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JEL Classification: D22, D74, O12, O47

Keywords: conflict, firms, Production Network, Aggregate Output Loss

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1 Introduction

The adverse effects of civil conflict hardly require elucidation. During the last decade, the number of areas subject to violent conflict has grown by 11%, thus affecting 12% of the global population (Bahgat et al., 2018; ACLED, 2018). The need for a reliable measure of its economic costs is clear, particularly in order to plan and design (costly) conflict prevention and conflict resolution policies and thus avoid the so-called conflict trap.[1]

The standard approach focuses on tangible costs directly observed in the areas of conflict, such as fatalities, displaced persons, or destruction of infrastructure (Mueller et al., 2017). Often added to this are the costs of direct exposure to the conflict, whether they are borne by individuals, political institutions or economic sectors.[2] However, this approach tends to neglect costs that are more challenging to measure, namely those related to the diffusion of the conflict's effects to areas outside the realm of conflict, through migration flows, the spread of disease, capital flight, or disruption of the supply chain.[3] We take a step toward filling this gap by developing a flexible methodology that, in addition to the direct costs of conflict suffered by firms in the area of conflict, takes into account propagation effects in peaceful areas. We are therefore able to quantify the total loss to firms due to a conflict.

Adopting this approach has two main motivations: First, the nature of armed conflict has evolved in past decades towards intra-state violence and armed insurgencies, such as secessionist conflicts or regional insurrections. Second, armed conflicts now affect complex economies that are characterized by dense production networks. As a result, local armed conflicts, with which small groups of firms or certain economic sectors can coexist, may nonetheless disrupt the supply chain and propagate through input-output connections to a wider group of firms and sectors, leading to amplification of the conflict's consequences. In such cases, the standard approach underestimates the actual cost of conflict, which in turn will bias the cost-benefit analysis carried out by policy makers.

In what follows, we theoretically and empirically explore the role played by the production network in spreading the effect of localized conflict to firms in peaceful areas, using the Maoist insurgency in India as a case study. In other words, we quantify the loss caused by a localized conflict at the nationwide level. More specifically, we make use of the Indian Annual Survey of Industries, a firm-level dataset that covers all registered manufacturers with more than 100 employees, as well as a representative sample of smaller manufacturers for the period 2000 to 2009.[4] After combining information on firm location and daily acts of violence perpetrated by Maoist groups, we define the set of firms that are directly exposed to the conflict. We then exploit the detailed information on each firm's output and input bundle in order to approximate the input-output network of the Indian economy. Equipped with this information, we are able to apply a

[1]The conflict trap relates to the vicious cycles between war and economic decline (Collier and Sambanis, 2002).

[2]The relationship between conflict and social norms has been extensively explored in the literature. For example, Blattman (2009) focuses on political participation, Rohner et al. (2013) look at trust and ethnic identity, Cassar et al. (2013) study social and political trust; Grosjean (2014) analyzes trust and preferences for market participation, Voors et al. (2012) consider social. Finally, Bundervoet et al. (2009), Arcand et al. (2014), and Akresh et al. (2012) study the impact of conflict on health. The impact of conflict on education and, more generally, on human capital has been explored by Akbulut-Yuksel (2014), Shemyakina (2011) and Saing and Kazianga (2020).

[3]In the recent literature, Hoenig (2021) explores how selective migration is a mechanism through which conflict affects aggregate income. Tapsoba (2021) studies how individuals are affected by the fear of exposure to conflict even prior to the manifestation of violence or in its absence.

[4]This dataset has been used by, among others, Hsieh and Klenow (2009) to study cross-country differences in aggregate productivity; by Martin et al. (2017) to look at the relationship between SME and job creation; and most recently by Boehm and Oberfield (2020) to study the impact of institutional quality on firms' output and sourcing decisions.

well-established model of production networks in the context of local conflict with the goal of quantifying the overall aggregate loss (Acemoglu et al., 2012). A key feature of this approach is that it can easily be adapted to other contexts, such as costs incurred by other countries, or the aggregate impact of social unrest.

The Maoist insurgency in India is an ideal case for testing the model. First, the activity of Maoist groups is localized in the eastern part of the country (the *Red Corridor*) and therefore a clear distinction can be made between firms in the area of conflict and firms outside it. Second, while deadly, the conflict remains at a low level of intensity, such that the firms in the area are impacted but not devastated and they are able to continue producing. Conflict-related disruptions can affect firm activity through various mechanisms, such as destruction of infrastructure, increased costs of insurance, security expenses, payment of protection money, and, specific to the Maoist insurgency, extortion. In short, we analyze how conflict affects the behavior of firms located in conflict-affected areas, and how these distortions propagate through the production network, thereby affecting firms located outside the area of conflict.

The analysis relies on firm-specific bundles of inputs to construct the production network. For each input needed for production, a firm faces a set of potential suppliers and selects the most cost-effective ones, based primarily on their size and the potential costs of trade. An exogenous shock, such as a conflict, in the area of one of the suppliers will lead to an increase in the supplier's output price (and a reduction of its output). Therefore, even if a given producer is located outside the affected area, it can incur costs due to the effect of the conflict on its suppliers. This can take three forms : (i) *inaction* – the producer continues to purchase inputs from the supplier affected by the conflict and absorbs the extra costs in the form of a higher input price; (ii) *supplier change* – if the producer switches to a different supplier located outside the area of conflict, then there may be adjustment costs or higher costs of transportation; and (iii) *input bundle change* – the producer is forced to modify its bundle of inputs because there is no other supplier of that input located outside the area of conflict. The aim of our paper is to allow for the network propagation of these effects in quantifying the overall cost of the conflict.

In the first part of the paper, and before turning to the structural estimation, we explore the impact of conflict on firm activity using a reduced form analysis. We obtain three main results: First, we show that firms located in an area of conflict incur greater costs in the form of losses due to theft, payment of protection money, additional security costs and reduced access to infrastructure. Second, we show that the price of a given product (5-digit level) is, on average, 3.6% higher and the quantity produced 1.3% lower for firms located in an area of conflict. Third, firms not located in areas of conflict but which are exposed to conflict through the production network charge a higher price and produce a significantly lower quantity of output.

In the second part of the paper, we construct a static model with an input-output network in the spirit of Hsieh and Klenow (2009) and Acemoglu et al. (2012). The model aims to explain how conflict distorts firm behavior and to capture the role of inter-firm connections as a propagation mechanism. Firms located in an area of conflict are subject to output and input distortions that increase their output prices. Since every producer in the economy is a potential input supplier for other firms, conflict-induced distortions propagate throughout the economy, including in firms located outside the area of conflict. Our main theoretical result characterizes the aggregate loss (at the national level) due to conflict as a function of the economy's production network.

We then apply the model using the firm-level data in order to structurally estimate the aggregate impact of the Maoist insurgency on the Indian economy. To this end, we first use variation in the value of a firm's output in order to quantify the direct loss from being located in an area of conflict. We use firm-level information on the output and input bundle in order to define the production network characterizing the Indian economy, which serves as a propagation channel from areas of conflict outward. We find that the Maoist insurgency brought about an average annual decline of 1.9% in aggregate output during the sample period, which corresponds to an annual loss of approximately 3.8 billion USD. Interestingly, only 27% of the loss can be attributed to the impact on firms located in areas of conflict. The remaining 73% depends on network propagation outside the area of conflict.

This baseline estimate includes the effects of *inaction*, *supplier change*, and *input bundle change*. We then explore the role of these mechanisms in more detail. First, we assume no network adjustment and find that the average annual loss is almost 3% (5.5 billion USD per year). This means that the *inaction* effect alone would imply an output loss which is more than 30% larger than that estimated in the baseline scenario (1.9%). Second, we contemplate network reshuffling and find that allowing for the *supplier change* effect would lead to an average annual loss of only 2.3% (4.5 billion USD per year), whereas combining the *supplier change* and the *input bundle change* effects reduces the output loss substantially, to 1.3% per year (2.6 billion USD per year).

Moreover, since Maoist groups are committed to extreme-left political ideology and therefore are more likely to organize attacks against large firms, we consider an alternative specification of the model in which we allow the level of conflict to be correlated with firm size. We find that the output loss increases considerably if violence is directed towards firms in the upper part of the distribution by size. For example, compared to our baseline estimate, if conflict affected only firms belonging to the top 20% of the firm distribution by size, then the average annual loss would more than double.

Finally, we perform several policy experiments. First, we estimate the potential loss in the counterfactual scenario where Maoist activity expands to neighboring districts. We find that the average annual monetary loss would increase substantially, to approximately 5.9 billion USD. Second, we explore the effect of various policies in support of firms in an area of conflict and firms located elsewhere that are impacted by the conflict through the production network. On the one hand, we show that the negative effect of conflict would be mitigated to a large extent by investment in protection for firms that occupy a "central" position in the economy's production network. On the other hand, we find that policy makers should design interventions that can effectively reduce the costs of trade, such as subsidization of shipping costs, and should implement policies to rapidly restore trade infrastructure damaged by conflict, such as road and railway reconstruction.

Taken together, the findings provide substantial evidence for the importance of the production network as a channel of diffusion and a multiplier of the adverse consequences of conflict suffered by firms located in areas of conflict. Our approach has the advantage to be easily adapted to different contexts, such as other types of conflict or social unrest, by observing firms' output and input bundle as well as firms' location.

Related literature and contribution. The paper contributes to several strands of the literature. The first is a voluminous literature on the economic consequences of conflict. From the macro perspective, the pioneering work of Collier (1999) lays the foundation for the economic consequences of civil war. Cross-country studies find that in countries characterized by high political instability, GDP per-capita growth is significant lower (Alesina et al., 1996), and that trade destruction due to conflict is significant (Martin et al., 2008). From the micro perspective, the literature offers plentiful evidence of the impact of being located in an area of conflict on firm behavior. Several mechanisms for these findings have been explored. First, conflict can reduce a firm's exports, thus leading to large negative labor supply shocks (Ksoll et al., 2021), and can affect its imports through the substitution of domestically produced inputs for imported ones (Amodio and Di Maio, 2018). Moreover, conflict and the threat of predation can induce firms to reallocate labor from production to protection (Besley and Mueller, 2018). Finally, conflict affects firms' location (Blumenstock et al., 2020) and induces producers to forgo otherwise profitable investments (de Roux and Martinez, 2021). We attempt to bridge these two strands of the literature by showing that firm-level distortions caused by a localized conflict can propagate by way of the production network and impact the entire economy. Similarly, Korovkin and Makarin (2021) document substantial propagation effects from localized conflict to inter-firm trade. They focus on how a country's production network is affected by localized conflict and uncover several indirect effects of conflict on firm behavior. We extend their analysis by providing the first explicit estimate of the total output loss by taking into account both the area of conflict itself and other impacted areas. Moreover, our structural model makes it possible to distinguish between the effect of the *direct* exposure to conflict, suffered by firms located within an area of conflict and the *indirect* effect due to network propagation.

We also contribute to the literature on the Maoist insurgency. First, Maoist groups concentrate their attacks, which are primarily directed against security forces, in areas rich in raw materials, which are a lucrative source of royalties for the State (Vanden Eynde, 2015; Shapiro and Vanden Eynde, 2020). With respect to interventions to resolve conflicts, there is mixed evidence on the effectiveness of development-oriented policies as a counterinsurgency strategy. Khanna and Zimmermann (2017) find that these policies lead to a short-run increase in police-initiated attacks and insurgent attacks on civilians, whereas Fetzer (2019) and Dasgupta et al. (2017) find that public employment programs have helped to reduce Maoist activity. We contribute to this literature by quantifying the long-term aggregate economic cost of the Maoist insurgency.

Finally, we contribute to the growing literature on the role of production networks as a mechanism for the propagation and amplification of shocks. The conditions under which the propagation of microeconomic shocks by way of input-output links can translate into sizable aggregate fluctuations have been characterized by Acemoglu et al. (2012, 2017) and Baqaee and Farhi (2019) (see Carvalho (2014) for a review of the literature). The first contributions to rely on exogenous and well-identified shocks to study the role of firm-level links in propagating input disruptions were provided by Barrot and Sauvagnat (2016) who analyze natural disasters in the US, and Boehm et al. (2019) and Carvalho et al. (2020) who show that the Great Japanese Earthquake led to cross-country transmission of its consequences and a substantial decline in Japanese real GDP. We contribute to this literature by relating to conflict as a micro-disturbance and study its propagation through the production network. Moreover, ours is the first analysis to provide an explicit estimate of the total loss to firms as a result of conflict. Finally, the input-output network structure in India has been shown to also play a substantial role in explaining variation in a firm's sales to other firms (Panigrahi, 2021).

The remainder of the paper is organized as follows. Section 2 presents a brief overview of the Maoist insurgency and some motivating evidence for the existence of firm-specific costs borne by producers in areas of conflict. Section 3 describes the modeling of the Indian production network. Section 4 presents the reduced-form analysis. Section 5 presents the conceptual framework, which is then used for aggregation and counterfactual analysis in Section 6 and Section 7, respectively. Section 8 concludes.

2 Firm Activity and Maoist Insurgency

In this section, we provide a brief overview of the Maoist insurgency and then quantitatively describe the costs borne by firms located in areas of conflict using data from the World Bank Enterprise Survey.

2.1 Background

The Maoist insurgency is a long-running and widespread conflict based on Communist ideology which seeks to overthrow the Indian government.[5] Maoist groups are active in numerous districts located in eastern India which are referred to collectively as the *Red Corridor* (Figure 1). The insurgency started in the early 1970s as a peasant uprising against landlords. Until the early 2000s, it involved sporadic violent acts carried out by various armed groups. The conflict shifted toward more organized and centralized armed activity in 2004, following the merger of a number of groups. This led to a sharp increase in violent incidents throughout the affected region.[6] The Maoist insurgency consists of the following armed groups: the Maoist Communist Center (MCC), the People's War Group (PWG), the Communist Party of India (CPI-Maoist), the People's Liberation Guerrilla Army (PLGA) and some other minor groups (an exhaustive list appears in Table A1.2). CPI-Maoist is the dominant player and is responsible for more than 60% of the Maoist-related fatalities. Most of the violence is committed against the Indian government (70.6%), but civilians are not spared and account for about 28.9% of the targets. The remaining 0.5% are the result of clashes between the various Maoist groups.

Several features of the Maoist insurgency make the Indian context an ideal setting for our study. First, although deadly, it remains at the level of low-intensity warfare and economic activity is able to continue despite the violence. According to the Ministry of Home Affairs, 8,197 individuals were killed by the insurgents between 2004 and 2019. While India ranks above the median of the Fragile States Index, it remains above the median of the Ease of Doing Business measure, unlike many fragile economies such as Syria and Yemen (Figure A1.1).[7] Second, there are many actions perpetrated by Maoist groups that hinder business activity (see Online Appendix Table A1.3 with some statistics on events during the 2000-2009 period) including: (i) explosions, which can affect the transportation network, trade infrastructure, and firms' assets, (ii) fatalities/incidents, which impact local demand and employment, and (iii) acts of extortion in order to support the Maoists' activities, such as collection of protection money, direct attacks on firms' assets, etc.(Besley and Mueller, 2018).[8] Third, the geographical scope of the conflict expanded between 2000 and 2009. In 2000, 26 districts (out of 492) across 8 states (out of 31) were affected by Maoist activities,

[5]The movement is also referred to as the *Naxalites* insurgency. The term *Naxalites* is derived from the place of origin of the insurgency, Naxalbari, while the term *Maoists* refers to the movement's communist ideology. The Ministry of Home Affairs prefers the term *Left Wing Extremist Insurgency.*

[6]In September 2004, the Maoist Communist Center (MCC) and the People's War Group (PWG) merged to form the largest Maoist faction, the Communist Party of India (Maoist), which includes an armed wing, the People's Liberation Guerrilla Army (PLGA).

