Money Illiquidity*

Dmitry Livdan
Haas School of Business
University of California, Berkeley
Berkeley, CA 94720

Norman Schürhoff
Faculty of Business and Economics and Swiss Finance Institute
University of Lausanne
CH-1015 Lausanne, Switzerland

Vladimir Sokolov
ICEF
Higher School of Economics
Moscow, Russian Federation

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Abstract

Disruptions to the payment system cause money to become illiquid. We show both theoretically and empirically that money illiquidity severely impairs economic activity through two channels: firms' direct loss of payment access and a payment network externality that amplifies the initial shock. We develop an equilibrium model in which payment shocks disrupt firms' access to bank-intermediated payment services and propagate upstream through firms' input-output network. Firms' resilience to payment disruptions is captured by the elasticity of the firm's eigenvector centrality to the payment shock. Using 133 million transactions from the Russian payment system, we quantify how payment disruptions spill over to the real economy. A banking panic in 2004 originating from the foreclosure of two mid-sized banks resulted in over 50% of interbank connections being severed, leading to disruptions in firm-to-firm payments that are persistent and asymmetric, hurting payment-sending firms more than payment-receiving firms. We estimate that a payment shock originating at a firm's own/supplier/customer banks reduces firm's revenue growth by 2.5%/3.1%/7%. Upstream/downstream firms' resilience dampens payment shock pass-through by 0.61/0.26.

JEL Classification: G21

Key words: Payment system, payment disruption, network economy, shock propagation, real resilience

1 Introduction

The payment system is one of the most critical parts in the plumbing of the financial system. It facilitates money flows that make the financial system and real economy function. If payments get "clogged," money becomes illiquid. Economic agents can then no longer settle accounts in a fast and reliable manner, economic activity declines, and consumer welfare shrinks. Understanding the functioning of the payment system is therefore as important as grasping the nature of money itself. In traditional models of banking and monetary policy, the payment system is assumed to be frictionless.[1] In practice, stress to the payment system occurs regularly.[2] However, little is known about how severely payment shocks can impair economic activity, how payment shocks propagate and amplify through bank-firm and firm-firm interactions, and what firms and sectors are more resilient to payment system disruptions than others?

To address these open issues, we start by developing an equilibrium model in which payment shocks disrupt firms' access to bank-intermediated payment services. The production side of the model builds on a static multisector model by Acemoglu et al. (2012) in which each sector operates a constant returns-to-scale production technology subject to a sector-specific productivity shock. The sectoral technology takes outputs of other sectors as intermediate input factors thus linking all sectors into an input-output production network. We modify the static input-output production network of Acemoglu et al. (2012) in two key ways, by (i) introducing an internal factor independent of the outside factors into the production technology and (ii) allowing for access-to-payment shocks. Unlike productivity shocks affecting external and internal production factors equally, shocks to the payment system, originated in the financial sector unrelated to the production sector, have a differential impact on them. Specifically, by altering firms' ability to pay for external inputs, shocks to the payment system make firms more/less reliant on internal production factor.

Payment system disruptions, hence, propagate upstream and diminish firms' growth and prof-

[1] The New Monetarist approach explicitly models frictions in monetary exchange (Williamson and Wright, 2010).

[2] September 2001 (09/11), September 2008 (Lehman), September 2019 (repo blowup), and March 2020 (Covid-19 pandemic) are four episodes of money illiquidity that illustrate how strains in money markets can originate and spread. See Testimony on "Perspectives on Money Market Mutual Fund Reforms," June 21, 2012 by SEC Chairman Mary L. Schapiro, retrieved at https://www.sec.gov/news/testimony/2012-ts062112mlshtm, FEDS Notes "What Happened in Money Markets in September 2019?," February 27, 2020 by Sriya Anbil, Alyssa Anderson, and Zeynep Senyuz, retrieved at https://www.federalreserve.gov/econres/notes/feds-notes/what-happened-in-money-markets-in-september-2019-20200227.htm, and Copeland, Duffie, and Yang (2021).

itability and distort the network structure of firm-to-firm payment flows between customers and suppliers. We show that a firm's resilience to payment disruptions can be captured by the elasticity to payment shocks of the firm's eigenvector centrality in the firm-to-firm input-output network of payment flows. GDP aggregates all payment shocks. Firms' eigenvector centrality captures the pass-through rate of payment shocks to GDP.

Using transaction-level data from the Russian payment system, we quantify how payment disruptions spill over to the real economy. A banking panic in 2004 originating from the foreclosure of two mid-sized banks resulted in a panic that caused over 50% of interbank connections to be severed. The interbank panic spilled over to the payment system and lead to disruptions in firm-to-firm payments. We use banks' interbank connection loss and firms' pre-panic exposure to these banks as a source of identification for firm-specific payment shocks. While the payment disruptions were transitory, we find that they lead to persistent and asymmetric declines in firm growth, profitability, other performance metrics, as well as to declining firm-to-firm payments, hurting money-sending firms more than money-receiving firms.

Consistent with the model, firms' payment network centrality declines after the payment shock. Payment shocks depress firm growth and profitability for several month after the initial shock. In particular, firm growth declines with the firm's own loss of access to payments. Moreover, not only firms' own payment shocks but other firms' payment shocks in the firm-to-firm network impact revenue growth. In particular, payment shocks propagate upstream. Firm growth declines with payment shocks of its customers more than suppliers. In the cross-section of firms, the model predicts that more central firms are more exposed to payment shocks. Eigenvalue centrality aggregates how payment shocks of customers and suppliers affect firms. Consistent with this notion, we find that more eigenvector-central firms are more sensitive to payment shocks and experience a large decline in growth. To measure a firm's resilience to payment shocks, we compute the change in each firm's eigenvector centrality before and after the interbank panic. We find that more resilient firms are less affected through payment shocks and their propagation that captures shocks originated at different firms.

In practice, payments get routed through a settlement system traditionally maintained by banks. The asyncronicity of money inflows and outflows exposes banks to short-term liquidity imbalances that they settle in the interbank market.[3] The interbank market allows banks in normal times to manage the liquidity mismatch that exists due to illiquid loans and securities on their balance sheet (Allen and Gale (2000); Bianchi and Bigio (2020)). However, the unsecured nature of interbank loans can cause the interbank network to freeze, as has happened during the financial crisis of 2008 and the Russian banking panic of 2004 (Afonso *et al.* (2010); Acharya and Merrouche (2013); Heider *et al.* (2015); Degryse *et al.* (2019)). Faced with uncertainty about their own and other banks' ability to manage imbalances externally, banks start hoarding liquidity and stop or slow down clients' payments for goods and services to other banks—banks run on the payment system.

We empirically document the payment systems run of 2004 and quantify its direct and indirect effects on the real economy. We show that the payment system disruption hinders firms' ability to effectuate payments to each other in the short term, thus deteriorating firms' liquidity conditions and financial flexibility. In the long term, it causes both a decline and a shift in firm-to-firm business relations. We show how a short-lived illiquidity shock that originates in the interbank market spills over to the firm-to-firm payment system thus triggering a system-wide payment system run. We document run dynamics and quantify the short- and long-term consequences for the real economy that include firms' financial conditions, firm-to-bank financial relations, and firm-to-firm business relations.

We use the most granular transaction-level data from the Moscow branch of the Central Bank of Russia (CBR)[4] to study the effects of the banking panic of 2004 on the functionality of a payment system. In 2004, Russia used a deferred net settlement (DNS) system that settles transfers between banks at the end of each business day (Bech et al. (2008)). The advantage of DNS systems is that banks save on intra-day liquidity, but they face the end-of-day risk of settlement failure against each other. On May 13, 2004, the CBR unexpectedly withdrew the banking licence of Sodbiznesbank, a bank that was involved in money laundering. The withdrawal caused the immediate collapse of another bank, Credittrust, that had the same owner as the closed bank. Following these events, the head of the Federal Financial Monitoring Service made a statement during the last week of May

[3]Banks not only facilitate payments but also cover timing gaps that arise between cash expenditures and receipts which reduces the cost of liquidity management for economic agents (e.g., Acharya *et al.* (2013); Acharya *et al.* (2014)).

[4]This data has been used in other research (Mironov (2013) and Mironov and Zhuravskaya (2016)).

2004 that "at least ten other banks are about to lose their banking licences for money laundering reasons." This statement caused an immediate banking panic. The interbank loan market effectively shut down, which resulted in a massive drop in bilateral lending relations in the interbank market. We combine detailed payments flow data that identifies sender firm, sender bank, receiver bank, and receiver firm for 133 million transactions between 1.168 mln. unique paying entities that use 1,413 sending banks and 1.245 mln. receiving entities and 1,418 receiving banks with time-stamped interbank unsecured short-term loan data between banks.

Transaction-level payment system data from the CBR for goods and services between firms, matched with information on the payment and receiving banks that intermediate these payments, allow to identify how the shift in the topology of the interbank network affects the firm-to-firm payment network. Most importantly, our setting allows to explore how the negative shock to the interbank network alters the flow of payments for goods and services in the firms-to-firm network. In order to trace the real effect of the interbank market panic on interfirm payments, we create a firm-level variable that captures the variation in firms' *ex-ante* exposure to the banking crisis. For each firm, we calculate the weighted average of the degrees to which banks dealing with this firm were affected by the panic where weights are pre-shock shares of these banks in firm's total payments to all other firms. This variable takes higher values for a given firm if banks through which the firm routes payments experienced a significant cut-off in the interconnectedness during the panic and the share of these banks is high in total flow of firm's payments. Note that after collapsing the banking dimension and moving to the paying firm-receiving firm panel structure we cannot employ interacted firm-firm fixed effects any longer as in the previous analysis. Here, we use firm-level fixed effects and first examine how payments growth *within the same paying firm* differs across receiving firms with high an low banking panic exposure.

Related literature: The closest to our paper is Copeland, Duffie, and Yang (2021) who document intraday payment timing stress in the U.S. financial system leading up to the mid-September 2019 Treasury repo blowup. They document that show large aggregate reserve balances held by the large dealer banks are required to stabilize liquidity in funding markets. When reserves became low, presumably because of post-crisis liquidity rules and supervision, banks started to delay payments causing payment timing stresses and repo rate spikes. The payment system was ultimately not disrupted because of swift Fed intervention. By contrast, we document the impact of an episode were the central bank was unable (or unwilling) to fully internalize the consequences of payment system stress. Payment timing stress in the Russian 2004 episode extended across days and adversely impacted real economic activity.

In a similar vein, Duffie and Younger (2019) and Eisenbach, Kovner, and Lee (2021) resort to counterfactual analysis and simulations to quantify the vulnerability of the payment system to cyber attacks and other disruptions. We provide empirical evidence using granular payment systems data from a large-scale financial system failure in Russia 2004 on the financial and real importance of the payment system.

After the recent financial crisis, there has been a growing interest in designing optimal financial architecture. Some of the recurring questions have been how the density and structure of connections in the interbank network affect the stability of the system and how financial shocks get transmitted to the real sector (e.g., Acemoglu *et al.* (2015), Gofman (2017)). We contribute to this debate by showing how the financial and real sectors are intertwined through the payment system.

Banks play two major roles in the functioning of the economy. They provide lending and intermediation services to economic agents, such as consumers and businesses. Banks' important role in lending is well understood and the transmission of lending shocks to the real economy has been extensively studied (e.g., Acharya *et al.* (2018), Chava and Purnanandam (2011), Dell'Ariccia *et al.* (2008), Khwaja and Mian (2008), Paravisini *et al.* (2014)).

Banks' role in intermediating payments between economic agents is of significant importance but has received little attention, mainly due to lack of granular data. We provide evidence on how banks' (in)ability to intermediate payments affects real activity. We document the extent and granular structure of spillover on interfirm payments for goods and services. To do so, we use the shock to the interconnectedness of paying and receiving banks in the interbank network to measure firms' heterogenous exposure to the shocks and then study the percolation in the firm-to-firm input-output network.

Our paper is also related to the burgeoning economic network literature. Acemoglu et al. (2012) build a multisector production model to study the percolation of sector-specific productivity shocks.

We modify the static input-output production network of Acemoglu et al. (2012) in two key ways; by introducing an internal production factor independent of the outside production factors into the production technology and by allowing for access-to-payment shocks.

The remainder is organized as follows. Section 2 develops the model to motivate our empirical analysis of payment system shocks. Section 3 describes the granular data for the Russian Payment System used in the analysis. In Section 4 we test model's predictions. Section 5 concludes.

2 Model

To motivate our empirical analysis of payment system shocks, we develop a model of a dynamic multi-firm production economy in which input-output relations yield a network structure of payments between customer and supplier firms. The production side of the model builds on a static multisector model by Acemoglu et al. (2012) in which each sector operates a constant returns-to-scale production technology subject to a sector-specific productivity shock. The sectoral technology takes outputs of other sectors as intermediate input factors thus linking all sectors into a input-output production network. We modify the static input-output production network of Acemoglu et al. (2012) in two key ways; by introducing an internal production factor independent of the outside production factors into the production technology and by allowing for access-to-payment shocks. Unlike productivity shocks affecting external and internal production factors equally, shocks to the payment system, originated in the financial sector unrelated to the production sector, have a *differential* impact on them. Specifically, by altering firms' ability to pay for external inputs, shocks to the payment system make firms more/less reliant on internal production factor. Consequently, the topology of the input-output network readjusts to accommodate the new firm-to-firm flows of goods which, in turn, affects firm-level cash flows and aggregate output.

2.1 Setup

There are $i = 1, \ldots, N$ competitive firms in the economy. The output good produced by firms can be used either for consumption or for production as an input. Firms use Cobb–Douglas technologies with the output of firm i at time Z, denoted as x_{it}, given by

$$x_{it} = e^{\varepsilon_{it}}(\prod_{j=1}^{N} x_{ijt}^{w_{ij}})^{1-z_{it}} k_{it}^{z_{it}}, \qquad z_{it} \in [0,1], \tag{1}$$

where x_{ijt} denotes the amount of external input good produced by firm j used in the production by firm i and k_{it} are internal inputs. As in Acemoglu et al. (2012), the exponent $w_{ij} \geq 0$ designates the share of good j in the total input use of firms i. We introduce two idiosyncratic stochastic productivity shocks—one to total factor productivity, ε_{it}, and another affecting the relative productivity of external and internal inputs, z_{it}. We interpret z_{it} as payment system shocks affecting firms ability to make external payments and, hence, the sourcing of external inputs. We assume that all shocks are independent across firms and time.

The M-shocks originate in banking services and are not a direct input to production in our setting. The distinction we highlight is externally sourced production factors require external payment and are, therefore, subject to payment system shocks while internal factors are insulated from these shocks. To make this distinction concretely, assume external factors require payment before delivery, while internal factors do not. Internal factors include know-how and ideas, owned production facilities, installed machinery, real estate, and local labor that can be paid without access to banking services. A higher/lower z_{it} means firm i is less/more able to make payments to its suppliers at time Z, in which case it must rely more/less on internal production factors. These modelling assumptions allow us to study how payment disruptions originating in the financial system propagate through the real economy.

The M-shocks are important for generating cross-sectional variation in cash flows across firms. We show later that without z-shocks the profit margins and market shares of the firms remain constant through time. Unlike us, Acemoglu et al. (2012) focus on how idiosyncratic productivity shocks lead to aggregate fluctuations. Their model assumes z_{it}'s do not vary across firms or over time. As a result, each firm or sector represents a constant share of the aggregate. This assumption makes it difficult for us to study the implications of payment system disruptions affecting payments between customer and supplier firms and the effect of alternative network structures on the aggregate impact of payment system shocks.

