Supply Chain Disruptions: Evidence from the Great East Japan Earthquake*

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Abstract

This paper examines whether propagation of idiosyncratic, firm-level shocks through input-output linkages can lead to sizable fluctuations at the aggregate level. Using a large-scale dataset on supply chain linkages among Japanese firms together with information on firm-level exposures to a large, but localized, natural-disaster — the Great East Japan Earthquake in 2011 — we quantify the earthquake's impact on firms that were (directly or indirectly) linked to affected firms. We find that having a supplier in the earthquake-hit region led to a 3% loss in terms of sales growth compared to firms with no such suppliers. We also find evidence for smaller but nevertheless significant upstream propagation from affected firms to their suppliers. Furthermore, we show that these losses do not remain confined to the disrupted firms' immediate customers and suppliers. Rather, firms that were only indirectly related to the firms in the affected areas (such as their customers' customers) were also negatively impacted. Even though our results suggest that such cascade effects decay with supply chain distance, the number of firms affected is large enough for this localized disruption to have a meaningful macroeconomic impact: the propagation of the earthquake shock over input-output linkages led to a 1% drop in Japan's aggregate output in the year following the earthquake.

Preliminary and incomplete.
Please do not circulate.

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1 Introduction

The production of goods and services in any modern economy is organized around complex, interlocking supply chains, as each firm may rely on a variety of different inputs for production. According to the U.S. Bureau of Economic Analysis (BEA), aggregate expenditure on intermediate goods and services in 2007 amounted to over 46% of the gross output in the United States.[1] In the same year, seventy-six of the 85 industries listed in the BEA's input-output tables relied on the outputs of at least 40 other industries for production.

Despite their vital role in the production process, supply chain linkages have also been increasingly recognized by policymakers as a source of aggregate risk in the economy. Overlapping policy initiatives at the international (World Economic Forum, 2012), regional (European Commission, 2013) and national levels, all rely on the premise that firm-level or regional shocks — such as natural disasters or terrorist attacks — can propagate through input-output linkages to a wide array of firms and adversely impact macroeconomic outcomes. For example, the U.S. National Strategy for Global Supply Chain Security is devised based on the idea that interconnections within global supply chains "serve to propagate risk that arises from a local or regional disruption across a wide geographic area," which in turn "can adversely impact global economic growth and productivity" (The White House, 2012, p. 2). Yet, evidence on the extent to which propagation of microeconomic shocks over input-output linkages can lead to macroeconomic risks remains limited. In large part, this shortcoming reflects the dual challenge of identifying plausible exogenous micro shocks in firm-level data and tracing their impact as they spread throughout the economy.

Exploiting a large, but localized, natural disaster — namely, the Great East Japan Earthquake of March 2011 — this paper provides a systematic quantification of the role of input-output linkages as a mechanism for translating microeconomic shocks into significant fluctuations at the aggregate level. By relying on information on firm locations, we first exploit the heterogeneous exposure of Japanese firms to the earthquake in order to obtain measures of firm-level shocks. We then combine this information with extensive micro-data on inter-firm transactions to trace out and quantify the impact of the shocks as they travel along supply chains and obtain an estimate for their overall macroeconomic impact, *above and beyond* the impact on firms directly affected by the earthquake. Our main findings establish that the propagation of the shock over supply chain linkages can account for Japan's weak aggregate economic performance in the year following the earthquake.

To guide our empirical analysis, we begin by developing a theoretical framework that explicitly takes the input-output linkages in the economy into account. Our model, which is a generalization of the framework in Long and Plosser (1983) and Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012), allows for general substitution patterns both within intermediate inputs and across intermediate inputs and primary factors (such as labor). Our theoretical results provide a characterization of how shocks to input producing firms impact the output of other firms as a function of the economy's input-output linkages and the corresponding elasticities of substitution. In particular, we show

[1] See Streitwieser (2009).

that depending on the extent of substitutability between different inputs, shocks not only propagate "downstream" to the affected firms' direct and indirect customers — as is well-understood from the Cobb-Douglas framework of Acemoglu et al. (2012) — but may also lead to an "upstream" cascade, propagating to the firms' suppliers, their suppliers' suppliers, and so on. Most notably, the model predicts that, for reasonable parameter values, this upstream effect is weaker than the downstream effect. Our results also provide a characterization of conditions under which shocks may propagate to firms who share common customers with the affected firms. The nature and size of this "horizontal" propagation depends on two distinct and potentially opposing forces. On the one hand, if a firm's output is a good substitute for the input supplied by another firm, a negative shock to the former would lead to an increase in the latter's output. On the other hand, however, if the primary input is also a good substitute for intermediate goods bundle, a negative shock to one of the suppliers would manifest itself as a negative demand shock to the other supplier, as it would force their common customers to substitute away from intermediate into primary inputs.

We then proceed to our empirical analysis, where we exploit two key features of the March 2011 earthquake in Japan. First, the large-scale destruction caused by the earthquake (which was followed by a massive tsunami and the failure of the Fukushima Daiichi Nuclear Power Plant) had a significant negative impact on the economic performance of the affected areas: by the end of 2011, the level of industrial production in the seven prefectures most severely affected by the earthquake was 7% lower than the corresponding level the year before. Second, despite their large impact on the coastal areas, the earthquake and its aftermaths were essentially local, regional shocks that directly affected only a small fraction of Japanese firms. In particular, the seven affected prefectures accounted for, at most, 9% of aggregate Japanese manufacturing shipments in 2010. These two features, together with the exogenous nature of the earthquake, provide us with an ideal natural experiment, with a small subset of firms exposed to a large negative shock. Crucially, the above numbers also suggest that the earthquake and its aftermaths cannot, in and of themselves, account for the large decline in aggregate Japanese industrial production in the following year. In particular, solely based on the economic size of the affected areas, aggregate industrial production in Japan should have been $0.07 \times 0.09 \approx 0.6\%$ lower than that of 2010, whereas the actual decline in Japanese industrial production was an order of magnitude larger (around 5%).

To quantify the role of supply chain linkages as a mechanism for propagation of the shock throughout the economy, we use a proprietary dataset compiled by a major private credit reporting agency. The dataset contains information on more than 800,000 firms for each yearly cross-section and represents more than half of all private and publicly listed firms in Japan, covering almost all Japanese firms with more than five employees across all sectors of the economy. For each firm-year, we observe a set of firm-level covariates as well as the identities of the firm's suppliers and customers, which enables us to construct the network of supply chain relationships for the firms in the sample. We then combine this dataset with information on firms' headquarters locations to identify the set of firms that were directly exposed to the shock.

Based on this information, we examine whether the presence of (direct and indirect) input-output

linkages to firms in the affected areas had an impact on firm performance in the year after the earthquake. As a first step, we quantify the impact of the shock on firms with transaction partners in the earthquake-hit region. To this end, we perform a difference-in-differences analysis of post-earthquake sales growth of firms with at least one supplier or customer in the affected areas (our treatment groups) relative to firms who had no direct supply chain linkages to disrupted firms (our control group). We find significant evidence for the propagation of the shock to the transaction partners of the affected firms. In particular, our estimates imply that input-disrupted firms (i.e., firms with at least one earthquake-hit supplier) under-performed the control group by 3% in the year following the earthquake. We also find an economically and statistically weaker effect on demand-disrupted firms (i.e. firms with at least one earthquake affected customer), amounting to 1% lower growth relative to the control group. Consistent with the predictions of the model, these estimates imply that downstream propagation of the shock was stronger than the upstream effect. Additionally, we show that these conclusions are not driven by pre-earthquake dynamics and are robust to a range of alternative specification and controls.

In the second step of our empirical analysis, we assess whether the shock propagated further over the supply chains, potentially affecting firms with no direct linkages to the disrupted firms. To this end, we expand our treatment group sequentially to include firms whose supply-chain network distance is two or more from earthquake-hit firms. In particular, we compare the sales growth performance of firms in the new treatment group to that of firms that were relatively more distant — in a supply chain network sense — from affected firms. Our empirical results indicate that the disruption caused by the earthquake led to significant downstream propagation, not only affecting the disrupted firms' customers, but also their customers' customers and so on. For example, we find that firms that were downstream to input-disrupted firms — i.e. customers of customers of firms in the earthquake-hit region — underperformed the control group by about 1%. Our estimates also point to smaller, yet significant negative effects on firms even further downstream in the supply chain. However, we do not find evidence for an upstream counterpart to this indirect, downstream propagation effect.

Based on these findings, we then obtain an estimate for the overall macroeconomic impact of the earthquake and its aftermaths. Importantly, our results indicate that the *indirect*, *downstream* propagation of the shock over input-output linkages played a significant role in shaping the overall economic performance of Japan in the year after the earthquake. More specifically, despite the relatively small number of firms with an immediate supplier in the earthquake-hit region — accounting for only 14% of total sales in our sample and thus explaining less than 0.4 percentage points of the decline in post-earthquake aggregate growth — firms that were indirectly affected were much more numerous (and economically important). In particular, firms that were downstream to firms with a supplier in the affected areas account for nearly 45% of total sales in our sample. Taking these indirect propagation effects into account, we find that the earthquake and its aftermaths effect of supply chain disruptions following the earthquake is much larger, leading to a 1% decline in Japan's aggregate output in the year following the earthquake.

Overall, our empirical findings provide substantial evidence that, by propagating shocks to other

firms in the economy, input-output linkages can play a significant role in translating firm-level disturbances into sizable fluctuations at the aggregate level, thus indicating the importance of microeconomic shocks in the origins of macroeconomic fluctuations.

Related Literature Our paper is most closely related to the recent literature that emphasizes the role of input-output linkages as a mechanism for propagation and amplification of shocks. Acemoglu et al. (2012, 2014) argue that, depending on the nature of the economy's underlying production network, input-output linkages can translate firm-level, idiosyncratic shocks into sizable fluctuations at the aggregate level.[2] Despite the theoretical plausibility of such a propagation mechanism, credible identification of firm-level shocks and tracing their propagation along production chains remain largely unexplored. In particular, even though recent works such as Foerster, Sarte, and Watson (2011), Carvalho and Gabaix (2013), and Atalay (2014) find the contribution of idiosyncratic shocks to aggregate volatility to be substantial, they invariably rely on strong identifying assumptions for backing out idiosyncratic shocks from sectoral data.[3]

Two exceptions are the contemporaneous works of Barrot and Sauvagnat (2015) and Boehm, Flaaen, and Pandalai-Nayar (2015), who also study the role of firm-level linkages in propagating input disruptions. Barrot and Sauvagnat (2015) combine county-level data on the occurrence of natural disasters in the U.S. with Compustat data on the identity of large (and publicly listed) customers of firms located in those counties, and find evidence for substantial downstream propagation to the immediate customers of firms located in the affected areas. Relatedly, by relying on a dataset linking U.S. Census Bureau micro-data to firms' international ownership structure, Boehm et al. (2015) find that American affiliates of Japanese multinationals suffered large drops in output in the months following the 2011 earthquake in Japan, providing evidence for cross-country transmission of shocks.[4] Relative to these works, our contribution is to exploit the much more detailed nature of firm-level input-output linkages to provide additional evidence on both *upstream* and *downstream* propagations, as well as documenting the transmission of the shock to firms that are *indirectly* linked to the affected firms through supply chain linkages. Furthermore, the large scale of our study at the national level (alongside its focus on both private and publicly traded firms) enables us to provide an estimate for the overall macroeconomic impact of the earthquake shock as it propagated throughout the Japanese economy.

