The Economic Impact of Payment System Stress: Evidence from Russia*

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Abstract

We explore the systemic importance of stress in the payment system. Analyzing 133 million transactions from the Russian payment system, we document that shocks affecting firms' payment access primarily propagate upstream within the customer-supplier network and affect central firms more. In a production economy model with access-to-payment shocks, payment stress disrupts firm-firm payments directly and indirectly through adjustments in the input-output network. The macroeconomic impact leads to a 7.5% GDP decline during the 2004 interbank loan market panic, contrasting with a 1.1% decline during the 2022 Russia-Ukraine conflict due to foreign bank departure. These findings highlight how real-financial network linkages matter in sanctioning nations.

JEL Classification: D57, E42, G21, L14

Key words: Payment system, access-to-payment shock, networks, sanctions

1 Introduction

The payment system is one of the most critical parts of the plumbing of the financial system. It facilitates money flows that make the real economy and financial system function. If payments get disrupted, firms and consumers can no longer settle accounts in a fast and reliable manner, real economic activity declines, and consumer welfare suffers. 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, the existing academic literature has very little to say about whether access-to-payment shocks impair real economic activity, how such shocks propagate and amplify through bank-firm and firm-firm interactions, which firms and sectors are more resilient to payment system stress, and how this *payment stress channel* aggregates at the macroeconomic level. This reflects the difficulties of pinpointing credible exogenous micro-level shocks affecting bank-firm and firm-firm relationships and tracking their impact as they ripple through the economy.

In this paper, we systematically quantify the effects of payment system stress spilling over into the real economy by leveraging the 2004 interbank loan market panic in Russia as an exogenous shock resulting in payment system stress. On May 13, 2004, the Central Bank of Russia (CBR) unexpectedly withdrew the banking license of Sodbiznesbank, a bank involved in money laundering using interbank loans. This withdrawal caused an 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 2004 that "at least ten other banks are about to lose their banking licenses for money laundering reasons." This statement caused the interbank loan market to effectively shut down, resulting in over 50% of interbank connections being severed. The investigation of the money laundering scheme by the two offending

[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 illustrating 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).

banks by the Russian government created uncertainty about every bank that had either directly or indirectly transacted with the two offending banks on the interbank loan market thus making them "toxic". Toxic banks could have been randomly subjected to the Russian government's audit and could have had all of their assets, including in-process payments for goods and services by and to their clients, frozen for the audit's duration. Non-toxic banks were therefore reluctant to transact, including payments for goods and services, with toxic banks anticipating payment holdups.

Relying on detailed interbank loan transaction data, we exploit the heterogeneous exposure of Russian banks and thus their client firms to toxic banks to obtain firm-specific access-to-payment shocks. We then combine this information with the firm-firm transaction data to trace and quantify the extent of access-to-payment shock propagation along the customer-supplier network. Using a general equilibrium model of production networks, we also obtain an estimate for the overall macroeconomic impact of the payment system stress that takes these propagation effects into account.

The unique granular transaction-level data is from the Moscow branch of CBR covering all transactions routed via this branch for the December 2003–December 2004 period.[3] Our payments data identifies the sender firm, sender bank, receiver bank, and receiver firm for 133 million transactions between 1.168 million unique paying entities that use 1,413 sender banks 1.245 million receiving entities and 1,418 receiving banks with time-stamped interbank unsecured short-term loan data between all bank pairs. From this data, we construct the customer-supplier network based on payment flows for goods and services between customers and suppliers, the magnitude of access-to-payment shocks based on interbank lending relationships, and firms' exposure to access-to-payment shocks based on firms' banking relationships. Specifically, we use banks' interbank connection loss during the 2004 events and firms' exposure to these banks prior to the 2004 events as a source of identification for firm-specific access-to-payment shocks. For each firm, we calculate the weighted average of the extent to which banks dealing with this firm were affected by the interbank shutdown, and the weights are pre-shock shares of these banks in firms' total payments to their suppliers. This shock-based 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 the total flow of the firm's payments.