The weights w_{ij} are equal to the entries in the input-output table with $w_{ij} = 0$ if firm i does not use good j as input for production. The degree centrality of a firm captures its direct customer-supplier connections with other firms. The in-degree centrality of firm i, $d_i^{in} \equiv \sum_{j=1}^{N} w_{ij}$, accounts for the input relations with suppliers and the out-degree centrality, $d_i^{out} \equiv \sum_{j=1}^{N} w_{ji}$, for the output relations with customers. Upstream firms have high out-degree, while downstream firms have high in-degree.

Denote by p_{it} the price of the goods produced by firm i and p_{kt} the cost of internal factors. The operating profits of firm i at time Z equal

$$\Pi_{it} = p_{it}x_{it} - p_{kt}k_{it} - \sum_{j=1}^{N} p_{jt}x_{ijt}. \tag{2}$$

Financial markets are complete and there exists a stochastic discount factor m_t. The market value of firm i is, hence, $S_{it} = \mathbb{E}\left(\sum_{s=t}^{\infty} m_s \Pi_{is}\right)$.

Consumers: To close the model we assume a representative consumer in the economy with Cobb-Douglas utility over consumption c_{it} from firm i. Her utility function is given by:

$$U = \mathbb{E}\left(\sum_{t=0}^{\infty} \beta^t \prod_{i=1}^{n} c_{it}^{\gamma/N}\right), \tag{3}$$

where β is the rate of time preference and $1/\gamma$ is the risk aversion coefficient. The consumer is endowed with q_{i0} shares of firm i, holds q_{it} shares in firm i at time Z and supplies internal input $k_t = \sum_{i=1}^{N} k_{it}$ at rate p_{kt}. We normalize the total number of shares for each firm to one. The consumer maximizes her utility subject to the standard budget constraint with the Lagrange multiplier μ_t.

It is easily shown that the consumption shares are the same for all firms: $p_{it}c_{it} = p_{jt}c_{jt} : \forall i, j$. Together with market clearing discussed later, this also implies that the consumption shares are given by $p_{it}c_{it} = C_t/N : \forall i$, where the aggregate consumption/GDP in the economy is $C_t = p_{kt}k_t + \sum_{i=1}^{N} \Pi_{it}$.

DEFINITION 1: *The competitive equilibrium in the economy is defined by quantities* $(x_{ijt}, k_{it}, x_{it})$, *consumption bundle c_{it}, prices p_{it}, p_{kt}, and S_{it} such that:*

(i) *Firms maximize profits Π_{it},*

(ii) *The representative consumer maximizes her period-by-period utility U_t,*

(iii) *The factor markets clear at all times*

$$\begin{aligned} c_{it} + \sum_{j=1}^{N} x_{jit} &= x_{it} \quad \forall i = 1, \dots, N :, \\ \sum_{i=1}^{N} k_{it} &= k_t, : \end{aligned}$$

(iv) *The stock market clears at all times: $q_{it} = 1 \quad \forall i = 1, \dots, N$.*

The next subsection outlines the solution to the model.

2.2 Model solution

To describe the equilibrium, it is useful to establish some notation. Collect the payment shocks $z_{it}, i = 1, ..., N$, in a diagonal matrix M_t and the factor input weights in an $N \times N$ matrix $W = [w_{ij}]_{N \times N}$. The composite matrix Σ_t with typical element $\Sigma_{ijt} = w_{ij}(1 - z_{it}) \geq 0$ embeds in contrast to Acemoglu et al. (2012) both the z-shocks and the factor weights w_{ij}:

$$\Sigma_t = M_t * W = \underbrace{\begin{bmatrix} 1 - z_{1t} & 0 & \cdots & 0 \\ 0 & 1 - z_{2t} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 - z_{Nt} \end{bmatrix}}_{\text{Payment shocks } M_t} * W =$$

$$= \begin{bmatrix} w_{11}(1 - z_{1t}) & w_{12}(1 - z_{1t}) & \cdots & w_{1N}(1 - z_{1t}) \\ w_{21}(1 - z_{2t}) & w_{22}(1 - z_{2t}) & \cdots & w_{2N}(1 - z_{2t}) \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}(1 - z_{Nt}) & w_{N2}(1 - z_{Nt}) & \cdots & w_{NN}(1 - z_{Nt}) \end{bmatrix}. \tag{4}$$

Define the Leontief inverse $L_t = (I - \Sigma_t)^{-1} = I + \sum_{s=1}^{\infty} \Sigma_t^s$ with elements l_{ijt}. The power series expansion of the Leontief inverse (assuming the spectral radius is $\rho(L) < 1$) illustrates how L

encodes an infinite sum of shock contributions. The first-order contribution accounts for the direct effect while the second-order contribution accounts for the impact of the firm's neighbors in the input-output network. The chain of kth order effects is encoded in the kth term of the expansion and shows how z-shocks propagate through the economy.

The set of eigenvector centralities $\delta_t = \frac{1}{N} L_t' \mathbf{1}$ capture the firms' exposures to z-shocks by measuring their global position in the directed network of flows between firms. The eigenvector centrality δ_{it} measures firm i's Domar weight adjusted for payment shocks:

$$\delta_{it} = \frac{1}{N} \sum_{j=1}^{N} l_{jit}. \tag{5}$$

The aggregate term

$$\psi_t = z_t' \delta_t = \sum_{i=1}^{N} z_{it} \delta_{it}, \tag{6}$$

measures the income share of the internal factors.

We obtain the following characterization of the goods market equilibrium.

PROPOSITION 1: *With ϵ_t defined as a vector of composite shocks with elements ϵ_{it} given by*

$$\epsilon_{it} = \varepsilon_{it} + z_{it} \ln \left(\frac{z_{it} \delta_{it}}{\psi_t} k_t \right) + \sum_{j=1}^{N} \Sigma_{ijt} \ln \left(\Sigma_{ijt} \frac{\delta_{it}}{\delta_{jt}} \right), \tag{7}$$

the equilibrium vector of production equals $\ln x_t = L_t \epsilon_t$, with typical element

$$\ln x_{it} = l_{it}' \epsilon_t = \sum_{j=1}^{N} l_{ijt} \epsilon_{jt} = \ln \mathcal{Z}_{it} + \sum_{j=1}^{N} l_{ijt} \varepsilon_{jt} + \sum_{j=1}^{N} l_{ijt} z_{jt} \ln k_t, \tag{8}$$

and a firm-specific term

$$\mathcal{Z}_{it} = \prod_{k=1}^{N} \left\{ \left(\frac{z_{kt} \delta_{kt}}{\psi_t} \right)^{l_{ikt} z_{kt}} \prod_{j=1}^{N} \left[\Sigma_{kjt} \frac{\delta_{kt}}{\delta_{jt}} \right]^{l_{ikt} \Sigma_{kjt}} \right\}. \tag{9}$$

Expression (8) shows that the firm i's output depends on its own productivity shock, ε_{it}, and productivity shocks in all directly and indirectly connected firms, $\varepsilon_{j \neq it}$, scaled by $l_{ij \neq it}$. The output of firms with low in-degree centrality for which $l_{ij \neq it}$ is small, that is, upstream and central firms, depends mostly on their own productivity shock, ε_{it}. The output of firms with high in-degree centrality for which $l_{ij\neq it}$ is large, that is, downstream and peripheral firms, depends more strongly on productivity shocks of the connected firms, $\varepsilon_{j\neq it}$. Nonetheless, payment shocks in every firm affect its supply and, hence, the output in all other firms so long as the l_{ijt} elements are non-zero. Also, payment-system dependent firms, that is, firms with large M, and "downstream" firms, that is, firms with large value of $\sum_{j=1}^{N} l_{ijt} z_{jt}$, depend more strongly on internal factors k_t than other firms.

Equilibrium prices, p_{it}, adjust to compensate for the payment system shocks. Even with fully flexible prices, they buffer the demand effects of ε- and M-shocks differently depending on the firms' centrality. Total revenues of firm i, $X_{it} = p_{it}x_{it}$, yield a revenues vector, X_t, that can be determined explicitly:

$$X_t = \frac{1}{N}(I - \Sigma_t')^{-1}\mathbf{1}C_t = \frac{1}{N}L_t'\mathbf{1}C_t. \tag{10}$$

The equilibrium profit margin varies one to one with the z-shocks and the in-degree of the firm:

$$\pi_{it} = (1 - z_{it})(1 - d_i^{in}), \tag{11}$$

where the in-degree centrality of firm i, d_i^{in}, accounts for the input relations with suppliers. Factor-intensive firms naturally generate lower profits margins. Condition (11) shows the profitability of more factor-intensive firms is less sensitive to payment shocks. Finally, the income share of internal factors as part of GDP is given by

$$K_t \equiv p_{kt}k_t = \psi_t C_t. \tag{12}$$

To determine how cash flows across firms depend on payment disruptions, we need to compute goods prices. Normalize the ideal price index as $\frac{1}{N}\prod_{i=1}^{N} p_{it}^{-1/N} = 1$. Since $X_{it} = \delta_{it}C_t$, this implies that $C_t = \frac{p_{it}x_{it}}{\delta_{it}}, \forall i$. Then GDP is given by

$$C_t = \prod_{i=1}^{N}\left(\frac{p_{it}x_{it}}{\delta_{it}}\right)^{1/N} = \frac{1}{N}\prod_{i=1}^{N}\left(\frac{x_{it}}{\delta_{it}}\right)^{1/N}. \tag{13}$$

Goods prices satisfy the inverse aggregate demand function $p_{it} = \frac{\delta_{it}}{\psi_t}\frac{k_t}{x_{it}}p_{kt}$, and the equilibrium factor price equals $p_{kt} = \psi_t C_t / k_t$. Firms' expenses on internal factors are $K_{it} = \delta_{it} z_{it} C_t$ and firm-to-firm payment flows correspond to the entries in the input-output flow table. Finally, aggregate profits equal $\sum_{i=1}^{N} \Pi_{it} = (1 - \psi_t) C_t$.

LEMMA 1: (i) Firm: *Firm revenues and profits are proportional to each firm's eigenvector centrality:*

$$\begin{aligned} \text{Firm revenues: } X_{it} &= \delta_{it} C_t, & (14) \\ \text{Firm profits: } \Pi_{it} &= \pi_{it} \delta_{it} C_t. & (15) \end{aligned}$$

(ii) Firm-to-firm: *Firm-to-firm payment flows are proportional to the firms' z-shocks and their eigenvalue centrality* δ:

$$\text{Firm-to-firm payment flows} : X_{ijt} = \Sigma_{ijt} \cdot \underbrace{\delta_{it} C_t}_{\text{Firm revenues } X_{it}}. \tag{16}$$

(iii) Aggregate: *The GDP aggregates all composite payment shocks* ϵ_{jt} *given by (7) according to:*

$$\text{GDP (in log)} : \ln C_t = -\ln N - \frac{1}{N} \sum_{i=1}^{N} \ln \delta_{it} + \sum_{i=1}^{N} \delta_{it} \epsilon_{it}. \tag{17}$$

Intuitively, higher centrality δ provides pricing power because many firms rely on central inputs. This implies profits tend to be larger in firms with large δ that are more central in the economy. Firm revenues X_t and profits Π_t in this input-output economy are given by an eigenvector corresponding to the unit eigenvalue of an augmented adjacency matrix that adjusts for z-shocks. Define the $N \times N$ augmented adjacency matrix Ω_t with a typical element

$$\Omega_{ijt} = \frac{1}{N}(z_{it} + \pi_{it}) + \Sigma_{ijt}. \tag{18}$$

Elements Ω_{ijt} depend on both the factor weights w_{ij} and the M-shock.

PROPOSITION 2: *Goods market clearing implies that firms' revenues adhere to a network structure* $X_{it} = \sum_{j=1}^{N} \Omega_{jit} X_{jt}$ *or, in matrix form,* $\Omega_t' X_t = \mathbf{1} X_t$*, that depends on the factor weights* *w and M-shocks of all firms in the economy.*

This result means the equilibrium firm revenues X_t are equal to the vector of eigenvector centralities of the firms. The reason is all N firms make supply (and intermediate goods demand) decisions taking goods prices as given. Market clearing ties the equilibrium goods prices back to firms' supply decisions. Eigenvectors represent the natural solution to such N-dimensional linear fixed point problems. Note also the switch of indices in the adjacency weight Ω_{jit}. This shows it is the out-degree—and not the in-degree—of the firm that matters for its importance in the economy.

2.3 Resilience to M-shocks

The previous result implies that payment shocks spill over to other firms and propagate through the entire input-output network. Firms have different resilience to the progagation of payment shocks. To determine the incremental effect of payment shocks z_t, consider the Leontief inverses before and after the shock, $L(0) = (I - W)^{-1} = I + \sum_{s=1}^{\infty} W^s$ and $L(z_t) = (I - \Sigma_t)^{-1} = I + \sum_{s=1}^{\infty}(M_t \cdot W)^s$ since $\Sigma_t = M_t \cdot W$ as defined in (4). $L(0)$ corresponds to the ε-shock propagation mechanism in Acemoglu et al. (2012). Then M-shocks propagate according to

$$L(z_t) - L(0) = (I - M_t \cdot W)^{-1} - (I - W)^{-1} = \sum_{s=1}^{\infty}((M_t \cdot W)^s - W^s). \tag{19}$$

The incremental change in eigenvector centrality $\delta_t = \delta(z_t)$ is, hence,

$$\begin{aligned} \delta(z_t) - \delta(0) &= \frac{1}{N} L(z_t)' \cdot \mathbf{1} - \frac{1}{N} L(0)' \cdot \mathbf{1} \\ &= \frac{1}{N} (\sum_{s=1}^{\infty}((M_t \cdot W)^s - W^s))' \cdot \mathbf{1} \leq 0. \end{aligned} \tag{20}$$

With transposed Leontief inverses before and after the shock, $\tilde{L}(0) = (I - W')^{-1}$ and $\tilde{L}(z_t) = (I - W' \cdot M_t)^{-1}$, using the tensor product $\otimes$ we can write the first-order expansion

$$\begin{aligned}
\delta(z_t) - \delta(0) &\approx \mathbf{D}\delta(0) \cdot z_t = \\
&= \frac{1}{N}\mathbf{D}\left((I - M_t \cdot W)^{-1\prime}\mathbf{1}\right)|_{M_t=I} \cdot z_t = \\
&= -\frac{1}{N}(\tilde{L}(0) \cdot \mathbf{1})' \otimes (\tilde{L}(0) \cdot W') \cdot z_t = \\
&= \underbrace{-[\delta(0) \otimes (W \cdot L(0))]'}_{\text{1st-order resilience } \mathcal{R}} \cdot z_t. \qquad (21)
\end{aligned}$$

The following result summarizes the first-order resilience of firms to payment shocks.

