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

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Abstract

How do localized conflicts disrupt supply chains and prompt firms to reorganize them? How do these forces affect firm-level and aggregate economic activity? Using firm-to-firm Ukrainian railway-shipment data before and during the 2014 Russia-Ukraine conflict, we document that firms with prior supplier and buyer exposure to the conflict areas substantially decreased their output. Simultaneously, firms reorganize their production linkages away from partners directly or indirectly exposed to the conflict shock. We build a general-equilibrium production-network model with endogenous link formation and show that our model's sufficient statistics accurately explain the observed relative decline in firm output once we take into account network reorganization. Calibrating our model to the Ukrainian economy, we find that the localized conflict decreased aggregate output in nonconflict areas by 5.6%. This effect increases to 8.4% if we abstract from endogenous link formation, suggesting that production-network reorganization partially mitigates the detrimental, far-reaching aggregate economic costs of conflicts.

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1 Introduction

How do wars or armed conflicts affect a country's economic activity? Existing research shows they have a large and devastating impact on national output (Rohner and Thoenig, 2021).[1] Yet, direct conflict zones are often confined to relatively small geographic areas, such as international borders or ethnic boundaries. These observations suggest that the economic costs of wars likely extend beyond the direct destruction of physical and human capital in localized battlegrounds. However, due to the lack of detailed data during wartime and exogenous variation in the occurrence of conflicts, the literature offers limited evidence on how these spillover effects operate and how much they matter for firm-level and aggregate economic activity.

This paper empirically and theoretically examines a key channel through which localized conflicts impact the broader economy: the disruption and reorganization of supply chain linkages.

Firms in conflict zones may face production disruption, e.g., due to the destruction of physical capital or trade relationships. These negative shocks may then be transmitted to other firms through production networks, increasing their input costs or reducing demand for their products.

Furthermore, faced with a large, persistent war shock, firms in nonconflict areas may also reorganize their supply chain linkages. How firms adjust their linkages is theoretically ambiguous. On one hand, firms may find alternative suppliers and buyers to mitigate the disruption. On the other hand, shocks may induce firms to scale down production and cease sourcing from or selling to existing trade partners, which could then result in cascading negative effects on the economy. How localized conflicts disrupt supply chains, induce firms to reorganize them, and affect aggregate economic activity remain open empirical questions.

We investigate these questions 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 (the Donbas region). The prolonged war devastated parts of Donbas through bombing, infrastructure destruction, and loss of life. However, the rest of the country remained unexposed to direct violence until February 24, 2022, when Russia launched its full-scale invasion of Ukraine. Nonetheless, despite the lack of violence there, the real gross regional products (GRP) of all provinces other than Crimea and Donbas declined by 11.7% by the end of 2016, prompting questions about what drove this decline and whether production-network-driven spillovers are responsible for some of it.

This context offers a unique opportunity to examine the effects of localized conflicts on supply

[1] For instance, Federle et al. (2024) find that an interstate war on a country's own soil, on average, results in a 30% decline in that country's GDP. See Rohner and Thoenig (2021) for a detailed overview of other cost-of-war estimates.

chain disruptions and their subsequent reorganization. We overcome the typical lack of data in war-affected countries by leveraging a unique dataset with the universe of firm-to-firm railway shipments within Ukraine, covering periods before and after the conflict's onset. This dataset is valuable for several reasons. First, it reveals which firms were sourcing from or selling into the conflict areas before the conflict began. Coupled with the conflict's sudden and unanticipated onset, this allows us to identify its impact on firms connected to the conflict zones through production networks using a difference-in-differences design. Second, the data allow us to investigate how firms reorganized their supplier and buyer linkages after the conflict started. Third, the richness of these data allows us to calibrate a multiregion, multisector general equilibrium model with endogenous production networks, which helps us assess the aggregate impact of localized conflict on the rest of the country and evaluate the role of supply chain reorganization in either mitigating or amplifying its impact.

We start by documenting that the railway shipment volume from and to conflict areas declined to practically zero within the first few years of conflict. This sudden decline in trade—coupled with the economic significance of the Donbas and Crimea, which together accounted for 18.2% of Ukraine's pre-2014 GDP—suggests potentially large disruptive effects across the country.

Next, we demonstrate that the conflict disrupted production in firms connected with the conflict areas via production networks. To this end, we construct proxies for firms' exposure to conflict areas (hereafter, simply *exposure*) through their suppliers and buyers—measured by the share of transactions with firms in the conflict areas before the conflict. Using a difference-in-differences design, we find that firms with positive supplier or buyer exposure experienced a sudden 16% decline in the value of sales compared to firms without any prior direct trade connections to the conflict areas. These effects hold for both supplier exposure and buyer exposure separately and remain robust across various checks, such as controlling for the province-industry-year fixed effects and firms' prior trade with Russia. Year-by-year estimates exhibit no pretrends and indicate that the negative impact persists and grows through the end of our sales data in 2018.

We next show that the conflict led to a systematic reorganization of production networks even outside the conflict areas. We document that the way in which firms reorganized their networks depended on whether those firms were exposed to the conflict through their suppliers or their buyers. First, firms with high supplier exposure increased their supplier linkages and decreased their buyer linkages strictly outside the conflict areas. This evidence indicates that, despite significant substitution, losing suppliers in the conflict areas hurts firms' production, resulting in the loss of buyers in the rest of the country. Second, firms with high buyer exposure decreased both supplier and buyer linkages strictly outside conflict areas. This result is consistent with an interpretation that those firms scaled down input sourcing in response to reduced demand, and this downscaling caused their buyers in nonconflict areas to substitute toward unexposed firms. Overall, our evidence broadly suggests that firms reorganize production linkages away from partners directly or indirectly exposed to negative shocks.

Our results so far indicate that a localized conflict led to the disruption and reorganization of production networks in the rest of the country. However, two crucial questions remain. First, what are the mechanisms behind the reduced-form effects on firm-level output and network reorganization? Does the reorganization of supply chains contribute to the large relative decline in firm output, and, if so, how much? Second, what are the aggregate effects of localized conflicts on aggregate economic activity and output through the production-network channels?

To answer these questions, we develop a multisector, multilocation general equilibrium trade model with endogenous production-network formation. Firms produce differentiated varieties of intermediate inputs. Production requires labor and intermediate inputs 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 effect in intermediate inputs. Firms endogenously form supplier and buyer connections by trading off the benefits and costs of establishing those connections. Productivity and 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 in response.

A key advantage of our model is that we can map it to observed rich patterns of production networks across firms in different regions and sectors. Using the model calibrated to our railway-shipment data, we first assess the mechanisms driving the observed firm-level output decline. To do so, we first show theoretically that *supplier access* and *buyer access* serve as sufficient statistics for a firm's output under general equilibrium, summarizing the direct and indirect cost- and demand-propagation effects. We then run a regression of observed changes in firm output on the estimated sufficient statistics. We estimate this equation using supplier and buyer exposure interacted with the postconflict indicator as instrumental variables (IV) following our reduced-form empirical strategy.

Our analysis reveals that the IV regression coefficients closely approximate the value one, which indicates that the cost- and demand-propagation effects of the localized conflict were the main channels that caused a large relative decline in exposed firms' output. Other factors, such as firm-level changes in productivity or other unmodeled factors (e.g., investment), are unlikely to drive the reduced-form effects. We also show that, when excluding the changes in supplier and buyer linkages during the estimation of supplier and buyer access, the regression coefficients tend to be significantly above one. This implies that, abstracting from reorganization, our model's sufficient statistics underpredict the observed output decline for exposed firms. In other words, reorganization of production networks amplifies the relative output decline for firms exposed to the conflict through supply chain linkages.

Having established that the cost- and demand-propagation and network reorganization account for the firm-level output changes, we use our model to assess the aggregate effects of the 2014 Russia-Ukraine conflict on the nonconflict areas of Ukraine. To do so, using the model calibrated to the preconflict period, we simulate shutting down trade linkages to and from the conflict areas (the self-proclaimed territories of the Donetsk People's Republic (DPR), the Luhansk People's Republic (LPR), and Crimea), reflecting that the conflict resulted in near-complete destruction of trade linkages to those areas within its first few years. In this simulation, we allow for the production networks within the rest of Ukraine to endogenously reorganize in response to shocks and calibrate the elasticities governing this network reorganization using the observed changes in supplier and buyer linkages. To assess the role of endogenous network reorganization, we compare this baseline scenario to a version where we fix the production linkages at the preconflict levels.

We find that the aggregate real GRP strictly outside conflict areas decreases by 5.6% in our baseline counterfactual simulation. This sizable magnitude suggests that supply chain disruption and reorganization could explain nearly half of the actual 11.7% decline in real GRP of nonconflict provinces from 2013 through 2016 observed in the official government statistics. These large aggregate output losses are consistent with the economic importance of the conflict areas within Ukraine's production network before the conflict erupted.

The output loss is larger for regions geographically close to the conflict areas. However, regions geographically remote from the conflict areas (e.g., in Western Ukraine), particularly those specializing in manufacturing, also face substantial output loss. Thus, the localized conflict triggers far-reaching adverse economic repercussions through the disruption of production networks.

We also find that, if we shut down the reorganization of production networks, the real GRP loss increases to 8.4%. Therefore, endogenous network responses mitigate the aggregate output losses. At first glance, this finding may sound contradictory to our finding that network reorganization amplifies the relative firm-level output loss. However, these two findings are perfectly consistent with each other. When firms reorganize production linkages, they do so to substitute away from those directly or indirectly exposed to negative shocks. While this reallocation implies a larger output loss for the exposed firms, it benefits aggregate production and output by reallocating production resources toward unaffected firms. Abstracting from those endogenous responses leads to a substantial overestimation of the aggregate economic cost of localized conflict.

Finally, we analyze counterfactual conflict shocks to only the DPR, the LPR, and Crimea, rather than the simultaneous shocks that occurred in reality. We find that the aggregate output outside the conflict zones falls by 1.8%, 2.6%, and 0.9%, respectively, in these scenarios. The larger effects from shocks in the DPR and the LPR compared to Crimea suggest that conflict shocks to regions with a higher intensity in manufacturing result in greater economic losses due to their higher reliance on intermediate inputs.

Furthermore, shocking all conflict areas simultaneously implies a slightly larger aggregate output effect (5.6%) compared to the cumulative impact of shocking each conflict area individually (5.3%). Theoretically, it is ambiguous whether simultaneous conflict shocks are more or less harmful than the sum of independent shocks. On one hand, if the conflict areas are fully integrated through production networks, a shock to one region would cause serious production disruption in the others, making a single shock as costly as simultaneous shocks. On the other hand, if the conflict areas are close substitutes for the rest of Ukraine, a shock to one region could be absorbed by substitution toward the other regions. In our context, we find that while the substitution effect slightly dominates the integration effect, they roughly offset each other.

Overall, our results suggest that, though production networks, localized conflicts generate detrimental, far-reaching economic costs of conflict beyond the direct battlegrounds. At the same time, endogenous firm-level responses to reorganize the production networks mitigate these shocks, thereby providing resiliency in aggregate economic activity.

Related literature. We make distinct contributions to the literature on the economic effects of wars and conflicts and the literature on supply chain disruptions.

With a few exceptions, the literature on the economic effects of wars and conflicts has largely focused on the impact on firms and regions directly exposed to violence.[2] However, a growing share of conflicts now occur in middle-income countries (Barron, 2022), which typically possess extensive supply chain networks and exhibit higher levels of regional interconnectedness relative to developing nations. Despite this, evidence on the role of production networks in driving conflict spillovers remains scarce.[3] This gap may stem from a lack of detailed wartime data to trace these spillovers, as well as limited exogenous variation to identify causal effects.

We contribute to this literature by (i) demonstrating that conflict disrupts production of firms even in areas far from the battleground, if they are connected to these areas through production net-

[2]See Guidolin and La Ferrara (2007), Amodio and Di Maio (2018), Del Prete, Di Maio, and Rahman (2023), and Utar (2024) for empirical evidence showing how conflict affects firms in immediate conflict areas. In the context of the Russia-Ukraine conflict, Coupé, Myck, and Najsztub (2016), Mirimanova (2017), and Kochnev (2019) investigate the direct effects of war on the Donbas economy using nightlight data and other indirect approaches.

[3]Hjort (2014) and Korovkin and Makarin (2023) explore alternative channels of spillover effects of conflicts, such as how conflict-induced intergroup tensions adversely affect both firm productivity and interfirm trade. Akgündüz, Aydemir, Cilasun, and Kïrdar (2024) analyze another alternative channel, examining how the influx of Syrian refugees has affected Turkish production networks. See Rohner and Thoenig (2021) for a broad overview.

works; (ii) showing that firms in unaffected regions systematically reorganize their supply chains away from those directly or indirectly affected by these shocks; and (iii) illustrating that this reorganization helps mitigate the aggregate impact of conflict on nonconflict areas, as firms tend to redirect their linkages toward more productive firms. We do so using granular firm-to-firm transaction data, an identification strategy leveraging the sudden and localized nature of the 2014 Ukraine conflict, and a general equilibrium model of endogenous production-network formation.

Existing research has been limited to documenting how negative conflict shocks transmit, given exogenously set supply chain or trade linkages. Using aggregate country-level international trade data, Martin, Mayer, and Thoenig (2008a,b) and Glick and Taylor (2010) show that wars and conflicts negatively affect countries' imports and exports. Using microdata, Ksoll, Macchiavello, and Morjaria (2022) show that Kenyan firms in areas directly affected by electoral violence reduced their exports, and that these exports were not substituted by other Kenyan firms. Alfano and Cornelissen (2022) document that conflict events in Somalia resulted in higher food prices in other parts of the country connected with the battleground areas via transportation networks. Couttenier, Monnet, and Piemontese (2022) show that the Maoist insurgency in India have negatively affected firm production depending on how their input and output bundles are related to the insurgent areas, inferred from a product-level input-output table, and they quantify the aggregate implications of these shocks in a framework with fixed production networks.[4] However, firms can adapt to adverse environments. We show, empirically and theoretically, that firms endogenously reorganize their production linkages as a reaction to a large-scale conflict and that this margin crucially affects firm-level and aggregate output.

We also contribute to the broader empirical literature on supply chain disruptions and their aggregate implications, providing evidence based on a sudden, intense, and persistent shock coming from armed conflicts. So far, this literature has focused mostly on transient shocks such as natural disasters. Carvalho, Nirei, Saito, and Tahbaz-Salehi (2021) show that the 2011 Tohoku earthquake and tsunami in Japan negatively affected the output of firms with suppliers and buyers in affected areas, and they quantify the aggregate effects using a model with fixed production networks. Balboni, Boehm, and Waseem (2024) and Castro-Vincenzi, Khanna, Morales, and Pandalai-Nayar (2024) study the impacts of floods on connected suppliers in Pakistan and India, respectively. The former study finds no long-run reorganization of supplier linkages, while the latter one finds sig-

[4]In earlier work with the same data, Korovkin and Makarin (2020) show that the conflict reduced trade volume between firm pairs, document that a positive conflict-induced shift in firm centrality is associated with better firm performance after the conflict's onset, and present an accounting decomposition of the change in firm sales distribution using a model with exogenous production networks.

nificant long-run reorganization yet modest aggregate effects of such reorganization.[5] In contrast, we focus on a more intense and persistent negative shock due to armed conflicts. We show that in this context, reorganization of supplier and buyer linkages plays a key role in driving the decline in firm-level output and mitigating aggregate output loss.

Our work also relates to a broader theoretical literature on endogenous formation of production networks, modeling firms' trade-off between the costs and benefits of establishing supplier and buyer connections.[6] We contribute to this literature by developing a sufficient statistics approach for testing whether the production networks and their reorganization explain observed changes in firm-level production in response to shocks. Our approach follows Donaldson (2018), who examines whether the enhancement of cross-regional trade is the mechanism behind the observed reduced-form effects of railways on regional economic growth in colonial India. We extend this approach in the presence of supply chain linkages and their reorganization, and we operationalize it to test the mechanism behind the output reduction during the 2014 Russia-Ukraine conflict.[7]

The rest of the paper is organized as follows. Section 2 describes the context and discusses our main data. Section 3 presents our reduced-form results on the conflict-induced 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)

Following the Ukrainian revolution in February 2014, Russia annexed Crimea and began supporting separatist movements in the Donetsk and Luhansk provinces (i.e., the Donbas region).[8]

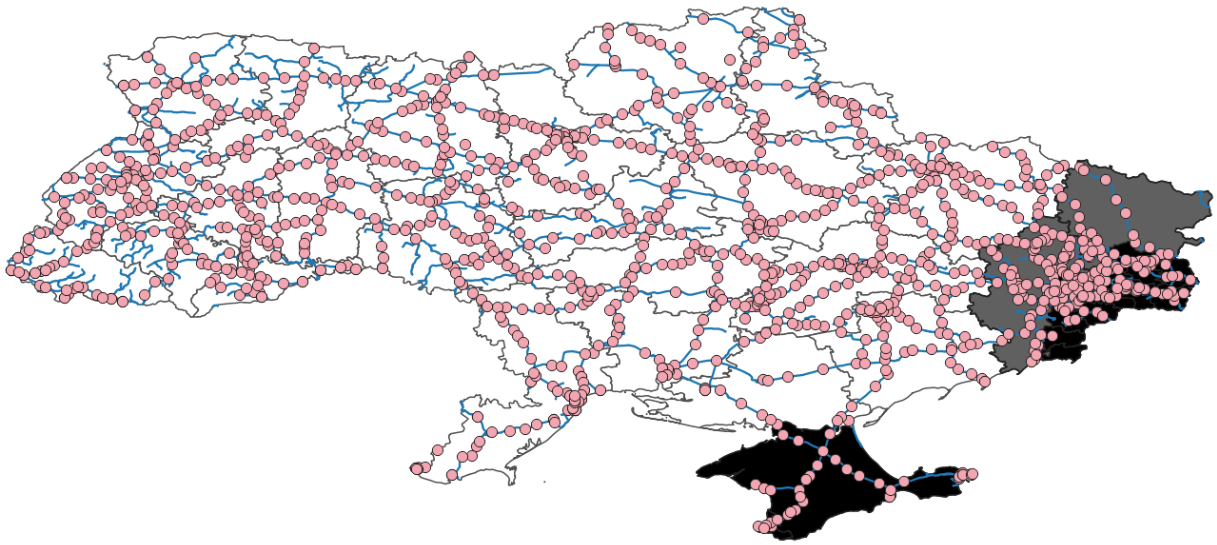
[5] Khanna, Morales, and Pandalai-Nayar (2022) study the impacts of suppliers' exposure to lockdowns on their buyers' output and retention of their supplier linkages during the COVID-19 pandemic in India. While focusing solely on the short-run, reduced-form firm-level effects of supplier exposure, they document a reorganization of supplier composition after the shock, which is consistent with our findings.

[6] For example, Lim (2018), Huneeus (2018), Bernard, Dhyne, Magerman, Manova, and Moxnes (2022), and Dhyne, Kikkawa, Kong, Mogstad, and Tintelnot (2023) model link formation under relationship-specific fixed costs; Chaney (2014), Arkolakis, Huneeus, and Miyauchi (2023), Boehm and Oberfield (2023), Miyauchi (2024), Demir, Fieler, Xu, and Yang (2024), and Huang, Manova, Perelló, and Pisch (2024) consider search decisions under matching frictions, while, Oberfield (2018), Acemoglu and Azar (2020), Lenoir, Martin, and Mejean (2023), Liu and Tsyvinski (2024), and Kopytov, Mishra, Nimark, and Taschereau-Dumouchel (2024) consider optimal supplier and input choice by buyers. Our modeling approach is closest to Arkolakis et al. (2023), Boehm and Oberfield (2023), and Demir et al. (2024), who model supplier and buyer acquisition decisions facing upward-sloping link-formation costs.

[7] Baqaee, Burstein, Duprez, and Farhi (2024) develop a nonparametric accounting framework for how firms' supplier access contributes to their marginal costs and, in turn, how it affects aggregate output. While related, our sufficient statistics focus on firm-level sales, where both supplier and buyer access matter, and we deliver a succinct analytical expression under a parsimonious parametric production function specification common in the existing literature.

[8] The decision to annex Crimea was made secretly by Vladimir Putin and a handful of senior security advisors, taking everyone else by surprise (Treisman, 2018).

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



Notes: This map showcases the areas directly impacted by the 2014 Russia-Ukraine conflict, highlighting the locations of railroads and railway stations. The Crimean Peninsula, shown in black at the bottom, was annexed by Russia in early 2014. The territories of the DPR and of the LPR, also in black, appear on the right. The rest of the Donbas region is depicted in light gray. Blue lines depict the Ukrainian railroads. Red dots indicate railway stations used in our data.

By early March 2014, the annexation had been completed without direct military confrontation. Subsequently, pro-Russian demonstrations erupted in Donbas, with protesters seizing key government buildings. Claiming independence from Ukraine, they formed the Donetsk People's Republic (DPR) on April 7, 2014, and the Luhansk People's Republic (LPR) on April 27, 2014.

In retaliation, Ukraine's interim president initiated an "antiterrorist operation" to quell the separatist actions. Russia bolstered the DPR and the LPR with military support, leading to a prolonged conflict that resulted in over 13,000 deaths, 30,000 injuries, and the displacement of hundreds of thousands of people (Lasocki, 2019). The conflict had remained relatively dormant since the Minsk agreements, particularly after President Zelensky was elected. This status quo dramatically shifted on February 24, 2022, when Russia launched a full-scale invasion of Ukraine.

Figure 1 illustrates the regions directly impacted by the 2014 Russia-Ukraine conflict, highlighting Crimea (in black at the bottom) and the DPR and LPR areas (in black on the right side of the map). While certain DPR and LPR territories experienced intense conflict, the rest of the country did not face direct violence.

Economic Activity in the Donbas Region and Crimea. Before the conflict, the Donbas and Crimea regions were crucial for Ukraine's economy, accounting for approximately 18.2% of the nation's GDP in 2013. The Donbas region, particularly known for its extractive industries such as coal, metallurgy, and manufacturing, played a vital role. Donetsk oblast—the most populous province, with 4.4 million residents (10% of Ukraine's population)—was responsible for over 20% of the country's manufacturing output and 20% of all Ukrainian exports in 2013. Similarly, Luhansk oblast—the sixth-most-populous province, with 2.16 million residents—contributed 6% to Ukraine's exports. By contrast, Crimea, with a population of 2.2 million, has been primarily recognized for its agricultural and tourism sectors but also played an important role in Ukraine's economy, hosting key industries like shipbuilding.[9]

The conflict had severe repercussions for these regions. Crimea was largely isolated from Ukraine's transportation network, severely disrupting supply chains. The DPR and LPR regions experienced extensive violence, infrastructure damage, and significant loss of human resources due to outmigration of the labor force. Within two years, manufacturing output plummeted by 50% in Donetsk oblast and by over 80% in Luhansk oblast (Amosha, Buleev, and Zaloznova, 2017), while nighttime light intensity declined by 40%–50% in the separatist-controlled areas (Kochnev, 2019).

