Production and Financial Networks in Interplay:
Crisis Evidence from Supplier-Customer and Credit Registers

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Abstract

We show that bank shocks originating in the financial sector propagate upstream and downstream along the production network and triple the impact of direct bank shocks. Our identification relies on the universe of both supplier-customer transactions and bank loans in Spain, a standard operationalization of credit-supply shocks during the 2008–09 global crisis, and the proposed theoretical framework. The impact on real effects is strong, and similarly so, when considering: (i) direct bank shocks to firms *versus* first-order interfirm contagion; (ii) first-order *versus* higher-order network effects; (iii) downstream *versus* upstream propagation; (iv) firm-specific *versus* economy-wide shocks. Market concentration amplifies these effects.

JEL Codes: D85; E44; E51; G01; G21.

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1 Introduction

The production and financial networks of a modern economy are complex interrelated structures. On its real side, goods and services are produced as part of a dense web of specialized units, each of them relying on inputs from their upstream suppliers to produce outputs, which are then routed downstream towards other production units (see e.g. Acemoglu et al. (2012); Carvalho (2014)). On its financial side, moreover, financial intermediaries (banks) and non-financial firms are also connected through a similarly complex network of credit flows (see e.g. Diamond (1984); Holmstrom and Tirole (1997); Amiti and Weinstein (2018)), while banks themselves are interconnected as well in an interbank network of financial claims (see e.g. Allen and Gale (2000); Elliott et al. (2014); Cabrales et al. (2017)).

All the three aforementioned networks are of course intimately inter-related, and hence must be studied as such in order to gain a proper understanding of how modern economies actually work — in particular, of how shocks propagate and what the macro effects are. Indeed, in the aftermath of the 2008 financial crisis, academics and policy-makers alike have largely come to accept that the role of these networks was not suitably recognized, that finance also matters, and that all of this led to the failure in foreseeing its deep impact and wide span (Bernanke (2013); Acemoglu et al. (2015); Freixas et al. (2015); Bernanke (2018)).

Despite this widely shared view, most of the existing research, both theoretical and empirical, has considered each of those networks in isolation — in the empirical case, largely due to a lack of reliable and comprehensive *matched* datasets on the production and financial networks. In this light, our main contribution can be described in a nutshell as follows: to provide an *integrated* analysis of real and financial networks that is *theoretically founded* and shows, *empirically*, that such an integration can lead to *large amplification effects* — indeed, in our empirical analysis, we find that the overall effect *triples* the direct impact of the shocks.

More concretely, our focus is on the process by which shocks originating in the financial system impinge, and then propagate, on the real production network. To this end, we develop a theoretical framework that allows us to compute and quantify the various effects induced, thus providing empirically testable predictions for the various effects resulting from the shock-propagation process. In particular, we are able to distinguish between direct and indirect financial shocks, first- and higher-order effects, upstream versus downstream propagation.[1]

Our empirical identification strategy exploits several matched administrative datasets from a bank-dominated economy (Spain), which include universal information on the following transactions: (i) supplier-customer trades gathered from the Treasury's Value Added Tax (VAT) Register, and (ii) bank-firm loans obtained from Banco de España's Credit Register. We rely as

[1] To clarify our terminology at this point, we advance informally that direct financial (bank credit supply) shocks are those impacting on a firm via its banks (direct suppliers of credit), while indirect financial shocks are those bank shocks operating via customer or supplier relationships in the production network. Among these, first-order effects embody propagation from direct customers (suppliers) to the firm, while higher-order ones involve propagation chains through customers of customers (or suppliers of suppliers). By upstream propagation we refer to the transmission of financial shocks from customers to suppliers, while by downstream propagation we refer to the transmission of financial shocks from suppliers to customers. Finally, we also differentiate between economy-wide credit supply shock affecting uniformly all firms in the economy and firm-specific credit supply shocks hitting individual firms.

well on the supervisory information concerning the interbank's position of each bank, together with the administrative data on bank and firm balance sheets. Moreover, we exploit differential bank credit supply shocks during the 2008–09 global financial crisis based on two financial networks: an overall bank-level credit supply shock (obtained from the credit network), and a bank-level shock stemming only from a bank's pre-crisis reliance on funding from the interbank network.

The empirical analysis starts at the most basic *link/firm-to-firm level.* By exploiting the variability displayed by the data on bilateral inter-firm transactions, we show that negative bank-credit supply shocks hitting any given firm propagate both downstream and upstream thus affecting, respectively, each of its direct customers (purchases) and suppliers (sales). Next, building upon our theoretical framework, for each firm we compute the aggregate credit supply shock hitting all its direct customers/suppliers (*first-order* effect), and the aggregate credit supply shock hitting all its indirect customers/suppliers of any order (*higher-order* effect). This aggregation fully reflects the production network structure, in particular accounting for the widely heterogeneous use of intermediate inputs observed across firms. Remarkably, we find that these effects are not only strong in affecting real activity, but of a similar magnitude when comparing:

(i) *direct bank shocks* impinging on firms versus the *indirect first-order effects* channeled through the customer-supplier network;
(ii) *first-order effects* impinging on direct customers or suppliers versus the *higher-order effects* that bear upon the customers/suppliers of customers/suppliers of any order;
(iii) *downstream shock propagation* flowing from suppliers to customers versus *upstream propagation* operating in the opposite direction;
(iv) individual bank shocks hitting *specific firms* versus an economy-wide shock affecting the *whole economy uniformly.*

Finally, as part of our heterogeneity analysis, we also show that market power (proxied by concentration) amplifies the spillover effects of bank credit supply shocks.

The remaining part of this Introduction is divided into two parts. First, we provide a detailed preview of the different parts of the paper. Second, we discuss at some length the related literature and its contrast with our present work.

A detailed preview of the paper. The paper includes four more core sections (Sections 2–5), a concluding section (Section 6), the Appendix with main tables, and three online appendices with formal proofs of our theoretical results, auxiliary tables, and figures, respectively. In what follows, we provide a preview of the core sections, which should enable a reader to grasp in advance the essence of our contribution.

Section 2 presents the theoretical framework, which sets up the problem formally and thus allows the operationalization and quantification of the network effects predicted for the empirical analysis. Our model follows Bigio and La'O (2016) in relating credit supply shocks to price distortions (or price wedges) in the real part of the economy. Thus, identifying the magnitudes of those shocks with the size of the induced distortions, we determine the induced network-channeled effects impinging on each firm. In general, the impact of a shock depends both on where it originates and on the network position of the firm under consideration. More specifically, our model tailors these effects to the direct and indirect real flows connecting the firm originally affected by the financial shock to all other firms, either as customers (i.e. downstream) or/and suppliers (upstream). As it turns out, while both propagation channels happen to be important, they are interestingly different as well in that they operate in a non-symmetric manner. That is, they are linear in the magnitude of the shock for downward propagation (i.e. when the *origin* is upstream), while the dependence is non-linear for upward propagation (when the *origin* is downstream).

Section 3 discusses the matched administrative datasets. A significant contribution of the paper is to match the administrative firm-to-firm register covering the VAT transactions in Spain (the Treasury's VAT Register) with the supervisory bank-firm credit register including the loans to corporates (the central bank's Credit Register). When a firm sells a product or service to another one, there is a VAT tax associated to the sale. Hence, by having access to all annual VAT transactions for 2008 and 2009 (above a threshold of only 3,005 euros), we can basically construct the whole weighted production network of Spain. Moreover, we also have access to all the loans given by each bank to any firm (with a threshold of just 6,000 euros). This, essentially, provides us with the complete (bank-firm) credit network. Finally, we match our data both to the Spanish Mercantile Register and to the bank dataset owned by Banco de España (in its role as banking supervisor), which provides us information on the funding of each bank in the interbank market as well as on firm-level investment and employment, among other variables. Overall, our sample consists of approximately 4.3 million VAT firm-to-firm transactions (2,328,908 transactions between 245,524 different firms in 2008 and 2,040,869 transactions between 243,936 firms in 2009), and 1,682,654 loans from 206 active banks.

Section 4 explains our empirical identification strategy. Concerning the identification of credit supply shocks we exploit the wide variability across banks and firms in exposure to the effects of the global 2008–09 financial crisis that followed the failure of Lehman Brothers in mid-September 2008. Specifically, to obtain suitable cross-sectional variation on bank shocks during the crisis, we consider the following two alternative routes in turn:

(a) First, we pursue the approach of Amiti and Weinstein (2018), itself following Khwaja and Mian (2008).[2] Their methodology, which has been widely used in the literature, estimates a bank credit supply shock as the change in credit, cleaned by time varying firm-level observed and unobserved fundamentals (proxying, for example, for firm-level credit demand, which is captured by firm-time fixed effects).

(b) Second, as a complementary exercise, we replicate the analysis with a different bank shock formulation, also extensively used in the literature. It is based on the ex-ante bank funding exposure to the interbank market, which was a market sharply affected by the global financial crisis (see e.g. Iyer et al. (2014)).

[2]For a related bank-level shock, see Chodorow-Reich (2014) and Jiménez et al. (2014). This approach exploits firms with at least two bank relationships at the same time. In Spain, during the sample period, approximately 75% of the credit comes from firms with at least two bank relationships. We get similar results when we use banks' exposure to the interbank network to identify bank credit supply shocks, which does not rely on firms with at least two bank relationships.

We show that the two alternative approaches, (a) and (b), lead to similar firm-level credit-supply negative effects, which are significant *only* during the financial crisis *but not* before.[3] Moreover, those bank shocks turn out to affect *total* debt liabilities at the firm level, including trade credit. Thus, in sum, we find that the global financial shock affected banks differentially (e.g. due to their specific pattern of interbank funding), thereby also affecting firms differently.

For the identification of propagation effects, we rely on the network-type transaction data available at the supplier-customer (i.e. firm-to-firm) level, controlling for substantial unobservables and then aggregating up at the firm level to analyze the firm-level real effects. More concretely, we exploit variability across supplier-customer purchases (sales), even within the same customer (supplier) across all its suppliers (customers), thereby controlling fully for unobserved or observed customer (supplier) heterogeneity.[4] Thus, for example, by exploiting within-customer variation in purchases (i.e. customer fixed effects), we identify downward propagation of bank shocks across suppliers; or, reciprocally, by exploiting within-supplier variation in sales (i.e. supplier fixed effects), we identify upstream propagation of bank shocks to customers.

Section 5 presents the core of our empirical analysis, whose main focus is on estimating the direction and range of shock propagation along the production network. First, we study propagation at the link (i.e. firm-to-firm) level and find strong empirical support for both downstream propagation of negative bank shocks hitting specific suppliers and upstream propagation of the bank shocks impinging on customers. In particular, we find that a negative bank shock to a supplier of a given firm on average implies a reduction of 3.7 percentage points (pp) in the growth rate of the firm's purchases from that supplier. Instead, if it is the customer of the firm that faces a bank credit supply shock, this leads on average to a reduction of a 5.1 pp in the growth of the corresponding sales to that customer. In economic terms, these two effects represent a substantial reduction of 29% and 37% of the median value for purchases and sales, respectively. In fact, these effects are of a comparable magnitude as those induced by a direct bank shock to the firm itself, since our estimates indicate that, on average, a direct negative bank-credit shock induces a reduction in the firm's growth rate of purchases and sales of 5.6 and 2.5 pp, respectively.

It is important to emphasize that, since firms' bank shocks happen to be strongly correlated with customers' and suppliers' bank shocks, the identification and measurement of the network effects also depend crucially on the availability of transaction-level data. In their absence, it would not be possible to disentangle the effects of bank shocks impinging directly on firms from those indirectly affecting them via customers or suppliers. For example, our results suggest that downward propagation more than doubles when we account for customer-supplier selection.

We also obtain strong (indirect) effects at the *individual firm level* across the bank shocks

[3] This is expected since, before the collapse of Lehman Brothers, firms could much more easily switch from more affected banks to less affected banks, thereby reducing substantially the effect of the credit supply shocks; instead, during the crisis, no such flexibility existed. We show, therefore, that bank shocks are binding at the firm level during the crisis but not before (i.e. in 2007). As regards to identification, it is important to highlight that Spain is a bank-dominated economy, which implies that we may abstract from the networks involving other financial intermediaries, such as the shadow banking system, which could be important, for example, in the USA.

[4] Though we control for firm unobservables (via different types of fixed effects), we also show that firm observed characteristics do not differ ex-ante across firms with stronger versus weaker bank credit shocks.

hitting all its direct (first-order) suppliers or customers.[5] Specifically, we find that a negative bank credit supply shock to suppliers (or customers) generates a 2.3 (or 1.9) pp reduction in the growth of firm-level purchases (sales). Thus, both downstream and upstream propagation effects are of a similar magnitude. Their overall economic impact on the firm-level employment growth and investment are 0.42 and 0.37 pp, respectively, while the effects are 0.41 and 0.55 pp for the direct bank shock to firms. Relative to the median value of employment and investment, these figures account for a 42% in the decrease of employment and 6% in that of investment, while we have 41% and 9% for the direct shock, respectively. In sum, we again find that the (strong) real effects of first-order bank (credit supply) shocks stemming from the customer-supplier network are of similar magnitude to the ones resulting from direct bank shocks.

We then study the higher-order effects that concern the firms that are indirectly connected — through a chain of multiple buying or selling relationships — to firms that are hit by a bank shock. Our empirical analysis shows that these higher-order effects are strong (2.0 pp) when they involve downward propagation, i.e. are associated to bank shocks that affect indirect suppliers (i.e. suppliers of suppliers). Their magnitude, therefore, is comparable to the first-order downstream effects. In contrast, when we consider upstream propagation, we find that only first-level connections (i.e. only bank shocks that affect direct customers) have a significant impact. Again, our theoretical model plays an important role in this respect, in that it provides the basis to compute and thus estimate higher-order indirect effects, also shedding light on the aforementioned contrast between the empirical support gathered on their downstream *versus* upstream propagation. At the firm level when we differentiate between direct versus indirect (first- and higher-order) effects, we find that the impact of negative bank shocks via direct effects is -0.98 pp on purchases and sales growth, while -0.91 pp in first-order effects and -1.07 pp in higher-order effects (26%, 24% and 29% of the overall reduction during the crisis relative to the median value). Hence we conclude that the overall (direct and indirect) effects triple the direct effects of bank credit shocks on firms' purchases and sales growth.

We find that the indirect effects of bank shocks to firm investment and employment growth are also very large. In particular, relative to the median value of employment and investment, the total (first-order and higher-order) indirect effects amount to 57% in the decrease of employment and 13% in that of investment, while we respectively have 40% and 9% for the direct effect.

Relying on the theoretical model we also estimate the effect of the economy-wide shock that affected all firms during the economic crisis under study. The model suggests that this economy-wide (i.e. perfectly correlated) shock propagates both downstream and upstream through the network, and its effect on any given firm depends, respectively, on what we call the firm's "customer" and "supplier" centrality in the production network. We estimate that a standard deviation increase in a firm's customer centrality is associated to a 3 pp decrease in the growth of its purchases, while an identical increase in its supplier centrality leads to a cut of 0.6 pp in the growth of firm's sales.

[5]For the overall real effects, it is crucial to aggregate results at the firm level, as firms could minimize shocks to some connected suppliers (or customers) by implementing changes across suppliers or customers. Moreover, there are some key real effects, as e.g. on employment and investment, which are only defined at the firm-level (in contrast with purchases/sales, which can also be defined at the firm-to-firm level).

To complement the main analysis, we empirically explore the impact of firm heterogeneity on the propagation of negative bank shocks. Concerning market power – which, for any given firm, we proxy by the concentration displayed by its own sector – we find that the extent to which a shock hitting a firm propagates to its customers and suppliers is amplified by the firm's market power. Firm-to-firm propagation is also enhanced, both upstream and downstream, if the pair of firms under consideration are both supplier to, and customer of, each other. And for the particular case of downward propagation, the effects become stronger as well when firms are more geographically distant and they do not work with the same main bank. This result is consistent with the bank internalizing the financial effects among its borrowers when they are connected on a supply chain.

A review of related literature. As already mentioned, the fast-growing literature studying the phenomenon of shock propagation in large economies has mostly evolved by studying separately the real and the financial networks. In the first case, the main focus has been on the supply chains that underlie the production of the non-financial firms of the economy, while in the second case the analysis has mainly centered on the banks alone, their links typically conceived as embodying some form of credit flows.

To summarize the literature studying the *real side of the economy* and its production networks, it is useful to organize it (roughly) into two different branches, one largely theoretical and the other mostly empirical. On its theoretical branch, besides the aforementioned papers by Acemoglu et al. (2012) and Bigio and La'O (2016) the reader can find in Carvalho (2014) a very good early discussion of both conceptual and technical matters. Other important contributions include the paper by Gabaix (2011), who highlights the importance of granularity as a source of aggregate risk, or the papers by Grassi (2017), Baqaee (2018), and Baqaee and Farhi (2019), who study how the problem is affected by various forms of imperfect competition and misallocations.

On the empirical side, the literature on production networks has striven to test the insights gathered from the theory by rendering operational its key notions, e.g. that of network centrality. From the point of view of identification, a particularly useful approach pursued by a series of papers has been to exploit natural disasters as exogenous shocks — see Barrot and Sauvagnat (2016), Boehm et al. (2016), and Carvalho et al. (2017). Another interesting paper is Acemoglu et al. (2016), which relies on industry-level data to quantify the propagation effects of different types of supply and demand shocks.[6] In all these cases, the authors show that the propagation effects on various economic outcomes are substantial.

Concerning the literature studying the *financial side of the economy*, the literature can again be divided into that part pursuing a largely theoretical approach and another one displaying mostly an empirical focus. On the theoretical side, following the seminal papers by Allen and Gale (2000) and Freixas et al. (2000), the issue of shock propagation in financial systems has been revisited by recent contributions of Elliott et al. (2014), Acemoglu et al. (2015), Glasserman and Young (2015), and Cabrales et al. (2017). These have largely focused on the key trade-off between risk-sharing and contagion in financial networks, with a particular emphasis on how free-

[6] Magerman et al. (2016) show that, in line with existing theory and other less-granular empirical research, interfirm asymmetries are an important factor in generating aggregate fluctuations from firm specific productivity shocks.

riding considerations typically lead to inefficient outcomes. Another branch of the theoretical literature has studied the so-called bank-lending channel (see e.g. Holmstrom and Tirole (1997), Stein (1998), Gertler and Kiyotaki (2010)). In the spirit of the present paper, they highlight how credit-supply shocks may lead to significant real effects on the production side of the economy.

Turning now to the empirical side of the financial network literature, an illustrative sample of papers that have analyzed the interbank network of the economy (including the study of indirect second-order effects) are e.g. Iyer and Peydro (2011), Buch and Neugebauer (2011), and Niepmann and Schmidt-Eisenlohr (2013). In addition, among the empirical papers belonging to the aforementioned strand of literature focused on the bank-lending channel, we may list Khwaja and Mian (2008), Chodorow-Reich (2014), Greenstone et al. (2014), Bentolila et al. (2017), Jiménez et al. (2012, 2014, 2017), Amiti and Weinstein (2018), and Galaasen et al. (2020).