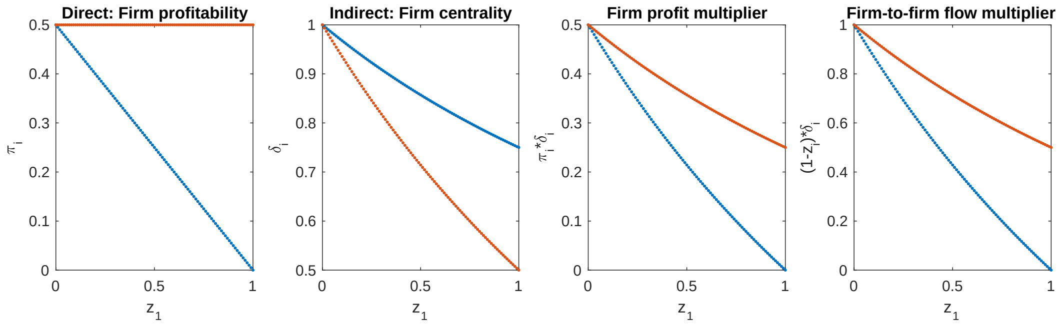
LEMMA 2: *Payment shocks originating at firm j spill over to firm i, affecting i's revenues, profits, and firm-to-firm payment flows according to Lemma 1 with incremental change in $\delta_{it}, \pi_{it}, \Sigma_{ijt}, \epsilon_{it}$ given by (19) and (20). Firm i is more resilient to M-shocks originating at firm j (z_{jt}), the less negative is i's M-sensitivity of its eigenvector centrality:*

$$\text{Resilience } \mathcal{R}_t \equiv \left[\frac{\partial \delta_{it}}{\partial z_{jt}}\right] = -[\delta(0) \otimes (W \cdot L(0))]' \leq 0, \qquad (22)$$

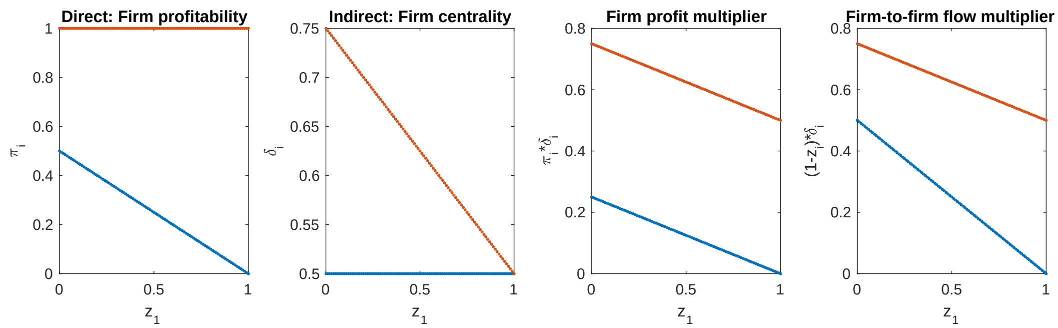
where $\delta(0)$ and $L(0)$ are the pre-crisis eigenvector centralities and Leontief inverse given input-output matrix W.

Lemma 2 illustrates that the network structure changes because of the propagation of payment shocks. As a result, the network centralities of the firms readjust. The higher the resilience of firm i, which is equivalent to $\mathcal{R}_t$ being less negative, the less do its revenues and profits drop due to payment shocks originating at j, that is, the less affected is firm i. $\mathcal{R}_t$ is an important characteristic capturing the cross-sectional response to M-shocks, both firm-specific and spilled-over through the firm-to-firm network from other firms. We use a simple example to illustrate the model's inner-workings in the next subsection.

Panel A: Symmetric economy with propagation of payment shock



Panel B: Downstream payment shock with upstream propagation



Panel C: Upstream payment shock without downstream propagation

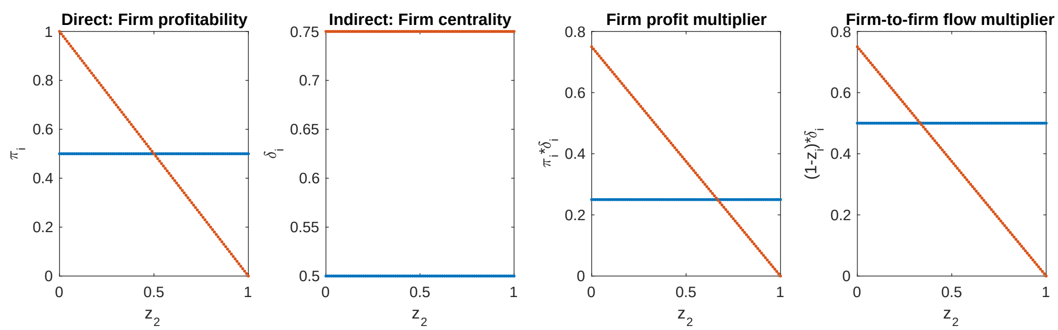


Figure 1: Direct and indirect impact of payment shocks

This picture shows the impact of M-shocks on input-output networks for three types of network structures. The first graphs plots firms' profitability π_i as a function of M-shocks. The second graph plots firms' eigenvector centrality δ_i as a function of M-shocks. The third graph plots firms' profit multiplier $\Pi_i/C = \pi_i * \delta_i$ as a function of M-shocks. The forth graph plots the firm-to-firm flow multiplier $X_{ij}/(w_{ij}C) = (1-z_i)*\delta_i$ as a function of M-shocks. In Panel A, we model a symmetric economy with $W = \begin{bmatrix} 0 & 0.5 \\ 0.5 & 0 \end{bmatrix}$. In Panels B and C, we model an asymmetric economy with $W = \begin{bmatrix} 0 & 0.5 \\ 0 & 0 \end{bmatrix}$ where firm 1 is customer and firm 2 is supplier. In Panel B, we model a payment shock originating at a customer. In Panel C, we model a payment shock originating at a supplier. The blue line corresponds to firm 1, and the red line to firm 2.

2.4 Model illustration

We use a simple 2-firm economy with

$$W = \begin{bmatrix} 0 & w_{12} \\ w_{21} & 0 \end{bmatrix},$$

to illustrates the inner-workings of the model.[5] The Leontief inverse $L = (I - \Sigma)^{-1}$ can be calculated to yield

$$L = \frac{1}{1 - w_{12}w_{21}(1-z_1)(1-z_2)} \begin{bmatrix} 1 & w_{12}(1-z_2) \\ w_{21}(1-z_1) & 1 \end{bmatrix},$$

from which we can immediately obtain each firm's Domar weight

$$\delta_1 = \tfrac{1}{2}\tfrac{1+w_{12}(1-z_1)}{1-w_{12}w_{21}(1-z_1)(1-z_2)},$$
$$\delta_2 = \tfrac{1}{2}\tfrac{1+w_{21}(1-z_2)}{1-w_{12}w_{21}(1-z_1)(1-z_2)}.$$

The expressions illustrate that δ_1 and δ_2 depend on both z_1 and z_2. The resilience matrix equals

$$\begin{aligned} \mathcal{R} &= -\frac{1}{2}\left(\frac{1}{1-w_{12}w_{21}(1-z_1)(1-z_2)}\right)^2 \\ &\quad \times \begin{bmatrix} w_{12}(1+w_{21}(1-z_2)) & w_{12}w_{21}(1+w_{12}(1-z_1))(1-z_1) \\ w_{12}w_{21}(1+w_{21}(1-z_2))(1-z_2) & w_{21}(1+w_{12}(1-z_1)) \end{bmatrix} \leq 0. \end{aligned}$$

When $w_{21} = 0$ and $w_{12} \neq 0$, firm 1 is customer and firm 2 is supplier. In this case, z_1 shocks affect firm 2's revenues and profits. That is, shocks propagate upstream from customer to supplier. By contrast, firm 1 is insulated from z_2 shocks so long as $w_{21} = 0$. When $w_{21} \neq 0$, z_2 shocks alter the network centrality of firm 1 and, hence, its revenues and profitability. In turn, firm 2 is insulated from z_1 shocks only if $w_{12} = 0$.

Figures 1 and 2 illustrate the effect of the payment shocks on both firms when only one of them is affected by payment shocks of different magnitudes. Figure 1 graphs the profitability, π_i, revenues scaled by the GDP, $X_i/C = \delta_i$, profit flow multipliers, $\Pi_i/C = \pi_i\delta_i$, and payment flow multipliers,

[5]We drop the time subscript for the sake of clarity for this example.

$X_{ij}/(w_{ij}C) = (1 - z_i)\delta_i$, for both firms as functions of z_1 and z_2. Figure 2 visualizes the network by graphing the directional payment flows, shown by a blue line with a thickness proportional to X_{ij}/C and the direction, that is, the relative order of i and j, shown by the arrow, and revenues, shown for each firm by a red circle with the area proportional to X_i/C, of both firms. We consider two alternative economies; symmetric, $w_{12} = w_{21} = 0.5$, and asymmetric, $w_{12} = 0.5$ and $w_{21} = 0$.

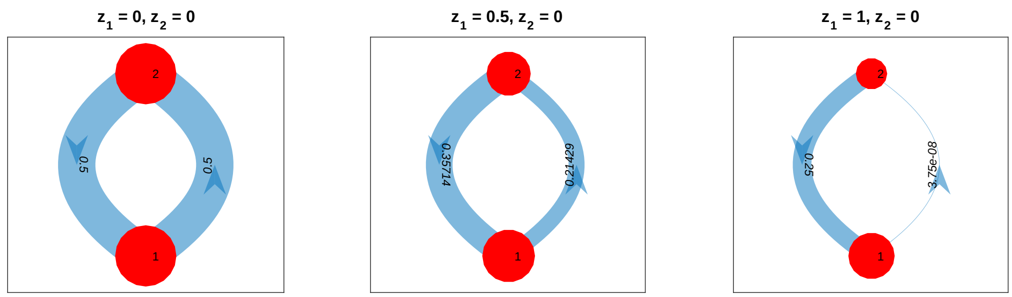
We start with a symmetric economy $w_{12} = w_{21} = 0.5$ and set $z_2 = 0$ for this exercise leading to

$$\pi_1 = \tfrac{1}{2}(1 - z_1), \delta_1 = \tfrac{3}{3+z_1}, \tfrac{\Pi_1}{C} = \tfrac{3(1-z_1)}{2(3+z_1)}, \tfrac{X_{12}}{w_{12}C} = \tfrac{3(1-z_1)}{3+z_1}, \mathcal{R}_{11} = -\tfrac{3}{(3+z_1)^2},$$
$$\pi_2 = \tfrac{1}{2}, \delta_2 = \tfrac{6}{3+z_1} - 1, \tfrac{\Pi_2}{C} = \tfrac{3-z_1}{2(3+z_1)}, \tfrac{X_{21}}{w_{21}C} = \tfrac{3-z_1}{3+z_1}, \mathcal{R}_{21} = -\tfrac{6}{(3+z_1)^2}.$$

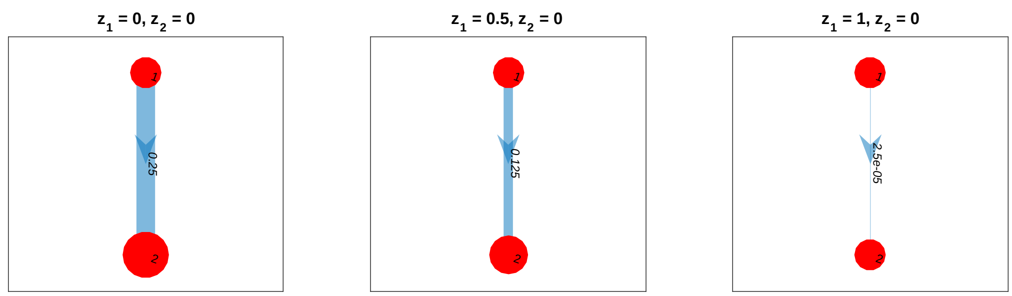
Panel A of Figure 1 graphs these four quantities in that order from left to right for the affected firm 1 (blue line) and the unaffected firm 2 (red line). In agreement with the relation (11), the profit margin, π_i, declines with z_1 for the affected firm 1 while it remains constant for the unaffected firm 2. The Domar weight for the unaffected firm 2, δ_2, declines faster with z_1 than the Domar weight of the affected firm 1, δ_1. This is because the payment shock z_1 reduces payment flows to the unaffected firm 2 by more than it reduces payment flows from it, thus making the unaffected firm 2 less "central" than the affected firm 1. This is clearly illustrated in the rightmost plot where $\frac{X_{21}}{w_{21}C} \geq \frac{X_{12}}{w_{12}C}$ for all z_1. Therefore, the affected firm's revenues are greater than the unaffected firm's revenues, $X_1 = \delta_1 C > X_2 = \delta_2 C$, for $z_1 \in (0, 1]$. However, since the unaffected firm 2 has higher profit margin than the affected firm, it also has higher profits, as illustrated in the third subplot from the left. Overall, these results show that the payment shocks affect symmetric firms asymmetrically mainly due to their asymmetric impact on the input-output network.

Panel A of Figure 2 further illustrates the impact of M-shocks on this two-firm network. We set z_1 to 0 (left subplot), 0.5 (middle subplot), and 1 (right subplot). Panel A of Figure 1 shows that revenues of the unaffected firm decline faster relative to revenues of the affected firm. Correspondingly, the red circle labeled 2 shrinks by more than the red circle labeled 1, going from the left subplot to the right subplot, implying that firm 1 becomes more central than firm 2. This is because as z_1 increases, firm-to-firm payment flows from the unaffected firm to the affected firm decline by less than flows from the affected firm to the unaffected firm, as illustrated by a thicker blue line showing flows from firm 2 to firm 1 when going from the left subplot to the right subplot. Thus, the payment shock makes the symmetric economy asymmetric by tilting a greater share of the equilibrium revenues towards the affected firm and by reducing payment flows from the affected to the unaffected firm by more than it reduces flows the other way.

Panel A: Symmetric economy becomes asymmetric and source of payment shock impacted less



Panel B: Upstream propagation is asymmetric—Payment shock originates at customer 1 and propagates to supplier 2



Panel C: Downstream propagation is symmetric—Payment shock originates at supplier 2 and affects customer 1 and supplier 2 symmetrically

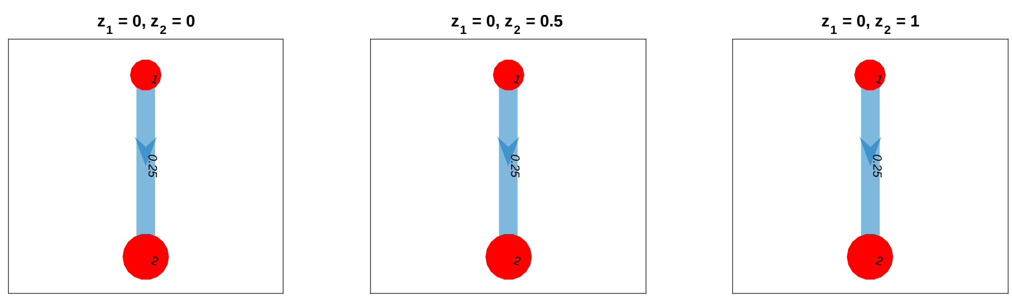


Figure 2: Impact of payment shocks in input-output networks

This picture shows the impact of M-shocks on input-output networks for three types of network structures. The shock originates at 1 and propagates to 2. The red nodes indicate the magnitude of firm i's X_i. The blue edges indicate the magnitude of the firm-to-firm flows X_{ij}. In Panel A, we model a symmetric economy with $W = \begin{bmatrix} 0 & 0.5 \\ 0.5 & 0 \end{bmatrix}$. In Panels B and C, we model an asymmetric economy with $W = \begin{bmatrix} 0 & 0.5 \\ 0 & 0 \end{bmatrix}$ where firm 1 is customer and firm 2 is supplier. In Panel B, we model a payment shock originating at a customer. In Panel C, we model a payment shock originating at a supplier.

Next, we consider the asymmetric economy with $w_{12} = 0.5$ $w_{21} = 0$. In this economy, we study the upstream, that is, payment shock originates in the supplier $z_1 \in [0,1]$ and $z_2 = 0$, and the downstream, that is, payment shock originates in the producer $z_1 = 0$ and $z_2 \in [0,1]$, propagation of the payment shock.

