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 reorganized 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 we show that our model's sufficient statistics accurately explain the observed relative decline in firm output once we account for network reorganization. Calibrating our model to the Ukrainian economy, we find that the localized conflict decreased aggregate output in nonconflict areas by 5.5%. 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 and armed conflicts affect a country's economic activity? Existing research shows they have a broad 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 the battlegrounds themselves. 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, for example, due to the destruction of physical capital. 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 and 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 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 conflict devastated parts of Donbas through bombing, infrastructure destruction, and loss of life. 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 throughout the rest of Ukraine, the real gross regional products (GRP) per capita of all provinces other than Crimea and Donbas had declined by 11.0% 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 20% 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 containing the universe of firm-to-firm railway shipments within Ukraine, covering periods before and after the onset of the conflict (hereafter, simply *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, unanticipated onset, this information 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 and estimate 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 the 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 by 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 17% 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 through their buyers. First, firms with high supplier exposure increased their supplier linkages. At the same time, those firms tended to decrease their buyer linkages strictly outside the conflict areas. This evidence indicates that, despite significant substitution, losing suppliers in the conflict areas may have hurt 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 the 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 reorganized 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 we estimate the elasticities governing this 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 per capita strictly outside the conflict areas decreases by 5.5% in our baseline counterfactual simulation. This sizable magnitude suggests that supply chain disruption and reorganization could explain nearly half of the actual 11.0% decline in real GRP per capita 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.

Overall, our results suggest that, through production networks, localized conflicts generate detrimental, far-reaching economic costs of conflict beyond the 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 contribute to the literature on the economic effects of wars and conflicts, as well as the broader literature on supply chain disruptions. We do so by leveraging a unique setting—a sudden, large, and permanent conflict shock—and granular firm-to-firm shipment data to show that the disruption and reorganization of production networks play a central role in shaping the firm-level and aggregate impacts of shock-induced spillovers.

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 address this gap by utilizing shipment-level data on within-country trade before and during an active conflict in a middle-income country with intricate supply chains—Ukraine.

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 has negatively affected firm production depending on how firm 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

[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) and Gulek and Garg (2025) analyze another channel, examining how the influx of Syrian refugees has affected Turkish production networks. See Rohner and Thoenig (2021) for a broad overview.

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 an armed conflict. 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. Castro-Vincenzi, Khanna, Morales, and Pandalai-Nayar (2024) and Balboni, Boehm, and Waseem (2024) study the impacts of floods on connected suppliers in India and Pakistan, respectively. The former study finds no long-run reorganization of supplier linkages, while the latter one finds significant 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 an armed conflict. 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 the theoretical literature on endogenous formation of production networks, modeling firms' trade-off between the costs and benefits of establishing supplier and buyer connections. In recent work, Arkolakis, Huneeus, and Miyauchi (2025) provide sufficient statistics for the aggregate effects of trade shocks in a broad class of general equilibrium trade models featuring endogenous production-network formation. Our model extends their framework to incorporate additional firm heterogeneity within a region and sector, which enables the analysis of how firms with different supplier and buyer exposure shape firm-level and aggregate effects of large shocks.

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.

[4] In earlier work with the same data, Korovkin and Makarin (2020) show that the 2014 Russia-Ukraine conflict, on average, reduced trade volume between exposed and nonexposed firms outside the conflict areas and present an accounting decomposition of the change in firm sales distribution using a model with exogenous production networks.

[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.

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). 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).[6] 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 end of 2015, especially after President Zelensky was elected in 2019. This status quo ended on February 24, 2022, when Russia launched its 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). Certain DPR and LPR territories experienced intense conflict, but the rest of the country did not face direct violence.

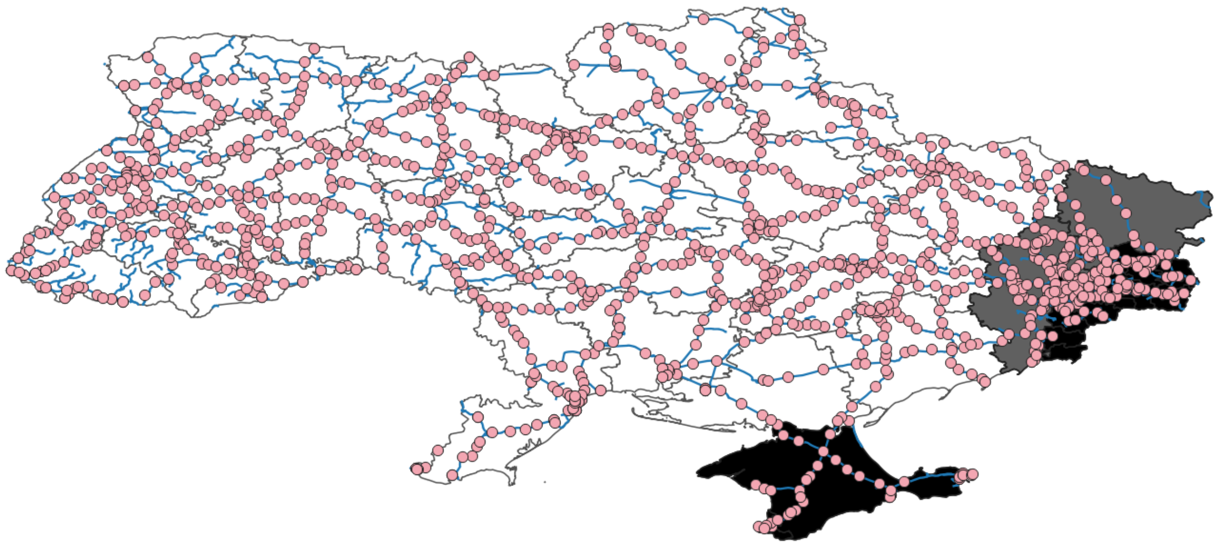
Economic Activity in the Donbas Region and Crimea. Before the conflict, the Donbas and Crimea regions were crucial for Ukraine's economy, accounting for approximately 18.2% of the nation's GDP in 2013. The Donbas region, particularly known for its extractive industries such as coal, metallurgy, and manufacturing, 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, home to key industries such as shipbuilding.[7]

The conflict had severe repercussions for these regions. Crimea was largely isolated from

[6] For instance, see Silva and Volkova (2018) for the sharp reaction of the Russian financial markets.

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

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 (blue lines) and railway stations (red dots) in our data. 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.