Finally, there is a very recent literature, closer to our paper, that also aims at understanding the process by which financial shocks not only affect financial networks but also propagate through the real production network and possibly amplify their overall effects. To the best of our knowledge, the following two contemporaneous papers are the most related to ours.[7]

One is the paper by Costello (2020), which studies the downstream propagation of shocks through their influence on the trade credit that firms extend to their customers and on total sales. Relying on data obtained from a third-party credit information platform, she documents that firms with greater exposure to a large decline in finance reduce their trade credit to customers, thus inducing significant negative effects on their real outcomes.[8] In contrast with her paper, we use administrative registers on the universe of transactions for both the real and financial networks and show that (a) besides downstream propagation, upstream propagation is also important and of similar magnitude in economic terms, and (b) in addition to first-order effects, also higher-order ones (e.g. bank shocks to suppliers' suppliers) do matter, and similarly so as well. We also find that negative bank shocks affect overall credit availability at the firm level (including debt liabilities such as trade credit), thereby affecting the real network along multiple channels.

The second paper is Cortes et al. (2019), which also estimates indirect effects of credit shocks — in this case using firm-to-firm transaction data from Brazil. Methodologically, this paper differs from ours in several key respects. First, as in Costello (2020), it only considers first-order propagation, while we also analyze the transmission of shocks through higher-order linkages.

[7]Another more distantly related paper is Alfaro et al. (2019), which investigates the propagation of credit shocks through *industry-level input-output relationships*. We mention here a few important differences. First, in contrast with that paper, we show that, given the correlation of bank shocks across the production network, transaction-level data at the firm level is crucial for the identification and quantification of the estimated effects (e.g. our estimated results more than double in downward propagation when we account for customer-supplier selection, or the direct bank shocks to firms halves). Second, Alfaro et al. (2019) estimate the first-order indirect effects by exploiting within sector variation across firms only with respect to firms' total input intensities and sales, while we also exploit the substantial variation associated to the individual positions of the firms in the production network. Third, Alfaro et al. (2019) does not investigate the higher order propagation effect.

[8]Related to this, Demir et al. (2018) show that a negative shock to the cost of import financing gets propagated from liquidity-constrained firms to their customers. Note that, in principle, the trade-credit channel may also explain upstream propagation of financial shocks if debtor (customer) failure triggers supplier's losses through both credit losses and demand shrinkage (see Jacobson and von Schedvin (2015)).

Second, it considers bank credit shocks by state-owned banks, while we consider bank shocks from the two main financial networks (credit supply shocks coming both from all banks and from the interbank market).[9] Third, due to data limitations, Cortes et al. (2019) only exploit transactions between firms working with different banks while we also consider firm-to-firm transactions within the same bank, which matter differently.

In sum, the key contrast with both papers is two-fold: (a) we rely heavily on a theoretical framework to guide the empirical analysis, and (b) use administrative matched datasets on the universe of both supplier-customer transactions and bank loans. Importantly, these two differences allow us to widen very substantially the scope of our analysis.

2 Theoretical framework

In this section we present the model postulated to study the propagation of financial shocks through the production network of the economy. More specifically, it is on the basis of this model that, in the empirical analysis, we shall undertake the following two key steps:

(a) establish an operational connection between the financial and real sides of the economy;

(b) aggregate the indirect shocks impinging on any given firm, not only at first order but at all other higher orders along the production network.

Our model is a variation on the framework proposed by Baqaee (2018). We simplify his framework by abstracting from entry or exit and assuming Cobb-Douglas[10] production technologies. On the other hand, we enrich it by introducing financial shocks, modeling them as a distortion on the cost of credit in the manner formulated by Bigio and La'O (2016) (see also Baqaee and Farhi (2019), which relies on a formally similar approach to study general market distortions). Since the theoretical framework is in many respects standard, we now present its different components in a quite compact manner. We focus in detail only on those features that, being less common, are also pertinent to the empirical analysis. When formal details and proofs are needed, they are relegated to the Appendix.

2.1 Production

The production side of the economy consists of a given set of firms, N, each of them producing a single non-differentiated good with constant returns to scale technology. The production

[9] There is a large literature showing that there are large inefficiencies of government banks (see e.g. La Porta et al. (2002), and hence changes in credit mediated through these government banks do not identify bank shocks appropriately, see e.g. La Porta et al. (2002)).

[10] Often, the Cobb-Douglas assumption is viewed as fairly restrictive in that its unit elasticity of substitution may limit the range of effects it allows. In our case, however, where the focus is on the propagation of *financial shocks*, it still delivers a rich set of network effects — including both upstream and downstream propagation as well as rich non-linearities (see the discussion following Proposition 2 for an elaboration). Since the main focus of our paper is a reduced form analysis of propagation of financial shocks, we believe that the unique theoretical tractability afforded by the Cobb-Douglas assumption is justified to guide us in our empirical analysis and to provide the intuition for our results.

possibilities of a typical firm i being described by a production function of the form:

$$y_i = f_i\left(\{z_{ji}\}_{j \in N_i^+}; \ell_i\right) = \zeta_i \ell_i^{\beta_i} \left(\prod_{j \in N_i^+} z_{ji}^{g_{ji}}\right)^{\alpha_i} \tag{1}$$

where y_i stands for the output of firm i, ℓ_i for its labor input, and z_{ji} for the amount of intermediate input it uses of each $j \in N_i^+$, where N_i^+ stands for the set of intermediate inputs used by firm i. Thus, all production functions $f_i : \mathbb{R}^{n_i^+} \times \mathbb{R} \to \mathbb{R}$ display the usual Cobb-Douglas form, with $\boldsymbol{\alpha} = (\alpha_i)_{i=1}^n$ and $\boldsymbol{\beta} = (\beta_i)_{i=1}^n$ being the (strictly positive) input elasticities ($\alpha_i + \beta_i = 1$ for all i) and $\boldsymbol{\zeta} = (\zeta_i)_{i=1}^n$ the classical Hicks productivity parameters. The non-negative vector $(g_{ji})_{j \in N_i^+}$ reflects the *relative* intensity with which firm i uses different intermediate inputs, so that it is normalized to satisfy $\sum_{j \in N} g_{jk} = 1$. Thus, overall, the interfirm production structure of the economy is characterized by the (column-stochastic) adjacency matrix $\mathbf{G} = (g_{jk})_{j,k=1}^n$.

Firms are assumed to set their price optimality, given the underlying competition structure of the economy. To account for different such structures, we follow Baqaee (2018) and use a reduced-form approach that postulates the assumption that every firm i sets its price by applying a markup μ_i to its marginal cost of production. As explained in that paper, different forms of competition (say, monopolistic or Cournot) give rise to alternative mark-up values, as a function of the parameters of the environment (elasticities, productivities, or number of firms in each industry). Thus, for our purposes, we shall make each μ_i a parameter of the model, conceiving it as a compact embodiment of the (non-explicitly modeled) competition structure of the economy.

2.2 Financial shocks

We posit a cash-in-advance context in which every firm i is required to pay in advance a share χ_i of its input expenditure, and to do so it needs to borrow at an interest rate R_i. Its net profit is then given by:

$$\begin{aligned}\pi_i &= p_i y_i - (1-\chi_i)\left(\sum_{j \in N_i^+} p_j z_{jk} + w\ell_i\right) - \chi_i(1+R_i)\left(\sum_{j \in N_i^+} p_j z_{ji} + w\ell_i\right) \\ &= p_i y_i - (1+\theta_i)\left(\sum_{j \in N_i^+} p_j z_{ji} + w\ell_i\right),\end{aligned}$$

where we use the notational shorthand $\theta_i = \chi_i R_i$. For convenience, we normalize matters and assume that under *normal conditions* $R_i = 0$, while if the firm is affected by a financial shock its borrowing cost rises to some $R_i > 0$. In this latter case, therefore, it faces a "financial distortion" in its decision problem, given by the aforementioned $\theta_i = \chi_i R_i$. Alternative, and formally similar, ways to model financial shocks are considered by Bigio and La'O (2016), Luo (2016), and Liu (2016). For our purposes, it is convenient to decompose each θ_i into a common component ν and an individual component τ_i, then writing $\theta_i = \nu + \tau_i$. We refer to ν as an economy-wide distortion/shock, and τ_i as the firm-specific distortion/shock.

2.3 Equilibrium analysis

To close the model, we need to formalize the consumption side of the economy and posit a suitable equilibrium notion. First, concerning consumption, we assume that it is carried out by a representative consumer who supplies a unit of labor inelastically and maximizes a Cobb-Douglas utility function given by $U(\boldsymbol{c}) = \prod_{i=1}^{m} c_i^{\gamma_i}$, subject to a budget constraint $\sum_i p_i c_i \leq E$, where $\boldsymbol{\gamma} = (\gamma_i)_{i=1}^{m}$ is a vector of preference weights for each good i and E is the consumer's income. The financial flows in the economic system are taken to be balanced, so the consumer's income (non-normalized expenditure) satisfies $E = w + \sum_{i \in N} \pi_i + \sum_{i \in N} \sum_{j \in N_i^+} \theta_i \left(p_j z_{ji} + w\ell_i\right)$. That is, it includes the wage w, the profits π_i of all firms, and the returns earned by the financial sector of the economy (equal to the interest payments by firms).

Finally, concerning the equilibrium concept, it embodies the usual requirements of individual (firm and consumer) optimality and market clearing. Verbally, it can be described as follows.

Definition 1. *Given a vector of financial distortions $\boldsymbol{\theta} = (\theta_i)_{i=1}^{n}$, a* Market Equilibrium *(ME) is an array $\left\{[(p_i^*)_{i=1}^{n}, w^*], [(c_i^*)_{i=1}^{n}, (y_i^*)_{i=1}^{n}, (z_{ij}^*)_{i=1,j}^{n}, (\ell_i^*)_{i=1}^{n}]\right\}$ that satisfies the following conditions:*

- *Each firm i minimizes production costs and applies its mark-up μ_i to set its price.*
- *The consumption plan maximizes consumer's utility subject to her budget constraint.*
- *Markets for each intermediate input and labor clear.*

The existence of a market equilibrium follows from standard arguments, and its uniqueness relies on our Cobb-Douglas assumption on preferences and technologies. To characterize this equilibrium, the following notation will prove useful. First, let $\mathbf{A}$, $\mathbf{M}$ and $\mathbf{T}$ stand for diagonal matrices with elements α_i, $\frac{1}{\mu_i}$ and $\frac{1}{1+\nu+\tau_i}$ on the main diagonal, respectively. Then define:

$$\boldsymbol{v}(\boldsymbol{\theta}) = (v_i(\boldsymbol{\theta}))_{i=1}^{n} = (\mathbf{I} - \mathbf{GAMT})^{-1}\boldsymbol{\gamma} \tag{2}$$

which is the vector whose ith component is what we shall call the centrality of firm i. Intuitively, it is a variation of the standard centrality notion proposed by Bonacich (1987), which aggregates the number of suitably weighted downstream paths that connect i to the consumer along the production network. Finally, we introduce the following convenient shorthand, which is used throughout the paper:[11] for any variable x, we denote $\hat{x} := \log x$, the only exception being when we write $\hat{\theta}_i$, which will stand for $\log(1 + \theta_i)$.

The following proposition, proven in the Appendix, provides an explicit expression for equilibrium outputs for any given vector of shocks $\boldsymbol{\theta}$.

Proposition 1. *For any $\boldsymbol{\theta}$, the vector of equilibrium outputs $\boldsymbol{y} \in \mathbb{R}^n$ satisfies:*

$$\hat{\boldsymbol{y}}(\boldsymbol{\theta}) = -(\mathbf{I} - \mathbf{AG}')^{-1}\hat{\boldsymbol{\theta}} + \hat{\boldsymbol{v}}(\boldsymbol{\theta}) + \hat{E}(\boldsymbol{\theta}) + K \tag{3}$$

while, for every firm $i \in N$, its expenditure on each input $j \in N_i^+$ is given by:

$$z_{ji}(\boldsymbol{\theta}) = \frac{\alpha_i\, g_{ji}}{\mu_i} \, \frac{p_i(\boldsymbol{\theta})\, y_i(\boldsymbol{\theta})}{p_j(\boldsymbol{\theta})(1+\theta_i)} = \frac{\alpha_i\, g_{ji}}{\mu_i} \, \frac{s_i(\boldsymbol{\theta})}{p_j(\boldsymbol{\theta})(1+\theta_i)} \tag{4}$$

[11] Motivated by our empirical analysis, whose econometric specifications are cast in logarithmic terms, the presented theoretical analysis is also formulated in this manner.

where $\hat{E}(\boldsymbol{\theta})$ represents the wage-normalized expenditure (or GDP), $s_i = p_i y_i$ denotes the sales of firm i, and K is a constant independent of $\boldsymbol{\theta}$.

The first, and most basic, implications of Proposition 1 pertain to how a financial shock hitting a production firm affects the bilateral interactions with any other firm directly related to it — be it a customer or a supplier. Note that, in network terms, the effect of the shock on the bilateral *customer/supplier relationship* between two firms, i and j, can be viewed as applying to a corresponding link $j \to i$ where j is interpreted as the supplier and i as the customer. If the shock in question hits firm j, its effect on i will be labeled as *downstream*; instead, if it hits firm i, its effect on j will be called *upstream.* In both cases, the focus is on what is the impact of the shock on the volume of the i-j trade — i.e. on the amount z_{ji} of input j demanded by i, as given by (4) above.

Let us start with the case where the bank shock affecting the link $j \to i$ hits firm j. For expositional simplicity, it is convenient to consider a situation where, *before* shock of magnitude $\theta_j > 0$ hits j, this firm was facing what we have called "normal conditions", i.e. the original value of the shock was equal to zero. Then, the induced *downstream* effect can be identified (using the notation introduced in Proposition 1) with the difference $\hat{z}_{ji}(\nu + \tau_j, \boldsymbol{\theta}_{-j}) - \hat{z}_{ji}(0, \boldsymbol{\theta}_{-j})$, i.e. with the impact that the shock has on j's supply of the input to i. As shown in the Appendix, our empirical identification strategy relies on control conditions under which the model predicts the aforementioned difference to be negative. An analogous conclusion applies if the shock hits firm i, in which case the (negative) *upstream* propagation effect is embodied by the difference $\hat{z}_{ji}(\nu + \tau_i, \boldsymbol{\theta}_{-i}) - \hat{z}_{ji}(0, \boldsymbol{\theta}_{-i})$.

For future reference, it is useful to summarize the above discussion in the following two most basic predictions induced by our theoretical framework at the link (firm-to-firm) level.

P1: Link-level (firm-to-firm) downstream propagation: The purchases of a firm from any one of its suppliers are negatively affected (grow at a lower rate) if that supplier is hit by a bank credit shock.

P2: Link-level (firm-to-firm) upstream propagation: The sales of a firm to any one of its customers are negatively affected (grow at a lower rate) if that customer is hit by a bank credit shock.

Next, we build upon Proposition 1 to produce predictions on how the shocks of an economy impact its different firms. To understand the problem in a systematic manner, it is useful to decompose the overall network effects in three dimensions:

(a) *local* effects, which aggregate the indirect impact on a given firm of all shocks hitting its *first-order* partners (direct customers and direct suppliers);

(b) *global* effects, which aggregate the indirect impact on a given firm of all shocks hitting its *higher-order* partners, as channeled through the economy-wide network;

(c) *income* effects, which aggregate the *changes in income* (or aggregate expenditure) induced by all shocks in the economy.

All three items (a)-(c) entail a *micro-founded aggregation* of the different effects arising on one of the following three dimensions: *locally* across multiple partners in the first case; *globally* along the full network in the second; through *income* adjustments in the third. The key step needed to conduct those aggregation exercises is provided by Proposition 2 below. However, before turning to a formal statement of this result, it is useful to formulate precisely the "flows" at work in the network-based shock propagation described in (a) and (b). As in the link-level (firm-to-firm) propagation considered in P1–P2, there are two directions in which such a propagation can flow when we undertake the analysis at the node (firm) level: *downstream* and *upstream*. In what follows we explain the two operators/matrices that embody each of them.

On the one hand, under ***downstream propagation***, it is the customers who are (indirectly) affected by shocks that hit their suppliers. Thus, in this case, propagation occurs from suppliers to customers, its magnitude depending on the intensity with which the corresponding inputs are used, either directly as in (a), or indirectly as in (b). This means that downstream propagation is governed by the matrix of intermediate input requirements $\mathbf{GA}$ — or, more precisely, by its transpose, $\mathbf{AG}'$.

On the other hand, the mechanism of ***upstream propagation*** is more complex, since its particular details depend on the shocks themselves, given by the vector $\boldsymbol{\theta}$. For, as shown in the Appendix, it is determined by the matrix $\mathbf{H}(\boldsymbol{\theta}) = ((h_{ij}(\boldsymbol{\theta}))_{i=1}^{n}$ whose typical element is given by

$$h_{ij}(\boldsymbol{\theta}) = \frac{\alpha_j g_{ij}}{(1+\nu+\tau_j)\mu_j} \frac{v_j(\boldsymbol{\theta})}{v_i(\boldsymbol{\theta})} = \frac{p_i z_{ij}}{p_i y_i} \quad (i, j = 1, 2, ..., n) \tag{5}$$

As it happens with the matrix $\mathbf{AG}'$ (which is substochastic since all $\alpha_i < 1$) the matrix $\mathbf{H}(\boldsymbol{\theta})$ is substochastic because $\sum_{j \in N} h_{ij}(\boldsymbol{\theta}) \leq 1$ for all $i \in N$, with this inequality being strict for all consumption goods $i' \in N$ with $\gamma_{i'} > 0$. There are however two important differences between them. One, already mentioned, is that $\mathbf{H}(\boldsymbol{\theta})$ is not exogenous but endogenous, as it depends (through the market equilibrium notion) on the shock realizations in $\boldsymbol{\theta}$. The second difference is that, for each row/good i, that matrix captures the strength $h_{ij}(\boldsymbol{\theta}) > 0$ of the downstream relationship between firm i and the customer firms j that use i in their production. Matrix $\mathbf{H}$, therefore, determines the different strengths with which shocks propagate upstream, from customers to suppliers.

Focusing first on the case where the shocks involved are sufficiently small, the specific ways in which the three propagation mechanisms (a)–(c) operate is precisely spelled out in the following proposition.