Our paper is also related to several recent works, such as Noy (2009), Raddatz (2009) and Strobl (2012), that study the macroeconomic impacts of natural disasters. In line with these papers, we find

[2] Earlier studies in this literature include Jovanovic (1987), Durlauf (1993), Horvath (1998, 2000), Dupor (1999) and Carvalho (2010). For a detailed survey, see Carvalho (2014). Somewhat relatedly, Gabaix (2011) argues that if the firm size distribution is sufficiently heavy-tailed (in the sense that the largest firms contribute disproportionally to aggregate output), firm-level idiosyncratic shocks may translate into fluctuations at the aggregate level, even in the absence of input-output linkages.

[3] Using a database covering the universe of French firms, di Giovanni, Levchenko, and Méjean (2014a) perform a similar exercise at the firm level.

[4] Relatedly, Acemoglu et al. (2015a,b) investigate the propagation of different types of shocks through the U.S. input-output network at the *sectoral* level. We, in contrast, document the role of supply chain linkages in the transmission of shocks at the *firm* level.

substantial evidence that the earthquake shock had a negative and significant effect on aggregate Japanese output. We contribute to this literature by exploiting detailed firm-level data in the disaster region and documenting that supply-chain linkages constitute a powerful transmission mechanism for otherwise localized shocks.

Our paper also belongs to the growing theoretical literature that focuses on the different roles played by production networks in shaping economic outcomes. For example, Bigio and La'O (2013) study how the presence of financial frictions in a production economy can lead to the emergence of a "liquidity multiplier" when firms rely on each other's outputs as intermediate goods for production. Relatedly, Jones (2011, 2013) argues that differences in the structure of production chains can explain cross-country divergences in income.[5] Our theoretical framework, however, is most closely related to the contemporaneous works by Baqaee (2015a,b), who also studies a multi-sector economy in which firms utilize CES production technologies. In particular, Baqaee (2015a) shows that the extensive margin of firm entry can locally amplify shocks. In contrast to these studies, the main focus of our theoretical results is to provide a characterization of how shocks to a given firm impact the output of other firms as a function of the economy's input-output linkages and the corresponding elasticities of substitution (both within intermediate inputs and across intermediate and primary inputs). Our characterization results provide sharp predictions for the nature and extent of upstream and downstream propagations in the economy.

The role of input-output linkages in propagating shocks has also been studied in the trade literature. For example, di Giovanni and Levchenko (2010), di Giovanni, Levchenko, and Méjean (2014b) and Johnson (2014) find evidence for the transmission of business cycle shocks through direct trade linkages at the firm level, thus arguing that intermediate input trade leads to business cycle comovements across countries. Relatedly, Caliendo, Rossi-Hansberg, Parro, and Sarte (2014) study the impact of intersectoral and interregional trade linkages in propagating disaggregated productivity changes across U.S. states.

Supply chain disruptions have also been studied extensively by the supply chain management literature. On the theoretical side, with the exception of the recent works of Federgruen and Hu (2014a,b), this literature focuses on models that consist of a handful of firms and studies their sourcing and inventory decisions.[6] We contribute to this literature by providing a framework for how shocks propagate over input-output linkages in general supply chain networks. On the empirical side, papers such as Cachon, Randall, and Schmidt (2007), Jain, Girotra, and Netessine (2014) and Wu and Birge (2014) document various stylized facts on the relationship between firms' supply chains on the one hand and their output volatility, inventory level and stock returns on the other. We, in contrast, leverage the exogenous nature of the earthquake to identify firm-level shocks, trace their propagation over input-output linkages, and thus provide causal evidence for the role of supply chains in transmitting

[5] See also Buraschi and Porchia (2014) and Herskovic (2015) who study the asset pricing implications of production networks and Kelly, Lustig, and Van Nieuwerburgh (2013) who show that the concentration of customer networks is an important determinant of firm-level volatility. A smaller set of papers, such as Chaney (2014), Oberfield (2013) and Carvalho and Voigtländer (2015), focuses on the evolution of production networks.

[6] Some of the recent examples include Tomlin (2006, 2009), Babich, Burnetas, and Ritchken (2007), Federgruen and Yang (2008) and Yang, Aydın, Babich, and Beil (2009).

shocks beyond the initially affected firms.

Finally, our paper is related to the small literature, such as Saito, Watanabe, and Iwamura (2007), Nakajima, Saito, and Uesugi (2012), Ohnishi, Takayasu, and Takayasu (2010) and Saito (2012, 2013), that analyzes the structure and geographical features of Japan's firm-level production network.[7] Finally, Bernard, Moxnes, and Saito (2015) complement our results by documenting the role of geography and firm characteristics in the formation of supply chain linkages and find evidence that the creation of new supply chain linkages in the aftermath of opening of a high-speed train line in Japan led to significant improvements in firm performance.

Outline The rest of the paper is organized as follows. Section 2 introduces the theoretical framework. Section 3 describes the Great East Japan Earthquake and its aftermaths. In Section 4, we present the firm-level data and the corresponding supply-chain data. Section 5 contains our main empirical results and Section 6 concludes. The proofs are provided in the Appendix.

2 Supply Chain Disruptions: Theoretical Framework

We start by developing a multi-firm, general equilibrium model in the spirit of Long and Plosser (1983) and Acemoglu et al. (2012), which captures how idiosyncratic, firm-level shocks propagate over input-output linkages.

2.1 Model

Consider a static economy consisting of n competitive firms denoted by $\{1, 2, \ldots, n\}$, each of which producing a distinct product. Each product can be either consumed by a mass of consumers or used as an input for the production of other goods.

Firms employ CES production technologies with constant returns to scale that transform labor and intermediate goods into final products. More specifically, the output of firm i is given by

$$y_i = A_i \left[(1-\mu)^{1/\sigma} \ell_i^{(\sigma-1)/\sigma} + \mu^{1/\sigma} M_i^{(\sigma-1)/\sigma} \right]^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where μ captures the material inputs' share, σ represents the elasticity of substitution between labor and material inputs, ℓ_i is the amount of labor hired by the firm, and A_i is the corresponding productivity shock. In the above expression, M_i denotes firm i's intermediate input bundle purchased from other firms, given by

$$M_i = \left[\sum_{j=1}^{n} w_{ij}^{1/\zeta} x_{ij}^{(\zeta-1)/\zeta} \right]^{\zeta/(\zeta-1)},$$

where x_{ij} is the amount of good j used in the production of good i and ζ is the elasticity of substitution between different intermediate goods. The weight $w_{ij} \geq 0$ designates the importance of good j as an

[7] See also Atalay, Hortaçsu, Roberts, and Syverson (2011), who study the input-output network derived from Compustat data on publicly listed firms in the United States.

intermediate input for the production of good i. In particular, a higher w_{ij} means that good j is a more important input in the production technology of firm i, whereas $w_{ij} = 0$ if firm i does not rely on good j as an intermediate good for production. Throughout, we assume that $\sum_{j=1}^{n} w_{ij} = 1$ for all firms i.

In addition to the firms, the economy is populated by a unit mass of identical consumers. Each consumer is endowed with one unit of labor, which she provides inelastically to the market. We assume that the representative consumer has symmetric, logarithmic preferences over the n goods, i.e.,

$$u(c_1, \ldots, c_n) = \sum_{i=1}^{n} \log(c_i),$$

where c_i denotes the amount of good i consumed.

Thus, aside from parameters μ, ζ and σ, the above economy can be represented by a matrix $W = [w_{ij}]$, which summarizes the relative importance of different goods as intermediate inputs in the production technology of all firms. In the special case that firms' production technologies are Cobb-Douglas (i.e., $\zeta = \sigma = 1$), w_{ij} is also proportional to the corresponding entry of the economy's input-output table, measuring the value of spending on input j per dollar of production of good i. Thus, with some abuse of terminology, we refer to W as the *input-output matrix* of the economy. Similarly, we also define the economy's *Leontief inverse* as $T = (I - \mu W)^{-1}$. The (i, j) element of this matrix, which can be rewritten as

$$t_{ij} = 1 + \mu w_{ij} + \mu^2 \sum_{k=1}^{n} w_{ik} w_{kj} + \ldots, \tag{2}$$

accounts for the direct and indirect role of firm j as an input-supplier to firm i.

The competitive equilibrium of the economy described above is defined in the usual way: it consists of a collection of prices and quantities such that (i) the representative consumer maximizes her utility; (ii) all firms maximize their profits while taking the prices and the wage as given; and (iii) all n commodity markets and the labor market clear.

2.2 Propagation of Shocks

Our goal is to characterize how shocks to a given firm propagate over input-output linkages and impact the output of the rest of the firms in the economy. Unfortunately, a closed-form characterization of the firms' equilibrium outputs does not exist in general.[8] To circumvent this issue, we log-linearize the equilibrium around the point $\epsilon_i = \log(A_i) = 0$ for all i. Such a log-linearization essentially provides a first-order approximation to the impact of small, firm-level productivity shocks on output.[9] Denoting the logarithm of firm i's output by $\hat{y}_i$, we have the following result:

[8] A closed-form characterization of equilibrium quantities is possible in the special case of $\zeta = \sigma$. Long and Plosser (1983) and Acemoglu et al. (2012) provide a characterization for the case in which firms' production functions are Cobb-Douglas. See Appendix A.1 for the system of equations that determines equilibrium prices and quantities for a general economy.

[9] For a discussion, see Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015c).

Proposition 1. *The impact of a productivity shock to firm s on the output of firm $i \neq s$ is equal to*

$$\begin{aligned}\frac{\partial \hat{y}_i}{\partial \epsilon_s} = t_{is} + \frac{1}{\mu v_i}(\sigma - 1)(1-\mu)\left(\sum_{m=1}^{n} v_m t_{ms} t_{mi} - v_i t_{is} - v_s t_{si}\right) \\ + \frac{1}{\mu v_i}(1-\zeta)\left(\sum_{m=1}^{n}\big((1-\mu)v_m + \mu\big) t_{ms} t_{mi} - v_i t_{is} - v_s t_{si}\right),\end{aligned} \tag{3}$$

where t_{ij}'s are the elements of the economy's Leontief inverse and $v_i = \sum_{j=1}^{n} t_{ji}$.

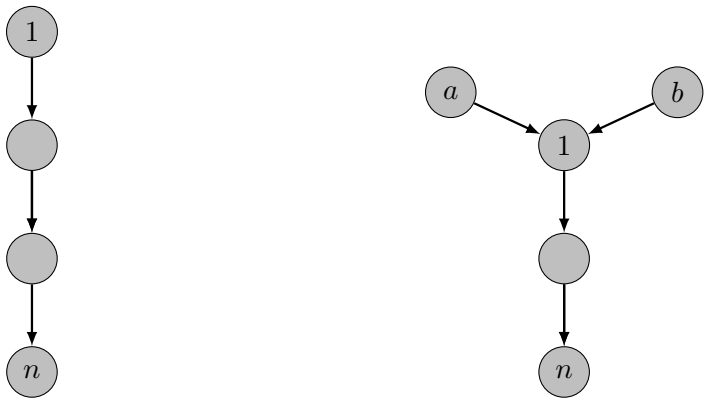
The above result highlights that the nature of input-output linkages in the economy — captured via its Leontief inverse — plays a central role in determining the nature and the extent to which shocks propagate from one firm to another.

The right-hand side of (3) consists of three terms, each of which capturing a distinct channel for how a shock to firm s impacts the output of firm i. The first term, which is equal to the corresponding element of the economy's Leontief inverse, captures the so called "output effect": a negative productivity shock to firm s increases the equilibrium price of good s, thus forcing the firm's customers to scale back their production by reducing their demand for good s. Such a reduction in turn increases the prices of goods produced by s's customers, leading to a second round of propagation to their respective downstream firms. Note that this effect is essentially a *downstream* propagation mechanism from a supplier to its customers, the customers of its customers and so on. In fact, equation (2) highlights that $t_{is} = 0$ if firm s is not a direct or indirect supplier of firm i. On the other hand, this effect is more pronounced the more important of a role firm s plays as a (direct or indirect) input-supplier to firm i.