Ukraine's transportation network, severely disrupting supply chains. The DPR and LPR experienced extensive violence, infrastructure damage, and significant loss of 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 Rail-*

ways, a state-owned railway monopoly company (Ukrainian Railways, 2016).[8] 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 (i.e., supplier and buyer exposure) and to construct outcome variables for the changes in production linkages before and after the 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 (Ukrainian Trade Data, 2013) 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 this limitation does not substantially bias our results 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 across firms. We argue that assuming away such time-varying factors is plausible, especially when we study the reorganization of production networks *strictly outside the conflict areas*, in Section 3.3, as there was no systematic disruption specific to railway networks

[8] These data were purchased by CERGE-EI from Statanaliz, LLC, a marketing company that collected and distributed 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 in the official records (Melnyk et al., 2021), with the discrepancy likely due to the differences in data-cleaning procedures.

relative to road networks outside Crimea and the Donbas region.[9]

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 (Bureau van Dijk, 2016) and SPARK-Interfax (SPARK-Interfax, 2018). Both of these sources are based on official government statistics, the provision of which is mandatory for all Ukrainian firms except individual entrepreneurs and small businesses registered under the simplified tax system. We combine these two datasets for their complementary coverage of available variables. Hereinafter, for brevity, we refer to the combined data as SPARK-Interfax. 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 shrinks from 6,400 to around 4,800–5,600 firms, depending on the specification.[10] Despite this shrinkage, we find that the matched railway-shipping firms jointly cover nearly 50% of aggregate sales of tradable industries, reinforcing the importance of railway shipping in Ukraine's economy.[11]

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, 2021). 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

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

[10] This incompleteness likely reflects the fact that some firms in the railway data operated under the simplified tax system (Kuziakiv, 2020). Alternatively, it may stem from some eligible firms not reporting sales data as required, or from data-quality issues in records provided by the tax authorities or SPARK/Interfax. However, our results are not driven by any potential systematic changes in data quality; see Appendix A.2 for further discussion.

[11] 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 rail.

substantially disrupted after the onset, as we document below.

Table A.1 displays the summary statistics for our datasets. Of the firms in our sample whose headquarters are strictly outside the conflict areas, 54% traded with the conflict areas in 2012–2013, that is, before the conflict started. An average firm received 10% of its 2012–2013 incoming shipments from the conflict areas in value (i.e., supplier exposure) and sent 9% 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 (see, 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. We make this choice because, for Ukrainian firms outside the conflict areas, trade exposure with the conflict areas is substantially larger than that with Russia. While more than half of the firms traded with the conflict areas in 2012–2013, 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 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.

3 Reduced-Form Evidence

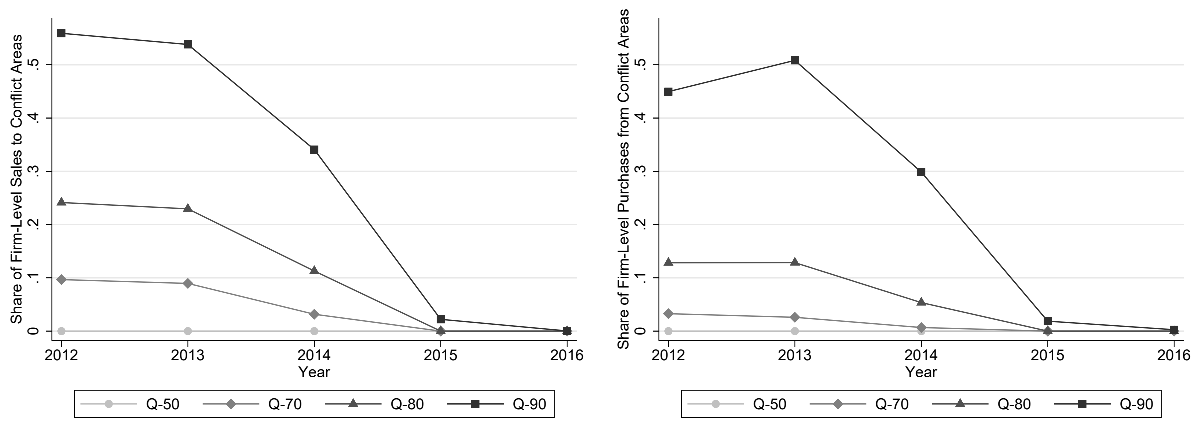
In this section, we provide reduced-form evidence on the impact of the 2014 Russia-Ukraine conflict on firm activity and production networks within Ukraine. Section 3.1 documents a substantial decline in shipment volume to and from the direct conflict areas. Section 3.2 shows that firms outside the conflict areas but with prior supplier or buyer linkages to those areas experienced 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,

Figure 2: Distribution of Firm-Level Trade 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.

which show that an average firm reduced its share of sales to (purchases from) the conflict areas by approximately 12 (8) percentage points by 2016—the almost entire aggregate shares of transactions to and from the conflict areas—with no 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, 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.[12] 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 of preconflict exposure through railway linkages. We start by estimating the following equation:

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

[12]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 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.

where f indexes a firm whose headquarters is located strictly outside the conflict areas,[13] 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.[14]

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 pretrends. We find no significant pretrends, 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 territories experienced a 17% decline in sales compared to firms without such connections on average over five years from the

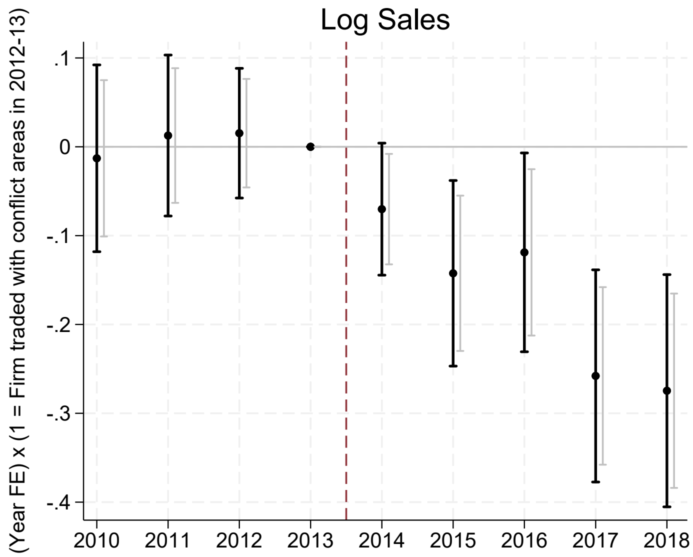
[13] Among the robustness checks in Appendix A.2, we show that our results are invariant to using alternative sample restrictions focusing on firms that never used the railway stations located in the conflict areas (Table A.6).

[14] Estimating second-order (or higher-order) network impacts of the conflict using a differences-in-differences design is challenging in this setting due to the high density of the production network—97.6% of firms had at least one trading partner that traded with the conflict area before the onset. Instead, we capture these higher-order effects through a quantitative general equilibrium model in Section 4.

[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 (see, e.g., Roth, Sant'Anna, Bilinski, and Poe (2023) and Arkhangelsky and Imbens (2024) for recent surveys).

[16] To further examine whether refugee migration could confound our estimates, in Appendix A.5, we show that changes in regional population size are not systematically related to regions' trade exposure to conflict areas.

Figure 3: Firm Sales and Conflict Exposure, Event Study



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.

onset. 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 prewar out-shipments being to the conflict areas and $\text{SupplierExposure}_{f,2012-13}$ is the share of firm's prewar 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 the 80th percentile in our sample.

These estimates are large compared to existing studies on the effects of supply chain disrup-

[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.