Proposition 2. *For any vector $\boldsymbol{\theta}$, the effect of a marginal change in τ_k on the equilibrium output y_i of firm i $(i, k = 1, 2, ..., n)$ is given by:*

$$\frac{\partial \hat{y}_i}{\partial \tau_k}(\boldsymbol{\theta}) = -\frac{1}{1+\theta_k}\, \boldsymbol{e}_i'(\mathbf{I} - \mathbf{AG}')^{-1}\boldsymbol{e}_k - \frac{1}{1+\theta_k}\boldsymbol{e}_i'(\mathbf{I} - \mathbf{H}(\boldsymbol{\theta}))^{-1}\mathbf{H}(\boldsymbol{\theta})\, \boldsymbol{e}_k + \frac{\partial \hat{E}(\boldsymbol{\theta})}{\partial \theta_k}, \tag{6}$$

while the effect on y_i of a marginal change in the economy-wide shock ν is given by:

$$\frac{\partial \hat{y}_i}{\partial \nu}(\boldsymbol{\theta}) = -\boldsymbol{e}_i'(\mathbf{I} - \mathbf{AG}')^{-1}\, \mathbf{T1} - \boldsymbol{e}_i'(\mathbf{I} - \mathbf{H}(\boldsymbol{\theta}))^{-1}\mathbf{H}(\boldsymbol{\theta})\, \mathbf{T1} + \sum_{k=1}^{n} \frac{\partial \hat{E}(\boldsymbol{\theta})}{\partial \theta_k}, \tag{7}$$

where $\boldsymbol{e}_i$ *is the (column) vector whose ith component is* 1 *while all others are* 0*, and* E *is the economy's wage-normalized income (or GDP).*

A well-known property of production-network models with Cobb-Douglas production technology is that demand shocks (i.e. shocks to the consumer's preferences) propagate only upstream while supply shocks (i.e. productivity shocks) propagate only downstream (see for instance Acemoglu et al. (2016)). In contrast, financial shocks in our model propagate both upstream and downstream, despite the Cobb-Douglas assumption. The reason is that these shocks have both a demand and a supply dimension. On the one hand, when a negative financial shock hits a given firm k, this renders its inputs more expensive. And, as a consequence, it *demands* less inputs from its *direct suppliers* at given prices (see equation (4)). This effect propagates *upstream* through the network in a *non-linear* way, as captured by matrix $(\mathbf{I}-\mathbf{H}(\boldsymbol{\theta}))^{-1}\mathbf{H}(\boldsymbol{\theta})$ in (6) and (7). On the other hand, if firm k becomes more financially constrained due to a financial shock, it demands sub-optimal amounts of its inputs, hence inducing a higher marginal cost of production. This effect is formally equivalent to a *negative productivity shock* (see Lemma 1 in Online Appendix A), and therefore propagates *downstream* through the network, as captured by matrix $(\mathbf{I}-\mathbf{AG}')^{-1}$ in (6) and (7).

The previous result is useful in that it provides a formal expression for how *small* shocks diffuse, locally and globally, through the production network. But, in order to get a more empirically relevant formulation, we need to address two further points:

- aggregate all shocks that simultaneously operate at any given point in time;
- allow for shocks that are heterogeneous and possibly sizable (not just small, as implicitly assumed in (6)).

To address the first point we simply add the different terms in (6) for all goods $k \in N$. The second point, however, is more delicate in that it requires extending the analysis to non-infinitesimal shocks (in effect, binary shocks as explained in Section 4). This extension is conducted by relying on (6) to approximate linearly the different effects involved, downstream and upstream. As we discuss next, such an approximation is in fact exact for all downstream effects but is imperfect for upstream ones.

Consider any given vector of shocks, $\boldsymbol{\theta} \in \mathbb{R}^n$ hitting simultaneously the economy at some point in time. As a constituent part of them, let $\boldsymbol{\tau} = (\tau_i)_{i=1}^n$ represent the vector of corresponding firm-specific shocks associated to $\boldsymbol{\theta}$. Using again as the benchmark of comparison a situation with uniformly "normal conditions" (no shocks), we can rely on (6) to linearly approximate the (logarithmically expressed) production profile $\hat{\boldsymbol{y}}(\boldsymbol{\theta}) = (\hat{y}_i(\boldsymbol{\theta}))_{i \in N}$ prevailing under any arbitrary vector of distortions as follows:

$$
\overbrace{
\begin{aligned}
\hat{y}_i(\boldsymbol{\theta}) - \hat{y}_i(\mathbf{0}) \;\simeq\; & -\overbrace{\boldsymbol{e}_i'(\mathbf{I}-\mathbf{AG}')^{-1}\boldsymbol{\tau}}^{\text{direct \& downstream effects}} - \overbrace{\boldsymbol{e}_i'(\mathbf{I}-\mathbf{H}(\mathbf{0}))^{-1}\mathbf{H}(\mathbf{0})\boldsymbol{\tau}}^{\text{upstream effect}} + \overbrace{\sum_{k=1}^{n}\left[\frac{\partial \hat{E}}{\partial \theta_k}(\mathbf{0})\,\tau_k\right]}^{\text{income effect}}
\end{aligned}
}^{\text{firm-specific shocks}}
$$

$$
\underbrace{
- \overbrace{\boldsymbol{e}_i'(\mathbf{I}-\mathbf{AG}')^{-1}\mathbf{1}\nu}^{\text{direct \& downstream effects}} - \overbrace{\boldsymbol{e}_i'(\mathbf{I}-\mathbf{H}(\mathbf{0}))^{-1}\mathbf{H}(\mathbf{0})\mathbf{1}\nu}^{\text{upstream effect}} + \overbrace{\nu\left[\sum_{k=1}^{n}\frac{\partial \hat{E}}{\partial \theta_k}(\mathbf{0})\right]}^{\text{income effect}}
}_{\text{economy-wide shock}}
\tag{8}
$$

We discuss the RHS of (8) starting with the first part of it dealing with the effects induced by the *firm-specific shocks.* This part can itself be decomposed into three components, which we now explain in turn.

The ***first*** component is best understood as reflecting a measure of centrality of each firm $i \in N$, which identifies all of i's suppliers of every order (direct and indirect, including itself) by proceeding upstream along the production structure. It is similar to the notion of *centrality* defined in (2), but for the following two differences.[12] First, since it proceeds upstream – in order to compute *downstream propagation* effects – it does not rely on the matrix $\mathbf{G}$ but on its transpose $\mathbf{G}'$ and its powers of all orders. Second, any of the paths induced is weighted by the shock τ_j that hits the end firm j reached, rather than by the corresponding preference weight γ_j. To understand better the various levels involved in this centrality measure, it is useful to break it down as follows:

$$
-\boldsymbol{e}_i'(\mathbf{I}-\mathbf{AG}')^{-1}\boldsymbol{\tau} = -\overbrace{\delta_{ik}\tau_i}^{\text{direct effect}} - \overbrace{\boldsymbol{e}_i'\mathbf{AG}'\boldsymbol{\tau}}^{\substack{\text{first-order}\\ \text{downstream effect}}} - \overbrace{\boldsymbol{e}_i'(\mathbf{I}-\mathbf{AG}')^{-1}\left(\mathbf{AG}'\right)^2\boldsymbol{\tau}}^{\substack{\text{higher-order}\\ \text{downstream effect}}}, \tag{9}
$$

The first term in the RHS of (9) is the direct effect, which is only applicable if the Kroenecker delta $\delta_{ik} = 1$ (i.e. if $i = k$). The second term captures the first-order network effects derived from the shocks experienced by the direct suppliers of the firm i in question. Finally, the third term aggregates all higher order effects, as derived from the shocks that hit all other firms connected upstream to i through intermediate stages of production. Note that these latter effects become progressively smaller (but also more numerous) as the network path length involved is longer, since the matrix $\mathbf{AG}'$ is substochastic. Another important feature to note here is that both the first-order downstream effects, as well as the network effects of *any* higher order, depend *linearly* on $\boldsymbol{\tau}$. Thus, in both of these two cases, the linearity displayed by the expressions in the RHS of (9) involves *no approximating error* whatsoever.

Our previous analysis of the first term of (8), as decomposed in (9), leads to three additional predictions that are separately listed below.

P3: Node-level (firm-level) direct effect: A bank credit supply shock hitting a firm affects negatively its total sales and total purchases — i.e. both grow at a lower rate.

P4: Node-level (firm-level) downstream propagation — first-order effects: The aggre-

[12] It also abstracts from the diagonal matrix $\mathbf{MT}$, which has no role to play in this case.

gate purchases of a firm are negatively affected by the financial shocks hitting *all of its (first-order) direct suppliers*, the impact on its growth rate induced by each supplier being proportional to the intensity with which the supplier's output is used (as input) in the firm's production.

P5: Node-level (firm-level) downstream propagation — higher-order effects: The aggregate purchases of a firm are negatively affected by the financial shocks hitting *all of its higher-order indirect suppliers*, the impact on its growth rate induced by each supplier being proportional to the intensity with which the supplier's output is indirectly used (as input) in the firm's production.

Next, we turn to studying the implications of the second term of of (8), where the aggregate impact of shock propagation can also be linked to a corresponding measure of centrality — in this case operating through the row-substochastic matrix $\mathbf{H}(\mathbf{0})$ that operates downstream by identifying customers of all orders (and hence computing *upstream propagation* effects).[13] Again, it is useful to decompose it into first-order and higher-order effects as follows.

$$-\boldsymbol{e}_i'(\mathbf{I}-\mathbf{H}(\mathbf{0}))^{-1}\mathbf{H}(\mathbf{0})\boldsymbol{\tau} = -\overbrace{\boldsymbol{e}_i'\mathbf{H}(\mathbf{0})\boldsymbol{\tau}}^{\substack{\text{first-order}\\ \text{upstream effect}}} - \overbrace{\boldsymbol{e}_i'(\mathbf{I}-\mathbf{H}(\mathbf{0}))^{-1}(\mathbf{H}(\mathbf{0}))^2\boldsymbol{\tau}}^{\substack{\text{higher-order}\\ \text{upstream effect}}}. \tag{10}$$

In contrast with our earlier expression (9), which accounted for the impact of downstream propagation, (10) must be conceived just as an approximation — and a reasonably good one only if the shocks $\boldsymbol{\theta} = (\theta_i)_{i=1}^n$ are quite small. Otherwise, errors will tend to be generally large since that expression approximates the highly non-linear functions functions $\phi_i(\cdot)$ given by:

$$\phi_i(\boldsymbol{\theta}) = -\boldsymbol{e}_i' \left\{(\mathbf{I}-\mathbf{H}(\boldsymbol{\theta}))^{-1}\mathbf{H}(\boldsymbol{\theta})\right\}\boldsymbol{\tau} = -\boldsymbol{e}_i' \left\{\mathbf{H}(\boldsymbol{\theta}) + \sum_{q=2}^{\infty}[\mathbf{H}(\boldsymbol{\theta})]^q\right\}\boldsymbol{\tau}.$$

To face this issue note that, since non-linearities are expected to be substantially more acute for higher powers of $\mathbf{H}(\boldsymbol{\theta})$, it is natural to conjecture that the approximation errors entailed by (10) should be significantly smaller for the first-order effects (the first term in the RHS of that expression) than for the higher-order effects (its second term). In this sense, it is reasonable to posit that, while the linearly approximated *first-order* effects may turn out to be empirically supported by the data, this is less likely to happen for the higher-order effects. Thus, in this light, the sole prediction we (tentatively) put forward for upstream propagation is the following.

P6: Node-level upstream propagation — first-order effects: The aggregate sales of a firm are negatively affected by the financial shocks hitting *all of its direct customers*, the impact on its growth rate induced by each customer being proportional to the customer's share in the firm's total sales.

Next, we complete our discussion of the firm-specific effects in (8) by turning to the income effect given by $\sum_{k=1}^n \left[\frac{\partial \hat{E}(\mathbf{0})}{\partial \theta_k}\tau_k\right]$. The effect operates through economy-wide (market-based) channels, and is a reflection of the fact that shocks decrease the economy's overall efficiency by

[13] As discussed in the Appendix entry h_{ij} specifies the fraction of sales by firm i that are purchased by firm j. Substochasticity (a property satisfied as well by the matrix $\mathbf{AG}'$) guarantees that the aggregation of all network effects is bounded and hence well-defined.

distorting the functioning of markets. This, in turn, ends up reducing the income/expenditure available to the consumer, who then decreases proportionally the amount spent on each good. Clearly, such an income effect affects all firms identically. Thus it does not contribute to explaining the differences in growth rates experienced by different firms, which is our focus here. No prediction, therefore, follows from our theory in this respect, so we shall abstract from the aforementioned income effect in our empirical analysis.

Now we turn to the second part of expression (8), which concerns the impact of the economy-wide shock ν that hits all firms in the economy. Its propagation embodies the same considerations as before except that, instead of a vector of firm-specific shocks $(\tau_i)_{i \in N}$, we now consider a set of perfectly correlated individual shocks formalized by the vector $\mathbf{1}\nu$. The expression in (8) describing the propagation of the economy-wide shock has the same structure as before, and can be decomposed in three components: (a) direct and downstream effects; (b) upstream effect; (c) income effect. In this case, not only the *income effect* but also the *direct effect* are uniformly equal across firms, and we again abstract from them in our empirical analysis. We are left, therefore, with the downstream and upstream effects, which are *exclusively* captured by corresponding measures of centrality, respectively upstream- and downstream-defined. Thus, in the case of the economy-wide shock, only the network position of a firm matters to determine the extent to which it will be affected by it.

For conciseness, the upstream-defined notion of centrality $\boldsymbol{e}_i'(\mathbf{I}-\mathbf{A}\mathbf{G}')^{-1}\mathbf{1}$ of any firm i will be called its *customer* centrality, while the downstream-defined counterpart $\boldsymbol{e}_i'(\mathbf{I}-\mathbf{H}(\mathbf{0}))^{-1}\mathbf{H}(\mathbf{0})\mathbf{1}$, will be labeled its *supplier centrality.* Heuristically, the customer centrality of a firm measures how much the production of this firm relies (directly and indirectly) on intermediate inputs. On the other hand, its supplier centrality measures what is the size of the direct and indirect demand of its good as input in the production undertaken by other firms in the economy.

In view of (8), we end our analysis of the model by postulating the following two additional predictions.

P7: Node-level downstream propagation of the economy-wide shock: The aggregate purchases of a firm are negatively affected by the economy-wide shock hitting all firms in the economy, the impact on its growth rate being proportional to the customer centrality of the firm.

P8: Node-level upstream propagation of the economy-wide shock: The aggregate sales of a firm are negatively affected by the economy-wide shock hitting all firms in the economy, the impact on its growth rate being proportional to the supplier centrality of the firm.

To recap, a comparison the above predictions with those listed before for the propagation of firm-specific shocks points to one difference and one similarity. On the one hand, the difference is that the overall effect of the economy-wide shock on a given firm solely depends on the position it occupies in the production network, *not* at all on the shocks that it happens to experience directly or indirectly. On the other hand, the similarity is that, as it happened for the propagation of firm-specific shocks, the aggregate effect induced by downstream propagation is linear in the economy-wide shock and thus can be accurately computed, while the upstream-propagation involves complex nonlinearities and can only be approximated.

Predictions P1–P8 will guide our ensuing empirical analysis. In fact, we shall find that all of them are quite strongly supported by the data. As a brief road map, let us advance that Tables 1–3 address P1–P3, whereas P3–P8 are addressed in Tables 5 and 6.

3 Datasets

In this section we describe the administrative datasets for the Spanish economy that we use in our analysis. They cover the universe of both firm-to-firm transactions from VAT register and the bank-firm lending relationships from the credit registry. We also use administrative firm-level and supervisory bank-level data, the latter including the interbank credit information.

3.1 VAT firm-to-firm data

We use the confidential administrative VAT register. Spanish corporations are subject to Value Added Tax (VAT) and as a part of an annual tax declaration to the Spanish tax agency (Agencia Estatal de Administración Tributaria, AEAT) report all annual paid and received transactions with third parties exceeding the amount of 3,005 euros (M.347 form).[14] We have access to this confidential dataset of all firm-to-firm transactions subject to VAT in years 2008 and 2009, and use them to construct the empirical counterpart of the firm level production network that we have analyze in the theoretical model.[15] The analysis of this model leads to the predictions P1–P8 (see Section 2) and we will empirically test them in Section 5. In the next paragraphs we describe how we have processed the raw data to get the final dataset on firm transactions that we use in the empirical analysis.

For each bilateral transaction between two VAT-liable enterprises, the dataset contains two observations: the value of the transaction reported by the supplier and the value of the same transaction reported by the customer. To construct the firm level network of transactions we need to assign a single value to each reported annual transaction. When the values reported by the supplier and the customer coincide, there is no ambiguity. However, it may happen that there is a discrepancy between the supplier's and the customer's declaration of the same transaction. For instance, this happens when the invoice received by the customer is registered in a calendar year different from the issuing of the same by the seller. When the discrepancy is small relative to the higher reported value, we select the value reported by the supplier. When the difference is relatively large, which is the case for 0.01% of observations, we choose the smaller of the two declared values (to be more conservative).

In our analysis we restrict ourselves to transactions where both the seller and the customer are publicly limited or limited liability companies (which applies to almost 95% of all non-financial firms), both are firms (IAE code starts with 1),[16] and neither is from the financial sector.[17] Our

[14]More information available at: https://www.agenciatributaria.gob.es.

[15]Our raw dataset covers the period 2008–2014.

[16]The IAE code (Impuesto sobre Actividades Económicas) is the code used by the tax agency to classify the main economic activity of a tax payer.

[17]A firm is taken to belong to the financial sector if its main activity, according to the IAE classification, is one of the following: (i) financial institution, (ii) insurance company, (iii) financial, insurance and real-estate service provider.

final dataset contains information on 2,328,908 transactions between 245,524 firms in 2008 and 2,040,869 transactions between 243,936 firms in 2009.[18] We provide a graphical illustration of the induced production network in Figure 1, and a further illustration of the topology of the network in Figure 2 for the region *Comunidad Valenciana*. This diagram provides information on the density of production in each zip code as well as on the significance of higher-order connections.

3.2 Credit Registry bank-to-firm data

We use the confidential, administrative loan-level data for Spanish non-financial companies from the Spanish Credit Register (CIR), which is maintained by the Banco de España in its role of banking supervisor. The CIR contains very detailed loan level data since 1984 on all loan commitments above 6,000 euro granted by any bank operating in Spain. We aggregate the different loans between a firm and a bank in each period, thus using data given at the bank-firm-time level. Even though the CIR is updated on a monthly basis, given the annual frequency of other datasets that we use in the paper, we record the credit data annually. The CIR also provides information about loan characteristics such as the type of instrument, currency, maturity, degree of collateralization, default status, or the amount drawn and committed by the firm. In this paper, we focus on commercial and industrial (C&I) loans granted by commercial banks, saving banks and credit cooperatives. For a more detailed description of the CIR see, for instance, Jiménez et al. (2020).