Ukrainian Railroad System. Railway transportation plays a vital role in Ukraine's economy. With the 13th-largest railroad network globally, Ukraine ranks as the seventh-largest railway freight transporter in the world. Railroads are the primary mode for transporting goods in the country, handling 80% of ton-kilometers of all freight transport, excluding pipeline transportation, according to the State Statistics Service of Ukraine (2018). The World Economic Forum's 2013–2014 Global Competitiveness Report rated Ukrainian railway infrastructure highly, placing it 25th worldwide (Schwab and Sala-i Martín, 2013). Conversely, the country's road and airway infrastructures were ranked poorly, 144th and 105th, respectively, in the same report.

2.2 Data

Firm-to-Firm Railway-Shipment Data. Our main dataset is the universe of railway shipments within Ukraine from 2012 through 2016. The data originate from the records of *Ukrainian Railways*, a state-owned railway monopoly company.[10] This dataset contains around 50 million transactions between approximately 6,400 firms. It includes shipment dates, weights (in kilograms), 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 for the sending and receiving firms, which enables us to merge it with other firm-level data. We use the railway-shipment data both to define firms' preexisting supplier and buyer linkages with the conflict areas

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

[10] These data were purchased by CERGE-EI from Statanaliz, LLC, a marketing company that collects and sells data on export and import transactions and domestic shipments for the post-Soviet states. The aggregate figures in our dataset align closely with official government statistics. For example, between 2012 and 2016, the total weight transported via railways was recorded at 1,942 million tons in our data, compared to 1,980 million tons according to official records (Melnyk et al., 2021), with the discrepancy likely due to the differences in data-cleaning procedures.

(i.e., supplier and buyer exposure) and to construct outcome variables for the changes in production linkages before and after the conflict's onset. To focus our analysis on trade between firms, we discard intrafirm trade, which constitutes 6.5% of all transactions in weight shares in 2013.

For some parts of the analysis, we use information about the value of transactions between firm pairs, in addition to the shipment weights and the presence of transaction linkages. Given that the value of transactions is not reported in our data, we impute transaction values using the detailed product codes and shipment weights associated with each transaction. 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 the HS-8-digit code and the ETSNV codes (the product-code classification in our railway-shipment data) to impute the value of each shipment. Appendix B further describes this procedure.

One limitation of this dataset is that we observe the shipment only over railways but not through other transportation modes. We believe our results are not substantially biased by this limitation, for two reasons. First, as noted earlier, railroads were responsible for 80% of ton-kilometers of all freight transport (excluding pipeline) due to the relatively high-quality railway network compared to other shipment modes. 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 shipments out of overall shipments are absorbed by the 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 was no systematic disruption specific to railway networks relative to road networks outside Crimea and the Donbas region.[11]

Figure 1 depicts the Ukrainian railway network, as well as the 1,200 railway stations in our dataset. The stations cover the entire country, indirectly confirming the universal nature of our railway-shipment data. As one can see, the network is especially dense in the Donbas region, consistent with the region's 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. Both of these sources are based on official government statistics, the provision of which is mandatory for all Ukrainian firms except individual entrepreneurs. We combine these two datasets for their complementary coverage of available variables. Hereinafter, for brevity, we refer to the combined data as SPARK-Interfax.

[11] See Appendix C.1 for a detailed discussion of this identification concern, using a formal model where firms choose shipment modes.

The datasets contain information on firm IDs, sales, profits, total costs, capital, and other variables from 2010 through 2018. We are able to merge nearly all of our railway firms to these data. Nevertheless, due to incompleteness of the sales data, our baseline sample for results related to firm sales is restricted to around 4,800 firms. Overall, we find that the railway-shipping firms cover nearly 50% of aggregate sales of tradable industries, reinforcing the importance of railway shipping in Ukraine's economy.[12]

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

2.3 Conflict Exposure and Summary Statistics

Our primary reduced-form empirical approach investigates the impact of conflict on firms' output and production linkages by their preexisting trade connections with conflict-affected regions. To do so, we define *conflict areas* as the combination of Crimea (including the city of Sevastopol) and the separatist-controlled parts of the Donbas region (the DPR and LPR). Although Crimea was not exposed to violence as much as the DPR and the LPR, the trade linkages to all three areas were substantially disrupted after the conflict's onset, as we document below.

Table A.1 displays the summary statistics for our datasets. Of the firms in our data whose headquarters are strictly outside the conflict areas, 55% traded with the conflict areas in 2012–2013, i.e., before the conflict started. An average firm received 9% of its 2012–2013 incoming shipments from the conflict areas in value (i.e., supplier exposure) and sent 10% of its 2012–2013 outgoing shipments to the conflict areas in value (i.e., buyer exposure).

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 (e.g., Korovkin and Makarin, 2023). In this paper, we focus primarily on the disruption of domestic production networks that reach into the conflict areas in Ukraine. We make this choice because, for Ukrainian firms outside the conflict areas, trade exposure with the conflict areas within Ukrainian borders is substantially larger than that with Russia. According to Table A.1, 55% of the firms in our sample traded with the conflict areas in 2012–2013, but only 24% traded with Russia in that same period. Furthermore, while trade with the conflict areas fell to almost zero (as we show below), trade with Russia as a fraction of GDP declined by only about a half (World Bank, 2016). We also present the robustness of our reduced-form analysis to international trade disruption by controlling for the firms' prewar trade with Russia using separate customs data.

[12] Specifically, we find that railway-shipping firms cover 45.2% of all firm sales in three-digit-SIC industries where at least 1% of firms sent a shipment via railways.

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 within Ukraine. Section 3.1 documents a substantial decline in shipment volume to and from the direct conflict areas. Section 3.2 shows that firms outside the conflict areas but with prior supplier or buyer linkages to those areas faced a significant relative output decline. Finally, Section 3.3 reveals that firms with prior supplier or buyer conflict exposure reorganized their supplier and buyer linkages outside those areas.

3.1 Impact on Trade With the Conflict Areas

We first examine how the conflict led to the disruption of trade between the affected areas and the rest of Ukraine. The left panel of Figure 2 illustrates the evolution of input-loading distribution for firms that received any shipments from the conflict areas in 2012–2013. We present the median and upper (70th, 80th, and 90th) percentiles 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 panel of Figure 2 performs the same analysis, focusing on firms sending their goods to Crimea and occupied Donbas. In both instances, the receiving and sending loading percentiles rapidly plummet, becoming close to zero by 2015 and precisely zero by 2016.

These sharp declining patterns are confirmed in the event-study graphs displayed in Figure A.2, which show that an average firm reduced its share of trade with the conflict areas by approximately 10 percentage points by 2016—the almost entire aggregate share of transactions to and from conflict areas—with negligible pretrends prior to the conflict.

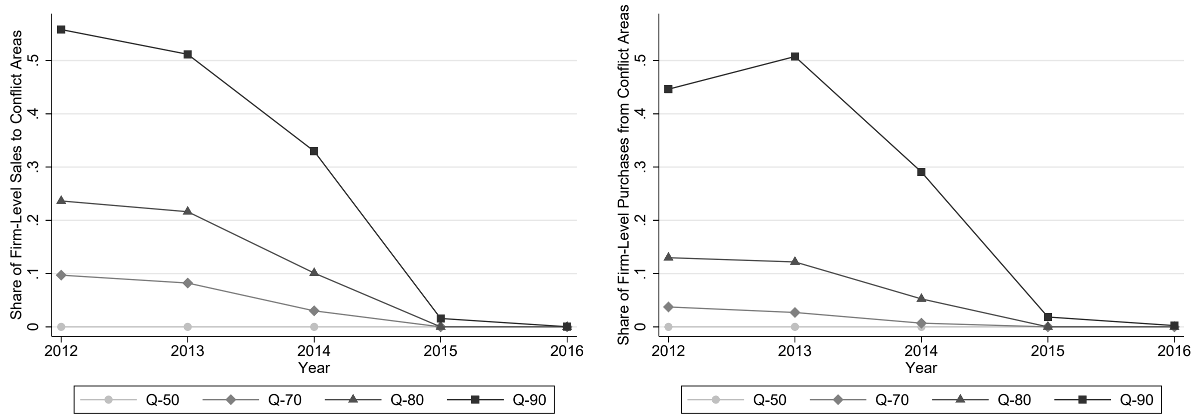
Overall, these estimates suggest that trade between the conflict areas and the rest of Ukraine was severely disrupted as a result of the annexation of Crimea and the war in the Donbas region. In the DPR and LPR areas, this disruption of transactions is likely driven by the severe disruption of firm operations in those areas, coupled with the disruption of transportation and boycotts.[13] In what follows, we analyze the implications of the disruption of trade with the conflict areas for firms' output and reorganization of production linkages strictly outside the conflict areas.

3.2 Impact on Firms Outside the Conflict Areas

Having established that the conflict disrupted trade to and from the conflict areas, we now investigate how it affected firms in the rest of the country depending on their trade linkages with the conflict areas. We combine the data on firms' yearly sales from SPARK-Interfax and measures

[13] The official trade blockade of the Donbas region 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). Therefore, the decline in trade with the conflict areas is not mechanical, with the possible exception of trade with Crimea in 2016.

Figure 2: Distribution of Firm Trade Value Shares With the Conflict Areas



Notes: This figure displays the evolution of the distribution of firm trade share with the DPR, the LPR, and Crimea. Q-50, Q-70, Q-80, and Q-90 refer to the median and upper percentiles of the distribution. The graph on the left (right) describes the distribution for the share of firm sales that went to (purchases that came from) the conflict areas, measured as the value of the shipments sent into (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.

of preconflict exposure through railway linkages. We start by estimating the following equation:

$$Y_{ft} = \alpha_f + \delta_t + \beta\left(\text{Post}_t \times \mathbb{1}[\text{TradeConflictExposure}]_{f,2012-13}\right) + \varepsilon_{ft} \qquad (1)$$

where f indexes a firm whose headquarters is located strictly outside the conflict areas,[14] t indexes the year, Y_{ft} is an outcome of firm f at year t, α_f and δ_t are the firm and year fixed effects, Post_t is the post-2014 dummy, and $\mathbb{1}[\text{TradeConflictExposure}]_{f,2012-13}$ is an indicator for whether firm f traded with the conflict areas in 2012–2013.

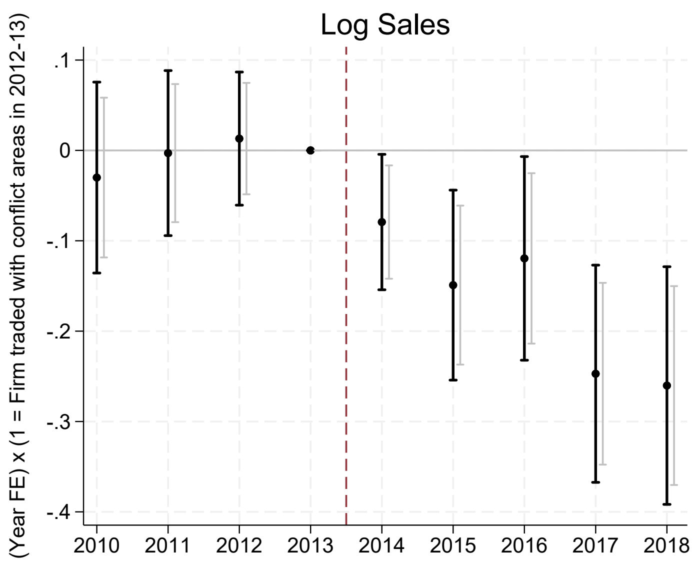
The specification raises two main concerns. First, one may worry about the plausibility of the parallel-trends assumption. Specifically, for β to accurately estimate the causal effect of conflict exposure on firms through production linkages, it is crucial that the outcomes of firms with varying degrees of trade engagement with the conflict areas would have evolved similarly in a counterfactual scenario absent the conflict. Second, the measure of firms' supplier and buyer exposure could be confounded with other conflict-induced shocks that affect either demand (for instance, due to military needs) or supply (such as through an increase in labor supply due to refugee resettlement).[15]

To address the first issue, we present the event-study figures and examine them for potential

[14] Among the robustness checks in Appendix A.2, we show that our results are invariant to using alternative sample restrictions focusing on firms that never used the railway stations located in the conflict areas (Table A.6).

[15] Since our research design does not rely on variation in treatment timing, it sidesteps the concerns associated with two-way fixed-effects models highlighted in the recent econometrics literature (e.g., see Roth, Sant'Anna, Bilinski, and Poe (2023) and Arkhangelsky and Imbens (2024) for recent surveys).

Figure 3: Conflict and Sales of Firms That Traded With the Conflict Areas



Notes: This figure displays the results of estimating Equation (1) and explores the impact of the conflict on firm sales by whether a firm had prior trade ties with the conflict areas. The sample is restricted to firms outside the conflict areas. Black bars represent 95% confidence intervals, gray bars represent 90% confidence intervals. Standard errors are clustered at the firm level.

pretrends. We find no statistically significant pretrends in most outcome variables, consistent with the interpretation that the conflict was unanticipated. To address the second issue, we provide a battery of robustness checks, including controlling for the province-industry-year fixed effects, as well as firms' trade with Russia.[16]

Baseline Results. Figure 3 presents our baseline estimates of the conflict's impact on firm sales; here, we have slightly modified Equation (1) by interacting the year fixed effects with the exposure indicator. The results show no pretrends, reinforcing the validity of the parallel-trends assumption introduced above, followed by a sharp, persistent differential drop in firm sales of 10 to 30 log points. This result confirms that the conflict negatively impacts not only firms located near the 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 are 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 a 16.2%

[16]To further examine whether refugee migration could confound our estimates, in Appendix A.4, we also provide an analysis of how regions' trade exposure to the conflict areas relates to changes in population size.

Table 1: Conflict and Sales of Firms Trading With the 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, 2012–2013]	-0.162***	0.070***				
	(0.046)	(0.010)				
Post-2014 × Firm's Buyer Conflict Exposure, 2012–2013			-0.215**	0.060***		
			(0.100)	(0.023)		
Post-2014 × Firm's Seller Conflict Exposure, 2012–2013			-0.280***	0.066***		
			(0.100)	(0.022)		
Post-2014 × 𝟙[High Firm's Buyer Conflict Exposure, 2012–2013]					-0.190***	0.058***
					(0.058)	(0.012)
Post-2014 × 𝟙[High Firm's Seller Conflict Exposure, 2012–2013]					-0.139**	0.043***
					(0.054)	(0.012)
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Mean	16.899	0.291	16.899	0.291	16.899	0.291
SD	2.482	0.454	2.482	0.454	2.482	0.454
Observations	35,439	50,202	35,439	50,202	35,439	50,202
Number of Firms	4,775	5,578	4,775	5,578	4,775	5,578

Notes: This table presents the estimates for the conflict's impact on firm sales and an indicator for missing sales data by firms' preexisting trade ties with the conflict areas. High exposure in columns (5) and (6) refers to exposure greater than the 80th percentile in the overall sample. The 80th percentile cutoffs are 0.086 for buyer exposure and 0.083 for supplier exposure. The average buyer and supplier exposures in the high-exposure category are 0.444 and 0.448, respectively, while those in the low-exposure category are 0.004 and 0.006, respectively. The sample is restricted to firms outside the conflict areas. The firm accounting data from SPARK/Interfax cover the 2010–2018 period. Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

decline in sales compared to firms without such connections on average over five years from the onset of the conflict. Column (2) shows that these firms were also 7.0 percentage points more likely to cease reporting sales data in a given year.

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

$$Y_{ft} = \alpha_f + \delta_t + \beta \left(\text{Post}_t \times \text{BuyerExposure}_{f,2012-13}\right) + \gamma \left(\text{Post}_t \times \text{SupplierExposure}_{f,2012-13}\right) + \varepsilon_{ft} \tag{2}$$

where $\text{BuyerExposure}_{f,2012-13}$ is measured as the share of firm's out-shipments being to the conflict areas and $\text{SupplierExposure}_{f,2012-13}$ 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) and (4) of Table 1, demonstrate that conflict negatively affects the performance of firms connected to the conflict areas regardless of trade direction and with broadly similar magnitudes. Columns (5) and (6) of Table 1 confirm that the patterns are robust to defining binary indicators for high supplier or high buyer exposure based on whether they lie above or below 80th percentile in our sample.

[17] Appendix Table A.4 shows that our results remain similar when exposure is defined by shipment weight or the number of links rather than transaction values.

These estimates are large compared to existing studies on the effects of supply chain disruptions from transient shocks. For instance, Carvalho et al. (2021) find that firms with at least one supplier or buyer directly exposed to the 2011 Tohoku earthquake and tsunami in Japan saw their sales reduced by 3%–4% the year after. This difference could be driven by the fact that the conflict we study was a larger, more prolonged, and persistent shock, which resulted in the changes in the architecture of production networks. In particular, we show in Section 3.3 that firms with conflict exposure lost buyer linkages even strictly outside the conflict areas. Such reorganization of production linkages is critical in explaining the large effects on firm sales—we revisit this in Section 5.2, with our general equilibrium model of production network reorganization.

Robustness and Heterogeneity. In Appendix A.2, we demonstrate that the findings above are robust to a battery of checks. Tables A.2 and A.3 show that the results are invariant to restricting the sample to firms that reported revenue every year, flexibly controlling for firms' location and distance to the conflict areas interacted with the post indicators, controlling for firms' prewar trade with Russia, including province-industry-year fixed effects, and excluding firms located in Kyiv or in non-occupied parts of the Donbas region. Table A.4 shows that the results remain similar if we define exposure using shipment weight or number of links instead of transaction values. Table A.5 shows that our estimates remain robust to controlling for placebo firm exposure, as suggested by Borusyak and Hull (2023), thereby dealing with the concern for firms' nonrandom exposure to conflict areas. Table A.6 demonstrates that our results are not due to firms having operations in the conflict areas, as the estimates remain unchanged when we exclude firms that ever used a railway station located in the conflict area.

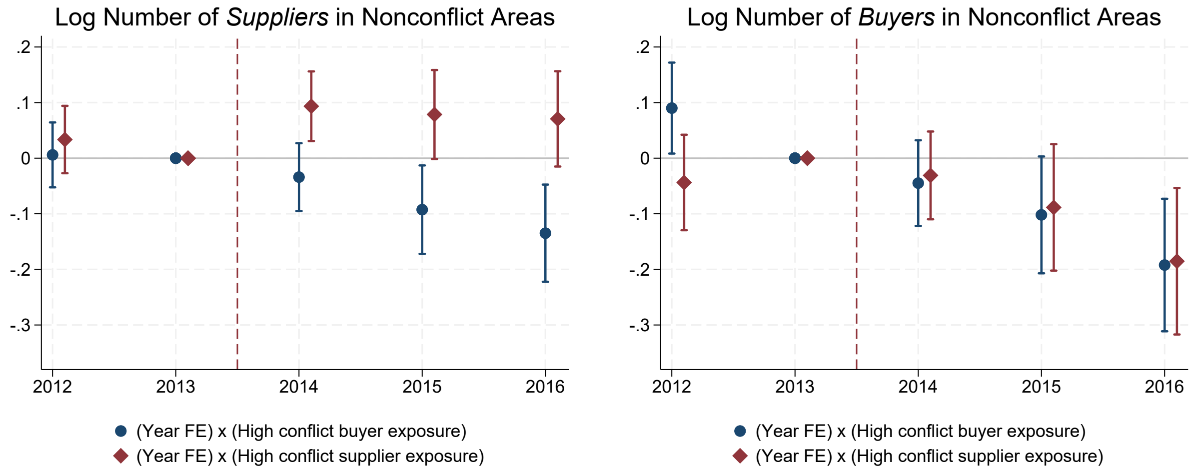
In terms of the results' heterogeneity, Table A.7 shows that the effects are larger for firms in manufacturing, consistent with the importance of input-output linkages in this sector. It also shows that exposures to Crimea and the DPR-LPR regions have similar effects when studied separately. Finally, the effects are not statistically significantly different for firms above and below the median in preconflict revenue.

3.3 Evidence of the Reorganization of Production Networks

We next show that the conflict shock has led to a systematic reorganization of the production-network structure strictly outside the 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 our difference-in-differences strategy to study how these linkages change depending on firms' supplier and buyer exposure.

To examine whether firms have reorganized their production linkages strictly outside the conflict areas, we estimate Equation (2) but with the number of trade linkages with nonconflict areas

Figure 4: Conflict Exposure and Firm's Linkages With Nonconflict Areas



Notes: This figure evaluates whether a firm's number of partners in nonconflict areas changed with the start of the conflict and how it depended on firm-level buyer and supplier exposure. The figure on the left (right) presents the estimates for Equation (2) with the logarithm of the number of suppliers (buyers) as the outcome variable and the indicators for high buyer and high supplier exposure (defined by 80th percentile) as the measures of trade connections with the conflict areas. The 80th-percentile cutoffs in our overall sample are 0.092 for buyer exposure and 0.084 for supplier exposure. The average buyer and supplier exposures in the high-exposure category are 0.450 and 0.446, respectively, while those in the low-exposure category are 0.005 and 0.006, respectively. Bars represent 95% confidence intervals. Standard errors are clustered at the firm level.

as outcomes. We utilize the data on railway stations to ensure that firms' partners were indeed located outside the conflict areas. To focus on firms for which reorganization of production linkages is well-defined, we restrict our sample to firms that appeared at least once in our dataset before the conflict's onset. To study pretrends and the effect dynamics, we estimate an event-study version of the equation whereby we interact firms' exposure with the year fixed effects.

Baseline Results. Figure 4 presents the resulting estimates for the number of suppliers and buyers in nonconflict areas. In the left panel, we find that firms with high supplier exposure increased the log number of suppliers strictly outside the conflict areas. There are no pretrends, and the effects occur immediately after the conflict's onset in 2014. The magnitudes of the coefficients suggest that if a firm had high supplier exposure to the conflict areas, they increased the number of suppliers from nonconflict areas by around 10 log points. Given that the difference in supplier exposure between the high and low exposure is approximately 45%, only a fraction of the loss of expenditure from suppliers in the conflict areas is substituted by new supplier linkages in nonconflict areas.[18]

We also find that firms with high buyer exposure decreased supplier linkages strictly outside the

[18]Table A.15 displays the estimates for the total number of linkages and shows that the impact of high supplier exposure on the total number of suppliers is negative (column 5), confirming that the substitution of supplier linkages is indeed imperfect.

conflict areas. In contrast to the responses of firms with high supplier exposure, this effect occurred relatively gradually over time and became significant in 2015. If a firm had a high buyer exposure to the conflict areas, it decreased the measure of supplier linkages from nonconflict areas by around 10 log points in 2015. This evidence is consistent with an interpretation that firms gradually scaled down supplier linkages in response to reduced demand.

