The Economic Costs of Conflict: A Production Network Approach*

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November 14, 2023

Abstract

We investigate the Maoist insurgency in Eastern India in 2000-2009 to develop a novel approach for estimating the economic costs of conflict. In this approach, the production network serves as a primary mechanism through which the disruptive effects of localized conflict spread to peaceful areas. By applying a model of production networks, we aim to quantify the overall impact of conflict, taking network propagation into account. Our key finding reveals that, regardless of the degree of conflict-induced distortion experienced by firms in conflict-affected areas, 73% of the total output loss can be attributed to network propagation.

Keywords: Conflict, Firms, Production Network, Aggregate Output Loss.

JEL classification: D22, D74, O12, O47.

*We are grateful to Pierre-Philippe Combes, Lucie Gadenne, Vasily Korovkin, Alexey Makarin, Julien Martin, Massimo Morelli, Hannes Mueller, Mathieu Parenti, Augustin Tapsoba, Angelos Theodorakopoulos, Mathias Thoenig, Cédric Tille, Farid Toubal, Oliver Vanden Eynde, and participants in the ENS de Lyon, ECARES, CEPR RPN Workshop on preventing conflict, Bristol University, CED, UNSW Australia, CREST Paris, Paris Empirical Political Economy Seminar, IIE, University of Geneva, UAB Barcelona, University of Orleans, CERGE-EI Prague, University of Louvain, University of Montreal, University of Paris 1, University of Bologna, ENS-CEPR Workshop on firms in hostile environments, Paris XI, AFSE Summer Congress, SIOE Summer Congress, University of Montpellier, 2021 Conference on Economic Development, IGIER Bocconi Conference on political economy of power relations for their valuable comments. Mathieu Couttenier acknowledges financial support from the IDEXLYON from the University of Lyon (French National Research Agency, "Programme Investissements d'Avenir" ANR-16-IDEX-0005). Nathalie Monnet acknowledges financial support from the Swiss National Research Foundation (grant *Economics of Conflict and Violence* P0GEP1-175125). Lavinia Piemontese acknowledges the financial support from the MSCA Actions (Project FIBRE 101063844). Nathalie Monnet would also like to thank Kritika Saxena for her invaluable assistance in obtaining the ASI data.

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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 by virtue of considering as non-affected a group of firms that are indirectly impacted by conflict. This is particularly relevant as the underestimation of the costs of conflict 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. We quantify the loss caused by a localized conflict at the nationwide

[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 topics 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 behaviors. 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), Couttenier et al. (2019) 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 (2023) studies how individuals are affected by the fear of exposure to conflict even prior to the manifestation of violence or in its absence. Spatial spillover of conflict incidence is also studied exploring the role of natural disasters, road network, and geographic proximity (Amarasinghe et al., 2021), and the interdependence between network of military alliances and international trade (Jackson and Nei, 2015).

level by making 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 acts of violence perpetrated by Maoist groups, we define the set of firms that are directly exposed to the conflict. Since we do not have information on firm-to-firm transactions, we approximate the input-output network of the Indian economy exploiting detailed information on each firm's output and input bundle. Equipped with this information, we apply a 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 conflict-affected districts and firms outside it. Second, while deadly, the conflict remains at a low level of intensity, such that the firms in conflict-affected districts 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 districts, and how these distortions propagate by way of the production network, thereby affecting firms located outside conflict-affected districts.

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. A 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, 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 conflict-affected districts are subject to output and input distortions that increase

[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 study the relationship between SME and job creation; and most recently by Boehm and Oberfield (2020) to estimate the impact of institutional quality on firms' output and sourcing decisions.

their output price. 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 in peaceful districts. Our main theoretical result characterizes the aggregate loss (at the national level) due to conflict as a function of the economy's production network.

In the second part of the paper, we bring our model to the data. First, we present and validate our methodology to approximate the input-output linkages using firm-to-firm transactions data for West Bengal (Gadenne et al., 2019). We find that our measure of input-output linkages is highly correlated with the observed probability of establishing a buyer-supplier link. Additionally, we test the validity of our methodology by comparing statistics derived from our imputed network with observable outcomes and with findings from existing literature (Carvalho, 2014; Acemoglu et al., 2012). We find a high degree of compatibility. Furthermore, by comparing conflict-affected districts to peaceful ones in several dimensions, such as market size and structure, firm-level age, size, production, entry, exit, and relocation decisions, we mitigate potential concerns related to network endogeneity to the Maoist insurgency.

Second, we structurally estimate the aggregate impact of the Maoist insurgency on the Indian economy. We assume that the direct output loss from being located in a conflict-affected district takes values from a range (bounded between 0.015 and 0.1, meaning that we assume that firms located in conflict-affected areas suffer a loss that ranges between 1.5% and 10% of their output), and then we employ our measure of the production network to characterize the propagation from conflict-affected districts outward. The magnitudes are economically significant: we find that the Maoist insurgency, in years 2000-2009, brought about a cumulative decline that ranges between 3.35%, assuming a direct output loss of 0.015, and 23.56%, assuming a direct loss of 0.1 in aggregate output of the manufacturing sector (0.6% to 3.6% decline of Indian GDP), which corresponds to a monetary loss between approximately 6.57 and 43.80 billion USD. Crucially, regardless the magnitude of the direct output loss, only 27% of the total loss can be attributed to the impact on firms located in conflict-affected districts. The remaining 73% depends on network propagation outside the conflict-affected districts.

Our estimates are likely to represent a lower bound of the actual loss due to conflict for two main reasons. First, Maoist groups are committed to extreme-left political ideology and therefore are more likely to organize attacks against large firms. In this perspective, 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 30% of the firm distribution by size, then the average annual loss would almost double. Second, the seriousness of the propagation of conflict-induced distortions might be linked to the specificity of the goods produced in conflict-affected districts. We explore this scenario in which conflict-induced distortions are correlated with the degree of homogeneity of goods produced in conflict-affected districts. We find that, relative to the baseline estimate, the total loss is 46% higher.

Overall, our findings indicate that the magnitude of total output loss is predominantly influenced by the firm-specific severity of the conflict-induced distortion, rather than the intensity or the length of violence at the district level.

Our baseline findings include the effects of *inaction*, *supplier change*, and *input bundle change*. We then explore the importance of these mechanisms in more detail. First, we assume no network adjustment and find that the average annual output loss of the manufacturing sector is almost 12% higher than the baseline. Second, we contemplate network reshuffling and find that allowing for the *supplier change* effect would lower the output loss by 10%, whereas combining the *supplier change* and the *input bundle change* effects reduces the output loss substantially, by 25% or 30% whether or not we allow for network adjustment costs.

Finally, we perform several policy experiments. First, we estimate the potential loss in the counterfactual scenario in which Maoist activity expands to neighboring districts. We find that the cumulative monetary loss would increase substantially, to approximately a range between 10.15 and 67.69 billion USD. Second, we explore the effect of various policies in support of firms in conflict-affected districts and firms located elsewhere that are impacted by the conflict by way of 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. For instance, we find that protecting the 4% most central firms would halve the output loss and achieve the same effect than another intervention that protects 50% of randomly chosen conflict-affected firms. On the other hand, we find that policy makers should design interventions that can effectively reduce the trade frictions between states, for example due to low institutional quality, 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 conflict-affected districts. 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.

Conflict can curtail a firm's exports, resulting in significant negative labor supply shocks (Ksoll et al., 2023), and it can impact imports by prompting the substitution of domestically produced inputs for imported ones Amodio and Di Maio (2018). Additionally, conflict can reduce the availability

of production inputs, including intermediates and labor, leading to factors substitution Del Prete et al. (2023). Furthermore, the threat of predation during conflict can drive firms to reallocate labor from production to protection (Besley and Mueller, 2018). Beyond these factors, conflict has been shown to influence firms' location decisions (Blumenstock et al., 2020), their decisions regarding exit (Camacho et al., 2013; Del Prete et al., 2023), firm productivity (Klapper et al., 2015), and can compel producers to forgo otherwise profitable investments (de Roux and Martinez, 2021).[5]
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. In a related study, Korovkin et al. (2023) develop sufficient aggregate statistics to quantify the region-specific welfare effect of the disruption and readjustment of production network due to localized conflict. We extend their analysis with our structural model, which makes it possible to distinguish between the effect of the *direct* exposure to conflict and the *indirect* effect due to network propagation, and perform heterogeneity analysis based on district-specific or firm-specific severity of the conflict-induced distortion.

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 (Shapiro and Vanden Eynde, 2023). 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 (2020) 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.

Furthermore, 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 to firms' activity and study its propagation through the production network. Ours is the first analysis to provide an explicit estimate of the total loss to firms as a result of conflict.

Finally, the relationship between production network and firm behavior in the Indian context has been explored by Panigrahi (2021), who shows that the input-output network structure plays a substantial role in explaining variation in firm's sales to other firms.

[5] Rohner and Thoenig (2021) provide an extensive literature review on the consequences of conflict.

The remainder of the paper is organized as follows. Section 2 presents a brief overview of the Maoist insurgency. Section 3 describes the modeling of the Indian production network. Section 4 presents the conceptual framework, which is then used for aggregation and counterfactual analysis in Section 5 and Section 6, respectively. Section 7 concludes.

2 Firm Activity and Maoist Insurgency

The Maoist insurgency is a long-running and widespread conflict based on Communist ideology which seeks to overthrow the Indian government.[6] Maoist groups are active in numerous districts located in eastern India which are referred to collectively as the *Red Corridor* (left panel of 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 (right panel of Figure 1).[7] On average, before 2004, there were 32 events per year resulting in 166 deaths. However, after 2004, the conflict underwent a transformation, becoming more organized and centralized in terms of armed activity. Consequently, there was a notable surge in violent incidents across the affected region from 2004 onward, with an average of 231 events per year and 500 yearly deaths.

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 (see Online Appendix Table OA2.3 for an exhaustive list). CPI-Maoist is the dominant group 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 below the median of the Ease of Doing Business measure, unlike many fragile economies such as Syria and Yemen (Figure OA2.1).[8] When compared to other guerrilla warfare conflicts occurring in the same time-frame, the Maoist insurgency resulted in 4,090 deaths during

[6]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*.

[7]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).

[8]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).

our study period from 2000 to 2009. In contrast, the Taliban's guerrilla warfare against Afghan and international forces caused 26,916 deaths, and the Colombian internal armed conflict led to 12,078 casualties (Sundberg and Erik, 2013). These statistics underscore the unique nature of the Maoist insurgency and highlight the resilience of economic activities despite the challenges posed by the conflict.

Second, there are many actions perpetrated by Maoist groups that hinder business activity including (Online Appendix Table OA2.4 for statistics on events from 2000 to 2009): (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).[9] Third, the geographical scope of the conflict expanded between 2000 and 2009. In our sample we observe that, in 2000, 29 districts (out of 558) across 8 states (out of 32) were affected by Maoist activities, while in 2009 Maoists were active in 64 districts across 9 states. Overall, during 2000-2009 a total of 121 districts across 12 states were impacted. Furthermore, Maoist activity is mainly concentrated in the eastern part of the country. Therefore, we are able to make a clear-cut distinction between firms located in conflict-affected districts and those located outside it.

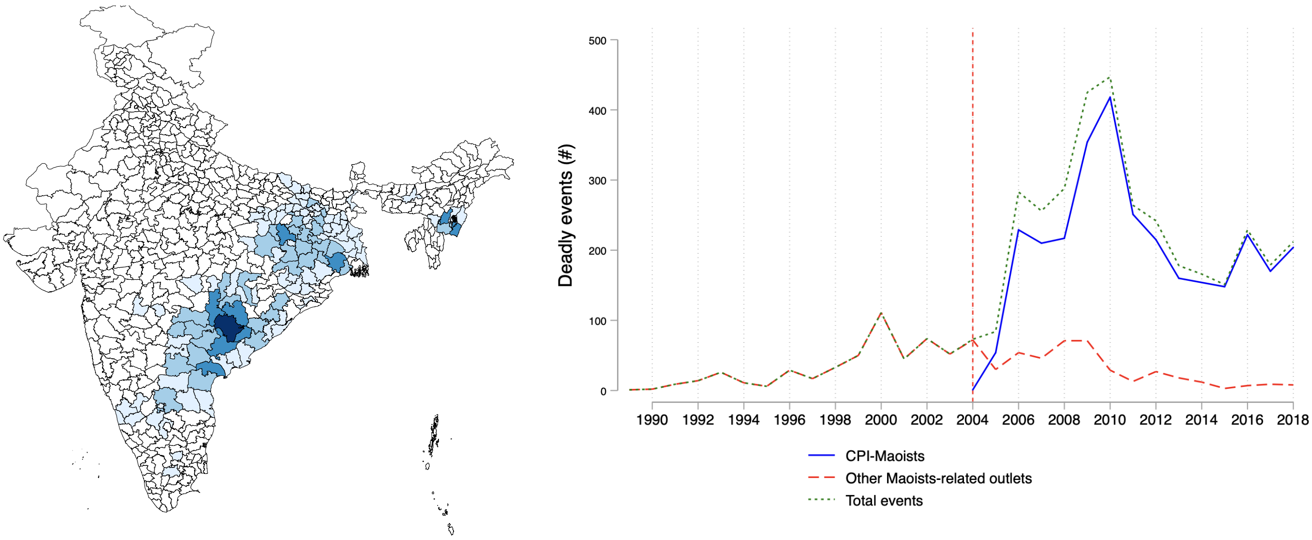
In Online Appendix OA1, we provide motivating evidence that firms located in districts impacted by Maoist activity bear additional costs linked to a wide range of constraints. We rely on cross-section data from the World Bank Enterprise Survey (World Bank, 2014), which provides information on the business constraints to which Indian firms are subject (access to inputs, crime, corruption). Our results indicate additional costs borne by firms located in conflict-affected districts. Moreover, they demonstrate the diversity of costs that can arise from a conflict. This becomes particularly useful in the conceptual framework derived in Section 3 to accurately model firm behavior in conflict-affected districts in accordance with the evidence for the existence of both output and input distortions.