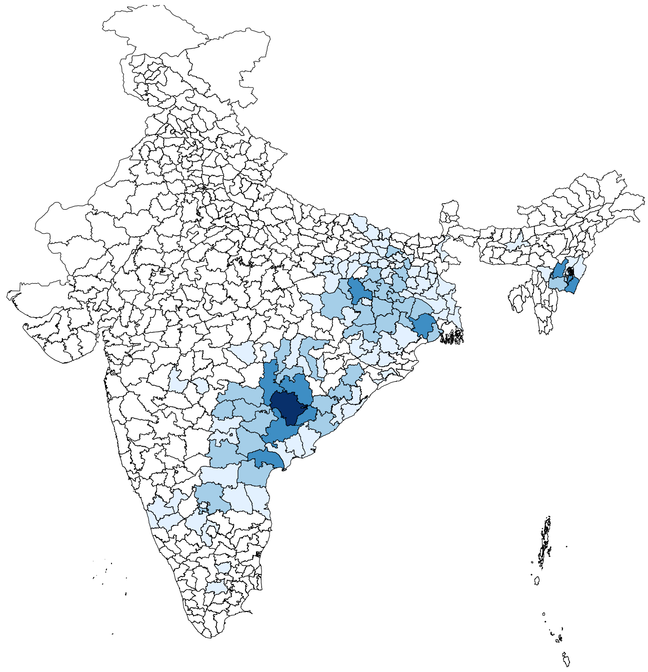
[7]India is ranked 74^{th} out of 178 according to the Fragile States Index (The Fund for Peace, 2020) and 63^{rd} out of 190 according to the Ease-of-doing-business measure (World Bank, 2019).

[8]Targets of the extortion are manifold, ranging from individual businesses to large industries and include both private and public companies.Ramana (2018) estimates an annual budget of around Rs. 4.2 billion (around $60 million). For instance, on March 11, 2005, The South Asia Terrorism Portal reports that "In Hyderabad, police arrested a cadre of the Janashakti faction of the Communist Party of India-Marxist-Leninist (CPI-ML), [...], while extorting money from businessmen in Lalaguda". Similarly, the Hindu, on April 24, 2008, reported that "Communist Party of India-Maoist (CPI-Maoist) cadres set fire to 47 vehicles of a private company, Essar Steels at Korandul in the Dantewada district on April 24 night. [...]".

while in 2009 Maoists were active in 55 districts across 11 states. Overall, during 2000-2009 a total of 109 districts across 12 states were impacted. Furthermore, Maoist activity is mainly concentrated in the eastern part of the country (Figure 1). Therefore, we are able to make a clear-cut distinction between firms located inside the area of conflict and those located outside it.

In what follows, we pay particular attention to the various ways in which firms can be impacted by the insurgency. In particular, in Section 2.2 we provide motivating evidence that firms located in districts impacted by Maoist activity bear additional costs linked to a wide range of constraints. In Section 5, we model firm behavior in areas of conflict while taking into account all of the possible activities of the Maoists.

Figure 1: The Maoist insurgency, 2000-2009



Note: Locations of the Maoist insurgency across districts between 2000 and 2009. The darker the shade of blue, the more intense is the conflict.

2.2 Evidence of additional costs imposed by the conflict

In this subsection, we provide an initial exploration of the costs borne by firms located in the areas of conflict. We rely on cross-section data from the World Bank Enterprise Survey (World Bank, 2014), which provides information on the business constraints to which Indian firms are subject.[9] This data is particularly well-suited for our purpose because the survey covers a broad range of business environment, crime, corruption, infrastructure and firm-level performance measures. To examine the additional costs borne by firms located in the areas of conflict, we estimate an equation of the following form:

$$Y_{id} = \beta \text{ Exposure-conflict-areas}_d + \mathbf{D'_{id}}\alpha + \theta_s + \varepsilon_{id} \tag{1}$$

[9]Data for India are only available for the year 2014. The WBES is a firm-level survey conducted on a representative sample of the private sector in 149 different countries. The dataset has been used in various contexts and to investigate various research questions, ranging from informal enterprises and female employment in developing countries to estimation of productivity. See De Haas and Poelhekke (2019) for a detailed literature review.

where Y_{id} are the various firm-level outcomes related to business constraints of firm i in district d: (i) an indicator that equals 1 if the firm reports losses due to theft; (ii) an indicator that equals 1 if the firm declares that it pays protection money; (iii) an indicator that equals 1 if the firm incurs expenses for security (such as expenditure on equipment, personnel, professional security services, etc.); (iv) an indicator that equals 1 if the firm reports problems of access to electricity; and (v) the total cost of production. The main explanatory variable, *Exposure-conflict-areas*$_d$, indicates whether the firm is located in a district affected by the insurgency since 2000 (see Section 3 for details on conflict data). In the sample, approximately 23% firms are located in a conflict-affected district. We also include (log) firm characteristics ($\mathbf{D'_{id}}$): number of facilities, facility type, manager's experience, value of sales, number of employees, percentage of working capital financed from internal funds, sector of activity, legal status and main product (see Online Appendix A1 for more details). Lastly, we include state fixed effects (θ_s) to capture state-level policies that may have an effect on the distortions experienced by a firm as a result of the conflict.

Table 1 displays the results. In columns (1)-(5) we control only for firm characteristics, whereas in columns (6)-(10) we add state fixed effects.[10] Firms located in conflict-affected districts are 92% more likely to report losses due to theft (column 1), 66% more likely to pay protection money (column 2), 17% more likely to pay for security (column 3), and 19% more likely to report access to electricity as an obstacle in business activity (column 4), relative to the sample mean. Finally, firms located in areas of conflict have, on average, 5% higher costs of production (column 5). By adding state fixed effects, firms located in a conflict-affected district can be compared to other firms outside the area of conflict within the same state. With the notable exception of losses due to theft, firms located in a conflict-affected district are even more likely to bear some additional costs. While the magnitude is slightly lower for payment of protection money (column 7), expenditure on security (column 8), and access to electricity (column 9), firms located in a conflict-affected district report a total cost of production that is on average 13% higher than other firms. This effect is almost three times larger than in the model without state fixed effects (column 5). Due to endogeneity concerns, this exercise cannot extend beyond correlation only. Even if somewhat limited, this preliminary evidence is nonetheless relevant for two main reasons. First, it indicates the large magnitude of additional costs borne by firms located in conflict-affected districts. Second, it demonstrates the diversity of costs that can arise from a conflict. This becomes particularly useful in the conceptual framework derived in Section 5. Indeed, we are able to accurately model firm behavior in an area of conflict in accordance with the evidence for the existence of both output and input distortions.

3 The Production Network

In this section, we present the dataset used in the empirical analysis, which combines firm-level data with information on Maoist activities. We then describe the production network that characterizes the Indian economy and how the effect of a localized conflict can spread to other areas through this network.

Plant data. We use plant-level information on Indian manufacturers from the Annual Survey of Industries (ASI), which was carried out by the Ministry of Statistics and Program Implementation for the period

[10] A preliminary balancing test suggests striking differences across firms: firms located in a conflict-affected district report having more facilities, managers with more experience and more working capital financed from internal funds; however, they have a lower number of employees and a lower level of sales (Table A1.1 in the Online Appendix).

Table 1: Additional costs due to conflict

Dep. var.	(1) Loss due to theft	(2) Protection money	(3) Expenditure on security	(4) Access to electricity	(5) Total cost of production
Exposure, conflict areas	0.039^a	0.040^a	0.118^a	0.093^a	0.046^a
	(0.006)	(0.008)	(0.044)	(0.013)	(0.016)
Firm's characteristics			——— Yes ———		
State FE			——— No ———		
Observations	8769	7159	8791	8801	8648
% exposed firms	23.06	23.91	23	22.97	23.08
Sample mean	0.04	0.06	0.69	0.48	17.04

Dep. var.	(6) Loss due to theft	(7) Protection money	(8) Expenditure on security	(9) Access to electricity	(10) Total cost of production
Exposure, conflict areas	-0.015	0.037^c	0.070^c	0.051^b	0.123^a
	(0.012)	(0.019)	(0.038)	(0.022)	(0.035)
Firm's characteristics			——— Yes ———		
State FE			——— Yes ———		
Observations	8769	7159	8791	8801	8648
% exposed firms	23.06	23.91	23	22.97	23.08
Sample mean	0.04	0.06	0.69	0.48	17.04

Note: ^{c} significant at 10%; ^{b} at 5%; ^{a} at 1%. Robust standard errors are reported in parentheses. The alternative dependent variables are : (i) an indicator that equals 1 if the firm reports any losses due to theft (as a percentage of the value of their production) (columns 1 and 6); (ii) an indicator that equals 1 if the firm pays protection money (columns 2 and 7); (iii) an indicator that equals 1 if the firm allocates resources to security (e.g., expenses on equipment, personnel, professional security services, etc.) (columns 3 and 8); (iv) an indicator that equals 1 if the firm reports access to electricity as an obstacle to business activity (columns 4 and 9); and (v) the cost of production (columns 5 and 10). Exposure-conflict-zone is an indicator that equals 1 if the firm is located in a conflict-affected district. Additional controls include (log) firm characteristics and state fixed effects (second panel). See Online Appendix for more details.

2000-2001 to 2009-2010.[11] The ASI provides a panel consisting of all registered manufacturers in India with more than 100 employees plus an annual sample of manufacturers with more than 20 employees (which represents about 20% of the total).[12]

Our identification strategy relies on two unique features of the data. First, they provide rich product-level information on each firm's output and intermediate inputs (i.e., up to 10 products per firm). Following the 5-digit ASI Commodity Classification (ASICC) codes, we are able to distinguish between 5,911 different products. This becomes important in the construction of firm-to-firm input-output links discussed in detail below. Second, we geo-localize firms by district in order to determine their exposure to the Maoist insurgency using the methodology in Martin et al. (2017).[13] The final sample consists of a panel of 61,061 distinct firms

[11] Accounting years run between April 1 - March 31. For simplicity, herein we refer to these years as 2000 through 2009.

[12] Since more than 95% of the manufacturers operate only one facility, the discussion will assume that figure to be 100%.

[13] Martin et al. (2017) created the first mapping of the panel dataset (including panel identifiers) to district locations by merging them with annual cross-sectional data (including district identifiers). The cross-sectional information does not include district information from 2009 onwards, and therefore our dataset ends with 2009.

observed between 2000 and 2009. About 33% of the firms were surveyed for at least 7 years, while 23% were surveyed for only 2. One-third of the firms are single-output producers, while two-thirds produce between 2 and 10 distinct goods (less than 0.1% produce up to 20 distinct goods). The data cover 30 different industries (1 and 2-digit level of NIC, Table A1.4) in 529 districts (across 31 states, Table A1.5).

In the empirical analysis, our outcomes of interest are product-specific price and quantity. The covariates included in each regression include intermediate input price, wages, interest rates and total factor productivity (TFP), all of them logged. The latter is computed by applying the proxy method proposed by Wooldridge (2009), which essentially utilizes consistent estimation within a single-step GMM framework to overcome endogeneity issues related to TFP estimation. Rovigatti and Mollisi (2018) examine this method and derive the appropriate moment conditions for the GMM framework. Furthermore, we control for (time-varying) input bundle fixed effects, defined at the 2-digit product code classification level. This firm-level measure is constructed by aggregating all intermediate input product codes at the 2-digit level. The descriptive statistics appear in Table 5 in the Appendix.

Firm-to-firm links. Ideally, the dataset would include the full input-output network formed by the universe of firm-to-firm transactions. However, since this information is incomplete in the ASI data, we develop a novel method to approximate the input-output network that characterizes the Indian economy.[14] It draws from the literature on the determinants of domestic sourcing, which emphasizes the key role of geographic proximity and suppliers' market power in establishing buyer-supplier links (Bernard et al., 2019).

This method relies on two main features of the ASI data. First, for every buyer i, we observe the bundle of inputs ($k \in K$) used in production. Second, for every good k, we observe the universe of its producers $j \in J$, their location, and their relative size (compared to other suppliers $r \neq j \in J$ of k). As such, for each good k within the input bundle of at least one firm i, we can approximate the buyer-supplier links by assigning to each potential supplier j an index of *importance*, $\rho_{ji(k)}$, such that $0 < \rho_{ji(k)} \leq 1$ and $\sum_{j \in J} \rho_{ji(k)} = 1$. This index has two components: the relative inverse distance between buyer i and every supplier $j \in J$ of k, and the share of output k produced by each supplier $j \in J$.[15] For each good k and potential supplier-buyer pair ji, our measure is a linear combination of the relative distance between buyer i and supplier j, and the relative size of each supplier j of good k. For a given good k, the index of importance of supplier j with respect to buyer i is given by:

$$\rho_{ji(k)} = \lambda \frac{D_{ji}}{\sum_{j \in J} D_{ji}} + (1 - \lambda) \frac{k_j}{\sum_{j \in J} k_j} \tag{2}$$

where we set $\lambda = 0.5$ such that the same weight is assigned to every component. D_{ji} measures the inverse bilateral distance between supplier j and buyer i, while k_j is the amount of good k produced by j.[16] The index of importance $\rho_{ji(k)}$ assigns to every supplier j the probability of being the actual supplier of good k

[14] Panigrahi (2021) uses data on Indian firm-to-firm transactions. Although the data are quite rich, they are not well-suited to our purposes, namely to examine the propagation effect in peaceful districts and computing the total welfare loss. Only five Indian states are covered, of which four are affected by the Maoist insurgency.

[15] Note that by using inverse distance, we implicitly assume that the elasticity of trade flows with respect to distance between buyers and producers is equal to -1. This is in line with the findings of Panigrahi (2021); however, other studies indicate that the value may be less than -1, especially in contexts related to domestic trade in developing countries (Donaldson, 2018). We therefore also consider alternative formulations of our measure of *importance*. Specifically, in Section 6.2, we relax this assumption and let the elasticity trade flows with respect to distance to vary between -2 and -5. The estimated aggregate output loss is not particularly sensitive to this value.

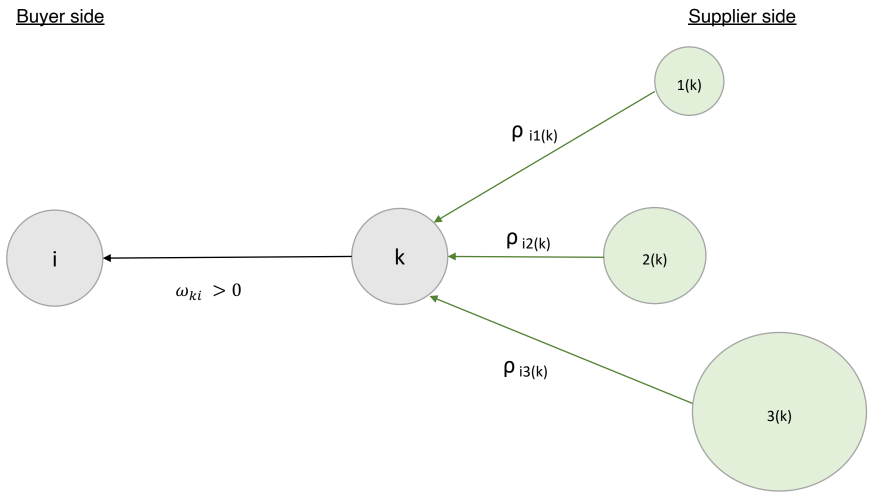
[16] For suppliers and buyers located in the same district, we set the distance to 1.

to firm i. By construction, these probabilities sum to one.[17]

The strategy is illustrated in Figure 2, where for a given buyer i and good k there are three suppliers $j = [1, 2, 3]$, i.e., $1(k)$, $2(k)$ and $3(k)$. As mentioned above, we do not observe which firm is the actual supplier of input k. If we were able to, $\rho_{i1(k)}$, $\rho_{i2(k)}$ and $\rho_{i3(k)}$ would be dummy variables equal to one if supplier $j = [1, 2, 3]$ is the actual supplier and zero otherwise. We approximate these links by assigning to each potential supplier j the probability of being the actual supplier of input k for firm i, based on the bilateral distance between buyer i and each supplier j and the size of each supplier j of k, represented in Figure 2 by the length of the arrow and the size of the circles.

Note that this index plays a critical role in both our conceptual framework and the structural estimation (Sections 5 and 6), where we model and describe the production network characterizing the Indian economy using the input-output matrix Ω. The entries of this matrix are the observed input shares, ω_{ki}, adjusted by the index of supplier importance $\rho_{ji(k)}$.

Figure 2: Buyer-supplier links



Note: An illustration of the procedure we develop to approximate the buyer-supplier links that characterize India's production network.

Conflict data. The UCDP Georeferenced Event Dataset provides daily reports of "incidents where armed force was used by an organized actor against another organized actor, or against civilians, resulting in at least one direct death at a specific location and a specific date" (Sundberg and Erik, 2013).[18] The dataset covers 1,775 events from 2000 to 2009, which involved 4,737 deaths. This information is collected from a wide range of sources, including news media and reports by international organizations and NGOs.