We start with the upstream shock propagation for which we have

$$\pi_1 = \tfrac{1}{2}(1-z_1), \delta_1 = \tfrac{1}{2}, \tfrac{\Pi_1}{C} = \tfrac{1-z_1}{4}, \tfrac{X_{12}}{w_{12}C} = \tfrac{1-z_1}{2}, \mathcal{R}_{11} = 0,$$
$$\pi_2 = 1, \delta_2 = \tfrac{3-z_1}{4}, \tfrac{\Pi_2}{C} = \tfrac{3-z_1}{4}, X_{21} = 0, \mathcal{R}_{21} = -\tfrac{1}{4}.$$

Panel B of Figure 1 graphs these four quantities in that order from left to right for the affected firm 1 (blue line) and the unaffected firm 2 (red line). The profit margin, π_i, declines linearly with z_1 for the affected firm while it is equal to 1 for the unaffected firm 2. The Domar weight for the unaffected upstream firm 2, δ_2, starts at 0.75 then declines with z_1 to the value of the Domar weight of the affected downstream firm 1, $\delta_1 = 0.5$, when $z_1 = 1$ and firms are no longer connected to each other. Therefore, the unaffected firm's revenues and profits are never less than the affected firm's revenues, $X_2 = \delta_2 C \geq X_1 = \delta_1 C$, and profits, $\Pi_2 = \pi_2\delta_2 C > \Pi_1 = \pi_1\delta_1 C$, for all values of $z_1 \in [0,1]$. Finally, $z_1 = 1$ reduces the asymmetry in this case and the asymmetric economy becomes symmetric when $z_1 = 1$ and $z_2 = 0$. This can be seen in the rightmost plot where $\frac{X_{12}}{w_{12}C} = 0$ when $z_1 = 0$.

Panel B of Figure 2 further illustrates the effects of the upstream propagation of the payment shock. Going from left to right, the unaffected firm starts as more central among the two firms, then its centrality declines with z_1, and both firms have the same centrality when $z_1 = 1$. Correspondingly, the size of the red circle labeled 1 remains the same, while the size of the red circle labeled 2 decreases going from the left subplot to the right subplot. The upstream payment flows from the affected firm to the unaffected firm decline with z_1, as illustrated by a thicker blue line showing flows from firm 1 to firm 2 when going from the left subplot to the right subplot. Thus, confirming the results from Panel A of Figure 1, the upstream payment shock propagation makes the asymmetric economy more symmetric by inhibiting the supplier firm's ability to get paid for its output product and thus reducing flows from it to the upstream firm and, in turn, reducing its revenues.

Next, we consider the downstream propagation for which we have

$$\pi_1 = \tfrac{1}{2}, \delta_1 = \tfrac{1}{2}, \tfrac{\Pi_1}{C} = \tfrac{1}{4}, \tfrac{X_{12}}{w_{12}C} = \tfrac{1}{2}, \mathcal{R}_{11} = 0,$$
$$\pi_2 = 1 - z_2, \delta_2 = \tfrac{3}{4}, \tfrac{\Pi_2}{C} = \tfrac{1-z_2}{4}, X_{21} = 0, \mathcal{R}_{21} = 0.$$

Panel C of Figure 1 graphs these four quantities in that order from left to right for the affected firm 2 (blue line) and the unaffected firm 1 (red line). The profit margin, π_i, declines as $1 - z_2$ for the affected firm while it is equal to 0.5 for the unaffected firm 2. Therefore, the affected upstream firm has a higher/lower profit margin than the unaffected downstream firm for $z_2 \in [0, 0.5)/(0.5, 1]$. The Domar weight for the affected upstream firm 2, $\delta_2 = 0.75$, is greater than the value of the Domar weight of the affected downstream firm 1, $\delta_1 = 0.5$, and both weight do not depend on the shock z_2. Correspondingly, Panel C of Figure 2 displays the size of the red circle labeled 1 is less than the size of the red circle labeled 2 and both circle sizes remain the same going from the left subplot to the right subplot. This is because the flows from the supplier to the customer are not affected by the shock z_2, as can be seen from the right-most subplot of Panel C, as well as from the Panel C of Figure 2 indicating the thickness of the blue line showing flows from firm 1 to firm 2 remains the same when going from the left subplot to the right subplot. Therefore, the downstream shock z_1 does not affect the network. Consequently, the model has a number of empirical predictions outlined in the next subsection.

2.5 Empirical predictions

Our model delivers a host of testable predictions on the effects of payment M-shocks on the firms' network and firm-level characteristics. Lemma 1 links key firm-level characteristics such as revenues, X_{it}, profits, Π_{it}, and firm-to-firm payment flows, X_{ijt}, to the firm's Domar weight, δ_{it}. We, therefore, start with the model predictions for the firms' network.

It follows from relations (4) and (5) that δ_{it} declines with its own payment shock z_{it}, $\partial\delta_{it}/\partial z_{it} < 0$, leading to the following empirical prediction.

PREDICTION 1: *Firms' payment network centrality declines after a payment shock.*

Payment shocks affect firm growth and profitability. The most basic prediction is the following.

PREDICTION 2: *Firm growth declines with its own payment shocks z_{it}.*

We now switch to model predictions for firm-level characteristics. Firms' own payment shocks and other firms' payment shocks in the firm-to-firm network reduce revenue growth.

PREDICTION 3: *Payment shocks propagate upstream. Firm growth declines with payment shocks of the customers (more than suppliers).*

In the cross-section of firms, the model predicts that more central firms are more exposed to payment shocks. Eigenvalue centrality aggregates how payment shocks of customers and suppliers affect firm growth. We have the following prediction for the eigenvector-central firms.

PREDICTION 4: *More eigenvector-central firms are more sensitive to payment shocks.*

The effect of the payment shocks on firm-level profitability can be directly deduced from equation (11). Two different centrality measures, eigenvector and in-degree, are relevant for firm profitability. The opposite to prediction 4 is true for more factor-intensive or higher in-degree-central firms. The profits of more factor-intensive firms are less sensitive to payment shocks.

Our last set of empirical predictions are about the firm-to-firm spillover of M-shocks. In a production economy with ε-shocks only, shocks propagate from one sector to another. Specifically, ε-shocks only propagate "downstream", from supplier to customer, and not upstream, customer to supplier.[6] The Leontief inverse is a sufficient statistic for how shocks propagate. Importantly, the Leontief inverse is deterministic and does not change with ϵ-shocks. By contrast, in a production economy with both ε- and M-shocks, shocks propagate both upstream and downstream. Importantly, the Leontief inverse is now stochastic and changes with M-shocks.

The relationship between firm-to-firm payment flows, X_{ijt}, and M_t determines a firm's resilience to M-shocks. According to Lemma 1, the logarithm of firm-to-firm payment flows can be written as

$$\ln X_{ijt} = \ln w_{ij} + \ln(1 - z_{it}) + \ln \delta_{it} + \ln C_t,$$

[6]This is an artifact of Cobb-Douglas technologies. Carvalho, Nirei, Saito and Tahbaz-Salehi (2015) extend the ϵ-shock setting to CES. Shocks then propagate both upstream and downstream. However, downstream effects are almost always larger than upstream effect, and Bonacich centrality is no longer a sufficient statistic for the importance of firms.

where the GDP, C_t, has a non-trivial dependence on z_{it} through the geometric average aggregate centrality and all firms' centrality-weighted composite payment shocks, ϵ_{kt}, defined in (7). The total impact of z_t on firm-to-firm payment growth can be expressed as

$$\text{Firm-to-firm payment growth } \Delta \ln X_{ijt} = \underbrace{-\frac{\Delta z_{it}}{1-z_{it}}}_{\text{Own shock}} + \underbrace{\Delta \ln \delta_{it}}_{\substack{\text{Resilience to} \\ \text{other firms' shocks}}} + \Delta \ln C_t, \tag{23}$$

where the last term is the GDP growth. In a competitive equilibrium firms do not incorporate the effect of their policies on the economy-wide quantities into their optimization. We therefore treat GDP growth as being exogenous to firm-to-firm payment flows.

The first two terms in the expression for $\Delta \ln X_{ijt}$ are negative. We use the resilience, $\mathcal{R}_{ijt}$, defined in Lemma 2 to capture the effects of the M-shock originated at firm j, z_{jt}, on firm i. The following prediction highlights how payment shocks affect the cross-section of firms.

PREDICTION 5: *Controlling for the GDP growth, firm-to-firm payment growth is negatively impacted by own and other firms' payment shocks. More resilient firms have higher $\mathcal{R}_t$ and are less affected by the payment shocks including shocks originated at different firms.*

We test these predictions in the next section.

3 Data description

Granular data for the Russian Payment System provides a unique setting in which we can test the model predictions. The structure of the Russian banking system is in large part shaped by privatization of the extended network of the Soviet banks. Berkowitz et al. (2014) and Bircan and De Haas (2019) provide a detailed account of its evolution.

The payment system was setup with the help of the IMF and by the end of the nineties it underwent a substantial progress in its efficiency (Summers (1994) and Roberts (1999)). The Central Bank of Russia (CBR) in 2004 used a large value payment system (LVPM) that belongs to the *deferred net settlement* (DNS) family of payment systems. Settlement of transfers between banks are done on a net basis at the end of each processing cycle (Bech et al., 2008). In DNS payment systems all transfers are provisional until all participants have discharged their settlement obligations. If a participant fails to settle, some or all of the provisional transfers involving that participant are deleted from the system and the settlement obligations from the remaining transfers are recalculated. Such a procedure has the effect of allocating liquidity pressures and losses attributable to the failure to settle to the counterparties of the participant that fail to settle (Bank for International Settlements, 2003). The consequence is that in DNS systems banks save on intra-day liquidity maintenance, but run counterparty settlement risks against each other.

3.1 Payments data

The data for our study come from the payment system of the CBR. It records all transactions between paying and receiving banks executed by banks on clients' behalf and for their own accounts. Mironov (2013) and Mironov and Zhuravskaya (2016) provide a detailed description of the source and scope of the data.

Mechanics of payment flows: In the CBR's payment system, a given bank accumulates incoming and outgoing payment orders from clients against other banks. All payment orders are settled at the end of the business day on the bank's CBR account. Suppose clients of bank s send more paying orders to bank r's clients during the day than clients of bank r send to bank s's client. The CBR then debits bank s's account and credits bank r's by the net outstanding value of the clients orders.

Figure 3 further illustrates the structure of the payment system. The unit of observation in the payment system is the payment $V^t_{i,s,r,j}$ where i denotes the paying entity, s is the sender bank, r is the receiver bank, j is the receiving entity, and t is the date of the payment instruction. After paying entity (firm or consumer) i becomes liable to receiving entity j for economic services, it receives the invoice from j stipulating the ruble amount V to be paid by i to j's account at receiving bank r. On date t, payer i fills up a standard payment order slip at its paying bank s ordering the bank to wire the amount V from its account at s to the account of j at bank r. Bank s submits the payment order into the CBR's payment system where the account of bank s with the CBR is debited by

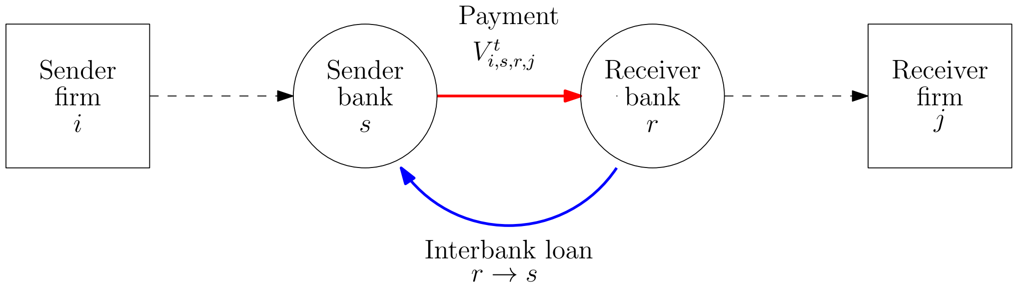


Figure 3: Structure of payment system and interbank market

This figure illustrates the structure of the payment system. The unit of observation in the payment system is the payment $V^t_{i,s,r,j}$ where i denotes the paying entity, s is the sender bank, r is the receiver bank, j is the receiving entity, and t is the date of the payment instruction. Blue arrow indicates an interbank loan between banks r and s with r being the originator bank.

amount V and the account of bank r with the CBR is credited by V. Upon receiving funds V through the payment system, bank r credits the account of j.

Payment types: The payment system accounts for various payment types. A useful feature of the transaction data is the information on the account types used by firms i and j. This feature allows us to identify the precise economic nature of each payment order, such as payment for goods and services, payment of federal taxes, purchasing of financial securities, etc. We assign each payment type a unique qualifier. For the purpose of this study, we focus on two payment types:

1. Payment orders between firms for goods and services. We keep only business related types of transactions of paying and receiving firms and throw out all other types of payments (taxes, financial transactions, etc.) and discard all other types of entities involved (state owned enterprises, individuals, municipalities, financial institutions, etc.).

2. Payment orders between banks for interbank loans. We restrict payment orders to those where paying entities i and j are banks and types of transactions between them are interbank loans.

Both types of payments are cleared by the CBR. When routing the first type of payments, commercial banks act as intermediaries of firms with whom they have banking relationships. As a result, banks are matched almost randomly with each other by firm's invoices for goods and services. The matching of banks is non-random if firms that exchange goods and services with each other were initially introduced by banks where these firms are clients.

The second type of payments are initiated by banks themselves where the exchange of funds occurs between banks that temporarily experience liquidity surplus and banks experiencing liquidity shortage. Matching of banks on the interbank market is non-random leading to a potential selection bias. Interbank loans are routed through the CBR's payment system allowing us to identify the network of banks that exchange liquidity with each other. Similarly to other countries' interbank markets, unsecured loans in Russia are exchanged on a bilateral over-the-counter basis. The loans are short-term and rolled over on a continuous basis making it easy for the lending party to withhold loans and hoard liquidity in case of an increase in the borrowing bank's perceived riskiness.[7]

Summary statistics: Raw CBR payment system data covers December 2003-December 2004 and contains over 133 million unique payment orders between different economic entities such as firms, individuals, municipalities, etc. The complete payment network consists of 1.168 million unique paying entities that use 1,413 paying banks and 1.245 million receiving entities and 1,418 receiving banks. Our focus is on payment orders between private firms for goods and services which comprise over 64% of all payment orders in the raw data. In addition, we effectively filter out the so-called "fly-by-night" firms (Mironov, 2013) created for the income diversion purposes and disposed after a single transaction.

The final sample includes 756,150 paying firms which on average use 1.2 paying banks to make payments to 792,283 recipient firms. Each paying firm on average transacts with 14.5 recipient firms through 9.7 recipient banks. The summary statistics of the firm-bank network is reported in Table 1 where Panel A represents the paying firms' angle while Panel B the recipient firms' angle.

We should stress that the core network here is build by 10,965,592 firm pairs that transact with each other for economic reasons. Firms use intermediation services of banks while routing their payments through banks and as a result of this activity banks are matched into the payment system network consisting of 555,360 unique bank pairs. Payments in this network are cleared through the banks' accounts with the CBR.

[7] In our data 75% of interbank loans are overnight and 22% are weekly.

Table 1: **Summary statistics of payment network**

This table reports the summary statistics of firms' payment network. The sample period covers December 2003-December 2004.

	Mean	SD	Min	Median	Max	N
Panel A: Paying firms						
No. payments originated	74.26	502.6	1	12	148,940	756,150
Total value sent (th. Rub)	20,110	385,172	0.001	450.9	132,207,818	756,150
No. pay banks per paying firm	1.202	0.5918	1	1	83	756,150
No. recipient banks per paying firm	9.685	19.83	1	3	786	756,150
No. recipient firms per paying firm	14.5	51.18	1	4	15,115	756,150
Panel B: Recipient firms						
No. payments received	70.87	1,447	1	4	694,440	792,283
Total value received (th. Rub)	19,193	432,092	0.001	208	190,221,807	792,283
No. recipient banks per recipient firm	1.177	0.8176	1	1	134	792,283
No. pay banks per recipient firm	8.198	25.93	1	1	1,097	792,283
No. paying firms per recipient Firm	13.84	151.4	1	2	54,298	792,283

3.2 May 2004 panic and collapse of interbank network

We use Russian interbank loan market panic and subsequent collapse in May 2004 as an exogenous payment shock. The idea is that as some banks become "toxic" due to an exogenous event, the non-toxic banks reduce their exposure to toxic banks by refusing to loan to them on the interbank market. The interruption of interbank market relations spills over into the payment system where the same bank-pairs are also likely to break their payment relations by refusing to accept/send payments from/to to each other thus affecting financing of their client firms.

