linkages and the resulting love-of-variety effects in intermediate inputs.

Second, our results remain similar even if we account for firms' entry and exit effects as a response to the shock. In Appendix C.3, we extend our model to incorporate firms' entry and exit effects as exogenous changes in $\{N_{i,k}(\omega)\}$. There, the only additional sources of welfare changes are due to its effect on final consumer prices through love-of-variety effects. To gauge the quantitative magnitude of this effect, we assume that $\{N_{i,k}(\omega)\}$ change in a way consistent with our difference-in-differences estimates of Column (6) of Table 1, interpreting "no sales reported" as the exit of the firm, and assuming that $\{N_{i,k}(\omega)\}$ do not change if firms have low supplier and buyer exposures. We find that this model predicts a 10.0 percent decline in welfare (Row c), larger but similar to our baseline specification.

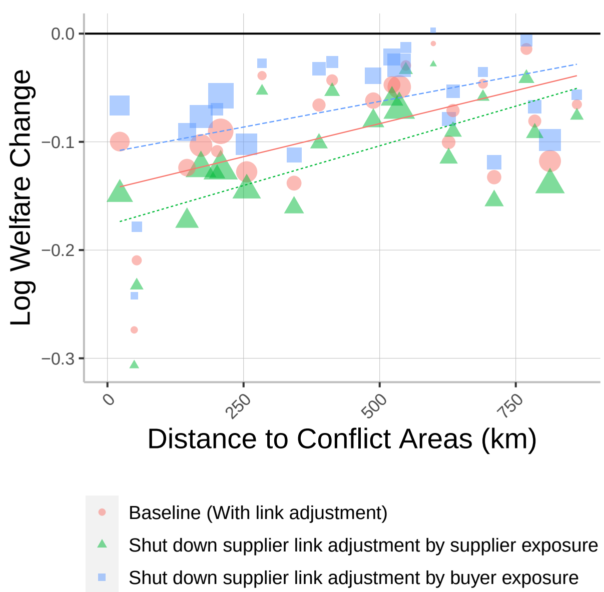
In Rows (d)-(f) of Appendix Table F.1, we report the results where we use alternative methods for the value imputation in our shipment data and find similar patterns of the results.[27] In Rows (g) and (h), we report the robustness where we define firm types using the exposures defined by the shares of links and shares of weights, instead of using value shares.

[27]See Section 2.2 and Appendix B for further details about value imputation for our railway shipment data. We show robustness by using simple means instead of geometric means to compute the value per weight and using export data only instead of both import and export data to compute the value per shipment weight.

Figure 5: Welfare Changes outside Conflict Areas



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



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

Notes: The figures present the predicted percent change in welfare (real income) for regions strictly outside conflict areas. In Panel (b), distance to conflict areas is defined as the straight-line distance between the centroid of each region with the closest point of the border to the conflict areas in Donbas region or Crimea region.

6 Conclusion

How does an intense localized conflict lead to disruption and reorganization of production networks? What are the consequences for firm production and aggregate welfare? This paper answers these questions in the context of the 2014 Russia-Ukraine conflict. We document that firms with prior supplier and buyer linkages to conflict areas experience a significant output decrease. Simultaneously, the former firms increase supplier linkages in peaceful areas, while the latter firms decrease them. Based on the evidence, we develop a model of how disruption and reorganization of production networks affect production and welfare. We show that our model with production network reorganization can accurately account for the observed output changes, while the model abstracting from the reorganization fails to do so. Our model predicts about nine percent reduction of aggregate welfare strictly outside conflict areas through the disruption and reorganization of production networks. The reorganization of supplier linkages changes by firms with both supplier and buyer conflict exposures have quantitatively large implications for the aggregate welfare. Overall, our analysis shows that localized conflicts can have far-reaching and detrimental economic consequences through production networks.

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Online Appendix for "Supply Chain Disruption and Reorganization: Theory and Evidence from Ukraine's War" (Not for Publication)

Vasily Korovkin, Alexey Makarin, Yuhei Miyauchi

A Appendix for Reduced-Form Evidence

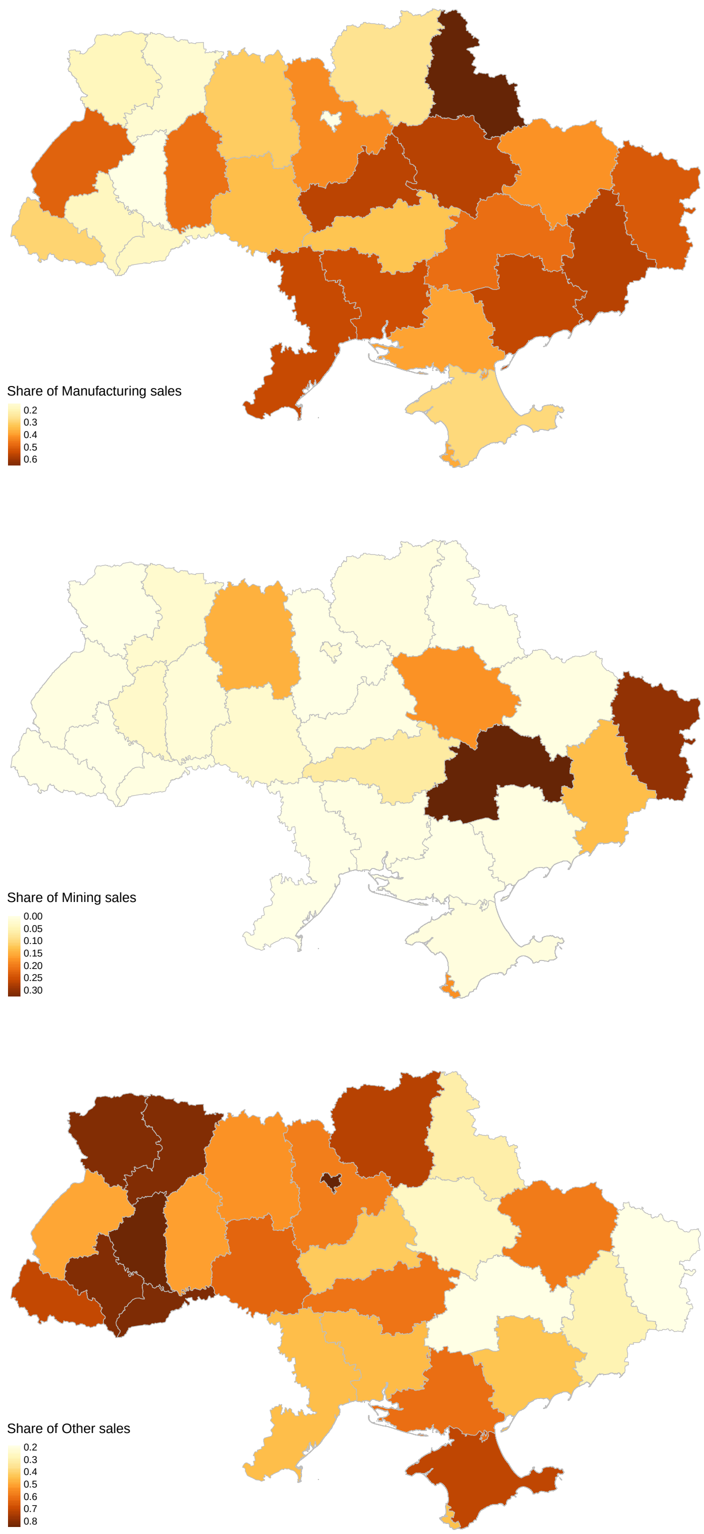
A.1 Summary Statistics

Table A.1: Summary Statistics

	Observations	Mean	SD	Min	Max
	Panel A: Conflict Exposures				
$\mathbb{1}$[Firm traded with conflict areas, 2012–13]	52,294	0.55	0.50	0	1
Firm's buyer conflict exposure, 2012–2013	52,294	0.09	0.21	0	1
Firm's supplier conflict exposure, 2012–2013	52,294	0.10	0.23	0	1
$\mathbb{1}$[High firm's buyer conflict exposure, 2012–13]	52,294	0.14	0.35	0	1
$\mathbb{1}$[High firm's supplier conflict exposure, 2012–13]	52,294	0.14	0.35	0	1
$\mathbb{1}$[Firm traded with Russia in 2012–2013]	52,294	0.23	0.42	0	1
	Panel B: Sales and Trade				
Log of firm sales, 2010–2018	35,190	16.88	2.49	4.61	25.13
No sales reported, 2010–2018	52,294	0.33	0.47	0	1
Log weight sent total, 2012–2016	14,924	15.37	3.05	1.61	24.86
Log weight sent to nonconflict areas, 2012–2016	14,568	15.32	3.03	1.61	24.72
Log weight received total, 2012–2016	21,743	15.66	2.40	3.00	24.57
Log weight received from nonconflict areas, 2012–2016	21,312	15.58	2.37	3.00	24.56
Log number of buyers total, 2012–2016	14,924	1.85	1.51	0	7.64
Log number of buyers in nonconflict areas, 2012–2016	14,568	1.81	1.49	0	7.64
Log number of suppliers total, 2012–2016	21,743	1.77	1.27	0	7.80
Log number of suppliers from nonconflict areas, 2012–2016	21,312	1.71	1.25	0	7.79
	Panel C: Industry				
Mining	52,294	0.05	0.21	0	1
Manufacturing	52,294	0.20	0.40	0	1
Other industry	52,294	0.75	0.43	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.