[17] Note that we could alternatively construct $\rho_{ji(k)}$ as a non-linear combination of relative distance and relative size:

$$\rho_{ji(k)} = \frac{\frac{D_{ji}}{\sum_{j\in J} D_{ji}} \times \frac{k_j}{\sum_{j\in J} k_j}}{\sum_{j\in J}\left(\frac{D_{ji}}{\sum_{j\in J} D_{ji}} \times \frac{k_j}{\sum_{j\in J} k_j}\right)}$$

This alternative specification is well-defined as it guarantees $0 < \rho_{ji(k)} \leq 1$ and $\sum_j \rho_{ji(k)} = 1$. Note that we mechanically attribute more (less) weight to the larger (smaller) and closer (farther) suppliers, compared the index described in Equation 2. Considering this alternative functional form leaves our main estimates essentially unchanged.

[18] These data have been widely used in recent conflict literature, including Nunn and Qian (2014), Michalopoulos and Papaioannou (2016), Berman et al. (2017) and König et al. (2017).

Exposure to conflict. The firm-level data do not provide information on whether and in what way firms were directly exposed to violent events. This prevents us from making a precise statement on the heterogeneous intensity of exposure across firms within the same district. Nonetheless, we are able to rely on district-level information on the location of firms and of violent events and assume that all firms located in the same district are equally affected by violence in the district. In the structural analysis carried out in Section 6.2, we relax this assumption to some extent. In the final sample, more than 9% of firms were exposed to conflict during at least one year between 2000 and 2009.

Exposure to conflict by way of the production network. Based on the location of each firm, we are able to distinguish between suppliers located in conflict-affected districts and the rest. We can therefore calculate a yearly measure of *exposure to conflict through the production network* ($exposure_i$) for each firm i. It is worth mentioning that this index (as well as the index of supplier *importance*) is calculated for each cross-section in the dataset separately (we omit the subscript t from $\rho_{ji(k)}$ and $exposure_i$ for ease of exposition). Thus, each firm's conflict exposure by way of the production network depends on: (i) whether any of the potential suppliers j of its inputs $k \in K$ are located in a conflict-affected district; (ii) the importance of a potential supplier j of input k, i.e., $\rho_{ji(k)}$; and (iii) the share of each input k used by firm i (ω_{ki}). We therefore construct $exposure_i$ as follows:

$$exposure_i = \sum_{k \in K} \left(\omega_{ki} * \sum_{j \in J} \left(\rho_{ji(k)} \times conflict_j \right) \right) \tag{3}$$

where $conflict_j$ is a dummy that equals 1 if firm j is located in a conflict-affected district. Note that a firm i can be located in a conflict-affected district *and* be affected by conflict by way of the production network. This occurs when a potential supplier of firm i is also located in a conflict-affected district. Unfortunately, due to data limitations, we cannot disentangle these two types of exposure to conflict for firms located in a conflict-affected district. In the final sample, there are 5,626 distinct firms that were directly exposed to conflict at least once (about 10% of the sample), and another 54,304 that were exposed at least once by way of the production network. Another 25,232 firms were not exposed through either channel.

4 The Impact of Conflict on Firms' Performance

4.1 Empirical strategy

We carry out a reduced-form analysis in order to explore the impact of conflict on firms' performance. We focus on two main channels: (i) distortions experienced by firms located in a conflict-affected district; and (ii) the spread of this effect to other firms by way of the production network. We estimate an equation of the following form:

$$Y_{i,k(d,t)} = \beta \, \text{Exposure-conflict-area}_{(d,t)} + \gamma \, \text{Exposure-peace-area}_{i(d,t)} + \mathbf{D}'_{\mathbf{i(d,t)}}\alpha + \theta_k + \theta_d + \theta_{ct} + \varepsilon_{i,k(d,t)} \tag{4}$$

where firm i produces good k in year t and is located in district d (in state c).[19] The dependent variable $Y_{i,k(d,t)}$ represents the firm's performance measured at the product level k (5-digit) by either (log) price or (log) quantity. First, we estimate the effect of conflict-induced distortions on firms located in a conflict-affected district by defining the variable Exposure-conflict-area$_{(d,t)}$ which equals 1 if firm i is located in district d that is affected by conflict at time t.[20] The variable Exposure-peace-area$_{i(d,t)}$ captures the effect of conflict on firms not located in a conflict-affected district by way of the production network (Equation 3). We also control for time-varying firm-level characteristics, $\mathbf{D'_{i(d,t)}}$, which includes wage, interest rates, input prices, TFP and (time-varying) input bundle fixed effects (see Section 3 for further details). Crucially, the richness of our dataset allows for the inclusion of fixed effects that account for unobserved heterogeneity in product (θ_k), district (θ_d) and state $\times$ year (θ_{ct}).[21] Finally, standard errors are clustered at district $\times$ year level. Since conflict and firm location are not random, the conclusions cannot go much beyond correlation.[22] Thus, while our findings are consistent with the idea that conflict has a causal impact on firm performance, the data do not allow us to rule out all potential confounders. Nonetheless, the empirical findings add to the literature.

4.2 Results

Baseline estimates. Table 2 provides the estimates of the performance differential between firms located in conflict-affected district and firms that are not but are nonetheless exposed to conflict by way of the production network. The implicit reference group consists of firms that are not located in a conflict-affected district *nor* are they exposed to conflict by way of the production network.[23] In column 1, the dependent variable is the (log) price of each good produced by firm i. The impact of being located in a conflict-affected district is positive and statistically significant. The effect of conflict increases prices on average by approximately 3.6%. For firms not located in a conflict-affected district but which are exposed to conflict by way of the production network, the estimated coefficient is again positive. In terms of magnitude, a 10% increase in exposure to conflict by way of the production network (equivalent to one standard deviation) leads to a 1.3% increase in price. In column 2, the dependent variable is the (log) quantity of output. Firms located in conflict-affected districts and firms that are not but are exposed to conflict by way of the production network produce a significantly lower quantity of output relative to the reference group. The magnitudes are economically significant: being located in a conflict-affected district reduces the quantity produced by 5.6% while a 10% increase in exposure to conflict by way of the production network leads to a 1.9% decrease in output.[24]

[19] We omit the subscript c because being located in a certain district d means being located in a certain state c. We use the subscript c to denote the State$\times$year fixed effect (θ_{ct}).

[20] As discussed previously, the data do not provide firm-specific information on the exposure to conflict, and therefore we assume that the effect of conflict on firms located in a conflict-affected district is homogeneous (and consequently, we omit the subscript i)

[21] The product fixed effects are defined at the 3-digit level.

[22] Various endogeneity issues may contaminate the estimates. First, firm performance may help to determine whether Maoist groups are present (such that the location of conflict will not be random). Second, a firm's decision whether to locate in a particular state or to leave a particular state may be affected by the presence of insurgent groups (Camacho et al. (2013) with respect to Colombia, Blumenstock et al. (2020) with respect to Afghanistan).

[23] More precisely, firms belonging to this reference group may be exposed to conflict from the 2^{nd} to the n^{th} degree of the production network. Specifically, firm i is second-degree exposed to conflict if one of its supplier, firm j, is located in a peaceful district and its exposure index defined in Equation 3 is greater than zero.

[24] In the Online Appendix – subsection A2.1, we examine the modulating effects of specific firm characteristics on firm performance. We allow the effect on a firm's price, quantity and sales, in both conflict-affected and peaceful districts, to vary

Table 2: Baseline results

Dep. var.	Price (1)	Quantity (2)
Exposure, conflict areas	0.035[c]	-0.055[c]
	(0.020)	(0.028)
Exposure, peaceful areas	0.132[a]	-0.193[a]
	(0.035)	(0.058)
Firm controls	Yes	Yes
Product FE	Yes	Yes
District FE	Yes	Yes
State × Year FE	Yes	Yes
Observations	357,627	357,627
R-squared	0.705	0.641

Note: [c] significant at 10%; [b] at 5%; [a] at 1%. Standard errors are clustered at the district × year level. The dependent variables are the (log) price and the (log) quantity of the firm's production defined at the 5-digit level of the product classification code. *Exposure, conflict areas* is an indicator that equals 1 if the firm is located in a conflict-affected district and *Exposure, peaceful areas* is a firm-level continuous measure calculated according to Equation 3. Firm controls include (log) input prices (intermediate inputs, wages, and interest rate), (log) TFP, and time-varying input bundle fixed effects (defined at the 2-digit level). Product (defined at the 4-digit level), district, and state × year fixed effects are included. See main text for further details and Table 5 for descriptive statistics.

Sensitivity analysis. In Appendix B, we show that results of Table 2 are robust to a battery of sensitivity checks. We first consider an alternative measure of conflict: the occurrence of at least one death related to the Maoist insurgency, rather than at least one violent event (Table 6). Second, we replicate the analysis on sub-samples of firms for which there is more than 1, 3, 5 or 7 years of data, respectively (Table 7). Third, we consider an alternative specification of the supplier importance index (Equation 2) which is a non-linear combination of relative distance and relative size (Table 8). Finally, we replicate the estimation using various values (from -2 to -5) for the elasticity of trade with respect to distance and with respect to size of suppliers (Table 9). The results are found to be robust to these alternatives. Interestingly, adding district×year fixed effects has no effect on the point estimates for exposure to conflict by way of the production network (Table 10).

4.3 Mechanisms

As discussed in Section 3, a firm selects from a set of potential suppliers for each of its inputs. When conflict occurs in a supplier's district, then the firm has three options: (i) *inaction*; (ii) *supplier change*; and (iii) *input bundle change*. In this section, and notwithstanding the data limitations, we estimate the likelihood of choosing options (ii) and (iii). Note that in the absence of information on firm-to-firm transactions, we are unable to evaluate the likelihood of the *inaction* option.

Supplier change. We overcome the lack of data on firm-to-firm transactions by developing an alternative empirical strategy. The results presented in Section 4.2 suggest that conflict correlates positively with output

according to the following firm characteristics: (i) number of years in operation; (ii) the number of affiliates (iii) whether the firm relies on imported inputs; and (iv) the level of insurance, as measured by the share of insurance within total expenses. There is no conclusive evidence that firm-specific characteristics modulate the effect of exposure to conflict on firm performance.

price and negatively with output quantity in the case of firms located outside conflict-affected districts but which are exposed to conflict by way of the production network. This implies that there may be firms that gain from conflict. This might occur if a firm replaces a supplier located in a conflict-affected district with one that is not. We therefore estimate whether this substitution of suppliers might be favorable for firms not located in a conflict-affected district.

We restrict the sample in this case to suppliers that are not located in a conflict-affected district and which have at least one competitor that is (and which is a firm producing the same good according to the 5-digit product code classification). We estimate the following equation at the product level k:

$$Y_{i,k,t} = \rho \,\text{competitors-conflict-areas}_{i,k,t} + \mathbf{D'_{i,t}}\alpha + \theta_k + \theta_d + \theta_t + \varepsilon_{i,k,t} \tag{5}$$

where $Y_{i,k,t}$ is firm i's share of total sales of product k at the state or national level in year t. We then calculate two alternative measures of the importance of a competitor (at the product level) located in a conflict-affected district (competitors-conflict-areas$_{i,k,t}$): (i) the percentage of firms producing product k; and (ii) the market share of each firm producing product k. We also include fixed effects for product (θ_k), district (θ_d) and year (θ_t) and firm-specific characteristics $\mathbf{D'_{i,t}}$ (wages, interest rate, input prices and TFP, all in log terms), and (time-varying) input bundle fixed effects. Robust standard errors are clustered at the district $\times$ year level.[25] Table 3 presents the results for market share at the state level (columns 1 and 2) and at the national level (columns 3 and 4). In each specification, state- and national-level market shares are positively associated with the existence of competitors in conflict-affected districts. An increase in the share of competing firms by 10% leads to an increase in market share of 6.43% at the state level (column 1) and 4.36% at the national level (column 3). Even if precisely estimated, the estimated increase is somewhat smaller for the alternative measure: a 10% increase in the market power of competitors translates into an increase of 1.75% in market share at the state level (column 2) and 1.27% at the national level (column 4).[26] These results suggest that *supplier change* is indeed the relevant mechanism.

Input bundle change. Up to this point, our baseline estimates have been based on the assumption that the firm-level input bundle is given, i.e., it is exogenous to exposure to conflict. In this subsection, we provide preliminary evidence that firms do indeed adjust their inputs as a result of exposure to conflict. Thus, we estimate whether contemporaneous and past exposure to conflict leads to a change in input bundle, while restricting the sample to firms not located in a conflict-affected district. To determine whether a firm changes its input bundle over time, we make use of the ASI data on a firm's 10 main intermediate inputs.[27] We therefore estimate the following equation at the firm level:

$$Y_{i,k(d,t)} = \beta\,\gamma\, \text{Exposure-peace-area}_{i(d,t)} + \mathbf{D'_{i(d,t)}}\alpha + \theta_d + \theta_{ct} + \varepsilon_{i,k(d,t)} \tag{6}$$

where $Y_{i,k(d,t)}$ is equal to 1 if the firm i has a different input bundle than in the previous year surveyed and

[25] For the sake of simplicity, the specification's subscripts for district d, state c and industry s are omitted since each firm is nested within a higher category (e.g., a firm is nested within a specific district, state and industry throughout time).

[26] Note that the dependent variable in columns 3 and 4 is the economy *sales vector* as defined in Acemoglu et al. (2012) that coincides with the *influence vector* (introduced in Section 5). This vector tells us which firms play a "central" role in the network representation of the economy and consequently play a more important role in determining aggregate output. The results are thus consistent with the intuition that distortions experienced by certain firms in the economy might mean that other producers are gaining "centrality".

[27] Although the data on firm's products and intermediate inputs is relatively detailed, it does not allow us to calculate a perfect input bundle change measure. This is because the ranking of the 10 most important inputs might vary over time due to unforeseen circumstances, such as an exogenous shock to international price levels.

Table 3: Supplier change

Dep. var.	——— Market share ———			
	— state-level —		— country-level —	
	(1)	(2)	(3)	(4)
% of competitor firms, conflict areas	0.643^a		0.436^a	
	(0.022)		(0.012)	
Market share of competitors, conflict areas		0.175^a		0.127^a
		(0.009)		(0.006)
Firm controls	——— yes ———			
Product FE	——— yes ———			
District FE	——— yes ———			
State × year FE	——— yes ———			
Observations	210,778	210,778	210,778	210,778
R-squared	0.418	0.411	0.309	0.279

Note: ^{c} significant at 10%; ^{b} at 5%; ^{a} at 1%. Standard errors are clustered at district × year level. Market share is defined as sales of the firm i for product p over the total sales at the state × year level (columns 1-2) or alternatively at the country × year level (columns 3-4). The alternative competitors measures are defined in the main text. Firm controls include (log) input prices (intermediate inputs, wages, and interest rate), (log) TFP, and time-varying input bundle fixed effects (defined at the 2-digit level). Product (defined at the 4-digit level), district, and state × year fixed effects are included. See main text for more details and Table 5 for descriptive statistics.

Exposure-peace-area$_{i(d,t)}$ captures the effect of conflict on firms not located in a conflict-affected district by way of the production network. We include district (θ_d) and state×year (θ_{ct}) fixed effects, and firm-specific characteristics $\mathbf{D'_{i,t}}$: wages, interest rate, input prices, TFP all in log-terms, and (time-varying) input bundle fixed effects. Finally, standard errors are clustered at district × year level. The results point to a positive and significant effect for contemporaneous exposure to conflict by way of the production network on input bundle change in the case of firms not located in a conflict-affected district (Table 4, column 1) and similarly for past exposure (Table 4, column 2).