May 2004 panic on interbank market: On May 13, 2004 the CBR unexpectedly withdrew banking licences of Sodbiznesbank blaming it for involvement in money laundering. This event caused the immediate collapse of another mid-sized bank Credittrust that had the same owner as Sodbiznesbank. In the last week of May 2004, the Head of Rosfinmonitoring—the financial monitoring service that is the federal executive body responsible for combating money laundering and terrorist financing, developing and implementing state policies and regulatory and legal frameworks—made a statement that there are at least ten other banks that are about to lose their banking licences for money laundering reasons. This statement caused panic on the interbank mar-

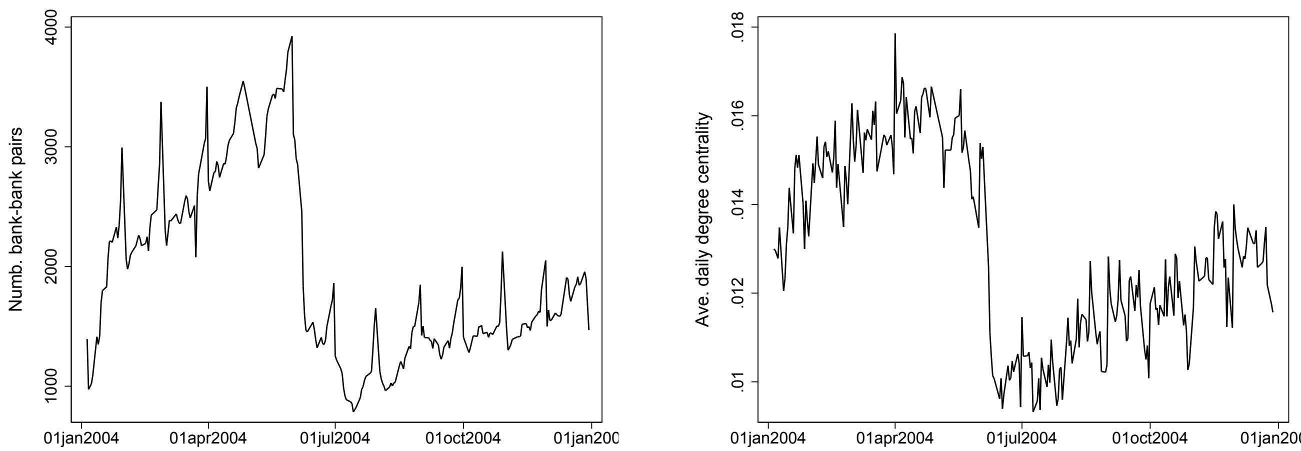


Figure 4: Dynamics in interbank connections and interbank market structure

The left figure documents the total number of daily interbank connections for the period from January 01, 2004 to January 01, 2005. The right figure shows the daily dynamics of the average degree centrality, capturing changes in the interbank network topology.

ket which resulted in a sudden drop in interbank volume and bilateral connections on the market.[8]

Here we provide some descriptive evidence on the effects of the panic on the interbank loan market. Figure 4 graphs the aggregate impact of the panic on interbank lending during the whole period of 2004. The left plot shows the number of unique bilateral bank-to-bank connections on the interbank market per day. Each connection represents an exchange of liquidity between a unique pair of banks on the interbank market in the form of a short-term unsecured loan. At its peak there were almost 4,000 unique bilateral connections per day. Following the panic the interbank market has experienced a sharp decline in a number of bilateral bank connections, that is its extensive margin. The decline in interbank connections has been persistent, lasting at least until early 2005. The plot demonstrates that the interbank market borrowing and lending shrunk at the aggregate level as the number of bilateral bank connections decreased.

The right plot in Figure 4 documents the impact on network structure. The plot shows the daily dynamics of average degree centrality of each bank in the interbank market. In agreement with the left plot of Figure 4, the average bank has sharply reduced the number of its interbank connections in the aftermath of the panic. Together, these two graphs imply that the closeness between all bank pairs measuring the strength of pair-wise relationship has sharply increased post May 2004. Effects on the interbank network topology were highly persistent. When put together,

[8]See Degryse *et al.* (2019) for the discussion of the banking panic episode.

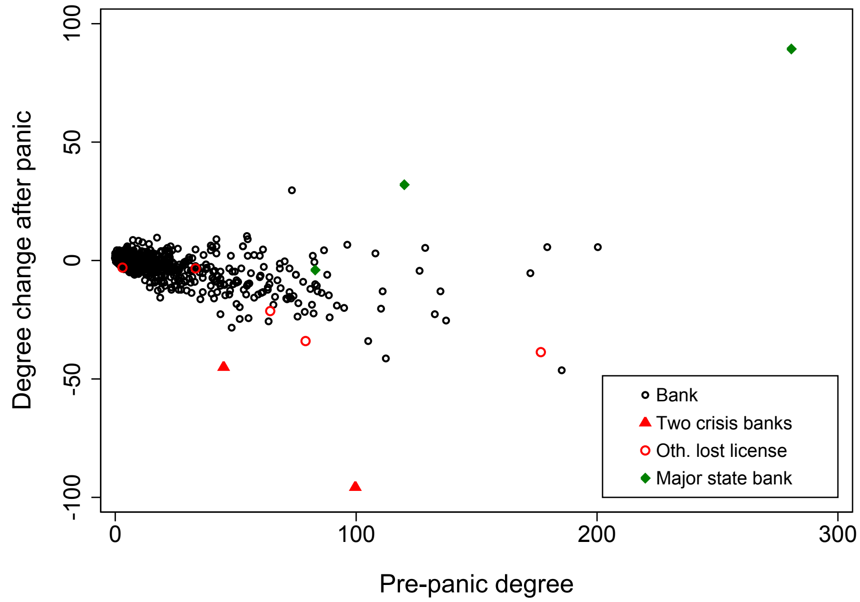


Figure 5: Panic effect on interbank connections

This figure plots the change in banks' interbank network connection pre- and post-panic, vertical axes, against the pre-panic number of network connections, horizontal axes. We use color-coding to highlight two banks that caused this crisis (red triangles), other banks that subsequently lost their licenses later during 2004 (red circles), and major state banks (green rhombus).

this evidence shows the response of Russian banks to the interbank panic was to substitute for the peripheral links with "nearby" connections to banks that were central to the network. Since the number of banks with a high degree centrality was small, the number of links per bank fell more sharply than the decline in the total volume, thus leading to an increase in the bilateral volume as the left plot of Figure 4 shows. Overall, these results highlight that the interbank market panic caused the interbank network to become more central.

Network loss of connectivity: Figure 5 sheds additional light on the cause of the interbank loan market panic. It graphs the change in banks' interbank network connection pre- and post-panic, vertical axes, against their average pre-panic eigenvector centrality, horizontal axes. Red triangles indicate two banks with revoked banking licences, red circles indicate banks that subsequently lost their licenses, and green rhombuses indicate major state banks. The plot is downward sloping thus indicating that more central banks experience a larger net loss of interbank connections. This is not surprising as they had much more connections than less central banks to begin with. State banks are the notable exception—all three state banks show a net gain in interbank connections which can be interpreted as a flight to safety. The figure also provides evidence as to why two medium-sized suddenly losing their banking licences caused an interbank market panic. Surprisingly, both defaulted banks were, prior to their demise, well connected and relatively central on the interbank market in terms of their eigenvector centrality prior to the panic thus resulting in a large number of banks becoming "toxic" post-factum.

We next introduce our empirical measure capturing the bank-level severity of the interbank loan market shock, which is based on the bank's loss of connectivity on this market. Motivated by Figure 5, we define the bank's loss of connectivity on the interbank market as a symmetric growth rate of the bank's connections over the pre-panic and post-panic periods. Let N_s^τ be a number of interbank market links of bank s in the corresponding interbank panic related period $\tau \in \{Pre, Panic\}$. Pre-panic period includes March-April 2004 while panic period covers June 2004. We then have that the panic–pre change in interbank connections is

$$\text{Interbank Connection Loss}_s = \frac{N_s^{Panic} - N_s^{Pre}}{\frac{1}{2}(N_s^{Panic} + N_s^{Pre})} \in [-2, 2]. \tag{24}$$

The advantage of this definition is that it accommodates entry and exit of relationships between banks on the interbank market. It is a second-order approximation to the standard growth rate around zero, and it is bounded by $[-2, 2]$, where -2 corresponds to exit and 2 to entry.

Interbank Connection Loss_s captures the degree of bank's "toxicity" with lower/higher value implying being less/more toxic. We associate high/lower toxicity with lower/higher transaction volume handled by the bank.

We now turn our attention to the interbank panic's implications to the real economy.

4 Payment system disruption and real economy

In this section we test empirical predictions from the model. We have documented that the interbank panic has resulted in the significant restructuring of the interbank loan network of banks. Unaffected banks have been reluctant to offer overnight loans not only to the directly affected banks, but also to banks connected to them and, potentially, to the second layer of connected banks, that is banks connected to affected banks' connections. However, the broken bank-to-bank links are not specific to the interbank loan market, but should also extend to all other bank-to-bank flows that may lead to federal scrutiny and the suspension of bank operations. Correspondingly, unaffected banks have stopped processing inflows/outflows from/to affected banks, including payments for goods and services thus disrupting the firm-to-firm payment network. This is precisely the scenario considered in the model.

4.1 Firm-level shocks and variable construction

We start by establishing that the firm-to-firm payment network has indeed being affected by the interbank loan market panic. The model's first prediction is that firms' network centrality declines after a shock inhibiting firms' abilities to make/receive payments. Figure 6 graphs daily dynamics of the average payment network degree centrality in our sample. The daily average degree centrality is constructed by calculating the degree centrality for each firm/day and taking the sample average. The figure clearly shows that in agreement with the model's prediction the average degree centrality significantly declined during the interbank panic indicated by the red circle.

The model links the firm-level real outcomes to firm's ability to pay upstream firms for inputs captured by payment shocks z_{it}. In the data, we construct a corresponding variable Z_i as the firm i's loss of access to payment services due to the interbank market panic effect on all N_i banks firm i uses to make/receive payments in the pre-panic period. Let $\kappa_{i,s} \in [0,1]$ be the pre-panic share of the sender bank s in total payments by firm i to all of its upstream (receiver) firms.[9] For each firm i and its sender banks, $s = 1...N_i$, we define firm i's loss of access to sending payment services as:

$$\mathrm{Z}_i = \sum_{s=1}^{N_i} \text{Interbank Connection Loss}_s \cdot \kappa_{i,s} \in [-2, 2]. \tag{25}$$

Z_i captures the shock to a firm's ability to make payments to its suppliers (upstream firms) through the firm's banks.[10] High/lower value of Z_i implies the firm is less/more able to make payments to

[9]As an example, consider a firm using 2 banks, $N_i = 2$, to make payments to 3 supplies with payment volumes equal to 40, 40, and 20 for a total volume of 100. The firm uses its first bank to pay 20, 10, and 10, and it uses its second bank to pay 20, 30, and 10. Then $\kappa_{i,1} = 2/5$ and Then $\kappa_{i,2} = 3/5$.

[10]While $\mathrm{Z}_i \in [-2, 2]$ does not match one-to-one with z_{it} used in the model, the proper match can be achieved using transformation $(\mathrm{Z}_i + 2)/4 \in [0, 1]$.

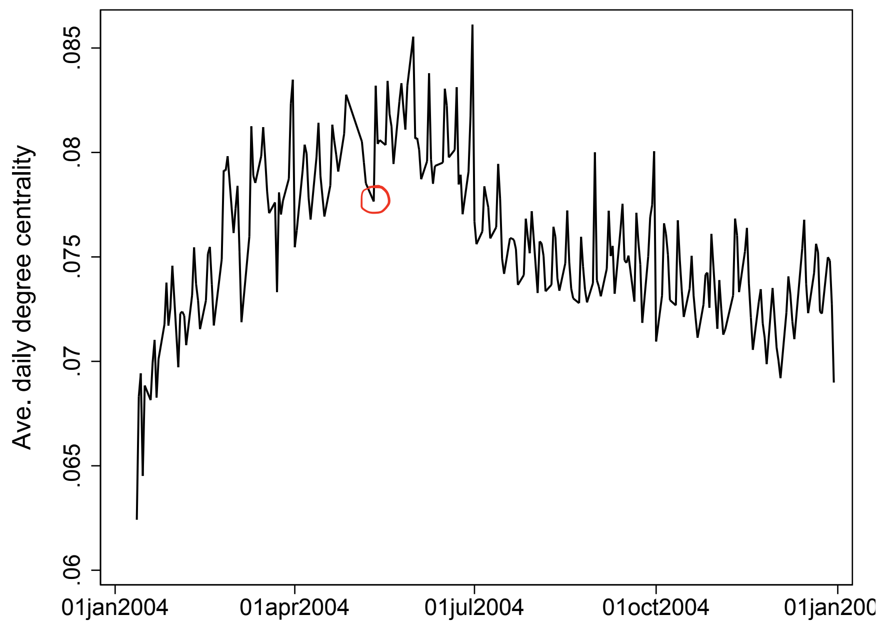


Figure 6: Dynamics of the average firm-to-firm payment network degree centrality

Network degree centrality is calculated for each bank through which firms make daily payments to each other and the figure reports the daily sample average across banks. Red circle indicates the interbank panic.

its suppliers due to the interbank loan panic. Table 2 reports summary statistics for Z_i. Its centered around zero with the mean/median equal to 0.033/0 and the standard deviation equal to 0.329.

Testing the upstream/downstream propagation of payment shocks requires us to construct the firm i's loss of access to payment services due to the interbank market panic effect on all n_i downstream/upstream firms the firm i receives/sends payments from/to in the pre-panic period. Let $\zeta_{i,s}^{d/u} \in [0,1]$ be the pre-panic share of the downstream/upstream firm s in total payment flow with the firm i. For each firm i and its pre-panic downstream/upstream firms, $s = 1...n_i^{d/u}$, we define firm i's loss of access to receiving/sending payment services as:

$$\mathrm{Z}_i^{\mathrm{d/u}} = \sum_{s=1}^{n_i^{d/u}} \mathrm{Z}_s \cdot \zeta_{i,s}^{d/u} \in [-2, 2]. \tag{26}$$

$\mathrm{Z}_i^{\mathrm{d/u}}$ is the flow-weighted payment shock from *all* downstream/upstream firms connected pre-panic to firm i. Similarly to Z_i, higher/lower value of $\mathrm{Z}_i^{\mathrm{d/u}}$ implies the firm is less/more affected by the interbank loan panic due to its connections to downstream firms. Table 2 reports summary statistics for $\mathrm{Z}_i^{\mathrm{d/u}}$. Both shocks have the same zero median value. The mean and volatility of the shock to downstream firms' banks, equal to 0.059 and 0.273, respectively, are larger than the mean and volatility of the shock to upstream firms' banks, equal to 0.038 and 0.198, respectively.