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

Empirically, we document several novel stylized facts. On the effects of the shock on the payment network, we find that a large number of firms have not been able to either receive or send payments after May 13, 2004. As a consequence, firms' input-output centrality declined. On the effects of the shock on firm-level real economic activity, we find that access-to-payment shocks depress firm growth and profitability. Firm growth declines with the firm's own loss of access to payments—a one-standard-deviation increase in the payment shock results in 2.1% reduction in revenue growth, both economically and statistically significant. Furthermore, not only firms' own shocks but other firms' shocks in the firm-firm customer-supplier network impact revenue growth. Access-to-payment shocks propagate upstream, that is, firm growth declines with the shocks of its customers more than with the shocks of its suppliers. More specifically, a one-standard-deviation increase in a firm's downstream sender banks' payment shock reduces the firm's revenue growth by 2.7%, while a similar increase in the firm's upstream banks' payment shock reduces revenue growth by only 0.7%.

In the cross-section of firms, we find that more eigen-central firms are more sensitive to access-to-payment shocks and experience a larger decline in growth. The interpretation of this finding is via the lens of the "resilience" to payment disruption which endogenously arises in the model we develop. Essentially, less eigen-central firms have less exposure to toxic banks and to other firms that are exposed to these banks. As a consequence, more pre-panic central firms, or less resilient firms, experience a greater reduction in revenue growth than less central firms when hit by the same shock to their own banks. Economically, a one-standard-deviation increase in the log centrality of a firm leads to a 1.1 percentage-point larger decrease in the firm's revenue growth for a one-standard-deviation payment shock.

To quantify the macroeconomic impact of payment system stress, we develop an equilibrium model of production in which access-to-payment shocks disrupt firms' access to bank-intermediated payment services and propagate via interfirm linkages. The model yields a micro-to-macro aggregation for the GDP impact of access-to-payment shocks. 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, originating in the financial sector and unrelated to the production sector, have a differential impact by hitting firms via direct and indirect channels. They force firms to substitute from the external to internal inputs thus directly reducing marginal productivity and, in agreement with our empirical findings, inhibiting growth. Access-to-payment shocks also propagate into profits via the firm's eigenvector centrality which is the indirect or network channel. Eigenvalue centrality in our model is stochastic; it is the firm's Domar weight in the input-output network adjusted for access-to-payment shocks. It hence summarizes how shocks of the firm's customers and suppliers affect its profits. Since GDP aggregates all shocks, firms' eigenvector centrality captures the pass-through rate of the access-to-payment shocks to GDP. By inhibiting a firm's own ability as well as the abilities of its customers and suppliers to exchange payments these shocks reduce the firm's eigenvector centrality. Consequently, and also in agreement with our empirical findings, more eigen-central firms are more sensitive to access-to-payment shocks. Finally, just like we find in the data, access-to-payment shocks propagate upstream in the model, that is, the firm's profit growth declines with the shocks of the customers more than with the shocks of suppliers. This is because in the former case when the sender banks cannot process payments the sales 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 on its internal inputs.

This framework allows us to microfound a measure of firms' real resilience to payment disruptions which can be captured by the elasticity to access-to-payment shocks of the firm's eigenvector centrality in the firm-firm input-output network of payment flows. As the input-output network structure changes because of the propagation of access-to-payment shocks, firms' network centralities readjust. Just like in the data, the higher is the firm's real resilience, the less its sales and profits drop due to its own payment shock as well as to shocks originating at its customers and suppliers. Such real resilience is an important characteristic capturing the cross-sectional response to access-to-payment shocks, both firm-specific and spilled-over through the firm-firm network from other firms.

We then combine the model with our payment-level data to obtain an estimate for the overall macroeconomic effect of the 2004 payment system stress on Russian GDP. In the model, the micro-to-macro aggregation expression depends on the input elasticity between internal and external factors of production, upstream payment shock propagation, and Domar weight readjustments. In equilibrium, access-to-payment shocks reduce GDP through two channels: Firms' sales drop in response to access-to-payment shocks and, due to the external-internal input elasticity, customer-supplier network readjustments occur that buffer the direct impact of the shocks. Implementing the micro-to-macro expression yields that the payment disruptions in 2004 caused a 7.5% decline in Russian GDP, driven by a large drop in average log sales and partially offset by payment network readjustments. The significant drop in GDP, with a range from 1.7% to 13% across specifications, attributable to the interbank loan market panic of 2004 highlights the severe economic consequences of systemic disruptions in the payment system. This substantial decline underscores the critical role of financial stability in maintaining economic activity.