3.3 Other datasets, including interbank credit

Other administrative datasets that we use in the analysis pertain to the balance sheets and income statements of non-financial companies and banks. At the non-financial firm level, we exploit information on firms' characteristics that is available at a yearly frequency from the Central Balance Sheet Data (CBI, Central de Balances Integrada), which comprises information gathered from the Spanish Mercantile Register — an administrative database that contains available information on firms' financial statements (required by law to be submitted to the commercial registry) as well as on their income corporate tax returns. The data cover around 90% of firms in the non-financial market economy for all size categories, including both turnover and number of employees. The correlation between micro-aggregated employment and output growth and the National Accounts counterparts is above 0.90.

Moreover, we rely on supervisory bank-level data, which is based on information from the December reports that banks have to submit to the supervisor: Banco de España. We obtain information on banks' overall interbank funding positions, balance-sheet variables, and profit and loss account data. This information allows us to have, for each bank, how much it borrows overall from the interbank market. On average each bank borrows 1.7 billion euros from the interbank market, 28% of total bank assets, with an inter-quantile range going from 2% to 53%.

[18] An annual transaction is an annual total sale from firm i to firm j (or, equivalently, an annual total purchase from firm i by firm j). See *Table B7* for additional summary statistics.

4 Empirical identification

Our main empirical challenge is to estimate how shocks originating in the financial system impinge, and then propagate, on the real production network. This section explains the strategy that we pursue for the identification of these different effects and in the next section we describe our main results. We start with the financial shocks. For their identification we exploit differential bank credit supply shocks during the 2008–09 global financial crisis, based on two financial networks: an overall bank-level credit supply shock obtained from the credit network, and a bank-level shock stemming from the interbank network. Then, we analyze the propagation along the production network, based on our model (see Section 2) and the customer-supplier data (see Section 3). Our theoretical framework — in particular, equations (8)–(10) — allows us to compute first- and higher-order effects along the production network, on the basis of the empirical counterparts of these equations that are described in this section. As we explained above (cf. P1–P8), this approach induces sharp predictions at the link (firm-to-firm) and node (firm) levels.

4.1 Identification of financial shocks

We start with the empirical formulation of the collection of *financial shocks* hitting firms, as well as its suppliers and customers. Our identification of these shocks is independent of the theory and follows the standard approach in the empirical literature. It must be viewed as an approximate counterpart of the vector $\boldsymbol{\tau}$ that models the distortion-inducing pattern of financial shocks. In our baseline specification, we follow Amiti and Weinstein (2018) and construct such bank-credit shocks as follows. We estimate, for each bank, a credit supply factor identified as the bank fixed effect in a bank-firm level regression of credit growth on bank- and firm- fixed effects that exploits the variability generated by the 2008–09 global financial crises. Thus, if we denote by $ChangeLoan_{ib}$ the variation in the lending to firm i from bank b and by η_i and δ_b firm and bank level fixed effects respectively, we estimate the following regression:

$$ChangeLoan_{ib} = \eta_i + \delta_b + \epsilon_{ib}. \tag{11}$$

We do this for 2009, 2008, and 2007. Then, we compute firm-specific credit supply shocks as the weighted average of the bank-specific factors δ_b using *pre-crisis* credit exposure of the firm to each particular bank as weights. For the bank credit supply shock pertaining to each firm, we use a dummy variable that takes the value of one if the firm-specific shock is below the median across all firm-specific shocks, and zero otherwise. Therefore, positive values of this firm-level bank-credit supply shock during the 2008–09 global crisis are associated to negative credit supply shocks from the main banks of each firm — in essence, therefore, a firm experiences a shock if it was exposed to financially constrained banks, i.e. those that reduce the credit supply the most.[19]

[19] It is worth highlighting that the firm-level (bank credit) shocks included in our regressions, following Amiti and Weinstein (2018), can be considered a shift-share instruments in the spirit of Bartik (1991). This is because they average a set of bank-level shocks to all firms using bank-firm specific weights as a proxy of firm-level shock exposure. There is a recent strand of the literature arguing that traditional inference may not be appropriate in the case of shift-share regression designs because residuals may be correlated across firms with similar (bank) shares (see Adão et al. (2018), Borusyak et al. (2018)). To alleviate the concern of correlation across firms with similar bank shares, in all our firm regressions below we cluster the standard errors at the level of the main bank (i.e., the bank with the largest value of outstanding loans for each firm). Moreover, our results are robust to bank specific sector or province matching, or if we run the model in levels to bank-firm matching.

Next, we analyze whether such a financial shock, coming from the bank supply side, is orthogonal to pre-crisis observable firm characteristics (see *Table B1* in the Online Appendix B for summary statistics). That is, we want to test whether firm i that works with the more financially constrained banks (i.e., $\tau_i = 1$) is similar to other firms j that work with the less constrained banks ($\tau_j = 0$). To do so, in *Table B2* we explore a relevant range of observed firm characteristics for both types of groups.[20] It shows that the firms exposed to negative bank credit supply shocks and those not exposed were not different prior to the global financial crisis. The first four rows of the table show basically identical numbers for the firm characteristics for the two group of firms (that is, not related to bank variables), while its column 5 reports the t-statistic of the differences in averages of the firm characteristics concerning the exposure of firms to the financial shock.

The aforementioned statistic, however, is sample-size dependent, as it was noted by Imbens and Wooldridge (2009). This would make the rejection of the null hypothesis more likely as the number of observations increases. To avoid the problem, these authors propose to test the null of no differences in means between the two groups through a scale-and-sample-size-free estimator. The proposed estimator is labeled the normalized difference and scales the difference in means of each variable in the two samples by the square root of the sum of the variances. Imbens and Rubin (2015) suggested a heuristic threshold of 0.25 for the statistic (in absolute value) to judge whether the differences should be considered significant or not. As column 6 of *Table B2* shows, no firm variable is greater than 0.01 in absolute value. This provides, therefore, support to the claim that the estimated effects of financial shocks on firms derived from equation (12) below are not driven by differential firm observable fundamentals (e.g. credit demand shocks).[21]

Importantly, when analyzing differences in pre-crisis bank characteristics, we find that banks that before the crisis relied more on the interbank market (or are smaller) reduced the supply of credit, and hence their associated firms may suffer in terms of credit (as column 5 and 6 suggest). We arrive to similar conclusions from a linear probability regression estimation of firm exposed to more financially constrained banks on all firm characteristics and four-digit $NACE \times province$ fixed effects, as reported in column 7 of *Table B2*. The estimation results show that the only two statistically significant variables are the two bank variables (the net interbank position of the firm's average bank and its corresponding size).

The fact that banks which became more acutely constrained during the crisis were borrowing more heavily from the interbank market before the crisis is not specific to our case but is a general one in financial crises, which is why researchers have used the net interbank position to identify bank credit supply shocks to firms (e.g. Portugal and Italy, see e.g. Iyer et al. (2014); Ippolito et al. (2016); Cingano et al. (2016)). Here, therefore, we also consider it as an alternative to the Amiti and Weinstein (2018) approach to singling out which banks experience (stronger) credit-supply shocks. More specifically, we use the bank's net exposure to interbank funding *before* Lehman's collapse. This is also a natural way of bringing into our analysis the other

[20] In *Table B2*, bank characteristics at the firm level are computed as a pre-crisis weighted average of the bank variables at the firm-bank level using as weights the credit amount of each relationship, then discretizing them to be one if the value is above the median of its distribution and zero otherwise.

[21] In regressions we will also control for unobservables via e.g. firm, customer or supplier fixed effects.

key financial network that has been considered in the literature: the interbank network (see e.g. Allen and Gale (2000)).

Thus, to sum up, our analysis relies on two distinct sources of financial-shock identification: an overall bank-level credit supply shock derived from the credit network, and a bank-level shock that stems from banks' reliance on interbank funding, as given by the interbank network. Importantly, these two different approaches lead to identifying effects on firm-level credit availability that are negative and significant only during the crisis and not before (see *Table B6*) — that is, the (negative) effects of a shock are significant in 2009, but not in 2007 and 2008. This is intuitive, since before the financial crisis that followed the failure of Lehman Brothers in mid-September 2008, firms could switch much more easily from more to less constrained banks, thereby reducing substantially the effects of credit shocks. In this respect, an important consideration to bear in mind concerning the strength of our identification strategy is that Spain is a bank-dominated economy. Hence we can safely abstract from other financial intermediaries (such as, say the shadow banking system) which would be crucial in other economies (e.g., in the US). Finally, note that the firm-level effects that we find are also on firm total debt, not just bank credit.

4.2 Link-level analysis and first-order propagation

In order to test whether the bank shocks originating in the financial networks propagate upstream and downstream along the production network, we bring customer-supplier data (see Section 3) to bear on the theoretical framework described in Section 2. We first test, at the firm-to-firm (link) level, predictions P1–P2 that follow from equation (4). These predictions are tested using the sample of supplier-customer pairs for the years 2008 and 2009. Specifically, for any given firm i with both suppliers and customers in our data, we consider the following two separate samples from the perspective of this firm: one that includes all suppliers selling to firm i; another one including all customers buying from firm i. We do this for every firm and then construct, for each sample, our dependent variables of interest: the *log* changes between 2008 and 2009 of purchases to suppliers and sales to customers, respectively.[22] As a robustness check, we also consider all firms, all suppliers and customers, in the same regression.

Armed with the data from those two samples, we consider a baseline specification that explores the effect on the purchases (sales) of any given firm i when either one of its suppliers (or, respectively, one of its customers) is hit by a credit supply shock. Thus, for any firm i we focus on the links of the form $\ell \to i$ or $i \to \ell$ and, taking the perspective of firm i, consider all possible cases of downstream propagation (when the shock hits some of its suppliers) or upstream propagation (when it is some of its customers that are hit).

More precisely, we study the following regression to estimate the firm-to-firm (link) impact of credit shocks on the interfirm commercial flows of the year 2009:

$$\Delta \ln s_{i\ell} = \alpha \tau_\ell + \boldsymbol{\beta}' \boldsymbol{x}_\ell + \boldsymbol{\gamma}' \boldsymbol{z}_i + \boldsymbol{\delta}' \boldsymbol{w}_{i\ell} + FE + \epsilon_{i\ell}, \tag{12}$$

where the sub-index ℓ refers to a generic supplier (customer) of any given firm i. Thus, $s_{i\ell}$ refers to the purchases by firm i from supplier ℓ when we estimate downstream propagation effects asso-

[22] We winsorize growth rates to be bounded by +200 and -100 percent to reduce the impact of outliers.

ciated to links of the form $\ell \to i$, and to sales from i to ℓ when we estimate upstream propagation effects associated to links of the form $i \to \ell$.[23] As usual, τ_ℓ stands for the bank-credit shocks hitting supplier (customer) ℓ. Finally, as explained below in detail, $\boldsymbol{z}$ represent characteristics of firm i (e.g. the direct bank credit supply shock to firm i), $\boldsymbol{x}$ represents observable characteristics of suppliers (customers) of i, $\boldsymbol{w}$ is a vector of relationship-specific characteristics, and FE stands for different fixed-effects configurations described below.

As advanced, the above equation allows us to test the predictions P1–P2 stated in Section 2. Note that the coefficient α above is our primary coefficient of interest in that it measures the impact of financial shocks hitting a supplier (customer) — that is, the effect of downstream (upstream) propagation. Equation (12) is estimated by weighted OLS, where the weights are the size of the firm-to-firm relationship captured by past purchases or sales between the two companies, and the standard errors are multi-clustered at the level of firm i, the supplier (customer), and its main bank.

Crucially, our firm-to-firm network data allow us to account for different configurations of fixed effects (FE) in our regressions, depending on the bank credit supply shock we want to identify. Thus, since we are interested in investigating suppliers' and customers' credit shocks, our most stringent specification includes firm i fixed effects. Hence the identification is based on within-firm variation from multi-supplier and multi-customer firms.[24] Intuitively, our approach compares purchases (sales) of the same firm with different suppliers (customers) that are hit by different credit shocks. Identification is enhanced, therefore, by controlling by firm unobserved heterogeneity, which accounts for firm-specific shocks and thus isolates the bank shock component associated to suppliers (respectively, customers).

Depending on the specification considered, we control for the following: a set of supplier (customer) variables included in vector $\boldsymbol{x}_\ell$, which coincides with the same set of controls that we use for the firm i under consideration (see below); relationship-specific characteristics in vector $\boldsymbol{w}_{i\ell}$, which includes the share of total purchases (sales) of firm i associated to supplier (customer) ℓ, the share of total sales (purchases) of supplier (customer) ℓ directed to firm i, and dummies indicating whether both firms share the same main bank or operate in the same province-industry pair. Additionally, in order to control for possible further selection effects between firm i and its suppliers or customers (beyond the aforementioned ones indicating same industry, same province, as well as the same main bank), some specifications include a large set of dummies capturing specific trends in industries and provinces in the form of (industry/province of firm i) $\times$ (industry/province of a supplier/customer).

Finally, in extended specifications of (12), we also consider the direct bank credit supply shock to firm i (τ_i) in the characteristics $\boldsymbol{z}_i$. In this case, obviously we cannot add firm i fixed effects, and we replace them by a set of this firm's observed characteristics $\boldsymbol{z}_i$. These controls include the size of the firm in terms of its *log* of total assets, *log* of age, capital-to-asset ratio (own

[23] As a robustness check, in some specifications we use the following definition of the dependent variable: $(s_{2009} - s_{2008})/(0.5(s_{2008} + s_{2009}))$ where s_t stands for the flows under consideration in year t. This formulation — which was originally proposed by Davis and Haltiwanger (1992) to study establishment-level data — allows us to account for both the extensive and the intensive margin.

[24] In our sample 85% of suppliers have two or more customers, while 77% of customers have two or more suppliers.

funds over total assets), working capital as a measure of liquidity (current assets minus current liabilities over total assets), and its ratio of short-term debt (less than 1 year) as a measure of its maturity structure. We also control for unobserved factors captured by the product of industry dummies (at 2-digit NACE level) and the province dummies.

4.3 Node-level analysis and higher-order propagation

Our empirical analysis is not only concerned with the basic first-order effects of financial shocks that arise at the link level (i.e. on pair-specific bilateral trade), but we are also strongly interested in estimating full-fledged propagation. This entails not only studying higher-order effects but also aggregating them. And to this end, of course, a detailed analysis of node-level (firm-level) effects is essential.

On the basis of the basic decomposition of node-based effects from equation (8) and the subsequent further decompositions described in (9) and (10), we can separately identify the following six constituent effects induced on the sales/purchases of a typical firm i as a result of different types of shocks hitting the economy:

(i) direct effect of shock τ_i,

(ii) first-order downstream effect, or the effect of shocks to direct suppliers,

(iii) higher-order downstream effect, or the effect of shocks to indirect suppliers,

(iv) first-order upstream effect, or the effect of shocks to direct customers,

(v) higher-order upstream effect, or the effect of shocks to indirect customers,

(vi) effect of the economy-wide shock ν.

Formally, these different effects are reflected by the following empirical (econometric) counterpart of expressions (8)–(10):

$$\begin{aligned}\Delta \ln s_i = & \overbrace{\alpha_D \tau_i}^{\text{(i) direct effect}} + \overbrace{\alpha_{FD}\xi_i^{FD}}^{\substack{\text{(ii) first-order}\\ \text{downstream effect}}} + \overbrace{\alpha_{HD}\xi_i^{HD}}^{\substack{\text{(iii) higher-order}\\ \text{downstream effect}}} + \overbrace{\alpha_{FU}\xi_i^{FU}}^{\substack{\text{(iv) first-order}\\ \text{upstream effect}}} + \overbrace{\alpha_{HU}\xi_i^{HU}}^{\substack{\text{(v) higher-order}\\ \text{upstream effect}}} \\ & + \overbrace{\alpha_{CC}\xi_i^{CC}}^{\text{(vi) customer centrality}} + \overbrace{\alpha_{SC}\xi_i^{SC}}^{\text{(vi) supplier centrality}} + \overbrace{\boldsymbol{\gamma}'\boldsymbol{z}_i}^{\text{controls}} + \overbrace{FE}^{\text{fixed effects}} + \epsilon_i\end{aligned} \tag{13}$$

where s_i refers to either sales or purchases of firm i (depending on the particular specification) and, as usual, τ_i stands for the bank-credit shocks directly hitting firm i. The different variables denoted by ξ_i^* stand for the shocks that originated elsewhere and affect i through the production network. The superscripts FD, HD, FU, and HU used in the first line of (13) are mnemonic references to the type of propagation of firm-specific shocks indicated in the upper description associated to the corresponding terms. In contrast, the superscripts CC, SC used in its second line correspond to the propagation of the economy-wide shock, captured by what we have called supplier and customer centralities (cf. Section 2).[25] Finally, $\boldsymbol{z}_i$ stands for various observable controls and FE for the set of fixed effects included in the concrete specification being considered.

[25] Note that the direct effect induced by the economy-wide shock on any given firm i is included on its customer centrality.

The different coefficients to be estimated are denoted by α, with the corresponding identifying indices attached.

The construction of variables ξ_i^* follows readily from Proposition 2 and its discrete counterpart given by expression (8). We recall matters briefly. Given the identification of the collection of bank-credit shocks hitting firms in the Spanish economy after the start of the global financial crisis, upstream and downstream propagation of each of these shocks takes place through the recursive application of the *downstream-propagation* and the *upstream-propagation* operator. For downstream propagation, the operator involved is linear in the shocks, as induced by the product of the matrices $\mathbf{A}$ and $\mathbf{G}'$. Thus, the resulting matrix is of a strictly technological nature, its entries being of the form $\alpha_i g_{ji}$ for all $i, j \in N$, where α_i is an intermediate-input elasticity and g_{ji} reflect the intensity of input j in the production of good i. Instead, recall that the upstream propagation is a more complex phenomenon, since the operator formalizing this process is a non-linear function of the vector of shocks. Nevertheless, we have shown in Section 2 that this operator can be linearly approximated by a matrix $\mathbf{H}$, whose entries h_{ij} correspond, for each firm i, to the share of its total sales that are purchased by every other firm j.[26] The extent to which this approximation will be valid is a priori unclear, so our conjecture has been that it is likely to be useful in approximating the effects derived from first-order customers but not for those of higher order.[27]

5 Results

This section summarizes the main results. Tables 1 to 4 exploit the firm-to-firm network data, and Tables 5 and 6 show the real effects at the firm level where the firm-to-firm network data are aggregated as prescribed by the theory (and explained in previous sections).

First, *Table 1* reports our baseline estimates from equation (12) of downstream and upstream propagation, respectively. More specifically, first in Panel A we analyze the impact on the firm's purchases of a bank credit supply shock to each firm's supplier versus a direct bank shock to the firm itself; then, in Panel B, the focus turns to the effect on the firm's sales of a credit shock to each of its customers versus a direct bank shock. We identify credit supply shocks on the basis of the Amiti and Weinstein (2018) approach, control for observable characteristics and individual fixed effects.