In the right panel of Figure 4, we find that firms with either high supplier or buyer exposure decreased buyer linkages strictly outside conflict areas. The effects increase gradually as time goes by, reaching a 20-log-point reduction by the end of our study period. This evidence is consistent with an interpretation that both supplier and buyer exposure translated into production disruption, which resulted in the loss of buyer linkages, even in nonconflict areas.

Table 2 displays the estimates of equation (2) for the number of linkages. Columns (1) and (2) present the results of the specification using continuous proxies for the supplier and buyer exposure, while columns (3) and (4) use binary indicators based on the 80th-percentile cutoff of the exposure proxies. The results confirm the estimates displayed earlier in Figure 4. Across the board, we find consistent patterns: firms with high supplier exposure increased supplier linkages in nonconflict areas, those with high buyer linkages decreased them, and firms with both high supplier and buyer exposure decreased buyer linkages in nonconflict areas.

Overall, our findings are consistent with the interpretation that firms reorganize production linkages away from those directly or indirectly exposed to negative shocks. Firms with higher supplier exposure substitute the loss of suppliers in conflict areas toward those in nonconflict areas. At the same time, these firms may have faced production disruption, leading their buyers to substitute away toward other firms. In turn, firms with higher buyer exposure decreased input demand and cut existing supplier relationships. This downscaling of production may have increased their production costs, leading their buyers to substitute to other firms. In section 4.4, we develop a model of endogeneous production-network formation that formalizes this intuition.

Robustness. In Appendix A.3, we establish the robustness of the above results. Tables A.8 and A.9 confirm that the findings withstand a battery of checks introduced in Tables A.2 and A.3, such as considering only firms that sent or received shipments every year or controlling for the province-industry-year fixed effects. Table A.10 shows that the estimates are similar when using weight-based or link-based exposures. Table A.11 demonstrates robustness to controlling for placebo exposure, following Borusyak and Hull (2023). Table A.12 ensures that our findings are not due to firms with establishments in the conflict areas by excluding firms that use stations in the conflict areas at least once throughout the data period. Table A.13 shows that the effects on shipment weight to and from nonconflict areas mirror those observed for the number of buyers and suppliers.

Table 2: Conflict Exposure and Firm's Linkages With Nonconflict 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, 2012–2013	-0.071	-0.156		
	(0.061)	(0.100)		
Post-2014 × Firm's Seller Conflict Exposure, 2012–2013	0.263^{***}	-0.203^{**}		
	(0.068)	(0.100)		
Post-2014 × $\mathbb{1}$[High Firm's Buyer Conflict Exposure, 2012–2013]			-0.089^{***}	-0.156^{***}
			(0.033)	(0.043)
Post-2014 × $\mathbb{1}$[High Firm's Seller Conflict exposure, 2012–2013]			0.064^{**}	-0.077^{*}
			(0.032)	(0.046)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean	1.790	1.945	1.790	1.945
SD	1.243	1.495	1.243	1.495
Observations	18,390	11,881	18,390	11,881
Number of Firms	4,281	3,031	4,281	3,031

Notes: This table presents the estimates for the conflict's impact on firms' outgoing and incoming trade with nonconflict areas by firms' preexisting trade connections with the conflict areas. The outcomes are the total number of distinct suppliers and buyers that engaged in trade with a given firm during a specific year using a railway station situated outside the conflict areas. High exposure refers to exposure greater than the 80th percentile in the overall sample. The 80th-percentile cutoffs are 0.092 for buyer exposure and 0.084 for supplier exposure. The average buyer and supplier exposures in the high-exposure category are 0.450 and 0.446, respectively, while those in the low-exposure category are 0.005 and 0.006, respectively. The sample is restricted to firms outside the conflict areas and to firms that existed in our data before the conflict. The railway shipment data cover the 2012–2016 period. Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

Panel A of Table A.14 shows that our results are robust if we count only trade partners present in the data before the conflict's onset; therefore, newly registered trading partners after the conflict's onset (e.g., who might have moved from the conflict areas as new entities) do not drive our results. Finally, Panel B of Table A.14 displays analogous estimates at the firm-region-year level, where *region* refers to the province of a railway station utilized by the firm.

4 Model

In the previous section, we provide reduced-form evidence for the supply chain disruption and reorganization based on our difference-in-differences method. These estimates, however, do not represent an economy-wide effect, because firms without direct production linkages with the conflict areas may also be affected by the shock, for instance, through their higher-order connections in production networks. Nor does the reduced-form evidence inform us about how the pattern of production-network reorganization is related to firm-level sales reduction and aggregate output. To overcome these challenges, in this section, we build a multisector, multilocation general equilibrium trade model of production-network disruption and reorganization.

The economy is segmented by a finite number of locations denoted by $u, i, d \in \mathcal{L}$. In each location, there is an 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 belongs to a sector denoted by $k, m, l \in K$. Firms produce goods that can be used both for intermediate use and for final use, combining 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 directly to local consumers.

4.1 Production

A continuum of firms produces a distinct variety of goods in each location and sector. To account for a flexible form of firm heterogeneity, we assume that each firm in location i and sector k belongs to a distinct firm type indexed by $\upsilon, \omega, \psi \in \Omega_{i,k}$. These firm types may 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 the conflict areas. We denote the measure of type ω firms in location i and sector k by $N_{i,k}(\omega)$.

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

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

where $Z_{i,m}\left(\omega\right)$ is the total factor productivity (TFP) of firm type ω, $L_{i,m}\left(f\right)$ is labor inputs, $Q_{i,km}\left(f\right)$ is the composite of intermediate inputs, $\beta_{m,L}$ and β_{km} are, respectively, the parameters proxying sector m's input share for labor and intermediate inputs from sector k.

The composite of intermediate inputs is a constant elasticity of substitution (CES) aggregator of the input varieties sourced from their connected suppliers. Denoting $\mathcal{S}_{u,k}(f)$ as the set of suppliers in sector k in location u that firm f is connected to (including but not exclusive to firm f's own location), the input composite $Q_{i,km}\left(\omega\right)$ is given by

$$Q_{i,km}\left(f\right) = \left(\sum_{u\in\mathcal{L}}\int_{s\in\mathcal{S}_{u,k}(f)} q_{ui,km}(s,f)^{\frac{\sigma_k-1}{\sigma_k}}\right)^{\frac{\sigma_k}{\sigma_k-1}} \tag{4}$$

where $q_{ui,km}(s,f)$ is the quantity of purchased intermediate inputs from each connected supplier s, and σ_k is the elasticity of substitution across goods within sector k. We assume that the production network structure $\mathcal{S}_{u,k}(f)$ is endogenously determined in equilibrium, as we further describe below.

4.2 Trade Costs, Market Structure, and Prices

We assume that, within a firm type, firms are ex post identical in terms of the marginal cost of production and the measure of supplier and buyer connections with all other firm types. Therefore, without risk of confusion, we suppress the index for each firm f from now on and instead use firm type $\omega \in \Omega_{i,m}$ to refer to each firm.[19]

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 a continuum of suppliers is connected to each buyer, suppliers charge a constant markup $\sigma_m / (\sigma_m - 1)$ on top of their production and shipment costs. 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

$$p_{id,ml}(\omega, \psi) = \frac{\sigma_m}{\sigma_m - 1} C_{i,m}(\omega) \, \tau_{id,ml}(\omega, \psi) \tag{5}$$

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

$$C_{i,m}(\omega) = \frac{1}{Z_{i,m}(\omega)} w_i^{\beta_{m,L}} \prod_{k \in K} P_{i,km}(\omega)^{\beta_{km}} \tag{6}$$

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

$$P_{i,km}(\omega) = \left(\sum_{u \in \mathcal{L}} \sum_{\upsilon \in \Omega_{u,k}} M_{ui,km}(\upsilon, \omega) p_{ui,km}(\upsilon, \omega)^{1-\sigma_k} \right)^{\frac{1}{1-\sigma_k}} \tag{7}$$

where $M_{ui,km}(\upsilon, \omega)$ is the measure of suppliers of type $\upsilon \in \Omega_{u,k}$ that firm type ω is connected with. Note that, given the assumption that firms are identical in terms of the measure of supplier and buyer connections within a firm type, $M_{ui,km}(\upsilon, \omega)$ is sufficient for keeping track of the production network structure $\mathcal{S}_{u,k}(f)$.

Given the vector of wages $\{w_i\}$ and the measure of supplier linkages $\{M_{ui,km}(\upsilon, \omega)\}$, Equations (5), (6), and (7) uniquely determine the set of prices $\{p_{id,ml}(\omega, \psi), C_{i,m}(\omega), P_{i,km}(\omega)\}$.

[19] This assumption is without loss of generality, as one can always define firm type ω such that this assumption holds. Note that our framework can be extended to a continuum of firm types by replacing summation with integrals.

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 $D^*_{i,km}(\omega)$.[20] Then, from the CES input demand (Equation 7), 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

$$X_{ui,km}(\upsilon,\omega) = \varsigma_k M_{ui,km}(\upsilon,\omega)\tau_{ui,km}(\upsilon,\omega)^{1-\sigma_k} C_{u,k}(\upsilon)^{1-\sigma_k} D_{i,km}(\omega) \tag{8}$$

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 the trade literature, except that production linkages $M_{ui,km}(\upsilon,\omega)$ now enter into 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*

$$R_{i,m}(\omega) = \tilde{\varsigma}_m Z_{i,m}(\omega)^{\sigma_m - 1} w_i^{\beta_{m,L}(1-\sigma_m)} \mathcal{A}^S_{i,m}(\omega)\mathcal{A}^B_{i,m}(\omega) \tag{9}$$

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

$$\mathcal{A}^S_{i,m}(\omega) \equiv \prod_{k\in K}\left(\sum_{u\in\mathcal{L}}\sum_{\upsilon\in\Omega_{u,k}} M_{ui,km}(\upsilon,\omega)\tau_{ui,km}(\upsilon,\omega)^{1-\sigma_k} C_{u,k}(\upsilon)^{1-\sigma_k}\right)^{\frac{1-\sigma_m}{1-\sigma_k}\beta_{km}} \tag{10}$$

$$\mathcal{A}^B_{i,m}(\omega) \equiv \sum_{l\in K}\sum_{d\in\mathcal{L}}\sum_{\psi\in\Omega_{d,l}} M_{id,ml}(\omega,\psi)\tau_{id,ml}(\omega,\psi)^{1-\sigma_m} D_{d,ml}(\psi) \tag{11}$$

The proposition states that, aside from the constant term $\tilde{\varsigma}_m$, firms' intermediate goods revenue is 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, which summarize the contribution of upstream and downstream production linkages to firm sales.

Supplier access represents the influence of the cost of intermediate inputs 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

[20] Specifically, from intermediate goods market clearing, $D^*_{i,km}(\omega) = \beta_{km}\frac{\sigma_m - 1}{\sigma_m} R^*_{i,m}$, where $R^*_{i,m}$ is the firms' total intermediate and final goods revenue defined in Equation (17).

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 3.2, we present evidence that firms outside the 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 $\{M_{ui,km}(\upsilon,\omega)\}$, as documented in Section 3.3, also affect sales through buyer and supplier access. Proposition 1 provides sufficient statistics that summarize these indirect effects. In Section 5.2, we empirically assess how much these sufficient statistics can explain the reduced-form effects on firms' output.

4.4 Endogeneous Production Network Formation

We assume that establishing production linkages is costly for both suppliers and buyers. Therefore, the equilibrium measure of production linkages is determined in a trade-off between those costs relative to their benefits. More concretely, we assume that the equilibrium measure of supplier linkages by firms of type $\omega \in \Omega_{i,m}$ for suppliers of type $\upsilon \in \Omega_{u,k}$ is given by

$$M_{ui,km}(\upsilon,\omega) = K_{ui,km}(\upsilon,\omega)\frac{X_{ui,km}(\upsilon,\omega)^{\lambda^B+\lambda^S}}{e_{u,k}(\upsilon)^{\lambda^B}e_{i,m}(\omega)^{\lambda^S}} \tag{12}$$

where $K_{ui,km}(\upsilon,\omega)$ are firm-pair-specific exogenous parameters capturing the difficulty of establishing production linkages. λ^B and λ^S are structural parameters capturing the elasticity of production links with respect to trade flows, capturing the benefit of establishing connections relative to the link-formation costs for the suppliers (to reach out to buyers) and for the buyers (to reach out to suppliers), $e_{u,k}(\upsilon)$ and $e_{i,m}(\omega)$. We assume that those link-formation costs are paid as a combination of labor and intermediate goods, such that

$$e_{i,m}(\omega) = w_i^{\mu}C_{i,m}(\omega)^{1-\mu} \tag{13}$$

where $0 \leq \mu \leq 1$ is the labor share in the link-formation costs.

Equation (12) can be microfounded in various ways based on explicit firm-level decisions. In Appendix C.2, we provide such microfoundations based on firms' search decisions under matching frictions (i.e., Arkolakis et al., 2023; Boehm and Oberfield, 2023; Demir et al., 2024), as well as firm-pair-specific entry or relationship costs (i.e., Melitz and Redding, 2014).[21]

The parameters λ^S and λ^B crucially govern the substitution of production linkages, as documented in Section 3.3. First, consider a firm with a high supplier conflict exposure. After the conflict's onset, these firms shift input demand toward nonconflict areas. Equation (12) shows that this increase in demand also leads to an increase in supplier linkages depending on the elasticities λ^S and λ^B. Simultaneously, these firms face an increase in production costs, which causes a reduction in buyer linkages depending on λ^S and λ^B. Similarly, consider a firm with a high buyer conflict exposure. These firms face a reduction in input demand, leading to a reduction of supplier linkages depending on λ^S and λ^B. This reduction in supplier linkages leads to an increase in input costs through the love-of-variety effect (Equation 7), resulting in the loss of buyer linkages depending on λ^S and λ^B. Building on this intuition, in Section 5, we calibrate λ^S and λ^B using the observed patterns of network reorganization, and we quantify how these firm-level network reorganizations affect the aggregate output.

4.5 Final Consumption

Households in location i have access to all firms in the region and purchase final goods. Their preferences are given by CES within a sector and the Cobb-Douglas production function across sectors. Therefore, the ideal price index for final consumers is given by

$$P_i^F = \prod_{k \in K} \left(\frac{P_{i,k}^F}{\alpha_k} \right)^{\alpha_k}, \qquad P_{i,k}^F = \left(\sum_{\omega \in \Omega_{i,k}} N_{i,k}(\omega) C_{i,k}(\omega)^{1-\sigma_k} \right)^{\frac{1}{1-\sigma_k}} \tag{14}$$

Households have two sources of income. First, they earn labor income, $w_{i,m}(\omega)$, which depends on the location, sector, and type of firms they work for. Second, households in each location own local firms. Denoting the profit of firm type $\omega \in \Omega_{i,m}$ (net of the link-formation cost) by $\pi_{i,m}(\omega)$,

[21] Huneeus (2018), Lim (2018), Bernard et al. (2022), and Dhyne et al. (2023) consider an alternative formulation where firms pay a firm-to-firm-specific fixed cost to establish a link (instead of paying a market-specific fixed cost, as in Melitz and Redding, 2014). While distinct in that these frameworks predict a discrete function instead of Equation (13), they share the feature that the equilibrium measure of links is determined in a trade-off between the expected trade flows relative to costs.

the total final expenditure in location i is given by

$$E_i = w_i + \frac{1}{L_i} \sum_{m \in K} \sum_{\omega \in \Omega_{i,m}} \pi_{i,m}(\omega) \tag{15}$$

4.6 Market Clearing and General Equilibrium

Labor market clearing implies that

$$w_i L_i = \sum_{m \in K} \sum_{\omega \in \Omega_{i,m}} \left(\beta_{L,m} \frac{\sigma_m - 1}{\sigma_m} + \mu \frac{\delta_m}{\sigma_m} \right) R^*_{i,m}(\omega) \tag{16}$$

where $R^*_{i,m}(\omega)$ denotes the aggregate intermediate and final sales of firm type $\omega \in \Omega_{i,m}$. The first term in the parentheses on the right-hand side captures the labor demand for production use; the second term captures the labor demand for link formation, where δ_m is a parameter capturing the share of variable profit spent for link-formation costs (Equation 13).[22]

Goods market clearing implies that the demand for final goods and intermediate goods add up to the firms' total revenue, such that $R^*_{i,m}(\omega)$ is the total firm sales (sum of intermediate and final goods sales), given by

$$R^*_{i,m}(\omega) = R_{i,m}(\omega) + R^F_{i,m}(\omega) + R^A_{i,m}(\omega) \tag{17}$$

where $R_{i,m}(\omega)$ are the intermediate goods sales to other firms, given by Equation (9); $R^F_{i,m}(\omega)$ are final goods demand, given by

$$R^F_{i,m}(\omega) = \frac{\varsigma_m N_{i,m}(\omega) \, C_{i,m}(\omega)^{1-\sigma_k}}{\left(P^F_{i,m}\right)^{1-\sigma_m}} \alpha_m E_i L_i \tag{18}$$

from CES demand, given by Equation (14); and $R^A_{i,m}(\omega)$ are the sales of intermediate goods used for link formation, given by

$$R^A_{i,m}(\omega) = (1-\mu) \frac{\delta_m}{\sigma_m} R^*_{i,m}(\omega) \tag{19}$$

The equilibrium is given by the set of prices $\{p_{id,ml}(\omega, \psi), C_{i,m}(\omega), P_{i,km}(\omega), P^F_i, w_i, e_{i,m}(\omega)\}$, nominal trade flows $\{X_{ui,km}(\upsilon, \omega)\}$, measure of production linkages $\{M_{ui,km}(\upsilon, \omega)\}$, firm revenue $\{R^*_{i,m}(\omega), R^A_{i,m}(\omega), R^F_{i,m}(\omega)\}$ and firm profit $\{\pi_{i,m}(\omega)\}$ that satisfy Equations (5), (6), (7), (8), (9), (12), (13), (14), (15), (16), (17), (18), (19), and firm profit net of link-formation cost is given by

$$\pi_{i,m}(\omega) = \frac{1}{\sigma_m} (1 - \delta_m) R^*_{i,m}(\omega) \tag{20}$$

[22] Appendix C.2 shows which structural parameters correspond to δ_m in microfounded models of production network formation. As we discuss below, this parameter has limited effects on our counterfactual simulation results.

5 Quantitative Analysis

In this section, we combine our theoretical framework in Section 4 with our production-network data to conduct a quantitative evaluation of the firm-level and aggregate impact of the localized 2014 conflict in Ukraine.

5.1 Calibration

We start by specifying the location $\mathcal{L}$ as oblasts (provinces) within Ukraine. As of 2012, there were 27 oblasts (including two cities of regional significance, Kyiv and Sevastopol), 23 of which are strictly outside conflict areas. In our model, we treat the occupied territories of the DPR, the LPR, and Crimea (combined with Sevastopol city), as three distinct *conflict* locations. Furthermore, we treat the parts of Donetsk and Luhansk oblasts under the control of the Ukrainian government as two *independent* locations. Thus, our location set $\mathcal{L}$ consists of 28 locations, 25 of which are strictly outside the conflict areas.

Next, we segment firms into three sectors: Mining, Manufacturing, and Other. This split reflects the importance of mining and manufacturing sectors in the 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 province of the railway stations.

In our context, a crucial aspect of firm heterogeneity is the firms' preexisting trade linkages with the conflict areas. To capture this heterogeneity, in our baseline analysis, we divide the set of firms within a location into four types based on the supplier and buyer exposure with the conflict areas before the onset of the conflict. Specifically, we define *high-supplier-exposure* firms as those where the value share of in-shipment from the conflict areas in our railway-shipment data is above the 80th percentile of all firms in our sample before 2013, following the definition of high/low exposure in Section 3. Similarly, we define *high-buyer-exposure* firms as those where the value share of out-shipment to the conflict areas is above the 80th percentile of all firms in our sample before 2013. We then divide firms in each region and sector into four types: (1) high supplier and buyer exposure, (2) high supplier exposure and low buyer exposure, (3) low supplier exposure and high buyer exposure, and (4) low supplier and buyer exposure. These four types of firms correspond to firm types $\Omega_{i,k}$ in our model.[23]

We also calibrate several structural parameters. First, we calibrate the values of parameters for production function and preferences $\{\beta_{L,m}, \beta_{km}, \alpha_k, \sigma_k\}$, using the aggregate input-output table for Ukraine described in Section 2.2. Specifically, for each sector m, we obtain $\{\beta_{L,m}, \beta_{km}\}$ as the

[23]Our counterfactual simulation results are similar if we alternatively define firm types using exposure defined by links or weights, as well as the combination of the conflict exposure and the dummy for above-median firm size within a region and a sector (Appendix D.4).

share of labor compensation and the input expenditure from sector k. We then obtain $\{\alpha_k\}$ from the household expenditure share for each sector k. Finally, we calibrate the elasticity of substitution $\{\sigma_k\}$ so that the variable profit margin $(1/\sigma_k)$ coincides with the ratio between pretax operation surplus and corporate income to nominal output.

Panel A of Table 3 summarizes these parameter choices. The calibrated parameters follow intuitive patterns. Labor share $\{\beta_{L,m}\}$ is 0.35 for Mining and 0.36 for Other, but just 0.10 for Manufacturing. Final expenditure share $\{\alpha_m\}$ is almost zero for Mining, while 0.6 for Manufacturing and 0.39 for Other. Finally, the elasticity of substitution $\{\sigma_k\}$ ranges from 4.8 (Mining) to 8.1 (Manufacturing). These values are within the range of values found in the existing literature.[24]

Table 3: Calibrated Parameters

	Sectors (m)		
	Mining	Manufacturing	Other
(i) 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
(ii) $\beta_{m,L}$	0.35	0.10	0.36
(iii) α_m	0.01	0.60	0.39
(iv) σ_m	4.8	8.1	5.0

(a) Parameters for Production and Preferences

Parameter	Values
$\lambda^S = \lambda^B$	0.15
μ	1.00

(b) Parameters for Production-Network Formation

Notes: These parameters are based on the description in Section 5.1.