3 Conceptual Framework

In this section, we outline a static model of perfect competition with heterogeneous firms (in terms productivity) 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 conflict-affected districts is affected; and (ii) how the distortions due to conflict spread by means of the production network, thus affecting firms outside the districts of conflict. Combining these two effects makes it possible to calculate the aggregate loss suffered by

[9] 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. [...]".

Figure 1: The Maoist insurgency, 2000-2009



Note: The left panel depicts locations of the Maoist insurgency across districts between 2000 and 2009. The darker the shade of blue, the more intense is the conflict. The right panel presents the number of Maoist-related deadly events per year and per factions. The dotted green line represents the total number of events, the blue line the number of events perpetrated by the CPI-Maoists and the dashed red line the number of events perpetrated by other Maoists outlets.

the entire economy.

Given that the production network is imputed and not observed, we adopt a static model with exogenous network formation (rather than endogenizing as in Acemoglu and Azar (2020), Oberfield (2018), Huneeus (2020), Taschereau-Dumouchel (2020), Lim (2018)). However, since possible network adaptation to conflict is an important factor, in Section 5.2 we provide a nuanced analysis to quantify the potential implications of these adjustments.

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:

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

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:

$$y_i = \tilde{a}_i (k_i^{\gamma} l_i^{1-\gamma})^{\alpha} \mathbf{x}_i^{1-\alpha} \tag{2}$$

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.[10]

The impact on firms located in conflict-affected districts. As described in Online Appendix OA1, firms located in conflict-affected districts 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 conflict-affected districts, we take into account all of the aforementioned distortions, which can be output-specific or input-specific. In particular, if firm i is located in a conflict-affected district, it then maximizes profits according to the following equation:

$$\max_{k_i, l_i, x_{ji}} \pi_i = (1 - \tau_{y,i}) p_i y_i - (1 + \tau_{kl,i})(R k_i + h l_i) - (1 + \tau_{x,i}) \sum_j p_j x_{ji} \tag{3}$$

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.[11]

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

$$p_i = \left[\left(\frac{R}{\gamma \alpha} \right)^{\gamma} \left(\frac{h}{(1-\gamma)\alpha} \right)^{1-\gamma} \right]^{\alpha} \left[\prod_j \left(\frac{p_j}{\omega_{ji}(1-\alpha)} \right)^{\omega_{ji}} \right]^{1-\alpha} \frac{(1+\tau_{kl,i})^{\alpha}(1+\tau_{x,i})^{1-\alpha}}{\tilde{a}_i (1-\tau_{y,i})} \tag{4}$$

In log-form firm-level optimal price is:

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

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

$$\log(p_i) = \log\left(\left[\left(\frac{1}{\gamma\alpha}\right)^{\gamma}\left(\frac{1}{(1-\gamma)\alpha}\right)^{1-\gamma}\right]^{\alpha}\left[\left(\frac{1}{1-\alpha}\right)\right]^{1-\alpha}\right) \tag{5}$$
$$+ \alpha\gamma\log(R) + \alpha(1-\gamma)\log(h) + (1-\alpha)\sum_j \omega_{ji}\log\left(\frac{p_j}{\omega_{ji}}\right) - \log(a_i) - \log(\Gamma_{ct})$$
$$+ \underbrace{\log\left(\frac{(1+\tau_{kl,i})^{\alpha}(1+\tau_{x,i})^{1-\alpha}}{1-\tau_{y,i}}\right)}_{\mathrm{T}_i}$$

where T_i represents a *comprehensive index* of conflict-induced distortions borne by firm i. This expression suggests that conflict-induced distortions increase the firm's optimal price. As demonstrated in the upcoming subsection, the rise in p_i attributable to conflict induces each buyer j to decrease its demand for the good y_i, consequently leading to a reduction in its production of the good y_j.

The impact on firms not located in conflict-affected districts. 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 conflict-affected districts among firms outside those districts. 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 2). 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 4) 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:

$$log(y_j) = log(\tilde{a}_j) + \alpha\gamma log(k_j) + \alpha(1-\gamma)log(l_j) \tag{6}$$
$$+ (1-\alpha)(\omega_{1j}log(x_{1j}) + ... + \omega_{ij}log(x_{ij}) + ... + \omega_{Ni}log(x_{Ni}))$$

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 6 suggests that any distortion experienced by firm i affects firm j's output, which decreases by a proportion of $(1-\alpha)\ \omega_{ij}$. 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 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:

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

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:

$$v = \frac{1}{N}\left[I-(1-\alpha)\Omega'\right]^{-1}\mathbf{1} \tag{7}$$

where $\mathbf{1}$ is a vector of ones.

The impact of conflict on aggregate output. 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.[12] (Log)-aggregate output is:

$$\mathbf{Y} = v'\epsilon + \mu \tag{8}$$

where v is the influence vector, ϵ is a vector containing (log) firm-level productivity and conflict-induced 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 to conflict, our main interest is to calculate the *percentage change* of aggregate output, which is expressed as follows:

$$\Delta\mathbf{Y} = v'\xi \tag{9}$$

[12]The proof that Equation 8 characterizes the equilibrium of this economy is developed in Acemoglu et al. (2012) in their Appendix A.

where vector ξ contains firm-specific conflict-induced distortions defined as follows:

$$\xi = \begin{cases} 0 & \text{if firm i is located in a peaceful district} \\ f(\mathrm{T}_i) & \text{if firm i is located in a conflict district} \end{cases} \tag{10}$$

For firms not located in conflict-affected districts the entries of ξ are equal to zero, while the entries for firms located in conflict-affected districts are a function of conflict-induced distortions, $f(\mathrm{T})$. To encompass various aspects of the impact of conflict on firms located in affected districts, $f(\mathrm{T})$ can take different functional forms (Equation 11). First, we assume a simplistic view that all firms located in an affected district suffer the same distortion, i.e., $f(\mathrm{T}_i) = \mathrm{T}$. Second, since Maoist groups might be more active in certain districts, there might be differences in their impact *across* districts, i.e., $f(\mathrm{T}_i) = \mathrm{T} \times \theta_d$. Third, we relax the assumption that conflict affects all firms located in a conflict-affected district in the same way, i.e., $f(\mathrm{T}_i) = \mathrm{T} \times \eta_i$.

$$f(\mathrm{T}_i) = \begin{cases} \mathrm{T} & \text{Homogeneous impact} \\ \mathrm{T} \times \theta_d & \text{Heterogenous impact } \textit{across} \text{ districts} \\ \mathrm{T} \times \eta_i & \text{Heterogenous impact } \textit{within} \text{ districts} \end{cases} \tag{11}$$

In what follows, we bring this model to the data. First, in Section 4 we introduce our data, how we construct the production network, and we validate our strategy. Then, in Section 5, we present the structural estimation of this model.

4 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 how we construct the production network that characterizes the Indian economy. Finally, we present some validation exercises to corroborate that our strategy to build the production network is a reasonable representation of the actual (unobserved) buyer-supplier linkages.

4.1 Data

Firm 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 2000-2001 to 2009-2010.[13] For simplicity, from now on we use the term *firm* to define a productive unit, i.e., a plant. The ASI provides a panel consisting of all registered manufacturers

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

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).
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).[14] The final sample consists of a panel of 187,283 distinct firms observed between 2000 and 2009. About 26% of the firms were surveyed for at least 7 years, while 38% were surveyed for only 2. More than half of the firms are single-output producers, while the rest produces between 2 and 10 distinct goods (less than 0.1% produce up to 23 distinct goods). The data cover 30 different industries (1 and 2-digit level of NIC) in 558 districts (across 32 states and union territories).

Conflict data. We gather data on conflict from the UCDP Georeferenced Event Dataset, which is collected from a wide range of sources, including news media and reports by international organizations and NGOs. It 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). The final dataset covers 1,775 events from 2000 to 2009, which involved 4,737 deaths (based on accounting years).
Although these data are quite rich and, thus, have been widely used in the recent conflict literature (Nunn and Qian, 2014; Berman et al., 2017; König et al., 2017), they do not include information on the specific type of the violent event (e.g., if a given violent event is targeted against public infrastructure, or if insurgents call for *Bandhs*, i.e., strikes). This type of information is reported in ACLED (2018) database, but only from 2016 onward. Another valuable source of information is the *South Asia Terrorism Portal* (SATP), however it does not distinguish further among different categories of violent events. Finally, our firm-level data do not provide information on whether and in what way firms were directly exposed to violent events. Overall, this prevents us from making a precise statement on the heterogeneous intensity of exposure across firms within the same district and on the network implications of different types of violent events. Therefore, we 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. Note that Indian districts are also

[14]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 onward, and therefore our dataset ends with 2009. The Indian Personal Data Protection Bill (approved in 2019) allows the processing of critical personal data, such as localization of firms, only within the territory of India. It also specifies that transfer of critical data outside India is subject to the Data Protection Authority approval in consultation with Government. Therefore, even if questionnaires and data manuals of more recent ASI waves report district information, in such waves the variable that gives district location is always missing from 2010 onward.

relatively small territories: the average internal distance is 25.5 km (max. 108 km).[15] In our final sample, which includes 187,283 distinct firms, about 10% of firms were directly exposed to conflict at least once (18,419 firms).

4.2 Production network

Firm-to-firm links. Ideally, our 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.[16] 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 its potential 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 in year t, we can approximate the buyer-supplier links by assigning to each potential supplier j an index of *importance*, $\rho_{jit(k)}$, such that $0 < \rho_{jit(k)} \leq 1$ and $\sum_{j \in J} \rho_{jit(k)} = 1$. 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 $j \in J$.[17] For each good k and potential supplier-buyer pair ji in year t, 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 in year t. For a given good k, the index of importance of supplier j with respect to buyer i in year t is given by:

$$\rho_{jit(k)} = \lambda \frac{D_{ji}}{\sum_{j \in J} D_{ji}} + (1 - \lambda) \frac{k_{jt}}{\sum_{j \in J} k_{jt}} \tag{12}$$

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_{jt} is the amount of good k produced

[15] To compute the internal distance, we follow Head and Mayer (2010) using the disk approximation: $d_{ii} = (2/3)\sqrt{area/\pi}$.

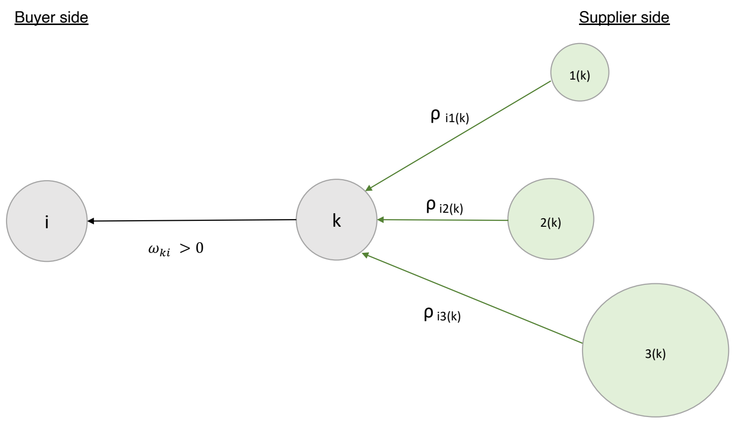
[16] Panigrahi (2021) uses data on Indian firm-to-firm transactions. Although the data are quite rich, they are not well-suited to our purpose of examining the propagation effect in peaceful districts and computing the associated total loss for two main reasons: First, "only" five Indian states are covered, of which four are affected by the Maoist insurgency. Second, information on the product sold is missing. Therefore, we would not be able to identify product-level effects on price and quantity.