In column (1) of *Table 1*, we explore the effects of direct bank credit supply shock, controlling fully for indirect credit shocks and other observed and unobserved variation via supplier fixed effects in Panel A and customer fixed effects in Panel B. We also use a large set of observable

[26]See Online Appendix A for details on how $\mathbf{A}$, $\mathbf{G}$ and $\mathbf{H}$ are constructed from the data.

[27]In their analysis of the propagation of supply and demand shocks through sector level input-output network, Acemoglu et al. (2016) calculate the network effects of different shocks in a similar way, also assuming Cobb-Douglas production technologies. However, as already explained in Section 2, there are two important differences between the financial shocks studied here and the supply and demand shocks considered in that paper. First, in our case the propagation of financial shocks has both a supply and a demand component, thus proceeding both upstream and downstream along the network, even under the Cobb-Douglas assumption. Second, the matrix $\mathbf{H}(\boldsymbol{\theta})$ (and therefore the matrix $(\mathbf{I} - \mathbf{H}(\boldsymbol{\theta}))^{-1}\mathbf{H}(\boldsymbol{\theta})$) which describes the upstream propagation depends on the shock itself, while this dependence is not present in the case of pure supply shocks (i.e.productivity shock), or pure demand shocks (i.e. a government spending shock) considered in Acemoglu et al. (2016).

own-firm characteristics as well as own-firm *province* $\times$ *industry* dummies to account for local and sectorial trends. The impact of the direct bank-credit supply shocks on purchases (sales) is negative and statistically significant, which corroborates that direct credit supply does affect firms' purchases and sales. In particular, a negative direct bank credit supply shock to the firm implies a reduction of 5.6 pp of purchases (2.5 pp sales), which is large relative to the median change of purchases, -12.7% (and sales, -13.9%) — see *Table B1* in the Online Appendix B for summary statistics.

In column (2), so as to estimate the effect of credit supply shocks to suppliers and customers, we substitute supplier (customer) fixed effects by a set of firm characteristics taken from balance sheet data and *province* $\times$ *industry* dummies at the supplier (customer) level, in conjunction with the supplier (customer) bank credit supply shock (see Section 4). The estimated effect of the direct bank credit supply shock remains similar in size,[28] while the effects derived from supplier and customer (bank credit supply) shocks are also negative and statistically significant in both panels. In particular, a negative bank credit supply shock to suppliers (customers) implies a reduction of 1.7 pp of purchases (5.7 pp sales), which is large. In column (3), we control for $firm$ $\times$ *supplier province* and *industry* fixed effects and find very similar results.

Finally, column (4) in *Table 1* refers to our most stringent specification for the identification of propagation of bank credit supply shocks that hit direct suppliers and customers. We include a set of (own) firm fixed effects (not supplier and customer fixed effects as otherwise we cannot estimate the network effects) and we thus compare purchases (sales) of the same firm from (to) different suppliers (customers) differentially affected by bank credit supply shocks. We consider this estimation as our baseline as it controls for unobserved matching between customers and suppliers. The estimated propagation effects are large and significant in both cases. Indeed, the estimated effects are double for the downstream propagation when we control for firm fixed effects (column (4) versus (3) in Panel A).

In particular, based on column (4), we estimate that a negative bank credit shock to a supplier of a firm on average implies a reduction of 3.7 pp in firm-supplier purchases. We also find that effects for customer bank shocks are even stronger than own (direct bank) shocks to firms. If a firm faces a customer who is subject to a bank credit supply shock, this implies on average a reduction of a 5.2 pp in firm-customer sales. In economic terms, these figures represent a reduction of 29% and 37% of the median value of purchases and sales, respectively, which implies large effects.

Finally, it is important to highlight that the different controls in the micro firm-to-firm data change significantly the results. For example, the estimated effect of (bank credit) shock to suppliers more than doubles from column (2) or (3) to (4) in Panel A, while the estimated direct effect almost halves in Panel B. This in turn suggests that transaction-level data is crucial for identification (and quantification) of the estimated effects, as banks shocks are correlated across the production network (as the estimated coefficients change dramatically with different controls) and therefore micro controls are necessary to isolate the credit supply shocks along the

[28] In column (2) of Panel B the direct bank shock to the firm loses statistical significance at conventional levels, but on column (3) it becomes significant again, though the estimated coefficients are substantially lower in value.

customer-supplier network.

Table 2 studies the channel of propagation for the effects just discussed and *Table B3* checks the robustness. In particular, we want to test for the following hypothesis: a firm affected by a negative bank credit supply shock will reduce its purchases or sales due to a restriction of *total* bank credit (or total debt) if it is not able to find other banks (or other financing sources), i.e. if it experiences a fall in total debt. *Table B6* shows that the bank shock is binding in firm level access to credit during the crisis (in 2009) but not in 2008 or 2007.

To test for this transmission channel, columns (1) to (4) in *Table 2* consider specifications analogous to columns (1) to (4) in *Table 1* but considering own or supplier (customer) bank credit growth (while column (5) considers total debt growth) as the regressors of interest, instrumented with the bank shock dummies. First-stage F-statistics are well above 10 in all cases except for one column for Panel B (in this case 9.79), thereby confirming that these bank shocks are strong predictors of total bank credit growth and total debt growth (the first-stage regressions are reported in the Online Appendix B, see *Table B5*).

According to column (4) of Panel A, 1 pp reduction in credit growth of a supplier of firm i (stemming from a bank shock) is associated to a 0.25 pp reduction in firm purchases growth from this supplier. Analogously, 1 pp reduction in credit growth (stemming from the bank shock) of a customer of firm i is associated to a 0.48 pp fall in sales growth of the firm to this customer.[29] Moreover, column (5) indicates that these sizable effects are even larger if one considers the change of total firm debt instead of only bank debt, which is not surprising as bank credit is only one part (though the most important part) of firms' total debt; effects increase to 0.42 and 0.67 for downstream and upstream, respectively.[30]

Regarding further robustness tests, *Table B3* shows the results also with OLS for the intensive margin, and with both WLS and OLS for a combination of the extensive and intensive margins based on Davis and Haltiwanger (1992). Results are similarly significant. When estimating downstream and upstream propagation separately a potential source of concern is that we may ignore possible correlations between shocks to suppliers and customers of a given firm. We address this concern by estimating both downstream and upstream propagation in a single regression, thus allowing for non-zero correlations among these shocks. Results are similarly significant, and reported in *Table B4*. Panel A reports the reduced form specifications using the shocks as regressors of interest while Panel B reports the IV strategy that instruments credit growth with the bank credit supply shocks. Column (1) shows that, for each of these two approaches, the average direct effect of customer and supplier shocks is negative and significant, while columns (2) and (3) confirm that supplier and customer shocks separately have large and significant effects on purchases and sales, even after accounting for potential cross-correlations among them.

Table 3 considers the alternative bank credit supply shock explained in Section 4, which is derived from the interbank network. Recall that our baseline analysis is based on bank credit

[29]Similarly to *Table 1*, controls are crucial in quantification of the effects (not just identification) for both direct bank shocks and indirect production and financial network effects.

[30]Even though our data are only from Spain, most countries in the world are bank dominated. In fact, even in U.S., bank loans are crucial for most firms, notably SMEs.

supply shocks identified through the Amiti and Weinstein (2018) approach. An implicit assumption in this baseline approach is that firms' credit demand is the same for all lenders (thus firm fixed effects account for demand effects). In *Table 3* we consider an alternative bank credit supply shock based on the exposure to the interbank market (interbank funding). This shock is again considered as a binary variable that takes the value of one when the net interbank funding of the weighted average lenders to the firm is above the median, and zero otherwise (see Iyer et al. (2014), and Cingano et al. (2016)). Then, we use such a measure of interbank-funding exposure as an instrument for our benchmark bank shock and for the change in bank debt and total debt.

Columns (1) to (5) of *Table 3* report the effects of the dry-up in the interbank market on purchases and sales using both a reduced form specification analogous to *Table 1* as well as the IV approach for the credit channel of *Table 2*. Estimates show that the interbank position is a relevant instrument given that the F-statistic of the first stage is well above 10 in all cases (the first stage can be found in *Table B5*). Our main findings on shock propagation remain robust when considering this alternative bank lending shock; moreover, firm-to-firm propagation of credit supply shocks is even larger.

Table 4 explores the impact on shock propagation of heterogeneity along several dimensions in supplier and customer characteristics. Specifically, we interact the supplier and customer shocks with a set of observed indicators capturing: (i) the market power of the supplier (customer) proxied by the Herfindahl-Hirschman index of the 4-digit industry in which the supplier (customer) operates; (ii) the size of the supplier (customer) proxied by the (*log* of) total assets; (iii) the reciprocity or affinity of the relationship between the firm and the supplier (customer) as identified in four different ways, through corresponding dummies that take the value one if each of the following applies: the firm is also supplier/customer of its supplier/customer; they share the same main bank; they work in the same province; they belong to a common industry.

Results are amplified by market power, which we proxy by the market concentration displayed by the firm's sector. We find that such a measure of market power has a significant amplifying impact on the extent to which a shock hitting the firm propagates to its customers and suppliers, suggesting that suppliers (customers) use their market power to pass the effects of shocks to their (customers) suppliers. Similarly, across both upstream and downstream propagation, effects are amplified if the pair of firms are both supplier and customer to each other, consistent with the fact that such firms more strongly depend on each other. Regarding downward propagation, results are also amplified if firms are more geographically distant and they do not work with the same main bank. The latter result is consistent with a bank internalizing the financial effects among its borrowers which are connected in a production supply chain.

Table 5 initiates the analysis of shock propagation at the firm/node-level. This firm-based perspective on the problem is important because, in principle, a firm might be able to undo a particular negative shock from a particular supplier or customer by resorting to some other supplier or customer for its inputs or sales. *Table 5* investigates such firm-level effects on two complementary dimensions: (a) first-order propagation induced by firm-specific shocks hitting direct suppliers or customers; (b) effects induced by the economy-wide shock ν. For the aggregation of all first-order specific effects impinging on any given firm — be they derived from its suppliers or its customers — we rely on the weights prescribed by our model (input elasticities in the first case (matrices **A** and **G**), and sale shares in the second (matrix **H**)). As discussed in Section 2, the relative effects of the economy-wide shock are captured by two different measures of centrality: customer centrality for the propagation unfolding downstream, and supplier centrality for the opposite upstream propagation. In both cases, therefore, the relevant feature that modulates the relative impact of the economy-wide shock on any particular firm is determined by that firm's (global) position in the production network as solely captured by the two aforementioned centrality measures.

Our analysis shows strong effects of local shock propagation of firm-specific shocks, both downstream and upstream. Specifically, our estimates in *Table 5* indicate that the aggregation of the credit shocks experienced by either the direct customers or direct suppliers of any given firm impose on it significant real effects. This suggests that, contrary to the possibility we considered before, firms fail to undo supplier- and customer-specific shocks. For example, a bank supply shock to suppliers or customers generates, respectively, a 2.3 and 1.9 pp reduction in the growth of firm-level purchases and sales, thus illustrating that both downstream and upstream propagation is of a similar magnitude.[31] Moreover, from *Table B6*, the effect of bank credit supply shocks on firm-level debt is only significant (being also sizable) for the year 2009 when the crisis had already bred its full-blown consequences, but not before. Not surprisingly, the same holds for the impact on firm-level sales and purchases (not reported).

Our estimates also provide support for the role of the production network in mediating the propagation of economy-wide shocks. We find that a one standard deviation increase in customer centrality is associated to a decrease of 3 pp in firm's purchases, and a reduction of 1.1 pp in firm's sales, while a standard deviation increase in supplier centrality is associated with a reduction of 0.6 pp in firm's sales, but does not have a statistically significant effect on firm's purchases.

Table 6 investigates the indirect effects of firm-specific bank shocks whose propagation involves network paths of length higher than one. This stands in contrast with our analysis so far, which has focused on the indirect effects of such financial shocks hitting the direct first-order suppliers/customers of firms — i.e. we have studied propagation along paths of length one. Thus, in other words, here we focus on the credit shocks experienced by the suppliers/customers of a firm's suppliers/customers to any recursive order, using our decomposition from (9) and (10) to construct these higher-order network shocks.

The results displayed in *Table 6* – both Panel A for firm (node) level and Panel B for firm-to-firm (link) level – indicate that the high-order shocks yield propagation effects that are substantial and significant downstream, but not upstream. Thus, on the one hand, when the suppliers of a firm's suppliers of any order are hit by negative credit shocks, these shocks are transmitted downstream through their customers, eventually affecting in a significant aggregate manner the firm itself. In fact, such effects are not only highly significant but *similar in magnitude* to the first-order effect. Instead, if we consider the firm-specific shocks hitting the customers of a

[31] It may be worth recalling that all our main results are alternatively confirmed for both the identification approach proposed by Amiti and Weinstein (2018) and the one based on inter-bank funding (non reported).

firm's customers of any order (i.e. the customer of order higher or equal than two), we find no significant upstream effects. A likely reason for this contrast was explained in some detail in the discussion of our model in Section 2: while our theory prescribes that the linear expressions used to compute downstream effects are exact, the upstream-propagation effects (which are highly non-linear in the shocks) can only be very imperfectly identified through a linear approximation.

The results displayed in Panel A make an important point: for sales and purchases, the overall (direct and indirect) effects *triple* the direct effects of bank credit shocks to firms. For example, in column (3) we estimate a coefficient of -2.21 for direct shocks, in contrast with -1.99 for the first-order suppliers' (bank) shocks and -2.06 for higher-order effects. In order to gauge the magnitude of those effects, it can be seen that they represent around 308% of the median growth rate of the dependent variable (purchases) in the sample, i.e. 2.03. Concerning upstream propagation, however, our results are weaker: while column (6) shows the (highly significant) coefficient -1.9 for first-order propagation from direct customers, the coefficient associated to higher-order propagation is insignificant. For the aggregate change of sales and purchases in column (7), we have the direct, first-order and higher-order effects as -0.99, -0.9 and -1.07 respectively.

Finally, in the last two columns we address two other firm outcomes: employment and investment. While we find that both first-order and higher-order propagation have a significant effect for investment, only first-order propagation is statistically significant for employment at conventional levels. For both employment and investment the effects are therefore large — overall effects double the direct effects of bank credit shocks to firms for employment, and almost triple the direct effects for investment.

6 Summary and conclusions

Despite the fact that both academics and policy-makers have often argued that networks are important to understand the real effects of financial shocks, evidence on it has been scant mainly due to unavailability of *matched* networks that suitably represent the customer/supplier trade flows and bank-firm loans. In this paper, we contribute to addressing the problem by studying two matched administrative datasets from a bank-dominated economy, Spain, that include the universe of: (i) supplier-customer transactions stemming from the Treasury's Value Added Tax (VAT) Register; and (ii) bank-firm loans gathered from the Credit Register of the Spanish Central Bank. Moreover, we use the balance sheet data from Spanish Mercantile Register and the supervisory data on banks' overall interbank funding position from Banco de España.

To address the identification problem, we follow a two-pronged strategy. First, to identify financial shocks we exploit information on differential bank-credit-supply shocks during the 2008–09 global financial crisis obtained from two financial networks: an overall bank-level credit supply shock derived from the credit network, and a bank-level shock originating from the interbank network. Second, to identify the different channels of shock propagation, we rely on a theoretical framework that models the interaction between the financial and real parts of the economy and allows the computation of propagation effects of all orders along the production network. In combination, this twin identification strategy allows us to test a wide range of empirical predictions.

We find that the estimated impact of bank shocks on firm real effects are not only overall strong, but of a similar magnitude when comparing: (i) direct bank shocks impinging on firms versus indirect first-order bank shocks channeled through the customer-supplier network; (ii) first-order effects impinging on immediate customers or suppliers versus higher-order effects that bear upon the customers/suppliers of customers/suppliers of any order; (iii) downstream propagation flowing from suppliers to customers versus upstream propagation operating in the opposite direction; and (iv) individual shocks hitting specific firms versus an economy-wide shock affecting the whole economy uniformly.

Overall, we find that an integrated analysis of the real and financial network leads to estimated real effects of bank credit supply shocks that triple their direct negative impact on the corporate borrowers. This provides a basis to maintain that such an integration is indeed an important feature of modern economies and therefore needs to be accounted for by researchers and policy makers alike. We leave other related questions for further research.