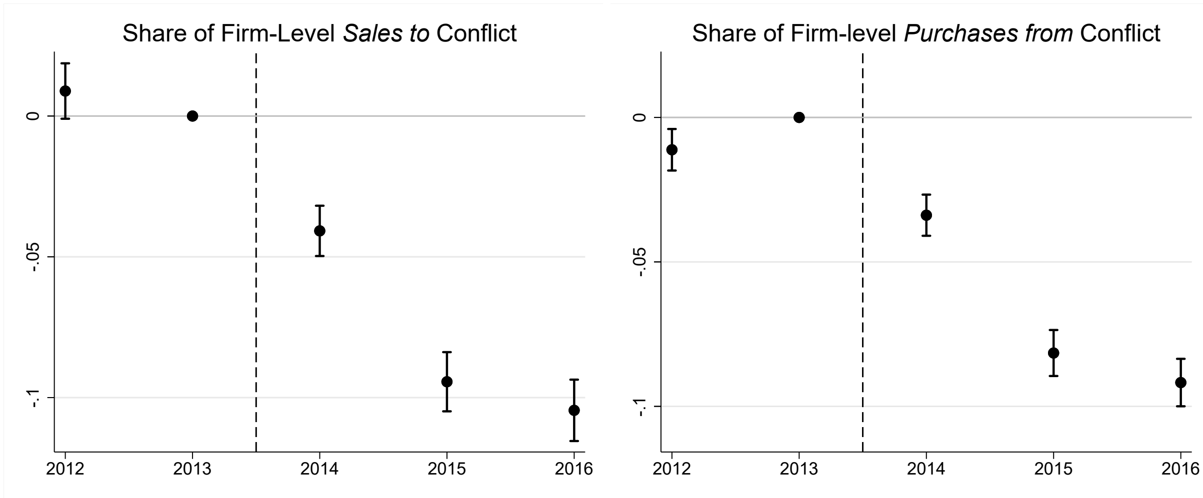
Figure A.1: Industry Composition of Regions in 2013 in Ukraine



Notes These maps represent the share of sales for each of the three industry classifications (manufacturing, mining, and others) within each region of Ukraine in 2013 using SPARK-Interfax data.

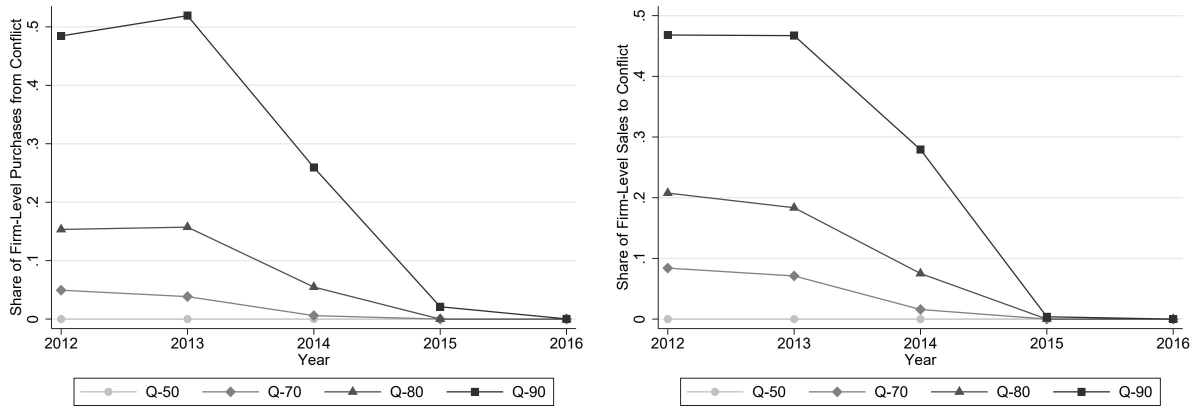
A.2 Robustness for the Impacts on Trade with Conflict Areas

Figure A.2: Share of Trade Value with Conflict Areas



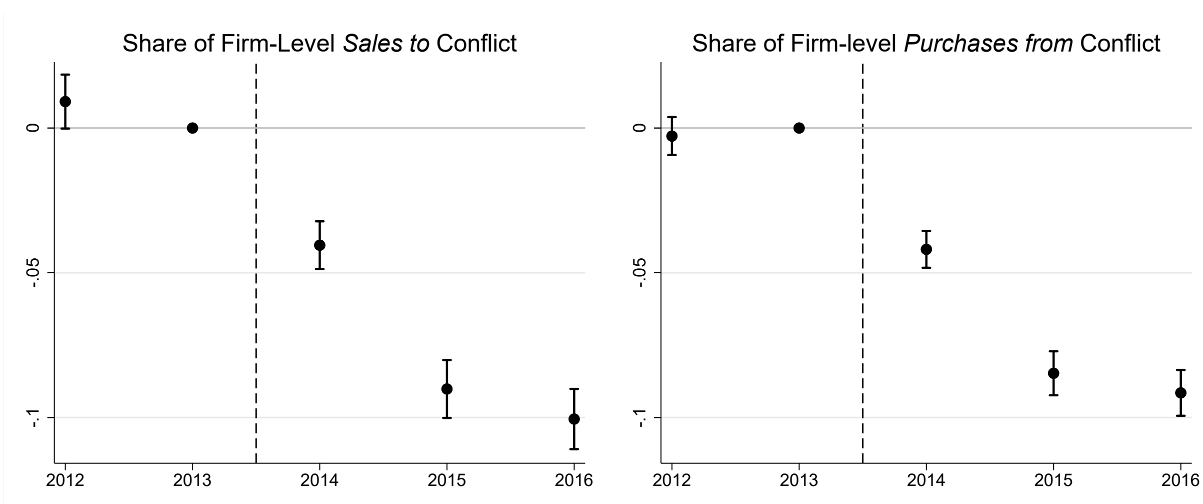
Notes This figure represents how the aggregate rayon-level buyer and supplier exposures to conflict areas changed over time. Specifically, the figure presents the estimates of the yearly fixed effect coefficients from the following specification: $Y_{it} = \alpha_i + \beta_t + \varepsilon_{it}$, where Y_{it} is the share of firm i's sales to or purchases from the conflict areas (in value) in year t and α_i and β_t are firm 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: Quartiles of Production Network Weights Distribution for Trade with Conflict Areas



Notes: This figure displays the evolution of the distribution of firm trade share with DPR, LPR, and Crimea. Q-50 refers to the median, Q-70 refers to the 70th percentile, Q-80 refers to the 80th percentile, and Q-90 refers to the 90th percentile of the distribution. The figure on the left (right) describes the distribution for the share of firm 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 firm that year.

Figure A.4: Share of Trade Weight 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: $Y_{it} = \alpha_i + \beta_t + \varepsilon_{it}$, where Y_{it} is the share of firm i's sales to or purchases from the conflict areas (in weight) in year t and α_i and β_t are firm 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.

A.3 Robustness for the Impacts on Sales

Tables A.2 and A.3 probe the robustness of the estimates in Table 1. First, we show that our estimates remain similar for both sales volume and the indicator of nonreported sales when we focus on a strictly balanced sample of firms (Column 2 in each table). This restriction addresses the possible changes in sample composition, which may be especially salient given that our results on nonreported sales suggest increased 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 possible concerns that conflict could induce concurrent spatially correlated common shocks, such as those related to the threat of future military expansion or migration.

Third, we control for firm's 2-digit industry fixed effects interacted with the year indicators (Column 7), which absorb any industry-specific time-varying shocks. This addresses possible issues, for instance, related to increased demand for military- or conflict-related products.

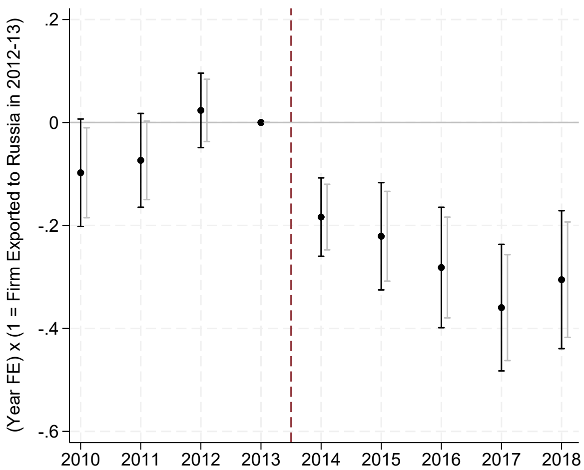
Fourth, we control for the region-year fixed effects (Column 8), which absorb the impact of any region-year shocks, such as region-specific refugee inflows. In Appendix A.6, we further confirm that region-level population and refugee movements are not related to our conflict exposure measures calculated at the region level.

Fifth, we show that our results are not driven by firms' prewar trade ties with Russia (Column 9), which accounts for the disruption of trade between non-conflict areas of Ukraine and Russia following the start of the conflict (Korovkin and Makarin, 2023). Figure A.5 shows that firms that traded with Russia before the conflict also saw sharp and substantial declines in their sales relative to firms that did not trade with Russia; still, the differential impact of conflict on sales by firms' connections to the conflict areas stays negative and of similar magnitude to Figure 3.

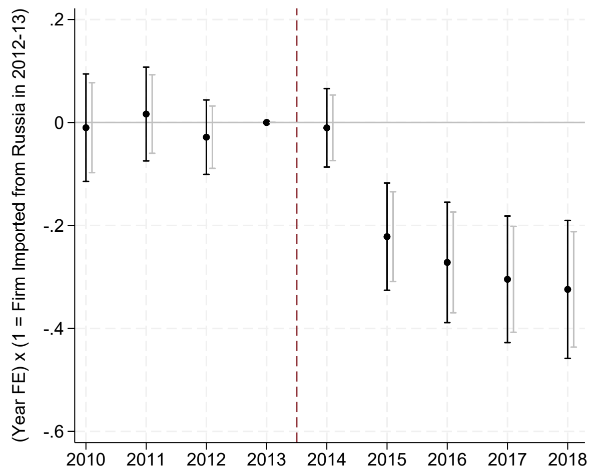
Sixth, we control for the total number of trade partners before the conflict interacted with post-2014 indicator (Column 10) thus assuaging the concern that peripheral firms are mechanically more likely to have lower conflict exposure (Borusyak and Hull, 2020).