For our counterfactual simulation in Section 5.3, we also need to know parameters that discipline the endogenous network formation $\{\lambda^S, \lambda^B, \mu\}$. We calibrate these parameters targeting the patterns of the network reorganization documented in Section 3.3. Specifically, given parameter values $\{\lambda^S, \lambda^B, \mu\}$, we undertake a counterfactual simulation of the localized conflict, which we

[24]For example, Broda and Weinstein (2006) show that the median estimate of the elasticity of substitution across varieties of imported goods in the United States is 3.1, ranging from 1.2 to 22.1 across sectors.

further describe in Section 5.3. We then take the difference between the model-predicted and observed log changes in the number of supplier and buyer linkages in nonconflict areas from 2013 (preconflict) to 2016 (postconflict). Next, we construct our moments as the interaction of these differences and the supplier and buyer exposure to conflict areas, residualized by location and sector. These moment conditions imply that the changes in unobserved idiosyncratic factors affecting supplier and buyer connections strictly outside the conflict areas (i.e., $K_{ui,km}(\upsilon, \omega)$) are orthogonal to firms' supplier and buyer conflict exposure conditional on a location and a sector. Finally, we look for the values that minimize the generalized method of moments (GMM) objective function given a constraint $0 \leq \mu \leq 1$. Appendix D.1 describes further details of this procedure. Appendix Table D.1 shows that this procedure closely replicates the observed patterns of the reorganizations of supplier and buyer linkages and revenue changes in response to shock.

Panel B of Table 3 summarizes the calibrated values for $\{\lambda^S, \lambda^B, \mu\}$ through this procedure. In our baseline calibration, we impose a symmetric restriction such that $\lambda^S = \lambda^B$. As we discuss further below, our counterfactual simulation results are similar as long as the sum of these two elasticties are kept unchanged, because they jointly govern the elasticity of production linkages with respect to trade flows (Equation 12). We find a value[25] of $\lambda^S = \lambda^B = 0.15$. This value is similar to yet smaller than the one in Arkolakis et al. (2023), who use the value around 0.2 (using an alternative calibration approach).

We also find $\mu = 1$, indicating that the link-formation costs are paid fully in the unit of labor (Equation 13). This finding is consistent with Dhyne, Kikkawa, Komatsu, Mogstad, and Tintelnot (2022), who estimate that in Belgium firms' overhead costs are mostly paid in labor. At the same time, if $\mu < 1$, a negative shock may be amplified through the change in link-formation cost (e.g., Buera, Hopenhayn, Shin, and Trachter, 2021; Arkolakis et al., 2023). Therefore, we also study below the sensitivity of our analysis to this parameter. We find that, in our context, this amplification effect is relatively small, even if we alternatively set $\mu = 0$.

5.2 Can Production-Network Disruption and Reorganization Explain Observed Firm-Level Output Decline?

Before presenting the simulation results, we first establish that the cost- and demand-propagation effects through supply chain disruption and reorganization can accurately account for the reduced-form effects on firm-level output, as documented in Section 3.

[25] We find a 10% bootstrapped confidence interval of $[0.11, 0.18]$ for $\lambda^S = \lambda^B$ and degenerate at one for μ at the boundary of the constraint ($0 \leq \mu \leq 1$).

5.2.1 Empirical Strategy

Proposition 1 shows that the total intermediate goods sales by firm type ω in sector m, location i, and year t can be given by

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

This expression summarizes two potential channels in which firm sales in nonconflict areas are affected by the localized conflict. The first term summarizes the equilibrium effects of the disruption and reorganization of their supply chain linkages, as well as the general equilibrium responses in wages. The second term, $Z_{i,m,t}(\omega)$, captures the direct effects on productivity. For example, the onset of the conflict may discourage investment or hinder efficient firm operation.

Here, we investigate the extent to which the first term can explain the observed decline in firm-level output documented in Section 3. To do so, we regress observed firm-level output on the empirical proxies for the first term. As we discuss below, we can directly estimate supplier and buyer access, $\mathcal{A}_{i,m,t}^{S}(\omega)$ and $\mathcal{A}_{i,m,t}^{B}(\omega)$, using observed trade flows and production networks for each year t. Denoting the corresponding estimates by $\tilde{\mathcal{A}}_{i,m,t}^{S}(\omega)$ and $\tilde{\mathcal{A}}_{i,m,t}^{B}(\omega)$, we run the following regression:

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

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 (22) capture the unobserved TFP term ($-\log Z_{i,m,t}(\omega)^{\sigma_m - 1}$) in Equation (21), including its time-varying components. Using regression (22), we test for $\gamma = 1$, i.e., whether the changes in our sufficient statistics for TFP-adjusted firm intermediate goods sales move one-for-one with the observed counterpart.

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 sufficient statistics on the right-hand side may involve estimation error, leading to an attenuation bias for γ.

To deal with these issues, we instead estimate Equation (22) using an 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 preconflict dummy and the dummy for high supplier and buyer exposure to the conflict areas. We test for $\gamma = 1$, which indicates that the effects of conflict shocks on firms with preexisting supplier and buyer linkages primarily manifest through the cost- and demand-propagation effects of supply chain disruption and reorganization (the first term of Equation 21) rather than through other channels influencing TFP (the second term).[26]

To estimate supplier access and buyer access, we use our model prediction of trade flows in Equation (8). By adding the time subscript t and manipulating the equation, the trade flow normalized by the measure of linkages is expressed as

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

where $\xi_{u,km,t}(\upsilon) \equiv \varsigma_k C_{u,k,t}(\upsilon)^{1-\sigma_k}$, $\zeta_{i,km,t}(\omega) \equiv D_{i,km,t}(\omega)$, and $\eta_{ui,km}(\upsilon,\omega) \equiv \mathbb{E}_t[\tau_{ui,km,t}(\upsilon,\omega)^{1-\sigma_k}]$, with $\mathbb{E}_t$ indicating expectation over time, and $\epsilon_{ui,km,t}(\upsilon,\omega) \equiv \tau_{ui,km,t}(\upsilon,\omega)^{1-\sigma_k}/\mathbb{E}_t\left[\tau_{ui,km,t}(\upsilon,\omega)^{1-\sigma_k}\right]$ capturing 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 (23) using a Pseudo-Poisson Maximum Likelihood estimator (see 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 $\tilde{x}$ denotes the estimates of parameter x. Once we estimate Equation (23), we can use the expressions for supplier and buyer market access up to scale using the empirical analogs of Equations (10) and (11), so that

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

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

In our baseline results, we use observed $\{M_{ui,km,t}(\upsilon,\omega)\}$ for each year to construct these measures. To benchmark our results, we also construct these access terms abstracting from production-network reorganization. That is, in estimating Equation (23) and constructing $\{\tilde{\mathcal{A}}^S_{i,m,t}(\omega), \tilde{\mathcal{A}}^B_{i,m,t}(\omega)\}$ using Equations (10) and (11), we fix the measure of supplier and buyer linkages $\{M_{ui,km,t}(\upsilon,\omega)\}$ at the level of 2013 instead of the actual values for each year.

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

5.2.2 *Results*

Table 4 presents our results of the IV regressions (Equation 22). In our baseline analysis, we focus on the long-run changes using 2013 as the preperiod and 2016 as the postperiod.[27] The dependent variable of the regression is the log of total values of out-shipments in our railway data by firms in region i, sector m, and year t. On the right-hand side, we proxy wages $w_{i,t}$ using the average labor compensation per worker by firms in region i in year t obtained from our SPARK-Interfax data.[28] For each specification, we also report the *p*-value for the Wald test for the null hypothesis that the regression coefficient equals one.

In Panel A, we present our results, taking into account the changes in production linkages when estimating supplier and buyer access. Column (1) starts with the specification where we control only for firm-type-region-sector fixed effects and year fixed effects. The regression coefficient is 0.85, with a standard error of 0.12. Therefore, while the coefficient is tightly estimated, we cannot reject the null hypothesis that it equals one (with a *p*-value of 0.23). In columns (2) and (3), we show that the patterns are similar by controlling for the sector-year fixed effects and the province-year fixed effects.

These patterns are in stark contrast with the specification in Panel B, where we abstract from the changes in production linkages when estimating supplier and buyer access. The regression coefficients range from 1.61 to 1.72, with standard errors of 0.36 to 0.41. Therefore, we can reject the null hypothesis that the regression coefficient equals one with a 10% significance level.[29] The fact that the coefficients are significantly above one indicates that, abstracting from reorganization, our model's sufficient statistics underpredict the observed firm-level output decline of exposed firms. In other words, reorganization of production linkages tend to amplify the relative firm-level output decline of the exposed firms. This observation is consistent with the finding in Section 3.3, where firms with higher supplier and buyer exposure faced a decline in buyer linkages in nonconflict areas. In Section 5.3, we revisit how these patterns relate to the aggregate output.

In Panel B of Appendix Table D.1, we repeat the same exercise by using the model-predicted measure of supplier and buyer linkages $\{M_{ui,km,t}(\upsilon, \omega)\}$ using Equation (12) and (13), given our choice of calibrated parameters $\{\lambda^S, \lambda^B, \mu\}$, observed trade flows $\{X_{ui,km,t}(\upsilon, \omega)\}$, and wages

[27] Panel A of Appendix Table D.3 shows that the regression coefficients are similar but slightly smaller if we use yearly panel of 2012–2016, indicating that yearly fluctuation of revenue may be partly influenced by additional factors such as adjustment costs.

[28] Panel B of Appendix Table D.3 shows that our results are similar if we omit $w_{i,t}$ from the right-hand side.

[29] The standard errors in Panel B are larger relative to Panel A due to lower first-stage F-statistics. In Appendix Table D.2, we report the results where we swap the right-hand side and left-hand side of Regression (22). While the coefficients are simply the reciprocals of Table 4, the first-stage F-statistics are larger in this specification. Consequently, we can reject the null hypothesis that the regression coefficient equals one in Panel B with a *p*-value less than 0.01, while the *p*-values for Panel A are still high at around 0.21 to 0.41.

Table 4: Can Production-Network Disruption and Reorganization Explain Observed Firm-Level Output Loss?

	$\log R_{i,m,t}(\omega)$		
	(1)	(2)	(3)
Panel A: With Link Adjustment			
$\log w_{i,t}^{\beta_{m,L}(1-\sigma_m)} \tilde{\mathcal{A}}_{i,m,t}^{S}(\omega) \tilde{\mathcal{A}}_{i,m,t}^{B}(\omega)$	0.85	0.88	0.83
	(0.12)	(0.13)	(0.11)
p-value (coefficient = 1)	0.23	0.35	0.13
Effective First-Stage F-Statistics	45.7	43.1	49
Panel B: No Link Adjustment			
$\log w_{i,t}^{\beta_{m,L}(1-\sigma_m)} \tilde{\mathcal{A}}_{i,m,t}^{S}(\omega) \tilde{\mathcal{A}}_{i,m,t}^{B}(\omega)$	1.61	1.72	1.71
	(0.36)	(0.41)	(0.37)
p-value (coefficient = 1)	0.09	0.08	0.06
Effective First-Stage F-Statistics	16.3	14.7	16.3
Firm-Type-Region-Sector Fixed Effects	X	X	X
Year Fixed Effects	X	X	X
Sector $\times$ Year Fixed Effects		X	X
Region $\times$ Year Fixed Effects			X
Observations	434	434	434

Notes: This table reports the results of estimating Equation (22). Panel A presents the case where we estimate supplier and buyer access in the dependent variable using observed $\{M_{ui,km,t}(\upsilon,\omega)\}$, Panel B presents the case where we fix $\{M_{ui,km,t}(\upsilon,\omega)\}$ at the level of 2013 instead. The level of observation is firm-type and year, for 2013 and 2016. The four firm-types are (1) high supplier and buyer exposure, (2) high supplier exposure and low buyer exposure, (3) low supplier exposure and high buyer exposure, and (4) low supplier and buyer exposure, for each province and sector, where supplier and buyer exposure are as defined in Section 3. $\log R_{i,m,t}(\omega)$ represents imputed total values of out-shipments in our railway data by firms in region i, sector m, and year t. Standard errors are clustered at the firm-type level. The effective first-stage F-statistics follow Montiel Olea and Pflueger (2013).

$\{w_{i,t}\}$, and assuming that the firm-pair-specific exogenous parameter for the link formation $\{K_{ui,km}(\upsilon,\omega)\}$ does not change from 2013 (preconflict) strictly outside the conflict areas.[30] We find that this version yields regression coefficients statistically indistinguishable from one (with coefficients of 1.28–1.34 with *p*-value of 0.16–0.34). This pattern is consistent with the observation that our model under our calibrated values for $\{\lambda^S, \lambda^B, \mu\}$ also replicates the observed patterns of link changes upon counterfactual simulation, as reported in Panel A of Appendix Table D.1.

To summarize, we find that the cost and demand linkages are the primary drivers of the reduced-

[30] With $\mu = 1$, the value for $C_{i,m}(\omega)$ is not required for constructing this prediction.

form effects on firm-level output reduction documented in Section 3. The reorganization of production linkages significantly contributes by amplifying these firm-level output changes. Other factors, such as firm-level changes in productivity, are unlikely to drive the reduced-form effects.

5.3 Aggregate Effects Outside the Conflict Areas

Finally, having established that the cost and demand propagation and production-network reorganization account for the observed firm-level output changes, we use our model to assess the aggregate effects of the localized conflict. To do so, we first calibrate our model using the trade and production linkages in 2013 using our railway-shipment data. We then run a simulation to make trading with firms in the three conflict areas (the DPR, the LPR, and Crimea) prohibitively costly, i.e., $\tau_{ui,km}(\upsilon, \omega) \to \infty$ if u or i are in the conflict areas. We choose this simulation strategy to reflect the fact that trade with the conflict areas became virtually absent within a few years after the onset of the conflict,[31] as we documented in Section 3.1. We also run a simulation of shocking the DPR, the LPR, and Crimea one by one, to assess the contribution of the shock from each region and whether the simultaneous conflict shocks lead to a larger or smaller aggregate output loss.

In the simulation, we fix trade costs $\{\tau_{ui,km}(\upsilon, \omega)\}$ and firm productivity $\{Z_{i,m}(\omega)\}$ strictly outside the conflict areas. This simulation strategy is consistent with the findings in Section 5.2, which show that these factors are unlikely to drive the observed firm-level output decline. We also adjust the baseline trade flows to satisfy all equilibrium conditions, including the aggregate sectoral expenditure shares implied by the input-output table (Panel A of Table 3), to enable a well-defined counterfactual simulation.[32]

We undertake this counterfactual simulations under two alternative scenarios. In our baseline scenario, we allow for the reorganization of production networks given the calibrated values for $\{\lambda^S, \lambda^B, \mu\}$ as reported in Panel B of Table 3. To benchmark our result, we also report the results where we shut down the reorganization of production linkages, i.e., we fix the production at the level of 2013 strictly outside the conflict areas.

Baseline Results. Table 5 reports our results. For each model specification, we report the percentage changes in population-weighted real GRP across provinces outside the conflict areas, calculated as the gross value added (15) divided by final price index (14). We also report the 25th, 50th, and 75th percentiles of the real GRP changes across provinces.

Row (1) shows that, in our baseline specification, we observe a 5.6% decline in aggregate real

[31] From the perspectives of the rest of Ukraine, this shock is isomorphic to infinitely negative TFP shocks in the conflict areas, i.e., $Z_{i,m}(\omega) \to 0$ if i is in the conflict areas.

[32] See Appendix C.3 for the system of equations to solve for counterfactual equilibrium and Appendix D.2 for the details of the calibration. When adjusting the baseline trade flows, we need to assume a value for δ_m, i.e., the share of link-formation costs in variable profit. We set this value to 0.25 in the baseline. As we discuss below, our results are virtually unchanged by using alternative values.

Table 5: Aggregate Real GRP Changes Outside Conflict Areas

Real GRP Changes (Percentage Points)	Mean	25%-ile	50%-ile	75%-ile
(1) With Link Adjustment	-5.6	-7.2	-6.3	-3.3
(2) No Link Adjustment	-8.4	-11.5	-8.6	-4.5
(3) With Link Adjustment (Shock to DPR)	-1.8	-2.2	-1.3	-0.4
(4) With Link Adjustment (Shock to LPR)	-2.6	-4.1	-2.4	-1.6
(5) With Link Adjustment (Shock to Crimea)	-0.9	-1.0	-0.3	0.1

Notes: This table presents the results of a counterfactual simulation of the localized conflict shock specified in Section 5.3. For each scenario of the counterfactual simulation, we report the percentage change in population-weighted real GRP across provinces strictly outside the conflict areas. We also report the 25th, 50th, and 75th percentiles of the real GRP changes across provinces. Rows 3–5 present the results of the simulation to shut down trade linkages to and from the territories of the DPR, the LPR, and Crimea (including Sevastopol) one by one, instead of shocking them simultaneously, as we do in our baseline simulation.

GRP strictly outside the conflict areas. This magnitude is sizable and explains nearly half of the actual 11.7% decline in the real GRP of nonconflict provinces from 2013 through 2016 observed in the official government statistics.[33] This large magnitude of the aggregate effects illustrates the intensity of the localized conflict in this context, in contrast to the existing literature focusing on smaller, more transient shocks. For example, Carvalho et al. (2021) quantify that the 2011 Tohoku earthquake and tsunami in Japan resulted in a 0.47% decline in Japan's real GDP growth in the following year (using a model without changes in production networks). We also find a large regional disparity in the real GRP loss: 7.2% at the 25th percentile and 3.3% at the 75th percentile. Below, we further examine the pattern of spatial disparity in the real GRP changes.

Role of Endogeneous Network Reorganization. In row (2) of Table 5, we report the results of our simulation where we fix the production linkages when running a counterfactual simulation. In this case, we find an 8.3% decline in aggregate real GRP, which is substantially larger than our baseline specification. Therefore, the endogeneous reorganization of production networks partially mitigates the aggregate output loss.

At first glance, this finding may seem to contradict our results in Section 5.2, where we showed that network reorganization amplifies the firm-level output loss. However, these two findings are perfectly consistent with each other. As discussed in Section 4.4, depending on the elasticities λ^S and λ^B, firms reallocate production linkages away from firms that are directly or indirectly exposed to negative shocks. This reallocation implies that exposed firms face a larger output decline due to production-network reorganization. However, for an economy overall, the reallocation of production linkages toward unaffected firms benefits aggregate output.

[33] Based on data from the State Statistics Service of Ukraine (2020).

Independent Shocks to Each Conflict Area. In rows 3–5 of Table 5, we present the results of the simulation to shut down trade linkages to and from the territories of the DPR, the LPR, and Crimea one by one, instead of shocking them simultaneously, as we do in our baseline simulation. We find that the aggregate real GRP outside each conflict area falls by 1.8%, 2.6%, and 0.9%, respectively.

Two key observations emerge. First, the shocks to the DPR and the LPR has relatively larger effects than the shock to Crimea. This is notable, given that Crimea's GDP share in the prewar Ukraine economy (3.7%) was at least as large as that of the LPR (the entire Luhansk province, including outside the LPR, contributed about 3.6% of GDP in prewar Ukraine economy). This finding stems from the fact that the DPR and LPR regions are more intensive in the manufacturing sector than Crimea (see Figure A.1 for the map of industry composition across Ukrainian provinces). The manufacturing sector relies more on intermediate inputs, particularly those from the manufacturing sector itself (Table 3). Therefore, a shock to a manufacturing-intensive region has a disproportionately larger aggregate effect relative to its size. This observation is also consistent with our finding that regions with a higher-intensity manufacturing sector are more severely affected, as we further discuss below. We also find that the shock to the DPR is smaller than that to the LPR, despite the larger GDP share of the entire Donetsk province (10.8%). Despite the similarity in the industry composition in the two regions, the proclaimed territory in the LPR is larger than that in the DPR, leading to a larger effect from the shock to the LPR.

Second, shocking all conflict areas simultaneously produces slightly larger aggregate real GRP effects (5.6% in row 1) than the cumulative effects of shocking each conflict area one by one (5.3% by summing rows 3–5). Therefore, the simultaneous occurrence of conflicts in multiple regions induced an additional economic cost in this context.

In theory, it is ambiguous whether simultaneous conflict shocks amplify or mitigate the cumulative effects from independent shocks. One one hand, if the conflict areas are deeply connected with each other through production networks, a conflict shock in just one region can cause serious production disruption in the other regions. This force implies that the cumulative effects from independent shocks are greater than the simultaneous shocks. On the other hand, if different conflict areas are close substitutes from the perspective of the rest of Ukraine, a conflict shock in just one region can be absorbed by the substitution toward the other regions. This force implies that the cumulative effects from independent shocks are smaller than the simultaneous shocks. In our context, we find that while the substitution effect slightly dominates the integration effect, they roughly offset each other.

Regional Heterogeneity. In Figure 5, we show the geographic patterns of these real GRP losses. In Panel A, we plot the simulated real GRP loss of each region on a map. We find that real GRP loss across regions in Ukraine varies greatly. GRP loss tends to be greater in regions that are geographically closer to the conflict areas. In particular, the region with the largest GRP loss is the Luhansk province, just north of the conflict area. Some provinces that are geographically far from the conflict areas even face GRP *gains*. These regions benefit from the reallocation of input demand and production linkages from the conflict areas.

To further emphasize this heterogeneity, in Panel B, we project the real GRP changes as a function of the distance to the conflict areas. We find a strong upward-sloping relationship in Panel B, confirming that regions closer to the conflict areas tended to suffer larger output loss.

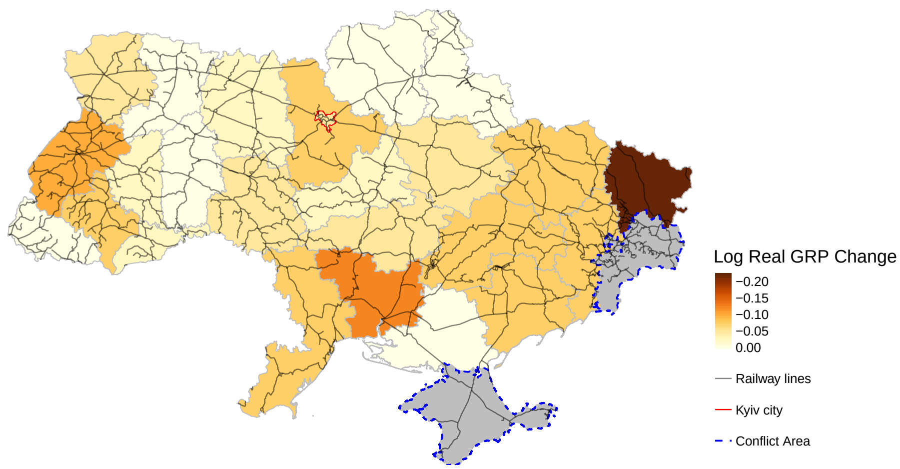
Even so, some regions far from the conflict areas, such as the Lviv province (in the west) and Mykolaiv and Odessa provinces (in the southwest), face large real GRP losses. These estimates indicate that localized conflicts can have far-reaching, detrimental economic consequences through production networks. One reason why far-away regions could be affected is their higher reliance on manufacturing. The manufacturing sector is more severely affected by the production network disruption due to its higher reliance on intermediate input trade (Table 3, Appendix Table A.7). Panel C confirms that regions with a higher sales share of manufacturing firms tend to face a larger real GRP loss. Therefore, regions with high reliance on the manufacturing sector, such as Lviv, Mykolaiv, and Odessa provinces (see Figure A.1 for the industrial composition across provinces), face a large real GRP loss even though they are geographically far from the conflict areas.