In addition to the output effect, shocks to firm s impact the output of firm i via two other channels. These effects, captured via the second and third terms on the right-hand side of (3), arise due to the fact that changes in input prices also affect the composition of inputs used by the firms. More specifically, the second term on the right-hand side of (3) captures how substitutability between labor and the intermediate goods bundle affects the extent of shock propagation: if labor and intermediate goods are gross substitutes, a negative shock to firm s makes utilizing labor more attractive to s's customers (at the expense of all other inputs), thus amplifying the effect of the shock. In fact, one can verify that the second term on the right-hand side of (3) is always non-negative for $\sigma > 1$.[10] Note that unlike the output effect captured by the first term on the right-hand side of (3), this "labor substitution effect" can result in both upstream and downstream propagation: as long as $\sigma \neq 1$, a shock to firm s can propagate to its (direct and indirect) suppliers as well as its customers.

Finally, the third term in Proposition 1 captures how substitutability between different intermediate inputs impacts the nature and extent of shock propagations in the economy: depending on the value of ζ, a negative shock to firm s may induce its downstream customers to substitute away from good s to other material inputs. Consequently, as long as $\zeta \neq 1$, shocks to firm s not only impact s's (direct or indirect) customers, but can also propagate to their other suppliers, creating yet another channel for upstream propagation.

[10] This is consequence of the fact that all elements of the Leontief inverse are non-negative and that $t_{jj} > 1$ for all j.



(a) The simple production chain (b) The Y-shaped production chain

Figure 1. Two stylized production chains.

2.3 Production Chains

To further clarify the nature and extent of shock propagations over input-output linkages, we focus on an economy in the form of a "simple production chain" depicted in Figure 1(a). In such an economy, each firm relies on the output of a single other firm for production. More specifically, we assume that that firm i is the unique supplier to firm $i+1$, i.e., $w_{i+1,i} = 1$ for all i. Despite its simplicity, this structure is rich enough to capture many of the effects discussed above.[11]

Downstream Propagation We first focus on how shocks propagate downstream from a firm to its customers. By Proposition 1, the impact of a shock to firm s on firm $i > s$ further downstream in the chain is given by

$$\frac{\partial \hat{y}_i}{\partial \epsilon_s} = \mu^{i-s} + (\sigma - 1)\frac{(\mu^i - \mu^n)}{(1+\mu)\mu^{s-1}}, \tag{4}$$

leading to the following result:

Corollary 1. *Suppose that a firm in the simple production chain is hit with a negative shock. Then, regardless of the value of σ,*

(a) The outputs of all its downstream firms decrease.

(b) The impact on a given firm is smaller, the further downstream it is from the shock's origin.

(c) The impact on all downstream firms increase as σ increases.

Statement (a) of the above result highlights that a negative productivity shock to firm s, not only reduces the output of its immediate customers, but also negatively impacts its customers' customers

[11] Even though we restrict our attention to the first-order effects of the shocks by log-linearizing of the firms' output around the point $\epsilon = 0$, all our insights remain unchanged when we use the exact expressions.

and so on. Thus, in this sense, such a negative shock propagates all the way downstream. Nevertheless, as statement (b) highlights, the size of this impact is diminished as the shock travels over the chain. Note that these results hold regardless of whether labor functions as a gross substitute or complement for the material inputs in the firms' production technology. Finally, part (c) states that as labor becomes a better substitute for the intermediate goods, productivity shocks would have a more pronounced effect on the downstream firms.

To see the intuition behind the above result, recall from the discussion following Proposition 1 that a negative shock to firm s impacts the output of its downstream firms via two distinct channels.[12] First, by increasing the price of good s, such a shock forces the downstream firm i to scale back operations, leading to a smaller equilibrium output. This effect is thus always negative regardless of the value of σ. The second channel, on the other hand, depends on the elasticity σ: when labor is a gross substitute for material inputs, a negative shock not only reduces $\hat{y}_i$ via the output effect, but also induces firm $i+1$ to substitute away from good i and instead rely more heavily on labor, thus further reducing the output of firm i. Therefore, when $\sigma > 1$, the output and substitution effects reinforce one another, leading to a stronger downstream propagation. In contrast, the two channels have opposing effects when labor and material inputs are gross complements. However, as part (a) highlights, the output effect always dominates the labor substitution effect, regardless of the value of σ.

Upstream Propagation In addition to their impact on a firm's customers, shocks may also propagate upstream to the the firm's suppliers. By Proposition 1, the impact of a shock to firm s on firm $i < s$ further upstream in the chain is given by

$$\frac{\partial \hat{y}_i}{\partial \epsilon_s} = (\sigma - 1)\left(\frac{\mu^s - \mu^n}{1+\mu}\right)\left(\frac{1-\mu^{n-s+1}}{\mu^{i-1}-\mu^n}\right), \tag{5}$$

thus leading to the following result:

Corollary 2. *Suppose that a firm in the simple production chain is hit with a negative shock. Then,*

(a) The output of all its upstream firms decrease if $\sigma > 1$, whereas their output increase if $\sigma < 1$.

(b) The impact on a given firm is smaller the further upstream it is from the shock's origin.

(c) There exists $\bar{\sigma} > 1$ such that for $\sigma \in (1, \bar{\sigma})$, the downstream effect is stronger than the upstream effect.

The above result thus establishes that as long as $\sigma \neq 1$, productivity shocks not only impact the output of the downstream firms, but also propagate upstream. In contrast to the downstream effects, however, the sign of this impact depends on whether labor and material inputs are gross substitutes or complements. In particular, as statement (a) of Corollary 2 shows, a negative shock to s reduces the output of its direct and indirect suppliers if and only if labor is a gross substitute for the intermediate

[12] Since in a production chain each firm relies on a single intermediate good, the channel that functions via the substitutability of different intermediate goods is not active.

goods in the firms' production technology. As expected, the size of this impact is diminished as the shock travels further upstream over the chain.

To understand the intuition underlying the upstream propagation mechanism, recall from Corollary 1 that a negative shock to firm s impacts the output of its downstream customers via the output and labor substitution effects. In particular, when $\sigma > 1$, firms downstream to s increase their reliance on labor at the expense of good s. This reduction in demand for good s due to the substitution effect in turn forces firm s to reduce its own input demand, thus manifesting itself as a negative demand shock to s's upstream suppliers. In this sense, upstream propagation over the chain emerges only as a by-product of downstream propagation effects.[13]

Finally, part (c) of Corollary 2 provides a comparison between the size of the upstream and downstream propagation effects. In particular, it shows that as long as the elasticity of substitution between labor and material inputs is not too large, shocks to a firm have a larger impact on its downstream customers than on its upstream suppliers. Furthermore, as we show in Appendix A.3, in a long enough production chain, the downstream impact is always larger than the upstream impact, regardless of the value of σ.[14] This is due to the fact that whereas upstream propagation arises as a consequence of the substitution effect, downstream propagation is generated by an equally sized substitution effect in addition to the output effect.

Horizontal Propagation Corollaries 1 and 2 provide a characterization of downstream and upstream propagation mechanisms in isolation. We now turn to a richer form of spillover, whereby the simultaneous presence of the two propagation mechanisms can result in shocks to a given firm propagating to other firms which are neither its (direct or indirect) suppliers nor customers. To capture such a possibility, consider the Y-shaped production network depicted in Figure 1(b), in which firm 1 relies on the outputs of firms a and b as intermediate goods for production. Using Proposition 1, one can show that the impact of a shock to firm b on the output of firm a is given by

$$\frac{\partial \hat{y}_a}{\partial \epsilon_b} = \frac{\mu(1-\mu^n)}{2(1-\mu)(2-\mu-\mu^{n+1})}\left[(1-\zeta)+(\sigma-1)\left(\frac{1-\mu^{n+1}}{1+\mu}\right)\right], \tag{6}$$

thus leading to the following result:

Corollary 3. *In the presence of a negative shock to firm b, the output of firm a is decreasing in σ and increasing in ζ.*

The above result shows that shocks may propagate horizontally from a firm to another even though neither firm is a direct or indirect supplier of the other. More importantly, however, it illustrates that the extent and nature of this propagation depends on the elasticity of substitution between different intermediate goods and that of between labor and material inputs. The intuition underlying Corollary 3 is along the lines of our earlier results: a negative shock to firm b, not only reduces the output of firm

[13] In fact, as equation (5) suggests, shocks to the firm at the very bottom of the chain (i.e., $s = n$) have no upstream effects, as such shocks do cannot propagate further downstream.

[14] Formally, $\lim_{n\to\infty} \bar{\sigma} = \infty$.

1, but may also induce it to alter the composition of its inputs. In particular, as labor becomes a better substitute for material inputs, such a negative shock forces firm 1 to utilize labor more intensely, and as a result impacting the output of firm a negatively. On the other hand, a higher ζ implies that good a is a better substitute for good b. Consequently, a negative shock to firm b would induce firm 1 to rely more on good a, thus increasing the output of firm a.

Corollary 3 also highlights that the sign of the horizontal propagation effect depends on a "race" between the elasticity of substitution between different material inputs, ζ, and that of between labor and the intermediate input bundle, σ. However, in the special in case that $\sigma > 1$ and $\zeta < 1$, a negative shock to firm b would unambiguously reduce the output of firm a.

3 The 2011 Great East Japan Earthquake

On March 11, 2011, a magnitude 9.0 earthquake occurred off the northeast coast of Japan. This was the largest earthquake in the history of Japan and the fifth largest in the world since 1900. The earthquake brought a three-fold impact on the residents of northeast Japan: (i) the main earthquake and its aftershocks, directly responsible for much of the material damage that ensued; (ii) the resulting tsunami, which flooded 561 square kilometers of the northeast coastline; and (iii) the failure of the Fukushima Daiichi Nuclear Power Plant that led to the evacuation of 99,000 residents of the Fukushima prefecture.

According to the National Police Agency of Japan, in addition to severe damage to infrastructure, the earthquake and its aftermaths resulted in 15,889 confirmed fatalities, a further 2,601 people missing, and the extensive or complete collapse of 401,306 buildings across twenty prefectures. The brunt of the damages, however, were mostly concentrated in the seven northeast prefectures of Iwate, Miyagi, Fukushima, Aomori, Ibaragi, Tochigi, and Chiba. Figure 2 depicts the geographical distributions of casualties and demolished structures.

Not surprisingly, this localized, yet large-scale shock had a significant negative impact on the economic performance of the affected areas. For the Japanese fiscal year running from April 2011 through March 2012 — that is, in the 12 months following the earthquake — average real GDP growth across the seven affected prefectures was 0.1%, revealing the weak economic performance of these prefectures in comparison both to their average growth rate in the previous fiscal year (2.8% real GDP growth) and to aggregate Japanese GDP growth (1.8% for the 2011–2012 fiscal year and 2.6% for the pre-earthquake fiscal year).