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 11 and 12, respectively), and removing firms in the capital city of Kyiv (Column 13).

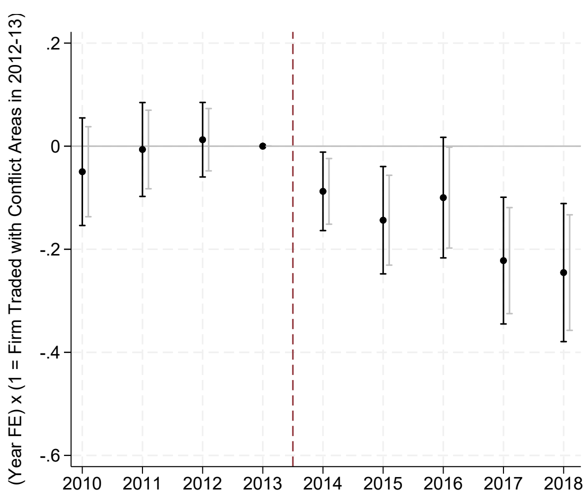
Figure A.5: The Impact of Conflict on Sales of Firms in Non-Conflict Areas by Their Trade with the Conflict Areas and Russia



(a) Firm exported to Russia preconflict



(b) Firm imported from Russia preconflict



(c) Firm traded with conflict areas preconflict

Notes: This figures display the impact of conflict on firm sales by whether a firm had prior trade ties with the conflict areas and with Russia. All coefficients are estimated within one equation. Black bars represent 95% confidence intervals, gray bars represent 90% confidence intervals. Standard errors are clustered at the firm level.

Table A.2: Robustness Checks: Conflict Exposures and Sales of Firms Trading With Conflict Areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Baseline	Strictly balanced panel	Latitude & longitude		Distance to conflict areas		2-digit industry × year FE	Region × year FE	Pre-conflict trade with Russia	Pre-conflict trade partners	Omitting Donetsk oblast	Omitting Luhansk oblast	Omitting Kyiv
Post-2014 ×	-0.183***	-0.116**	-0.152***	-0.138***	-0.155***	-0.161***	-0.134***	-0.116**	-0.146***	-0.167***	-0.147***	-0.176***	-0.151***
𝟙[Firm traded with conflict areas, 2012–13]	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.048)	(0.046)	(0.046)	(0.047)	(0.047)	(0.047)	(0.048)
Post-2014 ×			0.073***	-1.380									
Latitude			(0.016)	(0.946)									
Post-2014 ×			-0.024***	-1.057***									
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 ×					0.614***								
Distance to conflict area					(0.101)								
Post-2014 ×						0.464***							
Distance to LPR or DPR						(0.082)							
Post-2014 ×									-0.221***				
𝟙[Firm imported from Russia, 2012–13]									(0.062)				
Post-2014 ×									-0.224***				
𝟙[Firm exported to Russia, 2012–13]									(0.064)				
Post-2014 ×										-0.000**			
# of pre-conflict trade partners										(0.000)			
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean	16.890	17.232	16.890	16.890	16.890	16.890	16.920	16.890	16.890	16.890	16.854	16.893	16.837
SD	2.484	2.289	2.483	2.483	2.483	2.483	2.475	2.484	2.484	2.484	2.458	2.478	2.439
Observations	35,029	23,616	34,922	34,922	34,922	34,922	33,520	35,029	35,029	35,029	32,920	34,316	30,176
Number of Firms	4,802	2,624	4,779	4,779	4,779	4,779	4,599	4,802	4,802	4,802	4,486	4,683	4,065

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} (Columns 3 and 4), 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 5 and 6), controlling for firm's 2-digit industry SIC code interacted with Post_{it} (Columns 7), controlling for firm's region fixed effects interacted with Post_{it} (Columns 8), controlling for whether a firm has been trading with Russia before the conflict (2012 or 2013) interacted with Post_{it} (Column 9), controlling for the total number of trade partners before the conflict (2012 or 2013) interacted with Post_{it} (Column 10), omitting firms near the conflict areas, i.e., Donetsk and Luhansk oblast (Columns 11 and 12, respectively), and omitting firms in Kyiv (Column 13). 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: Conflict Exposures and Dummy for No Sales Reported by Firms Trading With Conflict Areas

	(1) Baseline	(2) Strictly balanced panel	(3) Latitude & longitude	(4)	(5) Distance to conflict areas	(6)	(7) 2-digit industry × year FE	(8) Region × year FE	(9) Pre-conflict trade with Russia	(10) Pre-conflict trade partners	(11) Removing Donetsk oblast	(12) Removing Luhansk oblast	(13) Removing Kyiv
Post-2014 ×	0.088***	0.090***	0.068***	0.060***	0.069***	0.074***	0.082***	0.061***	0.083***	0.090***	0.078***	0.079***	-0.151***
𝟙[Firm traded with conflict areas, 2012–13]	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.048)
Post-2014 ×			-0.028***	-1.196***									
Latitude			(0.004)	(0.198)									
Post-2014 ×			0.012***	0.344***									
Longitude			(0.001)	(0.065)									
Post-2014 ×				0.015***									
Latitude^2				(0.002)									
Post-2014 ×				0.002***									
Longitude^2				(0.000)									
Post-2014 ×				-0.010***									
Latitude × longitude				(0.001)									
Post-2014 ×					-0.280***								
Distance to conflict area					(0.022)								
Post-2014 ×						-0.195***							
Distance to LPR or DPR						(0.018)							
Post-2014 ×									0.031**				
𝟙[Firm imported from Russia, 2012–13]									(0.014)				
Post-2014 ×									0.025*				
𝟙[Firm exported from Russia, 2012–13]									(0.014)				
Post-2014 ×										-0.000*			
# of pre-conflict trade partners										(0.000)			
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean	0.327	0.306	0.304	0.304	0.304	0.304	0.308	0.306	0.327	0.327	0.325	0.325	16.837
SD	0.469	0.461	0.460	0.460	0.460	0.460	0.462	0.461	0.469	0.469	0.469	0.468	2.439
Observations	52,272	50,679	50,418	50,418	50,418	50,418	48,708	50,679	52,272	52,272	49,032	51,075	30,176
Number of Firms	6,071	5,631	5,602	5,602	5,602	5,602	5,412	5,631	6,071	6,071	5,711	5,938	4,065

Notes: The table presents the robustness checks for the estimates of the conflict's indirect impact on a dummy variable that takes one if the firm has no positive reported sales. 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 whether a firm has been trading with Russia before the conflict (2012 or 2013) interacted with Post_{it} (Column 8), controlling for the total number of trade partners before the conflict (2012 and 2013) interacted with Post_{it} (Column 9), omitting firms near the conflict areas, i.e., Donetsk and Luhansk oblast (Columns 10 and 11, respectively), and removing firms in Kyiv (Column 12). 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: The Impact of Conflict on Sales of Firms Trading With Conflict Areas—Weight-Based Exposure

	(1) Log Sales	(2) No Sales Reported	(3) Log Sales	(4) No Sales Reported
Post-2014 × Firm's buyer conflict exposure, 2012–13	-0.187*	0.068***		
	(0.106)	(0.025)		
Post-2014 × Firm's supplier conflict exposure, 2012–13	-0.372***	0.128***		
	(0.103)	(0.022)		
Post-2014 × $\mathbb{1}$[High firm's buyer conflict exposure, 2012–13]			-0.207***	0.068***
			(0.062)	(0.013)
Post-2014 × $\mathbb{1}$[High firm's supplier conflict exposure, 2012–13]			-0.229***	0.059***
			(0.059)	(0.012)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean	16.891	0.327	16.891	0.327
SD	2.483	0.469	2.483	0.469
Observations	34,998	52,247	34,998	52,247
Number of Firms	4,798	6,069	4,798	6,069

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. Exposure is calculated as weight share. High exposure refers to exposure greater than the 80th 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.

A.4 Robustness for the Impacts on Reorganization of Production Linkages

Table A.5: Log total weight of incoming and outgoing shipments from and to the non-conflict areas

	(1) Log Weight Received from Nonconflict Areas	(2) Log Weight Sent to Nonconflict Areas	(3) Log Weight Received from Nonconflict Areas	(4) Log Weight Sent to Nonconflict Areas
Post-2014 × Firm's buyer conflict exposure, 2012–13	-0.314***	0.152		
	(0.115)	(0.214)		
Post-2014 × Firm's supplier conflict exposure, 2012–13	0.611***	-0.441**		
	(0.139)	(0.196)		
Post-2014 × $\mathbb{1}$[High firm's buyer conflict exposure, 2012–13]			-0.146**	-0.112
			(0.068)	(0.093)
Post-2014 × $\mathbb{1}$[High firm's supplier conflict exposure, 2012–13]			0.234***	-0.266**
			(0.070)	(0.106)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean	15.664	15.530	15.664	15.530
SD	2.337	2.979	2.337	2.979
Observations	20,628	13,410	20,628	13,410
Number of Firms	4,983	3,600	4,983	3,600