[17] 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 5.1, 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.

by j in year t.[18] The index of importance $\rho_{jit(k)}$ assigns to every supplier j the probability of being the actual supplier of good k to firm i at year t. By construction, these probabilities sum to one.[19] 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, $\rho_{1i(k)}$, $\rho_{2i(k)}$ and $\rho_{3i(k)}$ 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 3 and 5), 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_{kit}, adjusted by the index of supplier importance $\rho_{jit(k)}$. Specifically, the input-output matrix Ω is the key element to construct the *influence vector*, which is a crucial component of the Indian aggregate output as it captures how conflict related idiosyncratic distortions propagate downstream to other firms by way of the production network (see Section 3).

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.

[18]For suppliers and buyers located in the same district, we set bilateral distance equal to district-specific internal distance (Head and Mayer, 2010).

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

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

This alternative specification is well-defined as it guarantees $0 < \rho_{jit(k)} \leq 1$ and $\sum_j \rho_{jit(k)} = 1$. Note that we mechanically attribute more (less) weight to the larger (smaller) and closer (farther) suppliers, compared the index described in Equation 12. Considering this alternative functional form leaves our main estimates essentially unchanged.

4.3 Validation of our strategy

As we do not observe firm-to-firm transactions, the production network is imputed using parametric assumptions as displayed in Equation 12. The absence of information on firm-to-firm transactions prevents us to perform an in-sample validation of our method to construct the Indian input-output network. Nonetheless, we corroborate our strategy developing several validation exercises.

Probability of establishing firm-to-firm links. We leverage administrative data from Gadenne et al. (2019) on firm-to-firm transactions data within West Bengal with product-level information (4-digit level) the postcode of firms, and a proxy of firms' size (turnout).[20][21] Specifically, we construct a cross section of more than 90 million potential buyer-supplier pairs for year 2011, where the unconditional probability of transaction is 0.217% (197,009 distinct transactions). We estimate the following equation:

$$T_{ji(k)} = \beta_0 + \beta_1 \rho_{ji(k)} + \mathbf{D}'_{\mathbf{ji(k)}} \beta_2 + \varepsilon_{ji(k)} \tag{13}$$

where $T_{ji(k)}$ is a dummy equal to 1 if firm i buys from supplier j good k and 0 otherwise, and $\rho_{ji(k)}$ is our index of supplier's importance defined in Equation 12. $\mathbf{D}'_{\mathbf{ji(k)}}$ is a set of fixed effects (sector, district of the seller, district of the buyer) according to the estimates. The results suggest that the index of supplier importance, $\rho_{ji(k)}$, correlates positively with the probability of firm-to-firm transaction (Table 1, columns 1 to 3). In columns 4 and 5 we add progressively dummies that mark whether the buyer and the seller share the same postcode and whether the seller and the buyer are located in the same district. The inclusion of these controls imply a modest decrease of our coefficient of interest: compared to column 3, the coefficient in column 5 is 15% smaller. In terms of magnitude, our results confirm the key role that proximity plays in determining domestic firm-to-firm transactions (Donaldson, 2018; Bernard et al., 2019). Column 5 suggests that having the same postcode is correlated with a 0.005 increase of the probability of firm-to-firm transaction, which is two times larger than the observed unconditional probability of trade. More importantly, our analysis suggests that our index has a considerable effect on the probability of firm-to-firm transactions: a 1 s.d. increase of $\rho_{ji(k)}$ ($s.d. = 0.0039$) doubles the observed average probability of trade.[22]

[20] We are deeply indebted to Lucie Gadenne, who estimated for us the validation exercise as the firm-to-firm data are confidential. Unfortunately, these data do not report firm-to-firm transactions across states.

[21] Panigrahi (2021) uses data on firm-to-firm transactions in five Indian states, which allow to discern whether the buyer and the supplier are located in the same district (58% of transactions corresponding to approximately 42% of total trade value), in different districts (37% of transactions corresponding to 43% of total trade value), or in different states (5% of transactions corresponding to 15% of total trade value). These data prove the existence of sizable inter-district and inter-state trade. Although the data are quite rich, based on our exchange with Piyush Panigrahi, they are not suitable for our purpose because information on the product sold is missing. Therefore, using this data, we would not be able to identify every potential seller j of good k.

[22] In Appendix, Table 3 displays estimates with alternative formulations of our index of supplier's importance. Specifically, we compute $\rho_{ji(k)}$ by setting the weight to relative buyer-supplier distance component, i.e., λ in Equation 12, equal to $0.1 - 0.9$, and the weight to relative supplier size component, i.e., $1 - \lambda$ in Equation 12, equal to $0.9 - 0.1$. We also propose an alternative specification of $\rho_{ji(k)}$ where we combine relative buyer-supplier distance and relative supplier size in a non-linear way (see footnote 19). In each of these alternative specifications, there is a positive and statistically significant correlation between $\rho_{ji(k)}$ and the probability of establishing a buyer-supplier link. Moreover, the magnitude of the estimated coefficients are relatively stable.

Table 1: The role of $\rho_{ji(k)}$ in predicting buyer-supplier links

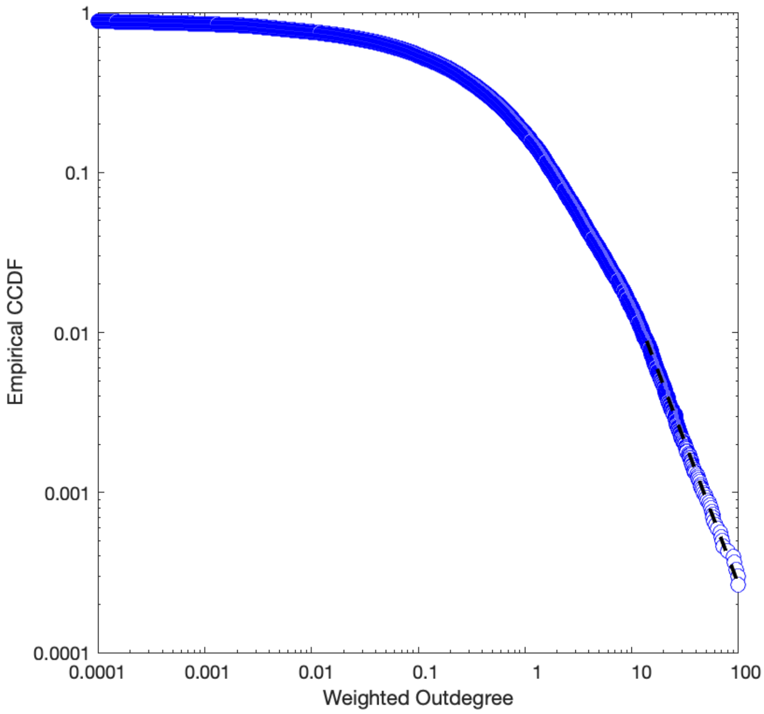
Dep. var.	$T_{ji(k)}$				
	(1)	(2)	(3)	(4)	(5)
$\rho_{ji(k)}$	0.684^a	0.684^a	0.615^a	0.537^a	0.526^a
	(0.049)	(0.047)	(0.038)	(0.029)	(0.027)
Shared postcode				0.005^a	0.004^a
				(0.001)	(0.001)
Same district					0.002^a
					(0.001)
Sector (4-digit) FE	Yes	Yes	No		
District supplier FE	No	Yes	No		
District buyer FE	No	Yes	No		
Supplier FE	No	No	Yes		
Buyer×Sector FE	No	No	Yes		
Observations	90,438,253				
Sample mean	0.00217				

Note: ^{c} significant at 10%; ^{b} at 5%; ^{a} at 1%. Standard errors in parentheses. The dependent variable is an indicator that takes a value of one if firm i buys the input k (defined at the 4-digit level) from supplier j. $\rho_{ji(k)}$ gives the importance of supplier j of good k, which is measured according to the relative distance between buyer i and supplier j and relative size of supplier j with respect to all the other suppliers of good k. These two components are combined linearly and have the same weight (see Equation 12 for further details). Shared postcode is an indicator that equals one if buyer i and supplier j share the same postcode. Same district is a indicator that equals 1 if buyer i and supplier j are located in the same district.

Relate network to observable statistics. We rely on the existing literature and use a "bottom-up" perspective by linking the imputed (not observed) production network to observable outcomes. First, we rely on Acemoglu et al. (2012) who show that the influence vector, which measures how "central" each firm is in the network representation of the economy, coincides with the *sales vector*, i.e., the vector containing firm-specific share of sales over the whole economy. In this perspective, we correlate the influence vector that arises from our measure of the production network and the observed sales vector. For each year, the coefficient of correlation is positive and fairly high, i.e., around 0.5. Moreover, using the Spearman correlation we get a coefficient equal to 0.53 and we reject the null-hypothesis that influence and sales vectors are independent (p-value equal to 0). Finally, regressing the sales vector on the influence vector for a given year (without controlling for any other covariate) yields a R^2 that is firmly in the vicinity of 0.24. These findings are consistent with applications based on observed networks. In fact, when we apply this methodology to firm-to-firm transaction data from Gadenne et al. (2019), we obtain similar results: a correlation coefficient of 0.45 and an R^2 value of 0.20.

Second, 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) nearly every 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 3: The weighted outdegree distribution associated with 2002 Indian input-output data



Note: This figure replicates 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 with weighted outdegree larger than or equal to x, that is the empirical counter-cumulative distribution (CCDF). We use 2002 as representative year as Carvalho (2014) (Figure 3). Distributions computed for years 2000, 2001, 2003-2009 are perfectly compatible with this figure.

4.4 Discussion on the endogeneity of the production network

One potential concern is that the input-output network is likely to be endogenous to the Maoist insurgency as location of firms could be affected by Maoist activities. In this section, we detail the different exercises designed to assess the extent to which the presence of conflict can distort firms' location and production decisions (Tables are relegated to Appendix 8.2). Note that, as discussed in the Section 2, the Maoist insurgency is long-lasting conflict that coexists with firms' activity. It is rather low in terms of intensity if compared to other contexts/papers, even after the sharp increase of Maoist events observed starting from 2004 (right panel of Figure 1). Therefore, if anything, we expect a narrow impact of conflict on firms' dynamics.

In what follows, to fully capture different exposure of district to violence, we define alternative measures for the presence of Maoists. First, a dummy that indicates whether the district hosted Maoist violence for at least one year over the period 1989-2009. Second, we refine this measure as district could host Maoist activities only before the beginning of the period in which we observe firms (i.e., before 2000), only after, or could be affected before and after.

Conflict & number of firms. The literature suggests that firms respond to violent shocks by reducing their presence in the affected areas. This is driven both by an increase in firm exit and a decrease in firm entry. In the short run, Blumenstock et al. (2022) finds that Afghan firms are 5-23% more likely to leave a district in the month after violence, and are 7-16% less likely to enter. Concerning long-term conflict, Camacho et al. (2013) focuses on the Colombian manufacturing sectors and estimate that a one-standard deviation increase of local armed groups attacks increases the probability of firm exit of 0.28 standard deviation. This effect is stronger for younger and smaller firms. These findings highlight the detrimental consequences of violence on the sustainability and viability of businesses, particularly those that are less established or have limited resources.
Through different sources of variation (e.g., cross-sectional data at district level, firm-level panel data, etc.), we estimate the impact of Maoist insurgency on the number of firms. Our findings suggest that there are no significant differences in terms of the number of firms between conflict and non-conflict districts, nor conflict incidence in the state where the district is located (Table 4).[23] This first set of results suggests that the Maoist insurgency does not significantly affect the number of firms. However, these results present a *net effect* and do not preclude for any potential *compensation effect* that may arise, such as if higher exit rates are compensated by higher entry rates.

Age & size of firms. If Maoist activity does affect firms' dynamics, we should observe significant differences in terms of firms' age and size when comparing firms in conflict and non-conflict districts. Over the 2000-2009 period at the district level, we compute the yearly (log-) average age (size) and standard deviation of age (size) for firms in districts that we correlate with different district specific measures of conflict (Tables 5 and 6). First, we do not find a significant difference in the average age of firms across districts that are affected and those that are not, but we do identify that firms affected before 2000 but not after display a lower age. Quantitatively, firms in those districts are, on average, 6% younger than firms in peaceful districts, translating broadly in a difference of one year (average age is 16 years). Second, the dispersion of firm's age is not significantly different across districts that are affected and those that are not. Interestingly, the dispersion of firm's age is lower in districts that are affected by Maoist activity before 2000 but also before and after 2000 (the dispersion is 15% lower). In regards of firm's size, we do not find any significant differences. Alternatively, we consider firm-level as unit of observations and estimate a standard sample mean comparison of firms' age and size between conflict and non-conflict districts: firms unaffected by Maoist activity are significantly older (16.89 years vs. 16.53 years), yet significantly smaller (129 employees vs. 165 employees). Overall, our findings indicate that there is no quantitatively large differences in terms of

[23]Reassuringly, in terms of data quality, the covariates have an expected effect on the number of firms: there are fewer firms in rural districts, and the higher the proportion of employment in the manufacturing sector and the level of development, the higher the number of firms.

firms' age and size between districts affected by Maoist insurgency and districts that are not.