Robustness. In Appendix Table D.4, we report the robustness of our results to alternative specifications. In rows (2) and (3), we find that alternatively setting $\{\lambda^S, \lambda^B\}$ to $\lambda^S = 0, \lambda^B = 0.30$, and $\lambda^S = 0.30, \lambda^B = 0$ instead of the baseline assumption of $\lambda^S = \lambda^B = 0.15$ yields virtually identical aggregate real GRP changes, underscoring the interpretation that these two parameters jointly govern the elasticity of production linkages with respect to trade flows (Equation 12).[34]

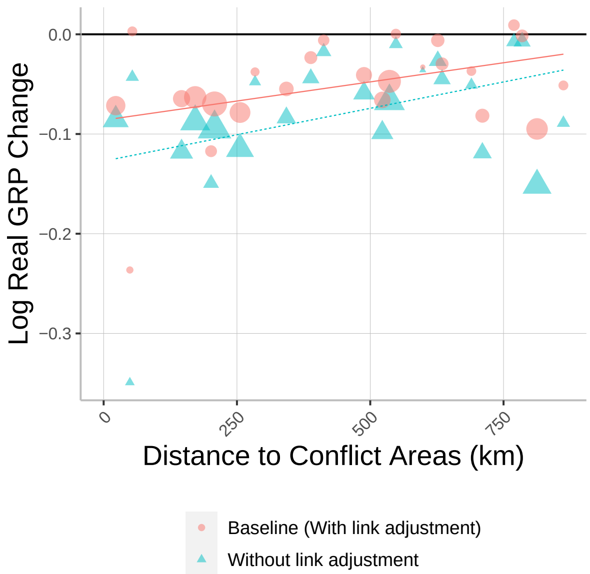
In row (4), we find that alternatively setting the value of μ to 0 increases the real GRP loss to 6.6%. This decline is consistent with Arkolakis et al. (2023), who argue that a negative shock may be amplified through the increase in link-formation cost. In this context, this decline is relatively modest compared to the reallocation effects of production network reorganization, partly because of smaller sectoral input-output multipliers in the Ukrainian economy context (Table 3). In row (5), we find that an alternative value for δ_m used in the calibration of trade flows (see Appendix D.2) does not affect the aggregate output changes. In rows (6), (7), and (8), we show robustness to alternative definitions of firm types. Our results are similar if we define firm types using link exposure (in row f) and weight exposure (in row g), as well as the combination of conflict exposure and the dummy for above-median firm size within a region and a sector (in row h).

[34] Relatedly, when we fix $\lambda^S = 0$ (or $\lambda^B = 0$) to estimate λ^B (or λ^S) following the procedure described in Section 3, we obtain the values approximately at 0.30.

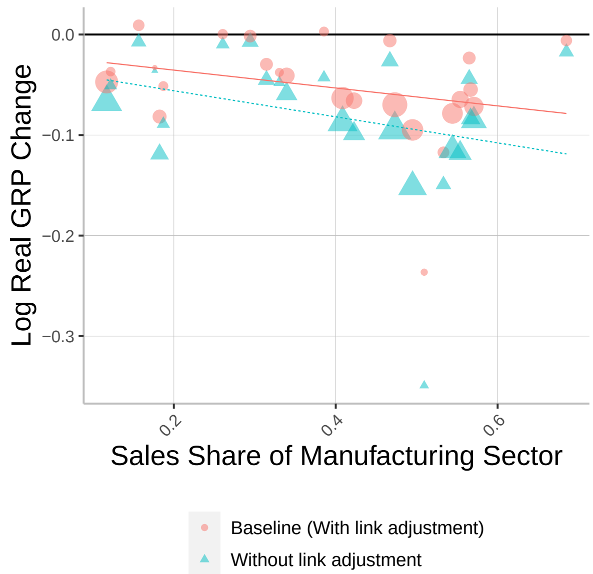
Figure 5: Real GRP Changes Outside Conflict Areas



(a) Real GRP Changes Across Provinces of Ukraine (with link adjustment)



(b) Province-Level Changes in Real GRP by Distance to the Conflict Areas



(c) Province-Level Changes in Real GRP by Share of Manufacturing Firms

Notes: These figures present the predicted percentage change in real GRP for regions strictly outside the conflict areas. In Panel B, distance to the conflict areas is defined as the straight-line distance between the centroid of each province and the closest point of the border to the conflict areas in the Donbas region or Crimea. In Panel C, sales share of the manufacturing sector is defined using SPARK-Interfax data in 2013. The size of the dot represents the population size of each province in 2013.

6 Conclusion

Do intense, prolonged localized conflicts lead to disruption of production networks? How do firms reorganize these networks? What are the consequences for firm production and aggregate output? This paper answers these questions in the context of the 2014 Russia-Ukraine conflict, analyzing the universe of firm-to-firm railway shipments in Ukraine from 2012 through 2016.

We document that firms with prior supplier linkages to the conflict areas and firms with prior buyer linkages to the conflict areas both experienced a significant reduction in output. Simultaneously, firms substitute production linkages away from those directly or indirectly exposed to negative shocks: firms with prior supplier exposure increase the number of suppliers but lose buyers in nonconflict areas, and firms with prior buyer exposure lose both suppliers and buyers in nonconflict areas.

Based on this evidence, we develop a multisector, multilocation general equilibrium model of production-network formation. We show that our model's sufficient statistics summarizing the demand and cost linkages can accurately account for the observed output changes as long as we account for the reorganization of production networks. Our model predicts about a 5.6% reduction of aggregate GRP strictly outside conflict areas through the disruption and reorganization of production networks. If we abstract from this reorganization, this effect increases to 8.4%, indicating that endogenous reorganization mitigates the aggregate output loss. Therefore, the endogenous firm-level responses to reorganize the production networks provide resiliency against the far-reaching and detrimental economic costs of localized conflicts.

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Online Appendix for "Supply Chain Disruption and Reorganization: Theory and Evidence From Ukraine's War" **(not for publication)**

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A Appendix for Reduced-Form Evidence

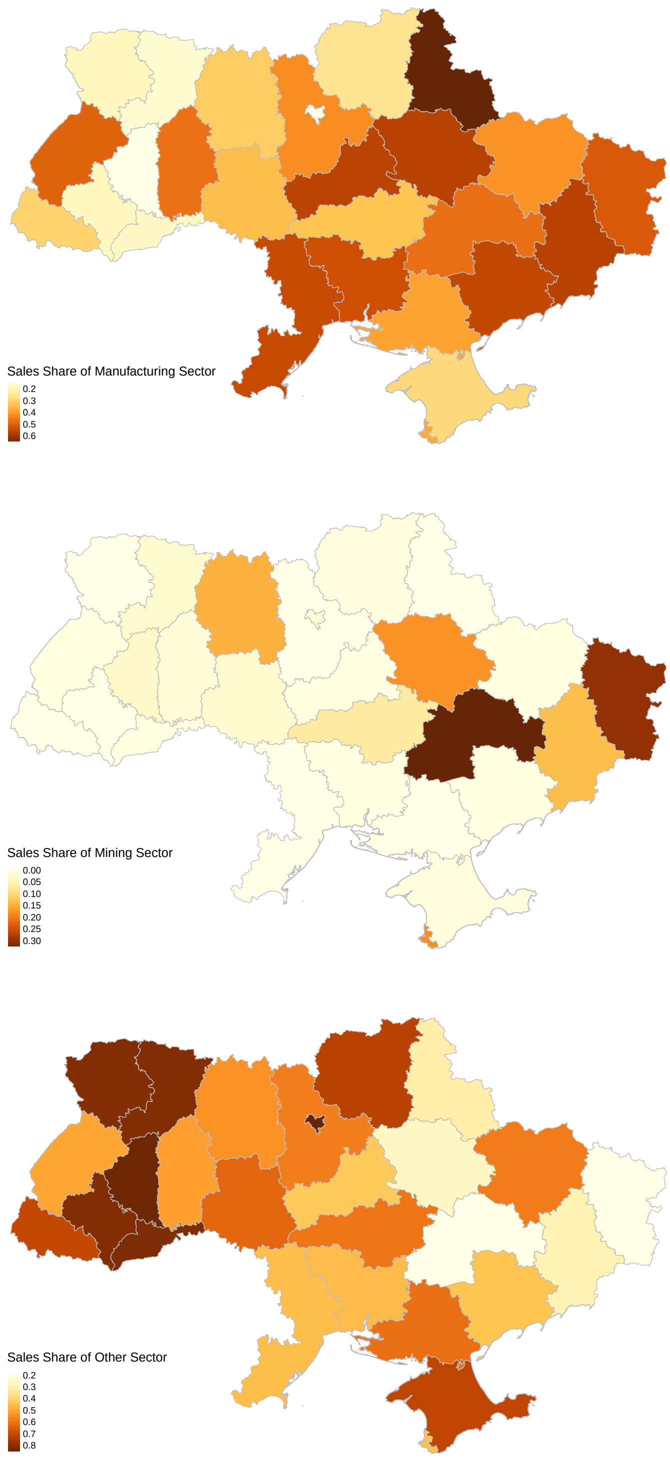
A.1 Summary Statistics and Additional Results on Reduction in Trade With the Conflict Areas

Table A.1: Summary Statistics

	Observations	Mean	SD	Min	Max
	Panel A: Conflict Exposure				
$\mathbb{1}$[Firm traded With conflict areas, 2012–13]	50,202	0.55	0.50	0	1
Firm's Buyer Conflict Exposure, 2012–2013	50,202	0.09	0.22	0	1
Firm's Supplier Conflict Exposure, 2012–2013	50,202	0.10	0.23	0	1
$\mathbb{1}$[High Firm's Buyer Conflict Exposure, 2012–2013]	50,202	0.19	0.39	0	1
$\mathbb{1}$[High Firm's Supplier Conflict Exposure, 2012–2013]	50,202	0.19	0.39	0	1
$\mathbb{1}$[Firm Traded With Russia in 2012–2013]	50,202	0.24	0.43	0	1
	Panel B: Sales and Trade				
Log of Firm Sales, 2010–2018	35,598	16.89	2.49	4.61	25.13
$\mathbb{1}$[No Sales Reported], 2010–2018	50,202	0.29	0.45	0	1
Log Weight Sent Total, 2012–2016	12,776	15.49	3.06	1.61	24.86
Log Weight Sent to Nonconflict Areas, 2012–2016	12,453	15.45	3.03	1.61	24.72
Log Weight Received Total, 2012–2016	19,089	15.73	2.38	3	24.57
Log Weight Received From Nonconflict Areas, 2012–2016	18,733	15.66	2.36	3	24.56
Log Number of Buyers Total, 2012–2016	12,776	1.92	1.52	0	7.64
Log Number of Buyers in Nonconflict Areas, 2012–2016	12,453	1.88	1.50	0	7.64
Log Number of Suppliers Total, 2012–2016	19,089	1.82	1.26	0	7.41
Log Number of Suppliers From Nonconflict Areas, 2012–2016	18,733	1.77	1.25	0	7.41
	Panel C: Industry				
$\mathbb{1}$[Firm Is in Mining]	50,202	0.05	0.21	0	1
$\mathbb{1}$[Firm Is in Manufacturing]	50,202	0.21	0.41	0	1
$\mathbb{1}$[Firm Is in Another Industry]	50,202	0.74	0.44	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 Other) within each province of Ukraine in 2013 using SPARK-Interfax data.

A.2 Robustness of the Effects on Firm Sales

This section probes the robustness of the estimates in Table 1.

Tables A.2 and A.3 show that the results for sales volume and nonreported sales, respectively, are robust to a battery of checks. First, we show that our estimates remain similar 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 may induce sample selection.

Second, the results remain unchanged after flexibly controlling for firms' geolocation (columns 3–4) and 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 armed conflict expansion.

Third, we control for the province-sector-year fixed effects, where sector is a 2-digit SIC code (column 7). This addresses possible issues related to increased demand for military- or conflict-related products, any province-year shocks, such as province-specific refugee inflows, as well as any complex yearly shocks that exhibit province-sector heterogeneity. In Appendix A.4, we further confirm that province-level population and refugee movements are unrelated to our conflict exposure measures calculated at the province level.

Fourth, we show that our results are not driven by firms' prewar trade ties with Russia (column 8), which accounts for the disruption of trade between nonconflict areas of Ukraine and Russia following the start of the conflict (e.g., Korovkin and Makarin, 2023).

Fifth, we control for the total number of trade partners before the conflict, interacted with the post-2014 indicator (column 9), thus assuaging the concern that firms with fewer trading partners are mechanically more likely to have lower conflict exposure.

Sixth, our results are not driven by outlier regions—they survive our omitting firms near the conflict areas, i.e., in the nonoccupied parts of Donetsk and Luhansk oblasts (columns 10 and 11, respectively, in Tables A.2 and A.3) and removing firms in the capital city of Kyiv (column 12).

Table A.4 shows that the results remain similar when exposure is defined by shipment weight or the number of links rather than transaction values, ensuring that value imputation does not influence our findings.

In Table A.5, we address the concern of nonrandom exposure in Borusyak and Hull (2023) by calculating a placebo firm exposure and controlling for it in our baseline specification. Specifically, we take a hundred random draws, selecting four placebo "conflict" provinces (imitating Crimea, Donetsk, Luhansk, and Sevastopol) out of all Ukrainian provinces, including those actually affected by conflict. We then compute a firm's average placebo conflict exposure across these draws based on the firm's actual trade connections with the placebo "conflict" provinces. Subsequently, we reestimate Table 1 controlling for the corresponding placebo exposure measures.[1] The results in Table A.5 show that while the estimates for missing revenue decrease in magnitude, the estimates for the reduction in sales stay similar, and both sets of estimates remain statistically significant.

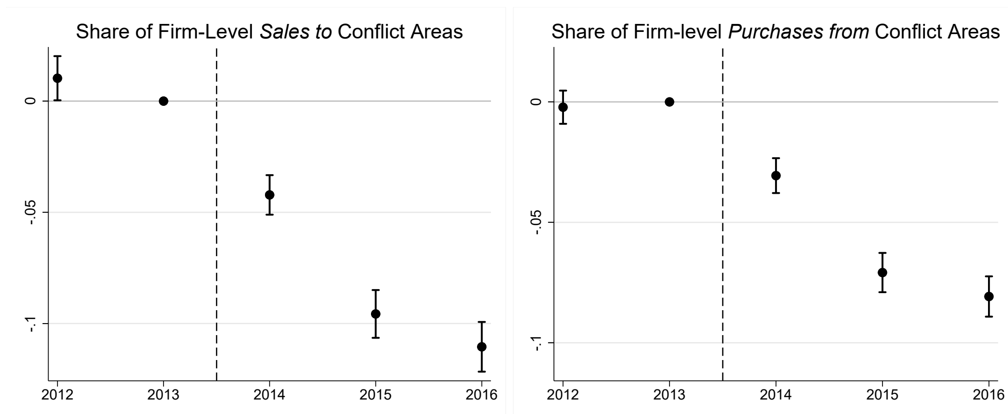
One might also worry that our findings are influenced by firms that have some operations in the conflict areas, which our headquarters-based sample definition does not exclude. Table A.6 demonstrates that our results remain unchanged when we use a stricter sample definition, where we include only firms that never used a railway station located in the conflict area, either for

[1]This approach is equivalent to recentering the exposure variables but allows the coefficients on actual and placebo exposure to differ in magnitude (Borusyak and Hull, 2023, p. 2166). Our results are similar with recentered exposure.

incoming or for outgoing shipments.

Further, in terms of results' heterogeneity, Table A.7 indicates that the effects are more pronounced for firms within the manufacturing sector, consistent with the importance of input-output linkages in this industry. The same table also shows that the effects of exposure to Crimea or the DPR-LPR region are comparable when analyzed separately. Finally, we cannot reject that the effects are similar for firms of different prewar sizes.

Figure A.2: Evolution of Firm Trade Value Share With the Conflict Areas



Notes: This figure represents how the firm-level buyer and supplier exposure to the conflict areas changed over time. Specifically, the figure presents the estimates of the year fixed effects 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.

Table A.2: Robustness Checks: Conflict and Sales of Firms That Traded With the Conflict Areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Baseline	Strictly Balanced Panel	Latitude & Longitude		Distance to Conflict Areas		Province × Sector × Year FE	Preconflict Trade With Russia	Preconflict Trade Partners	Removing Donetsk Oblast	Removing Luhansk Oblast	Removing Kyiv
Post-2014 ×	-0.162***	-0.100**	-0.139***	-0.130***	-0.141***	-0.146***	-0.110**	-0.125***	-0.149***	-0.133***	-0.159***	-0.126***
𝟙[Firm Traded With Conflict Areas, 2012–2013]	(0.046)	(0.045)	(0.046)	(0.046)	(0.046)	(0.046)	(0.047)	(0.046)	(0.046)	(0.046)	(0.046)	(0.047)
Post-2014 ×			0.061***	-1.251								
Latitude			(0.016)	(0.923)								
Post-2014 ×			-0.020***	-1.055***								
Longitude			(0.005)	(0.290)								
Post-2014 ×				0.006								
Latitude^2				(0.009)								
Post-2014 ×				-0.002								
Longitude^2				(0.001)								
Post-2014 ×				0.023***								
Latitude × Longitude				(0.006)								
Post-2014 ×					0.505***							
Distance to Conflict Area					(0.098)							
Post-2014 ×						0.388***						
Distance to the LPR or the DPR						(0.079)						
Post-2014 ×								-0.218***				
𝟙[Firm Imported From Russia, 2012–2013]								(0.060)				
Post-2014 ×								-0.224***				
𝟙[Firm Exported to Russia, 2012–2013]								(0.061)				
Post-2014 ×									-0.000*			
# of Preconflict Trade Partners									(0.000)			
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean	16.899	17.237	16.900	16.900	16.900	16.900	16.934	16.899	16.899	16.857	16.901	16.847
SD	2.482	2.291	2.481	2.481	2.481	2.481	2.473	2.482	2.482	2.455	2.479	2.435
Observations	35,439	24,273	35,334	35,334	35,334	35,334	33,812	35,439	35,439	33,640	34,888	30,383
Number of Firms	4,775	2,697	4,753	4,753	4,753	4,753	4,558	4,775	4,775	4,530	4,700	4,007

Notes: This table presents the robustness checks for the conflict's impact on firm sales by firms' preexisting trade ties with the conflict areas. 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 a firm's distance (in 1,000 km) to the conflict areas (the DPR, the LPR, and Crimea) and distance to the DPR and the LPR interacted with Post$_{it}$ (columns 5 and 6), controlling for a firm's sector interacted with province and year fixed effects (column 7), controlling for whether a firm had been trading with Russia before the conflict (2012 or 2013) interacted with Post$_{it}$ (column 8), controlling for the total number of trade partners a firm had preconflict interacted with Post$_{it}$ (column 9), omitting firms near the conflict areas, i.e., the nonoccupied parts of Donetsk and Luhansk oblasts (columns 10 and 11, respectively), and omitting firms in Kyiv (column 12). 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 and Nonreporting of Sales by Firms That Traded With the Conflict Areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Baseline	Strictly Balanced Panel	Latitude & Longitude		Distance to Conflict Areas		Province × Sector × Year FE	Preconflict Trade With Russia	Preconflict Trade Partners	Removing Donetsk Oblast	Removing Luhansk Oblast	Removing Kyiv
Post-2014 × 𝟙[Firm Traded With Conflict Areas, 2012–2013]	0.070***	0.070***	0.062***	0.061***	0.062***	0.063***	0.058***	0.065***	0.071***	0.064***	0.068***	0.055***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Post-2014 × Latitude			-0.003	0.167								
			(0.004)	(0.212)								
Post-2014 × Longitude			0.006***	0.158**								
			(0.001)	(0.063)								
Post-2014 × Latitude^2				-0.001								
				(0.002)								
Post-2014 × Longitude^2				0.000								
				(0.000)								
Post-2014 × Latitude × longitude				-0.004***								
				(0.001)								
Post-2014 × Distance to Conflict Area					-0.106***							
					(0.021)							
Post-2014 × Distance to the LPR or the DPR						-0.093***						
						(0.017)						
Post-2014 × 𝟙[Firm Imported From Russia, 2012–2013]								0.037***				
								(0.013)				
Post-2014 × 𝟙[Firm Exported From Russia, 2012–2013]								0.023*				
								(0.012)				
Post-2014 × # of Preconflict Trade Partners									-0.000			
									(0.000)			
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean	0.291	0.291	0.289	0.289	0.289	0.289	0.292	0.291	0.291	0.292	0.292	0.278
SD	0.454	0.454	0.453	0.453	0.453	0.453	0.455	0.454	0.454	0.455	0.455	0.448
Observations	50,202	50,202	49,950	49,950	49,950	49,950	48,060	50,202	50,202	47,754	49,500	42,264
Number of Firms	5,578	5,578	5,550	5,550	5,550	5,550	5,340	5,578	5,578	5,306	5,500	4,696

Notes: This table presents the robustness checks for the conflict's impact on whether a firm reported any sales in a given year by firms' preexisting trade ties with the conflict areas. 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 the conflict areas (the DPR, the LPR, and Crimea) and distance to the DPR and the LPR interacted with Post_{it} (columns 5 and 6), controlling for firm's sector interacted with province and year fixed effects (column 7), controlling for whether a firm had been trading with Russia before the conflict (2012 or 2013) interacted with Post_{it} (column 8), controlling for the total number of trade partners a firm had preconflict interacted with Post_{it} (column 9), omitting firms near the conflict areas, i.e., the nonoccupied parts of Donetsk and Luhansk oblasts (columns 10 and 11, respectively), and omitting firms in Kyiv (column 12). Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.4: Conflict and Sales of Firms That Traded With the Conflict Areas—Alternative Measures of Exposure