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Appendix: Tables

TABLE 1:
LINK-LEVEL: PROPAGATION OF BANK CREDIT SUPPLY SHOCKS THROUGH THE NETWORK OF SUPPLIERS/CUSTOMERS

Panel A. Downstream propagation (indirect shocks via bank credit supply shocks to first-order suppliers)

	Dependent Variable: Δlog(purchases from suppliers)			
	(1)	(2)	(3)	(4)
Direct (Bank Credit Supply) Shock	-5.620**	-5.162**	-5.441**	
	(2.811)	(2.339)	(2.452)	
Supplier (Bank Credit Supply) Shock		-1.672*	-1.463**	-3.719**
		(0.895)	(0.691)	(1.778)
Supplier:				
Controls	-	Yes	Yes	Yes
Province*Industry Fixed Effects	-	Yes	Yes	Yes
Fixed Effects	Yes	No	No	No
Firm:				
Controls	Yes	Yes	Yes	-
Province*Industry Fixed Effects	Yes	Yes	Yes	-
Fixed Effects	No	No	No	Yes
Firm*Supplier Province & Industry FE	No	No	Yes	Yes
R-squared	0.337	0.090	0.124	0.395
Observations	1,114,421	1,114,421	1,114,421	1,114,421

Panel B. Upstream propagation (indirect shocks via bank credit supply shocks to first-order customers)

	Dependent Variable: Δlog(sales to customers)			
	(1)	(2)	(3)	(4)
Direct (Bank Credit Supply) Shock	-2.506**	-1.949	-1.551*	
	(1.267)	(1.354)	(0.903)	
Customer (Bank Credit Supply) Shock		-5.675**	-5.686**	-5.161**
		(2.346)	(2.374)	(2.513)
Customer:				
Controls	-	Yes	Yes	Yes
Province*Industry Fixed Effects	-	Yes	Yes	Yes
Fixed Effects	Yes	No	No	No
Firm:				
Controls	Yes	Yes	Yes	-
Province*Industry Fixed Effects	Yes	Yes	Yes	-
Fixed Effects	No	No	No	Yes
Firm*Customer Province & Industry FE	No	No	Yes	Yes
R-squared	0.378	0.101	0.140	0.377
Observations	1,119,169	1,119,169	1,119,169	1,119,169

Notes: This table reports estimates from WLS results. See Sections 4 and 5. Observations are at the level of the firm-supplier (Panel A) or firm-customer (Panel B), i.e. link-level. The dependent variable is the change in the log of purchases (Panel A) or sales (Panel B) between 2008 and 2009. Bank shocks are dummy variables that take the value of one if the firm was borrowing before the global financial crisis from banks which significantly reduced credit supply during the global financial crisis, and zero otherwise. To construct these variables, first, we estimate for each bank a supply factor based on Amiti and Weinstein (2018). Then, for each firm, we compute the weighted average of those supply factors that are associated to each of the banks which the firm works with before the global crisis. Finally, the firm shock dummy results of comparing its value with the median (equal to 1 if below the median in credit supply). Coefficients for each regressor are listed in the first row, while robust standard errors are reported in the row below (corrected for clustering at the firm, main bank, and supplier or customer levels). In each column, the word Yes indicates that the corresponding set of characteristics or fixed effects (FE) is included, No that it is not included, and - that it is comprised by the set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 2:
LINK-LEVEL: IV ESTIMATION OF THE CREDIT CHANNEL THROUGH THE NETWORK OF SUPPLIERS/CUSTOMERS

Panel A. Downstream propagation (indirect shocks via bank credit supply shocks to first-order suppliers)

	Dependent Variable: Δlog(purchases from suppliers)				
	IV Estimation: Second Stage. Instrument: Bank Shock Dummy				
	(1)	(2)	(3)	(4)	(5)
Own Reduction of Bank Debt	-0.673***	-0.478***	-0.606***		
	(0.141)	(0.072)	(0.091)		
Supplier Reduction of Bank Debt		-0.126*	-0.091*	-0.255***	
		(0.067)	(0.048)	(0.056)	
Supplier Reduction of Total Debt					-0.421***
					(0.141)
Supplier:					
Controls	-	Yes	Yes	Yes	Yes
Province*Industry Fixed Effects	-	Yes	Yes	Yes	Yes
Fixed Effects	Yes	No	No	No	No
Firm:					
Controls	Yes	Yes	Yes	-	-
Province*Industry Fixed Effects	Yes	Yes	Yes	-	-
Fixed Effects	No	No	No	Yes	Yes
Firm*Supplier Province & Industry FE	No	No	Yes	Yes	Yes
First Stage F-tests	33.84	25.06;16.85	28.82;16.04	15.09	46.45
Observations	1,114,421	1,114,421	1,114,421	1,114,421	1,112,954

Panel B. Upstream propagation (indirect shocks via bank credit supply shocks to first-order customers)

	Dependent Variable: Δlog(sales to customers)				
	IV Estimation: Second Stage. Instrument: Bank Shock Dummy				
	(1)	(2)	(3)	(4)	(5)
Own Reduction of Bank Debt	-0.186*	-0.287***	-0.255***		
	(0.105)	(0.108)	(0.077)		
Customer Reduction of Bank Debt		-0.567***	-0.542***	-0.480***	
		(0.148)	(0.143)	(0.175)	
Customer Reduction of Total Debt					-0.669**
					(0.315)
Customer:					
Controls	-	Yes	Yes	Yes	Yes
Province*Industry Fixed Effects	-	Yes	No	Yes	Yes
Fixed Effects	Yes	No	No	No	No
Firm:					
Controls	Yes	Yes	Yes	-	-
Province*Industry Fixed Effects	Yes	Yes	Yes	-	-
Fixed Effects	No	No	No	Yes	Yes
Firm*Customer Province & Industry FE	No	No	Yes	Yes	Yes
First Stage F-tests	12.46	13.75;25.15	11.77;38.55	31.64	9.79
Observations	1,119,169	1,119,169	1,119,169	1,119,169	1,117,322

Notes: This table reports estimates from IV-WLS. See Sections 4 and 5. Observations are at the level of the firm-supplier (Panel A) or firm-customer (Panel B). The dependent variable in the second stage is the change in the log of purchases (Panel A) or sales (Panel B) between 2008 and 2009. The reduction in bank debt or total debt between 2008 and 2009 is instrumented with the firm financial shock that we use in Table 1. Coefficients for each regressor are listed in the first row, while robust standard errors are reported in the row below (corrected for clustering at the firm, main bank, and supplier or customer levels). F-tests of the first stage are shown at the bottom (see Online Appendix Tables for the first stage results). In each column, the word Yes indicates that the set of characteristics or fixed effects is included, No that is not included, and - that is comprised by the set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 3:
LINK-LEVEL: THE INTERBANK EXPOSURE AS THE CREDIT CRUNCH SOURCE IN THE PROPAGATION THROUGH THE NETWORK OF SUPPLIERS/CUSTOMERS

Panel A. Downstream propagation (indirect shocks via bank credit supply shocks to first-order suppliers)

	Dependent Variable: Δlog(purchases from suppliers)				
	IV Estimation: Second Stage. Instrument: Bank Net Interbank Borrowing Shock Dummy				
	(1)	(2)	(3)	(4)	(5)
Direct (Bank Credit Supply) Shock	-7.868**				
	(3.890)				
Own Reduction of Bank Debt		-0.419**			
		(0.200)			
Supplier (Bank Credit Supply) Shock			-9.369***		
			(3.440)		
Supplier Reduction of Bank Debt				-0.435***	
				(0.167)	
Supplier Reduction of Total Debt					-1.397***
					(0.417)
Supplier:					
Controls	-	-	Yes	Yes	Yes
Province*Industry Fixed Effects	-	-	Yes	Yes	Yes
Fixed Effects	Yes	Yes	No	No	No
Firm:					
Controls	Yes	Yes	-	-	-
Province*Industry Fixed Effects	Yes	Yes	-	-	-
Fixed Effects	No	No	Yes	Yes	Yes
Firm*Supplier Province & Industry FE	No	No	Yes	Yes	Yes
First Stage F-test	13.57	14.75	524.57	98.88	18.03
Observations	1,114,421	1,114,421	1,114,421	1,114,421	1,114,421

Panel B. Upstream propagation (indirect shocks via bank credit supply shocks to first-order customers)

	Dependent Variable: Δlog(sales to customers)				
	IV Estimation: Second Stage. Instrument: Bank Net Interbank Borrowing Shock Dummy				
	(1)	(2)	(3)	(4)	(5)
Direct (Bank Credit Supply) Shock	-7.422**				
	(3.509)				
Own Reduction of Bank Debt		-0.506**			
		(0.203)			
Customer (Bank Credit Supply) Shock			-12.000**		
			(5.946)		
Customer Reduction of Bank Debt				-0.412**	
				(0.177)	
Customer Reduction of Total Debt					-0.584**
					(0.277)
Customer:					
Controls	-	-	Yes	Yes	Yes
Province*Industry Fixed Effects	-	-	Yes	Yes	Yes
Fixed Effects	Yes	Yes	No	No	No
Firm:					
Controls	Yes	Yes	-	-	-
Province*Industry Fixed Effects	Yes	Yes	-	-	-
Fixed Effects	No	No	Yes	Yes	Yes
Firm*Customer Province & Industry FE	No	No	Yes	Yes	Yes
First Stage F-test	20.54	20.77	443.48	55.91	20.28
Observations	1,119,169	1,119,169	1,119,169	1,119,169	1,119,169

Notes: This table reports estimates from IV WLS. See Sections 4 and 5. Observations are at the level of the firm-supplier (Panel A) or firm-customer (Panel B). The dependent variable of the second stage is the change in the log of purchases (Panel A) or sales (Panel B). The firm bank shock, the reduction in total bank debt and the reduction in total debt are instrumented with the firm financial shock derived from the (weighted) average net interbank borrowing of the firm across all its banks before the crisis, and then discretized depending on whether they are above the median (equal to 1) or not (equal to 0). Coefficients for each regressor are listed in the first row, while robust standard errors are reported in the row below (corrected for clustering at the firm, main bank, and supplier or customer levels). F-tests of the first stage are shown at the bottom (see Online Appendix Tables for the first stage results). In each column, the word Yes indicates that the set of characteristics or fixed effects is included, No that is not included, and - that is comprised by the set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 4:
LINK-LEVEL: HETEROGENEITY IN THE PROPAGATION OF BANK SHOCKS THROUGH THE NETWORK OF SUPPLIERS/CUSTOMERS

Panel A. Downstream propagation (indirect shocks via bank credit supply shocks to first-order suppliers)

	Dependent Variable: Δlog(purchases from suppliers)				
	(1)	(2)	(3)	(4)	(5)
Supplier (Bank Credit Supply) Shock	-5.045**	-4.298**	-3.604**	-3.298**	-4.606***
	(2.335)	(2.013)	(1.803)	(1.666)	(1.730)
Supplier Shock*HHI of the Supplier	-0.008**				-0.007*
	(0.004)				(0.003)
Supplier Shock*Ln(Assets of the Supplier)	0.051				0.035
	(0.493)				(0.491)
Supplier Shock*Reciprocal Relationship (Firm & Supplier)		-8.672**			-4.400**
		(4.270)			(1.957)
Supplier Shock*Commom Bank (Firm & Supplier)			6.694*		8.567*
			(4.018)		(4.589)
Supplier Shock*Same Province (Bank & Supplier)				5.352**	5.217***
				(2.154)	(1.936)
Supplier Shock*Same Industry (Bank & Supplier)				4.127	1.888
				(4.696)	(4.300)
Supplier:					
Controls	Yes	Yes	Yes	Yes	Yes
Province*Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Fixed Effects	No	No	No	No	No
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.376	0.376	0.374	0.375	0.378
Observations	1,114,421	1,114,421	1,114,421	1,114,421	1,114,421

Panel B. Upstream propagation (indirect shocks via bank credit supply shocks to first-order customers)

	Dependent Variable: Δlog(sales to customers)				
	(1)	(2)	(3)	(4)	(5)
Customer (Bank Credit Supply) Shock	-7.000***	-5.605***	-5.305***	-5.331***	-7.268***
	(2.240)	(2.757)	(2.470)	(2.640)	(2.308)
Customer Shock*HHI of the Customer	-0.014***				-0.013***
	(0.004)				(0.004)
Customer Shock*Ln(Assets of the Customer)	0.241				0.433
	(0.401)				(0.380)
Customer Shock*Reciprocal Relationship (Firm & Customer)		-9.693			-4.765*
		(6.211)			(2.634)
Customer Shock*Common Bank (Firm & Customer)			-7.641***		-4.479
			(2.929)		(4.050)
Supplier Shock*Same Province (Bank & Customer)				1.448	1.363
				(5.457)	(4.821)
Supplier Shock*Same Industry (Bank & Customer)				-0.719	-2.730
				(6.342)	(5.572)
Customer:					
Controls	Yes	Yes	Yes	Yes	Yes
Province*Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Fixed Effects	No	No	No	No	No
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.360	0.359	0.354	0.351	0.364
Observations	1,119,169	1,119,169	1,119,169	1,119,169	1,119,169

Notes: This table reports estimates from WLS. Observations are at the level of the firm-supplier (Panel A) or firm-customer (Panel B). The dependent variable is the change in the log of purchases (Panel A) or sales (Panel B) between 2008 and 2009. Bank shocks are the same as in Table 1. Interactions variables (HHI, size, and distance measures as same bank, industry and location, and reciprocal relationship) are explained in Sections 4 and 5. Coefficients for each regressor are listed in the first row, while robust standard errors are reported in the row below (corrected for clustering at the firm, main bank, and supplier or customer levels). In each column, the word Yes indicates that the set of characteristics or fixed effects is included, No that is not included, and - that is comprised by the set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 5:
NODE-LEVEL: FIRM-LEVEL EFFECTS OF BANK SUPPLY SHOCKS THROUGH THE (FIRST-ORDER) NETWORK OF SUPPLIERS/CUSTOMERS

Dependent Variable:	Δlog(purchases)			Δlog(sales)		
	(1)	(2)	(3)	(4)	(5)	(6)
Direct Shock	-2.367**	-2.233*	-2.220*	-1.014**	-0.994**	-1.000**
	(1.142)	(1.144)	(1.141)	(0.485)	(0.482)	(0.475)
Suppliers Shock		-2.399***	-2.325***			0.111
		(0.745)	(0.745)			(0.383)
Customers Shock			-1.175		-1.888***	-1.896***
			(1.094)		(0.571)	(0.562)
Supplier Centrality	-0.219	-0.217	-0.203	-0.530**	-0.493**	-0.493**
	(0.514)	(0.510)	(0.511)	(0.229)	(0.229)	(0.229)
Customer Centrality	-2.648***	-2.544***	-2.534***	-0.888***	-0.888***	-0.890***
	(0.504)	(0.498)	(0.495)	(0.208)	(0.210)	(0.208)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Industry & Zip Code Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.416	0.417	0.417	0.282	0.282	0.282
Observations	170,942	170,942	170,942	155,065	155,065	155,065

Notes: This table reports estimates from WLS. See Sections 4 and 5. Observations are at the level of the firm (node-level). The dependent variables are the change, between 2008 and 2009, in the log of aggregate purchases at the firm level from all suppliers (columns 1, 2 and 3) and the log of firm-level aggregate sales to all customers (columns 4, 5 and 6). Bank shocks are dummy variables that take the value of one if the firm was borrowing before the global financial crisis from banks which significantly reduced credit supply during the global financial crisis, and zero otherwise. To construct these variables, first, we estimate for each bank a supply factor based on Amiti and Weinstein (2018). Then, for each firm, we compute the weighted average of those supply factors that are associated to each of the banks which the firm works with before the global crisis. Finally, the firm shock dummy results of comparing its value with the median (equal to 1 if below the median in credit supply). Supplier and Customer centrality are defined in Section 2. As we cannot control for firm fixed effects, we control for zip code fixed effects, differently from previous link-level regressions. For the list of firm controls, see Section 5. Coefficients for each regressor are listed in the first row, while robust standard errors are reported in the row below (corrected for clustering at the level of the main bank). In each column, the word Yes indicates that the set of characteristics or fixed effects is included, No that is not included and - that is comprised by the set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 6:
HIGHER-ORDER versus FIRST-ORDER versus DIRECT PROPAGATION OF BANK CREDIT SUPPLY SHOCKS THROUGH THE NETWORK OF SUPPLIERS/CUSTOMERS

Panel A. Node level: firm-level real effects

Dependent Variable:	Δlog(purchases)			Δlog(sales)			Δlog(purchases+sales)	Δlog(employment)	Investment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Direct Shock	-2.156*	-2.410**	-2.210*	-0.933*	-0.999**	-0.929*	-0.985*	-0.403**	-0.542***
	(1.128)	(1.137)	(1.124)	(0.479)	(0.482)	(0.477)	(0.485)	(0.189)	(0.138)
Suppliers Shock	-2.066**		-1.985**	0.260		0.397			
	(0.808)		(0.803)	(0.434)		(0.419)			
Suppliers Higher-Order Shocks	-2.031**		-2.056**	-1.766***		-1.738***			
	(0.833)		(0.858)	(0.402)		(0.411)			
Customers Shock		-1.494	-1.319		-1.950***	-1.932***			
		(1.025)	(1.020)		(0.532)	(0.524)			
Customers Higher-Order Shocks		1.017	1.105		0.327	0.410			
		(1.028)	(1.025)		(0.427)	(0.435)			
Suppliers & Customers (First-Order) Average Shock							-0.906**	-0.396**	-0.300*
							(0.461)	(0.190)	(0.178)
Suppliers & Customers Higher-Order Average Shock							-1.074*	-0.176	-0.468**
							(0.640)	(0.145)	(0.193)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry & Zip Code Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.417	0.416	0.418	0.282	0.282	0.283	0.404	0.085	0.043
Observations	170,942	170,942	170,942	155,065	155,065	155,065	178,007	169,283	169,038

Panel B. Link level: supplier-firm data (downstream) and customer-firm data (upstream)

	Downstream propagation		Upstream propagation	
Dependent Variable:	Δlog(purchases to suppliers)		Δlog(sales to customers)	
	(1)	(2)	(3)	(4)
Supliers or Customers Shock	-3.719**	-2.880*	-5.161**	-4.689**
	(1.778)	(1.533)	(2.513)	(2.239)
Suppliers or Customers Higher-Order Shocks		-1.701**		2.051
		(0.763)		(1.951)
Supplier or Customer:				
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Firm*Supplier Province & Industry Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.395	0.380	0.377	0.362
Observations	1,114,421	1,114,421	1,119,169	1,119,169

Notes: This table reports estimates for higher-order effects versus first-order and direct and direct effects. We control for the customer and supplier centrality considered in Table 5. For the sake of focus, we do not report here the coefficients (whose size and significance remains unaltered). The dependent variables are the change, between 2008 and 2009, in the log of aggregate purchases (columns 1, 2 and 3), the log of aggregate sales (columns 3, 4 and 5), the log of aggregate purchases plus sales (column 7), the log of total employment (column 8) and total investment (column 9) of Panel A. For Panel B, the dependent variable is the change in the log of purchases between a firm and its supplier (columns (1) and (2)) or sales between a firm and its customer (columns (3) and (4)) between 2008 and 2009. Bank shocks for direct and first-order effects are explained in Table 5 and 1. Higher order effects are discussed in Section 2 and 4. Average supplier&customer shocks are obtained from a corresponding discretization of the weighted average purchases and and sales. As we cannot control for firm fixed effects, we control for zip code fixed effects, differently from previous link-level regressions. For the list of firm controls, see Section 5. Coefficients for each regressor are listed in the first row, while robust standard errors are reported in the row below (corrected for clustering at the level of the main bank). In each column, the word Yes indicates that the set of characteristics or fixed effects is included, and No that is not included *** Significant at 1%, ** significant at 5%, * significant at 10%.

For Online Publication — Appendix A: Proofs

Before proving Proposition 1 we state and prove two useful lemmas:

Lemma 1. *The cost function of firm i is given by*

$$c(y_i\,;\ w, \boldsymbol{p}, \theta_i) = \lambda_i y_i, \tag{14}$$

where $\lambda_i = \frac{1+\theta_i}{\zeta_i}\beta_i^{-\beta_i}\left(\prod_{j\in N_i^+}(g_{ji}\alpha_i)^{g_{ji}}\right)^{-\alpha_i} w^{\beta_i}\left(\prod_{j\in N_i^+}p_j^{g_{ji}}\right)^{\alpha_i}$.