Table 1: Firm Sales and Conflict Exposure

	(1) Log Sales	(2) No Sales Reported	(3) Log Sales	(4) No Sales Reported	(5) Log Sales	(6) No Sales Reported
Post 2014 × $\mathbb{1}$[Firm Traded With Conflict Areas, 2012–2013]	-0.170***	0.070***				
	(0.045)	(0.010)				
Post 2014 × Firm's Buyer Conflict Exposure, 2012–2013			-0.201**	0.058**		
			(0.101)	(0.023)		
Post 2014 × Firm's Supplier Conflict Exposure, 2012–2013			-0.330***	0.067***		
			(0.102)	(0.022)		
Post 2014 × $\mathbb{1}$[High Firm's Buyer Conflict Exposure, 2012–2013]					-0.176***	0.054***
					(0.057)	(0.012)
Post 2014 × $\mathbb{1}$[High Firm's Supplier Conflict Exposure, 2012–2013]					-0.198***	0.048***
					(0.055)	(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	35,451	50,220	35,451	50,220	35,451	50,220
Number of Firms	4,777	5,580	4,777	5,580	4,777	5,580

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 0.089 for buyer exposure and 0.079 for supplier exposure. The average buyer and supplier exposures in the high-exposure category are 0.443 and 0.448, 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. 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.

tions 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, more persistent shock, which resulted in 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 and Tables A.2–A.6, we show that our findings are robust to a wide range of checks. First, we relax the parallel-trends assumption and find similar estimates using the synthetic difference-in-differences (SDID) method of Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021).[18] Second, we address a variety of potential confounding conflict-induced shocks correlated with firm exposure. Specifically, we account for: (i) spatially correlated shocks, such as perceived risks of future conflict encroachment, by flexibly controlling for firms' location and distance to conflict areas interacted with post indicators; (ii) Russia-related

[18]See also Appendix A.3 for robustness to the approach by Rambachan and Roth (2023).

shocks, such as increased trade costs with Russia, by controlling for firms' trade with Russia interacted with the post indicator; (iii) any province-sector-specific shocks using province-industry-year fixed effects; (iv) nonrandom exposure concerns using the method of Borusyak and Hull (2023); and (v) direct-exposure contamination by conservatively excluding firms that ever used a railway station in the conflict area. Our results remain robust across all of these and other specifications.

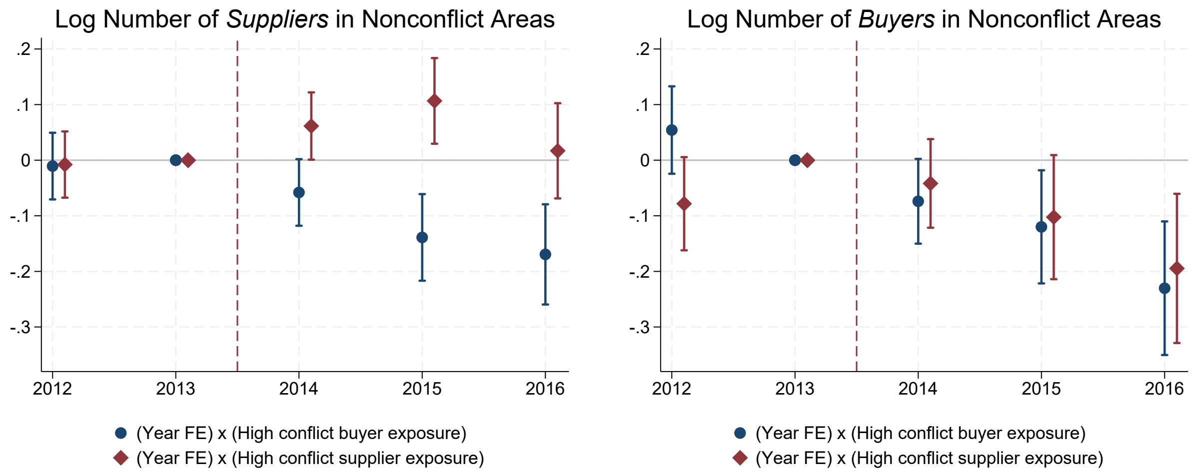
In terms of the results' heterogeneity, Table A.7 shows that the adverse effects are larger for firms in manufacturing, consistent with the importance of input-output linkages in this sector. It also shows that exposures to Crimea and the DPR and LPR regions yield similar estimates when studied separately.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

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. We then implement our difference-in-differences strategy to study how these linkages change depending on firms' supplier and buyer exposure. Specifically, we estimate Equation (2) but with the number of trade linkages with nonconflict areas 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 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 their log number of suppliers strictly outside the conflict areas. There are no pretrends, and the effects occur immediately after the onset. The magnitudes of the coefficients suggest that if a firm had high supplier exposure, they increased the number of suppliers from nonconflict areas by around 6 to 10 log points in the next two years, with a potential reversion three years later. Given that the difference in supplier exposure between the high and low exposure is nearly 45%, only a fraction of the loss of expenditure from suppliers in the conflict areas is substituted by new supplier linkages in nonconflict areas. Accordingly, Table A.16 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

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 the 80th percentile) as the measures of trade connections with the conflict areas. The 80th percentile cutoffs are 0.089 for buyer exposure and 0.079 for supplier exposure. The average buyer and supplier exposures in the high-exposure category are 0.443 and 0.448, 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.

negative (column 5), confirming that the substitution of supplier linkages is indeed imperfect.[19]

We also find that firms with high buyer exposure decreased supplier linkages strictly outside the conflict areas. In contrast to the responses of firms with high supplier exposure, this effect is persistent and does not exhibit a reversion pattern. If a firm had a high buyer exposure, it decreased the measure of supplier linkages from nonconflict areas by around 14 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 high buyer exposure decreased buyer linkages strictly outside the conflict areas. Although slightly noisier, the coefficients also show no significant pretrends. 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. The loss of buyers for firms with high supplier exposure may rationalize the reversing pattern in supplier linkages in 2016.

[19]Table A.14 shows that the results are virtually unchanged by eliminating the trading partners that newly entered or exited the market after the onset, suggesting that the results are driven by the reorganization of relationships among the same set of potential trading partners.

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	-0.097	-0.147		
	(0.060)	(0.098)		
Post 2014 × Firm's Supplier Conflict Exposure, 2012–2013	0.283***	-0.173*		
	(0.066)	(0.100)		
Post 2014 × $\mathbb{1}$[High Firm's Buyer Conflict Exposure, 2012–2013]			-0.115***	-0.168***
			(0.032)	(0.042)
Post 2014 × $\mathbb{1}$[High Firm's Supplier Conflict exposure, 2012–2013]			0.065**	-0.070
			(0.031)	(0.046)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean	1.746	1.867	1.746	1.867
SD	1.223	1.459	1.223	1.459
Observations	17,851	11,539	17,851	11,539
Number of Firms	4,180	2,945	4,180	2,945

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 0.089 for buyer exposure and 0.079 for supplier exposure. The average buyer and supplier exposures in the high-exposure category are 0.443 and 0.448, 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.

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 buyer and high supplier exposure tended to decrease buyer linkages in nonconflict areas (with a caveat that the latter effect is not statistically significant).