In a counterfactual exercise, we use our estimated input-output linkages between customers and suppliers and banks' position in the interbank network to obtain equilibrium forecasts for the macroeconomic impact of geopolitical tensions. As an exogenous shock, we study how the exodus of major foreign banks at the onset of the Russia-Ukraine conflict spilled into the payment system and disrupted the Russian economy in 2022. We find that the causal impact of access-to-payment shocks on the Russian economy during the 2022 Russia-Ukraine conflict is estimated to be -1.1%. This decline highlights that geopolitical tensions can deteriorate economic stability. However, the magnitude of the effect in 2022 is much smaller than the magnitude during 2004. An important difference with the 2004 access-to-payment shocks and the counterfactual 2022 exercise is that here we have only foreign banks leave the Russian interbank loan market and these banks, while being large in size and customer base, have been less intertwined within the Russian economy. As a result, fewer firms experienced direct and indirect payment disruptions during the Ukraine-Russia conflict thus mitigating spillover effects.

Overall, our analysis stresses the vulnerability of the economy to payment system stress depending on the network positions of the banks being affected and how they are intertwined with the firms for which they provide intermediation services, highlighting the importance of robust financial infrastructures in fostering economic resilience.

Related literature. There has been growing interest after the 2007-8 financial crisis in designing optimal financial architectures. 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), Bigio and La'O (2020)). However, the payment system has received little attention. We contribute to this debate by using granular four-dimensional bank-firm-firm-bank data to show how the financial and real sectors are intertwined through the payment system.

More broadly, 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 by, e.g., Acharya *et al.* (2018), Chava and Purnanandam (2011), Dell'Ariccia *et al.* (2008), Khwaja and Mian (2008), Paravisini *et al.* (2015). By contrast, banks' role in intermediating payments has received little attention in the literature 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 an exogenous shock to the interconnectedness of sending and receiving banks in the interbank loan network to measure firms' heterogeneous exposure to the shocks and then study the percolation in the firm-firm input-output network.

Copeland, Duffie, and Yang (2021) document intraday payment timing stress in the U.S. financial system leading up to the mid-September 2019 Treasury repo blowup. They document that large aggregate reserve balances held by 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. 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 on the financial and real importance of the payment system. We document the impact of an episode where the central bank was unable (or unwilling) to fully internalize the consequences of payment system stress, similar to the situation at the onset of the 2022 Russia-Ukraine war. Payment system stress in the Russian 2004 episode extended across days and adversely impacted real economic activity, much like in 2022.

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. Carvalho *et al.* (2021) quantifies the down- and upstream propagation and amplification of supply chain shocks in this framework. Barrot and Sauvagnat (2016) study the downstream propagation of idiosyncratic productivity shocks in the U.S. due to natural disasters. Huremovic *et al.* (2020) study the upstream propagation of credit-supply shocks during the 2008–9 financial crisis. La'O and Tahbaz-Salehi (2022) introduce nominal rigidities and information frictions in a network economy which leads to sticky customers, which we document empirically. 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 that propagate through the input-output economy differently than productivity shocks (Baqaee and Farhi (2019), Bigio and La'O (2020)). Our work is also related to papers using administrative firm-level data from countries with value-added tax (see Bernard *et al.* (2022) for Belgium and Demir *et al.* (2023) for Turkey) to study properties of input-output networks. However, unlike our paper, these papers lack information on the intermediaries facilitating firm-firm transactions and cannot reconstruct the payment networks.

The remainder is organized as follows. Section 2 describes the granular data for the Russian payment system used in the analysis. Section 3 provides our empirical hypotheses and tests based on an instrumental variables approach. Section 4 develops the model to motivate our aggregate analysis of payment system shocks in Section 5. Section 6 concludes.

2 Payments Data and 2004 Interbank Loan Market Panic

The structure of the Russian banking system is in large part shaped by the privatization of the extended network of the Soviet banks.[4] The payment system was set up with the help of the IMF and by the end of the 1990s underwent 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 is 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.

2.1 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 on clients' behalf and for their own accounts.[5] 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 clients. The CBR then debits bank s's account and credits bank r's by the net outstanding value of the clients' orders.

Figure 1 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

[4] Berkowitz *et al.* (2014) and Bircan and De Haas (2019) provide a detailed account of its evolution.

[5] Mironov (2013) and Mironov and Zhuravskaya (2016) provide a detailed description of the source and scope of the data.