	(1)	(2)	(3)	(4)
	Log Sales	No Sales Reported	Log Sales	No Sales Reported
Panel A: Weight-Based Exposure				
Post-2014 × Firm's Buyer Conflict Exposure, 2012–2013	-0.158	0.051**		
	(0.097)	(0.023)		
Post-2014 × Firm's Seller Conflict Exposure, 2012–2013	-0.325***	0.084***		
	(0.099)	(0.021)		
Post-2014 × $\mathbb{1}$[High Firm's Buyer Conflict Exposure, 2012–2013]			-0.182***	0.060***
			(0.058)	(0.012)
Post-2014 × $\mathbb{1}$[High Firm's Seller Conflict Exposure, 2012–2013]			-0.205***	0.040***
			(0.056)	(0.012)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean	16.899	0.291	16.899	0.291
SD	2.482	0.454	2.482	0.454
Observations	35,439	50,202	35,439	50,202
Number of Firms	4,775	5,578	4,775	5,578
Panel B: Link-Based Exposure				
Post-2014 × Firm's Buyer Conflict Exposure, 2012–2013	-0.182*	0.059**		
	(0.106)	(0.026)		
Post-2014 × Firm's Seller Conflict Exposure, 2012–2013	-0.276**	0.075***		
	(0.110)	(0.024)		
Post-2014 × $\mathbb{1}$[High Firm's Buyer Conflict Exposure, 2012–2013]			-0.156***	0.059***
			(0.058)	(0.012)
Post-2014 × $\mathbb{1}$[High Firm's Seller Conflict Exposure, 2012–2013]			-0.154***	0.034***
			(0.057)	(0.012)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean	16.899	0.291	16.899	0.291
SD	2.482	0.454	2.482	0.454
Observations	35,439	50,202	35,439	50,202
Number of Firms	4,775	5,578	4,775	5,578

Notes: This table presents the estimates for the conflict's impact on firm sales and an indicator for sales data missing by firms' preexisting trade connections with the conflict areas. In Panel A, exposure is calculated as a weight share. In Panel B, exposure is calculated as a links share. *High exposure* refers to exposure greater than the 80th percentile in the overall sample. The sample is restricted to firms outside the conflict areas. The firm accounting data, from SPARK-Interfax, cover the 2010–2018 period. Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.5: Conflict and Sales of Firms That Traded With the Conflict Areas—Borusyak and Hull (2023) Method

	(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, 2012–2013]	-0.156***	0.024**				
	(0.054)	(0.011)				
Post-2014 × Firm's Buyer Conflict Exposure, 2012–2013			-0.149	0.032		
			(0.104)	(0.024)		
Post-2014 × Firm's Supplier Conflict Exposure, 2012–2013			-0.259***	0.047**		
			(0.100)	(0.021)		
Post-2014 × 𝟙[High Firm's Buyer Conflict Exposure, 2012–2013]					-0.160***	0.043***
					(0.060)	(0.013)
Post-2014 × 𝟙[High Firm's Supplier Conflict Exposure, 2012–2013]					-0.129**	0.029**
					(0.054)	(0.012)
Placebo Exposure Means	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Mean	16.899	0.291	16.899	0.291	16.899	0.291
SD	2.482	0.454	2.482	0.454	2.482	0.454
Observations	35,439	50,202	35,439	50,202	35,439	50,202
Number of Firms	4,775	5,578	4,775	5,578	4,775	5,578

Notes: This table presents the estimates for the conflict's impact on firm sales and an indicator for missing sales data by firms' preexisting trade connections with the conflict areas after applying the Borusyak and Hull (2023) adjustment. Specifically, we amend the estimates in Table 1 by controlling for the mean firm-level placebo conflict exposure, where placebo exposures are estimated using a sample of 100 random draws of four placebo "conflict" provinces (imitating Crimea, Donetsk, Luhansk, and Sevastopol) out of all Ukrainian provinces, including those actually affected by conflict. Columns (1)–(2) control for the placebo exposure, defined as the share of simulated province draws during which a firm was connected to at least one placebo "conflict" province. Columns (3)–(4) control for a firm's average placebo conflict exposure, calculated across the random draws based on the firm's actual trade connections with the placebo "conflict" provinces. Columns (5)–(6) control for the placebo exposure, defined as the share of simulated province draws during which firm's placebo conflict exposure was greater than the 80th percentile in the sample. The sample is restricted to firms outside the conflict areas. The firm accounting data come from SPARK-Interfax and cover the 2010–2018 period. Standard errors in parentheses are clustered at the firm level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A.6: Conflict and Sales of Firms That Traded With Conflict Areas—Stricter Definition of Nonconflict Firms

	(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, 2012–2013]	-0.172***	0.066***				
	(0.050)	(0.011)				
Post-2014 × Firm's Buyer Conflict Exposure, 2012–2013			-0.311**	0.054*		
			(0.125)	(0.030)		
Post-2014 × Firm's Supplier Conflict Exposure, 2012–2013			-0.211*	0.072***		
			(0.115)	(0.024)		
Post-2014 × 𝟙[High Firm's Buyer Conflict Exposure, 2012–2013]					-0.232***	0.050***
					(0.070)	(0.015)
Post-2014 × 𝟙[High Firm's Supplier Conflict Exposure, 2012–2013]					-0.129**	0.048***
					(0.064)	(0.013)
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Mean	16.748	0.298	16.748	0.298	16.748	0.298
SD	2.421	0.457	2.421	0.457	2.421	0.457
Observations	28,123	40,248	28,123	40,248	28,123	40,248
Number of Firms	3,825	4,472	3,825	4,472	3,825	4,472

Notes: This is a version of Table 1 restricted to firms that never used railway stations in the conflict areas throughout the data period. *High exposure* refers to exposure greater than the 80th percentile in the overall sample. The sample is restricted to firms outside the conflict areas. The firm accounting data come from SPARK-Interfax and cover the 2010–2018 period. Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.7: Conflict and Sales of Firms That Traded With Conflict Areas, Heterogeneity by Industry and Conflict Location

	By Industry				By Conflict Location			By Size
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Manufac-turing	Mining	Other Industries	Industry Indicators	Traded with DPR-LPR	Traded With Crimea	Traded With DPR-LPR and Crimea	
Post-2014 × $\mathbb{1}$[Firm Traded With Conflict Areas, 2012–2013]	-0.263***	-0.080	-0.123**	-0.121**				-0.211***
	(0.083)	(0.264)	(0.056)	(0.050)				(0.069)
Post-2014 × $\mathbb{1}$[Firm Traded With Conflict Areas, 2012–2013] × $\mathbb{1}$[Firm is in manufacturing]				-0.130**				
				(0.064)				
Post-2014 × $\mathbb{1}$[Firm Traded With Conflict Areas, 2012–2013] × $\mathbb{1}$[Firm is in mining]				-0.106				
				(0.123)				
Post-2014 × $\mathbb{1}$[Firm Traded With the DPR or the LPR, 2012–2013]					-0.146***			
					(0.045)			
Post-2014 × $\mathbb{1}$[Firm Traded With Crimea, 2012–2013]						-0.195***		
						(0.057)		
Post-2014 × $\mathbb{1}$[Firm Traded With the DPR or the LPR and Crimea, 2012–2013]							-0.187***	
							(0.061)	
Post-2014 × $\mathbb{1}$[Firm Traded With Conflict Areas, 2012–2013] × $\mathbb{1}$[Above the Median, 2012–2013]								0.112
								(0.092)
Post-2014 × $\mathbb{1}$[Above the Median, 2012–2013]								✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean	17.528	17.314	16.648	16.899	16.899	16.899	16.899	16.880
SD	2.509	2.650	2.416	2.482	2.482	2.482	2.482	2.489
Observations	8,814	1,723	24,902	35,439	35,439	35,439	35,439	35,836
Number of Firms	1,101	223	3,451	4,775	4,775	4,775	4,775	4,806

Notes: This table presents the heterogeneous estimates for the conflict's impact on the sales of firms with preexisting trade connections with conflict areas, by industry and by conflict location. Columns (1), (2), and (3) present the baseline results restricting the sample, respectively, to manufacturing firms, mining firms, and firms in other industries. Column (4) contains the regression results with industry indicators interacted with the conflict-trade-exposure indicator, where the "other" industry is used as a base group. Columns (5), (6), and (7) are the baseline estimates looking at firms' prior trade ties with the occupied Donbas areas (the DPR or the LPR), Crimea, or both. Column (8) uses a triple difference specification, splitting the sample of firms by whether they were above or below the median in the revenue distribution before 2014. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

A.3 Robustness of the Effects on the Reorganization of Production Linkages

This section probes the robustness of the estimates in Table 2.

Tables A.8 and A.9 show that the estimated changes in supplier and buyer linkages, respectively, are robust to the checks introduced in Tables A.2 and A.3. Specifically, they remain similar when using a strictly balanced sample of firms that sent or received shipments from nonconflict areas every year (column 2 in each table), flexibly controlling for time-varying importance of firms' location and distance to the conflict areas (columns 3–4 and 5–6, respectively), controlling for the province-sector-year fixed effects (column 7), controlling for firms' preconflict trade with Russia (column 8) and firms' total number of preconflict trade partners (column 9) interacted with the post-2014 indicator, and excluding firms located in the nonoccupied parts of Donbas (columns 10–11) or in Kyiv (column 12).

Table A.10 shows that the estimates are similar when using weight-based or link-based exposures. Links-based exposures in Panel B give slightly noisier results for some specifications, likely because they ignore the intensive margin of shipments, which might lead to attenuation.

Table A.11 demonstrates robustness to controlling for firms' placebo "conflict" exposure, following recommendations in Borusyak and Hull (2023). See Section A.2 for more details on the exact procedure used.

Table A.12 confirms that our results are unlikely to be driven by firms with prewar operations in the conflict areas, as the estimates remain robust to focusing on firms that never sent or received shipments through railway stations located in the conflict areas.

Further, we explore three additional robustness checks that are especially relevant for the results on production-network reorganization. First, Table A.13 indicates that changes in the weight of shipments to and from nonconflict areas (as opposed to the number of linkages) align closely with the patterns observed in Table 2. This suggests that the changes in the number of buyers and suppliers are crucial drivers of the overall trade pattern. Second, Panel A of Table A.14 shows that our results are unchanged if we count only trade partners present in the data before the conflict; therefore, newly registered trade partners (e.g., that might have moved from the conflict areas as new entities) do not drive our results. Third, Panel B of Table A.14 shows that the estimates remain consistent at the firm-region-year level, where *region* refers to the province of a railway station utilized by the firm.

Finally, Table A.15 presents the estimates for the total number of linkages and total weight of all shipments, including those involving the conflict areas. The effects are negative across all outcomes. The estimates in column (5) suggest that an increase in nonconflict suppliers for firms with high supplier exposure does not fully compensate for the loss of suppliers in the conflict areas.

Table A.8: Robustness Checks: Number of Suppliers in Nonconflict Areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Baseline	Strictly Balanced Panel	Latitude & Longitude		Distance to Conflict Areas		Province × Sector × Year FE	Preconflict Trade With Russia	Preconflict Trade Partners	Removing Donetsk Oblast	Removing Luhansk Oblast	Removing Kyiv
Post-2014 ×	-0.089***	-0.089**	-0.088***	-0.077**	-0.089***	-0.089***	-0.066*	-0.084**	-0.068**	-0.067*	-0.082**	-0.117***
$\mathbb{1}$[High Firm's Buyer Conflict Exposure, 2012–2013]	(0.033)	(0.036)	(0.033)	(0.033)	(0.033)	(0.033)	(0.034)	(0.033)	(0.033)	(0.034)	(0.033)	(0.034)
Post-2014 ×	0.064**	0.098***	0.064*	0.070**	0.063*	0.063*	0.050	0.074**	0.081**	0.081**	0.061*	0.050
$\mathbb{1}$[High Firm's Seller Conflict Exposure, 2012–2013]	(0.032)	(0.036)	(0.033)	(0.033)	(0.033)	(0.033)	(0.034)	(0.032)	(0.032)	(0.034)	(0.033)	(0.034)
Post-2014 ×			0.008	0.889								
Latitude			(0.009)	(0.592)								
Post-2014 ×			0.002	-0.317*								
Longitude			(0.003)	(0.177)								
Post-2014 ×				-0.012**								
Latitude^2				(0.006)								
Post-2014 ×				-0.002***								
Longitude^2				(0.001)								
Post-2014 ×				0.009***								
Latitude × Longitude				(0.003)								
Post-2014 ×					-0.009							
Distance to Conflict Area					(0.057)							
Post-2014 ×						-0.008						
Distance to the LPR or the DPR						(0.047)						
Post-2014 ×								-0.116***				
$\mathbb{1}$[Firm Imported From Russia, 2012–2013]								(0.037)				
Post-2014 ×								-0.016				
$\mathbb{1}$[Firm Exported to Russia, 2012–2013]								(0.040)				
Post-2014 ×									-0.000***			
# of Preconflict Trade Partners									(0.000)			
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean	1.790	2.067	1.789	1.789	1.789	1.789	1.802	1.790	1.790	1.768	1.790	1.789
SD	1.243	1.197	1.243	1.243	1.243	1.243	1.248	1.243	1.243	1.231	1.244	1.230
Observations	18,390	13,455	18,326	18,326	18,326	18,326	17,688	18,390	18,390	17,322	18,108	15,983
Number of Firms	4,281	2,691	4,265	4,265	4,265	4,265	4,121	4,281	4,281	4,039	4,217	3,693

Notes: This table presents the robustness checks for the conflict's impact on firms' supplier linkages in nonconflict areas by firms' preexisting trade connections with the conflict areas. The outcome is the total number of distinct suppliers that engaged in trade with a given firm during a specific year using a railway station situated outside the conflict areas. *High exposure* refers to exposure greater than the 80th percentile in the overall sample. 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 the conflict areas (the DPR, the LPR, and Crimea) and distance to the DPR and the LPR interacted with Post_{it} (columns 5 and 6), controlling for firm's sector interacted with province and year fixed effects(column 7), controlling for whether a firm had been trading with Russia before the conflict (2012 or 2013) interacted with Post_{it} (column 8), controlling for the total number of trade partners a firm had preconflict interacted with Post_{it} (column 9), omitting firms near the conflict areas, i.e., the nonoccupied parts of Donetsk and Luhansk oblasts (columns 10 and 11, respectively), and omitting firms in Kyiv (column 12). Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.9: Robustness Checks: Number of Buyers in Nonconflict Areas

	(1) Baseline	(2) Strictly Balanced Panel	(3) Latitude & Longitude	(4)	(5) Distance to Conflict Areas	(6)	(7) Province × Sector × Year FE	(8) Preconflict Trade With Russia	(9) Preconflict Trade Partners	(10) Removing Donetsk Oblast	(11) Removing Luhansk Oblast	(12) Removing Kyiv
Post-2014 ×	-0.156***	-0.088*	-0.160***	-0.158***	-0.160***	-0.161***	-0.138***	-0.156***	-0.139***	-0.128***	-0.158***	-0.159***
𝟙[High Firm's Buyer Conflict Exposure, 2012–2013]	(0.043)	(0.049)	(0.043)	(0.043)	(0.043)	(0.043)	(0.047)	(0.043)	(0.043)	(0.045)	(0.043)	(0.045)
Post-2014 ×	-0.077*	-0.042	-0.082*	-0.080*	-0.083*	-0.082*	-0.041	-0.065	-0.046	-0.063	-0.077	-0.057
𝟙[High Firm's Seller Conflict Exposure, 2012–2013]	(0.046)	(0.055)	(0.047)	(0.047)	(0.047)	(0.047)	(0.050)	(0.047)	(0.047)	(0.049)	(0.047)	(0.049)
Post-2014 ×			-0.005	0.334								
Latitude			(0.014)	(0.897)								
Post-2014 ×			0.006	0.173								
Longitude			(0.005)	(0.263)								
Post-2014 ×				-0.003								
Latitude^2				(0.009)								
Post-2014 ×				-0.001								
Longitude^2				(0.001)								
Post-2014 ×				-0.002								
Latitude × Longitude				(0.005)								
Post-2014 ×					-0.113							
Distance to Conflict Area					(0.086)							
Post-2014 ×						-0.094						
Distance to the LPR or the DPR						(0.070)						
Post-2014 ×								-0.140***				
𝟙[Firm Imported From Russia, 2012–2013]								(0.053)				
Post-2014 ×								0.034				
𝟙[Firm Exported to Russia, 2012–2013]								(0.051)				
Post-2014 ×									-0.000***			
# of Preconflict Trade Partners									(0.000)			
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean	1.945	2.476	1.946	1.946	1.946	1.946	1.932	1.945	1.945	1.923	1.951	1.943
SD	1.495	1.433	1.494	1.494	1.494	1.494	1.492	1.495	1.495	1.492	1.496	1.474
Observations	11,881	7,100	11,843	11,843	11,843	11,843	11,172	11,881	11,881	11,027	11,658	10,096
Number of Firms	3,031	1,420	3,021	3,021	3,021	3,021	2,867	3,031	3,031	2,826	2,971	2,566

Notes: This table presents the robustness checks for the conflict's impact on firms' buyer linkages in nonconflict areas by firms' preexisting trade connections with the conflict areas. The outcome is the total number of distinct buyers that engaged in trade with a given firm during a specific year using a railway station situated outside the conflict areas. *High exposure* refers to exposure greater than the 80th percentile in the overall sample. 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 the conflict areas (the DPR, the LPR, and Crimea) and distance to the DPR and the LPR interacted with Post_{it} (columns 5 and 6), controlling for firm's sector interacted with province and year fixed effects (column 7), controlling for whether a firm had been trading with Russia before the conflict (2012 or 2013) interacted with Post_{it} (column 8), controlling for the total number of trade partners a firm had preconflict interacted with Post_{it} (column 9), omitting firms near the conflict areas, i.e., the nonoccupied parts of Donetsk and Luhansk oblasts (columns 10 and 11, respectively), and omitting firms in Kyiv (column 12). The outcome variable is the indicator for whether a firm did not report sales in a given year. Standard errors in parentheses are clustered at the firm level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A.10: Conflict Link Exposure and Firm's Linkages With Nonconflict 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
Panel A: Weight-Based Exposure				
Post-2014 × Firm's Buyer Conflict Exposure, 2012–2013	-0.106*	-0.083		
	(0.062)	(0.098)		
Post-2014 × Firm's Seller Conflict Exposure, 2012–2013	0.335***	-0.189**		
	(0.065)	(0.096)		
Post-2014 × $\mathbb{1}$[High Firm's Buyer Conflict Exposure, 2012–2013]			-0.116***	-0.174***
			(0.033)	(0.044)
Post-2014 × $\mathbb{1}$[High Firm's Seller Conflict Exposure, 2012–2013]			0.107***	-0.050
			(0.033)	(0.048)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean	1.790	1.945	1.790	1.945
SD	1.243	1.495	1.243	1.495
Observations	18,390	11,881	18,390	11,881
Number of Firms	4,281	3,031	4,281	3,031
Panel B: Link-Based Exposure				
Post-2014 × Firm's Buyer Conflict Exposure, 2012–2013	-0.082	-0.100		
	(0.071)	(0.133)		
Post-2014 × Firm's Seller Conflict Exposure, 2012–2013	0.554***	-0.066		
	(0.083)	(0.116)		
Post-2014 × $\mathbb{1}$[High Firm's Buyer Conflict Exposure, 2012–2013]			-0.103***	-0.074*
			(0.034)	(0.044)
Post-2014 × $\mathbb{1}$[High Firm's Seller Conflict Exposure, 2012–2013]			0.220***	0.009
			(0.033)	(0.049)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean	1.790	1.945	1.790	1.945
SD	1.243	1.495	1.243	1.495
Observations	18,390	11,881	18,390	11,881
Number of Firms	4,281	3,031	4,281	3,031

Notes: This table presents the estimates for the conflict's impact on firms' outgoing and incoming trade with nonconflict areas by firms' preexisting trade connections with the conflict areas. Exposure is calculated as a weights share in Panel A and a links share in Panel B. The outcomes are the total number of distinct suppliers and buyers engaged in trade with a given firm during a specific year using a railway station outside the conflict areas. *High exposure* refers to exposure greater than the 80th percentile in the overall sample. The sample is restricted to firms outside the conflict areas (the DPR, the LPR, and Crimea) and to firms that existed in our data before the conflict. The railway shipment data cover the 2012–2016 period. Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.11: Conflict Exposure and Firm's Linkages With Nonconflict Areas—Borusyak and Hull (2023) Method

	(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, 2012–2013	-0.052	-0.142		
	(0.062)	(0.101)		
Post-2014 × Firm's Seller Conflict Exposure, 2012–2013	0.270***	-0.153		
	(0.066)	(0.100)		
Post-2014 × $\mathbb{1}$[High Firm's Buyer Conflict Exposure, 2012–2013]			-0.082**	-0.153***
			(0.034)	(0.042)
Post-2014 × $\mathbb{1}$[High Firm's Seller Conflict Exposure, 2012–2013]			0.068**	-0.051
			(0.031)	(0.046)
Placebo Exposure Means	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean	1.745	1.867	1.745	1.867
SD	1.223	1.458	1.223	1.458
Observations	17,849	11,531	17,849	11,531
Number of Firms	4,180	2,944	4,180	2,944

Notes: This table presents the estimates for the conflict's impact on firms' outgoing and incoming trade with nonconflict areas by firms' preexisting trade connections with the conflict areas after applying the Borusyak and Hull (2023) adjustment. Specifically, we amend the estimates in Table 2 by controlling for the mean firm-level placebo conflict exposure, where placebo exposures are estimated using a sample of 100 random draws of four placebo "conflict" provinces (imitating Crimea, Donetsk, Luhansk, and Sevastopol) out of all Ukrainian provinces, including those actually affected by conflict. Columns (1)–(2) control for a firm's average placebo conflict exposure calculated across the random draws based on the firm's actual trade connections with the placebo conflict provinces. Columns (3)–(4) control for the placebo exposure defined as the share of simulated province draws during which firm's placebo conflict exposure was greater than the 80th percentile in the sample. The sample is restricted to firms outside the conflict areas (the DPR, the LPR, and Crimea) and to firms that existed in our data before the conflict. The railway shipment data cover the 2012–2016 period. The outcomes are the total number of distinct suppliers and buyers that engaged in trade with a given firm during a specific year using a railway station situated outside the conflict areas. Standard errors in parentheses are clustered at the firm level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A.12: Conflict Exposures and Firm's Linkages With Nonconflict Areas—Stricter Definition of Nonconflict Firms