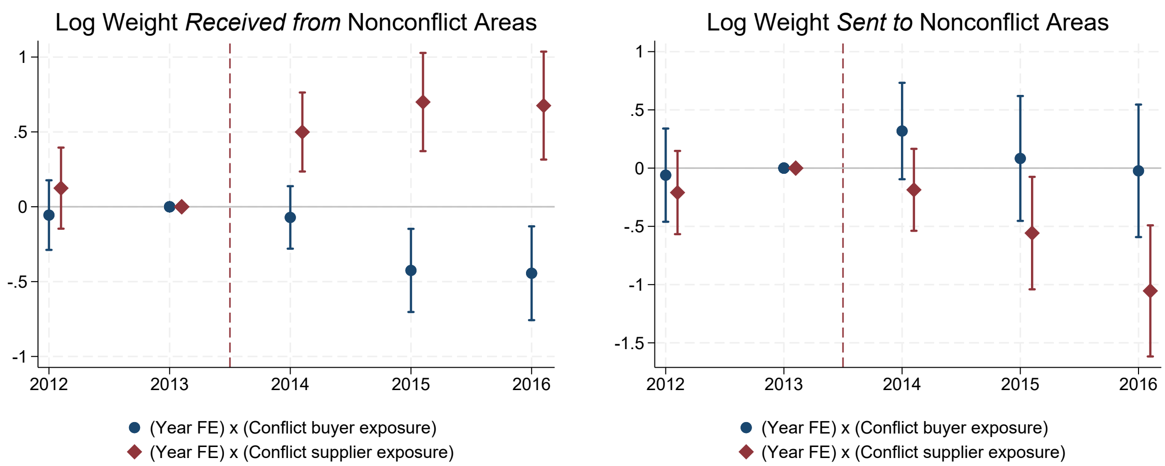
Notes: The table presents the estimates for the conflict's impact on firm total outgoing and incoming trade with nonconflict areas by firms' preexisting connectedness with the conflict areas. High exposure refers to exposure greater than the 80th percentile in the sample. The sample is restricted to 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.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log # of Suppliers Total	Log Weight Received Total	Log # of Buyers Total	Log Weight Sent Total	Log # of Suppliers Total	Log Weight Received Total	Log # of Buyers Total	Log Weight Sent Total
Post-2014 × Firm's buyer conflict exposure, 2012–13	-0.107*	-0.288***	-0.255***	-0.548***				
	(0.060)	(0.110)	(0.087)	(0.189)				
Post-2014 × Firm's supplier conflict exposure, 2012–13	-0.147***	-0.495***	-0.195**	-0.395**				
	(0.055)	(0.108)	(0.094)	(0.195)				
Post-2014 × 𝟙[High firm's buyer conflict exposure, 2012–13]					-0.066*	-0.127*	-0.244***	-0.447***
					(0.036)	(0.066)	(0.045)	(0.089)
Post-2014 × 𝟙[High firm's supplier conflict exposure, 2012–13]					-0.113***	-0.279***	-0.099*	-0.223**
					(0.034)	(0.063)	(0.051)	(0.107)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean	1.813	15.738	1.950	15.572	1.813	15.738	1.950	15.572
SD	1.260	2.357	1.507	3.006	1.260	2.357	1.507	3.006
Observations	21,078	21,078	13,793	13,793	21,078	21,078	13,793	13,793
Number of Firms	5,082	5,082	3,701	3,701	5,082	5,082	3,701	3,701

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 80th 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. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Figure A.6: The Impact of Conflict on Firm's Trade with Non-Conflict Areas



Notes: This figure displays the results of estimating Equation (2) evaluating whether a firm's trade activity with 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.

A.5 Impacts on Firm Sales in Conflict Areas

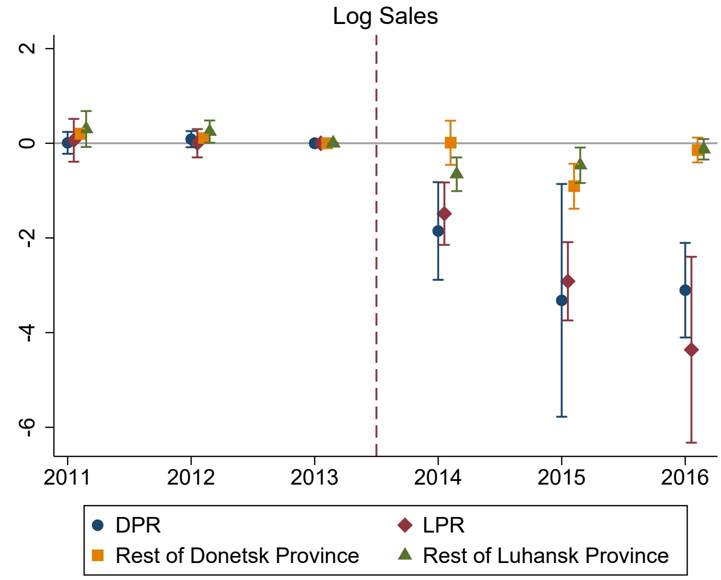
In this appendix, we show that the conflict had a profound negative effect on the economic activity of directly affected territories of the self-proclaimed Donetsk and Luhansk People's Republics (DPR and LPR). To demonstrate this quantitatively, we utilize data for the near-universe of Ukrainian firms 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. Specifically, we estimate:

$$Y_{rt} = \alpha_r + \kappa_t + \beta_t^{LPR} \times \text{LPR}_r + \beta_t^{DPR} \times \text{DPR}_r + \beta_t^{DON} \times \text{Donetsk}_r + \beta_t^{LUH} \times \text{Luhansk}_r + \varepsilon_{rt} \tag{A.1}$$

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 A.7 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. Figure A.7 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.

Figure A.7: 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.

A.6 Impacts of Supplier and Buyer Conflict Exposures on Local Population Size

One may wonder whether our reduced-form estimates could be confounded by refugee movements correlated with our measures of production network conflict exposures. In this Appendix, we investigate this concern by analyzing whether population movements during 2012–2016 within Ukraine show any differential changes in areas with greater buyer or supplier conflict exposure.

Although detailed, rayon-level panel data for population flows are unavailable, each region (oblast) provides annual reports on population and refugee statistics to the National Statistical Bureau.[1] As such, we have compiled a panel dataset for the regions over 2012–2016. In our analysis, we focus on 25 regions that were neither occupied nor directly affected by the war.

The primary outcome variable in Table A.7 is the logarithm of the total population of a region,

[1] https://ukrstat.gov.ua/druk/publicat/Arhiv_u/13/Arch_nnas_zb.htm.

which combines refugee flows and general population dynamics. Furthermore, we address the notable issue of individuals receiving pensions from both sides of the conflict line, which involves registering in areas under central government control.[2] Columns (1)–(3) of Table A.7 focus on unadjusted refugee numbers, while columns (4)–(6) adjust these figures based on regional age demographics to account for the distortion caused by 'phantom retirees.'[3]

Columns (1) and (4) of Table A.7 report the results for weight exposure, columns (2) and (5) for value exposure, and columns (3) and (6) for the number of links. Given that our analysis is restricted to 25 regions, the asymptotic standard errors (shown in parentheses) may not give the right coverage, prompting us to also present Wild bootstrap p-values from 999 bootstrap samples.

Our analysis does not reveal a statistically significant link between exposure levels and regional population for most of the specifications. An exception is observed with value exposure in the unadjusted dataset, yet this is only marginally significant at the 10% level.

[2]https://voxukraine.org/velyke-pereselennya-skilky-naspravdi-v-ukraini-vpo-ua.

[3]To adjust for retirees, we take the ratio of retirees and disabled to the rest of the population in eight Western Ukrainian regions that are not affected by the phenomenon: Chernivtsi, Ivano-Frankivsk, Lviv, Ternopil, Zakarpattia, Volyn, Rivne, and Khmelnytskyi Oblasts. We then use the same ratio for the rest of the country, assuming the younger refugee cohorts are unaffected. Finally, we project the number of younger refugees to correct the number of refugees of older age.

Table A.7: Robustness Check: Impact on Region-Level Population

Dependent Variable: Log Total Population

	(1)	(2)	(3)	(4)	(5)	(6)
	Unadjusted Refugees			Adjusted Refugees		
Exposure Type:	Weight	Value	Links	Weight	Value	Links
Post-2014 × Region's buyer conflict exposure, 2012–13	0.134	0.112*	0.203	0.058	0.045	0.111
	(0.079)	(0.065)	(0.127)	(0.052)	(0.036)	(0.065)
Post-2014 × Region's supplier conflict exposure, 2012–13	0.080	0.182*	0.209	0.032	0.072	0.013
	(0.053)	(0.098)	(0.150)	(0.043)	(0.042)	(0.062)
Wild bootstrap p-value, buyer	[0.158]	[0.149]	[0.192]	[0.334]	[0.272]	[0.146]
Wild bootstrap p-value, seller	[0.242]	[0.094]	[0.368]	[0.636]	[0.111]	[0.841]
Provinces	25	25	25	25	25	25
Observations	125	125	125	125	125	125

Notes: Regression is run on the panel of the non-occupied and not directly affected regions. Standard errors are clustered on the region level in parentheses. Columns (1)-(3) and then (4)-(6) report three exposure types: weight, value, and links. For columns (4)-(6), we adjust refugees by population share of retirees to avoid including people eligible for pensions on two sides of the border and thus traveling outside conflict zones solely to receive pensions. * p<0.1, ** p<0.05, *** p<0.01.

B Value Imputation of Railway Shipment Data

As discussed in Section 2.2, our railway shipment data reports detailed product classification (ETSNV code) and shipment weight but not the value of each transaction. In this appendix, we describe our procedure of imputing transaction values in our railway shipment data using separate customs data. We do so in three steps: First, we define the mapping between the product code classification in our railway shipment data (ETSNV code) and a separate customs data (HS code). Second, we estimate the value per shipment weight for each ETSNV code using the customs data. Third, we use the estimated value per shipment weight to impute transaction values from the weight of each shipment in our railway shipment data.

Step 1. Create product code correspondence between railway shipment Data (ETSNV code) and customs data (HS code).. We start by creating a correspondence between the railway cargo codes (ETSNV codes) and the product codes available in the customs data (HS codes). We start this merge using the crosswalks for different periods, 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. There are 9,296 (9,360 for the rest of the period) unique HS8 codes and 4,673 (4,669 for the rest of the period) unique ETSNV (cargo) codes.

We first establish a many-to-one match of ETSNV (railway) codes to a unique custom (HS) code. We assign a unique HS-8 code to ETSNV code whenever the match is unique within our crosswalk. This first step covers 71.9% of ETSNV codes before the classification change and 66.7% – after. In the remaining cases, an ETSNV code corresponds to multiple HS-8 codes. In this case, we find the finest aggregation of HS code above HS-8 where we can create a correspondence (e.g., HS6, HS5, or HS4).