Motivated by the model, we are interested in the dependent variable that captures the total firm i's revenue growth between post- and pre-panic periods. Let $n_i^{\text{Pre/Post}}$ be the number of the firm i customers pre/post-panic. Let $V_{i,k}^{Pre/Post}$ be the revenue received by the firm i from its kth customer pre/post-panic. Then the total pre/post-panic revenue of the firm i is equal to $V_i^{Pre/Post} = \sum_{k=1}^{n_i^{\text{Pre/Post}}} V_{i,k}^{Pre/Post}$. Figures A.2 and A.3 in the Appendix illustrate the data and the construction of the variable of interest. We then define the symmetric growth rate of the firm i's revenues between the post- and pre-panic periods as:

$$\mathrm{Y}_i = \frac{V_i^{Post} - V_i^{Pre}}{\frac{1}{2}(V_i^{Post} + V_i^{Pre})} \in [-2, 2]. \tag{27}$$

Pre-panic period here covers six month before the payment system shock December 2003-May 2004, while the post-panic period covers six month July 2004 - December 2004 (we exclude the panic month: June 2004). Once again we use symmetric growth as it captures the entry and exit of links between firms. The measure has been used by Davis and Haltiwanger (1992, 1999) and Chodorow-Reich (2014). Table 2 reports summary statistics for Y_i. Its mean/median is equal to 0.113/0.239 with the standard deviation equal to 1.647 due to a number outlier firms with the maximum value of $\mathrm{Y}_i = 2$.

In the model, the relationship between firm-to-firm payment flows and the magnitude of the payment shock determines the firm's resilience to M-shocks, $\mathcal{R}$. Formally, resilience is defined in Lemma 2 as the sensitivity of a firm's eigenvector centrality to a payment shock. In the data, we use two alternative measures of resilience

$$\begin{aligned} \widehat{\text{Resilience}}_i \text{ (sym. growth)} &= \frac{\delta_i^{Post} - \delta_i^{Pre}}{\frac{1}{2}(\delta_i^{Post} + \delta_i^{Pre})}. && (28) \\ \widehat{\text{Resilience}}_i \text{ (alternate)} &= \ln \delta_i^{Post} - \ln \delta_i^{Pre}, && (29) \end{aligned}$$

where the first measure is the symmetric growth in the firm i's centrality pre- and post-shock, and the alternate one is the %-change in firm i's eigenvector centrality pre- and post-shock. We

Table 2: Summary statistics for the cross-sectional data

This table reports the summary statistics for the cross-sectional data of firms receiving and sending payments in December 2003- December 2004.

	Mean	St. Dev.	Min	p50	Max	N
Panel A: Payment network (all firms)						
Payment inflow (revenue) growth Y_i	0.113	1.647	-2	0.239	2	792,283
Shock to firm's own banks Z_i	0.033	0.329	-2	0	2	792,283
Shock to downstream firms' banks $\mathrm{Z}_i^{\mathrm{d}}$	0.059	0.273	-2	0	2	792,283
Shock to upstream firms' banks $\mathrm{Z}_i^{\mathrm{u}}$	0.038	0.198	-2	0	2	792,283
Pre-panic firm's eig. centrality $\ln \delta_i$	-6.792	4.941	-19.36	-4.96	-0.558	602,724
$\widehat{\text{Resilience}}_i$ (Firm's eig. centr. symm. grth)	0.072	1.683	-2	0.067	2	792,283
$\widehat{\text{Resilience}}_i$ (Firm's eig. centr. ln-grth)	-0.057	1.952	-17.31	-0.234	17.32	479,381
Panel B: Firm-level characteristics (public firms)						
ln(Assets)	14.28	2.748	0	14.35	28.24	313,496
ROA	-0.004	0.618	-4.333	0.024	1.45	268,547
Cash-to-assets	0.167	0.257	0.001	0.045	1	294,950
Age (days)	1610	1350	25	1168	4820	486,548
Panel C: Bank-level characteristics						
Wgt. ave. bank size (ln)	13.75	7.59	0	15.98	21.18	602,661
Wgt. ave. bank loan-to-assets	0.562	0.17	0.004	0.601	1	602,661
Wgt. ave. bank deposit growth	0.012	0.029	-0.088	0.002	0.081	602,661

compute the pre-(post-)shock centrality using all firm-to-firm payments over the 6-month period prior (after) to the banking panic. Table 2 reports summary statistics for both resilience measures. The symmetric growth measure, which is on the $[-2, 2]$ support, has mean/median of 0.072/0.067 with the standard deviation equal to 1.683 which is once again is due to a number of firms with the highest resilience of 2. The eigencentrality growth-based measure has mean/median of 0.511/0.007 with the standard deviation equal to 15.19 due to a number of highly resilient firms.

Finally, we use firm-level characteristics such as size (we use ln(Assets) as its proxy), age, return-on-assets (ROA), and cash-to-assets ratio, and bank-level characteristics such as size, loan-to-assets ratio, and average deposit growth as controls, $\boldsymbol{X}_i$. In the case of bank-level controls we use weighted averages with same weights $\kappa_{i,s}$ as in relation (25). Summary statistics for these variables are reported in Table 2. The average/median value of ln(Assets) is equal to 14.28/14.35 with the standard deviation of 2.748. The average/median ROA is equal to -0.004/0.024 with the standard deviation of 0.618, while the average/median cash-to-assets ratio is equal to 0.167/0.045 with the standard deviation of 0.257, indicating that the median firm in our sample is small. The median firm age is equal to 4.4/3.2 years thus indicating that the median firm in the sample has originated after the market reforms. Several firms dating their origins to the Soviet period are the outliers and have been winsorized from the data.

The average/median natural logarithm of bank size (all bank characteristics are weighted averages as mentioned above) is equal to 13.75/15.98 with the standard deviation of 7.59, with the average/median loan-to-assets ratio equal to 0.562/0.601 with the standard deviation of 0.17. The average/median deposit growth rate is equal to 1.2%/0.2% with the standard deviation of 2.9% and max value of 8.1% thus indicating that the deposit growth is quite low during our sample period.

We also control for the firm's location by using postal codes fixed effects. This is important in the context of Russia where remotely located firms may have much more limited access to banking services than centrally located firms have.

We now have all the necessary variables to test the model's predictions.

4.2 Testing the model predictions

Firm revenue growth and payment shock to its own banks: We start by testing the model-implied relation between the revenue growth and the payment shock. We use the following panel regression specification:

$$\mathrm{Y}_i = \alpha_I \times \alpha_{PC} + \beta \times \mathrm{Z}_i + \gamma' \boldsymbol{X}_i + \varepsilon_i, \tag{30}$$

where α_I and α_{PC} are industry and postal code fixed effects, respectively.[11] Standard errors are double-clustered at the firm industry and postal code levels.

Table 3 reports results for several variants of specification (30). Column 1 reports results without controls $\boldsymbol{X}_i$, while Columns 2 and 3 report results with firm-level controls only and all controls, respectively. According to the model the regression coefficient β should be negative. In agreement with the model it is negative, statistically significant at 1%, and equal to -0.082/-0.106/-0.038 in Columns 1/2/3. Economically, an increase of the firm's own banks' payment shock metric Z_i from 0 to 1 reduces the firm revenue growth by 0.082/0.106/0.038, all economically significant.[12]

[11] To deal with missing data, for firms with some missing characteristics we keep the firm in the sample and include a missing-observation dummy for all missing observations, instead of dropping the firm completely. This approach allows us to keep the number of observations stable across specifications.

[12] We are using symmetric revenue growth defined by (27) with the support on $[-2, 2]$.

Table 3: Firm revenue growth and its own payment shock

The table reports estimation results of specification (30). Standard errors are clustered at the firm industry*postal code levels. Significance levels are * 5%, ** 1%, *** 0.11%.

Dependent variable:	Payment inflow (revenue) growth		
	(1)	(2)	(3)
Shock to firm's own banks Z_i	-0.082***	-0.106***	-0.038***
	(0.008)	(0.008)	(0.007)
Firm-level controls			
ln(Assets)		0.025***	0.026***
		(0.005)	(0.003)
ROA		0.014**	0.033***
		(0.005)	(0.004)
Cash-to-Assets		0.088***	0.058***
		(0.014)	(0.011)
Age		-0.001***	-0.001***
		(0.000)	(0.000)
Bank-level controls			
Wgt. ave. bank size (log)			-0.005***
			(0.001)
Wgt. ave. bank loan-to-asst			0.080***
			(0.047)
Wgt. ave. bank deposit growth			0.896***
			(0.504)
Dummy paying missing	0.270**	0.441***	-1.00***
	(0.130)	(0.124)	(0.137)
Dummy fin. var. missing		0.202***	0.214***
		(0.074)	(0.040)
Dummy bank. var. missing			3.182***
			(0.147)
Industry*Postal code FE	YES	YES	YES
Num. Industry*Postal code	9,252	9,252	9,252
Observations	792,283	790,641	790,641
Adj. R-squared	0.023	0.033	0.508

Specification 3 has the largest explanatory power with the R^2 equal to 50.8%. Signs of regression coefficients on firm- and bank-level characteristics are all in agreement with the existing literature.

Upstream propagation of payment shocks: We now turn to the model prediction on the upstream propagation of payment shocks. To do this, we add the supplier firm i's loss of access to payment services due to the interbank market panic effect on all downstream firms the firm i

Table 4: Upstream propagation of payment shocks

The table documents the growth of firms' payment inflows and payment shocks to firm's banks, downstream and upstream firms' banks. It reports the estimates from specification (31). Significance levels are * 5%, ** 1%, *** 0.1%.

Dependent variable:	Payment inflow (revenue) growth		
	(1)	(2)	(3)
Shock to firm's own banks Z_i	-0.025***	-0.038***	-0.025***
	(0.005)	(0.006)	(0.005)
Shock to downstream firms' banks Z_i^d	-0.071***		-0.070***
	(0.005)		(0.005)
Shock to upstream firms' banks Z_i^u		-0.042***	-0.031***
		(0.010)	(0.009)
Firm and Bank Controls	YES	YES	YES
Industry*Zip FE	YES	YES	YES
Num. Industry*Postal code	9,252	9,252	9,252
Adj. R-squared	0.615	0.508	0.615
Observations	790,641	790,641	790,641

receives payments from, Z_i^d, and all upstream firms the firm i sends payments to, Z_i^u, to specification (30) to obtain

$$Y_i = \alpha_I \times \alpha_{PC} + \beta_1 \times Z_i + \beta_2 \times Z_i^d + \beta_3 \times Z_i^u + \gamma' \boldsymbol{X}_i + \varepsilon_i. \tag{31}$$

We use the same controls, $\boldsymbol{X}_i$, as in specification (30) and double-cluster standard errors at the firm industry and postal code levels.

Table 4 presents results for several variants of specification (31). Column 1 reports regression coefficients for the payment shock to firm's own banks, β_1, and shock to its downstream firms' banks, β_2. Column 2 reports regression coefficients for the payment shock to firm's own banks, β_1, and the shock to its upstream firms' banks, β_2. Column 3 reports β_1, β_2, and β_3 together. We omit reporting regression coefficients on the firm- and bank-level characteristics.

Column 1 shows that, in agreement with the model, the revenue growth declines both due to the payment shock to firm's own banks and shock to its downstream firms' banks with both regression coefficients being statistically significant at 1%. In agreement with the model prediction 3, shocks to payer firms' banks have much larger effect on the supplier firm i's revenue growth, $\beta_2 = -0.071$, than shocks to its own banks have, $\beta_1 = -0.025$. Economically, an increase of the firm i's downstream payer banks' shock metric Z_i^d from 0 to 1 reduces the firm revenue growth by 0.071, while a similar increase in the firm i's own banks' payment shock metric Z_i reduces the revenue growth by only 0.025. This is because in the former case when the payer banks cannot process payments the revenues are affected directly, while in the latter case the firm can mitigate its reduced ability to pay upstream firms for external inputs by relying more into internal inputs.

Column 2 reveals that the revenue growth also declines due to the payment shock to firm's downstream firms' banks. In this case, shocks to upstream firms' banks have quantitatively similar effect on the downstream firm i's revenue growth, $\beta_2 = -0.042$, to the effect of shocks to its own banks, $\beta_1 = -0.038$, with both regression coefficients being statistically significant at 1%. This is because in both cases payment shocks affect firm's ability to purchase external inputs rather than directly affecting its revenues.

Column 3 reports results for the specification that has all three shocks included. It reaffirms results from Columns 1 and 2. The revenue growth declines due to the firm's own payment shock, as well as due to payment shocks to its downstream, and upstream firms' banks, with all three regression coefficients being statistically significant at 1%. Once again, in agreement with the model prediction 3 that payment shocks propagate upstream, shocks to payer firms' banks have much larger effect on the supplier firm i's revenue growth, $\beta_2 = -0.070$, than shocks to its own banks, $\beta_1 = -0.025$, and shocks to firm i's upstream firms' banks, $\beta_3 = -0.031$. All specifications have pretty large explanatory power with R^2 equal to 61.5%/50.8%/61.5% for specification 1/2/3.

Eigenvector-centrality and sensitivity to payment shocks: Next, we investigate the model-implied relation between the firm's revenue growth, network centrality, and the payment shock to its own banks. To do this, we add the natural logarithm of firm i's pre-panic Domar weight, $\ln \delta_i$, and its interaction with the shock to firm i's own banks, $\mathrm{Z}_i \times \ln \delta_i$, to specification (30) to obtain

$$\mathrm{Y}_i = \alpha_I \times \alpha_{PC} + \beta_1 \times \mathrm{Z}_i + \beta_2 \times \log \delta_i + \beta_3 \times (\mathrm{Z}_i \times \ln \delta_i) + \gamma' \boldsymbol{X}_i + \varepsilon_i. \tag{32}$$

As in previous specifications, we use the same controls, $\boldsymbol{X}_i$, and double-cluster standard errors at the firm industry and postal code levels.

Table 5 presents results for specification (32) without firm- and bank-level controls (Column

Table 5: Eigenvector-centrality and sensitivity to payment shocks

The table documents the growth of firms' payment inflow (revenue) and pre-crisis centrality. Significance levels are * 5%, ** 1%, *** 0.1%.

Dependent variable:	Payment inflow (revenue) growth		
	(1)	(2)	(3)
Shock to firm's own banks Z_i	-0.145***	-0.142***	-0.109***
	(0.033)	(0.036)	(0.030)
Firm's eig. centrality $\ln \delta_i$	-0.083***	-0.085***	-0.086***
	(0.016)	(0.016)	(0.016)
$Z_i \times \ln \delta_i$	-0.012***	-0.011***	-0.011***
	(0.004)	(0.004)	(0.004)
Firm Controls	NO	YES	YES
Bank Controls	NO	NO	YES
Industry*Postal code FE	YES	YES	YES
Num. Industry*Postal code	8,701	8,701	8,701
Observations	601,037	601,037	601,037
Adj. R-squared	0.240	0.247	0.249

1), with firm-level controls but without bank-level controls (Column 2), and with both firm- and bank-level controls included (Column 3). Including firm-level controls improves R^2 from 24% in Column 1 to 24.7% in Column 2, and including bank-level controls lads to a minimal improvement in R^2 from 24.7% in Column 2 to 24.9% in Column 3. Regression coefficients β_2 and β_3 do not vary across the specifications, while the regression coefficient on the shock to firm i's own banks, Z_i, reduces -0.142 in Column 2 to -0.109 in Column 3. We, therefore, use Column 3 as the focus of our discussion.

First notable result is that the regression coefficient on the shock to firm i's own banks, $\beta_1 = -0.105$, is much larger than its estimates from Column 3 of Tables 3 and 4 equal to -0.038 and -0.025, respectively. This indicates that the firm i's pre-panic Domar weight dampens the mitigating effect of bank-level controls, which share some of the information with Z_i, on β_1.

Second notable result is that the revenue growth declines with the the firm i's pre-panic Domar weight, δ_i, as the regression coefficient β_2 is negative and equal to -0.086, both statistically and economically significant. Economically it means that doubling the pre-panic Domar weight results in 0.086 reduction in the revenue growth. In other words, firms that are more central pre-panic experience larger decline in revenue growth during the panic. This is in agreement with the model's

Table 6: Resilience to payment shocks

The table documents the growth of firms' payment inflows and its relation to the shocks to firms' own banks and the firms' change in eigenvector centrality. Significance levels are * 5%, ** 1%, *** 0.1%.