	(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, 2012–2013	-0.121	-0.146		
	(0.078)	(0.133)		
Post-2014 × Firm's Supplier Conflict Exposure, 2012–2013	0.331***	-0.080		
	(0.082)	(0.125)		
Post-2014 × $\mathbb{1}$[High Firm's Buyer Conflict Exposure, 2012–2013]			-0.097**	-0.133**
			(0.043)	(0.052)
Post-2014 × $\mathbb{1}$[High Firm's Supplier Conflict Exposure, 2012–2013]			0.081**	-0.007
			(0.040)	(0.060)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean	1.644	1.749	1.644	1.749
SD	1.165	1.397	1.165	1.397
Observations	13,783	8,227	13,783	8,227
Number of Firms	3,250	2,153	3,250	2,153

Notes: This is a version of Table 2 restricted to firms that never used railway stations in the conflict areas throughout the data period. The outcomes are the total number of distinct suppliers and buyers that engaged in trade with a given firm during a specific year using a railway station situated outside the conflict areas. *High exposure* refers to exposure greater than the 80th percentile in the overall sample. The sample is restricted to firms outside the conflict areas and to firms that existed in our data before the conflict. Standard errors in parentheses are clustered at the firm level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A.13: Conflict Exposure and Firm's Trade (Shipment Weight) With Nonconflict 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, 2012–2013	-0.240**	0.054		
	(0.115)	(0.223)		
Post-2014 × Firm's Supplier Conflict Exposure, 2012–2013	0.685***	-0.409**		
	(0.140)	(0.207)		
Post-2014 × $\mathbb{1}$[High Firm's Buyer Conflict Exposure, 2012–2013]			-0.176***	-0.237***
			(0.061)	(0.084)
Post-2014 × $\mathbb{1}$[High Firm's Supplier Conflict Exposure, 2012–2013]			0.143**	-0.207**
			(0.060)	(0.095)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean	15.713	15.585	15.713	15.585
SD	2.335	2.993	2.335	2.993
Observations	18,390	11,881	18,390	11,881
Number of Firms	4,281	3,031	4,281	3,031

Notes: This is a version of Table 2 that uses shipment weight as the outcome variable instead of the number of linkages. *High exposure* refers to exposure greater than the 80th percentile in the overall sample. The sample is restricted to firms outside the conflict areas and to firms that existed in our data before the conflict. Standard errors in parentheses are clustered at the firm level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A.14: Conflict Exposure and Firm's Linkages With Nonconflict Areas—Additional Checks

	(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
Panel A: Trading Partners Present in Dataset Before the Conflict				
Post-2014 × Firm's Buyer Conflict Exposure, 2012–2013	-0.069	-0.154		
	(0.060)	(0.100)		
Post-2014 × Firm's Supplier Conflict Exposure, 2012–2013	0.247***	-0.188*		
	(0.067)	(0.100)		
Post-2014 × 𝟙[High Firm's Buyer Conflict Exposure, 2012–2013]			-0.086***	-0.153***
			(0.033)	(0.043)
Post-2014 × 𝟙[High Firm's Supplier Conflict Exposure, 2012–2013]			0.053*	-0.070
			(0.032)	(0.046)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean	1.765	1.936	1.765	1.936
SD	1.234	1.490	1.234	1.490
Observations	18,297	11,833	18,297	11,833
Number of Firms	4,266	3,018	4,266	3,018
Panel B: Firm Defined as a Firm-Region Combination				
Post-2014 × Firm's Buyer Conflict Exposure, 2012–2013	-0.376***	0.060		
	(0.065)	(0.086)		
Post-2014 × Firm's Seller Conflict Exposure, 2012–2013	0.374***	-0.246***		
	(0.053)	(0.069)		
Post-2014 × 𝟙[High Firm's Buyer Conflict Exposure, 2012–2013]			-0.176***	-0.203***
			(0.028)	(0.028)
Post-2014 × 𝟙[High Firm's Seller Conflict Exposure, 2012–2013]			0.062***	-0.045
			(0.021)	(0.032)
Firm-Region FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean	1.312	1.560	1.312	1.560
SD	1.111	1.293	1.111	1.293
R^2	0.80	0.81	0.80	0.81
Observations	27,884	17,616	27,884	17,616
Number of Firm-Regions	7,375	4,871	7,375	4,871

Notes: Panel A is a version of Table 2 that presents the estimates for the conflict's impact on firms' outgoing and incoming trade with nonconflict areas by firms' preexisting trade connections with the conflict areas for firms where both of the partners had positive trade before 2014. The sample in Panel A is restricted to firms outside the conflict areas. Panel B is a version of Table 2 that presents the estimates for the conflict's impact on firms' total outgoing and incoming trade with nonconflict areas by their preexisting connectedness with the conflict areas, where firm is defined as firm-region combination. The sample in Panel B is restricted to firms outside the conflict areas and to firms that existed in our data before the conflict. *High exposure* refers to exposure greater than the 80th percentile in the overall sample. The railway shipment data cover the 2012–2016 period. Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.15: Firms' Total Trade (Linkages and Weight) With Both Conflict and Nonconflict 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, 2012–2013	-0.070	-0.211*	-0.161*	-0.495**				
	(0.059)	(0.117)	(0.087)	(0.192)				
Post-2014 × Firm's Supplier Conflict Exposure, 2012–2013	-0.093	-0.312***	-0.210**	-0.331				
	(0.059)	(0.120)	(0.099)	(0.208)				
Post-2014 × 𝟙[High Firm's Buyer Conflict Exposure, 2012–2013]					-0.090***	-0.168***	-0.271***	-0.484***
					(0.032)	(0.060)	(0.042)	(0.082)
Post-2014 × 𝟙[High Firm's Supplier Conflict Exposure, 2012–2013]					-0.127***	-0.229***	-0.087*	-0.190**
					(0.031)	(0.058)	(0.046)	(0.095)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean	1.846	15.778	1.979	15.623	1.846	15.778	1.979	15.623
SD	1.256	2.352	1.513	3.017	1.256	2.352	1.513	3.017
Observations	18,775	18,775	12,232	12,232	18,775	18,775	12,232	12,232
Number of Firms	4,351	4,351	3,120	3,120	4,351	4,351	3,120	3,120

Notes: This table presents the estimates for the conflict's impact on firms' total outgoing and incoming trade (in both linkages and weight) with both conflict and nonconflict areas by firms' preexisting connectedness with the conflict areas. *High exposure* refers to exposure greater than the 80th percentile in the overall sample. The sample is restricted to firms outside the conflict areas. The railway shipment data cover the 2012–2016 period. Standard errors in parentheses are clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

A.4 Effects of Supplier and Buyer Conflict Exposure 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 exposure. As shown in Appendix Tables A.2 and A.3, our results of the effects of conflict supplier and buyer exposure are robust to controlling for province-sector-year fixed effects, alleviating such concern to the extent that refugee-flow data is available only at the province level. In this appendix, we also investigate whether population movements during the 2012–2016 period within Ukraine show any differential changes in areas with greater buyer or supplier exposure.

Each province provides annual reports on population and refugee statistics to the State Statistics Service of Ukraine (2021b). From this source, we construct a panel dataset for the provinces over the 2012–2016 period. Our analysis focuses on 25 provinces that were neither occupied nor directly exposed to violence. We then run the analogous difference-in-differences regression as Equation (2) at the province-year level, with the province's total population as an outcome variable.

Table A.16 presents our results. The outcome variable is the logarithm of the total population of a province, which combines refugee flows and general population dynamics. Column (1) of Table A.16 reports the results for weight exposure, column (2) for value exposure, and column (3) for link-based exposure. Since our analysis is restricted to 25 provinces, the asymptotic standard errors may not give the right coverage, prompting us to present wild-bootstrap p-values.

Our analysis does not reveal a statistically significant link between exposure levels and province population for the three exposure measures.

Table A.16: Robustness Check: Effect on Region-Level Population

Dependent Variable: Log Total Population

	(1)	(2)	(3)
Exposure Type:	Weight	Value	Links
Post-2014 × Region's Buyer Conflict Exposure, 2012–2013	0.058	0.045	0.111
	(0.052)	(0.036)	(0.065)
Post-2014 × Region's Seller Conflict Exposure, 2012–2013	0.032	0.072	0.013
	(0.043)	(0.042)	(0.062)
Wild Bootstrap p-value, Buyer	[0.342]	[0.260]	[0.137]
Wild Bootstrap p-value, Seller	[0.624]	[0.131]	[0.854]
Provinces	25	25	25
Observations	125	125	125

Notes: This table tests whether refugee flows after the onset of the conflict resettled in ways correlated with the region-level buyer and supplier exposure. Regressions are run on the panel of non-occupied provinces and provinces not directly affected by violence. Columns (1)–(3) report the coefficients for three exposure types: weight, value, and links. We adjust the number of refugees by population share of retirees to avoid including people eligible for pensions on both sides of the border and thus traveling outside the conflict zones solely to receive pensions. A region's buyer (seller) exposures are calculated as the total weight, value, or linkages to (from) the conflict areas normalized by the total amount of weight, value, or linkages to (from) a given region. Standard errors clustered at the region level are in parentheses. Wild bootstrap p-values from 999 bootstrap samples are reported in brackets. * p<0.1, ** p<0.05, *** p<0.01.

B Imputation of Railway-Shipment Value

As discussed in Section 2.2, our railway-shipment data reports detailed product classifications (ETSNV codes) and shipment weights but not the value of each transaction. This appendix describes our procedure for 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 customs data (HS code). Second, we estimate the value per shipment weight for each ETSNV code within 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.[2]

Step 1: Create a product code correspondence between railway-shipment data (ETSNV code) and customs data (HS code). We start this merge using the crosswalks for different periods, available from the National Railways website.[3] A relatively major change in the correspondence occurred on October 10, 2012, that affected approximately 3% of the codes. Therefore, we merge separately before and after this date. There are 9,296 (9,360 after the classification change) unique HS8 codes and 4,673 (4,669 after the classification change) unique ETSNV codes.

We first establish a many-to-one match of ETSNV codes to a unique HS code. We assign a unique HS-8-digit code to the ETSNV code whenever the match is unique within our crosswalk. This first step covers 71.9% of ETSNV codes before the major classification change and 66.7% afterward. In the remaining cases, an ETSNV code corresponds to multiple HS8 codes. In this case, we find the finest aggregation of HS codes above HS8 where we can create a correspondence (e.g., HS6, HS5, or HS4). This procedure assigns 97.9% (94.8% after the classification change) of ETSNV codes to some HS codes.

Step 2: Construct value-per-shipment-weight for each ETSNV code using customs data. Next, we construct the value-per-shipment-weight for each ETSNV code. To do so, we compute the corresponding information in our customs data at the HS8-code level, where we observe both the shipment weight and the value for each transaction. We then use the crosswalk from Step 1 to impute the value-per-shipment-weight for each ETSNV code.[4]

Step 3: Use the constructed value-per-shipment-weight to impute transaction value for railway-shipment transaction. Finally, we return to our railway-shipment data and obtain the value for each transaction by multiplying the reported shipment weight and the estimated value-per-shipment weight for the corresponding ETSNV code.

Validity of Value Imputation. We now validate our imputation method. Since transaction value is not directly reported in our railway-shipment data, we cannot directly assess the validity of imputation in our railway-shipment data. However, we can assess the performance of our approach strictly within the customs data. Specifically, for a random 80% subsample of observations in the customs data—the "training dataset"—we run the procedure described above to construct the

[2]We 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), Ukrainian firm's tax ID, and counterpart firm's country. We use this data to control for international transactions in some of our regressions and to impute transaction values for our railway-shipment data.

[3]The correspondence can be downloaded from 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/.

[4]To probe robustness, we execute this imputation in four alternate ways. First, we use either (i) all of the custom transactions (both import and export) or (ii) only the export transactions; (i) provides 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 (e.g., Chalendard, Fernandes, Raballand, and Rijkers, 2023). Second, we use either (a) geometric mean or (b) simple mean to compute the product-level value-per-shipment-weight. Specifically, for the geometric mean, for transaction i in goods category j we use $\widehat{\text{Unit Value}}_j = \exp\{(1/N_j)\sum_i \log(\text{Value}_{ij}/\text{Weight}_{ij})\}$, where N_j is the number of observations in the j-th HS code. For the simple mean, we use $\sum_i \text{Value}_{ij}/\sum_i \text{Weight}_{ij}$. The combination of (i) and (a) constitutes our preferred specification.

value-per-shipment-weight for each product category. We then use the remaining 20% of the sample—the "test dataset"—to predict their transaction values and assess their accuracy.

The results are reported in Table B.1. This table presents regressions of the actual log values of the transactions on the predicted ones in the test dataset without including intercepts. The four columns correspond to four alternative approaches for our prediction.

Across the board, the regression coefficients in Table B.1 are close to one, suggesting a tight, one-to-one relationship between the actual and predicted transaction values. We also find relatively small root-mean-square errors in comparison with the standard deviation of the log values. These results indicate that our value imputation has strong internal validity. Given the best performance of column (1) in terms of the root-mean-square error, we use this specification for our baseline analysis and use other measures for robustness.

Table B.1: Predictive Performance for Value Imputation Within Customs Data

	(1) All exp-log	(2) Exports Only exp-log	(3) All	(4) Exports Only
Panel A: 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
Panel B: 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

Notes: This table presents regressions of the actual log values of the transactions on the predicted ones in the test dataset (20% of customs data) without including intercepts. The four columns correspond to four alternative approaches for our prediction. Columns (1) and (3) use all transactions, while columns (2) and (4) use export transactions. Columns (1) and (2) use geometric means, while columns (3) and (4) use simple means to compute value-per-shipment-weight. Panels A and B correspond to the periods before and after the major classification change.

C Model Appendix

C.1 Extension to Multiple Shipment Modes

In our baseline model, we abstracted from 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 when suppliers of type $\omega \in \Omega_{i,k}$ sell to buyers of type $\upsilon \in \Omega_{j,m}$, they can choose whether to ship via railways or 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 $\tau^m_{ij,km}(\upsilon,\omega)$ denotes the common component of mode-specific shipment cost, and $\varepsilon^m_{ij,km}(\upsilon,\omega)$ denotes the idiosyncratic components for each supplier. Following Allen and Arkolakis (2014), we assume that $\varepsilon^m_{ij,km}(\upsilon,\omega)$ follows i.i.d. Fréchet distribution with a shape parameter κ. Then, the probability that suppliers choose to ship via railways is given by

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

and the probability they choose to ship via roads 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

$$X^{\text{Rail}}_{ij,km}(\upsilon,\omega) = \pi^{\text{Rail}}_{ij,km}(\upsilon,\omega)X_{ij,km}(\upsilon,\omega), \quad M^{\text{Rail}}_{ij,km}(\upsilon,\omega) = \pi^{\text{Rail}}_{ij,km}(\upsilon,\omega)M_{ij,km}(\upsilon,\omega) \tag{C.2}$$

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

This analysis justifies 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 shipments out of the overall shipments, i.e., $\pi^{\text{Rail}}_{ij,km}(\upsilon,\omega)$, may systematically differ across firms and locations. However, under our difference-in-differences approach, all time-invariant firm-specific components of $\pi^{\text{Rail}}_{ij,km}(\upsilon,\omega)$ will drop out. Therefore, the identification concern arises only if the supplier exposure and the buyer exposure 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 disruptions in shipment costs for either railways or roads outside the 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

$$\tau_{ij,km}(\upsilon,\omega) = \varrho\left(\left(\tau^{\text{Rail}}_{ij,km}(\upsilon,\omega)\right)^{\kappa} + \left(\tau^{\text{Road}}_{ij,km}(\upsilon,\omega)\right)^{\kappa}\right)^{\frac{1}{\kappa}} \tag{C.3}$$

where ϱ is a constant. Therefore, our model remains isomorphic by replacing $\tau_{ij,km}(\upsilon,\omega)$ with the expression given by Equation (C.3).

C.2 Microfoundations of Endogenous Production-Network Formation

In this section, we provide microfoundations of production-network formation given by Equation (12). We first provide a microfoundation based on the search-and-matching framework, following the formulations of Arkolakis et al. (2023), Boehm and Oberfield (2023), and Demir et al. (2024). We then discuss how one can interpret this microfoundation alternatively as network formation under firm-pair-specific entry or relationship costs (i.e., Melitz and Redding, 2014).

Firms in location i, sector k, and type ω determine how much to search for suppliers $\{n^S_{ui,km}(\upsilon,\omega)\}_{u,k,\upsilon}$ and buyers $\{n^B_{id,ml}(\omega,\psi)\}_{d,l,\psi}$ in many different locations, sectors, and firm types. Each unit of supplier search $\{n^S_{ui,km}(\upsilon,\omega)\}_{u,k,\upsilon}$ will turn into a successful supplier relationship at rate $\{m^S_{ui,km}(\upsilon,\omega)\}_{u,k,\upsilon}$, and each unit of buyer search $\{n^B_{id,ml}(\omega,\psi)\}_{d,l,\psi}$ will turn into a successful buyer relationship at rate $\{m^B_{id,ml}(\omega,\psi)\}_{d,l,\psi}$, where $\{m^S_{ui,km}(\upsilon,\omega)\}_{u,k,\upsilon}$ and $\{m^B_{id,ml}(\omega,\psi)\}_{d,l,\psi}$ are endogeneously determined in the equilibirum. At the same time, each firm takes them as given in their decisions. The total search costs paid by the firm are given by

$$e_{i,m}(\omega)\left\{\sum_{d,l,\psi} f^B_{id,ml}(\omega,\psi)\frac{\left(n^B_{id,ml}(\omega,\psi)\right)^{\gamma^B}}{\gamma^B}+\sum_{u,k,\upsilon} f^S_{ui,km}(\upsilon,\omega)\frac{\left(n^S_{ui,km}(\upsilon,\omega)\right)^{\gamma^S}}{\gamma^S}\right\} \tag{C.4}$$

where $e_{i,m}(\omega)$ is the unit cost of search for firms of type $\omega\in\Omega_{i,m}$, and $\gamma^B>1$ and $\gamma^S>1$ are parameters capturing the decreasing returns in search investment. $\{f^B_{id,ml}(\omega,\psi)\}$ and $\{f^S_{ui,km}(\upsilon,\omega)\}$ are firm-type-pair-specific search cost shifters. Firms choose the optimal level of $\{n^S_{ui,km}(\upsilon,\omega)\}_{u,k,\upsilon}$ and $\{n^B_{id,ml}(\omega,\psi)\}_{d,l,\psi}$ to maximize profit minus the search cost in Equation (C.4).

The measure of total matches created for each pair of locations is determined by the Cobb-Douglas matching function that takes the aggregate unit of supplier and buyer search as arguments:

$$\tilde{M}_{ud,kl}(\upsilon,\psi)=\kappa_{ud,kl}(\upsilon,\psi)\left(N_{d,l}(\psi)n^S_{ud,kl}(\upsilon,\psi)\right)^{\tilde{\lambda}^S}\left(N_{u,k}(\upsilon)n^B_{ud,kl}(\upsilon,\psi)\right)^{\tilde{\lambda}^B} \tag{C.5}$$

where $\tilde{\lambda}^S$, $\tilde{\lambda}^B\geq 0$ denote the elasticities of total matches created for the pair of regions with respect to the supplier and buyer search, respectively, and $\kappa_{ud,kl}(\upsilon,\psi)$ is the parameter governing the efficiency of matching technology. The matching rates are given by $m^S_{ud,kl}(\upsilon,\psi)=\tilde{M}_{ud,kl}(\upsilon,\psi)/\left(N_{d,l}(\psi)n^S_{ud,kl}(\upsilon,\psi)\right)$ and $m^B_{ud,kl}(\upsilon,\psi)=\tilde{M}_{ud,kl}(\upsilon,\psi)/\left(N_{u,k}(\upsilon)n^B_{ud,kl}(\upsilon,\psi)\right)$. The measure of links per buyer, as defined in Equation (4), is given by $M_{ud,kl}(\upsilon,\psi)=\tilde{M}_{ud,kl}(\upsilon,\psi)/N_{d,l}(\psi)$.

As shown in Arkolakis et al. (2023), the solution to this problem, together with the Cobb-Douglas matching function in Equation (C.5), yields the following solution of the equilibrium measure of supplier linkages by firms of type $\omega\in\Omega_{i,m}$ for suppliers of type $\upsilon\in\Omega_{u,k}$:

$$M_{ui,km}(\upsilon,\omega)=K_{ui,km}(\upsilon,\omega)\frac{X_{ui,km}(\upsilon,\omega)^{\lambda^S+\lambda^B}}{e_{u,k}(\upsilon)^{\lambda^B}e_{i,m}(\omega)^{\lambda^S}} \tag{C.6}$$

where $\lambda^S\equiv\tilde{\lambda}^S/\gamma^S$, $\lambda^B\equiv\tilde{\lambda}^B/\gamma^B$, and $K_{ui,km}(\upsilon,\omega)$ is a combination of parameters given by

$$K_{ui,km}(\upsilon,\omega)=\frac{\iota_{km}}{N_{u,k}(\upsilon)}\left(Z_{u,k}(\upsilon)^{\frac{\sigma_k-1}{\delta_k}}N_{u,k}(\upsilon)f^B_{ui,km}(\upsilon,\omega)\right)^{-\lambda^B}\left(Z_{i,m}(\omega)^{\frac{\sigma_m-1}{\delta_m}}N_{i,m}(\omega)f^S_{ui,km}(\upsilon,\omega)\right)^{-\lambda^S} \tag{C.7}$$

where $\iota_{km}=\sigma_k^{-\lambda^B}\sigma_m^{-\lambda^S}\left(\frac{\beta_{km}}{\sum_{k'}\beta_{k'm}}\frac{\sigma_m}{\sigma_k-1}\right)^{\lambda^S}$; and $\delta_k\equiv 1-\frac{1}{\gamma^B}-\frac{1}{\gamma^S}\sum_h\beta_{hk}\frac{\sigma_k-1}{\sigma_h-1}$ corresponds to the share of variable profit that goes to search cost in Equation (16).

One can alternatively interpret this microfoundation as network formation under firm-pair-specific entry or relationship costs (see Melitz and Redding, 2014). In particular, consider a special case where we abstract from matching frictions by setting $\kappa_{ud,kl}(\upsilon,\psi)=1$, $\tilde{\lambda}^S=1$, and $\tilde{\lambda}^B=0$ in Equation (C.7), so that $m^B_{ud,kl}=1$, and hence $n^B_{ud,kl}$ simply corresponds to the measure of buyers that the supplier obtains. Then, one can interpret suppliers' decision (13) as paying an iso-elastic firm-pair-specific cost to establish those buyer links. A special case where $\gamma^S \to 1$ can be interpreted as relationship costs in the form of fixed costs. The scenario where buyers pay those costs instead of suppliers can be considered symmetrically.