Figure 2 also highlights that the impact of the shock was far from homogenous, even within the seven affected prefectures. In particular, even though the main earthquake itself resulted in damages in some inland areas, the ensuing tsunami meant that the most severely affected areas were located in the coastal regions. As a result, rather than covering the entirety of the seven affected prefectures, the Disaster Relief Act enacted by the government of Japan concentrated the rescue and reconstruction operations to 59 municipalities within those prefectures. These municipalities thus constitute one natural definition for the broad area that was affected by the shock. Alternatively, given that the large

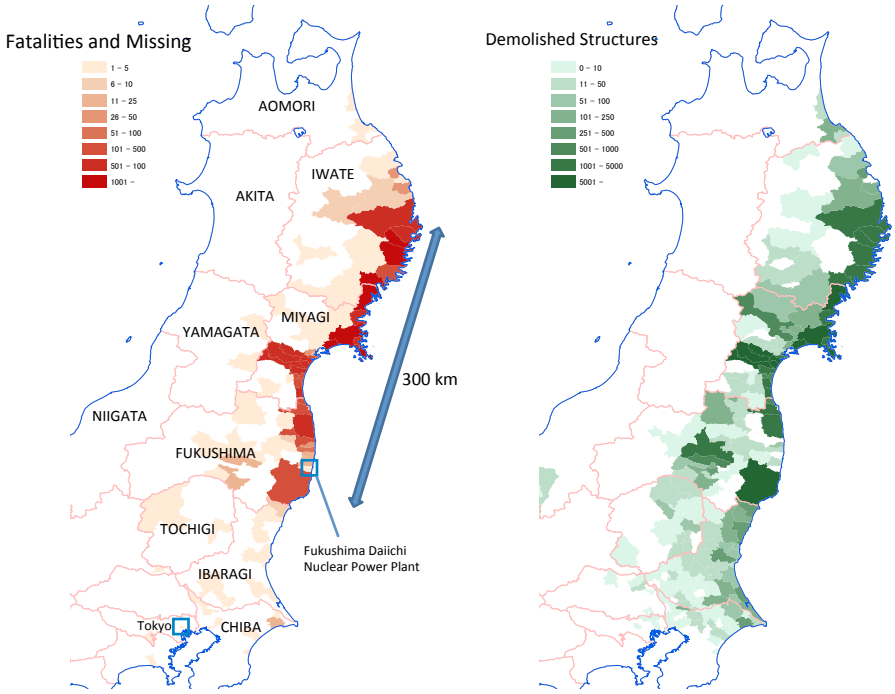


Figure 2. Geographical distributions of losses in northeast Japan.

Source: National Research Institute for Earth Science and Disaster Prevention of Japan.
Notes: The figure depicts the number of casualties (left panel) and the number of demolished structures (right panel) incurred by the earthquake and its aftermaths at the municipality level.

majority of loss of life occurred as a consequence of the tsunami, we can define the worst hit areas by considering regions that were flooded. This latter definition does not correspond to prefecture or municipality boundaries. Rather, it is based on aerial photos and satellite imagery of flooded areas, provided by the Geospatial Information Authority of Japan.[15]

Concentrating on manufacturing activity provides a more detailed picture of the economic impact of the earthquake in different areas. Figure 3 depicts the monthly (year-on-year) growth rate of the industrial production index for Japan as a whole, the Disaster Relief Act municipalities and the flooded areas. This data is based on monthly surveys compiled by the Ministry of Economy, Trade and Innovation of Japan (henceforth, METI) in the months following the March earthquake.

Figure 3 confirms that the flooded areas were most severely affected by the shock: industrial production in these areas in May 2011 was 80% lower relative to May 2010. Even though economic activity in the flooded areas did eventually recover, industrial production by December 2011 was still 50% lower than that of December 2010. The Disaster Relief Act municipalities display a similar qualitative pattern, though in a less extreme fashion: industrial production in this area declined on impact by 30% relative to the previous year followed by a partial rebound throughout the year, where by Decem-

[15]We maintain the distinction between Disaster Relief Act municipalities and flooded areas throughout our empirical analysis, using the latter — the worst hit area — as our baseline case and the former — the broader earthquake and tsunami hit area — for robustness checks.

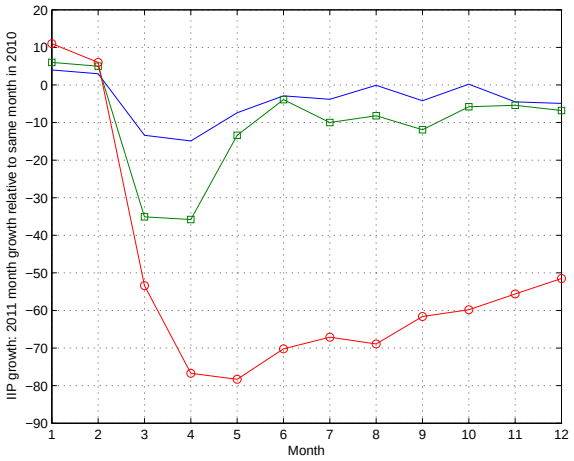


Figure 3. Year-on-year variation of Index of Industrial Production from January (1) to December (12) 2011.

Source: Ministry of Economy, Trade and Industry of Japan.
Notes: The figure plots the growth rate of IIP relative to the same month in 2010. Solid line (in blue) gives IIP growth for Japan. Solid-square line (in green) gives IIP growth for 59 Disaster Relief Act municipalities. Solid-circle line (in red) gives IIP growth for areas flooded by the tsunami.

ber 2011 it was about 7% lower than the corresponding level a year earlier. In comparison, industrial production in Japan as a whole had declined by 15% by April and was 5% lower than the previous year by the end of 2011.

Two points are in order. First, despite their large impact on the local economy of northeast Japan, the earthquake and its aftermaths cannot, in and of themselves, account for the nationwide decline in industrial production. Based on the Census of Industry and Commerce, the 59 Disaster Relief Act municipalities host 7% of business establishments, employ 9.6% of employees, and are responsible for 8.9% of shipments of manufacturing sectors in Japan. Thus, based on the contribution to total manufacturing shipments by these municipalities alone, the end-of-year figures for aggregate industrial production in Japan would have been only $0.07 \times 0.09 \approx 0.6\%$ lower than those of 2010. However, as Figure 3 renders clear, the decline in aggregate Japanese industrial production was an order of magnitude larger.

Second, earthquake-hit areas were not overly specialized. Focusing on manufacturing activities for which information is publicly available, METI reports that the 59 municipalities to which official relief efforts were directed had a relatively well-diversified industrial structure, comparable to that of Japan as a whole. The three largest industries in terms of shipments in these municipalities were food products manufacturing, chemicals manufacturing, and information and communication equipment, responsible for 9.6%, 8.7% and 7.1% of the area's total manufacturing sales, respectively. These figures are comparable to the shares of the same sectors in Japanese manufacturing (7.9%, 9.0% and 3.8%, respectively). With the exception of transportation equipment manufacturing (responsible for 6.1% of shipments in the earthquake area relative to 16.3% nationwide), the scale of activity of other industries in these municipalities is also comparable to that of entire Japan.

Finally, we remark that even though infrastructure (such as roadways, railways and ports) across northeast Japan was severely affected by the shock, pre-earthquake levels of activity were largely resumed by late March (and in most cases, before that). The one area where activity was disrupted well into the summer of 2011 was electricity supply. Several nuclear — notably the Fukushima Daiichi plant — and conventional power plants in northeast Japan went offline following the earthquake and tsunami, affecting the supply capacity of two regional electricity providers, Tohoku Electric Power and Tokyo Electric Power Company. This resulted in rolling (controlled) blackouts throughout March and again — at a smaller scale — during the summer months of 2011, when demand was higher. It is important to note that these blackouts occurred at the prefecture level and were confined to prefectures that were supplied by these two firms. To control for these blackouts, we employ prefecture fixed effects throughout our empirical analysis.

4 Data

The data employed in this paper comes from a proprietary dataset collected by Tokyo Shoko Research Ltd. (henceforth, TSR), which is a private credit reporting agency. Firms provide information to TSR in the course of obtaining credit reports on potential suppliers and customers or when attempting to qualify as a supplier. The resulting database contains information on more than 800,000 firms for each yearly cross-section and represents more than half of all private and publicly listed firms in Japan, covering all sectors of the economy. For each firm-year, we observe a set of firm-level covariates as well as information on the identity of the firm's suppliers and customers.

4.1 Firm-Level Data

TSR collects information on employment, the number of establishments, up to three (Japanese Industrial Classification 4-digit) industries the firm may belong to, three years of sales and profits, the resulting credit-score, and a physical address for the firm's headquarters. The dataset provided to us by RIETI consists of data for the years 2006, 2010, 2011, and 2012. In addition, we also observe sales figures from 2005 and 2009, enabling us to obtain annual sales growth rates over the periods 2009–2012 (as well as 2005–06).

The TSR sample is neither a census nor a representative survey, as the entry of any particular firm takes place at the request of TSR's clients. In order to check for biases in our sample, we start by comparing the TSR data with the Japanese firm census of 2006. The total number of firms in the TSR dataset is about 860,000, compared to 1.5 million in the census data. The TSR sample thus includes more than half of all firms in Japan.

Table 1 shows the distribution of the number of employees in TSR's 2006 cross-section versus that of the corresponding firm census. The percentage of firms with less than five employees in the TSR dataset is 33%, compared to 51% in the census data. Thus, TSR under-samples very small firms. However, for firms with five or more employees, the firm size distribution in TSR is very similar to that of the census data.

	0-4	5-9	10-19	20-29	30-49	50-99	100-299	300-999	1000-1999	2000-4999	5000+
TSR	0.33	0.24	0.18	0.07	0.06	0.05	0.04	0.01	0.002	0.001	0.008
Census	0.53	0.19	0.13	0.05	0.04	0.03	0.02	0.006	0.001	0.001	0.003

Table 1. Firm-size distribution (measured in terms of number of employees) in the 2006 TSR dataset and Census (2006).

4.2 Supply Chain Network Data

Each firm in the TSR dataset also provides a list of its most important suppliers and customers, thus enabling us to construct the network of supply chain relationships for the firms in the sample.

This supply chain data has two limitations. First, we only observe a binary measure of inter-firm supplier-customer relations. That is, even though we know whether one firm is another firm's supplier, we do not have a yen measure associated with their transactions. Second, the TSR forms truncate the number of suppliers and customers that a firm can report at 24 each. Given that each firm in the dataset can also be reported by other firms as a transaction partner, we can overcome this limitation by combining the self-reported customer and supplier relations with those reported by other firms. More specifically, we construct a firm's transaction network by augmenting the list of suppliers (customers) reported by the firm itself with the reports of others that state the firm as their customer (supplier). This procedure enables us to construct the list of suppliers and customers of firms that have more than 24 transaction partners per category, including very large firms that transact with several thousand firms.

In constructing the network of supply chain relationships, we discard reported transaction partners that fall outside the TSR database. Therefore, a firm may appear to have no customers because all its customers are domestic firms that fall outside the TSR sample, are foreign firms, or are non-firms (such as final demand customers or the government of Japan). Similarly, a firm may appear to have no suppliers because either all its reported suppliers are foreign or fall outside the TSR database. We choose to work only with the set of firms with at least one transaction partner (being it a customer or a supplier) within the TSR database, thus discarding firms that are isolated from the rest of the supply chain network. We find no evidence of systematic bias in the subsample of firms with at least one TSR partner.

Overall, the 2010 (i.e., pre-earthquake) TSR supply chain network consists of 861,318 nodes (firms) and 3,783,711 directed links (supplier-customer relations).[16] Out of these, a total of 771,107 (676,320) firms have at least one supplier (customer) within the TSR sample. The average and median in-degrees (i.e., the number of suppliers) of firms with at least one TSR supplier are 3.9 are 2, respectively. The average out-degree (i.e., the number of customers) of firms with at least one customer in the dataset is 4 and the median is one.

Figure 4 depicts the counter-cumulative distribution functions (CCDF) of firms' in-degrees and out-degrees. As the figure suggests, both distributions are well-approximated by a Pareto (power law)

[16] This is 961,318 in Yukio's other paper. Is this a typo? On the other hand, her paper, footnote 7, says the numbers are from the 2005 network, not 2010.