Below are the links to the crosswalks we used:

- Codebooks from 01.07.2011 to 01.07.2012: http://uz.gov.ua/files/file/cargo_transportation/smgs/G_142_izm_2011.rar

- Codebooks from 01.07.2012 to 10.10.2012: http://uz.gov.ua/files/file/cargo_transportation/smgs/G_142_03_07_2012.xls

- Codebooks from 10.10.2012 to 01.07.2013 : http://uz.gov.ua/files/file/cargo_transportation/smgs/G_142_2012.xls

- Codebooks from 01.07.2013 onward: http://uz.gov.ua/files/file/cargo_transportation/smgs/G_142_01.07.2013.xls

- Links to the website archive: https://web.archive.org/web/20121014063056/http://uz.gov.ua/cargo_transportation/legal_documents/nomenklatura/table_gnv_snd/ and 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.

A relatively major change in the coding correspondence occurred on 10.10.2012, with approximately 3% of the codes affected. The rest of the codes are unaffected.

Step 2. Estimate value-per-shipment-weight for each ETSNV Code using customs data.. In our second step, we extract the value-to-weight ratio for each ETSNV code using the custom data. To do so, we first assign an ETSNV code to each transaction in customs data. We then use the reported transaction value and shipment weight to compute the value-per-shipment-weight.

To probe the robustness, we execute this imputation in several alternate ways. First, we use either (i) all of the custom transactions (both import and export) or (ii) only the export transactions. (i) provides a higher precision using a larger sample, while (ii) potentially addresses a concern that import transactions have a higher chance of being misreported than export transactions (Fisman and Wei (2004); Chalendard, Fernandes, Raballand, and Rijkers (2023)). Second, we use two different ways of computing the value per shipment weight: (a) applying a log transformation for each transaction and then exponentiating after averaging to smooth out the outliers,[4] or (b) total value for the HS code divided by total shipment weight. These four approaches are highly correlated; the correlation coefficients range from 0.85 to 0.98 (see Table B.1 below).

Step 3. Use the estimated value-per-shipment-weight to impute transaction value for railway shipment data.. Finally, we return to our railway shipment data and obtain transaction value by

[4]Specifically, for transaction i in good category j we use $\widehat{\text{Unit Value}}_j = \exp((1/N_j)\sum_i(\log(\text{Value}_{ij}/\text{Weight}_{ij})))$, N_j is the number of observations in the j-th HS code.

Table B.1: Raw correlations of the four measures on the product level

	(1)	(2)	(3)	(4)
	Raw Correlations			
(1) average $\log$(Value/Weight), All	1.00			
(2) average $\log$(Value/Weight), Export	0.92	1.00		
(3) $\log$(HS-code average Value/Weight), All	0.91	0.85	1.00	
(4) $\log$(HS-code average Value/Weight), Export	0.90	0.98	0.86	1.00

Notes: The table reports correlation coefficients between the four measures: export-based and based on all transactions and averaged within product categories log-value-to-weight ratio vs. log average value-to-weight ratio.

multiplying the reported shipment weight and the estimated value-per-shipment weight for the corresponding ETSNV code.

All iterative procedure steps combined cover 97.9% (94.8%) of ETSNV codes. The remaining codes are the HS codes that exist in classification but never appeared in Ukrainian import or export transactions.

Validity of Value Imputation.. We think our algorithm delivers an accurate value prediction for several reasons.

Crucial for the validity of our approach is the premise that the estimated value-per-shipment-weight from customs data has good predictive power for our firm-to-firm railway shipment data. Since transaction value is not directly reported in our railway shipment data, we cannot directly assess this claim. However, we can assess the performance of our approach strictly within our customs data.

We rely on an out-of-sample test to verify our value-prediction algorithm. More specifically, for a random 80% subsample of observations in the customs data – "training dataset," we run the iterative procedure described above and get the predicted log-unit values and log-total values by multiplying the former by the weight of the transaction: $\log(\widehat{\text{Value}}_{ij}) = \log(\widehat{\text{Unit Value}}_j \times \text{Weight}_{ij})$.

We then use the remaining 20% of the sample – "test dataset" to predict the $\log(\text{Value}_{ij})$ by $\log(\widehat{\text{Value}}_{ij})$. The results are reported in Table B.2. Given that the perfect prediction will mean $\log(\text{Value}_{ij}) == \log(\widehat{\text{Value}}_{ij})$, we are reporting the regressions without a constant.

Columns (1)-(4) of Table B.2 correspond to the four approaches we rely on: all transactions vs. export, with exp-log transformation, and without. Panels A and B correspond to two periods where the code book changes.

The first thing to notice from Table B.2 is that all coefficients are close to one, suggesting a reasonable relation between the actual and predicted transaction values.

Since we are not using the constant in this regression, we compare the root-mean-square errors for the training and test data to the standard deviation in the raw data, and we see a reasonable predictive pattern across the specifications.

Table B.2: Predicting per unit value with HS-FEs, in-sample

	(1) All exp-log	(2) Exports Only exp-log	(3) All	(4) Exports Only
Panel A: November 2012 - December 2013				
$\log(\widehat{\text{Value/Weight}})$	0.990***	0.971***	1.052***	0.983***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	882,584	795,052	882,584	795,052
St. Dev. Raw Data	2.06	2.06	2.06	2.06
RMSE Test Data	1.43	1.52	1.90	1.60
RMSE Training Data	1.53	1.68	1.92	1.74
Panel B: January 2012 - October 2012				
$\log(\widehat{\text{Value/Weight}})$	0.992***	0.994***	1.015***	1.014***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	672,430	671,766	672,430	671,766
St. Dev. Raw Data	1.96	1.96	1.96	1.96
RMSE Test Data	1.02	1.06	1.15	1.19
RMSE Training Data	1.02	1.05	1.15	1.19

Notes: The table presents regressions of log-unit-values on HS fixed effects. Columns (1) and (2) use HS8-level fixed effects, and columns (3) and (4) redo it for HS6-level fixed effects. Columns (1) and (3) use all transactions, and columns (2) and (4) use export transactions.

C Appendix for Model

C.1 Proof of Proposition 1

From Equation (10),

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

Furthermore, from Equations (6), (7) and (8),

$$\begin{aligned}C_{i,m}(\omega)^{1-\sigma_m} &= Z_{i,m}(\omega)^{\sigma_m-1}w_i^{\beta_{m,L}(1-\sigma_m)}\prod_{k\in K}P_{i,km}(\omega)^{\beta_{km}(1-\sigma_m)}\\ &= Z_{i,m}(\omega)^{\sigma_m-1}w_i^{\beta_{m,L}(1-\sigma_m)}\prod_{k\in K}\left[\left(\sum_{u\in\mathcal{L}}\sum_{\upsilon\in\Omega_{u,k}} M_{ui,km}(\upsilon,\omega)p_{ui,km}(\upsilon,\omega)^{1-\sigma_k}\right)^{\frac{1}{1-\sigma_k}}\right]^{\beta_{km}(1-\sigma_m)}\\ &= Z_{i,m}(\omega)^{\sigma_m-1}w_i^{\beta_{m,L}(1-\sigma_m)}\mathcal{A}^S_{i,m}(\omega)\prod_{k\in K}\varsigma_k^{\beta_{km}(1-\sigma_m)}. \end{aligned} \tag{C.2}$$

By combining, we obtain the desired results.

C.2 Equilibrium Conditions for Counterfactual Simulation

In this appendix, we derive the system of equations for counterfactual simulation.

We first reproduce the equilibrium conditions. 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 $\{p_{id,ml}(\omega,\psi), C_{i,m}(\omega),, P_{i,km}(\omega), P_i^F, w_i\}$, 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

$$p_{id,ml}(\omega,\psi) = \frac{\sigma_m}{\sigma_m-1}C_{i,m}(\omega)\,\tau_{id,ml}(\omega,\psi), \tag{C.3}$$

$$C_{i,m}(\omega) = \frac{1}{Z_{i,m}(\omega)} w_i^{\beta_{m,L}} \prod_{k \in K} P_{i,km}(\omega)^{\beta_{km}}, \tag{C.4}$$

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

$$X_{ui,km}(\upsilon, \omega) = \varsigma_k M_{ui,km}(\upsilon, \omega) \tau_{ui,km}(\upsilon, \omega)^{1-\sigma_k} C_{u,k}(\upsilon)^{1-\sigma_k} D_{i,km}(\omega), \tag{C.6}$$

$$D_{i,km}(\omega) = \frac{1}{P_{i,km}(\omega)^{1-\sigma_m}} \beta_{km} \frac{\sigma_m - 1}{\sigma_m} R^*_{i,m}(\omega), \tag{C.7}$$

$$R_{i,m}(\omega) = \sum_{l \in K} \sum_{d \in \mathcal{L}} \sum_{\psi \in \Omega_{d,l}} X_{id,ml}(\omega, \psi), \tag{C.8}$$

$$R^F_{i,m}(\omega) = \frac{\varsigma_m N_{i,m}(\omega) C_{i,m}(\omega)^{1-\sigma_k}}{\left(P^F_{i,m}\right)^{1-\sigma_m}} \alpha_m E_i L_i, \tag{C.9}$$

$$P^F_{i,m} = \left(\varsigma_m \sum_{\omega \in \Omega_{i,m}} N_{i,m}(\omega) C_{i,m}(\omega)^{1-\sigma_m} \right)^{\frac{1}{1-\sigma_m}}, \tag{C.10}$$

$$R^*_{i,m}(\omega) = R_{i,m}(\omega) + R^F_{i,m}(\omega), \tag{C.11}$$

$$w_i L_i = \sum_{m \in K} \sum_{\omega \in \Omega_{i,m}} \beta_{L,m} \frac{\sigma_m - 1}{\sigma_m} R^*_{i,m}(\omega), \tag{C.12}$$