Dependent variable:	Payment inflow (revenue) growth	
	Full sample	Active firms in both periods
	(1)	(2)
$\widehat{\text{Resilience}}_i$ (Firm's eig. centrality, symmetric growth)	0.841***	
	(0.036)	
$\widehat{\text{Resilience}}_i$ (Firm's eig. centrality, ln-growth)		0.057***
		(0.001)
Shock to firm's own banks Z_i	-0.023***	-0.016***
	(0.006)	(0.004)
Controls	YES	YES
Industry*Zip FE	YES	YES
Adj. R-squared	0.747	0.459
Observations	790,641	431,221

predictions and is due to the fact that is a weighted average of payment shocks affecting all firms and thus captures the likelihood of being exposed to payment shocks with more central firms being more likely to be exposed than less central firms.

Finally, the regression coefficient on the interaction term $Z_i \times \ln \delta_i$ is negative and statistically significant at 1% level. It implies that, everything being equal, more pre-panic central firms experience more reduction in revenue growth than less central firms when hit by the same shock to their own banks, Z_i. This is in agreement with the model prediction 4.

Resilience to payment shocks: Next, we study how network effects affect the cross-sectional propagation of payment shocks. We proceed by adding the resilience measure(s) to specification (30) to obtain

$$Y_i = \alpha_I \times \alpha_{PC} + \beta_1 \times Z_i + \beta_2 \times \widehat{\text{Resilience}}_i + \gamma' \boldsymbol{X}_i + \varepsilon_i, \tag{33}$$

where the explanatory variables $\boldsymbol{X}_i$ include the same controls as in previous specifications and we double-cluster standard errors at the firm industry and postal code levels.

Table 6 reports the results for the first resilience measure and the full sample in Column 1, and for the alternate resilience measure and the sample of firms active both pre- and post-panic. In

Table 7: Persistent real effects of payment shocks

This table reports regression results from specification (33). The dependent variables are: Column 1: Return on assets, ROA_{2004}; Column 2: Growth of the turnover ratio = $\ln(\text{Revenue}_{2004}/\text{Assets}_{2004})$ - $\ln(\text{Revenue}_{2003}/\text{Assets}_{2003})$; Column 3: Cash-to-assets ratio = $\text{Cash}_{2004}/\text{Assets}_{2004}$; Column 4: Growth of days payable outstanding = $\ln(\text{DPO}_{2004})$ - $\ln(\text{DPO}_{2003})$; Column 5: Growth of receivables collection period = $\ln(\text{RCP}_{2004})$ - $\ln(\text{RCP}_{2003})$. DPO stands for days payable outstanding, and RCP stands for receivables collection period. $\widehat{\text{Resilience}}_i$ is the %-change in firm i's eigenvector centrality pre- and post-shock. Significance levels are * 5%, ** 1%, *** 0.1%.

Dependent variable:	ROA	Turnover growth	Cash-to-Assets	DPO growth	RCP growth
	(1)	(2)	(3)	(4)	(5)
Z_i	-0.006**	-0.489***	-0.005**	0.022***	0.017***
	(0.003)	(0.092)	(0.001)	(0.006)	(0.006)
$\widehat{\text{Resilience}}_i$	0.004**	-0.051*	0.003**	-0.059***	-0.065***
	(0.001)	(0.029)	(0.001)	(0.002)	(0.002)
Controls	YES	YES	YES	YES	YES
Industry*Zip FE	YES	YES	YES	YES	YES
Adjusted R-squared	0.037	0.005	0.276	0.013	0.009
Observations	284,909	248,612	318,699	241,995	219,493

agreement with the model prediction 5, the regression coefficients on both resilience proxies, β_2, are positive and both statistically (1% level) and economically significant. $\beta_2 = 0.845$ in Column 1, which economically translates into 10% increase in resilience leads to 0.0845 increase in the revenue growth. Both specifications display large explanatory power with R^2 equal to 74.7% and 45.9% in Columns 1 and 2, respectively. Overall, these results confirm that more resilient firms are less affected by their own payment shocks and by payment shocks to other firms in the whole payment network.

We next investigate the effects of the panic/payment shocks on the real firm-level outcomes post panic. We construct several variables measuring the firm-level real outcomes: (1) Return on assets, ROA_{2004}; (2) Growth of the turnover ratio = $\ln(\text{Revenue}_{2004}/\text{Assets}_{2004})$ - $\ln(\text{Revenue}_{2003}/\text{Assets}_{2003})$; (3) Cash-to-assets ratio = $\text{Cash}_{2004}/\text{Assets}_{2004}$; (4) Growth of days payable outstanding = $\ln(\text{DPO}_{2004})$ - $\ln(\text{DPO}_{2003})$; (5) Growth of receivables collection period = $\ln(\text{RCP}_{2004})$ - $\ln(\text{RCP}_{2003})$. The asset turnover ratio measures the value of a company's sales/revenues relative to the value of its assets. The asset turnover ratio can be used as an indicator of the efficiency with which a company is using its assets to generate revenues. Days payable outstanding (DPO) is a financial ratio that indicates the average time (in days) that a firm takes to pay its bills and invoices to its trade creditors, which may include suppliers, vendors, or financiers. Receivables collection period (RCP) is an average time an invoice that hits accounts receivable, and enters what's called the collection period, takes to collect. We use these characteristics as explanatory variables in specification (33) with the %-change in firm i's centrality pre- and post-shock as a resilience proxy.

Table 7 presents these results. Column 1 shows that the ROA declines with the firm's own banks' payment shock metric Z_i, $\beta_1 = -0.006$ statistically significant at 5% level, and that more resilient firms have higher ROA, $\beta_2 = 0.004$ statistically significant at 5% level. However, both coefficients are not economically significant. Column 2 shows that the asset turnover growth also declines firm's own banks' payment shock metric Z_i, $\beta_1 = -0.489$. The regression coefficient is both statistically (at 1% level) and economically significant. Economically, an increase of the firm's own banks' payment shock metric Z_i from 0 to 1 reduces the the asset turnover growth, that is the growth of the asset utilization efficiency, by almost half (48.9%). The resilience does not mitigate the effects of payment shocks on the asset turnover growth as $\beta_2 = -0.051$, but statistically significant only at 10% level. Economically, it implies that doubling the firm's eigenvector centrality results in only 5% decline in its asset turnover growth. This is because payment shocks affect both firm's revenues and asset values and resilience mitigates shocks' effects on the asset value more then it does for revenues. Column 3 shows that cash-to-assets ratio weakly declines with the firm's own banks' payment shock, $\beta_1 = -0.005$ statistically significant at 5% level, and that more resilient firms have slightly higher cash-to-assets ratio, $\beta_2 = 0.003$ statistically significant at 5% level. This regression has the highest $R^2 = 27.6\%$ among all five specification presented in Table 7.

Column 4 of Table 7 reports results for the DPO growth. As we have already pointed out, days payable outstanding is captures the average number of days it takes a firm to pay its bills and invoices. We, therefore, expect that it would take longer for an average firm to pay its bills post-panic, and that more resilient firms should be less affected by the panic. Indeed, DPO growth increases with the firm's own banks' payment shock metric Z_i, $\beta_1 = 0.022$, statistically significant at 1% level. Economically it implies that an increase of the firm's own banks' payment shock metric Z_i from 0 to 1 leads to 2.2% increase in the DPO growth. Also in agreement with our intuition the DPO growth declines with resilience as $\beta_2 = -0.059$ and statistically significant at 1% level. Economically, 10% increase in the resilience leads to 0.59% decline in the DPO growth. Finally,

Table 8: Summary statistics for disaggregated cross-sectional data

This table reports the summary statistics for disaggregated data cross-sectional data.

	Mean	St. Dev.	Min	p50	Max	N
Panel A: Upstream (receiver) firms						
Payment growth $Y_{i,j}$	0.086	1.810	-2	0.218	2	10,760,520
Shock to upstream firm's banks Z_j	0.063	0.376	-2	0.006	2	10,760,520
$\widehat{\text{Resilience}}_j$	0.043	1.041	-2	0.003	2	10,760,520
Panel B: Downstream (sender) firms						
Payment growth $Y_{i,j}$	0.087	1.808	-2	0.217	2	10,571,649
Shock to downstream firm's banks Z_i	0.069	0.400	-2	0.005	2	10,571,649
$\widehat{\text{Resilience}}_i$	0.041	1.200	-2	-0.061	2	10,571,649

Column 5 of Table 7 reports results for the RCP growth where the receivables collection period is an average time to convert an invoice in the accounts receivable into cash. Just like with the DPO growth, expect that it would take longer for an average firm to convert invoices into cash, and that more resilient firms should be less affected by the panic. Column 5 shows that RCP growth increases with the firm's own banks' payment shock metric Z_i, $\beta_1 = 0.017$, statistically significant at 1% level. Economically it implies that an increase of the firm's own banks' payment shock metric Z_i from 0 to 1 leads to 1.7% increase in the RCP growth. Moreover, the DPO growth declines with resilience as $\beta_2 = -0.065$ and statistically significant at 1% level. Economically, 10% increase in the resilience leads to 0.65% decline in the DPO growth.

Overall, payment shocks have persistent negative real effects at the firm level, but these effects are dampen for more resilient firms, that is firms whose degree centrality is less elastic to the payment shocks. These results suggest that money liquidity is endogenous and depends on the location of the payment shock in the network of firm-to-firm flows.

Disaggregated firm-to-firm analysis: The last model prediction is for the firm-to-firm payment flows. We, therefore, switch to the disaggregated analysis of firm-to-firm payment flows. Motivated by the model, we define the symmetric growth rate of the firm-to-firm $i - j$'s revenues between the post- and pre-panic periods as:

$$\mathrm{Y}_{i,j} = \frac{V_{i,j}^{Post} - V_{i,j}^{Pre}}{\frac{1}{2}(V_{i,j}^{Post} + V_{i,j}^{Pre})} \in [-2, 2]. \tag{34}$$

Pre-panic period here covers six month before the payment system shock December 2003-May 2004, while the post-panic period covers six month July 2004 - December 2004 (we exclude the panic month: June 2004).

According to expression (23), the total impact of the panic on the firm-to-firm payment growth depends on the payment shock to firm's own banks and its resilience to payment shocks to other firms' banks. Thus, we use the following panel regression specification:

$$\mathrm{Y}_{i,j} = \alpha_{F_{j/i}} + \alpha_{I_{j/i}} \times \alpha_{PC_{j/i}} + \beta_1 \times \mathrm{Z}_{i/j} + \beta_2 \times \widehat{\mathrm{Resilience}}_{i/j} + \gamma' \boldsymbol{X}_{i/j} + \varepsilon_{i/j}, \tag{35}$$

where the explanatory variables $\boldsymbol{X}_{i/j}$ include the same controls for firm i or, respectively, firm j as in previous specifications and we double-cluster standard errors at the firm industry and postal code levels. $\widehat{\mathrm{Resilience}}_{i/j}$ is the %-change in firm i/j's eigenvector centrality pre- and post-shock. Fixed effects at the firm level, $\alpha_{F_{j/i}}$, control for omitted variables in firm-to-firm flows that could correlate with firms' resilience. The following analysis is therefore robust to such confounding effects. We estimate specification (35) for the sender and receiver firms.

Table 8 reports summary statistics for main variables of interest from specification (35) such as $\mathrm{Y}_{i,j}$, $\mathrm{Z}_{i/j}$, and $\widehat{\mathrm{Resilience}}_{i/j}$. Panel A/B shows results for upstream/downstream firms. The average/median payment growth with upstream firms is equal to 0.086/0.218 and it is almost identical to the average payment growth with downstream firms equal to 0.087/0217. The standard deviations are also quite close at 1.810/1.808 for upstream/downstream firms. Shocks to upstream and downstream firms' banks also have quite similar distributions with means/medians/volatility equal to 0.063/0.006/0.376 and 0.069/0.005/0.400 for upstream and downstream firms, respectively. Upstream and downstream firms have similar average resiliences equal to 0.043 and 0.041, respectively. However, median resilience for upstream firms equal to 0.003 is much higher than the median resilience of downstream firms which is negative at -0.061.

Table 9 reports our results for receiver (Panel A) and sender (Panel B) firms. We estimate specification (35) with (Column 1) and without firm-level controls (Column 2). The results are very similar between the columns and we focus our discussion on Column 1. The first notable result is that, in agreement with the model prediction 5, the firm-to-firm payment growth declines with

Table 9: Disaggregated firm-to-firm analysis

This table reports regression results from specification (35). Column 1 reports results for the full sample of firms without controls. Column 2 reports results for all firms with controls. In Panel A, standard errors are double clustered at the sender firm and receiving industry*postal code levels. $\widehat{\text{Resilience}}_i$ is the %-change in firm i's eigenvector centrality pre- and post-shock. In Panel B, standard errors are double clustered at the sender firm and receiving industry*postal code levels. Significance levels are * 5%, ** 1%, *** 0.1%.

	Dep. variable: *Payment growth* $Y_{i,j}$	
	All firms	All firms with Controls
	(1)	(2)
Panel A: OLS estimates for upstream (receiver) firms		
Z_j	-0.044***	-0.038***
	(0.005)	(0.005)
$\widehat{\text{Resilience}}_j$	0.613***	0.610***
	(0.012)	(0.011)
Receiver firm postal code*industry FE (j)	YES	YES
Receiver firm controls (j)	NO	YES
Sender firm FE (i)	YES	YES
Adj. R^2	0.372	0.373
Observations	10,760,512	10,760,512
Num. sender firms	551,949	551,949
Num. receiver postal*indust. clusters	10,006	10,006
Panel B: OLS estimates for downstream (sender) firms		
Z_i	-0.039***	-0.037***
	(0.005)	(0.005)
$\widehat{\text{Resilience}}_i$	0.261***	0.258***
	(0.013)	(0.013)
Sender firm postal code*industry FE (i)	YES	YES
Sender firm controls (i)	NO	YES
Receiver firm FE (j)	YES	YES
Adj. R^2	0.315	0.316
Observations	10,571,613	10,571,613
Num. sender firms	398,943	398,943
Num. receiver postal*indust. clusters	10,450	10,450

the shock to firm's own banks, Z, and the magnitude of the decline is quite similar for upstream (receiver) firms, $\beta_1 = -0.044$, and downstream (sender) firms, $\beta_1 = -0.039$. Both coefficients are statistically significant at 0.1% level.

Second notable result from Column 1 of Table 9 is that, in agreement with the model prediction 5, the the firm-to-firm payment growth increase with the resilience. The magnitude of the effect is, however, 2.35 times larger for the upstream firms for whom the regression coefficient is equal to $\beta_2 = 0.613$, while it is equal to $\beta_2 = 0.261$ for the downstream firms. Economically, it implies that 1% increase in resilience results in 6.13%/2.61% in crease in the firm-to-firm payment growth for upstream/downstream firms. This is because payment shocks propagate upstream thus making resilience more important for the upstream firms.

Overall, the disaggregated firm-to-firm results are in agreement with our findings for the aggregated firm-to-all connected firms flows.

5 Conclusion

The payment system is assumed to be frictionless in traditional models of banking and monetary policy. However, payment system disruptions can severely impair economic agents' ability to send and receive money in a fast and reliable manner. Money becomes liquid.

To show how severely payment shocks can impair economic activity and what firms and sectors are more resilient to payment system disruptions than others, we first develop an equilibrium model in which payment shocks disrupt firms' access to bank-intermediated payment services. We modify the static input-output production network of Acemoglu et al. (2012) by introducing an internal factor independent of the outside factors into the production technology and allowing for access-to-payment shocks.