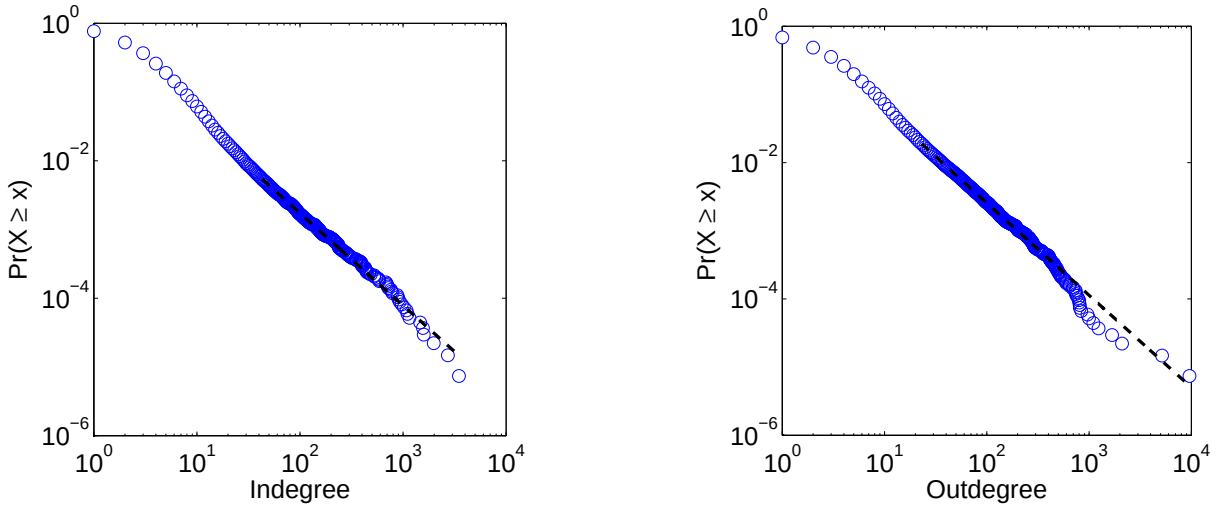


Figure 4. Degree distributions of the Japanese supply chain network

Source: TSR.
Notes: The figure depicts the counter-cumulative distribution functions (CCDF) of the in-degrees (left) and out-degrees (right) of TSR firms in the log-log scale. The dashed lines depict the MLE fit to the tails of the distributions.

distribution. The estimated Pareto tail index parameters for the in-degree and out-degree distributions are –1.34 (standard error of 0.10) and –1.35 (s.e. of 0.16), respectively. Both distributions exhibit deviations from the Pareto distribution at the extreme tails, suggesting that firms with very large number of transaction partners are somewhat under-represented relative to what is predicted by the Pareto distribution, while firms with very few transactions partners appear in greater numbers. These deviations from the Pareto distribution, however, are much smaller in magnitude compared to those documented by Atalay et al. (2011) for supplier-customer connections derived from Compustat data on publicly listed U.S. firms. Overall, the picture that emerges suggests the relative commonness of highly connected firms with a large number of transaction partners.

5 Supply Chain Disruptions: Empirics

In this section, we examine whether the presence of (direct or indirect) input-output linkages with firms in the affected areas had an impact on firm performance in the year subsequent to the earthquake. In a first instance, we quantify the impact of direct supply chain disruptions. To this end, we estimate the differential sales growth performance of firms who either supplied to or were supplied by affected area firms directly (our treatment group), relative to firms who had no direct supply chain linkages in the affected area (our control group).

In the second step of the analysis, we aim to establish whether this disruption cascaded across the supply chain, potentially affecting sales of firms who had no direct linkages to affected firms. To do this, we expand our treatment group sequentially to include firms whose supply-chain network



Figure 5. Headquarters' location for firms in flooded areas.

Source: TSR.

distance is two or more from earthquake hit firms. We compare their sales growth performance to that of firms that were relatively more distant—in a supply chain network sense—from affected firms (i.e., the control group are firms that were five or more degrees away from firms in the affected area).

We measure firms' performance by their real sales growth after the earthquake. We restrict our attention to firms with a fiscal year ending between April 2010 and February 2011. Note that when we compile network variables before the earthquake, we restrict them to firms whose latest fiscal year-end is between January 2010 and February 2011. For sales growth, we use a stricter restriction, by which we keep only firms whose latest fiscal year-end is between April 2010 and February 2011 in the data for 2011 and between April 2011 and February 2012 in the data for 2012. We choose not to include firms with end-month in March, because it is unclear to what extent such firms' sales incurred before or after the earthquake.

We control for the age and size of firms — as proxied by the number of employees — the distance of the firm's location from the flooded area, and the number of "partners," i.e., the number of customers and suppliers for the firm, that are observed before the earthquake.

In order to factor out the direct damage incurred by firms, we drop firms in the seven prefectures that were severely hit by the earthquake, tsunami, and the nuclear plant failure. We also control for the fixed effects of two-digit level industries and of prefectures. The estimated equation has the following form:

$$\Delta(Real\ Sales)_{i,p,s} = c + \mu_p + \lambda_s + \beta(Network\ Distance_i) + \gamma(Firm\ Controls_i) + \varepsilon_i,$$

	N	Mean	St.Dev.	P33	P50	P66
Post-Earthquake Sales Growth						
$\Delta Sales_{2010-11,Flooded}$	3,531	– 0.053	0.329	– 0.149	– 0.026	0.0626
$\Delta Sales_{2010-11,Non-Flooded}$	812,767	0.009	0.485	– 0.051	0.005	0.0697
Pre-Earthquake Sales Growth						
$\Delta Sales_{2009-10,Flooded}$	3,531	0.016	0.283	– 0.038	0.011	0.032
$\Delta Sales_{2009-10,Non-Flooded}$	812,767	0.013	0.346	– 0.042	0.009	0.045

Table 2. Pre vs post earthquake real sales growth of firms according to exposure to floods caused by the tsunami.

where μ_p is a prefecture fixed effect, λ_s is a two-digit industry fixed effect and $Firm\ Controls_i$ include age, number of employees, number of transaction partners and geographical distance to the flooded area. $Network\ Distance_i$ is a set of dummy variables. In the first subsection below, this variable is a simple dummy variable denoting whether firm i reported one or more firms in the flooded area as a transaction partner in the year preceding the earthquake. In the second subsection, we look at the effect of higher-order connections by considering the impact on firms that are only indirectly linked to the affected area through the supply chain. We do this by expanding this set of dummies, each of which assumes the value of 1, whenever firm i is distance-x away from flooded area firms (where x is an integer number greater than 1). Throughout we distinguish between upstream and downstream propagation.

5.1 Impact on Flooded Area Firms

We start by analyzing the impact of the earthquake and tsunami on firms in the TSR sample located in the flooded areas. Recall that this geographical definition corresponds to the areas most severely affected by the shock, with the tsunami responsible for a large fraction of physical and human capital destruction. The definition of flooded areas is taken from the Geospatial Information Authority of Japan (2011) by analyzing aerial photos and satellite imagery. Using an address matching service provided by the Center for Spatial Information Science at the University of Tokyo, we are able to match a firm's headquarters address to longitude and latitude data. Figure 5 depicts the geographical location of firms located within these areas. As expected, the headquarters of TSR firms which were situated in the flooded areas are located along Japan's northeast coastline.

This procedure identifies 3,531 firms with headquarters in the flooded area. To analyze the impact of the earthquake/tsunami, we compare the 2010–2011 real sales growth of these firms. Note that we do not have access to information on firm specific prices. Hence, we deflate nominal sales values reported by TSR by the producer price index of the corresponding 4-digit industry during the same period. Table 2 provides the relevant statistics.

According to Table 2, in the aftermath of the earthquake, both the average and the median real sales growth of firms in flooded areas was negative yielding a much worse performance than that of the typical firm located outside the flooded area. Thus, the average firm in this area saw its sales

2010 Characteristics	Log Employees	Log Sales	Firm Age	Firm Outdegree	Firm Indegree	Customers' Sales	Suppliers' Sales
Flooded Area Firms	1.998	11.674	29.01	2.945	3.677	14.624	15.027
	(1.205)	(1.504)	(14.86)	(0.882)	(0.739)	(2.342)	(2.301)
1st tercile ($\Delta Sales_{10-11}$)	2.019	11.789	29.85	2.915	3.816	14.827	14.983
	(1.232)	(1.532)	(15.20)	(0.895)	(0.740)	(2.258)	(2.195)
2nd tercile ($\Delta Sales_{10-11}$)	1.986	11.688	29.79	2.765	3.585	14.577	15.345
	(1.237)	(1.442)	(14.46)	(0.859)	(0.679)	(2.338)	(2.292)
3rd tercile ($\Delta Sales_{10-11}$)	1.996	11.544	27.39	3.281	3.718	14.453	14.766
	(1.137)	(1.498)	(14.51)	(0.886)	(0.679)	(2.323)	(2.319)
Non-flooded Area Firms	1.990	11.748	29.54	3.158	3.320	14.843	14.534
	(1.286)	(1.663)	(16.11)	(2.484)	(2.356)	(2.623)	(2.516)

Table 3. Pre-earthquake average characteristics of flooded vs. non-flooded area firms.

decline by 5.3% in 2011 while those outside the affected area actually increase their real sales (by 0.9%). It is also clear that there is much heterogeneity beyond these average numbers. In particular, the best performing firms in the flooded areas — the upper third in terms of real sales growth — are comparable to those outside the earthquake affected areas. The key difference seem to reside in the lower tercile of firm growth, where flooded area firms contracted by 14.9% in real terms while those outside the flooded areas only declined by 5.1%.

Note also that for the year preceding the earthquake, the sales growth performance of firms in this flooded area did not seem to differ from those located outside the flooded area. For 2009–2010 both the average performance of these firms and its distribution across quantiles are comparable to the typical Japanese firm. We can complement this analysis by looking at the characteristics of firms pre-earthquake, sorted by their post-earthquake performance. Table 3 summarizes the results.

The key point from Table 3 is that for the year preceding the earthquake, the average flooded area firm did not differ along observables from firms located outside the earthquake area. This is true both for typical firm characteristics such as size — as measured by employees and sales — and age, and with regards to the number and characteristics of its customers and suppliers. Furthermore, when we disaggregate flooded area firms by terciles of post-earthquake growth, this observation still holds. In particular, in the year preceding the earthquake, flooded area firms whose subsequent real sales growth was particularly affected by the earthquake/tsunami (i.e. those in the lower tercile) did not differ along observables from the average firm in non-flooded areas.

Up till now we focused on the performance of continuing firms. We now look at the extensive margin, in particular at the exit rate of firms. Here, a firm is defined as having exited if it could not be contacted by TSR after the earthquake. The raw exit rate in affected areas after the earthquake is 4.66% while that of firms in other areas is 2.98%. This is in contrast with the figures before the earthquake in 2006, where the exit rate in the flooded area, 4.1%, was lower than that in the other areas, 4.8%. We can formally test whether the probability of firm exit is higher in the affected areas, by running a simple probit regression where we additionally control for standard firm-level determinants of firm exit, such as size and age. The coefficient of interest — on the dummy variable, taking the value of one if the firms' headquarters was in the affected area — is positive and significant. Holding size (proxied



Figure 6. Headquarters' location for firms that were either suppliers or customers of flooded area firms in the pre-earthquake year (2010).

Source: TSR

by log of sales) and age constant at their means, the effect of being located increases the probability of exit by 1.3 percentage points, a 40% increase relative to the baseline of 3.01%.

5.2 First-Round Impact

We now assess the impact of the disruption described above on firms which transacted with flooded area firms. Based on TSR's supply chain network data, we identify all firms that were either customers or suppliers of firms in the flooded areas in 2010. In all, we obtain about 20,000 distinct firms that were engaged in transactions with flooded area firms. In network parlance, these are "distance 1" firms, i.e. they are a single edge away from the affected area firms. Figure 6 gives the location of these distance 1 firms.