5 Conceptual Framework

In this section, we outline a static model of perfect competition with heterogeneous firms in a production network in the spirit of Hsieh and Klenow (2009) and Acemoglu et al. (2012). The model is able to capture two crucial aspects of the impact of conflict on firm activity: (i) how the behavior of firms located in an area of conflict is affected; and (ii) how the distortions due to conflict spread by means of the production network, thus affecting firms outside the areas of conflict. Combining these two effects makes it possible to calculate the aggregate loss suffered by the entire economy.
The economy is populated by a representative household that is endowed with one unit of labor, which is supplied inelastically, and that owns one unit of capital. This household has Cobb-Douglas preferences over N distinct goods:

$$u(c_1, c_2, ..., c_N) = \prod_{i=1}^{N} (c_i)^{\frac{1}{N}} \tag{7}$$

Table 4: Input bundle change

Dep. var.	—— Input bundle change ——	
	(1)	(2)
Exposure, peaceful areas t	0.035^a	0.088^a
	(0.012)	(0.018)
Exposure, peaceful areas $t-1$		0.009
		(0.019)
Firm controls	——— Yes ———	
District FE	——— Yes ———	
State × Year FE	——— Yes ———	
Observations	175,198	88,126
R-squared	0.275	0.377

Note: ^{c} significant at 10%; ^{b} at 5%; ^{a} at 1%. Standard errors are clustered at the district × year level. Input bundle change equals 1 when the firm has changed its inputs bundle composition compared to the previous year according to the 5-digit product classification code. *Exposure, peaceful areas* is a firm-level continuous measure calculated according to Equation 3. Firm controls include (log) input prices (intermediate inputs, wages, and interest rate), (log) TFP, and time-varying input bundle fixed effects (defined at the 3-digit level). Product (defined at the 4-digit level), district, and state × year fixed effects are included. District, and state × year fixed effects are included. See main text for more details and Table 5 for descriptive statistics.

where c_i is consumption of good by firm i. We assume that the household consumes the same fraction $\frac{1}{N}$ of each good. These N goods, produced by N heterogeneous firms, are either consumed by the representative household or used by other firms as intermediate inputs. Each firm i has a constant returns-to-scale Cobb-Douglas technology whose inputs are capital, labor and intermediate goods:

$$y_i = \tilde{a}_i (k_i^{\gamma} l_i^{1-\gamma})^{\alpha} \mathbf{x}_i^{1-\alpha} \tag{8}$$

where $\tilde{a}_i$ is firm's productivity, which is the product of two components: (i) a firm-specific component a_i, (ii) a time-varying state-specific component Γ_{ct}. The latter is assumed to depend on the quality of institution at the state level, along the lines articulated by Boehm and Oberfield (2020). Firm i's intermediate goods basket is a Cobb-Douglas composite given by:

$$\mathbf{x}_i = \prod_j x_{ji}^{\omega_{ji}}$$

where x_{ij} is the amount supplied by firm j. The exponent $\omega_{ji} \geq 0$ is the share of good j within firm i's total use of intermediate inputs. In particular, $\omega_{ji} = 0$ if firm i does not use good j as input. We assume that $\sum_{i \in j} \omega_{ji} = 1$ for every i.[28]

Effect on firms in areas of conflict. As described in Section 2.2, firms located in areas of conflict are more likely to incur additional costs, such as loss from theft, payment of protection money, or additional expenditure on security. When modeling the behavior of firms located in an area of conflict, we take into account all of the aforementioned distortions, which can be output-specific or input-specific. In particular, if

[28]This condition guarantees that production technology exhibits constant returns to scale.

firm i is located in a conflict-affected district, it then maximizes profits according to the following equation:

$$\max_{k_i,l_i,x_{ji}} \pi_i = (1-\tau_{y,i})p_i y_i - (1+\tau_{kl,i})(Rk_i + hl_i) - (1+\tau_{x,i})\sum_j p_j x_{ji} \tag{9}$$

where p_i is firm i's output price; R, h, and p_j are the exogenous input prices of capital, labor and intermediate inputs, respectively; and the different τ's represent conflict-induced idiosyncratic distortions. As in Hsieh and Klenow (2009), we denote output distortions by $\tau_{y,i}$, and input distortions by $\tau_{kl,i}$ and $\tau_{x,i}$. In this way, we account for multiple ways in which Maoist activity can impact firms located in a conflict-affected district, as discussed in Section 2.2.[29]

Profit maximization yields the standard condition that the firm's output price is equal to its marginal cost:

$$p_i = \left[\left(\frac{R}{\gamma\alpha}\right)^{\gamma}\left(\frac{h}{(1-\gamma)\alpha}\right)^{1-\gamma}\right]^{\alpha}\left[\prod_j\left(\frac{p_j}{\omega_{ji}(1-\alpha)}\right)^{\omega_{ji}}\right]^{1-\alpha}\frac{(1+\tau_{kl,i})^{\alpha}(1+\tau_{x,i})^{1-\alpha}}{\tilde{a}_i(1-\tau_{y,i})} \tag{10}$$

This expression suggests that conflict-induced distortions increase the firm's optimal price. In what follows, we show that the increase in p_i due to conflict leads to each buyer j reducing its demand for good y_i and therefore reducing its output of good y_j accordingly.

The impact on firms not located in areas of conflict. At the core of the analysis is the central role played by the production network in the propagation of the distortions experienced by firms in areas of conflict among firms outside those areas. Recall that a firm's output can either be consumed by the representative household or used by other firms as an input for production.

For example, consider firm i and firm j: if firm i's output appears in firm j's input bundle, then the share of good i within the total intermediate inputs used by firm j is positive and given by ω_{ij} (Equation 8). Note that at the level of the economy, the parameters ω_{ij} correspond to the entries of the $N \times N$ input-output matrix Ω, where N is the total number of firms in the economy. The rows of Ω sum up to one because we assume constant return-to-scale technology. The sum of each column of Ω represents firm-level weighted outdegree, i.e., the share of firm i's output within the total inputs used by the other firms in the economy (Acemoglu et al., 2012). The increase in firm i's price, p_i, due to conflict (Equation 10) implies that firm j will reduce its demand for x_i, and will therefore reduce its output accordingly. To see this, consider firm j's output in log form:

$$\begin{aligned} log(y_j) &= log(\tilde{a}_j) + \alpha\gamma log(k_j) + \alpha(1-\gamma)log(l_j) \\ &\quad + (1-\alpha)(\omega_{1j}log(x_{1j}) + ... + \omega_{ij}log(x_{ij}) + ... + \omega_{Ni}log(x_{Ni})) \end{aligned} \tag{11}$$

where x_{ij} is the output produced by firm i and ω_{ij} the share of good i within the total intermediate inputs used by firm j. Equation 11 suggests that any distortion experienced by firm i affects firm j's output, which decreases by a proportion of $(1-\alpha)$ ω_{ij}. This is the first-order propagation effect of conflict through the production network. Specifically, the increase in firm i's output price due to conflict implies that firm j, whose input bundle includes firm i's output, will reduce its demand for firm i's output, thus reducing its

[29] The existence of a large variety of output and input distortions in documented in the literature (see, for example, Amodio and Di Maio (2018) and Besley and Mueller (2018)).

own output proportionally. We summarize this first-order effect as follows:

$$(1-\alpha)[\omega_{i1}, ..., \omega_{iN}] = (1-\alpha)\Omega_i'$$

where Ω_i' is the i^{th} column of the matrix Ω.
Importantly, this is not the end of the adjustment. All firms whose input bundle includes firm j's output are subject to a second-order effect of distortions experienced by firm i. This is captured as follows:

$$(1-\alpha)^2[\omega_{i1}, ..., \omega_{iN}]^2 = (1-\alpha)\Omega_i'^2$$

Continuing in this fashion with higher-order effects, the impact of conflict-induced distortions experienced by firm i on the entire economy is given by:

$$\sum_k^{\infty}(1-\alpha)^k(\Omega_i')^k = \left(\left[I-(1-\alpha)\Omega'\right]^{-1}\right)_i'$$

which is the i^{th} column of Leontief inverse matrix. Finally, if we consider all firms impacted by conflict-induced distortions, we derive the *influence vector*, which captures the total effect of conflict by way of the production network. Its ith element represents the cumulative effect of a shock to firm i on the other firms in the economy. The influence vector is expressed as follows:

$$v = \frac{1}{N}\left[I-(1-\alpha)\Omega'\right]^{-1}\mathbf{1} \tag{12}$$

where $\mathbf{1}$ is a vector of ones. Since we are applying the model proposed by Acemoglu et al. (2012) in the context of civil conflict, we can exploit their results by expressing (log) aggregate output as a weighted sum of firm-level productivity, in which the weight is given by the influence vector.[30] (Log)-aggregate output is:

$$\mathbf{Y} = v'\epsilon + \mu \tag{13}$$

where v is the influence vector, ϵ is a vector containing (log) firm-level productivity and conflict related distortions (experienced by firms directly exposed to conflict), and μ is a constant independent of vectors ϵ and v. As noted in Acemoglu et al. (2012), the influence vector is closely related to the *Bonacich centrality vector*. Therefore, firms that occupy more "central" positions in the network play a more important role in determining aggregate output.
Since our goal is to quantify the aggregate output loss due conflict, our main interest is to calculate the *percentage change* of aggregate output, which is expressed as follows:

$$\Delta\mathbf{Y} = v'\xi \tag{14}$$

where vector ξ contains firm-specific cost of conflict. The entries of ξ for firms not located in areas of conflict are equal to zero, while the entries for firms located in areas of conflict are a function of conflict-induced distortions, i.e., $\tau_{y,i}$, $\tau_{kl,i}$, and $\tau_{x,i}$, whose estimation is described in Section 6.2.

[30] The proof that Equation 13 characterizes the equilibrium of this economy is developed in Acemoglu et al. (2012) in their Appendix A.

6 The Aggregate Output Loss due to Conflict

In this section, we apply the theoretical model to the data. In the first stage, we use plant-level data and information on the locations of conflict in order to quantify the losses suffered by firms in conflict-affected districts. We then use this estimate to measure the output loss of the entire Indian economy due to the Maoist insurgency. We consider in turn three possible mechanisms through which localized conflict can affect the performance of firms not located in conflict-affected districts. In particular, buyers that purchase inputs from suppliers in conflict-affected districts have three alternatives: (i) to continue buying inputs from the supplier affected by conflict (*inaction*), (ii) to buy the same inputs from a supplier located in a peaceful district (*supplier change*), or (iii) to modify their input bundle and purchase different inputs from suppliers in peaceful districts (*input bundle change*).

6.1 The cost of conflict in conflict-affected districts

The first stage of the structural estimation is aimed at measuring the additional cost to firms located in conflict-affected districts, or in other words determining the vector ξ which is a function of the conflict-induced distortions $\tau_{y,i}$, $\tau_{kl,i}$, and $\tau_{x,i}$. We start by expressing firm-level optimal prices (Equation 10) in log form since they are the source for the propagation throughout the economy:[31]

$$\begin{aligned}\log(p_i) = &\log\left(\left[\left(\frac{1}{\gamma\alpha}\right)^{\gamma}\left(\frac{1}{(1-\gamma)\alpha}\right)^{1-\gamma}\right]^{\alpha}\left[\left(\frac{1}{1-\alpha}\right)\right]^{1-\alpha}\right) \\ &+\log\left(\frac{(1+\tau_{kl,i})^{\alpha}(1+\tau_{x,i})^{1-\alpha}}{1-\tau_{y,i}}\right) \\ &+\alpha\gamma\log(R)+\alpha(1-\gamma)\log(h)+(1-\alpha)\sum_j \omega_{ji}\log\left(\frac{p_j}{\omega_{ji}}\right) \\ &-\log(a_i)-\log(\Gamma_{ct})\end{aligned} \tag{15}$$

Since it is not feasible to quantify the three conflict-induced types of distortions separately using OLS, we estimate a *comprehensive index* of conflict-induced costs, which is a function of firm-level distortions $\tau_{y,i}$, $\tau_{kl,i}$, and $\tau_{x,i}$. Note that the only element of Equation 15 that depends on conflict-induced distortions is the second addend of the RHS. Assuming that conflict affects all firms in conflict-ridden districts in the same way, we can take advantage of the richness of the data to estimate the following equation:

$$y_{i(d,t)} = \alpha + \beta conflict_{(d,t)} + \eta_1 x_{1,i(d,t)} + \eta_2 x_{2,i(d,t)} + \eta_3 x_{3,i(d,t)} + \gamma\log(TFP)_{i(d,t)} + \theta_{ct} + u_{i(d,t)} \tag{16}$$

where the dependent variable is the (log) optimal price charged by firm i, which is located in district d and observed at time t. The constant α represents the first term of the RHS of Equation 15, which is a combination of factor shares. The variables $x_{1,i(d,t)}$, $x_{2,i(d,t)}$, and $x_{3,i(d,t)}$ are the (observed) firm-level prices of capital, labor, and intermediate inputs, respectively. Finally, we control for firm-level (log) TFP and state-year fixed effects θ_{ct}, since we allow firm productivity to be impacted by state-specific time-varying

[31] Note that, in principle, we could approximate these distortions using the results presented in Table 2. However, Equation 4 is not the best specification for our purposes, since it includes the effect of conflict for firms located in peaceful districts by way of the production network (which represents the first-degree indirect impact of conflict). Since we wish to distinguish between the *overall* indirect effect of conflict, i.e., including first-order and all possible higher order effects, and the direct effect of conflict, we calculate the latter using the predictions of our theoretical model.

characteristics (Boehm and Oberfield, 2020). The key variable is $conflict_{(d,t)}$ which takes a value of 1 if conflict has occurred in district d at time t. Thus, the estimate of β captures the effect of conflict incidence on the value of output of firms located in conflict-affected districts. As described in Section 5, conflict-induced distortions lead to an increase in firm's optimal price (Equation 10), and therefore, we expect $\hat{\beta}$ to be positive. And indeed the results show that $\hat{\beta}$ equals 0.077 (s.e. = 0.032) and that it is statistically significant. In what follows, we use $\hat{\beta} = 0.077$ as a proxy for the increase in price charged by suppliers located in conflict-affected districts, which in turn reduces the demand for their output among their buyers; this continues as a ripple effect throughout the production network. We also estimate $\tau_{y,i}$, $\tau_{kl,i}$, and $\tau_{x,i}$ separately through a GMM estimation strategy and reassuringly, the magnitude of the distortions is comparable to that in the baseline estimation.[32]

6.2 Aggregate output loss

Baseline specification. In the second stage of the structural estimation, we measure the loss in aggregate output suffered by the Indian economy due to the Maoist insurgency between 2000 and 2009. For each year, we quantify the loss as the product of the annual conflict cost vector ξ_t (whose estimation is described in Section 6.1) and the annual influence vector v_t, which is derived from the matrix defining the production network Ω_t (Equation 12).[33,34] In this setup, the annual output loss is the sum of the *inaction*, the *supplier change*, and the *input bundle change* effects.

Our results suggest that during the period 2000-2009, the annual average loss due to conflict was equal to 1.91% and that only 27% of this loss can be explained by the direct impact of conflict in the affected districts (see Table 11 for the annual losses).[35] Importantly, the remaining 73% of the loss depends on the spread of a

[32] The GMM estimation relies on the finding of Hsieh and Klenow (2009) that idiosyncratic distortions increase the dispersion of TFP. We estimate the three parameters τ_y, τ_{kl}, and τ_x in an overidentified model that uses the state-level standard deviation of TFP as moment conditions. According to our results, $\hat{\tau}_y$ equals 0.05, $\hat{\tau}_{kl}$ equals 0.01, and $\hat{\tau}_x$ equals 0.04.

[33] The inverse of the Leontief matrix, $[I - (1-\alpha)\Omega_t']^{-1}$, is calculated using the estimated weight α ($\hat{\alpha} = 0.26$) obtained from the estimation of the firm's production function with plant-level data following Wooldridge (2009).

[34] The way in which we construct the influence vector depends on our approximation of the input-output network, which relies on Equation 2. The absence of information on firm-to-firm transactions rules out an in-sample validation of the method. Nonetheless, we corroborate the robustness of our strategy in three ways: First, we look at the distribution of the weighted outdegree of each firm i, defined as the share of firm i's output in the input supply of the entire economy, calculated using the column sum of the input-output matrix Ω. The shape of the yearly distribution of the weighted outdegree is comparable with that appearing in Carvalho (2014) (although specific quantile values differ because our statistical unit is firm whereas the statistical unit is sector in Carvalho (2014)). Second, and as shown in Acemoglu et al. (2012), the influence vector coincides with the *sales vector*, i.e., $v_i = \frac{p_i y_i}{\sum_{j=1}^{N}(p_j x_j)}$, which can be easily calculated with our data. For each year t, the correlation coefficient between the constructed influence vector and the observed sale vector is positive and fairly high, i.e. around 0.4. Finally, for each year, we regress the sales vector on the influence vector (without adding any controls) and find that the R^2 is firmly in the vicinity of 0.15.