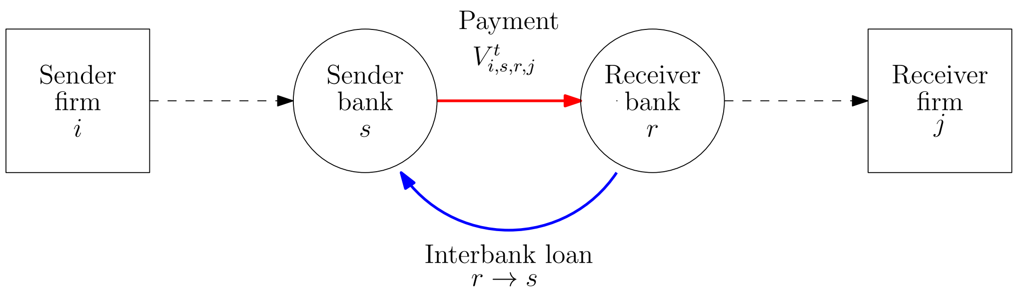

Figure 1: Structure of payment system and interbank loan market

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. The blue arrow indicates an interbank loan between banks r and s with r being the originator bank.

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, sender i fills 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 is in charge of submitting the payment order into the CBR's payment system where the account of bank s with the CBR is debited by 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 receiver 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 the types of transactions between them are interbank

loans.

Both types of payments are cleared by the CBR. When routing the first type of payment, commercial banks act as intermediaries of firms with whom they have banking relationships. As a result, banks are matched with each other by firms' invoices for goods and services based on firms' customer-supplier relationships.

The second type of payment is initiated by banks themselves where the exchange of funds occurs between banks that temporarily experience liquidity surplus and banks experiencing liquidity shortage. Similarly to other countries' interbank loan 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.[6] These interbank loans are routed through the CBR's payment system allowing us to identify the network of banks that exchange liquidity.

Summary statistics. The 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 using 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 so-called "fly-by-night" firms (Mironov (2013)) created for income diversion purposes and dissolved after a single transaction. The final sample includes 756,150 sender firms that on average use 1.2 sender 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.

Table 1 reports summary statistics of the firm-bank network where Panel A documents payments by sender firms and Panel B by recipient firms. The network here is built by 10,965,592 firm pairs that transact with each other. Firms use the intermediation services of banks while routing their payments 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'