$$E_i = w_i + \frac{1}{L_i} \sum_{m \in K} \sum_{\omega \in \Omega_{i,m}} \pi_{i,m}(\omega), \tag{C.13}$$

$$\pi_{i,m}(\omega) = \frac{1}{\sigma_m} R^*_{i,m}(\omega). \tag{C.14}$$

Now, we rewrite the equilibrium conditions given counterfactual changes in fundamentals. We denote the variable x in counterfactual equilibrium by x' (with a prime) and that as a ratio to baseline equilibrium as $\hat{x} = x'/x$ (with a hat). Given the change in TFP $\{\hat{Z}_{i,m}(\omega)\}$ and production linkages $\{M_{id,ml}(\omega, \psi)\}$, the counterfactual equilibrium is derived as a solution to the following system of equations:

$$\hat{C}_{i,m}(\omega) = \frac{1}{\hat{Z}_{i,m}(\omega)} \hat{w}_i^{\beta_{m,L}} \prod_{k \in K} \hat{P}_{i,km}(\omega)^{\beta_{km}}, \tag{C.15}$$

$$\hat{P}_{i,km}(\omega) = \left(\sum_{u \in \mathcal{L}} \sum_{\upsilon \in \Omega_{u,k}} \Lambda_{ui,km}(\upsilon,\omega) \hat{\tau}_{ui,km}(\upsilon,\omega) \hat{M}_{ui,km}(\upsilon,\omega) \hat{C}_{u,k}(\upsilon)^{1-\sigma_k} \right)^{\frac{1}{1-\sigma_k}}, \tag{C.16}$$

$$\hat{X}_{ui,km}(\upsilon,\omega) = \hat{\tau}_{ui,km}(\upsilon,\omega) \hat{M}_{ui,km}(\upsilon,\omega) \hat{C}_{u,k}(\upsilon)^{1-\sigma_k} \frac{1}{\hat{P}_{i,km}(\omega)^{1-\sigma_k}} \hat{R}^*_{i,m}(\omega), \tag{C.17}$$

$$\hat{R}_{i,m}(\omega) = \sum_{l \in K} \sum_{d \in \mathcal{L}} \sum_{\psi \in \Omega_{d,l}} \Psi_{id,ml}(\omega,\psi) \hat{X}_{id,ml}(\omega,\psi), \tag{C.18}$$

$$\hat{P}^F_{i,m} = \left(\sum_{\omega \in \Omega_{i,m}} \Lambda^F_{i,m}(\omega) \, \hat{C}_{i,m}(\omega)^{1-\sigma_m} \right)^{\frac{1}{1-\sigma_m}}, \tag{C.19}$$

$$\hat{R}^F_{i,m}(\omega) = \frac{\hat{C}_{i,m}(\omega)^{1-\sigma_m}}{\left(\hat{P}^F_{i,m}\right)^{1-\sigma_m}} \hat{E}_i, \tag{C.20}$$

$$\hat{R}^*_{i,m}(\omega) = S_{i,m}(\omega) \hat{R}_{i,m}(\omega) + \left(1 - S_{i,m}(\omega)\right) \hat{R}^F_{i,m}(\omega), \tag{C.21}$$

$$\hat{w}_i = \sum_{m \in K} \sum_{\psi \in \Omega_{i,m}} \Phi^W_{i,m}(\omega) \hat{R}^*_{i,m}(\omega), \tag{C.22}$$

$$\hat{E}_i = \sum_{m \in K} \sum_{\omega \in \Omega_{i,m}} \Phi_{i,m}(\omega) \hat{R}^*_{i,m}(\omega), \tag{C.23}$$

where $\{\Lambda_{ui,km}(\upsilon,\omega), \Psi_{id,ml}(\omega,\psi), S_{i,m}(\omega), \Phi^W_{i,m}(\omega), \Phi_{i,m}(\omega), \Lambda^F_{i,m}(\omega)\}$ are shares in baseline equilibrium, defined by

$$\Lambda_{ui,km}(\upsilon,\omega) = \frac{X_{ui,km}(\upsilon,\omega)}{\sum_{\tilde{u} \in \mathcal{L}} \sum_{\tilde{\upsilon} \in \Omega_{u,k}} X_{\tilde{u}i,km}(\tilde{\upsilon},\omega)}, \tag{C.24}$$

$$\Lambda^F_{i,m}(\omega) = \frac{R^F_{i,m}(\omega)}{\sum_{\tilde{\omega} \in \Omega_{i,m}} R^F_{i,m}(\tilde{\omega})}, \tag{C.25}$$

$$\Psi_{id,ml}(\omega,\psi) = \frac{X_{id,ml}(\omega,\psi)}{\sum_{\tilde{l} \in K} \sum_{\tilde{d} \in \mathcal{L}} \sum_{\tilde{\psi} \in \Omega_{d,l}} X_{i\tilde{d},m\tilde{l}}(\omega,\tilde{\psi})}, \tag{C.26}$$

$$S_{i,m}(\omega) = \frac{R_{i,m}(\omega)}{R_{i,m}(\omega) + R^F_{i,m}(\omega)}, \tag{C.27}$$

$$\Phi^W_{i,m}(\omega) = \frac{\beta_{L,m} \frac{\sigma_m - 1}{\sigma_m} R^*_{i,m}(\omega)}{\sum_{\tilde{m} \in K} \sum_{\tilde{\omega} \in \Omega_{i,\tilde{m}}} \beta_{L,\tilde{m}} \frac{\sigma_{\tilde{m}} - 1}{\sigma_{\tilde{m}}} R^*_{i,\tilde{m}}(\tilde{\omega})}, \tag{C.28}$$

$$\Phi_{i,m}(\omega)=\frac{\left(\beta_{L,m}\frac{\sigma_m-1}{\sigma_m}+\frac{1}{\sigma_m}\right)R^*_{i,m}(\omega)}{\sum_{\tilde{m}\in K}\sum_{\tilde{\omega}\in\Omega_{i,\tilde{m}}}\left(\beta_{L,\tilde{m}}\frac{\sigma_{\tilde{m}}-1}{\sigma_{\tilde{m}}}+\frac{1}{\sigma_{\tilde{m}}}\right)R^*_{i,\tilde{m}}(\tilde{\omega})}. \tag{C.29}$$

C.3 Incorporate Entry/Exit Effects

In the counterfactual simulation in Section 5.3, we abstract from the changes in the measure of active firms. In this section, we explore how the changes in active firms through entry/exit affect our analysis. To do so, we assume that the measure of firms $\{N_{i,m}(\omega)\}$ may change as a response to shock. The system of equations for the counterfactual equilibrium remains the same from Appendix C.2, except that Equations (C.19) and (C.20) are modified as follows:

$$\hat{P}^F_{i,m}=\left(\sum_{\omega\in\Omega_{i,m}}\Lambda^F_{i,m}(\omega)\,\hat{N}_{i,m}(\omega)\,\hat{C}_{i,m}(\omega)^{1-\sigma_m}\right)^{\frac{1}{1-\sigma_m}}, \tag{C.30}$$

$$\hat{R}^F_{i,m}(\omega)=\frac{\hat{N}_{i,m}(\omega)\,\hat{C}_{i,m}(\omega)^{1-\sigma_m}}{\left(\hat{P}^F_{i,m}\right)^{1-\sigma_m}}\hat{E}_i. \tag{C.31}$$

C.4 Multiple Shipment Modes

In our baseline model in Section 4, we abstracted the presence of multiple shipment modes. In reality, firms may source from multiple shipment modes, not only through railways. This appendix discusses how our analysis is affected by incorporating multiple shipment modes.

Suppose that, suppliers of type $\omega\in\Omega_{i,k}$ to sell to buyers of type $\upsilon\in\Omega_{j,m}$, they can choose to ship through railways or through roads. The iceberg shipment cost is $\tau^m_{ij,km}(\upsilon,\omega)\varepsilon^m_{ij,km}(\upsilon,\omega)$ for $m\in\{\text{Rail},\text{Road}\}$, respectively, where $\tau^m_{ij,km}(\upsilon,\omega)$ denote the common component of mode-specific shipment cost, and $\varepsilon^m_{ij,km}(\upsilon,\omega)$ denotes the idiosyncratic components for each supplier. We follow Allen and Arkolakis (2014) and assume that $\varepsilon^m_{ij,km}(\upsilon,\omega)$ follows i.i.d. Frechet distribution with shape parameter κ. Then, the probability that suppliers choose to ship through railways is given by

$$\pi^{\text{Rail}}_{ij,km}(\upsilon,\omega)=\frac{\left(\tau^{\text{Rail}}_{ij,km}(\upsilon,\omega)\right)^{\kappa}}{\left(\tau^{\text{Rail}}_{ij,km}(\upsilon,\omega)\right)^{\kappa}+\left(\tau^{\text{Road}}_{ij,km}(\upsilon,\omega)\right)^{\kappa}}, \tag{C.32}$$

and that through road is given by $\pi^{\text{Road}}_{ij,km}(\upsilon,\omega)=1-\pi^{\text{Rail}}_{ij,km}(\upsilon,\omega)$. Therefore, trade flows and the measure of supplier linkages over railway networks are given by

$$X_{ij,km}^{\text{Rail}}(\upsilon,\omega) = \pi_{ij,km}^{\text{Rail}}(\upsilon,\omega) X_{ij,km}(\upsilon,\omega), \quad M_{ij,km}^{\text{Rail}}(\upsilon,\omega) = \pi_{ij,km}^{\text{Rail}}(\upsilon,\omega) M_{ij,km}(\upsilon,\omega), \tag{C.33}$$

where $X_{ij,km}(\upsilon,\omega)$ and $M_{ij,km}(\upsilon,\omega)$ are overall trade flows and the measure of supplier linkages.