Relocation, entry & exit. Finally, we aim to disentangle precisely the impact of conflict on firms' dynamics, such as firms' relocation, entry, and exit. However, as discussed in Section 4.1, the original ASI data lack both information on district location (that we impute following Martin et al. (2017)), and firm-level panel identifiers that prevents to follow firm overtime as soon as location changes. Nevertheless, to overcome this data limitation, we follow a six-step procedure to assign every firm a panel-indentifier that takes into account their possible mobility, and their actual entry or exit (Bollard et al., 2013).[24] This procedure comes at the cost of a reduction in the number of distinct firms we have in the data.[25] Concerning manufacturing firms' relocation from 2000 to 2009, we find that very few did: 0.39% of firms located in peaceful districts changed district between 2000 and 2009, and 0.25% moved to another district located in a different state. Concerning firms located in conflict-districts, 0.29% of them moved to another district and 0.19% moved to another district located in a different state.[26] These magnitudes are in line with the existent, though restricted, literature on firm relocation.[27] Going further we estimate a model of relocation choices at the firm level controlling for firm-level costs (wages, interest rates, and input prices), time-varying district characteristics (sector employment and district-level wealth), and district, year and sector fixed effects, respectively. We find that conflict incidence (at the district nor state level) does not affect significantly the decision to change district (Table 7). We also investigate the impact of conflict on a firm's choice to initiate production in a particular district. Specifically, we construct an entry-decision model that concentrates on a subset of firms that commenced operations between 2000 and 2009. None of our conflict incidence indicators show a statistically significant impact on a firm's entry (Table 7). Finally, we investigate whether conflict influences the firm-level decision to cease production. In

[24]The six-step procedure is the following: i) we identify the least recent and the most recent year in which a given firm identifier appears in the panel; ii) we assume that firms that are not observed every year between their least and most recent observations did not change location in the unobserved years; iii) for years outside of this range, we match observations based on year-to-year transitions; iv) To account for issues resulting from misreporting of closing or opening values, we create a tolerance interval based on the observed differences between year-to-year closing and opening values of firms that we observe for subsequent years. We compute the difference between closing and opening values for each of the three variables at the firm-level, remove outliers by trimming the top and bottom 1% of the three distributions, and consider two potential intervals for each variable (±1 and ±3 standard deviations); v) we pair observations that match uniquely on all three matching variables, selecting the pair with the smallest bilateral difference on the three matching variables for each set of potential matches; and vi) we assign a unique panel identifier to the matched firm, corresponding to its least recent observation.

[25]Specifically, the dataset we use in this paper includes 187,283 firms. Instead, when we account for relocation number of firms decreases to 177,758, whereas when we account for exit and entry we are left with 60,931 and 41,854 firms, respectively.

[26]Looking at the history of Maoist activity, a similar pattern emerges: 0.27% of firms located at least one year in districts affected by Maoist activity before our time-span of interest moved, 0.24% for firms located at least one year in districts affected by Maoist activity before 2000 and between 2000 and 2009, and 0.26% for firms located at least one year in districts affected by Maoist activity between 2000 and 2009.

[27]For OECD countries, Hospers (2011) and Conroy et al. (2016) find a low propensity of firms to relocate, which is even lower for firms belonging to the manufacturing sector (Pellenbarg et al., 2002). Concerning developing countries, the effects of conflict on firm performance identified by Del Prete et al. (2023) in the Libyan context remain unchanged if they exclude movers from their sample. We are grateful to Michele Di Maio for sharing the following information: In their sample of almost 390 Libyan firms, 66 of them have relocated due to conflict. Among the movers, only 5 firms belong to the manufacturing sector. Moreover, nearly 80% of the movers relocated within the same town.

this perspective, we focus on a sub-sample of firms that we observe for at least two subsequent years and we model firm-level decision to exit as a function of conflict incidence both at district and state level. Once again, we find no statistically significant relationship between conflict incidence, both at district and state level, and the firm-level decision to exit (Table 7).
Overall, these results suggest that the relocation of Indian manufacturing firms is a rare phenomenon, and conflict is not a major driver of entry and exit. It supports the idea that possible network readjustments due to Maoist insurgency would not invalidate our main results.

Market structure. Recent literature suggests that violence diminishes market competition by prompting firm exits (Del Prete et al., 2023). Note that, if conflict-affected firms face fewer competitors, their transmission of conflict-induced distortions to other firms in the production network might be more pronounced than in a more competitive market. We analyze this potential concern in a cross-sectional analysis aimed to compare markets in conflict and non-conflict districts in terms of their level of concentration, by computing a Herfindahl-Hirschman market concentration index at the industry and district level. Overall, we do not find significant differences in market concentration between conflict and non-conflict districts (Table 8).

Labor vs. capital intensive technologies. As armed group activity can damage firms' physical assets, firms located in conflict areas might choose labor-intensive production technologies. Consequently, a certain good produced by firms located in conflict districts is more likely to be produced in a labor-intensive manner compared to if it were produced by firms located in peaceful districts. We perform a cross-sectional analysis to compare conflict and non-conflict districts in terms of the adoption of labor or capital intensive technologies. Specifically, we aggregate our data at product level (6-digit of ASICC classification) and district level to compute the share of the producers for which the production involves higher labor costs than capital costs. We show that in conflict-affected districts, it is less likely for a certain good to be produced using labor-intensive technology compared to non-conflict districts (Table 9). If anything, these findings suggest that the Maoist insurgency has not compelled firms to adopt less sophisticated production processes.

Overall, this battery of exercises provide evidence that firm dynamics and market structure do not significantly correlate with conflict incidence. Therefore, we believe that it is very unlikely that our results are mostly driven by the potential endogeneity of the production network with respect to conflict.

5 The Aggregate Output Loss due to Conflict

In this section, we apply the theoretical model presented in Section 3 to the data. Our goal is 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 in order to purchase different inputs from suppliers in peaceful districts (*input bundle change*). Moreover, we examine different methods to measure conflict and consider two distinct aspects of heterogeneity of the impact of conflict on firms' activity. First, we allow conflict-induced distortions to be district-specific. Second, we encompass firm heterogeneity allowing conflict-induced distortions to vary according to firm-level characteristics.

5.1 Aggregate output loss: Baseline results

The aim of the structural estimation is to measure the loss in aggregate output of the manufacturing sector 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 and the annual influence vector v_t, which is derived from the matrix defining the production network Ω_t (Equation 7).[28] To facilitate the comparisons across our exercises, we first assume that all firms located in an affected district suffer the same distortion and all affected districts bear the same distortion ($\xi_t = f(\mathrm{T}_i) = \mathrm{T}$). In Section 5.3, we estimate the total loss with alternative functional form of $f(\mathrm{T}_i)$.

In the absence of precise estimation of conflict-induced distortions at firm nor district levels, we measure the average annual loss for a wide range of conflict distortion values: from 0 to 0.1 (Figure 4). The solid blue line, which displays the average annual loss for different conflict-induced distortions, suggests that the average annual loss varies from 0 to 4.7%.[29] In Panel A of Table 2 we present the cumulative loss suffered by the Indian economy during the period 2000-2009 for values of T. Our results suggest that during the ten years of conflict the total loss of the manufacturing sector due to conflict ranges between 3.53% (for $\mathrm{T} = 0.015$) to 23.56% (for $\mathrm{T} = 0.1$). These values translates to a GDP loss that ranges between 0.6% to 3.6%, since manufacturing sector accounts for 15% of Indian GDP (Kapoor, 2018). Using data from the World Bank Development Indicators (World Bank, 2021) for value added in Indian manufacturing (in constant 2010 USD), the cumulative losses range between 6.57 and 43.80 billion USD.

Quite remarkably, the key finding of our paper, which disregards the estimation of the conflict-induced distortion, is that for any value of T only 27% of the loss can be explained by the direct impact of

[28] The inverse of the Leontief matrix, $[I - (1-\alpha)\Omega_t']^{-1}$, is calculated using the estimated weight α ($\hat{\alpha} = 0.28$) obtained from the estimation of the firm's production function with firm-level data following Wooldridge (2009).

[29] Note that, as explained in Section 4, in each year t, the entries of the input-output matrix Ω_t, which is used to quantify the aggregate loss, are the observed input shares of firm i, i.e., ω_{kit}, weighted by $\rho_{jit(k)}$, the importance of every possible supplier j of k. The calculation of the former component, $\rho_{jit(k)}$, 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_t, in which $\rho_{jit(k)}$ 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 are not substantially different from our baseline results (Panel B of Table 10 Appendix 8.3). Moreover, we estimate the aggregate output loss using an alternative specification of $\rho_{jit(k)}$, 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 detailed in footnote 19. The estimated average output loss does not differ from the baseline ones (Panel B of Table 10 Appendix 8.3).

conflict in the affected districts. Importantly, the remaining 73% of the loss depends on the spread of a conflict's effects to peaceful districts by way of the production network. By omitting the propagation mechanism, the aggregate impact of conflict would be significantly underestimated: the cumulative loss ranges between 0.95% (for T = 0.015) and 6.36% (for T = 0.1).

Alternative production function. Our baseline 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. 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 up to 7). We find that the average annual loss decreases as the elasticity of substitution σ increases (Online Appendix 8.4). Regardless the value of conflict induced distortion T, the loss declines rapidly for $1 < \sigma < 3$ (for example, if $\sigma = 2$ the average annual loss is halved). Then, it converges to a constant (that depends on the assumed value of T) where it remains stable.

Alternative network construction method. The methodology we develop to construct the yearly production network relies on the universe of producers within the sample of firms that appear in the ASI database. This sampling may omit a sizable number of medium-sized firms and, in turn, might make our method overlook multiple potential buyer-supplier links. Given the data available, we make an effort to gauge both the direction and magnitude of this potential bias. We devise an alternative methodology to construct the production network, aiming to maximize the number of firms observed annually. This alternative specification pulls all the ASI cross-sections together and provides a time-invariant production network. Specifically, as described in Section 4.2, the components needed to set up the production network are input share (ω_{ji}) buyer-supplier bilateral distance, and potential supplier size, which in turn are needed to compute supplier importance ($\rho_{ji(k)}$). As this production network is time-invariant, we impute the values of input share related to the first occurrence of each potential buyer-supplier link. For comparison's sake, we reconstruct the baseline time-varying network, using the first-occurrence values of input share, bilateral distance, and supplier size to establish annual buyer-supplier links. The countervailing mechanisms that are in play depend on where the higher number of firms captured by the time-invariant network is located: (i) these firms are mainly located conflict-affected districts, thus more firms are spreading conflict-induced distortions; and (ii) these firms are located mainly in peaceful districts, are linked to conflict-affected firms, and the value of their influence vector is high. When comparing the time-invariant and time-varying networks, the estimation implies that incorporating more firms into the network results in an estimated loss that is 10% higher (Table 10, Panel C). The result suggests that mechanism (i) is more pronounced — with the time-invariant network, on average, we observe 12% more firms in conflict zones compared to the alternative scenario. This indicates that our baseline results are somewhat biased downward. Consequently, our results are likely to represent a conservative estimate of the true output loss.