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

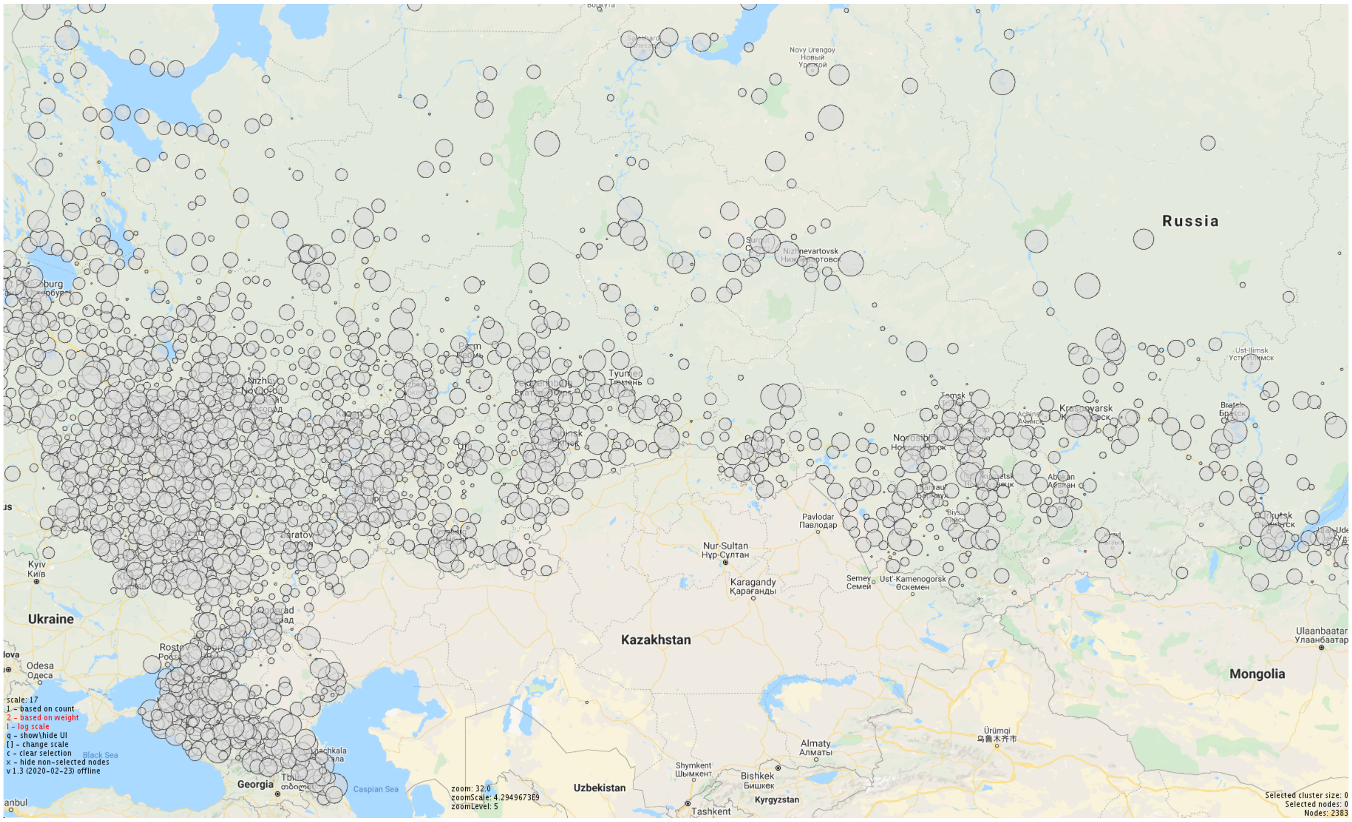

Figure 2: Map of firm locations

This figure plots the location of firms in our sample. The size of each circle shows the aggregate ruble volume of firms' outgoing payments from a given location.

accounts with the CBR.

Figure 2 plots the location of firms in our sample. The total firm activity is captured by the size of each circle. It shows that the distribution of the payments routed through the CBR's Moscow branch corresponds to the geographic distribution of economic activity in Russia.

2.2 May 2004 panic and collapse of interbank network

The Russian interbank loan market panic and subsequent collapse in May 2004 served as an exogenous shock to the payment system. During the panic, some banks became "toxic" due to an exogenous event. As a result, non-toxic banks reduced their exposure to toxic banks by refusing to loan to them on the interbank loan market. The disruption of the interbank loan market relations spilled over into the payment system where the same bank-pairs were also likely to break their payment relations by refusing to accept/send payments from/to each other, thus disrupting business relationships between their client firms.

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

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

	Mean	Std. Dev.	Min	Median	Max	N
Panel A: Sender 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 sender firm	1.202	0.5918	1	1	83	756,150
No. recipient banks per sender firm	9.685	19.83	1	3	786	756,150
No. recipient firms per sender 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

May 2004 panic on the interbank loan market. On May 13, 2004, the CBR unexpectedly withdrew the banking licenses 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 licenses for money laundering reasons. This statement caused panic on the interbank loan market which resulted in a sudden drop in interbank volume and bilateral connections on the market.[7]

Figure 3 graphs the aggregate impact of the panic on interbank lending during 2004. The left plot shows the number of unique bilateral bank-bank connections on the interbank loan market per day. Each connection represents an exchange of liquidity between a unique pair of banks on the interbank loan 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 loan market experienced a sharp decline in the number of bilateral bank connections. The decline in interbank

[7]See Degryse *et al.* (2019) for the discussion of the interbank loan market panic episode.