[35] Note that, as explained in Section 3, the entries of the input-output matrix Ω, which is used to quantify the aggregate loss, are the observed input shares of firm i, i.e., ω_{ki}, weighted by $\rho_{ji(k)}$, the importance of every possible supplier j of k. The calculation of the former component, $\rho_{ji(k)}$, assumes that the elasticity of bilateral trade with respect to distance is equal to -1. However, its actual value might of course be less than that. Therefore, we calculate four versions of input-output matrix Ω, in which $\rho_{ji(k)}$ is measured assuming an elasticity of trade with respect to distance equal to -2, -3, -4, and -5, respectively. The corresponding estimates of aggregate output loss range from 1.77% to 1.86%, which is not substantially different from our baseline results. Moreover, we estimate the aggregate output loss using an alternative specification of $\rho_{ji(k)}$, which combines the relative inverse distance between each buyer-supplier pair and the relative size of each potential supplier in a non-linear way as follows:

$$\rho_{ji(k)} = \frac{\frac{D_{ji}}{\sum_{j\in J} D_{ji}} \times \frac{k_j}{\sum_{j\in J} k_j}}{\sum_{j\in J}\left(\frac{D_{ji}}{\sum_{j\in J} D_{ji}} \times \frac{k_j}{\sum_{j\in J} k_j}\right)}$$

conflict's effects to peaceful districts by way of the production network. If this propagation is not taken into account, the aggregate impact of conflict would be significantly underestimated (yielding an average annual loss of only 0.52%). Using data from the World Bank Development Indicators (World Bank, 2021) for value added in Indian manufacturing (in constant 2010 USD), we calculate the average loss in monetary terms to be 3.8 billion USD per year (Table 12).

Since conflict-induced distortions are estimated rather than observed, we also measure the average annual loss for a wide range of conflict distortion values: from 0 to 0.2 (Figure 3). The solid blue line represents the average annual loss for each possible value of conflict distortion; the dotted black line corresponds to our original estimate ($\hat{\beta}$); and the dotted red lines represent confidence bands given by $\hat{\beta} \pm 1s.e.$ The average annual loss varies from 0 to 5% (corresponding to a range of 0-9.3 billion USD per year) for the entire range of distortions and from 1.1% to 2.7% when using the confidence interval of our original estimate. Finally, Figure 4 presents the cumulative loss suffered by the Indian economy during the ten years of conflict, which is more than 19% (blue line). This loss corresponds to a total cost of approximately 38 billion USD (Table 12).

These results rely on the assumption that firm-level intermediate inputs enter into firm-level production functions as a Cobb-Douglas aggregate of good k, $k = N$. This implies that the elasticity of substitution between any version of input k (produced by different suppliers $j \in J$) is equal to 1. In Appendix D, we relax this assumption and assume that each input k, produced by a set of J producers, is a CES aggregate with elasticity of substitution $\sigma > 1$. We simulate the average output loss by letting σ vary from $1 + \epsilon$ (with ϵ close to 0) to 10. We find that the average annual loss decreases as the elasticity of substitution σ increases. It declines rapidly for $1 < \sigma < 3$ (for example, if $\sigma = 2$ the average annual loss is halved) and then converges to an annual loss of 0.8%, where it remains stable.

Inaction effect. We compute the yearly output loss in the scenario where conflict does not lead to any network adjustment. In this case, producers do not change their suppliers and thus bear the indirect costs of conflict. To quantify the annual output loss, we assume that the initial network structure (i.e. the input-output matrix for the year 2000) does not change over time, while allowing the direct exposure to conflict to change over time according to the data. In practice, we estimate the annual output loss as follows (Equation 14): $\Delta \mathbf{Y}_t = v'_{2000} \times \xi_t$ with $t = [2000, ..., 2009]$ where v_{2000} is the influence vector calculated for 2000 and ξ_t contains the conflict-induced distortions for the period 2000-2009.[36]

The average annual loss is calculated to be 2.96%, which corresponds to an average monetary loss of almost 5.5 billion USD per year (Table 12 and Figure 3, red dot-dashed line). The cumulative loss during the period 2000-2009 is 29.64%, which is equivalent to almost 55 billion USD (Figure 4, red line). These results suggest that allowing for network adjustment (even if only partial) through supplier change and input bundle change substantially reduces output loss. Thus, the average annual loss estimated from our baseline specification is approximately two-thirds of that arrived at in this scenario.

Supplier change & input bundle change effects. Relaxing the assumption of the absence of reshuffling of the production network, we now allow firms to substitute suppliers of inputs located in conflict-affected districts with suppliers of those same inputs located in peaceful districts (the *supplier change* effect). To simulate this network adjustment, we construct an alternative input-output matrix $\tilde{\Omega}_t$ where buyers do not

The estimated aggregate output loss equals 1.82%. We omit the subscript t to simplify the notation.

[36]For the sake of precision, we add firms observed starting from year 2001 to v_{2000}. We adopt this strategy in order to maximize the number of firms tracked over time.

purchase inputs from suppliers located in districts that have been affected by conflict for two or more years. In practice, we construct the input-output matrix by setting the measure of the supplier's importance, $\rho_{ji(k)}$, to zero. In other words, allowing for network adjustment implies that, at $t+1$, we force every buyer to change its supplier as long as that supplier has been impacted by conflict at both $t+1$ and t. We then consider two alternative scenarios: (i) the network adjustment involves only the *supplier change* effect; and (ii) the network adjustment involves both the *supplier change* effect and the *input bundle change* effect.

In the first scenario, and given that we want to rule out the *input bundle change* effect, we calculate the annual output loss as the product of the influence vector derived from the adjusted input-output matrix for 2000, i.e., $\tilde{v}_{2000}$ from $\tilde{\Omega}_{2000}$ (which we construct using conflict data prior to 2000), and the conflict-cost vector ξ_t for the period 2000-2009. In other words, we rely on the assumption that the input-output matrix characterizing the Indian economy remains unchanged from 2000 until 2009. Unfortunately, we are not able to fully rule out the *inaction* effect because if all the suppliers of a given input are located in conflict-affected districts, then there is no possibility for adjustment.

The resulting average annual loss is 2.34%, which corresponds to a monetary loss of 4.52 billion USD (Table 12, and Figure 3, yellow dotted line), while the cumulative loss is approximately 23.37% (Figure 4, yellow line) which corresponds to a cumulative monetary loss of approximately 45.2 billion USD.

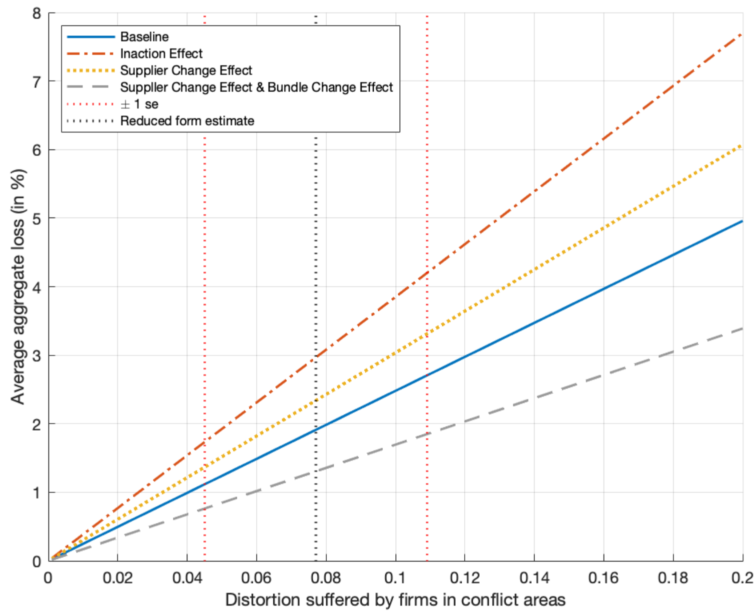
The second scenario of network adjustment encompasses both the *supplier change* effect and *input bundle change* effect. We calculate the annual loss as the product of the annual adjusted influence vector $\tilde{v}_t$ and the annual cost-of-conflict vector ξ_t. The results suggest that allowing buyers to switch suppliers or to alter their input bundles reduces the output loss substantially. Indeed, the average annual loss is now only 1.31%, which corresponds to a loss of almost 2.6 billion USD per year (Table 12 and Figure 5, dashed grey line) while the cumulative loss during the period 2000-2009 is approximately 13% (Figure 4, grey line).

Heterogeneous direct effect of conflict. We have so far assumed that conflict affects all firms located in a conflict-affected district in the same way. As a result, β in Equation 16 represents the average impact of conflict which is common to every firm located in a conflict-affected district. In what follows, we instead assume that Maoist groups target their attacks against specific groups of firms. More specifically, we let the proportion of firms located in a conflict-affected district that are affected by the conflict to vary between 10% and 90% (i.e., we allow for $\alpha \in [0.1, 0.9]$, whereas in Section 6.2 we assume that $\alpha = 1$). We also assume the Maoist targeting rule is correlated with firm size (measured by number of employees) and divide firms into three categories according to the size distribution. For example, if Maoist groups target large firms, then we might set $\alpha = 0.1$ which means that firms above the 90th percentile in the firm size distribution are subject to conflict-induced distortions. If, instead, Maoist groups target small firms, then we might set $\alpha = 0.3$ which means that firms below the 30^{th} percentile of the firm size distribution are subject to conflict-induced distortions. Finally, if Maoist groups target middle-sized firms, then we might set $\alpha = 0.5$ which implies that firms between the 25^{th} and 75^{th} percentile of the firm size distribution are subject to conflict-induced distortions. We measure the direct loss suffered by impacted firms, i.e. $\tilde{\beta}$, using the estimate of conflict-induced distortions obtained in Section 6.1. We now re-scale $\hat{\beta}$, which is equal to 0.077, as follows:

$$\begin{aligned} \hat{\beta} &= \alpha \times \tilde{\beta} + (1-\alpha) \times 0 \\ \Rightarrow \tilde{\beta} &= \frac{\hat{\beta}}{\alpha} \end{aligned} \tag{17}$$

Therefore, when $\alpha = 1 \Rightarrow \tilde{\beta} = \hat{\beta}$, and $\tilde{\beta}$ increases as α decreases.

Figure 3: Yearly average loss due to conflict



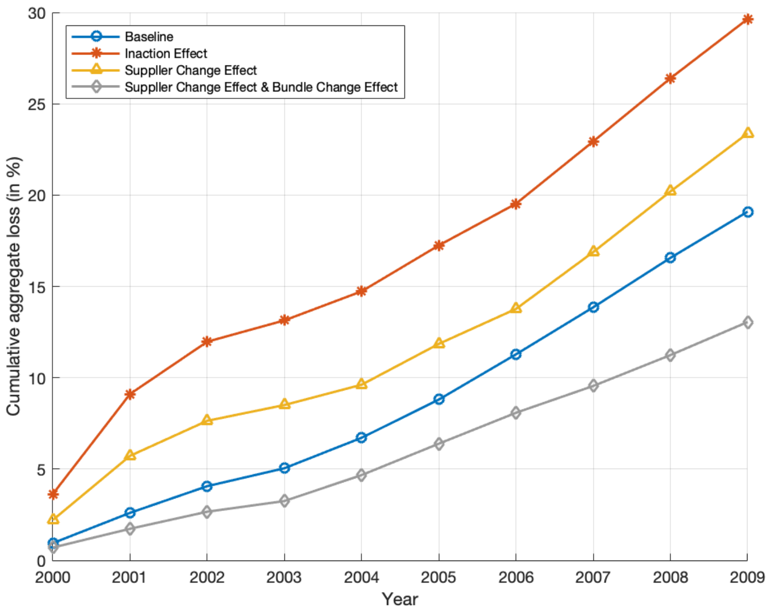
Note: this figure depicts yearly average loss (in %) for a range of conflict distortion's values that goes between 0 and 0.2. The blue solid line concerns our baseline specification, in which we let the *inaction*, *supplier change*, *input bundle change* effects play a role simultaneously. The dash-dotted red line refers to the *inaction* effect alone. The grey dashed line concerns the scenario where both *supplier change* and *input bundle change* effects are present. The yellow doted line concerns the *supplier change* effect alone. The dotted black line indicates the original estimate of conflict-induced distortions ($\hat{\beta}$ Section 6.1). The dotted red lines represent the confidence bands given by $\hat{\beta} \pm 1 s.e.$

Figure 5 reports the results for the baseline scenario. The blue line represents the aggregate output loss as the proportion of impacted firms varies in the case that Maoist groups target small firms (where each dot represents the loss relative to each value of α). The red line represents the scenario in which middle-sized firms are targeted while the yellow line represents the scenario in which large firms are targeted (asterisks in the red line and triangles in the yellow line represent the aggregate loss for each value of α). According to Figure 5, if Maoist groups target middle-sized firms then the average annual loss does not vary substantially with the proportion of impacted firms. In contrast, the annual loss decreases with α if the Maoist groups target small firms. Conversely, if Maoist activity is directed against large firms, then the average annual output loss increases substantially as α increases (and the extent of firm-specific costs, denoted by $\tilde{\beta}$, increases according to Equation 17). This last result is of particular relevance because Maoist groups are more likely to attack large firms (Section 2) which implies that the estimate of aggregate output loss due to the Maoist insurgency represents a lower bound on the actual loss.

7 Policy Experiments

In this section, we use the structural model to examine several counterfactuals. The aim is to analyze the potential effectiveness of policies designed either to prevent conflict or to promote interventions, whether military, institutional or diplomatic, that can reduce the costs incurred by impacted firms and facilitate domestic trade. Our main assumption is that the policymaker's objective is to minimize the costs of both

Figure 4: Cumulative loss from 2000 to 2009



Note: This figure depicts the cumulative aggregate loss (in %) suffered by the Indian economy during the period 2000-2009. The blue line represents the baseline estimate, which includes *inaction*, *supplier change*, and *input bundle change* effects, where each dot represents the cumulative loss for a specific year. The red line represents the scenario in which only the *inaction* effect plays a role, where the asterisks correspond to the cumulative loss for each year. The yellow line represents the scenario of only the *supplier change* effect, while the gray line represents the scenario with both the *supplier change* effect and the *input bundle change* effect.

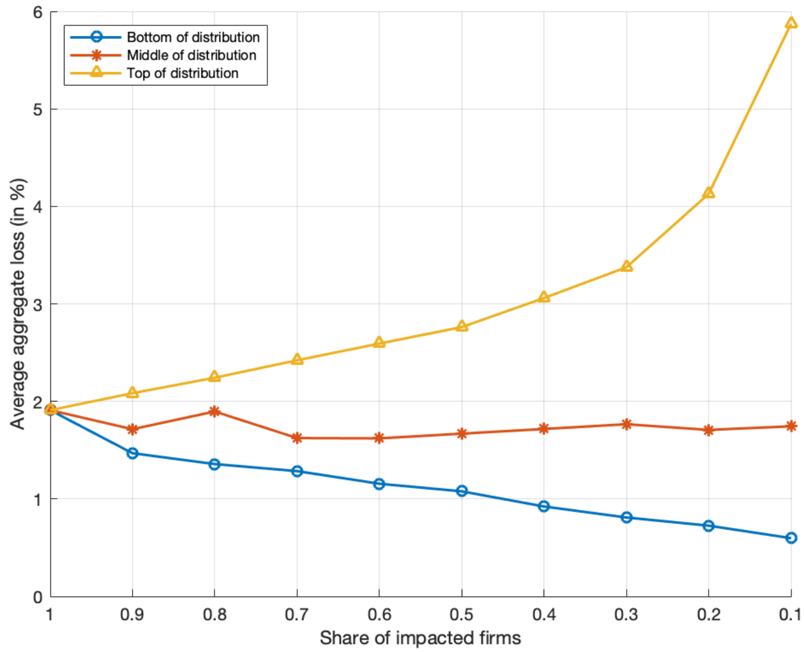
conflict and policy interventions. In this context, we estimate two types of policies: (i) preventing the spread of conflict to neighboring districts, and (ii) facilitating trade within conflict-affected districts and between them and peaceful districts.