Proof of Lemma 1. Given any feasible production plan $[\ell_i, (z_{ij})_{j=1}^n]$ and distortion θ_i, the induced cost of firm i is obtained by minimizing

$$(1+\theta_i)\left(w\ell_i + \sum_{j\in N_i^+} p_j z_{ji}\right) \tag{15}$$

subject to the technological constraint:

$$y_i \leq \zeta_i \ell_i^{\beta_i}\left(\prod_{j\in N_i^+} z_{ji}^{g_{ji}}\right)^{\alpha_i}.$$

The above constraint above must always hold with equality. Hence the Langragian of this problem is:

$$\mathscr{L} = (1+\theta_i)\left(w\ell_i + \sum_{j\in N_i^+} p_j z_{ji}\right) - \lambda_i\left[\zeta_i\ell_i^{\beta_i}\left(\prod_{j\in N_i^+} z_{ji}^{g_{ji}}\right)^{\alpha_i} - y_i\right].$$

From the first-order necessary conditions (and also sufficient, given the postulated convexity conditions) we are led to the following conditional demand functions:

$$z_{ji}\left(y_i\,;\ w, \boldsymbol{p}, \theta_i\right) = \lambda_i\frac{1}{1+\theta_i}\alpha_i g_{ji}\frac{y_i}{p_j}; \qquad \ell_i\left(y_i\,;\ w, \boldsymbol{p}, \theta_i\right) = \lambda_i\frac{1}{1+\theta_i}\beta_i\frac{y_i}{w}. \tag{16}$$

Substituting (16) in (15) we get (14). Then, to derive the expression for λ_i, substitute (16) into the production function and obtain:

$$y_i = \zeta_i\left(\frac{\lambda_i\beta_i y_i}{(1+\theta_i)w}\right)^{\beta_i}\prod_{j\in N_i^+}\left(\frac{\lambda_i\alpha_i g_{ji}y_i}{(1+\theta_j)p_j}\right)^{g_{ji}\alpha_i} = \frac{\zeta_i}{1+\theta_i}\lambda_i y_i\left(\frac{\beta_i}{w}\right)^{\beta_i}\prod_{j\in N_i^+}\left(\frac{g_{ji}\alpha_i}{p_j}\right)^{g_{ji}\alpha_i},$$

which gives:

$$\lambda_i = \frac{1+\theta_i}{\zeta_i}\beta_i^{-\beta_i}\left(\prod_{j\in N_i^+}(g_{ji}\alpha_i)^{g_{ji}}\right)^{-\alpha_i} w^{\beta_i}\left(\prod_{j\in N_i^+}p_j^{g_{ji}}\right)^{\alpha_i}.$$

as desired. □

Lemma 2. *Let $s_i = p_i y_i$ denote revenue of firm i, and let $\theta_i \equiv \nu + \tau_i$. Define $\boldsymbol{v} = (\mathbf{I} - \mathbf{GAMT})^{-1}\boldsymbol{\gamma}$, where recall that $\mathbf{A}$, $\mathbf{M}$ and $\mathbf{T}$ are diagonal matrices with elements α_i, $\frac{1}{\mu_i}$ and $\frac{1}{1+\nu+\tau_i}$ on the main diagonal, respectively. The following condition holds at equilibrium:*

$$\boldsymbol{s} = E\boldsymbol{v}. \tag{17}$$

Proof of Lemma 2. Substituting (16) and the optimal consumer's demand into the market clearing condition for good i, we get:

$$y_i = c_i + \sum_{j \in N_i^-} z_{ij}$$

or

$$p_i y_i = E\gamma_i + \sum_i \frac{\lambda_j}{1+\nu+\tau_j} \alpha_j g_{ij} y_j \tag{18}$$

which leads to

$$\boldsymbol{s} = E\left(\mathbf{I} - \mathbf{GAMT}\right)^{-1} \boldsymbol{\gamma}, \tag{19}$$

where we have used $p_j = \mu_j \lambda_j$. $\square$

Proof of Proposition 1. First we note that the demand for intermediate goods and labor (16) at equilibrium can be written as:

$$\begin{aligned} z_{ji} &= \alpha_i g_{ji} \frac{p_i y_i}{\mu_i (1+\nu+\tau_i) p_j} = \frac{\alpha_i g_{ji}}{(1+\nu+\tau_i)\mu_i} \frac{v_i}{v_j} y_j \\ \ell_i &= \frac{\beta_i}{(1+\nu+\tau_i)\mu_i} \frac{p_i y_i}{w} = \frac{\beta_i}{(1+\nu+\tau_i)\mu_i} \frac{E}{w} v_i. \end{aligned} \tag{20}$$

Substituting (20) in (1) and taking logarithms, we get that, at equilibrium,

$$\hat{y}_i = \hat{\zeta}_i + \beta_i \left(-\hat{\theta}_i - \hat{\mu}_i + \hat{\beta}_i + \hat{E} - \hat{w} + \hat{v}_i\right) + \alpha_i \sum_{j \in N_i^+} g_{ji} \left(-\hat{\theta}_i - \hat{\mu}_i + \hat{\alpha}_i + \hat{g}_{ji} + \hat{v}_i - \hat{v}_j + \hat{y}_j\right),$$

where recall that we use $\hat{\theta}_i$ to denote $\log(1+\theta_i) = \log(1+\nu+\tau_i)$, and $\hat{x}$ to denote $\log x$ for any other variable x. We note that $\alpha_i + \beta_i = 1$ and $\sum_j g_{ji} = 1$ imply that $\beta_i = 1 - \alpha_i \sum_j g_{ji}$. After simplification (and relying on the normalization $w = 1$), the previous equation becomes:

$$\hat{y}_i = -\hat{\theta}_i + \hat{v}_i - \alpha_i \sum_{j \in N_i^+} g_{ji} \hat{v}_j + \alpha_i \sum_{j \in N_i^+} g_{ji} \hat{y}_j + \left(1 - \alpha_i \sum_{j \in N_i^+} g_{ji}\right) \hat{E} + q_i \tag{21}$$

where $q_i = \hat{\zeta}_i - \mu_i + \beta_i \hat{\beta}_i + \alpha_i \hat{\alpha}_i + \alpha_i \sum_{j \in N_i^+} g_{ji} \hat{g}_{ji}$. Writing (21) for all i in vector notation we get:

$$\begin{aligned} \hat{\boldsymbol{y}} &= -\hat{\boldsymbol{\theta}} + \left(\mathbf{I} - \mathbf{AG}'\right) \hat{\boldsymbol{v}} + \mathbf{AG}' \hat{\boldsymbol{y}} + \hat{E}(\mathbf{I} - \mathbf{AG}')\mathbf{1} + \boldsymbol{q} \Rightarrow \\ \hat{\boldsymbol{y}} &= -(\mathbf{I} - \mathbf{AG}')^{-1} \hat{\boldsymbol{\theta}} + \hat{\boldsymbol{v}} + \mathbf{1}\hat{E} + (\mathbf{I} - \mathbf{AG}')^{-1} \boldsymbol{q} \end{aligned} \tag{22}$$

which gives (3). $\square$

Link-based propagation. Here we spell out the reasoning underlying Predictions P1-P3 in Section 2. Consider any given link $j \to i$ (where j is the supplier and i the customer). We address first the statement concerning upstream propagation (P1) and then that of downstream propagation (P2). Once they are confirmed, the own effect formulated in P3 follows trivially.

Thus let us start by supposing that an individual bank credit shock of magnitude $\tau_i > 0$

hits firm i. Then, using the null shock as the benchmark of comparison, we transform (4) to its logarithmic counterpart in order to compute the induced changes in relative terms, arriving at the following expression:

$$\hat{z}_{ji}(\nu+\tau_i,\boldsymbol{\theta}_{-i}) - \hat{z}_{ji}(0,\boldsymbol{\theta}_{-i}) = \Delta\hat{s}_i - \Delta\hat{p}_j - \log\left(1+\nu+\tau_i\right), \tag{23}$$

where the Δ-denoted changes in the RHS of the above expression represent the changes of the variables under consideration that are induced by the credit shock experienced by firm i when all other firms are fixed at the credit conditions given by the vector $\boldsymbol{\theta}_{-i}$.

As we explain in Section 4, our empirical strategy for identifying the indirect non-financial shock experienced by firm j is to control for the fixed characteristics of this firm and exploit the variation realized within the set formed by firm i and the other customer firms of j. This implies that the change $\Delta\hat{p}_j$ in (23) can be assumed controlled for. Hence any unaccounted effect must come from the other two terms, $\Delta\hat{s}_i$ and $-\log\left(1+\nu+\tau_i\right)$. The latter is negative by assumption, whereas the former is non-positive, as can be readily confirmed by derivating (17), then using (25) below and the fact that the consumer's income cannot increase with the distortion induced by the credit shock.

Next, consider the case where, on a link $j \to i$ as above, it is the supplier j that is hit by a distortionary bank shock. Then, the downstream counterpart of (23) reads:

$$\hat{z}_{ji}(\nu+\tau_j,\boldsymbol{\theta}_{-j}) - \hat{z}_{ji}(0,\boldsymbol{\tau}_{-j}) = \Delta\hat{s}_i - \Delta\hat{p}_j = \Delta\hat{s}_i - \Delta\hat{\lambda}_j, \tag{24}$$

where the Δ-denoted changes have the same interpretation as before and recall that $\hat{\lambda}_j$ denotes the logarithm of the marginal cost of firm j. As shown in Lemma 1, this marginal cost, $\lambda_j(\nu+\tau_j,\boldsymbol{\theta}_{-j})$, is proportional to $(1+\nu+\tau_j)\lambda_j(0,\boldsymbol{\tau}_{-j})$ and therefore positive. This is enough to sign as desired the change predicted by our empirical analysis since our identification of the supplier effect (on j) relies on fixed customer effects (for i) that will account for $\Delta\hat{s}_i$ in (24). $\square$

Proof of Proposition 2. We derivate the four terms of (3) both with respect to the individual and the aggregate shock.

For the *first term* we have:

$$\frac{\partial}{\partial\tau_k}\left[-(\mathbf{I}-\mathbf{AG}')^{-1}\hat{\boldsymbol{\theta}}\right] = -\frac{1}{1+\nu+\tau_k}(\mathbf{I}-\mathbf{AG}')^{-1}\boldsymbol{e}_k$$

and

$$\frac{\partial}{\partial\nu}\left[-(\mathbf{I}-\mathbf{AG}')^{-1}\hat{\boldsymbol{\nu}}\right] = -(\mathbf{I}-\mathbf{AG}')^{-1}\mathbf{T}\mathbf{1}.$$

Next, in order to calculate the second term of (3), $\frac{\partial\hat{v}}{\partial\tau_k}$, we start by deriving the expression for $\frac{\partial \boldsymbol{v}}{\partial \tau_k}$. Doing so and simplifying, we obtain:[32]

$$\begin{aligned}\frac{\partial \boldsymbol{v}}{\partial \tau_k} &= -\frac{1}{(1+\nu+\tau_k)^2}(\mathbf{I}-\mathbf{GAMT})^{-1}\alpha_k\mu_k\mathbf{G}_{*,k}(\mathbf{I}-\mathbf{GAMT})^{-1}\boldsymbol{\gamma} = \\ &- \frac{1}{(1+\nu+\tau_k)^2}(\mathbf{I}-\mathbf{GAMT})^{-1}\alpha_k\mu_k\mathbf{G}_{*,k}\boldsymbol{v} = \\ &- \frac{1}{(1+\nu+\tau_k)^2}v_k(\mathbf{I}-\mathbf{GAMT})^{-1}\alpha_k\mu_k\boldsymbol{g}_{*,k} = \\ &- \frac{1}{(1+\nu+\tau_k)}v_k(\mathbf{I}-\mathbf{GAMT})^{-1}\mathbf{GAMT}\boldsymbol{e}_k,\end{aligned} \tag{25}$$

where $\mathbf{G}_{*,k}$ denotes the matrix with the k-th column of $\mathbf{G}$ and 0 everywhere else, while $\boldsymbol{g}_{*,k}$ denotes the vector given by the k-th column of matrix $\mathbf{G}$.

Define $\mathbf{V}$ to be a diagonal matrix with v_i on the main diagonal. Differentiating with respect to the common shock ν, we get:

$$\frac{\partial \boldsymbol{v}}{\partial \nu} = -(\mathbf{I}-\mathbf{GAMT})^{-1}\mathbf{GAMT}^2(\mathbf{I}-\mathbf{GAMT})\gamma = -(\mathbf{I}-\mathbf{GAMT})^{-1}\mathbf{GAMT}^2\mathbf{V1}. \tag{26}$$

Finally, define the matrix $\mathbf{H}(\boldsymbol{\tau}) = (h_{ij})_{i,j=1}^n$ whose typical elements $h_{ij} = \frac{p_i z_{ij}}{p_i y_i}$ represent the share of firm i's sales coming from j in the *equilibrium* induced by $\boldsymbol{\tau}$. Equation (20) implies:

$$h_{ij} = \frac{\alpha_j g_{ij}}{(1+\nu+\tau_j)\mu_j}\frac{v_j}{v_i}. \tag{27}$$

Then, from (27), it follows that $\mathbf{H}(\boldsymbol{\theta}) = \mathbf{V}^{-1}\mathbf{GAMTV}$, where we emphasize the dependence of $\mathbf{H}$ on $\boldsymbol{\theta}$. Furthermore let $\frac{\partial \hat{\boldsymbol{v}}}{\partial \tau_k}$ be a column vector with i-th element equal to $\frac{\partial \hat{v}_i}{\partial \tau_k} = \frac{1}{v_i}\frac{\partial v_i}{\partial \tau_k}$. Using (25) we can write:

$$\begin{aligned}\frac{\partial \hat{\boldsymbol{v}}}{\partial \tau_k} &= -\frac{1}{1+\nu+\tau_k}\mathbf{V}^{-1}(\mathbf{I}-\mathbf{GAMT})^{-1}\mathbf{GAMTV}\boldsymbol{e}_k \\ &= -\frac{1}{1+\nu+\tau_k}\mathbf{V}^{-1}\left(\sum_{i=0}^{\infty}(\mathbf{GAMT})^i\right)\mathbf{GAMTV}\boldsymbol{e}_k \\ &= -\frac{1}{1+\nu+\tau_k}(\mathbf{V}^{-1}\mathbf{GAMTV} + \mathbf{V}^{-1}\mathbf{GAMTVV}^{-1}\mathbf{GAMTV} \\ &\quad + \mathbf{V}^{-1}\mathbf{GAMTVV}^{-1}\mathbf{GAMTVV}^{-1}\mathbf{GAMTV} + ...)\boldsymbol{e}_k \\ &= -\frac{1}{1+\nu+\tau_k}\left(\sum_{i=1}^{\infty}(\mathbf{H}(\boldsymbol{\theta}))^i\right)\boldsymbol{e}_k \\ &= -\frac{1}{1+\nu+\tau_k}(\mathbf{I}-\mathbf{H}(\boldsymbol{\theta}))^{-1}\mathbf{H}(\boldsymbol{\theta})\,\boldsymbol{e}_k.\end{aligned}$$

Differentiating with respect to the common shock we get:

$$\begin{aligned}\frac{\partial \hat{\boldsymbol{v}}}{\partial \nu} &= -\mathbf{V}^{-1}(\mathbf{I}-\mathbf{GAMT})^{-1}\mathbf{GAMT}^2\mathbf{V1} \\ &= -\mathbf{V}^{-1}(\mathbf{I}-\mathbf{GAMT})^{-1}\mathbf{GAMTVT1} = -(\mathbf{I}-\mathbf{H}(\boldsymbol{\theta}))^{-1}\mathbf{H}(\boldsymbol{\theta})\,\mathbf{T1}.\end{aligned}$$

Combining all of the above with the observation that the fourth term of (3) does not depend on τ_k nor ν leads to the desired conclusion. □

[32] Recall that $\mathbf{A}$, $\mathbf{M}$ and $\mathbf{T}$ are diagonal matrices with elements α_i, μ_i^{-1} and $\frac{1}{1+\nu+\tau_i}$ on the main diagonal, respectively.

Construction of A, G, and H. From conditional demand (16) and the cost function (15). together with the fact that $\sum_{j\in N} g_{ji} = 1$ and $\alpha_i + \beta_i = 1$ for all $i \in N$ it directly follows that α_i is firm i' cost share to intermediate inputs, which we observe. Analogously g_{ji} is equal to cost share of input j in spending on intermediate inputs of firm i, observed in the VAT data. Finally, from (16) and (17) we get that:

$$p_j z_{ji} = \frac{\alpha_i g_{ji} p_i y_i}{\mu_i(1+\nu+\tau_i)} = \frac{\alpha_i g_{ji} v_i E}{\mu_i(1+\nu+\tau_i)},$$

which implies:

$$h_{ji} = \frac{\alpha_i g_{ji}}{(1+\nu+\tau_i)\mu_i}\frac{v_i}{v_j} = \frac{\alpha_i g_{ji}}{(1+\nu+\tau_i)\mu_i}\frac{Ev_i}{Ev_j} = \frac{p_j z_{ji}}{p_j y_j},$$

where both the numerator and the denominator are gathered from the VAT data.

For Online Publication — Appendix B: Additional Tables

TABLE B1:
SUMMARY STATISTICS

		Mean	S.D.	P25	Median	P75
Link Level						
Downstream propagation: purchases from suppliers						
Δlog(purchases to suppliers)	%	-11.932	60.414	-52.008	-12.730	16.381
Direct (Bank Credit Supply) Shock	0/1	0.541	0.498	0.000	1.000	1.000
Supplier (Bank Credit Supply) Shock	0/1	0.505	0.500	0.000	1.000	1.000
Own Reduction of Bank Debt	%	12.067	55.840	-28.485	-8.264	5.813
Supplier Reduction of Bank Debt	%	10.071	58.433	-28.814	-8.696	6.275
Supplier Reduction of Total Debt	%	-3.147	204.330	-20.818	-4.997	11.560
Change in purchases using Davis and Haltiwanger (1992)	%	-26.771	148.726	-200.000	-25.846	72.225
Bank Net Interbank Borrowing Shock	0/1	0.674	0.469	0.000	0.000	1.000
Supplier Bank Net Interbank Borrowing Shock	0/1	0.613	0.487	0.000	1.000	1.000
Supplier High-Order Shocks	0/1	0.499	0.500	0.000	0.000	1.000
Upstream propagation: sales to customers						
Δlog(sales to customers)	%	-12.062	61.407	-53.513	-13.894	17.599
Direct (Bank Credit Supply) Shock	0/1	0.544	0.498	0.000	1.000	1.000
Customer (Bank Credit Supply) Shock	0/1	0.497	0.500	0.000	0.000	1.000
Own Reduction of Bank Debt	%	12.578	52.451	-5.670	9.741	29.602
Customer Reduction of Bank Debt	%	8.563	61.479	-7.496	7.449	27.897
Customer Reduction of Total Debt	%	-6.533	209.909	-14.739	2.385	18.510
Change in sales using Davis and Haltiwanger (1992)	%	-27.686	149.284	-200.000	-27.817	73.509
Bank Net Interbank Borrowing Shock	0/1	0.650	0.477	0.000	1.000	1.000
Customer Bank Net Interbank Borrowing Shock	0/1	0.627	0.484	0.000	1.000	1.000
Customer High-Order Shocks	0/1	0.474	0.499	0.000	0.000	1.000
Node Level						
Δlog(purchases)	%	6.490	40.513	-15.030	2.031	21.798
Δlog(sales)	%	11.311	44.379	-11.624	6.496	28.408
Δlog(purchases+sales)	%	7.256	36.541	-11.774	3.740	21.377
Own Bank Shock	0/1	0.513	0.500	0.000	1.000	1.000
Suppliers Bank Shock	0/1	0.538	0.499	0.000	1.000	1.000
Customers Bank Shock	0/1	0.556	0.497	0.000	1.000	1.000
Average Suppliers&Customers Shock	0/1	0.477	0.499	0.000	0.000	1.000
Suppliers High Order Shocks	0/1	0.505	0.500	0.000	1.000	1.000
Customers High Order Shocks	0/1	0.483	0.500	0.000	0.000	1.000
Average Suppliers&Customers High Order Shocks	0/1	0.524	0.499	0.000	1.000	1.000
Δlog(employment)	%	-8.974	30.074	-20.759	-0.995	0.000
Investment	%	-4.963	38.112	-18.543	-5.952	0.000

Notes: This table reports means, standard deviations and first, second and third quartiles of the firms in the year 2008.