As Figure 6 renders clear, most suppliers/customers of flooded area firms tend to be located close to their transaction partners. This is consistent with a large literature on co-agglomeration in input-supplying relations. However, for our purposes, including these firms might lead to contamination issues as such firms are themselves located in earthquake affected areas. Therefore we remove all distance 1 firms located in the seven prefectures affected by the earthquake. For the same reason, in the control group — i.e. firms that are not direct transaction partners of flooded area firms — we also remove all firms whose headquarters locate in these prefectures. As discussed above we further control for firm-level observables — size as proxied by the log of the number of employees, age, the log number of transaction partners — geographical distance to the affected area and include prefecture

	(1)	(2)	(3)	(4)	(5)	(6)
Distance 1 Customers	-0.0124^{**}		-0.0111^{**}			
	(-2.018)		(-1.976)			
of 1st tercile				-0.0229^{***}		-0.0210^{***}
				(-2.692)		(-2.432)
of 2nd tercile				-0.0342		-0.0321
				(-1.601)		(-1.701)
of 3rd tercile				0.0137		1.140
				(1.123)		(1.138)
Distance 1 Suppliers		-0.0104^{**}	-0.0087^{*}			
		(-1.968)	(-1.840)			
of 1st tercile					-0.0154^{**}	-0.0128^{*}
					(-1.982)	(-1.830)
of 2nd tercile					-0.0228^{*}	-0.021
					(-1.803)	(-1.590)
of 3rd tercile					0.0049	0.0058
					(0.376)	(0.386)
Constant	-0.0231^{***}	-0.0232^{***}	-0.0232^{***}	-0.0233^{***}	-0.0233^{***}	-0.0234^{***}
	(-3.375)	(-3.387)	(-3.392)	(-3.413)	(-3.416)	(-3.431)
Firm Controls	Y	Y	Y	Y	Y	Y
Prefecture/Sector F.E.	Y	Y	Y	Y	Y	Y
N	489,132	489,132	489,132	489,132	489,132	489,132

Table 4. First round impact of customer/supplier disruption by terciles of flooded area firm growth.

and sector fixed effects. Table 4 gives the estimation results.

First, in the year after the earthquake, the typical firm immediately downstream of flooded area firms grows by 1.25% less than the typical non-linked firm (across firms located in the same prefecture and within the same sector). Second, firms immediately upstream of flooded area firms grow by 1% less than non-linked firms. Third, unsurprisingly these effects are heterogeneous and a function of the post-earthquake performance of flooded area firms which, as we have seen, varied markedly. In particular, the negative effects seem to be only present for firms whose suppliers or customers in the affected area were badly affected. Thus, customers (suppliers) of flooded area firms in the bottom tercile of post-earthquake growth grew by 2.1% (1.28%) less than the typical firm in the sample.

Table 5 adds to the analysis by looking at the performance of downstream and upstream firms whose transactions partners in the flooded areas exited. As the table clearly shows, the negative effect of supplier/customer exit in the flooded areas is substantially more pronounced, even when compared to the effect of badly performing (but continuing) earthquake-hit firms. Firms whose supplier (customer) exited as a result of the earthquake/tsunami underperformed by 10% (9%) when compared to non-linked firms. Based on the union of firms who buy (or sell) inputs from (to) either badly performing or exiting firms in the flooded area, we then form our baseline group for the subsequent analysis: that of "disrupted" firms, i.e. firms who had their direct partners in the supply chain affected by the earthquake. For supply-disrupted firms, we see that they under-perform the control group by 3%. For demand-disrupted firms we again see that the effects are less strong (and more noisy) as they under-perform the control group by 1%.

	(1)	(2)	(3)	(4)	(5)
Distance 1 Customers					
of 1st tercile	-0.0254^{***}		-0.0230^{**}		
	(-2.629)		(-2.458)		
of exiters	-0.0985^{***}		-0.0988^{**}		
	(-2.784)		(-2.256)		
of disrupted				-0.0312^{***}	-0.0303^{***}
				(-3.356)	(-3.231)
Distance 1 Suppliers					
of 1st tercile		-0.0151^{*}	-0.0111		
		(-1.847)	(-1.447)		
of exiters		-0.0834^{***}	-0.0881^{***}		
		(-3.509)	(-2.018)		
of disrupted					-0.0110^{*}
					(-1.822)
Constant	-0.0222^{***}	-0.0221^{***}	-0.0212^{***}	-0.0228^{***}	-0.0229^{***}
	(-3.340)	(-3.281)	(-3.086)	(-3.340)	(-3.416)
Firm Controls	Y	Y	Y	Y	Y
Prefecture/Sector F.E.	Y	Y	Y	Y	Y
N	489,251	489,251	489,251	489,251	489,251

Table 5. The effect of low customer/supplier growth performance, the effect of customer/supplier exit and the effect of disruptions in the supply chain.

Robustness Checks We now provide a series of robustness checks for our findings above. We first explore the robustness of our findings with respect to plant location, the definition of affected area firms and to possible variation at the prefecture-sector level.

A first possible concern with our estimates above is related to the fact that we only have firm- and not plant-level data. This raises the possibility that the treatment group — customers or suppliers of flooded area firms — may include multi-plant firms which have plants in the earthquake affected areas, even though their headquarters are located outside of it. This would therefore confound our estimates: the significant negative effect on firm growth we have established could then be due to the fact that these firms had plants that were directly hit by the earthquake.

While our data does not give us information on plant locations, we do have information on whether a firm is a single- or multi-plant firm. To alleviate this concern we run our baseline specification on the sample of single plant firms only. Necessarily, the location of single-plant firms coincides with that of their headquarters which, by the same sample selection criteria, is outside the broader earthquake affected area. Column (1) in Table 6 summarizes the result. The magnitude and significance of our results is largely unchanged.

A second potential concern lies with our affected area definition. Recall that in our baseline estimation we only used information of customers and suppliers of the flooded coastal area firms. The latter is, by design, a very narrow and specific location. Firms who had customer or suppliers in the area might therefore have very specific reasons, unobservable to us, to engage in transactions with flooded area firms. For example, our treatment groups might be active in very narrow product markets — which our relative coarse sectoral fixed effects cannot capture — and our baseline estimates could then reflect unobservable shocks to demand or supply to these markets. To alleviate this con-

	Baseline	(1)	(2)	(3)
Distance 1 Customers	-0.0303^{***}	-0.0270^{**}	-0.0334^{***}	-0.0329^{***}
	(-3.231)	(-2.501)	(-3.440)	(-3.017)
Distance 1 Suppliers	-0.0110^{*}	-0.0135^{**}	-0.0128^{**}	-0.0124^{*}
	(-1.822)	(-2.316)	(-2.202)	(-1.911)
Firm Controls	Y	Y	Y	Y
Fixed Effects	Prefecture & Sector	Prefecture & Sector	Prefecture & Sector	Prefecture $\times$ Sector
N	489251	70616	489251	489251

Table 6. Robustness checks for first-round impact.

cern, in column (2) of Table 6 we redefine the set of disrupted firms by changing our affected area definition. In (2) we take firms whose headquarters were located in the much broader Disaster Relief Act municipalities. Column (2) confirms that our baseline results are unaltered when we utilize this alternative definition.

A third objection to our baseline estimates is that they might be capturing local demand effects for particular goods. Suppose, for example, that firms with suppliers or customers in affected areas themselves cluster across space. If additionally, these firms are specialized in only a few sectors then our estimates could be capturing local demand shocks for particular classes of goods rather than supply chain linkages. In order to deal with this concern, in Column (3) we implement an alternative specification controlling for prefecture-sector fixed effects (rather than entering them separately as in our baseline specification). Once again, our results remain unchanged.

Our second set of robustness checks deals with the possibility of pre-trends. As we have shown, customers and suppliers from flooded area firms did not seem to differ from other firms along observables in levels prior to the earthquake. These firms could however already be in a declining trajectory pre-earthquake. If so, our baseline estimates would be capturing these dynamics rather than the effects of supply chain disruption.

In order to assess whether this is the case, we rerun our estimates replacing our dependent variable by the yearly growth rate of these firms in the year before the earthquake, i.e. for the year ending in February 2011. Table 7 summarizes our results. As the second column shows, distance 1 firms did not display statistically different growth rates in the year prior to the earthquake.

5.3 Higher-Order Impacts and Cascades

In this subsection, we assess whether the supply chain disruption caused by the earthquake cascaded throughout the supply chain, also affecting firms only indirectly linked to flooded area firms. To understand the importance of establishing this note the following: while the estimates above provide evidence that the disruption brought about by the earthquake did affect directly linked firms — and in particular, customers of firms in the affected area — taken together, these firms account for less that 15% of total sales in our pre-earthquake sample (in 2010). Taking these weights as a baseline, and holding all else constant, the macro impact of the earthquake in terms of the aggregate growth rate of

	$Baseline$	$Pre-Trend$
Distance 1 Customers	-0.0303^{***}	0.002
	(-3.231)	(0.240)
Distance 1 Suppliers	-0.0110^{*}	-0.007
	(-1.822)	(-1.018)
Firm Controls	Y	Y
Fixed Effects	Prefecture & Sector	Prefecture & Sector
N	489251	488448

Table 7. Pre-trend checks for the first-round impact.

sales would be smaller than 0.4%.

To understand whether the earthquake shocks propagated over the supply chain linkages and led to disruptions throughout the entire production network or whether it only affected firms directly engaged in input transactions with earthquake area firms, we extend our empirical framework by expanding the set of network distance dummies considered. Thus, while in our analysis above we compared the performance of distance 1 firms to all other firms in our sample, we now explicitly compare the performance of firms only indirectly linked by including higher-order (network) distances, up to 4 links removed from the source of the shocks. The control group now constitutes all firms that, prior to the earthquake, were 5 or more supply chain links away from firms in the affected area.

To this end, we compute supply chain distances for all firms in our dataset. In particular, for each firm in our dataset, we compute the shortest (directed) path to an earthquake-hit firm following along supply chain linkages. This allows us to obtain, for each firm in the TSR sample, its supply chain distance for flooded area firms, both downstream and upstream. We stop at distance 4 as going further downstream (or upstream) would reduce our control group to a very small number of firms. This is because, as we explained above, the production network has a relatively short diameter. Table 8 collects the results regarding the impact on higher-order customers (i.e. downstream of affected area firms) and suppliers (i.e. upstream).

According to Column (2) in Table 8, the supply chain disruption brought about by the earthquake entailed significant downstream propagation, consistent with cascade effects. Further, as our model in Section 2 predicts, this effect declines with (supply-chain) distance to the source of the shocks. Thus, relative to our control group, the impact on downstream "distance 2" firms — i.e. customers of customers of flooded area firms — is almost four times smaller than that of directly affected, distance 1 firms. The point estimates point are consistent with even smaller effects regarding firms even further downstream in the supply chain.

Note also that the point estimate on the size of the impact on distance 1 firms increases somewhat relative to our baseline numbers in the previous section. As the results in Table 8 render clear, this is because our control group in that section was contaminated: it contained firms that were only indirectly linked to, but nevertheless affected by, flooded area firms. Thus, the effect of including these firms in the control group was to lower its average sales growth performance. As a result, distance 1 firms' poor performance was masked by the presence of indirectly affected firms in the control group.

	Downstream		Upstream	
	(1)	(2)	(3)	(4)
Distance 1	-0.0312^{***}	-0.0373^{***}	-0.0185^{**}	-0.0121^{*}
	(-3.356)	(-4.419)	(-1.997)	(-1.833)
Distance 2		-0.0101^{***}		-0.0072
		(-3.264)		(-1.442)
Distance 3		-0.0063^{***}		-0.0066
		(-3.398)		(-1.330)
Distance 4		-0.0046^{**}		0.0001
		(-2.005)		(1.058)
Firm Controls	Y	Y	Y	Y
Fixed Effects	Prefecture & Sector	Prefecture & Sector	Prefecture & Sector	Prefecture & Sector
N	489,251	489,251	489,251	489,251

Table 8. Higher-order impact.