Preventing the spread of conflict. In our baseline estimate, the Maoist insurgency has been responsible for an average annual output loss of 1.91%. Since accurate data on the costs and effectiveness of prevention policies are hard to come by (Mueller and Rauh, 2021), a different approach to preventing the spread of conflict is needed. We therefore examine a scenario in which firms located in adjacent districts are also affected by the activity of Maoist groups. In this case, a total of 90 districts (out of 492) would now be directly affected by the insurgency. The results point to a surprisingly large increase of 55% in the total loss due to the conflict (Table 12) relative to the baseline specification (2.95% vs. 1.91%), which translates into an average monetary cost of more than 5.9 billion USD per year. This result suggests that any policy to prevent conflict whose price is less than 2.1 billion USD, i.e., the difference in annual output loss between the two scenarios, is likely to be worthwhile.

Trade facilitation in conflict-affected districts. The goal of this simulation is to understand which firms in conflict-affected districts would be most worthwhile protecting in order to preserve trade connections and prevent losses to those firms and, at the same time, avoid the propagation of conflict-induced distortions in the rest of the economy.[37] This is particularly relevant when policy makers have limited resources to

[37] A policy to protect firms can take different forms, such as subsidization of security costs or military intervention in strategic districts.

Figure 5: The annual average loss due to conflict with heterogeneous direct effect



Note: The blue line plots the average annual loss which varies according to the proportion of impacted firms $\alpha \in [0, 1]$ when Maoist groups target small firms; the red line represents the scenario in which attacks are directed at middle-sized firms; and the blue line represents the scenario in which violence is directed at large firms. Note that the x-axis is reversed.

invest in the protection of these firms and must prioritize between them.

For the purpose of exposition, we assume that the objective of the policy maker is to halve the average annual loss, i.e., from 1.91% to 0.95%. One possibility is to randomly choose 50% of the firms located in conflict-affected districts. However, there are alternatives that could achieve the same result while protecting a smaller proportion of firms and therefore this is not an optimal policy. We therefore consider two alternative interventions.

In the first, resources for protection would be provided to firms that play a more "central" role in the economy. Therefore, we estimate the average annual output loss as the inclusion of firms is broadened – starting from the most important firms and ending with the least. We measure the centrality of a firm using the influence vector v (see Section 5). Figure 6 shows the simulated average annual loss according to the proportion of firms provided with protection (between 0 and 100%). It can be seen that the greatest benefit is achieved when resources for protection are allocated to the most important firms. In particular, the average annual output loss is halved when resources are allocated to the top 4% according to the influence vector distribution.

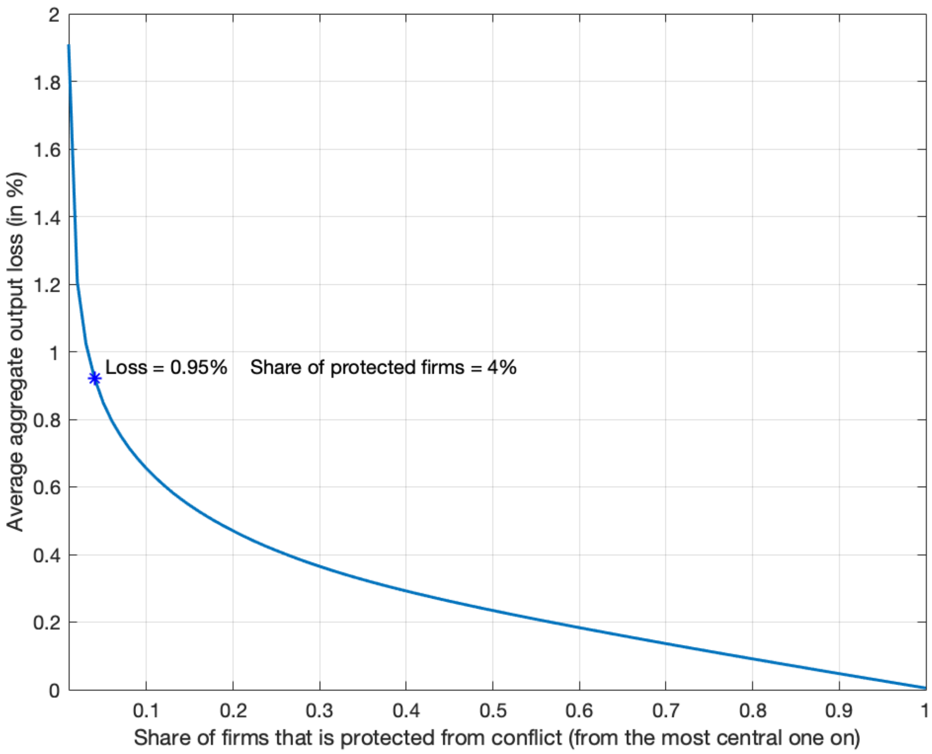
In the second alternative, we assume that the policy maker wishes to protect certain clusters of firms. This might be relevant if a given good k is produced primarily by firms located in conflict-affected districts.[38] We assume that a certain proportion of a good k is produced by at least one firm located in a conflict-affected district and define a *threshold for protection*, above which firms will be allocated resources for protection. We consider a policy intervention that relies on this threshold: the policy maker chooses a given *threshold for*

[38]The data suggest that there are several goods produced entirely by firms located in conflict-affected districts, including tobacco (Virginia), tobacco oil, natural asphalt, absorbent paper, spun silk yarn, and unblended wool.

protection and allocates resources for protection to all conflict-affected firms that produce goods whose share of production in conflict-affected districts is equal to or larger than this threshold. We allow the threshold to vary between 0 and 100% and calculate the corresponding average annual losses. Then, for each value of the threshold, we calculate the proportion of firms (in conflict-affected districts) that would be allocated resources for protection.

As can be seen from the top panel of Figure 7, adopting a threshold of 7% would halve the average annual output loss. In other words, resources for protection would be allocated to firms in conflict-affected districts when they account for at least 7% of total production. The bottom panel of Figure 7 suggests that 42% of the relevant firms would be allocated resources for protection. Therefore, this alternative would be significantly more costly than the one based on firm-level centrality, which would allocate resources for protection to only 4% of firms in conflict-affected districts.

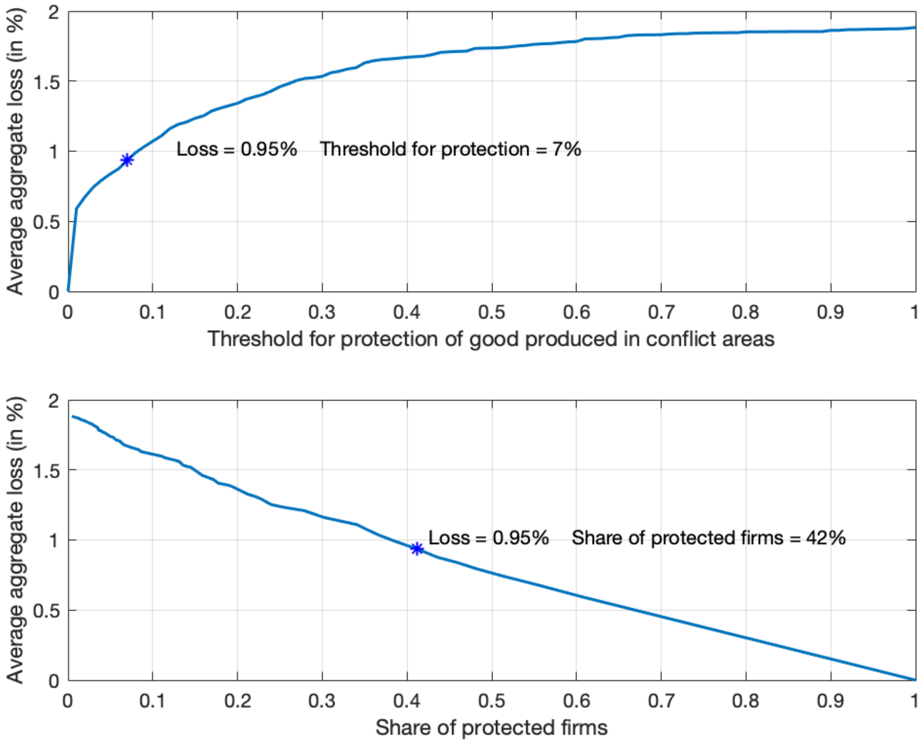
Figure 6: Protection policy - firm-level centrality



Note: This figure presents the results of a policy experiment in which the importance of a firm in the production network, according to the influence vector v (Equation 12), is used as the criterion to allocate resources for protection. We assume that the policy maker first prioritizes the most important firms and progressively adds less important ones. The blue line represents the simulated average aggregate loss as the proportion of firms provided with protection varies from 0% to 100%.

Trade facilitation in peaceful districts. We now examine the benefit of facilitating trade (subsidizing transportation costs, repairing infrastructure, such as roads and railways, that have been damaged by conflict, etc.) with firms located in peaceful districts. In this simulation, we examine the results from the opposite perspective. In other words, we measure output loss as the elasticity of trade with respect to distance between any buyer-supplier pair in the production network decreases, while allowing for network adjustment (i.e., while accounting for the supplier change and input bundle change effects, but not for the inaction effect). In

Figure 7: Protection policy - threshold for protection



Note: This figure reports results of a policy simulation based on a *threshold for protection* that varies between 0 and 1 (x-axis). For a given good k, this threshold is defined as the share of production accounted for by firms located in conflict-affected districts. The top panel shows how the aggregate loss varies with the threshold. The bottom panel shows the proportion of firms (within the total number of firms in conflict-affected districts) who will be allocated resources for protection for each possible value of the average annual loss.

Section 3, we measured the importance of each potential supplier j ($\rho_{ji(k)}$) to each buyer i of good k on the assumption that the elasticity of trade with respect to distance is equal to -1. In this simulation, we relate to -1 as a lower bound, i.e., as the most desirable situation for a policy maker, and examine the aggregate output loss when its value varies between -2 and -5. For each value and each potential buyer-supplier pair of good k, we calculate a new measure of supplier importance ($\rho_{ji(k)}$) and the corresponding input-output matrix. Moreover, we assume that network adjustment involve some cost, which we proxy using the inverse of the difference between the average distance between a buyer i and all of its possible suppliers j in the input-output matrix with network adjustment and that in the input-output matrix of our baseline model.[39] We let these costs increase linearly as the elasticity of trade with respect to distance decreases. For example, if elasticity is equal to -2, then the adjustment cost is twice that associated with an elasticity equal to -1. As shown in Table 12, the results suggest that the decrease in elasticity of trade with respect to distance and the resulting increase in adjustment costs (in the absence of any policy intervention to facilitate trade), lead to a corresponding increase in the average annual output loss. For example, when the elasticity of trade with respect to distance decreases from -1 to -3, the average annual loss increases from 1.59% (3.35 billion USD per year) to 2.15% (4.2 billion USD per year). This simulation is particularly relevant since the elasticity of

[39]Once constructed, we add this vector of firm-specific costs of adjustment to the cost-of-conflict vector. The expression of aggregate output loss is: $\mathbf{\Delta Y} = v'\tilde{\xi}$ where $\tilde{\xi} = \xi + \zeta$ and $\zeta > 0$ is the cost of network adjustment.

trade with respect to distance is likely to be low in the context of domestic trade in developing countries.

8 Concluding remarks

We develop a novel approach to quantifying the economic costs of conflict. The methodology is particularly suited to the nature of current conflicts (that is, intra-state warfare and local insurgencies) and the complexity of the economic setting in countries affected by such conflict. We examine, both theoretically and empirically, the spread of a localized conflict's effects to peaceful areas through the disruption of the supply chain. The methodology is applied to the Maoist insurgency in eastern India using a rich firm-level dataset of manufacturers which is combined with data on the conflict. We focus on the set of firms that are directly exposed to conflict in order to quantify firm-level conflict-related distortions. We then exploit the information on each firm's output and input bundle in order to construct the input-output network that characterizes the Indian economy. This makes it possible to apply a well-established model of production networks in the context of conflict and in this case to quantify the aggregate loss due to the Maoist insurgency. In the first stage, we provide robust evidence of the negative impact of conflict on firms (a higher price for their products and a lower quantity) and that firms located in areas of conflict are more likely to be affected than other firms. Importantly, there are negative consequences also for firms located in peaceful areas that are exposed to the conflict through the production network. We then theoretically describe the mechanism through which distortions caused by a localized conflict can spread to the rest of the economy. To do so, we construct a simple static model of an input-output network in the spirit of Acemoglu et al. (2012). The model is applied to the data in order to structurally estimate the aggregate loss to the Indian economy due to the Maoist insurgency, which is found to be about 1.9% of annual aggregate output on average (equivalent to approximately 3.9 billion USD). Interestingly, only 27% of the loss can be explained by the direct impact of conflict on firms, while the remaining 73% is due to spread via the supply network to peaceful areas. Several alternative specifications of the model are examined and it is found that allowing for network adjustment through modifications of buyer-supplier connections can substantially mitigate the aggregate loss. Finally, we perform several policy experiments. It is found that policy should be directed toward: (i) preventing the spread of the conflict to neighboring districts, (ii) allocating resources for the protection of firms located in conflict-affected districts that play an important role in the supply network of the economy, and (iii) decreasing the costs of trade between firms located in an area of conflict and firms outside it. In sum, the results support the conclusion reached by Rohner and Thoenig (2021) on *a better understanding of these channels of transmission linking war to development slowdown is important to guide policy measures in a post-conflict environment.* The novelty of our approach is that it can easily be adapted to other types of conflict or to measuring the economic cost of social unrest.

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Appendices

Appendix A Data

Table 5: Descriptive Statistics

	Obs.	Mean	S.D.	Min	Max
Product and Firm characteristics					
price (log)	357,627	7.44	3.14	-5	22
quantity (log)	357,627	9.12	3.91	-5	26
labor cost (log)	357,627	14.99	2.02	7	23
interest rates (log)	357,627	14.13	2.53	0	23
intermediate inputs price (log)	357,627	9.28	1.91	-1	20
TFP (log)	357,627	-6.08	2.94	-20	11
years in activity (log)	357,627	2.65	0.94	0	5
units (log)	357,627	0.07	0.27	0	4
nb of employees (#)	357,627	295.75	1006.53	1	41774
imports (0/1)	357,627	0.26	0.44	0	1
insurance (%)	357,627	0.05	0.06	0	1
input bundle change	194,975	0.41	0.49	0	1
market share, state-level	210,895	28.43	37.87	0	100
market share, country-level	210,895	3.86	12.29	0	100
market share of competitors, conflict areas	210,895	7.45	12.39	0	100
% of competitor firms, conflict areas	210,895	7.99	8.47	0	97
Conflict-related measures					
exposure, conflict areas	357,627	0.06	0.23	0	1
exposure, peaceful areas	357,627	0.06	0.10	0	1
exposure, conflict areas (fatalities)	357,627	0.05	0.23	0	1
exposure, peaceful areas (fatalities)	357,627	0.06	0.10	0	1
exposure, peaceful areas (dist. elast. -2)	357,627	0.05	0.10	0	1
exposure, peaceful areas (dist. elast. -3)	357,627	0.05	0.10	0	1
exposure, peaceful areas (dist. elast. -4)	357,627	0.05	0.10	0	1
exposure, peaceful areas (dist. elast. -5)	357,627	0.05	0.11	0	1
exposure, peaceful areas (supplier size elast. 2)	357,627	0.06	0.11	0	1
exposure, peaceful areas (supplier size elast. 3)	357,627	0.06	0.11	0	1
exposure, peaceful areas (supplier size elast. 4)	357,627	0.06	0.11	0	1
exposure, peaceful areas (supplier size elast. 5)	357,627	0.06	0.12	0	1

Source: authors' computation from ASI and UCDP data. See main text for more details. Note that the *Exposure, peaceful areas* measured with different distance and supplier size elasticities vary to the thousandth decimal units.