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. The loss of buyers over time may have led those firms to shrink, which offset the increase in supplier linkages after three years. 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.4 and Tables A.8–A.16, we establish the robustness of the above results. First, we repeat the checks from Tables A.2–A.6. These include relaxing the parallel-trends assumption by employing the SDID method of Arkhangelsky et al. (2021) and addressing a range of potential conflict-induced confounders: (i) spatially correlated shocks, by flexibly controlling for firms' location and distance to conflict areas interacted with post indicators; (ii) Russia-related trade shocks, by controlling for firms' prewar trade with Russia; (iii) province-sector-specific shocks, using province-industry-year fixed effects; (iv) nonrandom exposure concerns, using the method of Borusyak and Hull (2023); and (v) direct-exposure contamination, by conservatively excluding firms that ever used a railway station in the conflict areas. Across all specifications, the results remain stable in magnitude.

We also report several additional checks specific to the reorganization analysis. As noted above, we show that the baseline estimates are not driven by the entry or exit of trading partners. Next, we demonstrate that the effects on shipment weights and values to and from non-conflict areas closely mirror those observed for the number of buyers and suppliers. Finally, the estimates are similar at the firm–region–year level, where *region* refers to the province of a station used by the firm.

4 Model

In the previous section, we provided 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 $i, j \in \mathcal{L}$. In each location, there is an L_i measure of households.[20] 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 $k, l \in K$. Firms produce goods that can be used both for intermediate use and for

[20]We abstract from population mobility because we do not find a significant correlation between regions' population changes and the regions' supplier and buyer exposure (Table A.17).

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 $\omega, \upsilon \in \Omega_{i,k}$. 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 $N_{i,k}(\omega)$. We assume that firms of the same type are symmetric within a region and sector and make identical decisions.

Production of intermediate goods requires labor and intermediate inputs. Intermediate inputs are sourced from firms that are directly connected by production networks. The production function of firm type ω in location i and sector k is given by

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

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

The composite of intermediate inputs is a constant elasticity of substitution (CES) aggregator of the input varieties sourced from their connected suppliers. The input composite $Q_{i,lk}(\omega)$ is given by

$$Q_{i,lk}(\omega) = \left(\sum_{j \in \mathcal{L}} \sum_{\upsilon \in \Omega_{j,l}} M_{ji,lk}(\upsilon, \omega) q_{ji,lk}(\upsilon, \omega)^{\frac{\sigma_l - 1}{\sigma_l}} \right)^{\frac{\sigma_l}{\sigma_l - 1}} \tag{4}$$

where $q_{ji,lk}(\upsilon, \omega)$ is the quantity of purchased intermediate inputs by firm type ω in location j and sector k from each connected supplier υ in location j and sector l, $M_{ji,lk}(\upsilon, \omega)$ is the measure of connections that each firm of type ω has for supplier type υ, and σ_l is the elasticity of substitution across goods within sector l. Notice that having more suppliers $M_{ji,lk}(\upsilon, \omega)$ benefits production through the love-of-variety effect. We assume that the production network structure $M_{ji,lk}(\upsilon, \omega)$ is endogenously determined in equilibrium, as we further describe below.

4.2 Trade Costs, Market Structure, and Prices

The shipment of goods from suppliers of type ω in location i and sector k to buyers of type υ in location j and sector l incurs an iceberg trade cost $\tau_{ij,kl}(\omega, \upsilon)$. 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 $\sigma_k / (\sigma_k - 1)$ on top of their production and shipment costs. The unit price charged by suppliers of type ω in location i and sector k to buyers of type υ in location j and sector l is given by

$$p_{ij,kl}(\omega, \upsilon) = \frac{\sigma_k}{\sigma_k - 1} C_{i,k}(\omega) \tau_{ij,kl}(\omega, \upsilon) \tag{5}$$

where $C_{i,k}(\omega)$ is the marginal cost of production by suppliers in location i and sector k, which is in turn derived from production functions (3) and (4) as

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

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

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

where $M_{ji,lk}(\upsilon, \omega)$ is the measure of suppliers of type υ in location j and sector l that firm type ω is connected with.

Given the vector of wages $\{w_i\}$ and the measure of supplier linkages $\{M_{ji,lk}(\upsilon, \omega)\}$, Equations (5), (6), and (7) uniquely determine the set of prices $\{p_{ij,kl}(\omega, \upsilon), C_{i,k}(\omega), P_{i,lk}(\omega)\}$.

4.3 Trade Flows and Firm Sales

We now derive the trade flows between firm-type pairs. Denote the aggregate input demand by firms of type ω in location i and sector k for input l by $D^*_{i,lk}(\omega)$.[21] Then, from the CES input demand (Equation 7), the nominal trade flow of intermediate goods from suppliers of type υ in location j and sector l to buyers of type ω in location i and sector k is given by

$$X_{ji,lk}(\upsilon, \omega) = \varsigma_l M_{ji,lk}(\upsilon, \omega) \tau_{ji,lk}(\upsilon, \omega)^{1-\sigma_k} C_{j,l}(\upsilon)^{1-\sigma_k} D_{i,lk}(\omega) \tag{8}$$

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

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

literature, except that production linkages $M_{ji,lk}(\upsilon,\omega)$ now enter into the expression.

Denote the aggregate sales of intermediate goods by firms of type ω in location i and sector k by $R_{i,k}(\omega) = \sum_{l\in K}\sum_{j\in\mathcal{L}}\sum_{\upsilon\in\Omega_{j,l}} X_{ij,kl}(\omega,\upsilon)$. The following proposition shows a convenient analytical expression for $R_{i,k}(\omega)$.

Proposition 1. *The aggregate sales of intermediate goods by firms of type ω in location i and sector k is given by*

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

where $\tilde{\varsigma}_k \equiv \varsigma_k \prod_{l\in K}\varsigma_l^{\beta_{lk}(1-\sigma_k)/(1-\sigma_l)}$, and $\mathcal{A}^S_{i,k}(\omega)$ and $\mathcal{A}^B_{i,k}(\omega)$ correspond to supplier and buyer access, defined by

$$\mathcal{A}^S_{i,k}(\omega) \equiv \prod_{l\in K}\left(\sum_{j\in\mathcal{L}}\sum_{\upsilon\in\Omega_{j,l}} M_{ji,lk}(\upsilon,\omega)\tau_{ji,lk}(\upsilon,\omega)^{1-\sigma_l} C_{j,l}(\upsilon)^{1-\sigma_l}\right)^{\frac{1-\sigma_k}{1-\sigma_l}\beta_{lk}} \tag{10}$$

$$\mathcal{A}^B_{i,k}(\omega) \equiv \sum_{l\in K}\sum_{j\in\mathcal{L}}\sum_{\upsilon\in\Omega_{j,l}} M_{ij,kl}(\omega,\upsilon)\tau_{ij,kl}(\omega,\upsilon)^{1-\sigma_k} D_{j,kl}(\upsilon) \tag{11}$$

This proposition states that, aside from the constant term $\tilde{\varsigma}_k$, firms' intermediate-goods revenue is exactly decomposed into four terms. First, firm revenue is higher if the firm's productivity $Z_{i,k}(\omega)$ 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, that is, $\mathcal{A}^S_{i,k}(\omega) \propto \left[\prod_{l\in K} P_{i,lk}(\omega)^{\beta_{lk}}\right]^{1-\sigma_k}$. It is a CES aggregate of the marginal cost of potential suppliers $C_{j,l}(\upsilon)^{1-\sigma_l}$ weighted by iceberg trade costs $\tau_{ji,lk}(\upsilon,\omega)^{1-\sigma_l}$ and the measure of supplier linkages $M_{ji,lk}(\upsilon,\omega)$ across all supplier types, locations, and sectors.