Table 2: Output Loss in Different Scenarios

		(1)	(2)	(3)	(4)	(5)
	T	0.015	0.03	0.05	0.08	0.1
Panel A	Loss in			Baseline		
	%	-3.53%	-7.07%	-11.78%	-18.85%	-23.56%
	bn. USD	6.57	13.14	21.90	35.04	43.80
Panel B	Loss in			Mechanisms		
Inaction	%	-3.94%	-7.88%	-13.14%	-21.02%	-26.27%
	bn. USD	7.33	14.65	24.42	39.08	48.85
Supplier change	%	-3.17%	-6.35%	-10.58%	-16.93%	-21.16%
	bn. USD	5.90	11.80	19.67	31.48	39.35
Supplier and Input Bundle Change (no costs)	%	-2.45%	-4.90%	-8.17%	-13.07%	-16.34%
	bn. USD	4.56	9.11	15.19	24.30	30.38
Supplier and Input Bundle Change (with costs)	%	-2.62%	-5.07%	-8.34%	-13.24%	-16.51%
	bn. USD	4.87	9.42	15.50	24.61	30.69
Panel C	Loss in			Heterogeneous impact across districts		
Conflict length	%	-1.17%	-2.33%	-3.88%	-6.22%	-7.77%
	bn. USD	2.17	4.33	7.22	11.56	14.45
Events per population	%	-3.76%	-7.53%	-12.55%	-20.07%	-25.09%
	bn. USD	7.00	14.00	23.33	37.32	46.65
Events per area	%	-3.67%	-7.34%	-12.23%	-19.56%	-24.45%
	bn. USD	6.82	13.64	22.73	36.37	45.46
Panel D				Heterogeneous impact within district		
Good specific extra cost	%	-5.16%	-10.33%	-17.22%	-17.22%	-34.43%
	bn. USD	9.60	19.21	32.01	51.22	64.02
Share of Impacted Firms = 30% (big firms)	%	-5.94%	-11.88%	-19.81%	-31.69%	
	bn. USD	11.05	22.09	36.82	58.92	
Share of Impacted Firms = 60% (big firms)	%	-4.53%	-90.52%	-15.09%	-24.14%	
	bn. USD	8.41	16.83	28.05	44.88	
Share of Impacted Firms = 90% (big firms)	%	-3.77%	-7.54%	-12.57%	-20.11%	
	bn. USD	7.01	14.02	23.37	37.39	
Share of Impacted Firms = 30% (small firms)	%	-1.97%	-3.94%	-6.57%	-10.52%	
	bn. USD	3.67	7.33	12.22	19.56	
Share of Impacted Firms = 60% (small firms)	%	-2.34%	-4.69%	-7.81%	-12.50%	
	bn. USD	4.36	8.71	14.52	23.23	
Share of Impacted Firms = 90% (small firms)	%	-2.93%	-5.85%	-9.75%	-15.61%	
	bn. USD	5.44	10.88	18.13	29.02	
Panel E	Loss in			Policy Experiments		
Spread to adjacent districts	%	-5.46%	-10.92%	-18.20%	-29.12%	-36.40%
	bn. USD	10.15	20.31	33.84	54.15	67.69
Trade facilitation peaceful districts	%	-3.30%	-5.75%	-9.02%	-13.92%	-17.19%
	bn. USD	6.14	10.70	16.77	25.89	31.96

Note: This table reports our estimates of output loss computed in for different scenarios: (i) baseline (Panel A); (ii) network mechanism such as inaction effect, supplier change effect, supplier change and input bundle change effects (Panel B); (iii) heterogeneous impact of conflict across districts, which encompass the role of conflict length and on conflict intensity measured with number of events perpetrated by Maoist groups adjusted by population size and district area (Panel C); (iv) heterogeneous impact of conflict within district in which Maoist groups target a certain share of firms (30%, 60%, 90%) from the left/right tail of firm-size distribution (Panel D); (v) policy experiments that include conflict spread to adjacent districts, supplier change and input bundle change effects with costly network adjustment (Panel E). For each specification, the first row reports the cumulative loss in % over the period 2000-2009, while the second row reports this loss in billion USD respectively.

5.2 Mechanisms

Inaction effect. We compute the yearly output loss in the scenario in which 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 9): $\Delta \mathbf{Y}_t = v'_{2000} \times \xi_t$ 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.[30]

The average annual loss, represented by the red dot-dashed line in Figure 4, is calculated to be almost 12% higher than the baseline one. The corresponding cumulative loss during the period 2000-2009 ranges between 3.94% (for T = 0.015) and 26.27% (for T = 0.1), which is equivalent to a monetary loss that goes between 7.33 and 48.85 billion USD (Table 2, Panel B). These results suggest that allowing for network adjustment (even if only partial) through supplier change and input bundle change reduces output loss.

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 purchase inputs from suppliers located in districts that have been affected by conflict for two or more years. 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 three alternative scenarios: (i) the network adjustment involves only the *supplier change* effect; (ii) the network adjustment involves both the *supplier change* effect and the *input bundle change* effect; and (iii) the network adjustment involves some costs.

In the first scenario, and as 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. 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 approximately 10% lower than the baseline (Figure 4, yellow dotted line), implying a cumulative loss ranging between 3.17% (for T = 0.015) and 21.16% (for T = 0.1), which corresponds to a cumulative monetary loss between 5.90 and 78.70 billion USD (Table 2, Panel B).

The second scenario of network adjustment encompasses both the *supplier change* effect and *input*

[30] 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.

bundle change effect. We calculate the annual loss as the product of the annual adjusted influence vector $\tilde{\upsilon}_t$ and the annual cost-of-conflict vector ξ_t. The results suggest that allowing buyers to switch suppliers or to alter their input bundles, and assuming that these adjustments do not involve any costs, reduces the output loss substantially. Indeed, the average annual loss is now 30% lower than the baseline (Figure 4, dashed grey line), which corresponds to a cumulative loss during the period 2000-2009 ranging between 2.45% (for $\mathrm{T} = 0.015$) and 16.34% (for $\mathrm{T} = 0.1$), or 4.56 and 30.38 billion USD (Table 2, Panel B). Finally, we consider the scenario in which network adjustment involves some costs, which depend, for example, on firms having to establish new trade relationships with new suppliers, i.e., the annual cost-of-conflict vector translates into $\xi_t + \lambda_t$ where λ_t represents the adjustment costs. We assume that these costs increase with the distance between every firm and the new pool of potential suppliers, and with the importance that the supplier that was previously discarded had for the firm. In this perspective, we build a cost vector multiplying two components: (i) a distance component measured as the inverse of the difference between the change in average distance between a buyer i and all of its possible suppliers j occurred because of network adjustment; (ii) a supplier-importance component measured with the value of the parameter $\rho_{jit(k)}$ corresponding to the suppliers whose link have been removed because of conflict adjustment.[31] Our results suggest that even allowing for potential costs, network adjustment helps significantly reducing the output loss. Indeed, the cumulative loss is now 25% lower than the baseline (Table 2, Panel B). These results suggest that encouraging network adjustment is key to alleviate the output loss due to conflict.

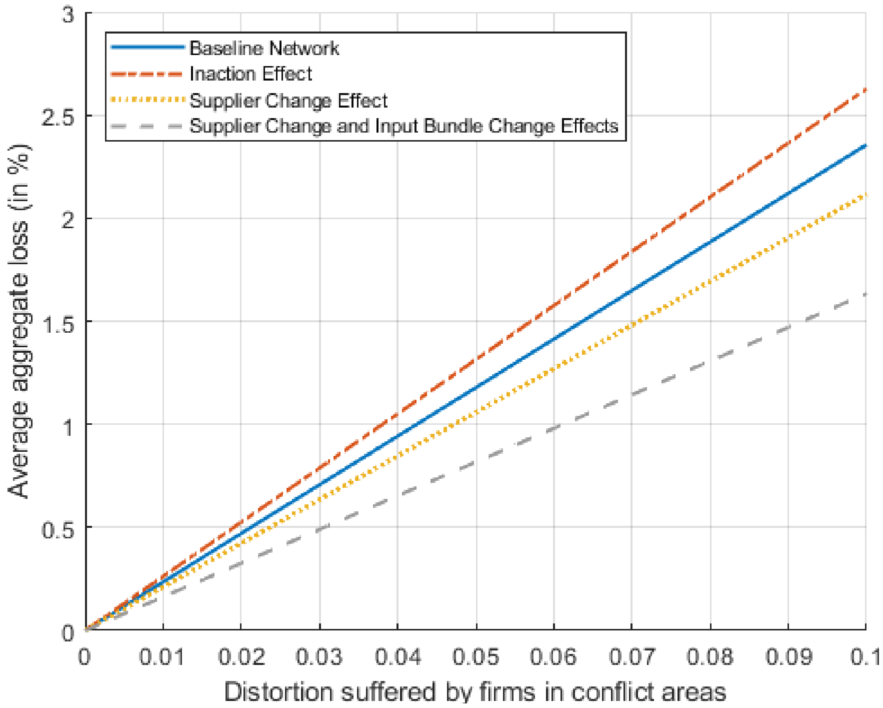
5.3 Alternative ways to measure conflict

Up to this point, we assumed that that $f(\mathrm{T}_i) = \mathrm{T}$. In what follows, we depart from this assumption and consider two distinct aspects of heterogeneity of the impact of conflict on firms' activity. First, we examine heterogeneity *across* districts, i.e., $f(\mathrm{T}_i) = \mathrm{T} \times \theta_d$ and estimate two alternative specifications of our baseline model that integrate the role of the intensity of conflict and of conflict length in determining conflict-related distortions. Second, we relax the assumption that conflict affects all firms located in a conflict-affected district in the same way and study heterogeneity *within* each district, i.e., $f(\mathrm{T}_i) = \mathrm{T} \times \eta_i$. In particular, we consider the role of firm heterogeneity in the output produced in the network propagation. Moreover, we assume that Maoist groups target their attacks against specific groups of firms based on firms' size.

Heterogeneous Maoist activity *across* districts. We address district heterogeneity in Maoist activity through two distinct approaches. Our first exercise concerns violence intensity where we add to the baseline distortion T a district-specific time-varying count of conflict events. We estimate the annual output loss (Equation 9) as follows: $\Delta Y_t = \upsilon_t \times \xi_t$, where $\xi_t = \mathrm{T} \times (1 + \mathrm{Events}_{dt})$. Here, Events_{dt} is the number of conflict-related events within district d at time t, adjusted by the district's

[31] Concerning the second component of the cost, for firms that have discarded more than one supplier, we take the maximum value of $\rho_{jit(k)}$.

Figure 4: 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 0.1. 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 in which both *supplier change* and *input bundle change* effects are present. The yellow doted line concerns the *supplier change* effect alone.

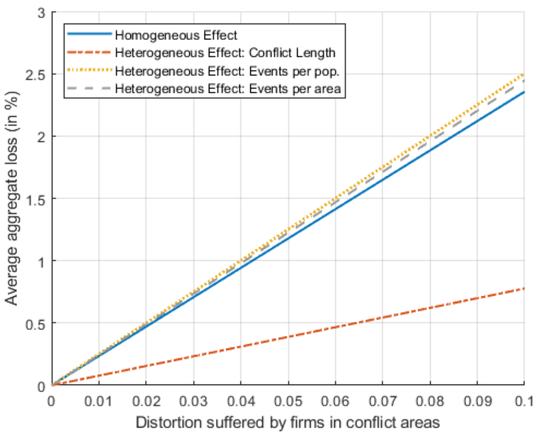
population size (or alternatively by surface area), and normalized to range between 0 and 1. Our second exercise allows for heterogeneity across districts in the history of violence. We assume that firms that are not used to conflict find harder to cope with violence by incorporating a district-specific time-varying weighting factor into the impact of T. Specifically, output loss is measured as follows: $\Delta_t = \upsilon_t \times \xi_t$, where $\xi_t = \mathrm{T} \times \frac{1}{\mathrm{Length}_{dt}}$, where Length_{dt} is the cumulative number of years district d has been affected by conflict in year t since 1989.

On the one hand, our results suggest that the average annual loss, which encompasses conflict intensity, does not significantly differ from the baseline specification. In fact, the dotted yellow line and the dashed grey line in Figure 5a are slightly above the blue solid line. Moreover, the cumulative losses closely match those estimated in the baseline scenario (Table 2, Panel C). On the other hand, when we allow firms to adapt to conflict, reducing conflict-induced distortions as conflict length increases, the corresponding output loss decreases substantially (dash-dot red line in Figure 5a). The cumulative loss over the period 2000-2009 ranges from 1.17% to 7.77%, or in monetary terms, from 2.17 to 14.45 billion USD (Table 2, Panel C).

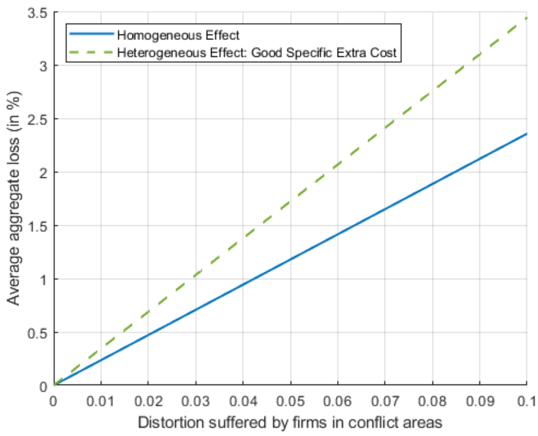
Heterogeneous Maoist intensity *within* district. So far, we have assumed that all firms in a district are affected in the same way. We depart from this hypothesis through two distinct approaches. First, we examine the role that firm heterogeneity in terms of output produced plays a

Figure 5: Conflict heterogeneity

(a) Across districts



(b) Within district



Note: This figure depicts yearly average loss (in %) for a range of conflict distortions' values that goes from 0 to 0.1. Panel (a) concerns heterogeneity of conflict across districts: the blue solid line is our baseline specification, in which we let the impact of conflict to be homogeneous across districts and firms. The dash-dotted red line refers to the scenario in which the detrimental effects of conflict decrease as the length of conflict increases. The grey dashed line and the yellow doted lines are the scenarios that allow for conflict intensity measured with number of Maoist-related events weighted by population size and district surface, respectively. Panel (b) focuses on heterogeneity of conflict within district: the blue solid line is our baseline specification, whereas dash-dotted green line refers to the scenario in which conflict-induced distortion changes according to the product that conflict-affected firms produce.

role in the network propagation. In fact, conflict-induced distortions borne by firms selling specific goods might imply different repercussions along the supply chain than distortions affecting firms selling homogeneous goods. In practice, output loss is measured as follows: $\Delta_t = \upsilon_t \times \xi_t$, where $\xi_t = \mathrm{T} \times (1 + \frac{1}{\mathrm{J}_{ik}})$, and J_{ik} is the total number of suppliers of good k (produced by firm i) in the whole country. The intuition here is that if the conflict affects firms producing goods for which there are few sellers, this will affect the total loss due to the conflict all the more. The results point to a 46% increase in the loss due to the conflict (Figure 5b and Table 2, Panel E) relative to the baseline specification (from 5.16% to 34.45% vs. from 3.53% to 23.56%) which translates into a cumulative monetary cost of between 9.6 and 64.02 billion USD.