C.3 Counterfactual Equilibrium

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 a subset of structural parameters $\{\beta_{L,m}, \beta_{km}, \alpha_k, \sigma_k, \lambda^S, \lambda^B, \mu\}$, baseline trade flows $\{X_{ui,km}(\upsilon, \omega)\}$, and final sales $\{R_{i,m}(\omega)\}$, the change in TFP $\{\hat{Z}_{i,m}(\omega)\}$ and trade costs $\{\hat{\tau}_{id,ml}(\omega, \psi)\}$, the counterfactual equilibrium is derived as a solution to the following system of equations:

$$\hat{C}_{i,m}(\omega) = \frac{1}{\hat{Z}_{i,m}(\omega)} \hat{w}_i^{\beta_{m,L}} \prod_{k\in K} \hat{P}_{i,km}(\omega)^{\beta_{km}} \tag{C.8}$$

$$\hat{P}_{i,km}(\omega) = \left(\sum_{u\in\mathcal{L}} \sum_{\upsilon\in\Omega_{u,k}} \Lambda_{ui,km}(\upsilon,\omega)\hat{\tau}_{ui,km}(\upsilon,\omega)\hat{M}_{ui,km}(\upsilon,\omega)\hat{C}_{u,k}(\upsilon)^{1-\sigma_k} \right)^{\frac{1}{1-\sigma_k}} \tag{C.9}$$

$$\hat{X}_{ui,km}(\upsilon,\omega) = \hat{\tau}_{ui,km}(\upsilon,\omega)\hat{M}_{ui,km}(\upsilon,\omega)\hat{C}_{u,k}(\upsilon)^{1-\sigma_k} \frac{1}{\hat{P}_{i,km}(\omega)^{1-\sigma_k}} \hat{R}^*_{i,m}(\omega) \tag{C.10}$$

$$\hat{R}_{i,m}(\omega) = \sum_{l\in K} \sum_{d\in\mathcal{L}} \sum_{\psi\in\Omega_{d,l}} \Psi_{id,ml}(\omega,\psi)\hat{X}_{id,ml}(\omega,\psi) \tag{C.11}$$

$$\hat{M}_{ui,km}(\upsilon,\omega) = \frac{\hat{X}_{ui,km}(\upsilon,\omega)^{\lambda^S+\lambda^B}}{\hat{e}_{u,k}(\upsilon)^{\lambda^B}\hat{e}_{i,m}(\omega)^{\lambda^S}} \tag{C.12}$$

$$\hat{e}_{i,m}(\omega) = \hat{w}_i(\omega)^{\mu} \hat{C}_{i,m}(\omega)^{1-\mu} \tag{C.13}$$

$$\hat{P}^F_{i,m} = \left(\sum_{\omega\in\Omega_{i,m}} \Lambda^F_{i,m}(\omega) \hat{C}_{i,m}(\omega)^{1-\sigma_m} \right)^{\frac{1}{1-\sigma_m}} \tag{C.14}$$

$$\hat{R}^F_{i,m}(\omega) = \frac{\hat{C}_{i,m}(\omega)^{1-\sigma_m}}{\left(\hat{P}^F_{i,m}\right)^{1-\sigma_m}} \hat{E}_i \tag{C.15}$$

$$\hat{R}^*_{i,m}(\omega) = S_{i,m}(\omega)\hat{R}_{i,m}(\omega) + (1 - S_{i,m}(\omega))\,\hat{R}^F_{i,m}(\omega) \tag{C.16}$$

$$\hat{w}_i = \sum_{m\in K} \sum_{\psi\in\Omega_{i,m}} \Phi^W_{i,m}(\omega)\hat{R}^*_{i,m}(\omega) \tag{C.17}$$

$$\hat{E}_i = \sum_{m\in K} \sum_{\omega\in\Omega_{i,m}} \Phi_{i,m}(\omega)\hat{R}^*_{i,m}(\omega) \tag{C.18}$$

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

$$\Lambda_{ui,km}(\upsilon,\omega) = \frac{X_{ui,km}(\upsilon,\omega)}{\sum_{\tilde{u}\in\mathcal{L}}\sum_{\tilde{\upsilon}\in\Omega_{u,k}} X_{\tilde{u}i,km}(\tilde{\upsilon},\omega)} \tag{C.19}$$

$$\Lambda^F_{i,m}(\omega) = \frac{R^F_{i,m}(\omega)}{\sum_{\tilde{\omega}\in\Omega_{i,m}} R^F_{i,m}(\tilde{\omega})} \tag{C.20}$$

$$\Psi_{id,ml}(\omega,\psi) = \frac{X_{id,ml}(\omega,\psi)}{\sum_{\tilde{l}\in K}\sum_{\tilde{d}\in\mathcal{L}}\sum_{\tilde{\psi}\in\Omega_{d,l}} X_{i\tilde{d},m\tilde{l}}(\omega,\tilde{\psi})} \tag{C.21}$$

$$S_{i,m}(\omega) = \frac{R_{i,m}(\omega)}{R_{i,m}(\omega) + R^F_{i,m}(\omega)} \tag{C.22}$$

$$\Phi^W_{i,m}(\omega) = \frac{\left(\beta_{L,m}\frac{\sigma_m-1}{\sigma_m} + \frac{\delta_m}{\sigma_m}\mu\right) R^*_{i,m}(\omega)}{\sum_{\tilde{m}\in K}\sum_{\tilde{\omega}\in\Omega_{i,\tilde{m}}}\left(\beta_{L,\tilde{m}}\frac{\sigma_{\tilde{m}}-1}{\sigma_{\tilde{m}}} + \frac{\delta_{\tilde{m}}}{\sigma_{\tilde{m}}}\mu\right) R^*_{i,\tilde{m}}(\tilde{\omega})} \tag{C.23}$$

$$\Phi_{i,m}(\omega) = \frac{\left(\beta_{L,m}\frac{\sigma_m-1}{\sigma_m} + \frac{1}{\sigma_m}\left(1-(1-\mu)\,\delta_m\right)\right) R^*_{i,m}(\omega)}{\sum_{\tilde{m}\in K}\sum_{\tilde{\omega}\in\Omega_{i,\tilde{m}}}\left(\beta_{L,\tilde{m}}\frac{\sigma_{\tilde{m}}-1}{\sigma_{\tilde{m}}} + \frac{1}{\sigma_{\tilde{m}}}\left(1-(1-\mu)\,\delta_{\tilde{m}}\right)\right) R^*_{i,\tilde{m}}(\tilde{\omega})} \tag{C.24}$$

D Appendix for Quantitative Analysis

D.1 Calibration and Validation for $\{\lambda^S, \lambda^B, \mu\}$

We calibrate parameters for network formation $\{\lambda^S, \lambda^B, \mu\}$ targeting the patterns of the network reorganization as documented in Section 3.3. Given parameter values $\{\lambda^S, \lambda^B, \mu\}$, we undertake a counterfactual simulation of the localized conflict as described in Section 5.3, i.e., making trade with the conflict areas prohibitively costly: $\tau_{ui,km}(\upsilon,\omega) \to \infty$ if u or i are in the conflict areas. Denote the model-predicted change in the measure of suppliers in nonconflict areas by

$$\Delta\log M^S_{j,m}(\omega) = \Delta\log\sum_{i\in\mathcal{L}^{\mathcal{N}},k,\upsilon} M_{ij,km}(\upsilon,\omega) = \sum_{i\in\mathcal{L}^{\mathcal{N}},k,\upsilon}\frac{M_{ij,km}(\upsilon,\omega)}{\sum_{i\in\mathcal{L}^{\mathcal{N}},k,\upsilon} M_{ij,km}(\upsilon,\omega)}\Delta\log M_{ij,km}(\upsilon,\omega) \tag{D.1}$$

where $\mathcal{L}^{\mathcal{N}} \subset \mathcal{L}$ denotes the nonconflict areas, and $M_{ij,km}(\upsilon,\omega)$ is the baseline number of supplier-buyer connections. Denote also the model-predicted change in the measure of buyers in nonconflict areas by

$$\Delta\log M^B_{i,k}(\upsilon) = \Delta\log\sum_{j\in\mathcal{L}^{\mathcal{N}},m,\omega} M_{ij,km}(\upsilon,\omega) = \sum_{j\in\mathcal{L}^{\mathcal{N}},m,\omega}\frac{M_{ij,km}(\upsilon,\omega)}{\sum_{j\in\mathcal{L}^{\mathcal{N}},m,\omega} M_{ij,km}(\upsilon,\omega)}\Delta\log M_{ij,km}(\upsilon,\omega) \tag{D.2}$$

Denote by $\Delta\log\widetilde{M^S_{j,m}}(\omega;\Theta)$ and $\Delta\log\widetilde{M^B_{j,m}}(\omega;\Theta)$ the difference between the model-predicted values for $\Delta\log M^S_{j,m}(\omega)$ and $\Delta\log M^S_{j,m}(\omega)$ and the observed counterpart from 2013 (preconflict) to 2016 (postconflict), where $\Theta \equiv \{\lambda^S, \lambda^B, \mu\}$. Our moments are defined by

$$\mathbf{g}_{j,m}(\omega;\Theta) = \begin{bmatrix} \Delta \log \widetilde{M^S_{j,m}}(\omega;\Theta) \\ \Delta \log \widetilde{M^B_{j,m}}(\omega;\Theta) \end{bmatrix} \otimes \begin{bmatrix} \text{SupplierExposure}_{j,m}(\omega) \\ \text{BuyerExposure}_{j,m}(\omega) \end{bmatrix} \tag{D.3}$$

where $\otimes$ is the Kronecker products, and $\text{SupplierExposure}_{j,m}(\omega)$ and $\text{BuyerExposure}_{j,m}(\omega)$ are the dummies of high supplier and buyer exposures for firm type ω, which corresponds to the same set of IVs used in Section 5.2. Our moment conditions are

$$\mathbb{E}_{j,m}[\mathbf{g}_{j,m}(\omega;\Theta)] = 0 \tag{D.4}$$

where $\mathbb{E}_{j,m}$ denotes the conditional expectation given location j and sector m. Given this moment condition, our generalized method-of-moments (GMM) estimator is defined by

$$\hat{\Theta} = \min_{\Theta:0\leq\mu\leq1} \mathbf{g}^*_{j,m}(\omega;\Theta)' W \mathbf{g}^*_{j,m}(\omega;\Theta) \tag{D.5}$$

where W denotes the weighting matrix, and $\mathbf{g}^*_n(\omega;\Theta)$ is the residual of $\mathbf{g}_{j,m}(\omega;\Theta)$ after taking out region and sector fixed effects.

We implement the two-step optimal GMM estimator to set the weighting matrix W. As discussed in the main text, in our baseline specification, we impose a symmetric restriction such that $\lambda^S = \lambda^B$, and we discuss the robustness in Appendix Table D.3. We find a value for $\lambda^S = \lambda^B = 0.15$ (with a 10% bootstrapped confidence interval of $[0.11, 0.18]$) and $\mu = 1$ (with a 10% bootstrapped confidence interval degenerate at 1).

In Table D.1, we provide a validation of these calibrated parameters. In Panel A, we run a regression of the observed changes in the number of buyer and supplier links for each firm type. Following the same idea as in Section 5.2 and Adão et al. (2023), we use supplier and buyer exposure as IVs to estimate these regressions to deal with other idiosyncratic factors that occur in reality (e.g., random regional growth) which are not included in the simulation. We find the coefficients close to one (0.85–0.88 for buyer links and 0.71–0.76 for supplier links), with *p*-value for the Wald test that the regression coefficient equals one being around 0.27–0.72. This evidence indicates that our calibrated values for $\{\lambda^S, \lambda^B, \mu\}$ indeed replicate the observed patterns of network reorganization in response to conflict shocks.

In Panel B, we also show that our model replicates the patterns of revenue changes in response to localized conflict shocks. In particular, we repeat the same exercises as Panel A of Table 4 in Section 5.2, while we replace the observed number of production links $\{M_{ui,km,t}(\upsilon,\omega)\}$ with the model-predicted one using Equation (12) and (13), using our choice of calibrated parameters $\{\lambda^S, \lambda^B, \mu\}$, observed trade flows $\{X_{ui,km,t}(\upsilon,\omega)\}$, and wages $w_{i,t}$, and assuming that the firm-pair-specific exogenous parameter for the link formation $K_{ui,km}(\upsilon,\omega)$ does not change from 2013 (preconflict). Note that, with $\mu = 1$, the value for $C_{i,m}(\omega)$ is not required to construct this prediction. We find that this version yields the regression coefficients statistically indistinguishable from one (with coefficients of 1.28–1.34 with *p*-value of 0.16–0.34 for the null hypothesis that the regression coefficient equals one). This pattern is consistent with Table 4, where we use the observed reorganization of production networks instead.

Table D.1: Model Validation for Calibrated $\{\lambda^S, \lambda^B, \mu\}$

	log Number of Links (Observed)					
	Buyer Links			Supplier Links		
	(1)	(2)	(3)	(4)	(5)	(6)
log Number of Links (Model-Predicted)	0.85	0.88	0.88	0.71	0.73	0.76
	(0.31)	(0.32)	(0.31)	(0.27)	(0.28)	(0.27)
p-value (coefficient = 1)	0.62	0.72	0.70	0.27	0.34	0.37
Effective First-Stage F-Statistics	22.1	21.6	18.9	32.7	29.4	28.7
Firm-Type-Region-Sector Fixed Effects	X	X	X	X	X	X
Year Fixed Effects	X	X	X	X	X	X
Sector $\times$ Year Fixed Effects		X	X		X	X
Region $\times$ Year Fixed Effects			X			X
Observations	512	512	512	512	512	512
Adjusted R^2	0.70	0.68	0.65	0.68	0.67	0.62

(a) Supplier and Buyer Links

	$\log R_{i,m,t}(\omega)$		
	(1)	(2)	(3)
$\log w_{i,t}^{\beta_{m,L}(1-\sigma_m)} \tilde{\mathcal{A}}^S_{i,m,t}(\omega) \tilde{\mathcal{A}}^B_{i,m,t}(\omega)$	1.33	1.28	1.34
	(0.35)	(0.30)	(0.24)
p-value (coefficient = 1)	0.33	0.34	0.16
Effective First-Stage F-Statistics	16.4	19.1	29.9
Firm-Type-Region-Sector Fixed Effects	X	X	X
Year Fixed Effects	X	X	X
Sector $\times$ Year Fixed Effects		X	X
Region $\times$ Year Fixed Effects			X
Observations	386	386	386
Adjusted R^2	0.74	0.76	0.81

(b) Revenue

Notes: Validation of calibrated values for $\{\lambda^S, \lambda^B, \mu\}$ as described in Appendix D.1.

D.2 Calibration for $\{X_{ui,km}(\upsilon, \omega)\}$ and $\{R^F_{i,m}(\omega)\}$

To execute the counterfactual simulation following the procedure specified in Section C.3, besides the structural parameters $\{\beta_{L,m}, \beta_{km}, \alpha_k, \sigma_k, \lambda^S, \lambda^B, \mu\}$, we need baseline trade flows of intermediate inputs $\{X_{ui,km}(\upsilon, \omega)\}$ and final-goods sales $\{R^F_{i,m}(\omega)\}$. However, the observed data do not necessarily satisfy all the equilibrium conditions, due to measurement error and unmodeled factors. To enable a well-defined counterfactual, we adjust the trade flows so that equilibrium conditions are satisfied in the following manner.

We start by assuming that the true baseline trade flow satisfies $X_{ui,km}(\upsilon, \omega) = \check{X}_{ui,km}(\upsilon, \omega)\chi_{i,m}(\omega)$, where $\check{X}_{ui,km}(\upsilon, \omega)$ is the observed imputed transaction values in our railway-shipment data, and $\chi_{i,m}(\omega)$ captures the buyer-specific measurement errors and unmodeled factors. We obtain $\chi_{i,m}(\omega)$ so that the following equilibrium conditions are exactly satisfied.

First, combining Equations (15), (16), (17), (18), (19), and (20), we have

$$E_i^* = \left[1 - \sum_{m \in K} \frac{\beta_{L,m} \frac{\sigma_m - 1}{\sigma_m} + \frac{1}{\sigma_m}\left(1 - (1-\mu)\,\delta_m\right)}{1 - (1-\mu)\frac{\delta_m}{\sigma_m}} \alpha_m\right]^{-1} \times \sum_{m \in K} \frac{\beta_{L,m} \frac{\sigma_m - 1}{\sigma_m} + \frac{1}{\sigma_m}\left(1 - (1-\mu)\,\delta_m\right)}{1 - (1-\mu)\frac{\delta_m}{\sigma_m}} \left(\sum_{\omega \in \Omega_{i,m}} R_{i,m}(\omega)\right) \tag{D.6}$$

where $E_i^* = E_i L_i$, 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, we simply assume that the final-goods sales are proportional to those of the intermediate-goods sales $\{R_{i,m}(\omega)\}$. That is,

$$R_{i,m}^F(\omega) = \frac{R_{i,m}(\omega)}{\sum_{\tilde{\omega} \in \Omega_{i,m}} R_{i,m}(\tilde{\omega})} \alpha_m E_i^* \tag{D.7}$$

Third, from Equations (8), (17), and (19),

$$\sum_{u,k,\upsilon} X_{ui,km}(\upsilon, \omega) = \frac{\beta_{km} \frac{\sigma_m - 1}{\sigma_m}}{1 - (1-\mu)\frac{\delta_m}{\sigma_m}} \left(R_{i,m}^F(\omega) + R_{i,m}(\omega)\right) \tag{D.8}$$

We back out $\{\chi_{i,m}(\omega)\}$, together with variables $\{X_{ui,km}(\upsilon, \omega)\}$, $\{R_{i,m}(\omega)\}$, $\{R_{i,m}^F(\omega)\}$, and $\{E_i^*\}$, so that Equations (D.6), (D.7), and (D.8) are exactly satisfied. Specifically, starting from a guess of $\{\chi_{i,m}(\omega)\}$, we iteratively use the three equations to update $\{R_{i,m}(\omega)\}$, $\{R_{i,m}^F(\omega)\}$, and $\{E_i^*\}$ using Equations (D.6) and (D.7), and we update the value of $\{\chi_{i,m}(\omega)\}$ using Equation (D.8). We repeat this process until the procedure converges.

In this procedure, we need to assume a value for δ_m, i.e., the share of link-formation cost in variable profit, in addition to the structural parameters given by Table 3. We set δ_m to 0.25 in the baseline for all $m \in K$. In Table D.4, we show that our results are virtually unchanged by using alternative values.

D.3 Additional Results for Quantitative Analysis

Table D.2: Robustness of Table 4: Reverse LHS and RHS

	$\log w_{i,t}^{\beta_{m,L}(1-\sigma_m)} \tilde{\mathcal{A}}_{i,m,t}^{S}(\omega)\tilde{\mathcal{A}}_{i,m,t}^{B}(\omega)$		
	(1)	(2)	(3)
Panel A: With Link Adjustment			
$\log R_{i,m,t}(\omega)$	1.18	1.14	1.20
	(0.17)	(0.17)	(0.16)
p-value (coefficient = 1)	0.30	0.41	0.21
Effective First-Stage F-Statistics	36.6	39.3	40.3
Panel B: No Link Adjustment			
$\log R_{i,m,t}(\omega)$	0.62	0.58	0.59
	(0.14)	(0.14)	(0.13)
p-value (coefficient = 1)	0.01	0.00	0.00
Effective First-Stage F-Statistics	36.6	39.3	40.3
Firm-Type-Region-Sector Fixed Effects	X	X	X
Year Fixed Effects	X	X	X
Sector × Year Fixed Effects		X	X
Region × Year Fixed Effects			X
Observations	434	434	434

Notes: This is a robustness table for Table 4, by flipping the right-hand side with left-hand side of the Regression (21).

Table D.3: Robustness of Table 4: Using All Years and Omitting Wages

	$\log R_{i,m,t}(\omega)$		
	(1)	(2)	(3)
Panel A: Use All Years			
$\log w_{i,t}^{\beta_{m,L}(1-\sigma_m)} \tilde{\mathcal{A}}_{i,m,t}^{S}(\omega) \tilde{\mathcal{A}}_{i,m,t}^{B}(\omega)$	0.77	0.78	0.71
	(0.12)	(0.12)	(0.10)
p-value (coefficient = 1)	0.05	0.08	0.00
Effective First-Stage F-Statistics	43.4	42.6	55.8
Observations	1,085	1,085	1,085
Panel B: Omit Wages			
$\log \tilde{\mathcal{A}}_{i,m,t}^{S}(\omega) \tilde{\mathcal{A}}_{i,m,t}^{B}(\omega)$	0.85	0.87	0.83
	(0.11)	(0.11)	(0.11)
p-value (coefficient = 1)	0.18	0.24	0.14
Effective First-Stage F-Statistics	48.8	46.4	49.5
Observations	434	434	434
Firm-Type-Region-Sector Fixed Effects	X	X	X
Year Fixed Effects	X	X	X
Sector $\times$ Year Fixed Effects		X	X
Region $\times$ Year Fixed Effects			X

Notes: This is a robustness table for Panel A of Table 4. Panel A uses yearly panel of 2012–2016 instead of the long-run change from 2013 to 2016 in Table 4. Panel B omits wages from the right-hand side.

Table D.4: Counterfactual Simulation: Robustness

Alternative Specifications	λ^S	λ^B	μ	GRP Change (Baseline)	GRP Change (No Link Adjustment)
(1) Baseline	0.15	0.15	1.00	-5.6	-8.4
(2) Set $\lambda^B = 0$	0.30	0.00	1.00	-5.5	-8.4
(3) Set $\lambda^S = 0$	0.00	0.30	1.00	-5.6	-8.4
(4) Set $\mu = 0$	0.15	0.15	0.00	-6.6	-8.5
(5) Set $\delta_m = 0.5$	0.15	0.15	1.00	-5.6	-8.4
(6) Define Types by Link Exposures	0.15	0.15	1.00	-5.9	-9.1
(7) Define Types by Weight Exposures	0.15	0.15	1.00	-5.6	-8.2
(8) Define Types by Exposure and Firm Size	0.15	0.15	1.00	-6.6	-9.9

Notes: This table presents the results of the alternative robustness specifications of counterfactual simulations in Table 5, reporting the percentage change in population-weighted real GRP. Rows (2)–(4) present the results based on the reported values of $\{\lambda^S, \lambda^B, \mu\}$. In row (5), we report the results by setting $\delta_m = 0.5$ (instead of $\delta_m = 0.25$ in our baseline) in the calibration of trade flows (See Appendix D.2). Rows (6) and (7) define firm types using the exposure defined by the shares of links and shares of weights instead of using value shares to conflict areas. Row (8) defines firm types using the combination of exposure and the dummy of whether the firms' revenue is above-median within the region and sector.