Importantly, we find no statistically significant evidence for upstream cascades. While the point estimates for direct suppliers of flooded area firms are now slightly larger, its significant is still marginal. More importantly, suppliers of suppliers of flooded area firms do not seem to have been affected by the downstream supply chain disruption. The same is true for firms further upstream.

To interpret these results through the lenses of our model notice the following. The negative sales growth impact on direct suppliers to flooded area firms is consistent with our model if intermediate and primary inputs are substitutable, downstream of the source of the shock. However, the fact that the disruption did not cascade further throughout the chain seems to imply that this elasticity of substitution is not too high. As Corollary 2 suggests, under such conditions, we expect the original shock to propagate upstream but to die out quickly relative to the downstream cascade.

Robustness Checks To assess the robustness of the empirical findings on cascades we perform the same set of checks as in the previous section. Namely, we again address concerns regarding: (i) the presence of multi-plant firms; (ii) the geographic definition for affected area firms; (iii) other sources of variation at the prefecture-sector level and (iv) the presence of pre-trends in the data. Differently from the previous section, we now assess these potential concerns not only for firms whose supply chain partners were directly affected but also for those indirectly affected by the earthquake.

Table 9 summarizes the results of our robustness exercise. The economic and statistical significance of our findings regarding the likely presence of cascading effects downstream are broadly unaffected. They are robust to considering only single-plant firms (Column 1), redefining the earthquake affected area (Column 2), deploying prefecture-sector fixed effects (Column 3). Additionally, the evidence for propagation further downstream does not seem to be driven by pre-trends, as evaluated by considering the 2010 sales growth rate as our dependent variable. Likewise, our conclusions regarding weak and statistically insignificant upstream cascades are unchanged.

	Baseline	(1)	(2)	(3)	Pre-Trend
Customers' Distance					
Distance 1	-0.0373^{***}	-0.0393^{***}	-0.0391^{***}	-0.0355^{***}	-0.0017
	(-4.419)	(-4.173)	(-3.922)	(-3.648)	(0.559)
Distance 2	-0.0101^{***}	-0.0132^{*}	-0.0074^{***}	-0.0134^{***}	0.0015
	(-3.264)	(-1.791)	(-3.453)	(-3.005)	(1.297)
Distance 3	-0.0063^{***}	-0.0132^{*}	-0.0054^{***}	-0.0088^{***}	-0.0029
	(-3.398)	(-1.775)	(-2.997)	(-2.998)	(0.863)
Distance 4	-0.0046^{**}	-0.0006	-0.0051^{**}	-0.0031^{**}	-0.0021
	(-2.005)	(-1.005)	(-2.112)	(-2.189)	(0.537)
Suppliers' Distance					
Distance 1	-0.0121^{*}	-0.0149^{*}	-0.0109^{**}	-0.0157^{*}	0.0067
	(-1.833)	(-1.865)	(-1.969)	(-1.833)	(0.559)
Distance 2	-0.0072	-0.0087	-0.0081	-0.0091^{*}	-0.0065^{*}
	(-1.442)	(-1.486)	(-1.550)	(-1.849)	(1.840)
Distance 3	-0.0066	0.0009	-0.0011	-0.0073	-0.0040
	(-1.330)	(0.781)	(0.977)	(-1.480)	(0.369)
Distance 4	0.0001	0.0003	-0.0001	0.0002	-0.007
	(1.058)	(0.516)	(0.882)	(0.927)	(1.126)
Firm Controls	Y	Y	Y	Y	Y
Fixed Effects	Prefecture & Sector	Prefecture & Sector	Prefecture & Sector	Prefecture $\times$ Sector	Prefecture & Sector
N	489,251	70,616	489,251	489,251	488,448

Table 9. Robustness checks for higher-order impacts.

6 Conclusions

The backbone of a modern economy is an intricately linked web of specialized production units, each relying on the flow of inputs from their suppliers to produce their own output, which, in turn, is routed towards other downstream units. An emerging literature on production networks suggests that the origins of aggregate fluctuations can be traced back to idiosyncratic disturbances—occurring at particular production units along the supply chain—which then cascade down via input-supply linkages, thereby inducing co-movement of fluctuations across different firms and affecting aggregate behavior. If this is the case, understanding whether, and how, shocks propagate across supply chains can therefore better inform both academics on the origins of aggregate fluctuations and policy-makers on how to prepare for and recover from adverse shocks that disrupt these production chains.

Using a large-scale dataset on supply chain linkages among Japanese firms together with information on firm-level exposures to the Great East Japan Earthquake in 2011, we quantified the shock's impact on firms that were (directly or indirectly) linked to affected firms. We find that having a supplier in the earthquake-hit region led to a 3% loss in terms of sales growth compared to firms with no such suppliers, as well as evidence for smaller but nevertheless significant upstream propagation. Furthermore, we find evidence for the propagation of the shock to firms that were only indirectly related to the firms in the affected areas (such as their customers' customers). Our findings suggest that such cascade effects had a sizable macroeconomic impact: the propagation of the earthquake shock over input-output linkages led to a 1% drop in Japan's aggregate output in the year following the earthquake.

A Technical Appendix

A.1 Equilibrium Characterization

We start by deriving equations the solutions to which characterize equilibrium prices and quantities in the economy described in Subsection 2.1.

The first-order condition of firm i's problem with respect to the units of goods purchased from firm j implies that

$$x_{ij} = \mu w_{ij} y_i A_i^{\sigma-1} \left(\frac{p_i}{p_j}\right)^{\zeta} \left(\sum_{q=1}^{n} w_{iq} \left(\frac{p_i}{p_q}\right)^{\zeta-1}\right)^{\frac{\sigma-\zeta}{\zeta-1}}.$$

On the other hand, the first-order condition with respect to ℓ_i leads to

$$\ell_i = (1-\mu) y_i A_i^{\sigma-1} {p_i}^{\sigma},$$

where we are taking the market wage as the numeraire. Plugging the expressions for ℓ_i and x_{ij} into firm i's production function (1) leads to

$$(p_i A_i)^{1-\sigma} = 1 - \mu + \mu \left(\sum_{j=1}^{n} w_{ij} p_j^{1-\zeta}\right)^{\frac{1-\sigma}{1-\zeta}}, \tag{7}$$

thus providing a system of equations that determine the equilibrium prices of all n goods in the economy.

On the other hand, the market clearing condition for good i requires that

$$y_i = c_i + \sum_{j=1}^{n} x_{ji},$$

where from the consumers' decision problem we have $c_i = 1/np_i$. Therefore, the market clearing condition for good i can be rewritten as

$$y_i = \frac{1}{np_i} + \mu p_i^{-\zeta} \sum_{j=1}^{n} w_{ji} y_j A_j^{\sigma-1} p_j^{\sigma} \left[\sum_{q=1}^{n} w_{jq} p_q^{1-\zeta}\right]^{\frac{\zeta-\sigma}{1-\zeta}}, \tag{8}$$

providing a system of equations that determine the equilibrium output of all firms in terms of equilibrium prices. Therefore, for any given economy, equilibrium prices and quantities are determined by solving system of equations (7) and (8).

A.2 First-Order Approximation: Proof of Proposition 1

Given that equations (7) and (8) do not have a closed-form solution in general, we next provide a first-order approximation of equilibrium prices and quantities by log-linearizing the two equations around the point $\epsilon_i = \log(A_i) = 0$ for all firms i.

As a first observation, note that if indeed $\epsilon_i = 0$ for all firms i, then (7) implies that $p_i = 1$ for all i. Consequently, (8) implies that the output of firm i is given by $y_i = v_i/n$, where $v_i = \sum_{j=1}^n t_{ji}$.

Now consider the small shock perturbation in which firm s is hit with a small productivity shock ϵ_s. Taking logarithms from both sides of (7), differentiating it with respect to ϵ_s and evaluating it at the point in which $\epsilon_j = 0$ for all j lead to

$$\frac{\partial \hat{p}_i}{\partial \epsilon_s} + \mathbf{1}_{\{i=s\}} = \mu \sum_{j=1}^n w_{ij} \frac{\partial \hat{p}_j}{\partial \epsilon_s},$$

where $\hat{p}_j = \log(p_i)$ and $\mathbf{1}$ denotes the indicator function. Therefore, it is immediate that the derivate of log prices around the point in which $\epsilon_j = 0$ for all firms j satisfies

$$\frac{\partial \hat{p}_i}{\partial \epsilon_s} = -t_{is}, \tag{9}$$

where, recall that $T = (I - \mu W)^{-1}$ is the Leontief inverse of the economy. The above equation thus provides a first-order approximation to the impact of a small shock to firm s on the price of good i in the economy.

To determine the impact on the quantities, we take logarithms from both sides of (8) and differentiate it with respect to ϵ_s. Evaluating the result at the point in which $\epsilon_j = 0$ for all firms j implies

$$\begin{aligned} v_i \frac{\partial \hat{y}_i}{\partial \epsilon_s} = &- \frac{\partial \hat{p}_i}{\partial \epsilon_s} - \mu\zeta \frac{\partial \hat{p}_i}{\partial \epsilon_s} \sum_{j=1}^n w_{ji} v_j + \mu \sum_{j=1}^n w_{ji} v_j \frac{\partial \hat{y}_j}{\partial \epsilon_s} \\ &+ \mu(\sigma - 1) w_{si} v_s + \mu\sigma \sum_{j=1}^n w_{ji} v_j \frac{\partial \hat{p}_j}{\partial \epsilon_s} + \mu(\zeta - \sigma) \sum_{j=1}^n w_{ji} v_j \sum_{q=1}^n w_{jq} \frac{\partial \hat{p}_q}{\partial \epsilon_s}. \end{aligned}$$

Replacing for the derivative of log equilibrium prices with respect to ϵ_s from (9) and using the fact that $\mu \sum_{j=1}^n w_{ji} v_j = v_i - 1$ imply that

$$v_i \frac{\partial \hat{y}_i}{\partial \epsilon_s} = (1 + \zeta(v_i - 1)) t_{is} + \mu \sum_{j=1}^n w_{ji} v_j \frac{\partial \hat{y}_j}{\partial \epsilon_s} + \mu(\sigma - 1) w_{si} v_s - \mu\sigma \sum_{j=1}^n w_{ji} v_j t_{js} - \mu(\zeta - \sigma) \sum_{j=1}^n \sum_{q=1}^n w_{ji} v_j w_{jq} t_{qs}.$$

The above term can be further simplified by replacing $\mu \sum_{q=1}^n w_{jq} t_{qs} = t_{js} - \mathbf{1}_{\{j=s\}}$.[17] Rearranging the terms implies

$$\begin{aligned} v_i \frac{\partial \hat{y}_i}{\partial \epsilon_s} - \mu \sum_{j=1}^n w_{ji} v_j \frac{\partial \hat{y}_j}{\epsilon_s} = &\left(v_i t_{is} - \mu \sum_{j=1}^n w_{ji} v_j t_{js} \right) + (\sigma - 1)(1 - \mu) \left(\sum_{j=1}^n w_{ji} v_j t_{js} - w_{si} v_s \right) \\ &+ (1 - \zeta) \left(\sum_{j=1}^n w_{ji} v_j t_{js} - w_{si} v_s - t_{is}(v_i - 1) \right). \end{aligned}$$

The solution to the system of equations above characterizes the partial derivatives $\partial \hat{y}_i / \partial \epsilon_s$. In particular, multiplying both sides of the above equality by t_{ji}, summing over all firms i and finally dividing