Buyer access represents the potential of making sales to other firms. It is the sum of demand shifter $D_{j,kl}(\upsilon)$, weighted by the iceberg trade costs $\tau_{ij,kl}(\omega,\upsilon)^{1-\sigma_k}$ and the measure of buyer linkages $M_{ij,kl}(\omega,\upsilon)$.

The observation that 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 $\{M_{ji,lk}(\upsilon,\omega)\}$.

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 $\{M_{ji,lk}(\upsilon,\omega)\}$, 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 now describe how production linkages $\{M_{ji,lk}(\upsilon,\omega)\}$ are determined in the equilibrium. 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 ω in location i and sector k for suppliers of type υ in location j and sector l is given by

$$M_{ji,lk}(\upsilon,\omega) = K_{ji,lk}(\upsilon,\omega)\frac{X_{ji,lk}(\upsilon,\omega)^{\lambda^B+\lambda^S}}{e_{j,l}(\upsilon)^{\lambda^B}e_{i,k}(\omega)^{\lambda^S}} \tag{12}$$

where $K_{ji,lk}(\upsilon,\omega)$ 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), $e_{j,l}(\upsilon)$ and $e_{i,k}(\omega)$. Parameters λ^B and λ^S play a crucial role in determining how flexibly production networks reorganize in response to a shock, as we further elaborate below.

We assume that the link-formation costs are paid as a combination of labor and intermediate goods, such that

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

where $0 \leq \mu \leq 1$ is the labor share in the link-formation costs. In particular, if $\mu < 1$, the link-formation costs depend on the cost of intermediate goods. We incorporate this feature given that theoretical literature highlighted this feature as a possible amplification of trade shocks through endogenous network formation or investment (see, e.g., Buera, Hopenhayn, Shin, and Trachter, 2021; Arkolakis et al., 2025).

Equations (12) and (13) imply that the measure of production linkages $M_{ji,lk}(\upsilon,\omega)$ is isoelastic to trade flows $X_{ji,lk}(\upsilon,\omega)$, factor prices w_j, w_i, and intermediate goods prices $C_{j,l}(\upsilon), C_{i,k}(\omega)$. In Appendix C.2, we show that they can be microfounded in various ways based on explicit firm-level decisions, extending the isomorphism result of Arkolakis et al. (2025) to the environment with within-region-sector firm heterogeneity. For example, they can be microfounded based on firms' search decisions under matching frictions (see, e.g., Boehm and Oberfield, 2023; Demir, Fieler, Xu, and Yang, 2024; Arkolakis et al., 2025) or firm-pair-specific entry or relationship costs (see, e.g., Melitz and Redding, 2014).[22] In Section 5, we demonstrate that this specification provides a tight approximation to observed changes in firm-level production and supplier and buyer linkages in response to conflict shocks as we find in Section 3.

The parameters λ^S and λ^B crucially govern the reorganization of production linkages in response to conflict shocks. First, consider firms with high supplier conflict exposure. After the 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 firms with 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 estimate 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, $w_{i,k}(\omega)$, 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 ω in location i and sector k (net of the link-formation

[22] Huneeus (2018), Lim (2018), Bernard, Dhyne, Magerman, Manova, and Moxnes (2022), and Dhyne, Kikkawa, Kong, Mogstad, and Tintelnot (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 unlike Equation (12), they share the feature that the equilibrium measure of links is determined in a trade-off between the expected trade flows relative to costs. See Arkolakis et al. (2025) for further isomorphism between these models in aggregates under Pareto productivity distribution.

cost) by $\pi_{i,k}(\omega)$, the total final expenditure in location i is given by

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

4.6 Market Clearing and General Equilibrium

Labor market clearing implies that

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

where $R^*_{i,k}(\omega)$ denotes the aggregate intermediate and final sales of firm type ω in location i and sector k. 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_k is a parameter capturing the share of variable profit spent for link-formation costs (Equation 13).[23]

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

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

where $R_{i,k}(\omega)$ is sales of intermediate goods to other firms, given by Equation (9); $R^F_{i,k}(\omega)$ is demand for final goods, given by

$$R^F_{i,k}(\omega) = \frac{\varsigma_k N_{i,k}(\omega) C_{i,k}(\omega)^{1-\sigma_k}}{\left(P^F_{i,k}\right)^{1-\sigma_k}} \alpha_k E_i L_i \tag{18}$$

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

$$R^A_{i,k}(\omega) = (1 - \mu) \frac{\delta_k}{\sigma_k} R^*_{i,k}(\omega) \tag{19}$$

The equilibrium is given by the set of prices $\{p_{ij,kl}(\omega, \upsilon)$, $C_{i,k}(\omega)$, $P_{i,lk}(\omega)$, P^F_i, w_i, $e_{i,k}(\omega)\}$, nominal trade flows $\{X_{ji,lk}(\upsilon, \omega)\}$, measure of production linkages $\{M_{ji,lk}(\upsilon, \omega)\}$, firm revenue $\{R^*_{i,k}(\omega), R^A_{i,k}(\omega), R^F_{i,k}(\omega)\}$ and firm profit $\{\pi_{i,k}(\omega)\}$ that satisfy Equations (5)–(19), and firm profit

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

net of link-formation cost is given by

$$\pi_{i,k}(\omega) = \frac{1}{\sigma_k}\left(1-\delta_k\right) R^*_{i,k}(\omega) \tag{20}$$

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 and Estimation

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 the conflict areas. In our model, we treat the occupied territories of the DPR, the LPR, and Crimea (combined with the city of Sevastopol), 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. 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: (i) high supplier and buyer exposure, (ii) high supplier exposure and low buyer exposure, (iii) low supplier exposure and high buyer exposure, and (iv) low supplier and buyer exposure. These four types of firms correspond to firm types $\Omega_{i,k}$ in our model.[24]

We also calibrate and estimate several structural parameters. First, we calibrate the values of parameters for production function and preferences $\{\beta_{L,k}, \beta_{lk}, \alpha_k, \sigma_k\}$, using the aggregate input-output table for Ukraine described in Section 2.2. Specifically, for each sector k, we obtain the labor and input-output coefficients $\{\beta_{L,k}, \beta_{lk}\}$ as the share of labor compensation and the materials in sector k's total input expenditure, consistent with our Cobb-Douglas production function specification. We 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. The labor input coefficient $\{\beta_{L,k}\}$ (output elasticity of labor) is 0.33 for Mining and 0.36 for Other, but just 0.10 for Manufacturing. The final expenditure share $\{\alpha_k\}$ is almost zero for Mining, but 0.60 for Manufacturing and 0.39 for Other. Finally, the elasticity of substitution $\{\sigma_k\}$ ranges from 4.8 (Mining) to 8.2 (Manufacturing). These values are within the range of values found in the existing literature.[25]

Estimation of Network Formation Parameters. The remaining key structural parameters for our counterfactual analysis in Section 5.3 are those that discipline the endogenous network formation $\{\lambda^S, \lambda^B, \mu\}$. We estimate these parameters as the generalized method of moments (GMM) estimator, 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 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, 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., $K_{ji,lk}(\upsilon, \omega)$) 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 GMM objective function given a constraint $0 \leq \mu \leq 1$. Appendix D.1 describes further details of this procedure.