In the second exercise, we assume that Maoist groups target their attacks against specific groups of firms based on firms' size.[32] 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 5.1 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 two 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 90^{th} 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

[32]Yet, Maoist groups are likely to target composite groups of firms that are not strictly based on their size, but also on other characteristics, e.g., ideology (Ramana, 2018). This is the best we can do with our data, as we do not observe whether and in what way firms are exposed to Maoist activity.

firms below the 30^{th} percentile of the firm size distribution are subject to conflict-induced distortions. We re-scale each value of the range from which T takes value (Section 5.1) as follows:

$$\begin{aligned} \hat{\mathrm{T}} &= \alpha \times \tilde{\mathrm{T}} + (1-\alpha) \times 0 \\ \Rightarrow \tilde{\mathrm{T}} &= \frac{\hat{\mathrm{T}}}{\alpha} \end{aligned} \tag{14}$$

Figure 6 and Table 2 Panel D report the results. The blue line represents the aggregate output loss as the proportion of impacted firms varies in the case that Maoist groups target small firms, while the yellow line represents the scenario in which large firms are targeted (where each dot represents the loss relative to each value of α). Clearly, the extent of the loss increases with the value of T. More importantly, our results suggest that if Maoist groups target small firms then the average annual loss decreases with α. Conversely, if Maoist activity is directed against large firms, then the average annual output loss increases substantially as α decreases (and the extent of firm-specific costs, denoted by $\tilde{\beta}$, increases according to Equation 14). This last result is of particular relevance because Maoist groups are more likely to attack capitalistic firms, which are likely to be large firms. This implies that, regardless the value of T, the estimate of aggregate output loss due to the Maoist insurgency computed in the baseline scenario represents a lower bound of the actual loss.

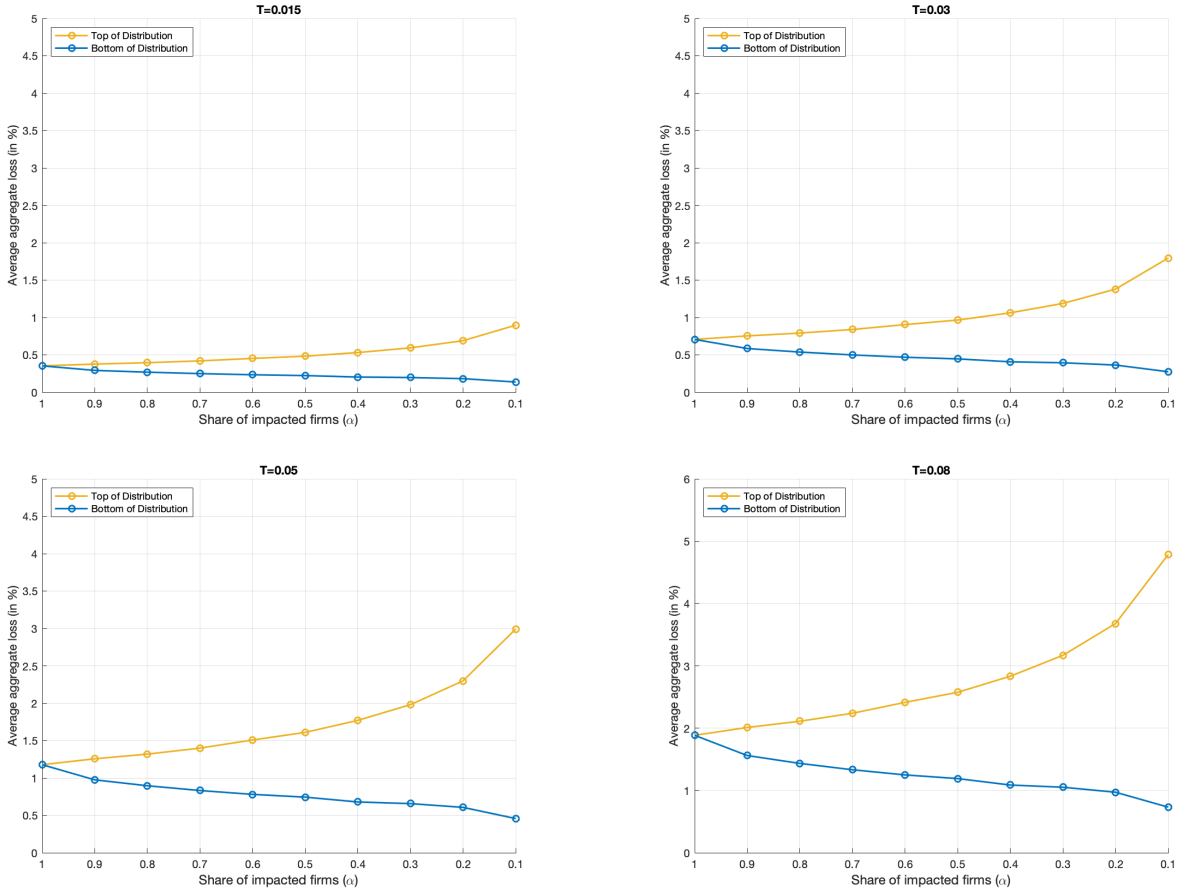
5.4 The cost of conflict in conflict-affected districts

To date, we have not quantified the initial distortion, providing only a range of potential distortion values. In the following section, based on the model developed in Section 3, we give an indication of the estimated average value of the distortion that are suffered by firms located in conflict-affected districts.[33] We start from firm-level optimal prices in log form (Equation 5 Section 3) since they are the source for the propagation throughout the economy. Note that the only element of Equation 5 that depends on conflict-induced distortions is the second addend of the right-hand side, T_i, which is a *comprehensive index* of conflict-induced distortions that firm i bears. As described in Section 3, the rise in (log-) p_i attributable to conflict induces each buyer j to decrease its demand for the good y_i, consequently leading to a reduction in its production of the good y_j. Therefore T can be seen 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.

Assuming that conflict affects all firms in conflict-affected districts in the same way, we can take

[33] In a earlier version of the paper (Couttenier et al., 2022), we developed in detail the role of direct exposure to violence, and also through the production network, in a reduced-form analysis. In addition, we estimated the mechanisms (*inaction*, *supplier change*, and *input bundle change*) through different empirical exercises. Nevertheless, in view of the potential endogeneity biases discussed in Section 4.4, all reduced-form material is relegated to the Online Appendix.

Figure 6: Maoist strategic targetin.



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 yellow line represents the scenario in which violence is directed at large firms. Note that the x-axis is reversed.

advantage of the richness of the data to estimate the following equation:

$$y_{i(d,t)} = \alpha + \beta conflict_{(d,t)} + \eta_1 x_{1,i(d,t)} + \eta_2 x_{2,i(d,t)} + \eta_3 x_{3,i(d,t)} + \gamma \log(TFP)_{i(d,t)} + \theta_{ct} + u_{i(d,t)} \quad (15)$$

where the dependent variable is the (log) 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 5, 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) total factor productivity (TFP) and state-year fixed effects θ_{ct}, since we allow firm productivity to be impacted by state-specific time-varying characteristics (Boehm and Oberfield, 2020).[34] Our main 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

[34]Firm-level TFP 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.

conflict-affected districts. Since conflict-induced distortions lead to an increase in firm's optimal price, we expect $\hat{\beta}$ to be positive. Our estimate shows that $\hat{\beta}$ is equal to 0.075 (s.e. = 0.045) and that it is statistically significant. Considering the premises of this estimation, the output loss due to conflict is close to that reported Table 2 Panel A (column 4), i.e., a cumulative loss over the period 2000-2009 of 18.85%, which corresponds to a monetary loss of 35.04 billion USD.

5.5 Discussion

The estimate of the direct cost of conflict presented in Section 5.4 is also in line with the literature. For instance, Pinotti (2015) estimates a loss of regional GDP of around 15% during the Mafia violence peak in the 1980's, and Abadie and Gardeazabal (2003) find a 10% regional GDP loss due to terrorism in the Basque Country for the 1980's and 1990's. By considering the propagation of conflict-induced distortions by way of the production network, our estimate of aggregate loss is remarkably higher than those that focus only on directly impacted territories. The share explained by propagation of conflict-related distortions outside conflict-affected districts is almost three times larger than that explained by the direct effect of conflict. This is in line with the results of Korovkin et al. (2023), who find that ignoring network propagation would lead to an underestimate of the total cost on firm-to-firm trade conflict by about 67%. Finally, the estimates obtained in the baseline scenario (Section 5.1) are likely to represent a lower bound of the actual cost of the Maoist insurgency, as we get much larger numbers when we consider the strategic targeting of firms by Maoist groups. For example, Table 2 Panel D suggests that if only the 60% largest firms were subject to conflict-induced distortions, the aggregate loss of the Indian manufacturing sector would be 28% than the baseline one.

6 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 policy maker's objective is to minimize the costs of both conflict and policy interventions. In this context, we estimate three types of policies: (i) preventing the spread of conflict to neighboring districts, (ii) restraining the aggregate loss, and (iii) facilitating trade between conflict-affected districts and and peaceful districts.

Preventing the spread of conflict. As a first exercise, we quantify the costs that could arise if the conflict were to spread to adjacent districts. Obtaining an assessment of the range of global costs that could arise in the event of contamination is a key issue. Indeed, since any public intervention to limit the spread of a conflict is costly by definition, having an estimate of the cost of non-intervention enables us to refine the cost-benefit analysis faced by the public authorities. 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 151 districts (out of 558) would now be directly affected by the insurgency. The results point to a large increase of 55% in the total loss due to the conflict (Table 2, Panel E) relative to the baseline specification (from 5.46% to 36.40%), which translates into a cumulative monetary cost between 10.15 and 67.69 billion USD. This result suggests that, depending on the output loss suffered by firms located in conflict-affected districts, any policy to prevent conflict is worthwhile if its cost is less than 0.4, 0.7, 1.2, 1.9, or 2.4 billion USD, i.e., the differences in annual output loss between the two scenarios.

Restraining the aggregate loss. To minimize the costs of the conflict, we identify the firms in conflict-affected districts that would be most beneficial to protect in order to preserve trade connections and prevent losses to those firms, while also avoiding the spread of conflict-induced distortions in the rest of the economy.[35] This is particularly relevant when policy makers have limited resources to invest in the protection of these firms and must prioritize between them.

For a sake of exposition, we consider two values of conflict-induced distortions, i.e., T = 0.03 and T = 0.08. Then, we assume that the objective of the policy maker is to halve the average annual loss, i.e., from 0.71% to 0.35%, and from 1.88% to 0.94%, respectively.[36] One possibility is to randomly choose 50% of the firms located in conflict-affected districts. However, this is not an optimal policy as there are alternatives leading to the same benefit while protecting a smaller proportion of firms and therefore reducing the cost of the intervention. We consider two alternative interventions.

In the first, resources for protection are 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. The top-panel of Figure 7 shows the simulated average annual loss according to the proportion of firms provided with protection (between 0 and 100%). The blue line denotes the scenario with T = 0.03, while the red one assumes T = 0.08. In both cases, the greatest benefit is achieved when resources for protection allocate to the most central 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.[37] 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:

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

[36] See columns 2 and 4 in Table 2 Panel A. Since these cumulative losses concern a period of ten years, the average annual loss is simply the value of the cumulative loss divided by ten.

[37] 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.

the policy maker chooses a given *threshold for 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 are protected.