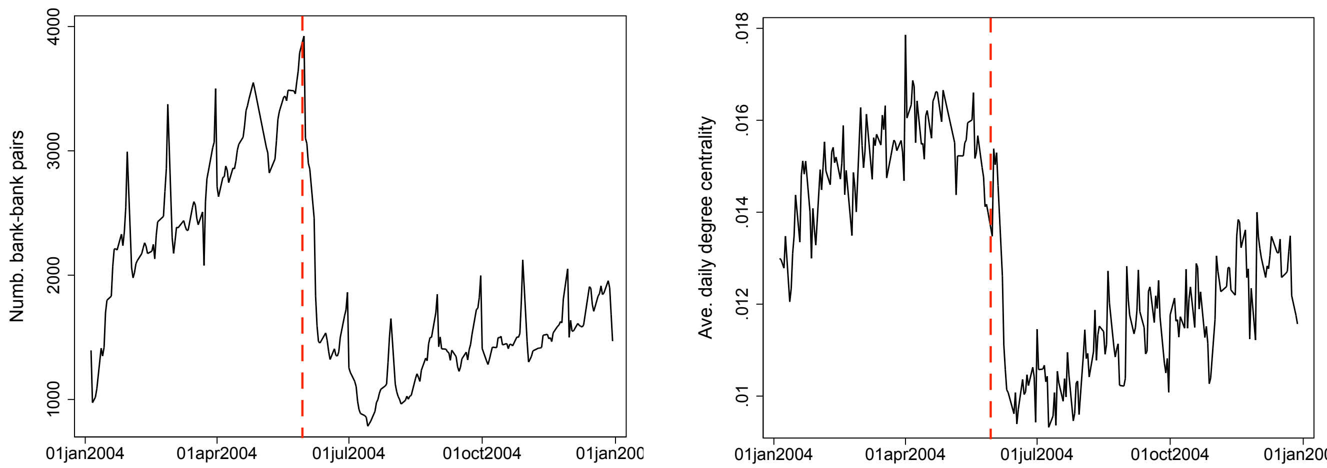

Figure 3: Dynamics in interbank connections and interbank loan market structure
The left figure documents the total number of daily interbank connections across bank-bank pairs for the period from January 01, 2004 to January 01, 2005. The right figure shows the daily dynamics of the average degree centrality across banks, capturing the interbank network topology for the period from January 01, 2004, to January 01, 2005.

connections was profound and persisted at least until early 2005. The plot demonstrates that the interbank loan market borrowing and lending shrunk at the aggregate level as the number of bilateral bank connections decreased.

The right plot in Figure 3 documents the impact on the interbank network structure. The plot shows the daily dynamics of the average degree centrality of each bank in the interbank loan market. In agreement with the left plot of Figure 3, the average bank has sharply reduced the number of its interbank connections in the aftermath of the panic. The effects on the interbank network topology were highly persistent. Overall, these results highlight that the interbank loan market panic caused the interbank network to become more centralized.

Banks' loss of interbank connectivity. The interbank loan market panic satisfies the relevance condition for at least two reasons. First, two medium-sized banks lost their licenses due to money laundering. Second, the subsequent panic caused a breakdown of bilateral relationships in the interbank loan market. The exclusion restriction is satisfied because, first, the panic started for exogenous reasons unrelated to the economy and overall banking system. Second, only a handful of banks actually lost their licenses while many banks not linked to the defaulted banks lost interbank connectivity.

Figure 4 sheds additional light on the consequences of the interbank loan market panic. It graphs

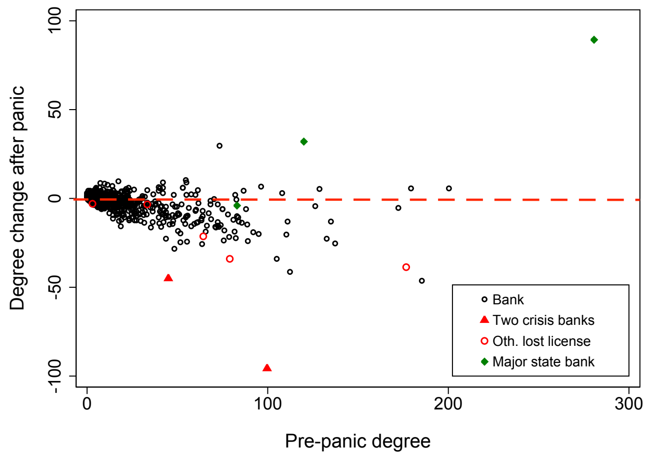

Figure 4: Panic effect on interbank connections

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-owned banks (green rhombus).

the change in banks' interbank network connection pre- and post-panic on the vertical axis against their average pre-panic degree centrality on the horizontal axis. Red triangles indicate the two banks with revoked banking licenses, red circles indicate banks that subsequently lost their licenses, and green rhombuses indicate major state-owned banks. The plot demonstrates that more central banks experienced a larger net loss of interbank connections. This is not surprising, as they had many more connections than fewer central banks to begin with. State-owned banks are the notable exception—all three state-owned 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 the two medium-sized banks suddenly losing their licenses caused an interbank loan market panic. Both defaulted banks were well connected prior to their demise and highly interconnected on the interbank loan market thus leading to a large number of banks becoming "toxic" post-factum.