Appendix B Reduced form: sensitivity analysis

We assess whether our baseline estimates in Table 2 are robust to various robustness checks. First, we use an alternative definition of conflict based on the incidence of at least one fatality, instead of violent event (Table 6). Second, we restrict the sample to firms surveyed for at least 1, 3, 5 and 7 years throughout the sample (Table 7). Third, we use an alternative measure of *Exposure, peaceful areas* in which $\rho_{ji(k)}$, our measure of *importance* of the supplier firm is estimated in a non-linear fashion as detailed in footnote 17 (Table 8). In the last exercise, we modify firm-to-firm linkages by using alternative measures of *Exposure, peaceful areas* in which $\rho_{ji(k)}$, our measure of *importance* of the supplier firm is estimated including various elasticities of distance (from -2 to -5) and supplier size (from 2 to 5) (Table 9). Results are stable across the sensitivity analysis exercises. Ultimately, we estimate the net effect of *Exposure, peaceful areas* by including district × year fixed effects (Table 10)

Table 6: Alternative conflict measure

Dep. var.	Price (1)	Quantity (2)
exposure, conflict areas (fatalities)	0.035^c	-0.051^c
	(0.019)	(0.029)
exposure, peaceful areas (fatalities)	0.102^a	-0.192^a
	(0.034)	(0.058)
Firm controls	yes	yes
Product FE	yes	yes
District FE	yes	yes
State × Year FE	yes	yes
Observations	357,627	357,627
R-squared	0.705	0.641

Note: ^{c} significant at 10%; ^{b} at 5%; ^{a} at 1%. Standard errors are clustered at the district × year level. The dependent variables are the (log) price and the (log) quantity of the firm's production defined at the 5-digit level of the product classification code. *Exposure, conflict areas* is an indicator that equals 1 if the firm is located in a conflict-affected district and *Exposure, peaceful areas* is a firm-level continuous measure calculated according to Equation 3. Conflict-affected districts are defined when there is at least one fatality in a district-year. Firm controls include (log) input prices (intermediate inputs, wages, and interest rate), (log) TFP, and time-varying input bundle fixed effects (defined at the 2-digit level). Product (defined at the 4-digit level), district, and state × year fixed effects are included. See main text for more details and Table 5 for descriptive statistics.

Table 7: Subsample of firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Years surveyed	> 1	> 3	> 5	> 7	> 1	> 3	> 5	> 7
Dep. var.	——— Price ———				——— Quantity ———			
Exposure, conflict areas	0.034^c	0.033	0.044	0.058^c	-0.059^b	-0.045	-0.030	-0.078^c
	(0.020)	(0.026)	(0.030)	(0.035)	(0.028)	(0.032)	(0.038)	(0.046)
Exposure, peaceful areas	0.143^c	0.168^c	0.102^c	0.130^c	-0.205^c	-0.135^b	0.081	-0.007
	(0.035)	(0.047)	(0.059)	(0.074)	(0.059)	(0.068)	(0.081)	(0.099)
Firm controls	——— yes ———							
Product FE	——— yes ———							
District FE	——— yes ———							
State × Year FE	——— yes ———							
Observations	345,049	202,449	139,327	93,187	345,049	202,449	139,327	93,187
R-squared	0.704	0.692	0.686	0.681	0.640	0.620	0.609	0.602

Note: ^{c} significant at 10%; ^{b} at 5%; ^{a} at 1%. Standard errors are clustered at the district × year level. The dependent variables are the (log) price and the (log) quantity of the firm's production defined at the 5-digit level of the product classification code. *Exposure, conflict areas* is an indicator that equals 1 if the firm is located in a conflict-affected district and *Exposure, peaceful areas* is a firm-level continuous measure calculated according to Equation 3. Firm controls include (log) input prices (intermediate inputs, wages, and interest rate), (log) TFP, and time-varying input bundle fixed effects (defined at the 2-digit level). Product (defined at the 4-digit level), district, and state × year fixed effects are included. See main text for more details and Table 5 for descriptive statistics.

Table 8: Alternative *Exposure, peaceful areas* measure

Dep. var.	Price (1)	Quantity (2)
Exposure, conflict areas	0.033	-0.047^c
	(0.020)	(0.028)
Exposure (non linear), peaceful areas	0.115^a	-0.129^a
	(0.029)	(0.043)
Firm controls	——— yes ———	
Product FE	——— yes ———	
District FE	——— yes ———	
State × Year FE	——— yes ———	
Observations	357,627	357,627
R-squared	0.705	0.641

Note: ^{c} significant at 10%; ^{b} at 5%; ^{a} at 1%. Standard errors are clustered at the district × year level. The dependent variables are the (log) price and the (log) quantity of the firm's production defined at the 5-digit level of the product classification code. *Exposure, conflict areas* is an indicator that equals 1 if the firm is located in a conflict-affected district and *Exposure, peaceful areas* is a firm-level continuous measure calculated according to Equation 3 where $\rho_{ji(k)}$ is estimated in a non-linear fashion (see footnote 17). Firm controls include (log) input prices (intermediate inputs, wages, and interest rate), (log) TFP, and time-varying input bundle fixed effects (defined at the 2-digit level). Product (defined at the 4-digit level), district, and state × year fixed effects are included. See main text for more details and Table 5 for descriptive statistics.

Table 9: Elasticities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Distance elasticity				Supplier size elasticity			
	-2	-3	-4	-5	2	3	4	5
Panel A								
Dep. var.	Price							
Exposure, conflict areas	0.035^c	0.035^c	0.034^c	0.033	0.030	0.028	0.027	0.027
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Exposure, peaceful areas	0.120^a	0.107^a	0.098^a	0.091^a	0.090^a	0.076^b	0.069^b	0.065^b
	(0.034)	(0.033)	(0.032)	(0.031)	(0.032)	(0.030)	(0.029)	(0.028)
Observations	357,627							
R-squared	0.705	0.705	0.705	0.705	0.705	0.705	0.705	0.705
Panel B								
Dep. var.	Quantity							
Exposure, conflict areas	-0.060^b	-0.060^b	-0.059^b	-0.057^b	-0.048^c	-0.046	-0.045	-0.045
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Exposure, peaceful areas	-0.210^a	-0.197^a	-0.181^a	-0.166^a	-0.138^a	-0.124^a	-0.119^a	-0.115^a
	(0.056)	(0.054)	(0.052)	(0.050)	(0.048)	(0.045)	(0.043)	(0.043)
Observations	357,627							
R-squared	0.641	0.641	0.641	0.641	0.641	0.641	0.641	0.641
Firm controls	yes							
Product FE	yes							
District FE	yes							
State × Year FE	yes							

Note: ^{c} significant at 10%; ^{b} at 5%; ^{a} at 1%. Standard errors are clustered at the district × year level. The dependent variables are the (log) price and the (log) quantity of the firm's production defined at the 5-digit level of the product classification code. *Exposure, conflict areas* is an indicator that equals 1 if the firm is located in a conflict-affected district and *Exposure, peaceful areas* is a firm-level continuous measure calculated according to Equation 3, however allowing for different distance and supplier size elasticities. Firm controls include (log) input prices (intermediate inputs, wages, and interest rate), (log) TFP, and time-varying input bundle fixed effects (defined at the 2-digit level). Product (defined at the 4-digit level), district, and state × year fixed effects are included. See main text for more details and Table 5 for descriptive statistics.

Table 10: Inclusion of district×year fixed effects

Dep. var.	Price	Quantity
	(1)	(2)
Exposure, peaceful areas	0.135^a	-0.202^a
	(0.036)	(0.061)
Firm controls	yes	
Product FE	yes	
District × Year FE	yes	
Observations	357,400	357,400
R-squared	0.708	0.645

Note: ^{c} significant at 10%; ^{b} at 5%; ^{a} at 1%. Standard errors are clustered at the district × year level. The dependent variables are the (log) price and the (log) quantity of the firm's production defined at the 5-digit level of the product classification code. *Exposure, peaceful areas* is a firm-level continuous measure calculated according to Equation 3. Firm controls include (log) input prices (intermediate inputs, wages, and interest rate), (log) TFP, and time-varying input bundle fixed effects (defined at the 2-digit level). Product (defined at the 4-digit level), district× year fixed effects are included. See main text for more details and Table 5 for descriptive statistics.

Appendix C Aggregate Loss

Table 11: Aggregate Loss (in %) - Baseline Specification

Year	(1) Aggregate Loss	(2) Share of Loss in Conflict Areas
2000	-0.95	0.48
2001	-1.66	0.30
2002	-1.46	0.28
2003	-0.98	0.27
2004	-1.67	0.24
2005	-2.09	0.24
2006	-2.48	0.22
2007	-2.57	0.22
2008	-2.71	0.20
2009	-2.53	0.21
Average	**-1.91**	**0.27**

Note: This table reports our estimates of yearly aggregate losses due to conflict, accounting for network propagation (Equation 14). Column (1) gives the yearly total losses (in %). Column (2) reports the shares of the yearly explained by the direct impact of conflict in conflict-ridden areas.

Table 12: Output Loss in Different Scenarios

	(1) Av. loss (in %)	(2) Av. loss (in bln USD)	(3) Cum. loss (in %)	(4) Cum. loss (in bln USD)
Baseline	-1.91	-3.80	-19.09	-38.01
Inaction	-2.96	-5.49	-29.64	-54.89
Supplier change	-2.34	-4.52	-23.37	-45.22
Supplier change and input bundle change	-1.31	-2.58	-13.05	-25.84
Spread to adjacent districts	-2.95	-5.91	-29.48	-59.12
Elasticity w.r.t distance -1	-1.59	-3.35	-15.91	-31.30
Elasticity w.r.t distance -2	-1.86	-3.64	-18.59	-36.42
Elasticity w.r.t distance -3	-2.15	-4.19	-21.46	-41.91
Elasticity w.r.t distance -4	-2.44	-4.75	-24.36	-47.47
Elasticity w.r.t distance -5	-2.73	-5.30	-27.27	-53.05

Note: this table reports our estimates of output loss computed in for different scenarios: (i) baseline; (ii) inaction effect; (iii) supplier change effect; (iv) supplier change and input bundle change effects; (v) conflict spread to adjacent districts; (vi)-(x) supplier change and input bundle change effects with costly adjustment and elasticity of trade with respect to distance from -1 to -5. Column (1) reports the average yearly loss in %. Column (2) reports the average yearly loss in billion USD. Columns (3) and (4) report the cumulative loss over the period 2000-2009 in % and billion USD respectively.

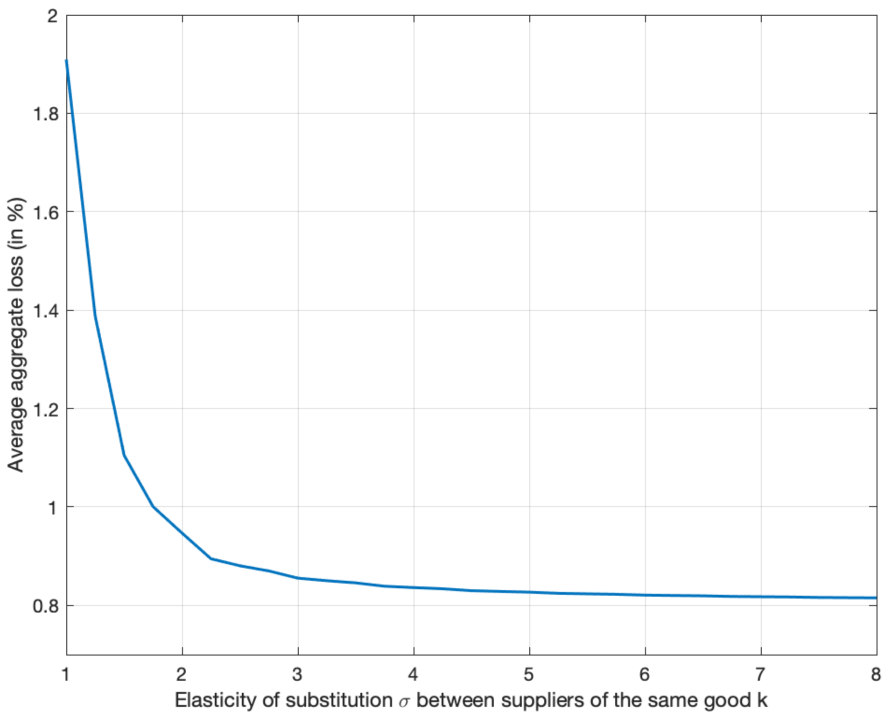
Appendix D CES Aggregation

We assume that each input k, produced by a set of J producers, is a CES aggregate with elasticity of substitution $\sigma > 1$:

$$k = \left[\sum_{j=1}^{J} k_j^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

We simulate what the average output loss would be by letting σ vary between $1 + \epsilon$ (with ϵ close to 0) and 10. Table 8 depicts the results: the average yearly loss decreases as elasticity of substitution σ increases. It falls quickly for $1 < \sigma < 3$ (for example, if $\sigma = 2$ the yearly average loss is halved), then it converges to a yearly loss of 0.8% and remains stable.

Figure 8: CES Aggregation of Inputs



Note: The blue line depicts the aggregate output loss we obtaining estimating an alternative specification of our model. In this version we assume that each input k, produced by a set of J producers, is a CES aggregate with elasticity of substitution $\sigma > 1$. We simulate what the average output loss would be by letting σ vary between $1 + \epsilon$ (with ϵ close to 0) and 10.

The Economic Costs of Conflict: A Production Network Approach
Online Appendix

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Contents

A1 Data and descriptive statistics

A1.1 World Bank Economic Survey Data

. We detail the costs borne by firms located in the conflict area by relying on the cross-sectional data from World Bank Enterprise Survey which provides information on the business constraints suffered by firms in 2014, the only year available for India (World Bank, 2014). The WBES is a firm-level survey conducted on a representative sample of the private sector of 149 different countries. The dataset has been used in different contexts and for different research questions, from the study of informal enterprises, female employment in developing countries to productivity estimates. See the paper of De Haas and Poelhekke (2019) for a detailed literature review. To study the extra costs suffered by firms located in conflict areas, we focus on five outcomes:

1. an indicator that equals 1 if the firm reports any losses due to theft (as percentage of the value of their products), built from the question: "losses due to theft, robbery, vandalism or arson experienced in last fiscal year? 1 if yes, 0 if no."

2. an indicator that equals 1 if the firm declares to provide informal payments or gifts to other actors, built from the question: "percent of total annual sales paid in informal payments? 1 if percentage is >0, and 0 if they report no payment or gifts are paid."

3. an indicator that equals to 1 if the firm allocates resources to pay for security (e.g. expenses on equipment, personnel, professional security services), built from the question: "how much of an obstacle: electricity to operations of this establishment? 1 if moderate, major or very severe obstacle; 0 if no obstacle or minor."

4. an indicator that equals 1 if the firm reports access to electricity as an obstacle in her business environment, built from the question: "how much of an obstacle: electricity to operations of this establishment? 1 if moderate, major or very severe obstacle; 0 if no obstacle or minor."

5. the total cost of production includes: total labor cost (including wages, salaries and bonuses), total annual costs of electricity, total annual costs of fuel, total annual cost of finished goods/materials bought to resell, other costs of production not included, total rental cost of machinery, vehicles and equipment, total rental cost of land and buildings

We also include (log) firm characteristics in our estimation: the number of establishments, establishment type, manager experience, value of sales, number of employees, percentage of working capital financed from internal funds, sector of activity, legal status and main product. Table A1.1 displays the balancing tests.

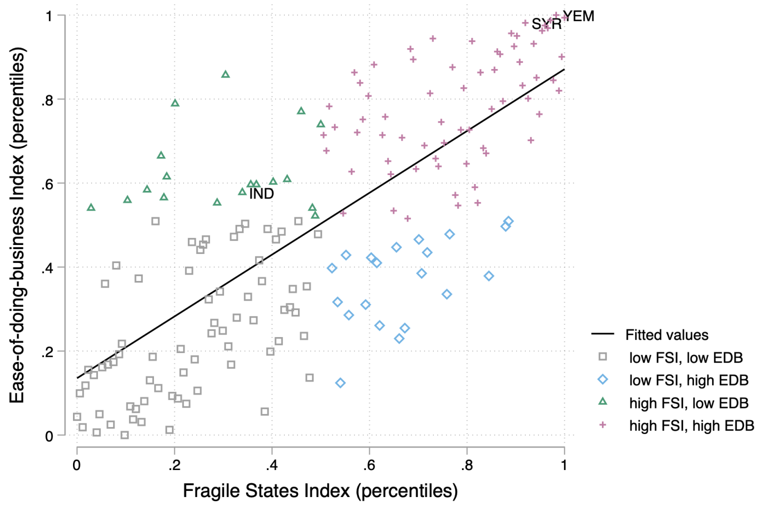
A1.2 Conflict data

Figure A1.1 plots the 2019 country-level indexes for the Fragile States (x-axis, hereafter FSI) and the Ease-of-doing-business (y-axis, hereafter EDB), in percentiles, using information from (The Fund for Peace, 2020) and (World Bank, 2019). Countries are classified in four categories with respect to their sample median: (i) low FSI, low EDB; (ii) low FSI, high EDB; (iii) high FSI, low EDB and (iv) high FSO, high EDB. India is at the 74^{th} position of the most Fragile States out of 178 countries and at the 63^{rd} position of the Ease-of-doing-business measure out of 190 States.