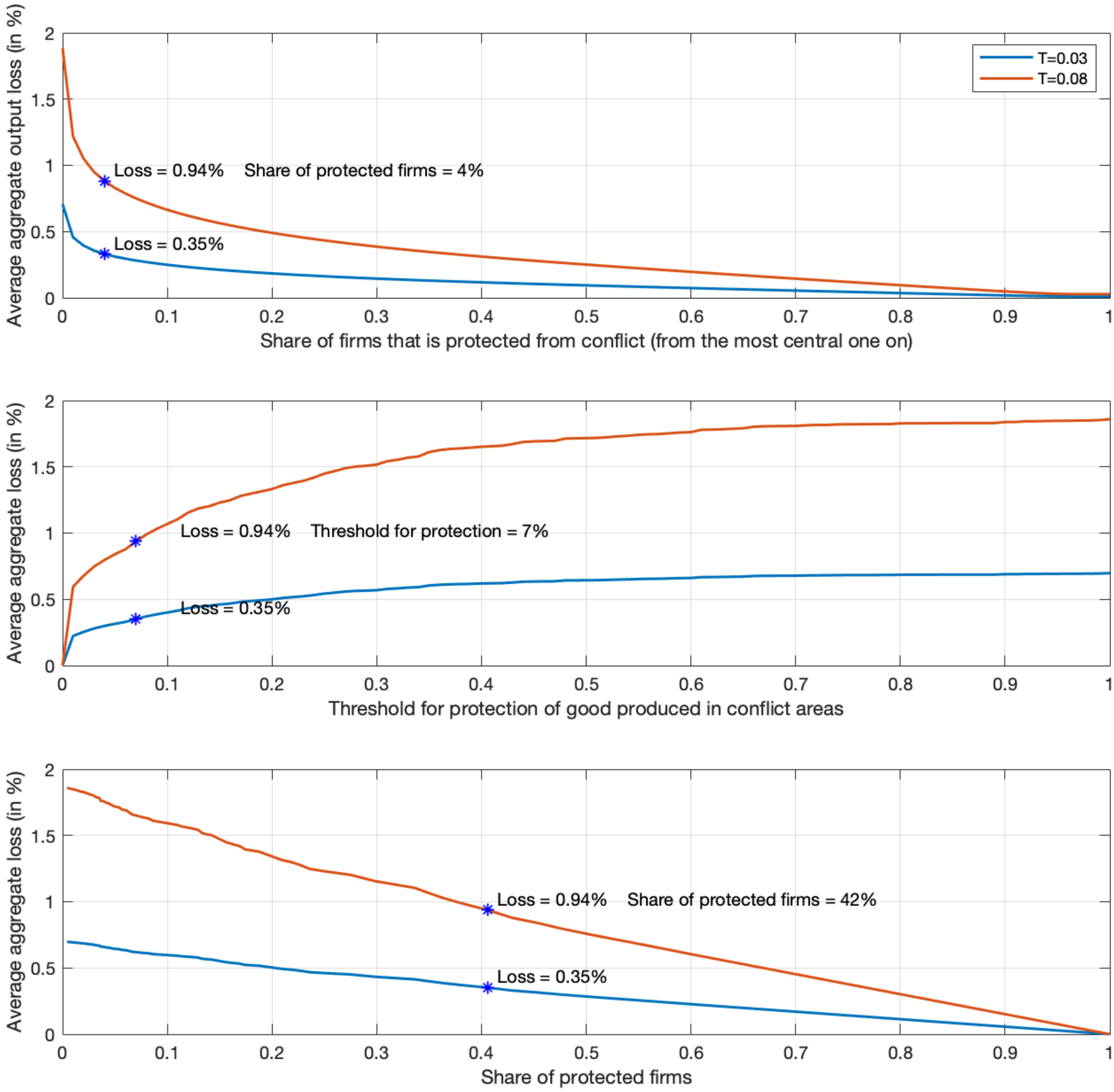
Regardless of the value of T, adopting a threshold of 7% would halve the average annual output loss (middle panel of Figure 7). In other words, resources for protection would be allocated to firms in conflict-affected districts when they account for at least 7% of total production. The bottom panel of 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.

Trade facilitation in peaceful districts. We now examine the benefit of facilitating trade across firms located in peaceful districts. For example, the policies aimed to subsidizing transportation costs, repairing infrastructure, such as roads and railways, that have been damaged by conflict, or reduce trade frictions between states due to institutional quality. Given the absence of exhaustive time-varying fine-grained data on this type of policy interventions, we adopt the following strategy. We measure output loss allowing for network adjustment, i.e., while accounting for both the supplier change and input bundle change effects, implying that firms substitute suppliers of inputs located in conflict-affected districts with suppliers of those same inputs located in peaceful districts, by assuming that the costs implied by network adjustment allow for potential trade frictions between states. To approximate them, we follow Boehm and Oberfield (2020) who show that, in the Indian manufacturing context, firm-level inputs sourcing and production organization are influenced by state-specific characteristics. Specifically, they find that these decisions are distorted in states with weaker enforcement. We approximate the cost through three components. First, we consider the firm-specific change in the share of suppliers located in different states due to network adjustment. The larger is the share the larger is the cost borne by the firm. Second, we take into account state-level quality of institutions, which we proxy as average age of pending civil cases in each State court (Boehm and Oberfield, 2020). Last, as above, we compute 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. To approximate these network adjustment costs, we multiply the three components. Once constructed, we add this new vector of firm-specific costs of adjustment to the cost-of-conflict vector. The expression of aggregate output loss translates into: $\Delta_t \mathbf{Y}_t = v_t' \tilde{\xi}_t$ where $\tilde{\xi}_t = \mathrm{T} + \zeta_t$ and $\zeta_t > 0$ is the cost of network adjustment.[38].

Results reported in Table 2 Panel E suggests that, when network adjustment costs encompasses potential trade frictions between states, the output loss approaches the baseline (Table 2 Panel A)

[38]The second component, i.e., proxy for institutional quality, has been re-scaled such it is bounded between zero and one. We are grateful to Johannes Boehm, who kindly shared the data on average age of pending civil cases in Indian courts.

Figure 7: Alternative protection policies



Note: This figure presents the results of two alternative policies aimed to halve the average loss due to conflict. The first panel reports results of an experiment in which the importance of a firm in the production network, according to the influence vector v (Equation 7) 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 assumes that the conflict-induced distortion T equal 0.03, while the red line assumes T to be equal to 0.08. In both cases, the curves represent the simulated average aggregate loss as the proportion of firms provided with protection varies from 0% to 100%. The second and third panels report 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 mid-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. Again, the blue curve assumes that T equals 0.03, while the red one assumes that T equals 0.08.

and advantages related to network adjustment are diminishing (Table 2 Panel B last two rows). This effect is especially pronounced when we consider lower values of conflict-induced distortions. For instance, for T = 0.015, the output loss that includes adjustment costs is 3.30%, while the baseline one is 3.53%. For T = 0.1, the output loss with adjustment costs equal 17.19%, while in the baseline equals 23.56%. These findings emphasize the significance of policy interventions aimed at minimizing trade frictions between firms in non-conflict districts. Such interventions are crucial in retaining the advantages brought about by network adjustments.

7 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 districts 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 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). In the second stage, 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 range between 3.52% and 23.56% of aggregate output over years 2000-2009 (equivalent to approximately a range between 6.57 and 43.80 billion USD). Importantly, regardless the extent of the conflict-induced distortions, 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 districts. Several alternative specifications of the model are examined and it is found that: (i) the severity of the total loss depends on the severity of the firm-specific direct loss, (ii) 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 frictions between firms states. 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.

8 Appendix

8.1 Validation of the approximation of the production network

Table 3: Alternative specifications of $\rho_{ji(k)}$

Dep. var.					$T_{ji(k)}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\rho_{ji(k)}$	0.355^a	0.396^a	0.442^a	0.489^a	0.533^a	0.481^a	0.357^a	0.193^a	0.277^a
	(0.020)	(0.022)	(0.022)	(0.022)	(0.045)	(0.068)	(0.071)	(0.045)	(0.028)
Shared postcode	0.003^a	0.004^a	0.004^a	0.004^a	0.004^a	0.005^a	0.005^a	0.006^a	0.004^a
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Same district	0.002^a	0.002^a	0.002^a	0.002^a	0.002^a	0.002^a	0.002^a	0.002^a	0.002^a
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Linear combination of relative distance & relative size $\rho_{ji(k)}$, value of λ	0.1	0.2	0.3	0.4	0.6	0.7	0.8	0.9	non-linear
Seller FE					Yes				
Buyer×Sector FE					Yes				
Observations					90,438,253				

Note: ^{c} significant at 10%; ^{b} at 5%; ^{a} at 1%. Standard errors in parentheses. The dependent variable is an indicator that takes a value of one if firm i buys the input k (defined at the 4-digit level) from supplier j. $\rho_{ji(k)}$ gives the importance of supplier j of good k, which is measured according to the relative distance between buyer i and supplier j and relative size of supplier j with respect to all the other suppliers of good k (see Equation 12 for further details). In columns 1-8 $\rho_{ji(k)}$ is measured by setting the weight to relative buyer-supplier distance equal to 0.1-0.9, and by setting the weight to relative supplier's size equal to 0.9-0.1. In column 9 $\rho_{ji(k)}$ results from a non-linear combination between relative buyer-supplier distance and relative supplier's size (see footnote 19 for further details). Shared postcode is an indicator that equals one if buyer i and supplier j share the same postcode. Same district is a indicator that equals 1 if buyer i and supplier j are located in the same district.

8.2 Results on the endogeneity of the production network

Table 4: Conflict and number of firms

Unit of obs.	District				District×year
Dep. var	(log-)number of manufacturing firms				
	(1)	(2)	(3)	(4)	(5)
Affected district	0.120		–0.069		
	(0.202)		(0.182)		
Affected district: Before & after		0.088		–0.034	
		(0.309)		(0.277)	
Affected district: Before		0.748		0.460	
		(0.688)		(0.615)	
Affected district: After		0.086		–0.113	
		(0.216)		(0.194)	
(log) Population (all)			1.203	1.158	2.246^a
			(0.773)	(0.775)	(0.218)
(log) Population (rural)			-1.363^b	-1.339^b	-2.037^a
			(0.544)	(0.546)	(0.168)
(log) Employment manufacturing			0.724^a	0.722^a	0.534^a
			(0.180)	(0.181)	(0.053)
(log) Employment services			0.334	0.353	0.075
			(0.331)	(0.332)	(0.088)
Nighttime light			0.018^c	0.018^c	0.017^a
			(0.010)	(0.010)	(0.003)
Forest cover (%)			–0.007	–0.007	–0.002
			(0.005)	(0.005)	(0.002)
Incidence (district)					–0.049
					(0.094)
Incidence (state)					0.085
					(0.064)
Sample mean	3.35	3.35	3.35	3.35	3.35
Observations	550	550	550	550	5280
State FE	No	No	Yes	Yes	Yes
Year FE	No	No	No	No	Yes

Note: ^{c} significant at 10%; ^{b} at 5%; ^{a} at 1%. Robust standard errors in parenthesis. From columns 1 to 4, the unit of observation is the district. We estimate the following equation: Number of firms$_{ds} = \beta_0 + \beta_1$Affected district$_{ds} + X'_{ds}\gamma + \theta_s + u_{ds}$, where *Number of firms*$_{ds}$ measures the (log-)average number of firms observed over the period 2000-2009 in district d in state s. *Affected district*$_{ds}$ corresponds to the indicators of Maoist activity defined as: (i) an indicator that indicates whether the district hosted Maoist violence for at least one year over the period 1989-2009; and (ii) three distinct dummies that mark whether Maoist insurgency impacted the district before 2000, after 2000, both before and after 2000. X'_{ds} stands for district level characteristics: population (Census of India, 2001), sectorial employment (Economic Census of India, 1998), average nighttime light (Henderson et al., 2011), and forest cover (% of the district cover by forest) (Dimiceli et al., 2015; Asher et al., 2021). In column 5, the unit of observation is district×year. We estimate the following equation: Number of firms$_{dst} = \beta_0 + \beta_1$Incidence$_{dst} + \beta_2$Incidence$_{st} + X'_{dst}\gamma + \theta_s + \theta_t + u_{dst}$, where *Number of firms*$_{dst}$) measures the number of firms (in logs) observed in district d, in state s, at year t. *Incidence*$_{dst}$ measures conflict incidence in district d, in state s at year t. *Incidence*$_{st}$ is a measure of conflict incidence at state level. X'_{dst} includes time-varying district-level characteristics, θ_s are state fixed effects and θ_t are year fixed effects.