[17] This is a consequence of the fact that $\mu W T = \mu W \sum_{k=0}^{\infty} (\mu W)^k = T - I$.

by v_i imply

$$\frac{\partial \hat{y}_i}{\partial \epsilon_s} = t_{is} + \frac{1}{\mu v_i}(\sigma - 1)(1-\mu)\left(v_s \mathbf{1}_{\{s=i\}} + \sum_{m=1}^{n} v_m t_{ms} t_{mi} - v_i t_{is} - v_s t_{si}\right)$$
$$+ \frac{1}{\mu v_i}(1-\zeta)\left(v_s \mathbf{1}_{\{i=s\}} + (1-\mu)\sum_{m=1}^{n} v_m t_{ms} t_{mi} + \mu \sum_{m=1}^{n} t_{ms} t_{mi} - v_i t_{is} - v_s t_{si}\right).$$

The above expression reduces to (3) when $i \neq s$. □

A.3 Comparison of Upstream and Downstream Effects

Suppose that firm s in the simple production chain is hit with the negative shock. Equation (4) implies that the impact on the output of firm $s+1$, which is immediately downstream to firm s is given by

$$\frac{\partial \hat{y}_{s+1}}{\partial \epsilon_s} = \mu + (\sigma - 1)\frac{(\mu^{s+1} - \mu^n)}{(1+\mu)\mu^{s-1}}.$$

On the other hand, by (5), the impact of the shock on the firm immediately upstream to firm s is

$$\frac{\partial \hat{y}_{s-1}}{\partial \epsilon_s} = (\sigma - 1)\left(\frac{\mu^s - \mu^n}{1+\mu}\right)\left(\frac{1-\mu^{n-s+1}}{\mu^{s-2} - \mu^n}\right).$$

Comparing the above two expressions implies that the downstream impact on firm $s+1$ is larger than the impact on the upstream firm $s-1$ if and only if $\sigma < \bar{\sigma}$ where

$$\bar{\sigma} = 1 + \frac{1-\mu^{n-s+2}}{\mu^{n-s}(1-\mu)^2},$$

which is a number strictly larger than 1. It is also immediate that $\bar{\sigma}$ is increasing in n and that $\lim_{n\to\infty} \bar{\sigma} = \infty$.

Finally, one can also use the above expression to provide an estimate for the value of $\bar{\sigma}$. Given that $s \leq n$, it is easy to verify that

$$\bar{\sigma} \geq \frac{2}{1-\mu}.$$

Therefore, for example, an estimate of $\mu = 1/3$ guarantees that $\bar{\sigma} \geq 3$.

References

Acemoglu, Daron, Ufuk Akcigit, and William Kerr (2015a), "Networks and the macroeconomy: An empirical exploration." In *National Bureau of Economic Research Macroeconomics Annual* (Martin Eichenbaum and Jonathan Parker, eds.), volume 30, MIT Press, Cambridge, MA.

Acemoglu, Daron, David Autor, David Dorn, Gordon H. Hanson, and Brendan Price (2015b), "Import competition and the Great U.S. Employment Sag of the 2000s." *Journal of Labor Economics*.

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi (2012), "The network origins of aggregate fluctuations." *Econometrica*, 80, 1977–2016.

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi (2014), "Microeconomic origins of macroeconomic tail risks." NBER Working paper No. 20865.

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi (2015c), "Networks, shocks, and systemic risk." In *The Oxford Handbook on the Economics of Networks* (Yann Bramoullé, Andrea Galeotti, and Brian Rogers, eds.), Oxford University Press.

Atalay, Enghin (2014), "How important are sectoral shocks?" Working paper.

Atalay, Enghin, Ali Hortaçsu, James Roberts, and Chad Syverson (2011), "Network structure of production." *Proceedings of the National Academy of Sciences*, 108, 5199–5202.

Babich, Volodymyr, Apostolos N. Burnetas, and Peter H. Ritchken (2007), "Competition and diversification effects in supply chains with supplier default risk." *Manufacturing & Service Operations Management*, 9, 123–146.

Baqaee, David R. (2015a), "Cascading failures in production networks." Working paper.

Baqaee, David R. (2015b), "Labor intensity in an interconnected economy." Working paper.

Barrot, Jean-Noël and Julien Sauvagnat (2015), "Input specificity and the propagation of idiosyncratic shocks in production networks." Working paper.

Bernard, Andrew B., Andreas Moxnes, and Yukiko U. Saito (2015), "Production networks, geography and firm performance." Working paper.

Bigio, Saki and Jennifer La'O (2013), "Financial frictions in production networks." Working paper.

Boehm, Christoph, Aaron Flaaen, and Nitya Pandalai-Nayar (2015), "Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake." Working paper.

Buraschi, Andrea and Paolo Porchia (2014), "Dynamic networks and asset pricing." Working paper.

Cachon, Gérard P., Taylor Randall, and Glen M. Schmidt (2007), "In search of the bullwhip effect." *Manufacturing & Service Operations Management*, 9, 457–479.

Caliendo, Lorenzo, Esteban Rossi-Hansberg, Fernando Parro, and Pierre-Daniel G. Sarte (2014), "The impact of regional and sectoral productivity changes on the U.S. economy." NBER Working Paper No. 20168.

Carvalho, Vasco M. (2010), "Aggregate fluctuations and the network structure of intersectoral trade." Working Paper.

Carvalho, Vasco M. (2014), "From micro to macro via production networks." *Journal of Economic Perspectives*, 28, 23–48.

Carvalho, Vasco M. and Xavier Gabaix (2013), "The great diversification and its undoing." *American Economic Review*, 103, 1697–1727.

Carvalho, Vasco M. and Nico Voigtländer (2015), "Input diffusion and the evolution of production networks." Working paper.

Chaney, Thomas (2014), "The network structure of international trade." *American Economic Review*, 104, 3600–3634.

di Giovanni, Julian and Andrei A. Levchenko (2010), "Putting the parts together: Trade, vertical linkages, and business cycle comovement." *American Economic Journal: Macroeconomics*, 2, 95–124.

di Giovanni, Julian, Andrei A. Levchenko, and Isabelle Méjean (2014a), "Firms, destinations, and aggregate fluctuations." *Econometrica*, 82, 1303–1340.

di Giovanni, Julian, Andrei A. Levchenko, and Isabelle Méjean (2014b), "Granular comovement." Working paper.

Dupor, Bill (1999), "Aggregation and irrelevance in multi-sector models." *Journal of Monetary Economics*, 43, 391–409.

Durlauf, Steven N. (1993), "Nonergodic economic growth." *Review of Economic Studies*, 60, 349–366.

European Commission (2013), "Customs risk management and security of the supply chain." Communication from the Commission to the European Parliament, The Council and the European Economic and Social Committee, URL http://ec.europa.eu/taxation_customs/resources/documents/customs/customs_controls/risk_management/customs_eu/com_2012_793_en.pdf.

Federgruen, Awi and Ming Hu (2014a), "Multi-product price and assortment competition." *Operations Research*.

Federgruen, Awi and Ming Hu (2014b), "Sequential multi-product price competition in supply chain networks." Working paper.

Federgruen, Awi and Nan Yang (2008), "Selecting a portfolio of suppliers under demand and supply risks." *Operations Research*, 56, 916–936.

Foerster, Andrew T., Pierre-Daniel G. Sarte, and Mark W. Watson (2011), "Sectoral versus aggregate shocks: A structural factor analysis of industrial production." *Journal of Political Economy*, 119, 1–38.

Gabaix, Xavier (2011), "The granular origins of aggregate fluctuations." *Econometrica*, 79, 733–772.

Herskovic, Bernard (2015), "Networks in production: Asset pricing implications." Working paper.

Horvath, Michael (1998), "Cyclicality and sectoral linkages: Aggregate fluctuations from sectoral shocks." *Review of Economic Dynamics*, 1, 781–808.

Horvath, Michael (2000), "Sectoral shocks and aggregate fluctuations." *Journal of Monetary Economics*, 45, 69–106.

Jain, Nitish, Karan Girotra, and Serguei Netessine (2014), "Managing global sourcing: Inventory performance." *Management Science*, 60, 1202–1222.

Johnson, Robert C. (2014), "Trade in intermediate inputs and business cycle comovement." *American Economic Journal: Macroeconomics*, 6, 39–83.

Jones, Charles I. (2011), "Intermediate goods and weak links in the theory of economic development." *American Economic Journal: Macroeconomics*, 3, 1–28.

Jones, Charles I. (2013), "Misallocation, economic growth, and input-output economics." In *Proceedings of Econometric Society World Congress* (Daron Acemoglu, Manuel Arellano, and Eddie Dekel, eds.), Cambridge University Press.

Jovanovic, Boyan (1987), "Micro shocks and aggregate risk." *The Quarterly Journal of Economics*, 102, 395–409.

Kelly, Bryan T., Hanno N. Lustig, and Stijn Van Nieuwerburgh (2013), "Firm volatility in granular networks." NBER Working Paper No. 19466.

Long, John B. and Charles I. Plosser (1983), "Real business cycles." *Journal of Political Economy*, 91, 39–69.

Nakajima, Kentaro, Yukiko U. Saito, and Iichiro Uesugi (2012), "Localization of inter-firm transaction relationships and industry agglomeration." RIETI Discussion Paper Series 12-E-023.

Noy, Ilan (2009), "The macroeconomic consequences of disasters." *Journal of Development Economics*, 88, 221–231.

Oberfield, Ezra (2013), "Business networks, production chains, and productivity: A theory of input-output architecture." Working paper.

Ohnishi, Takaaki, Hideki Takayasu, and Misako Takayasu (2010), "Network motifs in an inter-firm network." *Journal of Economic Interaction and Coordination*, 5, 171–180.

Raddatz, Claudio E. (2009), "The wrath of god: macroeconomic costs of natural disasters." World Bank Policy Research Working Paper 5039.

Saito, Yukiko U. (2012), "The impact of the Great East Japan earthquake on companies in the non-affected areas: Structure of the inter-company network of supply chains and its implication (in Japanese)." RIETI Discussion Paper Series 12-J-020.

Saito, Yukiko U. (2013), "Role of hub firms in geographical transaction network." RIETI Discussion Paper Series 13-E-080.

Saito, Yukiko U., Tsutomu Watanabe, and Mitsuru Iwamura (2007), "Do larger firms have more inter-firm relationships?" *Physica A: Statistical Mechanics and its Applications*, 383, 158–163.

Streitwieser, Mary L. (2009), "A primer on BEA's industry accounts." *Survey of Current Business*, 40–52.

Strobl, Eric (2012), "The economic growth impact of natural disasters in developing countries: Evidence from hurricane strikes in the Central American and Caribbean regions." *Journal of Development Economics*, 97, 130–141.

The White House (2012), "National strategy for global supply chain security." URL https://www.whitehouse.gov/sites/default/files/national_strategy_for_global_supply_chain_security.pdf.

Tomlin, Brian (2006), "On the value of mitigation and contingency strategies for managing supply chain disruption risks." *Management Science*, 52, 639–657.

Tomlin, Brian (2009), "Impact of supply learning when suppliers are unreliable." *Manufacturing & Service Operations Management*, 11, 192–209.

World Economic Forum (2012), "New models for addressing supply chain and transport risk." URL http://www3.weforum.org/docs/WEF_SCT_RRN_NewModelsAddressingSupplyChainTransportRisk_IndustryAgenda_2012.pdf.

Wu, Jing and John R. Birge (2014), "Supply chain network structure and firm returns." Working paper.

Yang, Zhibin (Ben), Göker Aydın, Volodymyr Babich, and Damian R. Beil (2009), "Supply disruptions, asymmetric information, and a backup production option." *Management Science*, 55, 192–209.