Panel B of Table 3 summarizes the estimated values for $\{\lambda^S, \lambda^B, \mu\}$ through this GMM procedure. In our baseline calibration, we impose a symmetric restriction such that $\lambda^S = \lambda^B$. As

[24] 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 Table D.5).

[25] 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.

Table 3: Parameterization

	Sectors (k)		
	Mining	Manufacturing	Other
(i) β_{lk}			
l =Mining	0.11	0.12	0.06
l =Manufacturing	0.18	0.33	0.18
l =Other	0.38	0.45	0.40
(ii) $\beta_{L,k}$	0.33	0.10	0.36
(iii) α_k	0.01	0.60	0.39
(iv) σ_k	4.8	8.2	5.0

Panel A: Calibrated Parameters for Production and Preferences

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

Panel B: Estimated Parameters for Production-Network Formation by GMM

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

we discuss further below, our counterfactual simulation results are similar as long as the sum of these two elasticities is kept unchanged, because they jointly govern the elasticity of production linkages with respect to trade flows (Equation 12). We find a value[26] of $\lambda^S = \lambda^B = 0.15$. The positive values of these parameters are required to rationalize the relatively large reorganization of production networks, as we documented[27] in Section 3.3. This estimated value is similar to the values estimated (0.15–0.25) by Arkolakis et al. (2025) in another context, using the reorganization of domestic production networks in response to import tariff changes in Chile.

We also find the estimate of $\mu = 1$, 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 Belgium firms' overhead costs are mostly paid in labor. In contrast, Arkolakis et al. (2025) estimate a value of μ close to zero in the context of Chile, as mentioned above, and they argue that this estimate influences the amplification of trade cost

[26]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 ($0 \leq \mu \leq 1$).

[27]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 the conflict shock.

shocks. 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.

5.2.1 Empirical Strategy

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

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

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, $Z_{i,k,t}(\omega)$, captures the direct effects on productivity. For example, the onset may have discouraged investment or hindered 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, $\mathcal{A}_{i,k,t}^{S}(\omega)$ and $\mathcal{A}_{i,k,t}^{B}(\omega)$, using observed trade flows and production networks for each year t. Denoting the corresponding estimates by $\tilde{\mathcal{A}}_{i,k,t}^{S}(\omega)$ and $\tilde{\mathcal{A}}_{i,k,t}^{B}(\omega)$, we run the following regression:

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

where the unit of observation of the regression is firm-type and year. $\eta_{i,k}(\omega)$ are the firm-type-location-sector fixed effects, $\nu_{i,t}$ are the location-time fixed effects, $\delta_{k,t}$ are the sector-time fixed effects, and $\epsilon_{i,k,t}(\omega)$ is the residual. These last four terms in Equation (22) capture the unobserved TFP term ($-\log Z_{i,k,t}(\omega)^{\sigma_k - 1}$) in Equation (21), including its time-varying components. Using regression (22), we test for $\gamma = 1$, that is, whether the changes in our sufficient statistics for TFP-adjusted firm sales of intermediate goods 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, $\epsilon_{i,k,t}(\omega)$, 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. 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).[28]

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

$$\frac{X_{ji,lk,t}(\upsilon,\omega)}{M_{ji,lk,t}(\upsilon,\omega)} = \xi_{j,lk,t}(\upsilon)\zeta_{i,lk,t}(\omega)\eta_{ji,lk}(\upsilon,\omega)\epsilon_{ji,lk,t}(\upsilon,\omega) \tag{23}$$

where $\xi_{j,lk,t}(\upsilon) \equiv \varsigma_l C_{j,l,t}(\upsilon)^{1-\sigma_l}$, $\zeta_{i,lk,t}(\omega) \equiv D_{i,lk,t}(\omega)$, and $\eta_{ji,lk}(\upsilon,\omega) \equiv \mathbb{E}_t[\tau_{ji,lk,t}(\upsilon,\omega)^{1-\sigma_k}]$, with $\mathbb{E}_t$ indicating expectation over time, and $\epsilon_{ji,lk,t}(\upsilon,\omega) \equiv \tau_{ji,lk,t}(\upsilon,\omega)^{1-\sigma_k}/\mathbb{E}_t\left[\tau_{ji,lk,t}(\upsilon,\omega)^{1-\sigma_k}\right]$ 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 $\tilde{\xi}_{j,lk,t}(\upsilon)$, $\tilde{\zeta}_{i,lk,t}(\omega)$, and $\tilde{\eta}_{ji,lk}(\upsilon,\omega)$, 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

$$\tilde{\mathcal{A}}^S_{i,k,t}(\omega) = \prod_{l\in K}\left(\sum_{j\in\mathcal{L}}\sum_{\upsilon\in\Omega_{j,l}} M_{ji,lk,t}(\upsilon,\omega)\tilde{\eta}_{ji,lk}(\upsilon,\omega)\tilde{\xi}_{j,lk,t}(\upsilon)\right)^{\frac{1-\sigma_k}{1-\sigma_l}\beta_{lk}} \tag{24}$$

$$\tilde{\mathcal{A}}^B_{i,k,t}(\omega) = \sum_{l\in K}\sum_{j\in\mathcal{L}}\sum_{\upsilon\in\Omega_{j,l}} M_{ij,kl,t}(\omega,\upsilon)\tilde{\eta}_{ij,kl}(\omega,\upsilon)\tilde{\zeta}_{i,kl,t}(\upsilon) \tag{25}$$

In our baseline results, we use observed $\{M_{ji,lk,t}(\upsilon,\omega)\}$ for each year to construct these mea-

[28] Our idea closely follows Donaldson (2018), who uses model-predicted sufficient statistics to test whether the trade mechanism is the main driver of the welfare gains from railway networks in colonial India. It also follows Adão, Costinot, and Donaldson (2025), who propose to test model predictions using orthogonality conditions.

sures. To benchmark our results, we also construct these access terms abstracting from production-network reorganization. That is, in estimating Equation (23) and constructing $\{\tilde{\mathcal{A}}^{S}_{i,k,t}(\omega), \tilde{\mathcal{A}}^{B}_{i,k,t}(\omega)\}$ using Equations (10) and (11), we fix the measure of supplier and buyer linkages $\{M_{ji,lk,t}(\upsilon, \omega)\}$ at the level of 2013 instead of the actual values for each year.