This analysis provides a justification for our reduced-form analysis in Section 3 to use railway shipment data as an outcome variable. It is certainly possible that the coverage of railway shipment out of the overall shipment, i.e., $\pi_{ij,km}^{\text{Rail}}(\upsilon,\omega)$, may systematically differ across firms and locations. However, under our difference-in-differences approach, all time-invariant firm-specific component of $\pi_{ij,km}^{\text{Rail}}(\upsilon,\omega)$ will drop out. Therefore, the identification concern arises only if the supplier and buyer conflict exposures are systematically related to the changes in *relative* shipment costs between railways and roads. This assumption is plausible especially when we study the reorganization of production networks *strictly outside conflict areas* (in Section 3.3), as there are no systematic disruption in shipment costs for both railways and roads outside conflict areas.

Next, we show that our model remains isomorphic by incorporating multiple shipment modes. To see this, note that the expected shipment cost is given by

$$\tau_{ij,km}(\upsilon,\omega) = \varrho \left(\left(\tau_{ij,km}^{\text{Rail}}(\upsilon,\omega) \right)^{\kappa} + \left(\tau_{ij,km}^{\text{Road}}(\upsilon,\omega) \right)^{\kappa} \right)^{\frac{1}{\kappa}}, \tag{C.34}$$

where ϱ is a constant. Therefore, our model remains isomorphic to Section 4 by replacing $\tau_{ij,km}(\upsilon,\omega)$ by the expression given by Equation (C.34). The only implication for this extension is that it may affect the baseline patterns of trade flows $\{X_{ij,km}(\upsilon,\omega)\}$. While the lack of data of trade flows over roads prevents us to assess the quantitative implication, we believe that using railway network data to calibrate the baseline trade flows provide a close approximation to the overall trade flows, based on the observation that the majority of long-distance shipment occurs through railways rather than other shipment modes due to a high-quality railway shipment technology relative to roads.[5]

[5] According to UkrStat, as of 2018, railroads were responsible for 80% of ton-km of all freight transport, i.e., http://www.ukrstat.gov.ua/operativ/operativ2018/tr/vtk/xls/vtk_2018_e.xlsx.

D Calibration Appendix

This appendix discusses the details of the model calibration. In order to execute the counterfactual simulation following the procedure specified in Section C.2, besides the structural parameters $\{\beta_{L,m}, \beta_{km}, \alpha_k, \sigma_k\}$, we need baseline trade flows of intermediate inputs $\{X_{ui,km}(\upsilon, \omega)\}$ and final goods sales $\{R^F_{i,m}(\omega)\}$. We calibrate these baseline variables based on our railway shipment data. However, directly using railway shipment data may be problematic if the data involves measurement errors and does not satisfy the equilibrium conditions implied by our model. To deal with this issue, we adjust the trade flows so that equilibrium conditions are satisfied in the following manner.

We start by assuming that the baseline trade flow follows $X_{ui,km}(\upsilon, \omega) = \check{X}_{ui,km}(\upsilon, \omega)\chi_{i,m}(\omega)$, where $\check{X}_{ui,km}(\upsilon, \omega)$ is the observed transaction values in our railway shipment data (see Appendix B for the details of the value imputation using product codes), and $\chi_{i,m}(\omega)$ capture the buyer-specific measurement errors. We obtain $\chi_{i,m}(\omega)$ using the following equilibrium relationships and assumptions about the final sales.

First, by summing up Equation (C.9) across all firm types $\omega \in \Omega_{i,m}$, we have $\sum_{\omega\in\Omega_{i,m}} R^F_{i,m}(\omega) = \alpha_m E_i L_i$. Combining with Equations (C.11), (C.12), (C.13) and (C.14),

$$\begin{aligned}
\tilde{E}_i &= \sum_{m\in K}\left(\beta_{L,m}\frac{\sigma_m - 1}{\sigma_m} + \frac{1}{\sigma_m}\right)\left(\sum_{\omega\in\Omega_{i,m}} R_{i,m}(\omega) + \alpha_m E_i L_i\right) \\
&= \left[1 - \sum_{m\in K}\left(\beta_{L,m}\frac{\sigma_m - 1}{\sigma_m} + \frac{1}{\sigma_m}\right)\alpha_m\right]^{-1} \sum_{m\in K}\left(\beta_{L,m}\frac{\sigma_m - 1}{\sigma_m} + \frac{1}{\sigma_m}\right)\left(\sum_{\omega\in\Omega_{i,m}} R_{i,m}(\omega)\right),
\end{aligned} \tag{D.1}$$

where $\tilde{E}_i = E_i L_i$, and $R_{i,m}(\omega) = \sum_{l\in K}\sum_{d\in\mathcal{L}}\sum_{\psi\in\Omega_{d,l}} X_{id,ml}(\omega, \psi)$.

Second, given the lack of data on final goods sales, we simply assume that the final goods sales are proportional to those of the intermediate goods sales $\{R_{i,m}(\omega)\}$. That is,

$$R^F_{i,m}(\omega) = \frac{R_{i,m}(\omega)}{\sum_{\tilde{\omega}\in\Omega_{i,m}} R_{i,m}(\tilde{\omega})}\alpha_m \tilde{E}_i. \tag{D.2}$$

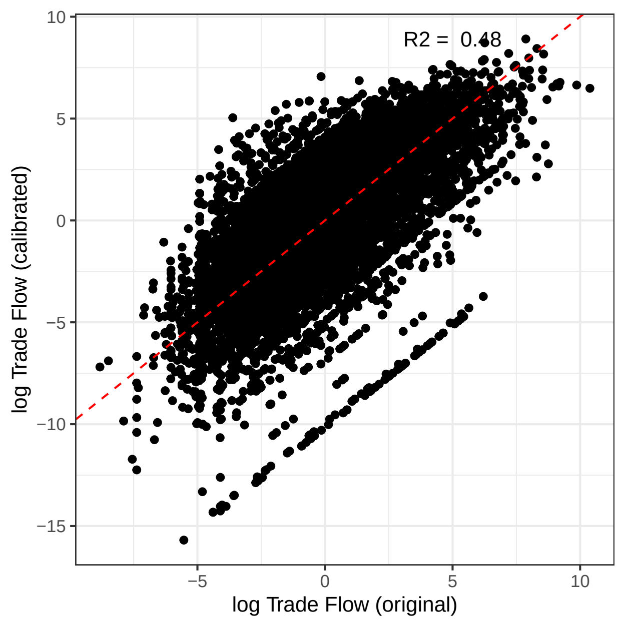
Third, by summing up Equations (C.6) and (C.7), we have

$$\sum_{u,k,\upsilon} X_{ui,km}(\upsilon,\omega) = \beta_{km}\frac{\sigma_m - 1}{\sigma_m}\left(R^F_{i,m}(\omega) + R_{i,m}(\omega)\right). \tag{D.3}$$

We back out $\{\chi_{i,m}(\omega)\}$, together with variables $\{X_{ui,km}(\upsilon,\omega)$, $\{R_{i,m}(\omega)\}$, $\{R^F_{i,m}(\omega)\}$, $\{\tilde{E}_i\})$ so that Equations (D.1), (D.2), (D.3). More specifically, starting from a guess of $\{\chi_{i,m}(\omega)\}$ (and hence $\{X_{ui,km}(\upsilon,\omega))$, we iteratively use the three equations to update $\{R_{i,m}(\omega)\}$, $\{R^F_{i,m}(\omega)\}$, $\{\tilde{E}_i\}$ using Equations (D.1) and (D.2), and update the value of $\{\chi_{i,m}(\omega)\}$ (and hence $\{X_{ui,km}(\upsilon,\omega))$ using Equation (D.3). We repeat this process until the procedure converges.

Figure D.1 shows that the recalibrated and original trade flows have high correlations with an R-squared of 0.48.

Figure D.1: Original and Calibrated Trade Flows



For our model validation, we also use proxies for wages $\{w_{i,t}\}$. 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 (16) for each year.

E Additional Tables for Model Validation

Table E.1: Model Validation: No Buyer Link Adjustment

	$\log w_{i,t}^{\beta_{m,L}(1-\sigma_m)} \tilde{\mathcal{A}}_{i,m,t}^S(\omega)\tilde{\mathcal{A}}_{i,m,t}^B(\omega)$				
	(1)	(2)	(3)	(4)	(5)
$\log R_{i,m,t}(\omega)$	0.42	0.40	0.44	0.25	0.70
	(0.13)	(0.14)	(0.13)	(0.17)	(0.41)
p-value (coefficient = 1)	0.00	0.00	0.00	0.00	0.46
Cluster-Robust First-Stage F-Statistics	26.4	27.6	27.3	11.5	4.2
IV	High Buyer and Supplier Exposures	High Buyer and Supplier Exposures	High Buyer and Supplier Exposures	High Buyer Exposure	High Supplier Exposure
Firm-Type-Region-Sector Fixed Effects	X	X	X	X	X
Year Fixed Effects	X	X	X	X	X
Sector × Year Fixed Effects		X	X	X	X
Region × Year Fixed Effects			X	X	X
Observations	426	426	426	426	426
Adjusted R^2	1.00	1.00	1.00	1.00	0.99

Notes: A version of Panel (A) of Table 4, where we construct supplier access using observed supplier link changes but construct buyer access abstracting changes in buyer links.