Table 5: Cross-sectional variations: Firms' age

Dep. Var. :	(log-) average firms' age		s.d. firms' age	
	(1)	(2)	(3)	(4)
Affected district	0.013		0.294	
	(0.055)		(0.978)	
Affected district: Before & After		–0.063		–1.538[b]
		(0.049)		(0.679)
Affected district: Before		–0.150[a]		–2.290[b]
		(0.054)		(1.013)
Affected district: After		0.098		2.232
		(0.082)		(1.545)
Sample mean	2.78	2.78	14.68	14.68
Observations	550	550	550	550

Note: [c] significant at 10%; [b] at 5%; [a] at 1%. Robust standard errors in parenthesis. Estimates are weighted by the number of firms in the district. The unit of observation is the district. We estimate the following equation: $Y_{ds} = \beta_0 + \beta_1 \text{Affected district}_{ds} + u_{ds}$, where the dependent variable (Y_{ds}) measures the average and the standard deviation of age of firms in district d in state s. *Affected district*$_{ds}$ is either an indicator that signales whether district d in state s has been affected by Maoist insurgency, or three distinct indicators that mark the time period when district d in state s was affected by conflict, i.e., before 2000, after 2000, both before and after 2000.

Table 6: Cross-sectional variations: Firms' size

	(1)	(2)	(3)	(4)
Dep. Var. :	(log-) average firms' size		s.d. firms' size	
Affected district	–0.021		0.107	
	(0.110)		(0.137)	
Affected district: Before & After		0.001		0.184
		(0.162)		(0.190)
Affected district: Before		–0.107		–0.203
		(0.140)		(0.143)
Affected district: After		–0.037		0.055
		(0.150)		(0.191)
Sample mean	4.44	4.44	5.02	5.02
Observations	545	545	544	544

Note: [c] significant at 10%; [b] at 5%; [a] at 1%. Robust standard errors in parenthesis. Estimates are weighted by the number of firms in the district. The unit of observation is district. We estimate the following equation: $Y_{ds} = \beta_0 + \beta_1 \text{Affected district}_{ds} + u_{ds}$, where the dependent variable (Y_{ds}) measures the average and the standard deviation of size of firms in district d in state s, measured with numbers of employees. We approximate firm's size with the number of workers. *Affected district*$_{ds}$ is either an indicator that signales whether district d in state s has been affected by Maoist insurgency, or three distinct indicators that mark the time period when district d in state s was affected by conflict, i.e., before 2000, after 2000, both before and after 2000.

Table 7: Conflict and firm relocation, exit, entry

Dep. var.	Change district (same state) (1)	Change district (different state) (2)	Entry (3)	Exit (4)
Incidence (district)	0.00015	–0.00028	0.00001	0.00042
	(0.00128)	(0.00092)	(0.00005)	(0.00288)
Incidence (state)	0.00081	0.00051	–0.00005	–0.00090
	(0.00069)	(0.00049)	(0.00003)	(0.00151)
Sample mean	0.008	0.004	0.002	0.024
Observations	251351	251351	24777568	152743
Firm level controls	Yes	Yes	No	Yes
District level controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes

Note: [c] significant at 10%; [b] at 5%; [a] at 1%. Robust standard errors in parenthesis. The unit of observation is the firm. We estimate the following regression (for columns 1 and 2): $\text{Relocation}_{idst} = \beta_0 + \beta_1 \text{Incidence}_{dst} + \beta_2 \text{Incidence}_{st} + X'_{idst}\gamma + Z'_{dst}\eta + \theta_d + \theta_t + \theta_c + u_{idst}$, where $Relocation_{idst}$ is an indicator that takes a value of one if firm i changed district d at time t. We consider two alternative measures: (i) moving to a different district within the same state (column 1), (ii) moving to a different district in a different state (column 2). $Incidence_{dst}$ measures conflict incidence in district d, in state s at year t and $Incidence_{st}$ is a measure of conflict incidence in state s at year t. X'_{idst} is a vector of firm-level characteristics: wages, interest rates, and input prices (all in logarithmic form). Z'_{dst} is a vector of time-varying district characteristics: employment (non-farm, manufacturing, services) and nightlight. Additionally, we include fixed effects for district θ_d, year θ_t and sector θ_c. For column 3, we estimate the decision of firm i to enter district d of state s in year t which we express as follows: $\text{Entry}_{idst} = \beta_0 + \beta_1 \text{Incidence}_{dst} + \beta_2 \text{Incidence}_{st} + Z'_{dst}\eta + \theta_d + \theta_t + \theta_c + u_{idst}$, where Entry_{idst} an indicator that takes the value of one if district d corresponds to the district in which firm i initiated its production in year t, and zero for all other districts in India. For column 4, we estimate the firm-level decision to exit: $\text{Exit}_{idst} = \beta_0 + \beta_1 \text{Incidence}_{dst} + \beta_2 \text{Incidence}_{st} + X'_{idst}\gamma + Z'_{dst}\eta + \theta_d + \theta_t + \theta_c + u_{idst}$, where $Exit_{idst}$ is an indicator that indicates the last year of production of firm i, located in district d of state s. See above for the definition of the covariates.

Table 8: Market concentration in conflict districts

Dep. var	HHI index			
	(1)	(2)	(3)	(4)
Affected district	–36.910	30.109		
	(66.500)	(84.422)		
Affected district: Before & After			–185.255^{b}	61.080
			(91.453)	(127.547)
Affected district: Before			221.626	318.746
			(237.611)	(247.255)
Affected district: After			30.711	–1.740
			(77.668)	(89.829)
Sample mean	5906	5906	5906	5906
Observations	17121	17121	17121	17121
District level controls	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes

Note: ^{c} significant at 10%; ^{b} at 5%; ^{a} at 1%. Robust standard errors in parenthesis. The unit of observation is industry×district. We estimate the following regression $\text{HHI}_{jds} = \beta_0 + \beta_1 \text{Affected district}_{ds} + X'_{ds}\gamma + \theta_j + \theta_s + u_{jds}$. The dependent variable is the Herfindahl-Hirschman market concentration index (HHI_{jds}) at the industry j district d in state s level. HHI is computed as the sum of the squares of the market share of all the firms in a given market, the larger the index the more concentrated the market is. The index ranges between 10,000 in a monopolistic market and 0 in a perfectly competitive market. *Affected district*$_{ds}$ is either an indicator that signales whether district d in state s has been affected by Maoist insurgency (columns 1 and 2), or three distinct indicators that mark the time period when district d in state s was affected by conflict, i.e., before 2000, after 2000, both before and after 2000 (columns 3 and 4). We include industry and state fixed effects. We also include district-specific controls (columns 2 and 4).

Table 9: Good produced in conflict districts

Dep. var	Labor-intensive product			
	(1)	(2)	(3)	(4)
Affected district	–0.046^{a}	–0.033^{a}		
	(0.005)	(0.005)		
Affected district: Before & After			–0.061^{a}	–0.043^{a}
			(0.008)	(0.008)
Affected district: Before			–0.011	–0.028^{c}
			(0.015)	(0.015)
Affected district: After			–0.045^{a}	–0.031^{a}
			(0.005)	(0.006)
Sample mean	0.74	0.74	0.74	0.74
Observations	125939	125939	125939	125939
District level controls	No	Yes	No	Yes
State FE	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes

Note: ^{c} significant at 10%; ^{b} at 5%; ^{a} at 1%. Robust standard errors in parenthesis. The unit of observation is at the product-district level. We estimate the following regression: Labor Intensive$_{gds} = \beta_0 + \beta_1$Affected district$_{ds} + X'_{ds}\gamma + \theta_g + \theta_s + u_{pds}$. The dependent variable (*Labor Intensive*$_{gds}$) is a binary indicator that equals one if more than half of the producers of good g located in district d in state s utilize a labor-intensive technology, meaning their production involves higher labor costs than capital costs. *Affected district*$_{ds}$ is either an indicator that signales whether district d in state s has been affected by Maoist insurgency (columns 1 and 2), or three distinct indicators that mark the time period when district d in state s was affected by conflict, i.e., before 2000, after 2000, both before and after 2000 (columns 3 and 4). We include industry and state fixed effects. We also include district-specific controls (columns 2 and 4).

8.3 Alternative specifications of the production network

Table 10: Output Loss in Different Scenarios

		(1)	(2)	(3)	(4)	(5)
	T	0.015	0.03	0.05	0.08	0.1
Panel A	Loss in			Baseline		
	%	-3.53%	-7.07%	-11.78%	-18.85%	-23.56%
Panel B	Loss in			Alternative specifications		
Non-linear ρ	%	-3.53%	-7.07%	-11.78%	-18.85%	-23.56%
Distance elasticity -2	%	-3.44%	-6.88%	-11.47 %	-18.36 %	-22.95%
Distance elasticity -3	%	-3.42%	-6.84%	-11.39 %	-18.23 %	-22.78%
Distance elasticity -4	%	-3.41%	-6.82%	-11.37 %	-18.19 %	-22.74%
Distance elasticity -5	%	-3.41%	-6.82%	-11.37 %	-18.19 %	-22.73%
Panel C	Loss in			Alternative network		
Time-invariant network	%	-1.54%	-3.09%	-5.14 %	-8.23 %	-10.29 %
Time-varying network	%	-1.40%	-2.80%	-4.60 %	-7.46 %	-9.32 %

Note: this table reports our estimates of cumulative output loss over the period 2000-2009 computed in the baseline scenario (Panel A); in two alternative ways to construct the production network (Panel B): (i) $\rho_{jit(k)}$ is computed combining the relative inverse distance between each buyer-supplier pair and the relative size of each potential supplier in a non-linear way according to footnote 19; (ii) $\rho_{jit(k)}$ is computed assuming an elasticity of trade with respect to distance from -2 to -5; in two alternative way of constructing the production network (Panel C), the first pulls all the ASI cross-sections together and provides a time-invariant production network and impute the first occurrence value of input share, ω_{ij}, buyer-supplier bilateral distance, and potential supplier size, which give $\rho_{ji(k)}$, the second alternative serves for comparison's sake and reconstruct the baseline time-varying network, using the first-occurrence values of input share, bilateral distance, and supplier size to establish annual buyer-supplier links.

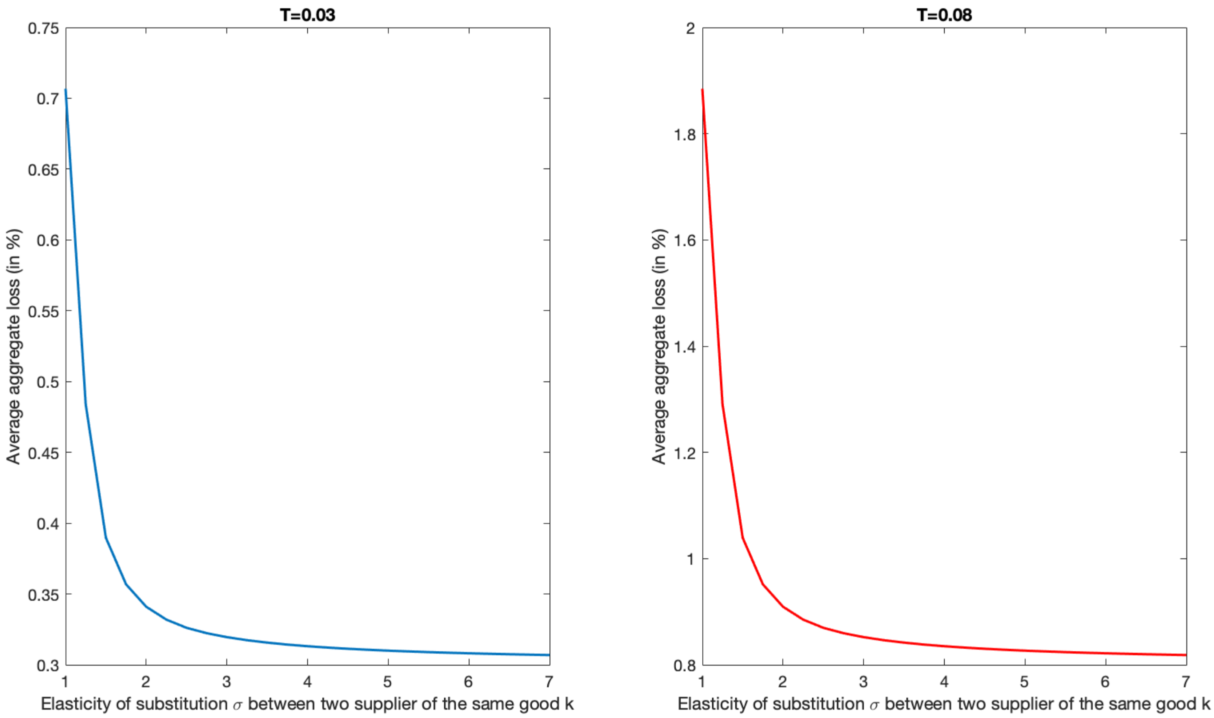
8.4 CES aggregation

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 for two values of conflict-induced distortions, i.e., T = 0.03 (blue curve) and T = 0.03 (red curve). Regardless the value of T, 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 approximately 0.3% and 0.8%, for T = 0.03 and T = 0.08 respectively.

Figure 8: CES Aggregation of Inputs



Note: This figure 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 7. The left panel (blue curve) assumes T = 0.03, the right panel (red curve) assumes T = 0.08.

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