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.[29] 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 k, 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.[30] 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 0.91, 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 0.48). 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 1.55 to 1.68, with standard errors of 0.30 to 0.33. Therefore, we can reject the null hypothesis that the regression coefficient equals one with a 10% significance level.[31] 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 tends 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

[29]Panel A of Appendix Table D.4 shows that the regression coefficients are similar but slightly smaller if we use the yearly panel of 2012–2016, indicating that yearly fluctuation of revenue may be partly influenced by additional factors such as adjustment costs.

[30]Panel B of Appendix Table D.4 shows that our results are similar if we omit $w_{i,t}$ from the right-hand side.

[31]The standard errors in Panel B are larger relative to Panel A due to lower first-stage F-statistics. In Appendix Table D.3, 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 0.52 to 0.78.

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

	$\log R_{i,k,t}(\omega)$		
	(1)	(2)	(3)
Panel A: With Link Adjustment			
$\log w_{i,t}^{\beta_{k,L}(1-\sigma_k)} \tilde{\mathcal{A}}_{i,k,t}^{S}(\omega)\tilde{\mathcal{A}}_{i,k,t}^{B}(\omega)$	0.91	0.96	0.93
	(0.12)	(0.13)	(0.11)
p-value (coefficient = 1)	0.48	0.77	0.55
Effective First-Stage F-Statistics	50	46	53.5
Panel B: No Link Adjustment			
$\log w_{i,t}^{\beta_{k,L}(1-\sigma_k)} \tilde{\mathcal{A}}_{i,k,t}^{S}(\omega)\tilde{\mathcal{A}}_{i,k,t}^{B}(\omega)$	1.55	1.66	1.68
	(0.30)	(0.33)	(0.30)
p-value (coefficient = 1)	0.07	0.05	0.02
Effective First-Stage F-Statistics	21.6	19.6	22.3
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 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 $\{M_{ji,lk,t}(\upsilon,\omega)\}$. Panel B presents the case where we fix $\{M_{ji,lk,t}(\upsilon,\omega)\}$ at the level of 2013 instead. The level of observation is firm-type and year, for 2013 and 2016. The four firm-types are (i) high supplier and buyer exposure, (ii) high supplier exposure and low buyer exposure, (iii) low supplier exposure and high buyer exposure, and (iv) low supplier and buyer exposure, for each province and sector, where supplier and buyer exposure are as defined in Section 3. $\log R_{i,k,t}(\omega)$ represents imputed total values of out-shipments in our railway data by firms in region i, sector k, and year t. Standard errors are clustered at the firm-type level. The effective first-stage F-statistics follow Montiel Olea and Pflueger (2013).

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 $\{M_{ji,lk,t}(\upsilon,\omega)\}$ using Equations (12) and (13), given our choice of calibrated parameters $\{\lambda^S, \lambda^B, \mu\}$, observed trade flows $\{X_{ji,lk,t}(\upsilon,\omega)\}$, and wages $\{w_{i,t}\}$, and assuming that the firm-pair-specific exogenous parameter for the link formation $\{K_{ji,lk}(\upsilon,\omega)\}$ does not change from 2013 (preconflict) strictly outside the conflict areas.[32] We find that this

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

version yields regression coefficients statistically indistinguishable from one (with coefficients of 1.28–1.34 with p-values of 0.24–0.35). This pattern is consistent with the observation that our model under our estimated 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-form effects on the firm-level output reduction documented in Section 3. The reorganization of production linkages significantly contributes by amplifying these relative firm-level output changes. Other factors, such as relative firm-level changes in productivity, are unlikely to drive the relative changes in firm-level production.

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, that is, $\tau_{ji,lk}(\upsilon, \omega) \to \infty$ if i or j is 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,[33] as we documented in Section 3.1. We also run separate simulations 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 $\{\tau_{ji,lk}(\upsilon, \omega)\}$ and firm productivity $\{Z_{i,k}(\omega)\}$ strictly outside the conflict areas. We use this simulation strategy to quantify the propagation effects of conflict shocks purely through supply chain disruption and reorganization. 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.[34]

We undertake these 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 this result, we also report outcomes under a scenario where reorganization of production linkages outside the conflict areas is shut

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

[34] 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_k, that is, 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 the Conflict Areas

Real GRP Changes (percentage points)	Mean	25%-ile	50%-ile	75%-ile
(1) With Link Adjustment	-5.5	-7.2	-6.3	-3.3
(2) No Link Adjustment	-8.4	-11.4	-8.6	-4.5

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.

down—that is, we fix production at 2013 levels strictly outside the conflict areas while severing production linkages to and from the conflict regions.

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 5.5% decline in aggregate real GRP strictly outside the conflict areas. This magnitude is sizable and explains nearly half of the actual 11.0% decline in the real GRP per capita of nonconflict provinces from 2013 through 2016 observed in the official government statistics (State Statistics Service of Ukraine, 2020).[35] These results indicate that the supply chain disruptions and reorganizations are important contributors to the aggregate output decline of Ukraine during this period, besides other aggregate shocks we have not incorporated into the simulation (such as overall decline in firm productivity or investment).

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 8.4% 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.

[35]Since our model abstracts from population mobility, real GRP changes coincide with those per capita.

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.

This role of endogenous network reorganization is consistent with the theoretical analysis of Arkolakis et al. (2025). They show that endogenous network reorganization influences the aggregate effects of large trade shocks (such as severing entire trade linkages with multiple locations as considered here) through two offsetting forces. On one hand, the aggregate output loss may become smaller because endogenous networks increase trade elasticity. On the other hand, the aggregate output loss may become larger if the link-formation costs are directly affected by the trade disruption through the costs of intermediate goods (i.e., $\mu < 1$; Equation 13). While our model deviates from Arkolakis et al. (2025) by incorporating additional firm heterogeneity, their insights can extend to our environment. Our large estimates of $\lambda^S = \lambda^B = 0.15$ and $\mu = 1$ indicate that the former force dominates the latter. Consistent with this interpretation, if we alternatively set $\mu = 0$, we find a 6.6% GRP loss, hence the mitigation effect becomes weaker (Appendix Table D.5). However, we still find a smaller effect than the fixed network environment, indicating that the reallocation effects of production-network reorganization are still dominant.[36]

Regional Heterogeneity. In Figure 5, we show the geographic patterns of the 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 see 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 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

[36] Arkolakis et al. (2025) also highlight that whether endogenous network reorganization amplifies or mitigates the aggregate impact of a shock depends on the shock's nature. The shock we study is most closely related to their conceptual experiment of partial regional autarky—i.e., the shutdown of trade with a subset of regions—in which case they show that endogenous network adjustments tend to mitigate aggregate output losses, consistent with our findings.