Table E.2: Model Validation: No Supplier Link Adjustment

	$\log w_{i,t}^{\beta_{m,L}(1-\sigma_m)} \tilde{\mathcal{A}}_{i,m,t}^S(\omega)\tilde{\mathcal{A}}_{i,m,t}^B(\omega)$				
	(1)	(2)	(3)	(4)	(5)
$\log R_{i,m,t}(\omega)$	1.11	1.17	1.18	0.98	1.69
	(0.16)	(0.17)	(0.16)	(0.18)	(0.50)
p-value (coefficient = 1)	0.48	0.32	0.27	0.90	0.17
Cluster-Robust First-Stage F-Statistics	31.4	33.7	36.8	15.1	6.1
IV	High Buyer and Supplier Exposures	High Buyer and Supplier Exposures	High Buyer and Supplier Exposures	High Buyer Exposure	High Supplier Exposure
Firm-Type-Region-Sector Fixed Effects	X	X	X	X	X
Year Fixed Effects	X	X	X	X	X
Sector × Year Fixed Effects		X	X	X	X
Region × Year Fixed Effects			X	X	X
Observations	427	427	427	427	427
Adjusted R^2	1.00	0.99	0.99	1.00	0.99

Notes: A version of Panel (A) of Table 4, where we construct buyer access using observed buyer link changes but construct supplier access abstracting changes in supplier links.

Table E.3: Model Validation: Use All Years

	$\log w_{i,t}^{\beta_{m,L}(1-\sigma_m)} \tilde{\mathcal{A}}_{i,m,t}^S(\omega) \tilde{\mathcal{A}}_{i,m,t}^B(\omega)$				
	(1)	(2)	(3)	(4)	(5)
$\log R_{i,m,t}(\omega)$	1.24	1.27	1.33	1.06	1.67
	(0.21)	(0.22)	(0.23)	(0.35)	(0.51)
p-value (coefficient = 1)	0.25	0.23	0.15	0.86	0.19
Cluster-Robust First-Stage F-Statistics	22	23.5	22.5	6.1	5.3
IV	High Buyer and Supplier Exposures	High Buyer and Supplier Exposures	High Buyer and Supplier Exposures	High Buyer Exposure	High Supplier Exposure
Firm-Type-Region-Sector Fixed Effects	X	X	X	X	X
Year Fixed Effects	X	X	X	X	X
Sector × Year Fixed Effects		X	X	X	X
Region × Year Fixed Effects			X	X	X
Observations	1,057	1,057	1,057	1,057	1,057
Adjusted R^2	0.99	0.99	0.99	1.00	0.99

Notes: A version of Panel (A) of Table 4, using all years of 2012-2016.

Table E.4: Model Validation: Estimate Gravity Equations and Accesses using Aggregate Flows

	$\log w_{i,t}^{\beta_{m,L}(1-\sigma_m)} \tilde{\mathcal{A}}_{i,m,t}^S(\omega) \tilde{\mathcal{A}}_{i,m,t}^B(\omega)$				
	(1)	(2)	(3)	(4)	(5)
$\log R_{i,m,t}(\omega)$	1.65	1.67	1.66	1.23	2.51
	(0.25)	(0.27)	(0.27)	(0.31)	(0.98)
p-value (coefficient = 1)	0.01	0.01	0.02	0.45	0.12
Cluster-Robust First-Stage F-Statistics	26.4	27.6	27.3	11.5	4.2
IV	High Buyer and Supplier Exposures	High Buyer and Supplier Exposures	High Buyer and Supplier Exposures	High Buyer Exposure	High Supplier Exposure
Firm-Type-Region-Sector Fixed Effects	X	X	X	X	X
Year Fixed Effects	X	X	X	X	X
Sector × Year Fixed Effects		X	X	X	X
Region × Year Fixed Effects			X	X	X
Observations	427	427	427	427	427
Adjusted R^2	0.99	0.99	0.99	0.99	0.97

Notes: A version of Panel (B) of Table 4, where we we estimate Equation (22) by eliminating $M_{ui,km,t}(\upsilon,\omega)$ from the denominator of the left-hand side, and compute the accesses using Equations (23) and (24) ignoring $M_{ui,km,t}(\upsilon,\omega)$.

F Appendix for Counterfactual Simulation

F.1 Additional Robustness

Table F.1: Counterfactual Simulation: Robustness

Alternative Specifications	(1) Baseline (With Supplier Link Adjustment)	(2) Shut Down Supplier Link Adjustment by Supplier Exposure	(3) Shut Down Supplier Link Adjustment by Buyer Exposure	(4) No Supplier Link Adjustment)
	Welfare Change (Percent)			
(a) Baseline	-9.1	-11.4	-6.8	-9.1
(b) Match Impacts on Both Supplier and Buyer Linkages	-8.8			
(c) Add Entry/Exit Effects	-10.0	-12.4	-7.7	-10.0
(d) Alternate Value Imputation (log(average Value/Weight))	-9.5	-11.9	-7.2	-9.5
(e) Alternate Value Imputation (average log(Value/Weight), Export)	-11.8	-13.9	-9.4	-11.6
(f) Alternate Value Imputation (log(average Value/Weight), Export)	-12.2	-14.3	-9.8	-12.0
(g) Define Types by Link Exposures	-9.0	-10.2	-7.0	-8.2
(h) Define Types by Weight Exposures	-7.8	-9.7	-5.8	-7.7

Notes: The results of the alternative robustness specifications of counterfactual simulations in Table 5, reporting the percent change in population-weighted welfare (real income). Row (a) replicates our baseline results in Table 5. Row (b) change the measure of supplier linkages depending on suppliers' conflict exposures, thereby rationalizing the patterns of the changes in buyer linkages as well (see Appendix F.2 for details). Row (c) assume that $\{N_{i,k}(\omega)\}$ change in a way consistent with our difference-in-differences estimates of Column (6) of Table 1, interpreting "no sales reported" as the exit of the firm, and assuming that $\{N_{i,k}(\omega)\}$ do not change if firms have low supplier and buyer exposures. Rows (d)-(f) calibrate the baseline trade flows using alternative methods for value imputation, i.e., by using simple means instead of geometric means to compute the value per weight (Rows d and f) and using export data only instead of both import and export data to compute the value per shipment weight (Rows e and f). Rows (g) and (h) define firm types using the exposures defined by the shares of links and shares of weights, instead of using value shares.

F.2 Rationalize Impacts on Both Supplier and Buyer Linkages

In this appendix, we show that our results remain similar even if we change the measure of supplier linkages depending on suppliers' conflict exposures, thereby rationalizing the patterns of the changes in buyer linkages as well. More specifically, instead of assuming that supplier linkages change uniformly across supplier types conditional on the buyers' conflict exposures, as our main specification, we assume that this change also differs by suppliers' conflict exposures.

Denote $D^S_{j,m}(\omega)$, $D^B_{j,m}(\omega)$ as a dummy variable that takes one if a firm type $\omega \in \Omega_{j,m}$ has high supplier and buyer exposures, respectively. We assume that the number links between suppliers and buyers increases according to the following function:

$$\Delta \log M_{ij,km}(\upsilon, \omega) = \left[\nu^{SS} D^S_{i,k}(\upsilon) + \nu^{SB} D^B_{i,k}(\upsilon) + 1\right] \left[\nu^{BS} D^S_{j,m}(\omega) + \nu^{BB} D^B_{j,m}(\omega)\right], \quad \text{(F.1)}$$

where $\{\nu^{SS}, \nu^{SB}, \nu^{BS}, \nu^{BB}\}$ are parameters. Notice that our main specification in Section 5.3 corresponds to the special case where we assume $\nu^{SS} = \nu^{SB} = 0$ and set ν^{BS} and ν^{SS} according to Column (3) of Table 2.

We estimate $\{\nu^{SS}, \nu^{SB}, \nu^{BS}, \nu^{BB}\}$ through indirect inference approach. Specifically, we choose these parameters to rationalize the reduced-form impacts of the supplier and buyer exposures on the measures of supplier and buyer linkages, targeting the reduced-form estimates reported in Columns (3) and (4) of Table 2.

Given $\{\nu^{SS}, \nu^{SB}, \nu^{BS}, \nu^{BB}\}$, the model-predicted changes in the measure of suppliers is given by

$$\Delta \log M^S_{j,m}(\omega) = \Delta \log \sum_{i,k,\upsilon} M_{ij,km}(\upsilon, \omega) = \sum_{i,k,\upsilon} \frac{M_{ij,km}(\upsilon, \omega)}{\sum_{i,k,\upsilon} M_{ij,km}(\upsilon, \omega)} \Delta \log M_{ij,km}(\upsilon, \omega). \quad \text{(F.2)}$$

The changes in the measure of buyers is given by

$$\Delta \log M^B_{i,k}(\upsilon) = \Delta \log \sum_{i,k,\upsilon} M_{ij,km}(\upsilon, \omega) = \sum_{i,k,\upsilon} \frac{M_{ij,km}(\upsilon, \omega)}{\sum_{i,k,\upsilon} M_{ij,km}(\upsilon, \omega)} \Delta \log M_{ij,km}(\upsilon, \omega). \quad \text{(F.3)}$$

We then project these model-predicted changes in the measure of suppliers and buyers on the dummies of high supplier and buyer exposures:

$$\Delta \log M^S_{j,m}(\omega) = \beta^{SS} D^S_{j,m}(\omega) + \beta^{SB} D^B_{j,m}(\omega) + \epsilon^S_{j,m}(\omega), \quad \text{(F.4)}$$

$$\Delta \log M^B_{j,m}(\omega) = \beta^{BS} D^S_{j,m}(\omega) + \beta^{BB} D^B_{j,m}(\omega) + \epsilon^B_{j,m}(\omega), \quad \text{(F.5)}$$

where $\epsilon^S_{j,m}(\omega)$ and $\epsilon^B_{j,m}(\omega)$ are residuals. We choose the values of parameters $\{\nu^{SS}, \nu^{SB}, \nu^{BS}, \nu^{BB}\}$ that generates $\{\beta^{SS}, \beta^{SB}, \beta^{BS}, \beta^{BB}\}$ that minimize the squared sum of the difference between the coefficients of reduced-form regression as reported in Columns (3) and (4) of Table 2 and the model counterpart. Through this procedure, we obtain the value of $\nu^{SS} = -1.04$, $\nu^{SB} = 0.30$, $\nu^{BS} = -0.14$, $\nu^{BB} = -0.16$, which generate approximately the same regression coefficients as Columns (3) and (4) of Table 2.