TABLE B2:
DIFFERENCE IN MEAN TESTS DEPENDING ON EX-ANTE LINKS WITH BANKS WITH STRONG NEGATIVE CREDIT SUPPLY

	Firms Exposed to Unconstrained Banks		Firms Exposed to Constrained Banks		Difference in Means	Normalized Differences	Dependent Variable: Firms Exposed to Constraint Banks (0/1)	
	Mean	S.D.	Mean	S.D.	t test	test	Coefficient	S.E.
Firm Characteristics								
Short Term Debt (%)	46.63	(22.78)	46.98	(22.65)	-3.14	-0.01	0.000	(0.000)
Log(Age)	3.08	(0.65)	3.08	(0.65)	-0.58	0.00	0.003	(0.005)
Own Funds/Total Assets (%)	38.97	(25.05)	38.68	(24.76)	2.34	0.01	0.000	(0.000)
Log(Total Assets)	8.76	(2.15)	8.77	(2.13)	-0.53	0.00	0.001	(0.002)
Liquidity Ratio (%)	20.14	(25.22)	19.88	(24.97)	2.16	0.01	0.000	(0.000)
Average Bank Characteristics								
Log(Total Assets)	0.66	(0.48)	0.27	(0.44)	174.99	0.60	-0.270***	(0.079)
Own Funds/Total Assets	0.46	(0.50)	0.52	(0.50)	-24.88	-0.09	-0.092	(0.083)
Net Interbank Borrowing	0.47	(0.50)	0.86	(0.34)	-190.91	-0.65	0.370***	(0.085)
ROA	0.43	(0.50)	0.48	(0.50)	-19.64	-0.07	0.067	(0.060)
NPL	0.44	(0.50)	0.52	(0.50)	-36.03	-0.12	-0.060	(0.051)
Loans/Deposits	0.43	(0.49)	0.44	(0.50)	-6.95	-0.02	0.071	(0.078)
% Construction & Real Estate	0.50	(0.50)	0.60	(0.49)	-39.99	-0.14	-0.065	(0.065)
Savings Bank	0.53	(0.50)	0.41	(0.49)	48.88	0.17	-0.114	(0.081)
R-squared							0.306	
No. of Observations	82,620		87,819				167,216	

Notes: This table (in the first four columns) reports means and standard deviations of firm characteristics in December 2008. Firms are classified in two groups. The first two columns refer to firms that ex-ante worked with a unconstrained bank (its credit supply is above the median of the bank supply factor estimated following Amiti and Weinstein (2018), see Table 1 and Section 4 and 5), while the third and fourth columns refer to firms that worked with constrained banks. Column 5 reports the t-statistic of the differences in mean and column 6 shows the normalized difference test proposed by Imbens and Wooldridge (2009), for which Imbens and Rubin (2015) suggested a heuristic threshold of 0.25 in absolute value for significant differences. The normalized differences test the null of no differences in means between treated and control groups through a scale-and-sample-size-free estimator. Bank characteristics at the firm level are computed as a weighted average of the bank variables at the firm-bank level, using as weights the credit amount of each relationship and then being discretized to be one if the value is above the median of its distribution and zero otherwise. Columns 7 and 8 shows the results of a OLS regressions where the dependent variable is a dummy that takes the value of one if the firms at the end of 2008 worked with an unconstrained bank and zero otherwise. Industry*province dummies are included. Coefficients are listed in the first column, while robust standard errors are reported in the adjacent column. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE B3:
LINK-LEVEL: PROPAGATION OF BANK CREDIT SUPPLY SHOCKS THROUGH THE NETWORK OF SUPPLIERS/CUSTOMERS. ROBUSTNESS

Panel A. Downstream propagation (indirect shocks via bank credit supply shocks to first-order suppliers)

	Dept. Var.: Δlog(purchases)		Dept. Var.: Change in purchases using Davis and Haltiwanger (1992)			
	Unweighted	Unweighted	Weighted		Unweighted	
		IV Estimation		IV Estimation		IV Estimation
Supplier Shock	-0.649***		-3.219		-1.743**	
	(0.249)		(2.581)		(0.672)	
Supplier Reduction of Bank Debt		-0.102***		-0.401**		-0.274***
		(0.017)		(0.175)		(0.034)
Supplier Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Supplier Province & Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
First Stage F-test	-	844.69	-	35.88	-	1,332.49
R-squared	0.199	0.194	0.318	0.307	0.173	0.170
Observations	1,114,421	1,114,421	2,422,203	2,422,203	2,422,203	2,422,203

Panel B. Upstream propagation (indirect shocks via bank credit supply shocks to first-order customers)

	Dept. Var.: Δlog(sales)		Dept. Var.: Change in sales using Davis and Haltiwanger (1992)			
	Unweighted	Unweighted	Weighted		Unweighted	
		IV Estimation		IV Estimation		IV Estimation
Customer shock	-0.808***		-4.293**		-2.170***	
	(0.172)		(1.811)		(0.335)	
Customer Reduction of Bank Debt		-0.113***		-0.377***		-0.290***
		(0.018)		(0.122)		(0.028)
Customer Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Customer Province & Industry Fixed Effec	Yes	Yes	Yes	Yes	Yes	Yes
First Stage F-test	-	1,283.96	-	46.95	-	1,602.39
R-squared	0.171	0.166	0.337	0.321	0.149	0.144
Observations	1,119,169	1,119,169	2,510,408	2,510,408	2,510,408	2,510,408

Notes: This table reports robustness for Table 1 and 2. See Sections 4 and 5. Observations are at the level of the firm-supplier (Panel A) or firm-customer (Panel B). The dependent variables are the change in the log of purchases (Panel A) or sales (Panel B), or the reduction in bank debt between 2008 and 2009, which is instrumented with the firm bank shock used in Table 1 and 2. Change in purchases (or sales) using Davis and Haltiwanger (1992) is change in purchases (sales) between 2009 and 2008 divided by the sum of purchases (sales) in 2008 and 2009. Coefficients for each regressor are listed in the first row, while robust standard errors are reported in the row below (corrected for clustering at the firm, main bank, and supplier or customer levels). F-tests of the first stage are shown at the bottom. In each column, the word Yes indicates that the set of characteristics or fixed effects is included. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE B4:
LINK-LEVEL: JOINT ESTIMATION OF DOWNSTREAM AND UPSTREAM PROPAGATION OF BANK CREDIT SUPPLY SHOCKS.

Panel A. Downstream and upstream propagation: Bank (credit supply) shocks

	Dependent Variable: Δlog(purchases or sales)		
	(1)	(2)	(3)
Joint (supplier & customer) Shock	-5.412**		
	(2.349)		
Supplier Shock		-3.911*	-3.092*
		(2.172)	(1.762)
Customer Shock		-6.766**	-5.697*
		(2.907)	(2.949)
Customer & Supplier Controls	Yes	Yes	Yes
Customer & Supplier Fixed Effects	No	No	Yes
Firm Fixed Effects	Yes	Yes	-
Firm*Customer/Supplier Province & Industry F.E.	Yes	Yes	Yes
R-squared	0.305	0.305	0.370
Observations	2,233,590	2,233,590	2,233,590

Panel B. Downstream and upstream propagation: IV credit channel estimation

	Dependent Variable: Δlog(purchases or sales)		
	IV Estimation: Second Stage. Instrument: Bank Shock Dummy		
	(1)	(2)	(3)
Joint Reduction of Bank Debt	-0.387***		
	(0.084)		
Supplier Reduction of Bank Debt		-0.211***	-0.209***
		(0.064)	(0.062)
Customer Reduction of Bank Debt		-0.580***	-0.519***
		(0.165)	(0.191)
Customer & Supplier Controls	Yes	Yes	Yes
Customer & Supplier Fixed Effects	No	No	Yes
Firm Fixed Effects	Yes	Yes	-
Firm*Customer/Supplier Province & Industry F.E.	Yes	Yes	Yes
First Stage F-tests	20.52	13.63/32.18	11.13/22.33
R-squared	0.227	0.204	0.295
Observations	2,233,590	2,233,590	2,233,590

Notes: This table reports a joint estimation of downstream and upstream propagation. See Sections 4 and 5. Observations are at the link level (of the firm-supplier or firm-customer). The dependent variable is the change in the log of purchases or sales between 2008 and 2009. In Panel B the reduction in total bank debt between 2008 and 2009 is instrumented with the firm bank shock used in Panel A. In column 3 we allow for two sets of firm fixed effects (F.E.), depending whether the firm acts as a customer or as a supplier. Coefficients for each regressor are listed in the first row, while robust standard errors are reported in the row below (corrected for clustering at the firm, main bank, and supplier or customer levels). F-tests of the first stage are shown at the bottom. In each column, the word Yes indicates that the set of characteristics or fixed effects is included, No that is not included, and - that is comprised by the set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE B5:
LINK LEVEL: FIRST STAGE OF IV ESTIMATIONS

Panel A. TABLE 2 first-stage results

	Dependent Variable: Reduction of Bank Debt			
	Panel A Table 2: Supplier		Panel B Table 2: Customer	
	(1)	(2)	(1)	(2)
Direct Shock	8.347***	10.687***	13.488***	12.750***
	(1.435)	(2.083)	(3.821)	(3.393)
Supplier or Customer Shock		16.013***		12.352***
		(3.904)		(2.273)
Supplier or Customer:				
Controls	-	Yes	-	Yes
Province*Industry Fixed Effects	-	Yes	-	Yes
Fixed Effects	Yes	No	Yes	No
Firm:				
Controls	Yes	Yes	Yes	Yes
Province*Industry Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,114,421	1,114,421	1,119,169	1,119,169

Panel B. TABLE 3 first-stage results

Dependent Variable:	Own Shock	Own Reduction of Bank Debt	Own Shock	Own Reduction of Bank Debt
	Panel A Table 3: Supplier		Panel B Table 3: Customer	
	(1)	(2)	(1)	(2)
Own Bank Net Interbank Position Shock				
Own Bank Net Interbank Borrowing Shock	0.356***	6.686***	0.375***	5.492***
	(0.097)	(1.741)	(0.083)	(1.205)
Supplier Bank Net Interbank Position Shock				
Supplier Fixed Effects	Yes	Yes	Yes	Yes
Firm:				
Controls	Yes	Yes	Yes	Yes
Province*Industry Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.499	0.599	0.525	0.554
Observations	1,114,421	1,114,421	1,119,169	1,119,169

Notes: This table reports first-stage estimates for Table 2 (Panel A) and Table 3 (Panel B); note that there are two columns with two different first-stage regressions. See Section 4 and 5. Observations are at the level of the firm-supplier or firm-customer. Panel A shows the first stage of some of the IV estimation showed in Table 2: columns 1 and 2 of Panel A and Panel B, respectively. Panel B shows the first stage of some of the IV estimation showed in Table 3: columns 1 and 2 of Panel A and Panel B, respectively. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for clustering at the firm, main bank and supplier or customer level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE B6:
NODE-LEVEL: FIRM-LEVEL CHANGE IN CREDIT DUE TO BANK SHOCKS

Dependent Variable:	Change Credit		
	(1)	(2)	(3)
	2009	2008	2007
Direct Shock	-5.704**	1.364	-0.211
	(2.948)	(7.759)	(3.831)
Firm Controls	Yes	Yes	Yes
Industry & Zip Code Fixed Effects	Yes	Yes	Yes
R-squared	0.653	0.546	0.496
Observations	150,510	92,309	87,521

Notes: This table reports estimates from WLS, where observations are at the level of the firm, on (dependent variables) change in log credit for the crisis and before. Direct shocks are dummy variables that take the value of one if the firm suffered a negative bank loan supply shock at the beginning of its corresponding year, and zero otherwise (see also Table 1 and Section 4 and 5). Coefficients for each regressor are listed in the first row, while robust standard errors are reported in the row below (corrected for clustering at the level of the main bank). In each column, the word Yes indicates that the set of characteristics or fixed effects is included, No that is not included and - that is comprised by the set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

TABLE B7:
SUMMARY STATISTICS ON THE CUSTOMER-SUPPLIER DATASET

	Num. Obs.	Mean	S.D.	P25	Median	P75
		Link Level				
Links by year:						
2008	2328908	53,357.92	1,484,740.00	4,961.21	9,423.18	24,396.64
2009	2040869	46,294.92	1,165,135.00	4,843.57	8,965.56	22,461.09
Links appearing in both years:						
2008	1399585	73,308.43	1,848,943.00	6,451.00	13,327.04	35,568.10
2009	1399585	58,657.07	1,389,605.00	5,556.98	10,864.73	28,150.53
		Node Level				
2008						
Suppliers:						
Number of Customers	189108	12.32	68.56	2.00	4.00	11.00
Sales to Customers	189108	657,114.90	10,470,280.00	28,291.50	103,008.00	348,174.50
Customers:						
Number of Suppliers	230173	10.12	19.96	3.00	6.00	12.00
Purchases from Suppliers	230173	539,879.50	7,365,801.00	26,788.00	87,423.00	275,191.00
2009						
Suppliers:						
Number of Customers	185224	11.02	78.00	2.00	4.00	10.00
Sales to Customers	185224	510,095.20	8,509,789.00	23,577.00	81,851.00	273,903.20
Customers:						
Number of Suppliers	224924	9.07	18.39	2.00	5.00	10.00
Purchases from Suppliers	224924	420,061.30	6,082,869.00	21,331.80	68,209.00	215,061.80

Notes: This table reports means, standard deviations and first/second/third quartiles of annual bilateral transactions for 2008 and 2009 (Link Level), as well as the number of suppliers/customers and sales/purchases from/to suppliers/customers for years 2008 and 2009 (Node level). A firm is a supplier (customer) if it has at least one customer (supplier) in the network in a given year. Link $i \to j$ between two firms appears in both years if i reports a sale to j (or j reports a purchase from i) in both 2008 and 2009.

For Online Publication — Appendix C: Figures

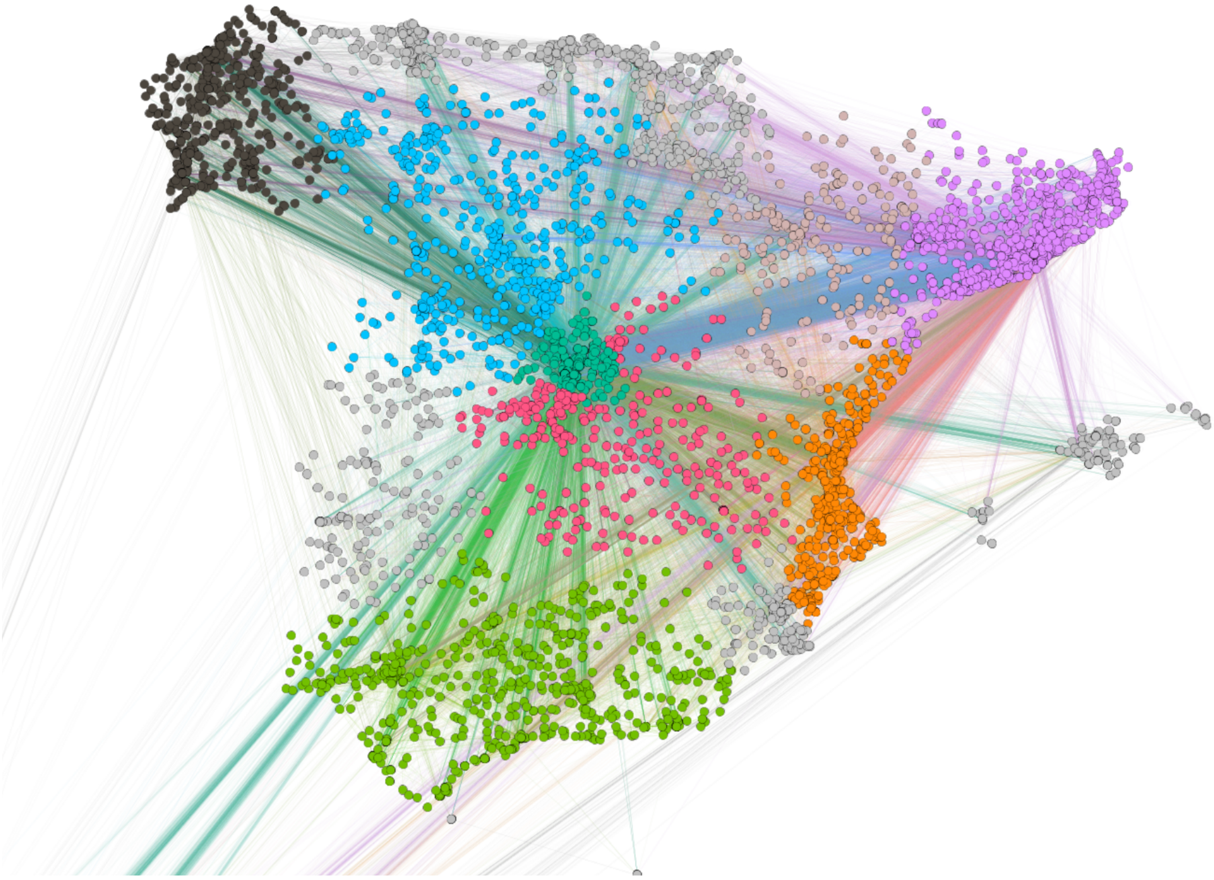

Figure 1: *Production network of Spain.* For visual clarity, the flows are aggregated at the zip-code level – that is, nodes represent all zip-code areas, and links indicate the transactions between firms located at corresponding zip-codes. The layout is based on the geographical coordinates of the corresponding zip-code areas, with the colors signal different autonomous regions.

Figure 2: *Production network of the autonomous region "Comunidad Valenciana." – direct and indirect connections.* We aggregate firms on the zip-code level. The size of a node is proportional to the aggregate sales of all firms in the same zip-code location. The thickness of a link is proportional to the value associated to that link. For visibility we keep only links that are in the 90th percentile with respect to their value. The links in the leftmost figure indicate direct connections. The links in the middle network represent indirect connections of length 2 (the network whose adjacency matrix is $\mathbf{G}^2$). The links in the rightmost figure indicate that two nodes are not directly connected but are indirectly connected through a path of length 2. The layout is based on the geographical coordinates of the corresponding zip-code areas.