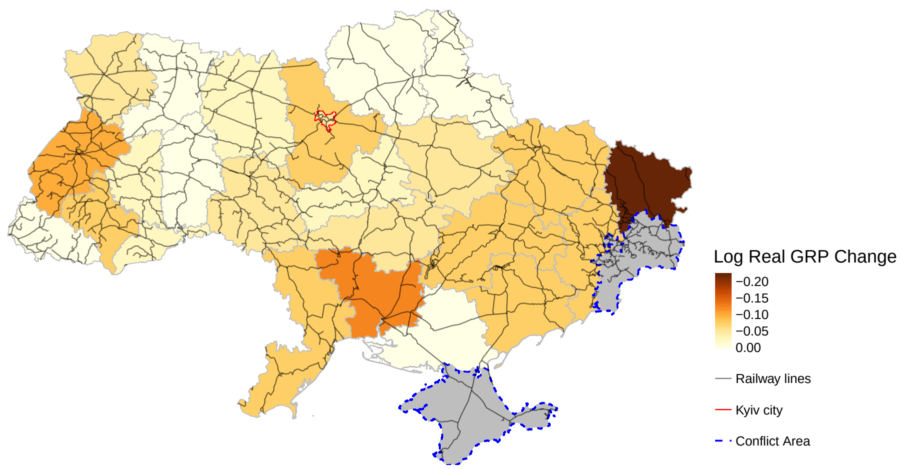
the Mykolaiv and Odessa provinces (in the southwest), face large real GRP losses. These estimates indicate that localized conflicts can have far-reaching, detrimental economic consequences through production networks. One reason why faraway regions could be affected is their higher reliance on manufacturing. 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 larger real GRP losses. 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 and Sensitivity. In Appendix Table D.5, 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).[37] In row (4), we find that alternatively setting the value of μ to 0 increases the real GRP loss to 6.6%, a modest increase, as discussed above. In row (5), we find that an alternative value for δ_k 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 6) and weight exposure (in row 7), as well as the combination of conflict exposure and the dummy for above-median firm size within a region and a sector (in row 8). In rows (9) and (10), we undertake additional sensitivity analyses for some parameters. In row (9), we show that the effects are smaller if we counterfactually set the input coefficients $\{\beta_{lk}\}$ using the values from "other" sector for all output sectors k, which generally exhibits smaller coefficients across input sectors (Table 3). In row (10), we show that the effects are larger if we counterfactually set smaller values for σ_k, confirming that the substitution of intermediate inputs plays a key role in driving spillover effects.

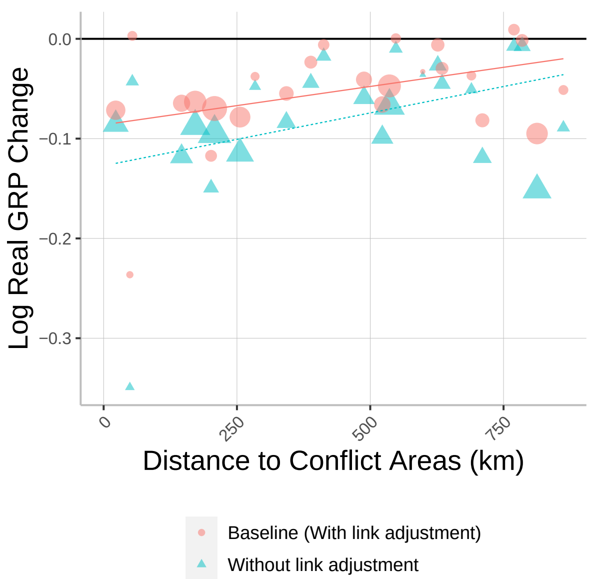
Alternative Scenarios of Conflict Shocks. In Appendix D.3, we undertake counterfactual simulations of alternative scenarios of the conflict shocks. Specifically, we explore the effects of a larger-scale conflict, in line with the 2022 full-scale Russian invasion. We find that the aggregate output loss in nonconflict areas rises disproportionately as the number of regions facing conflict shocks increases. In particular, when we shut down trade linkages with all regions occupied or invaded by Russia in February–March 2022 (jointly covering 35% of preconflict GRP in Ukraine), aggregate output loss outside these areas surmounts 37%, nearly seven times larger than our base-

[37] 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.

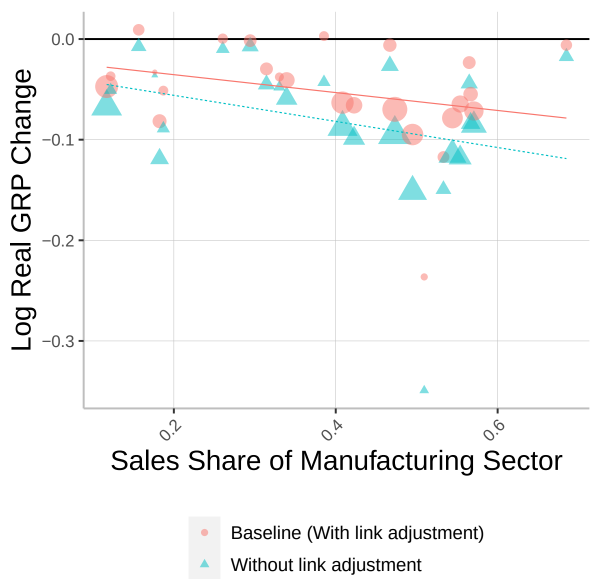
Figure 5: Real GRP Changes Outside Conflict Areas



Panel A: Real GRP Changes Across Provinces of Ukraine (with link adjustment)



Panel B: Province-Level Changes in Real GRP by Distance to the Conflict Areas



Panel 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.

line specification.[38] This pattern is consistent with the interpretation that a larger conflict shock has a disproportionately larger economic impact because it limits the scope of substituting production linkages within the remaining regions.

We also consider an independent shock to the DPR, the LPR, and Crimea individually. We find that the shocks to the DPR and the LPR have relatively larger effects (1.8% and 2.6%) than the shock to Crimea (0.9%). This is notable, given that Crimea's GDP share in the prewar Ukrainian 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 the prewar Ukrainian economy). This finding is consistent with the fact that the DPR and LPR regions are more manufacturing-intensive 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. 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 document in Figure 5.

6 Conclusion

Do intense, prolonged localized conflicts lead to disruption of production networks? If so, 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 5.5% reduction of aggregate GRP strictly outside the conflict areas through the disruption and reorganization of production networks. If we abstract from this reorganization, this effect increases to 8.4%, indicating

[38] Specifically, we consider a shock to the regions of Chernihiv, Donetsk, Kharkiv, Kherson, Kyiv (excluding the city of Kyiv), Luhansk, Sumy, Zaporizhzhia, Crimea, and Sevastopol.

that endogenous reorganization mitigates the aggregate output loss. Therefore, endogenous firm-level responses to reorganize the production networks provide resiliency against the far-reaching and detrimental economic costs of localized conflicts.

Data and Code Availability

The replication code and a portion of the data underlying this research are publicly accessible on Zenodo at https://doi.org/10.5281/zenodo.16614282. However, several key datasets are not publicly available and are therefore not included in the replication package.

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