Table A1.1: World Bank Economic Survey Data: Balancing test

Variable	(1) Peace Zone	(2) Conflict Zone	(3) Difference
Loss due to theft	0.032	0.074	0.042[a]
	(0.176)	(0.262)	(0.005)
Loss due to payment	0.054	0.080	0.026[a]
	(0.227)	(0.272)	(0.007)
Pay for security	0.662	0.767	0.105[a]
	(0.473)	(0.423)	(0.012)
Access to electricity	0.448	0.561	0.113[a]
	(0.497)	(0.496)	(0.012)
Total cost of production	17.074	16.790	-0.284[a]
	(2.022)	(2.136)	(0.052)
(log) establishments (#)	0.228	0.271	0.043[a]
	(0.510)	(0.562)	(0.013)
(log) manager experience	2.340	2.399	0.059[a]
	(0.773)	(0.631)	(0.019)
Manufacturing	0.778	0.760	-0.018[c]
	(0.416)	(0.427)	(0.010)
(log) sales	17.663	17.262	-0.401[a]
	(1.872)	(2.078)	(0.048)
(log) employees (#)	3.738	3.505	-0.233[a]
	(1.259)	(1.230)	(0.031)
(log) capital (#)	3.914	4.045	0.131[a]
	(1.026)	(0.881)	(0.025)
Observations	7,131	2,059	9,190

Figure A1.1: Ease-of-Doing-Business and Fragile States



Note: This figure plots the 2019 country-level indexes for the Fragile States (x-axis, hereafter FSI) and the Ease-of-doing-business (y-axis, hereafter EDB), in percentiles. Countries are classified in four categories with respect to their sample median: (i) low FSI, low EDB; (ii) low FSI, high EDB; (iii) high FSI, low EDB and (iv) high FSO, high EDB.

Table A1.2: List of Maoist-related Armed Groups

Maoist Outfit	Abbreviation	Share of fatalities
Communist Party of India (Maoist)	CPI-Maoist	60.37
Communist Party of India (Marxist-Leninist) People's War	PWG	12.86
Maoist Communist Centre of India	MCC	7.75
United National Liberation Front	UNLF	6.88
People's Liberation Army	PLA	4.67
Kangleipak Communist Party	KPC	2.88
The People's Revolutionary Party of Kangleipak	PREPAK	2.68
Communist Party of India (Marxist-Leninist) Janashakti	CPI-ML-J	1.15
Communist Party of India (Marxist-Leninist)	CPI-ML-WM	0.76
People's Liberation Front of India	PLFI	0

Note: This table presents a simplified list of Maoist-related armed groups between 2000 and 2008, for which UCDP data provides information on conflictual events and related fatalities. Source: Authors' computation using information from South Asia Terrorism Portal and UCDP data.

Table A1.3: Maoist insurgency

	2000-2009
Violent events	1775
Fatalities	4737
Major incidents	563
Explosions	750

Note: This table gives the number of maoist-related violent event or fatalities between 2000 and 2009. Source: Authors' computation using information from South Asia Terrorism Portal and UCDP data.

A1.3 Plant data

Table A1.4: List of Industrial Sectors within the Manufacturing Industry

Section	Sector
Agriculture (A)	Agriculture, hunting and related service activities
Mining (C)	Other mining and quarrying
Manufacturing (D) (manufacture of)	food products and beverages tobacco products textiles wearing apparel; dressing and dyeing of fur tanning and dressing of leather; luggage, handbags saddlery, harness and footwear wood and of products of wood and cork, except furniture, articles of straw and plating materials paper and paper products publishing, printing and reproduction of recorded media coke, refined petroleum products and nuclear fuel chemicals and chemical products rubber and plastic products other non-metallic mineral products basic metals fabricated metal products, except machinery and equipments machinery and equipment n.e.c. office, accounting and computing machinery electrical machinery and apparatus n.e.c. radio, television and communication equipment and apparatus medical, precision and optical instruments, watches and clocks motor vehicles, trailers and semi-trailers other transport equipment furniture; manufacturing n.e.c. recycling
Electricity (E)	Electricity, gas and water supply
Wholesale (G)	Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods
Transport (I)	Transport, storage and communications
Real Estate (K)	Real estate, renting and business activities
Other (O)	Other community, social and personal service activities

Note: Authors' computation using information from ASI data.

A1.3.1 Digging Deeper in Firm-specific Production

Interestingly, different firms producing the same output could use different set of inputs. Figure A3.3 shows the combination of intermediate inputs for a certain output, for different firms. Each dot represents a firm-input observation, for single-product plants (one color is one distinct firm). The x-axis presents three distinct products: aromatic chemicals (36148); articles & novelties, leather (44111); paper for printing & writing paper (55199). The y-axis represents the intermediate inputs used to produce the x-axis output by each firm. One salient fact is that, even within narrow product classification, firms use different combinations of intermediate inputs. For example, in our sample, five distinct firms are single-producers of paper in the

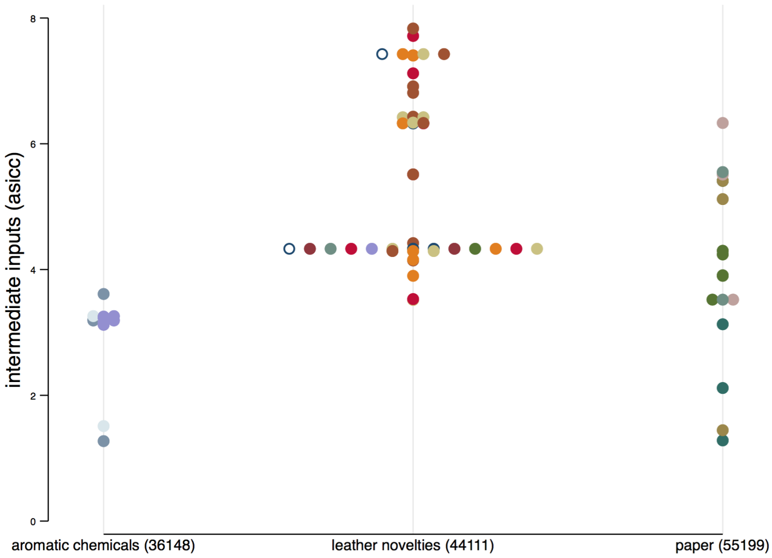
Table A1.5: List of Indian States and Union Territories

State	Districts (#)
Andaman & Nicobar Islands	1
Andhra Pradesh	23
Assam	21
Bihar	36
Chandigarh	1
Chhattisgarh	15
Dadra & Nagar Haveli	1
Daman & Diu	2
Delhi	9
Goa	2
Gujarat	24
Haryana	19
Himachal Pradesh	11
Jammu & Kashmir	9
Jharkhand	16
Karnataka	27
Kerala	14
Madhya Pradesh	43
Maharashtra	34
Manipur	4
Meghalaya	6
Nagaland	4
Odisha (Orissa)	28
Puducherry (Pondicherry)	4
Punjab	17
Rajasthan	32
Tamil Nadu	31
Tripura	4
Uttar Pradesh	69
Uttarakhand	10
West Bengal	19

Note: Authors' computation using information from UCDP and ASI data.

year 2005. Each of them uses paper, however, with different quality: some firms use directly wood products, while other use different types of paper (waste paper, paper with polytene coated, or card board). The figure also show that in some instances, there is a common major input. When producing leather articles and novelties, 13 over 19 firms in the sample use tanned leather (43301). Finally, while the bundles of narrow industries, such as the aromatic chemicals products, might be showing a cluster of similar inputs, the details of the ASICC classification allow for a variety of input-output combinations.

Figure A1.2: Heterogeneity in bundles of intermediate inputs for output production



Note: This figure presents the inputs-output composition for single-product plants. Each dot represents a firm-input observation and each color a distinct firm. The x-axis presents three distinct products, following the 5-digit ASICC classification. The y-axis represents the intermediate inputs used to produce the x-axis output by each firm, using the 5-digit ASICC classification. For simplicity, the classification labels of the y-axis are displayed in then thousands (ASICC divided by $10,000$). The three examples are taken from the year 2005.

A2 Reduced form: additional results

A2.1 Firm characteristics

We examine the modulating effect of firm characteristics on firm's performance. We allow the decrease in firms' price in both conflict and peaceful territories to differ along the line of firm characteristics: (i) the number of years in activity; (ii) the number of units that the firm (plant) is part of; (iii) whether the firm relies on imported inputs; and (iv) the level of insurance, measured as the share of insurance costs over total expenses. The differential effect of conflict on firm's performance may depend on these dimensions, as suggested by the literature. For instance, Del Prete et al. (2021) provide suggestive evidence that the mechanism through which firms located in the conflict districts suffer might be disruptions to international supply linkages, especially for relatively small and young firms. A similar result shows that the negative effect of conflict is larger for firms that do not have access to a credit line. The role of these dimensions may thus be key in understanding the effect of conflict on firms' competition, both in conflict and peaceful territories. Table A2.6 reports estimates. There is no conclusive evidence that firm-specific characteristics modulate the effect of exposure to conflict on firm performance.

Table A2.6: Firms Heterogeneity

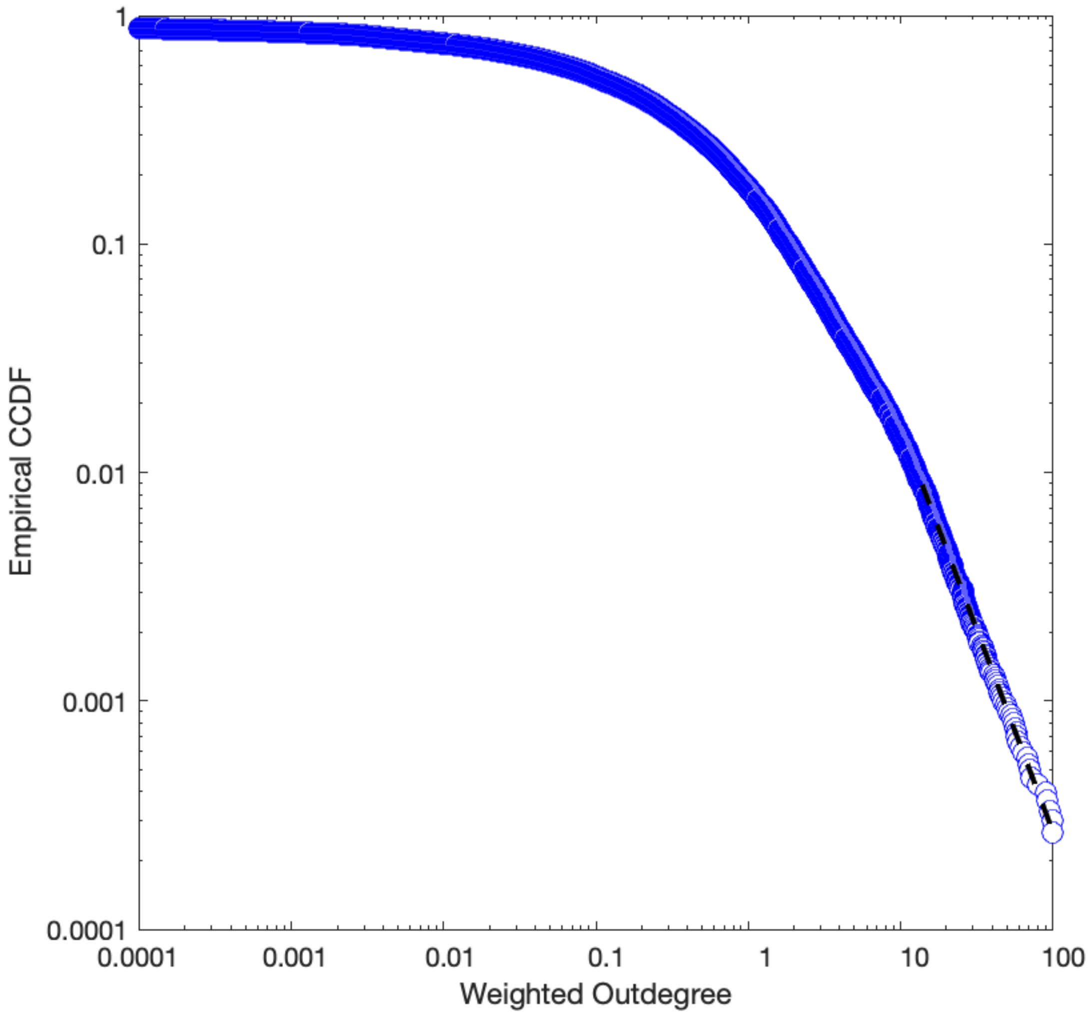
Dep. var.	Price (1)	Quantity (2)
Exposure, conflict areas	-0.060[c]	-0.186[a]
	(0.037)	(0.061)
× years in activity (log)	0.035[a]	0.051[a]
	(0.013)	(0.019)
× units (log)	-0.101[c]	0.086
	(0.060)	(0.094)
× insurance (%)	0.196	-0.059
	(0.134)	(0.276)
× imports (0/1)	-0.002	-0.030
	(0.043)	(0.067)
Exposure, peaceful areas	-0.066	-0.376[b]
	(0.087)	(0.156)
× years in activity (log)	0.073[b]	0.092[c]
	(0.030)	(0.051)
× units (log)	0.123	-0.032
	(0.114)	(0.169)
× insurance (%)	0.416	-1.584[b]
	(0.399)	(0.660)
× imports (0/1)	-0.070	0.173
	(0.081)	(0.127)
years in activity (log)	-0.032[a]	-0.214[a]
	(0.005)	(0.007)
units (log)	-0.040[b]	0.051[b]
	(0.016)	(0.024)
insurance (%)	-0.024	0.218[b]
	(0.059)	(0.093)
imports (0/1)	0.131[a]	0.185[a]
	(0.012)	(0.017)
Firm controls	Yes	
Product FE	Yes	
Technology FE	Yes	
District FE	Yes	
State × Year FE	Yes	
Observations	357,623	357,623
R-squared	0.705	0.643

Note: [c] significant at 10%; [b] at 5%; [a] at 1%. Standard errors are clustered at the district × year level. Dependent variables represent the (log) price and (log) quantity of firm's product(s) defined at the 5-digit level of the product classification code. *Exposure, conflict areas* is an indicator that equals 1 if the firm is located in a conflict-affected district and *Exposure, peace areas* is a firm-level continuous measure according to Equation 3. Firm controls include (log) input prices (intermediate inputs, wages, and interest rate) and (log) TFP. Product (defined at the 4-digit level), technology (time-varying input bundle defined at the 2-digit level), district and state × year fixed effects are included. See main text for more details and Table 5 for descriptive statistics.

A3 Validation Exercise: Weighted Outdegree

We validate our construction on the input-output network comparing the weighted outdegree distribution associated with 2002 Indian firm level data to that computed with 2002 US sector level shown in Carvalho (2014) (Figure 3). The weighted outdegree of a given firm i is defined as the sum over all the weights of the network in which firm i appears as an input-supplying firm. This measure ranges from 0 if a firm does not supply inputs to any other firm, to N if a single firm is the sole input supplier of every firm in the economy. The shape of the weighted outdegree distribution is comparable to that presented in Carvalho (2014): (i) almost each firm has an outdegree greater than 0.01, (ii) one-tenth of firms have an outdegree greater than 1, and (iii) about 1 percent of all sectors have an outdegree measure greater than 10, these are producers of "general purpose" manufactured goods like iron and steel or oil.

Figure A3.3: The Weighted Outdegree Distribution Associated with 2002 Indian Input-Output Data



Note: This figure aims to replicate Figure 3 in Carvalho (2014) with Indian data. The x-axis gives the weighted outdegree for each sector, presented on a log scale. The y-axis, also in log scale, gives the probability of finding a sector withmweighted outdegree larger than or equal to x, that is the empirical counter-cumulative distribution (CCDF). We use 2002 as representative year (year 2002 is also used by Carvalho (2014) in Figure 3. Distributions computed for years 2000, 2001, 2003-2009 are perfectly compatible with this figure.

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