Our instrument capturing the bank-level shock in the interbank loan market is based on the bank's loss of interbank connectivity. Motivated by Figure 4, we define the bank's loss of connectivity on the interbank loan market as the symmetric growth rate of the bank's connections over the pre-panic and post-panic periods. Let N_s^t be the number of interbank loan market links of the bank s in the corresponding interbank loan market panic-related period $t \in \{\text{pre}, \text{panic}\}$. The pre-panic period for measuring interbank connections before the shock is March-April 2004, and the panic period covers June 2004.[8] The shock-based instrument is the panic minus the pre-panic change in interbank connections for bank s:

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

Interbank Connection Loss$_s$ captures bank s's toxicity with lower/higher values implying being less/more toxic. We associate high/lower toxicity with lower/higher transaction volume handled by the bank due to loss/gain in interbank connectivity.[9]

3 Evidence on Firm-Level Effects of Payment System Stress

Granular data from the Russian payment system on firm-firm payments provides a unique setting in which to test how payment system stress affects and propagates through firms' input-output network. We have documented in Section 2 that the interbank loan market panic has resulted in a 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-bank links are not specific to the interbank loan market but extend to other bank-bank flows that may lead to federal scrutiny and suspension of bank operations. Correspondingly, unaffected banks stopped processing inflows/outflows from/to affected banks including payments for goods and services thus disrupting the firm-firm payment network. This is the economic scenario we test by constructing Bartik (1991) type shift-share shocks from the granular bank-firm and firm-firm data.

[8] In our analysis of real activity, we extend the pre-panic period from December 2003 to May 2004, the panic period is June 2004, and the post-panic period includes July 2004 to December 2004.

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

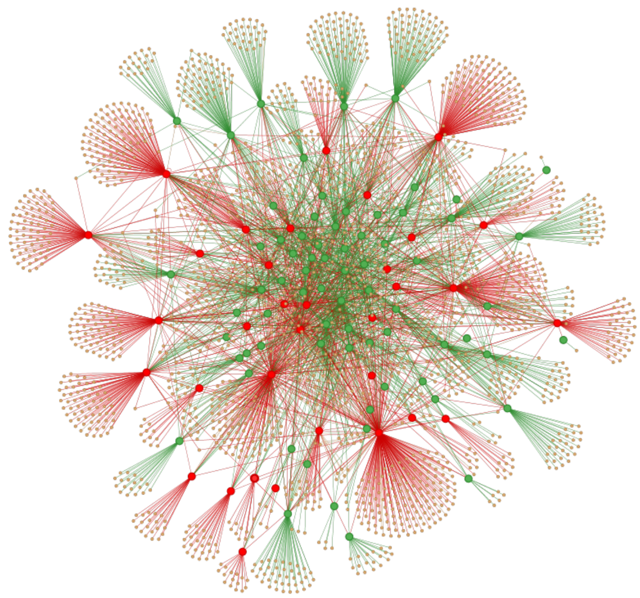

Figure 5: Firm-firm payment network

The plot shows the pre-panic payment network of the top 0.5 percent sender firms through their top 10 percent banks to their top 50 percent of receiver 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 loan market. Green circles are banks that were not their partners.

3.1 Variable construction and empirical strategy

Our empirical strategy to identify the impact of exogenous variation in firms' ability to wire payments on payment flows in the customer-supplier network of firms relies on the construction of Bartik share-shift payment shocks and controls for unobserved confounders with firm and industry-location fixed effects at both ends of the payment flows and by rejecting alternative explanations.

Figure 5 illustrates the pre-panic firm-firm payment and firm-bank relationship networks. We only show the largest firms and their top suppliers measured by the total payment volume going through each entity. The small brown nodes are firms that make and receive payments. The figure also illustrates the pre-panic firm-bank links for these firms. The large nodes indicate the banks used by the firms. The different colors indicate the exposure of the firms' banks to the two crisis banks in the pre-crisis period on the interbank loan market (red = yes, green = no exposure). The figure shows that the exposure to the two crisis banks varies significantly across firms.

Growth in firm-firm payments and firms' sales. We start by aggregating daily payment flows $V^t_{i,s,r,j}$ between sender firm i and receiver firm j across all sender banks s and receiver banks

r that intermediate the transactions in the pre- and post-panic half-year periods $t \in \{\text{pre}, \text{post}\}$. The pre-panic period covers six months before the payment system shock (December 2003 - May 2004) and the post-panic period covers six months after the shock (July 2004 - December 2004). We exclude the panic month of June 2004.