We show that payment system disruptions propagate upstream and diminish firm growth and distort the network structure of firm-to-firm payment flows. A firm's resilience to payment disruptions can be captured by the elasticity to payment shocks of the firm's eigenvector centrality in the firm-to-firm network. Firms' eigenvector centrality also captures the pass-through rate of payment shocks to GDP.

Using payment level data from the Central Bank of Russia for goods and services between firms matched with information on banks that intermediate these payments, we provide evidence on how the disruption of the payment system affects firm growth and payment flows between firms. We find that transitory payment disruptions spill over to reduce economic activity. Firms that are more exposed to the payment shock experience larger decline in firm growth as measured by various metrics. In the cross-section, firms with larger eigenvector centrality are more exposed to payment shocks and, consecutively, are hurt more. More resilient firms, as captured by the firm's change in eigenvector centrality, are less affected, as predicted by the model. Firm-to-firm payments also decline less for more resilient firms. These results suggest that money liquidity is endogenous and depends on the location of the payment shock in the network of firm-to-firm flows.

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Appendix A Proofs

Profit maximization: The FOCs for period t profit maximization yield:

$$\begin{aligned} (1-z_{it})w_{ij}p_{it}x_{it} &= p_{jt}x_{ijt}, \\ z_{it}p_{it}x_{it} &= p_{kt}k_{it}. \end{aligned} \tag{A.1}$$

It immediately follows from the FOCs

$$\begin{aligned} \Pi_{it} &= p_{it}x_{it} - p_{kt}k_{it} - \sum_{j=1}^{N} p_{jt}x_{ijt} = \\ &= p_{it}x_{it}(1-z_{it})\left[1-\sum_{j=1}^{N} w_{ij}\right], \end{aligned} \tag{A.2}$$

thus yielding the following expression for the marginal profit function

$$\pi_{it} = \frac{\Pi_{it}}{p_{it}x_{it}} = (1-z_{it})\left[1-\sum_{j=1}^{N} w_{ij}\right]. \tag{A.3}$$

Utility maximization: The agent's time t utility maximization problem can be written as a Lagrangian with multiplier λ_t:

$$\mathcal{L}_{ct} = \beta^t \prod_{i=1}^{N} c_{it}^{\gamma/N} - \lambda_t \left[\sum_{i=1}^{N} p_{it}c_{it} - p_{kt}k_t + \sum_{i=1}^{N} S_{it}(q_{it}-q_{it-1}) - \sum_{i=1}^{N} \Pi_{it}q_{it-1}\right] \tag{A.4}$$

Then the FOCs with respect to consumption c_{it} yield:

$$\frac{\gamma\beta^t}{N}\prod_{i=1}^{N} c_{it}^{\gamma/N} = \lambda_t p_{it}c_{it}. \tag{A.5}$$

Market clearing: Market clearing yields that the equilibrium price p_{kt} satisfies

$$p_{kt}k_t = \sum_{i=1}^{N} z_{it}p_{it}x_{it}. \tag{A.6}$$

In combination with stock market clearing, the GDP can be written as

$$C_t = \sum_{i=1}^{N}(z_{it}+\pi_{it})p_{it}x_{it}. \tag{A.7}$$

The goods market clearing implies

$$
\begin{aligned}
& p_{it}c_{it} + \sum_{j=1}^{N} p_{it}x_{jit} = p_{it}x_{it}, \\
\Leftrightarrow\quad & \frac{1}{N}C_t + \sum_{j=1}^{N}(1 - z_{jt})w_{ji}p_{jt}x_{jt} = p_{it}x_{it}, \\
\Leftrightarrow\quad & \sum_{j=1}^{N}\left[z_{jt}\frac{1}{N} + \pi_{jt}\frac{1}{N} + (1 - z_{jt})w_{ji}\right]p_{jt}x_{jt} = p_{it}x_{it}.
\end{aligned}
\tag{A.8}
$$

Implications: It is useful to define some additional notation at this stage. Collect the factor input weights in the $N \times N$ matrix Σ_t with elements $\Sigma_{ijt} = (1 - z_{it})w_{ij} \geq 0$. Define $L_t = (I - \Sigma_t)^{-1}$ with elements L_{ijt}. Also define a $N \times N$ adjacency matrix Ω_t with elements $\Omega_{ijt} = (z_{it} + \pi_{it})/N + \Sigma_{ijt}$.

Define the revenues of firm i as $X_{it} = p_{it}x_{it}$ and collect these in vector X_t. It is easy to see that X_t is an eigenvector corresponding to the unit eigenvalue of the transformed adjacency matrix Ω. Equation (A.8) amounts to $X_{it} = \sum_{j=1}^{N} \Omega_{jit}X_{jt}$ or, in matrix form, $\Omega_t' X_t = \mathbf{1}X_t$. That is, the equilibrium revenues X_t are equal to the vector of eigenvector centralities of the firms. Note also the switch of indices in the adjacency weight Ω_{jit}. This shows it is the out-degree (and not the in-degree) of a firm that matters for its importance in the economy.

The optimal X_t can be determined explicitly from the second line in equation (A.8) which amounts to

$$X_{it} = \frac{1}{N}Y_t + \sum_{j=1}^{N}\Sigma_{jit}X_{jt}.$$

In matrix form, this can be rewritten as $X_t = \frac{1}{N}\mathbf{1}C_t + \Sigma_t' X_t$, the solution of which is given by

$$X_t = \frac{1}{N}(I - \Sigma_t')^{-1}\mathbf{1}C_t = \frac{1}{N}L_t'\mathbf{1}C_t. \tag{A.9}$$

We can, thus, write revenues as $X_{it} = \delta_{it}C_t$ with $\delta_{it} = \frac{1}{N}\sum_{j=1}^{N} L_{jit}$ and $\sum_{i=1}^{n}(z_{it}+\pi_{it})\delta_{it} = 1$. Define $\psi_t = \sum_{i=1}^{N} z_{it}\delta_{it}$. The internal-factor income share of the GDP is given by

$$K_t \equiv p_{kt}k_t = \psi_t C_t. \tag{A.10}$$

Correspondingly, profits (and thus dividends) are proportional to each firm's eigenvector centrality:

$$\Pi_{it} = \pi_{it}\delta_{it}C_t. \tag{A.11}$$

This implies profits tend to be larger in firms that are more central in the economy, except for labor intensive firms. Centrality provides pricing power because many firms rely on central inputs.

Aggregate dividends equal

$$\sum_{i=1}^{N}\Pi_{it} = \sum_{i=1}^{N}(1 - z_{it})\left(1 - \sum_{j=1}^{N} w_{ij}\right)\delta_{it}C_t = (1 - \psi_t)C_t.$$

Cross firm input-output flows and, respectively, capital shares are

$$\begin{aligned} p_{jt}x_{ijt} &= \Sigma_{ijt}X_{it} = \Sigma_{ijt}\delta_{it}C_t, \\ p_{kt}k_{it} &= z_{it}X_{it} = z_{it}\delta_{it}C_t. \end{aligned}$$

Goods market equilibrium: Equilibrium goods prices satisfy the inverse aggregate demand function

$$\frac{p_{it}}{p_{kt}} = \frac{\delta_{it}}{\psi_t}\frac{k_t}{x_{it}}, \tag{A.12}$$

and $p_{kt} = \psi_t C_t/k_t$. The equilibrium output of each firm is given by

$$x_{it} = e^{\varepsilon_{it}}\left(\frac{z_{it}\delta_{it}}{\psi_t}k_t\right)^{z_{it}}\prod_{j=1}^{N}\left[\Sigma_{ijt}\frac{\delta_{it}}{\delta_{jt}}x_{jt}\right]^{\Sigma_{ijt}}. \tag{A.13}$$

Taking logs,

$$\ln x_{it} = \varepsilon_{it} + z_{it}\ln\left(\frac{z_{it}\delta_{it}}{\psi_t}k_t\right) + \sum_{j=1}^{N}\Sigma_{ijt}\ln\left[\Sigma_{ijt}\frac{\delta_{it}}{\delta_{jt}}\right] + \sum_{j=1}^{N}\Sigma_{ijt}\ln(x_{jt}).$$

We can thus write the output in matrix form as $\ln x_t = z_t + \Sigma_t \ln x_t$.

Panel A: Pre-crisis payment network

Panel B: Post-crisis payment network

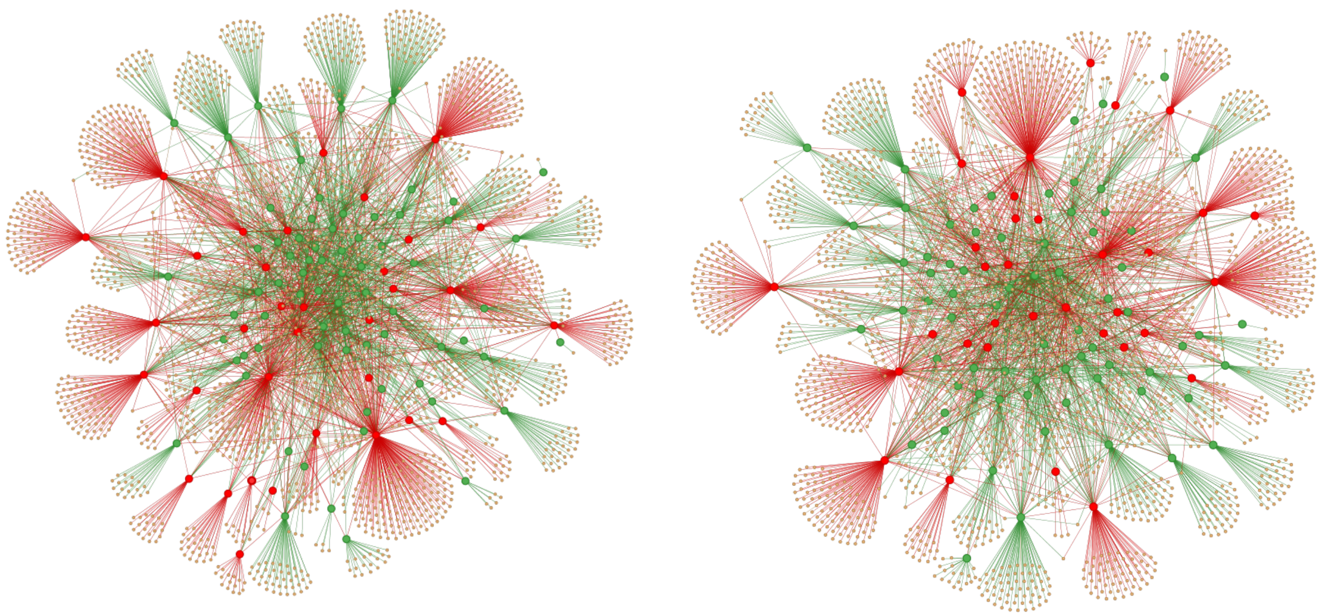

Figure A.1: Firm-to-firm network

The plot shows the pre-panic (Panel A) and post-panic (Panel B) payment network of top 0.5 percent sending firms through their top 10 percent banks to their top 50 per cent of receiving firms by total payment volume going through each entity. Brown circles are firms that make and receive payments. Red circles are banks that were partners of two crisis banks in the pre-crisis period on the interbank market. Green circles are banks that were not their partners.

Sender firm *i*	**Sender bank *s***	*Payment flow*	**Receiver bank *r***	**Receiver firm *j***
A	B1	$\longrightarrow$	B2	X
A	B1	$\longrightarrow$	B3	X
A	B1	$\longrightarrow$	B4	Y
A	B5	$\longrightarrow$	B6	Z
A	B5	$\longrightarrow$	B2	Z
C	B6	$\longrightarrow$	B2	X
C	B6	$\longrightarrow$	B3	X
C	B1	$\longrightarrow$	B2	B
	$\Uparrow$		$\Uparrow$	
	Interbank connections loss *s*		Interbank connections loss *r*	
	$\Uparrow$		$\Uparrow$	
	Interbank panic exposure *s*		Interbank panic exposure *r*	

Figure A.2: Structure of the raw payment data

This picture illustrates a hypothetical example of our 4-dimensional payment data between sending and receiving firms through their banks. Horizontal arrows represent monetary values of payment flows V within each quadruple (i, s, r, j) in each of the Pre- and Post-panic periods. Grey vertical arrows represent the interbank loss of connectivity by s and r banks between Pre- and Post-panic periods. Red vertical arrows represent the Pre-panic exposure of banks s and r to affected banks.

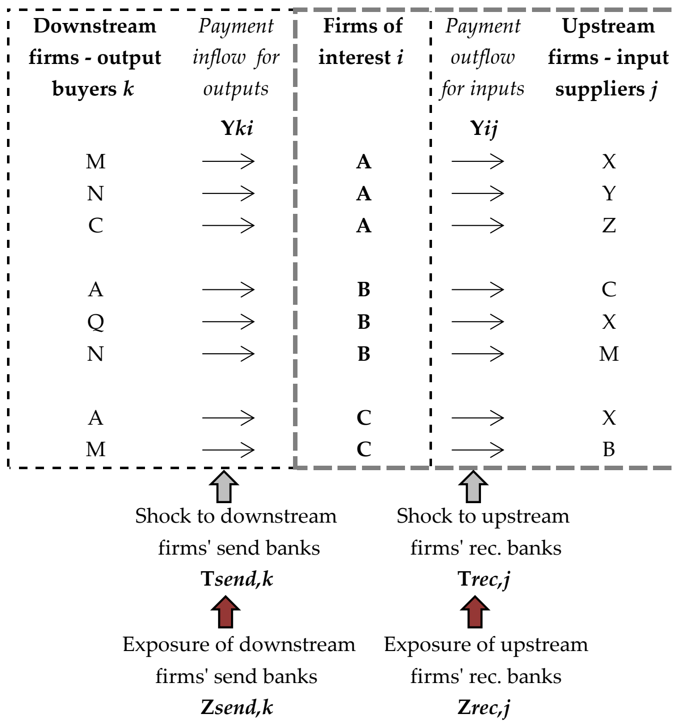

Figure A.3: Structure of firm-to-firm data

This picture illustrates a hypothetical example of the firm-to-firm payment panel data. For each firm of interest i in the middle column we have payments inflow from the downstream firms k in the first columns in each of the Pre- and Post-crisis periods. We also have payment outflows for each firm of interest i to the upstream suppliers j in the last column during each of the Pre- and Post-crisis periods. Horizontal arrows represent monetary values of payment flows V within each firm pair (k, i) or (i, j) in each of the Pre- and Post-crisis periods.

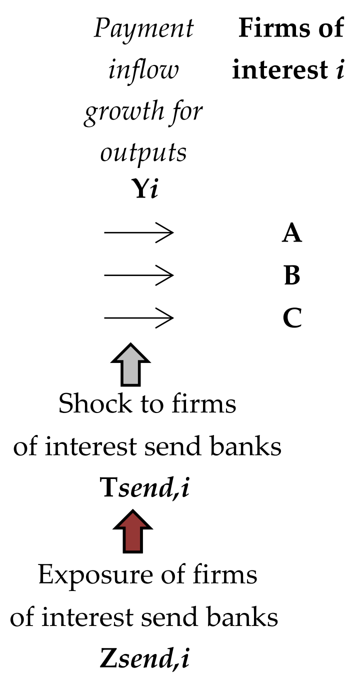

Figure A.4: Structure of the cross-sectional payment data

This picture illustrates a hypothetical example of the cross-sectional payment data which we have obtained after collapsing the firm-to-firm panel data circled by the black dotted line in Figure A.3. Horizontal arrows represent the Pre-Post-Crisis growth Y of monetary values of payment inflows to each firm of interest i from all its downstream firms k. Grey vertical arrows represent the Z shock to the firms i ability to make payments to its upstream firms. Red vertical arrows represent the Pre-crisis exposure M of banks through which the firms of interest make payments to its upstream firms j.