The total pre/post-panic payment flow between firms i and j in period $t \in \{\text{pre}, \text{post}\}$ equals

$$V_{i,j}^{t} = \sum_{s=1}^{S_i^t} \sum_{r=1}^{R_j^t} V_{i,s,r,j}^{t}, \tag{2}$$

where S_i^t denotes the number of sender banks s of firm i and R_j^t denotes the number of receiver banks r of firm j during the pre/post-panic periods. $V_{i,j}^t$ represents the value of goods and services delivered by supplier j to its customer i in the given period and is measured by the total payment inflows (i.e., revenue) received by supplier firm j from its customer i.

To identify the impact of payment disruptions at the firm level, we aggregate firm-firm payments at the receiver firm level. Let $n_j^{\text{pre/post}}$ be the number of firm j's customers and $V_j^{\text{pre/post}} = \sum_{i=1}^{n_j^{\text{pre/post}}} V_{i,j}^{\text{pre/post}}$ the total pre/post-panic revenue of firm j from all its customers i during the pre/post-panic periods . We define two main outcome variables. First, the growth rate $Y_{i,j}$ in firm-firm payment flows from customer firm i to supplier firm j between the post- and pre-panic periods is equal to

$$Y_{i,j} = \frac{V_{i,j}^{\text{post}} - V_{i,j}^{\text{pre}}}{\frac{1}{2}(V_{i,j}^{\text{post}} + V_{i,j}^{\text{pre}})} \in [-2, 2]. \tag{3}$$

Defining the outcome variable as the symmetric growth rate has the advantage of capturing both the intensive and extensive margins of the payment disruptions on firm-firm payment growth.[10] In order to restrict the sample to firm pairs (i, j) that wire economically meaningful payments, we filter out all firm pairs for which the average payment $\frac{1}{2}(V_{i,j}^{\text{pre}} + V_{i,j}^{\text{post}}) < 30,000$ Rubles (approx. $1,000$ USD).[11] Second, the growth rate of firm i's sales between the post- and pre-panic periods is equal to

$$Y_{i} = \frac{V_{i}^{\text{post}} - V_{i}^{\text{pre}}}{\frac{1}{2}(V_{i}^{\text{post}} + V_{i}^{\text{pre}})} \in [-2, 2]. \tag{4}$$

[10] We use symmetric growth as it captures the entry (value 2) and exit (value -2) of links between firms. The measure has been used by Davis and Haltiwanger (1992, 1999) and Chodorow-Reich (2014).

[11] We also conduct the empirical tests of this section on the full sample of firm pairs and find that all estimation results remain unchanged.

Table 2: Summary statistics for payments data

Panel A reports the summary statistics for disaggregated firm-firm payment data. Panel B reports the summary statistics for the cross-sectional data of firms receiving and sending payments in December 2003 to December 2004.

	Mean	Std. Dev.	Min	Median	Max	N
Panel A: Summary statistics for firm-firm payments data						
Payment growth $Y_{i,j}$	0.166	1.726	-2	0.334	2	3,903,484
Payment value before panic $V_{i,j}^{\text{pre}}$ (thsd. RUB)	2,339	44,300	0	203	41,526,164	2,437,111
Payment value after panic $V_{i,j}^{\text{post}}$ (thsd. RUB)	2,634	52,613	0	216	39,108,604	2,730,565
Shock to sender (downstream) firm's banks Z_i	0.059	0.344	-2	0.005	2	3,904,908
Shock to receiver (upstream) firm's banks Z_j	0.045	0.330	-2	0.005	2	4,032,137
No. receiver firms per sender firm	125.5	415.2	1	40	7,840	3,904,908
No. sender firms per receiver firm	302.1	1364	1	54	17,190	4,032,137
Panel B: Summary statistics for firm-level payments data						
Payment inflow (revenue) growth Y_i	0.169	1.505	-2	0.26	2	524,387
Shock to firm's own banks Z_i	0.045	0.349	-1	0	2	524,387
Shock to downstream firms' banks Z_i^{d}	0.062	0.208	-0.409	0	0.916	524,387
Shock to upstream firms' banks Z_i^{u}	0.046	0.175	-0.409	0	0.840	524,387
Pre-panic firm's eig. centrality $\log \delta_i$	-4.503	1.193	-9.995	-4.368	-0.558	298,019
Pre-panic downstream eig. centrality $\log \delta_i^d$	-3.169	0.938	-19.36	-3.002	-0.558	298,019
Pre-panic upstream eig. centrality $\log \delta_i^u$	-2.516	0.833	-11.94	-2.470	-0.558	227,577

In order to restrict the sample to firms that receive economically meaningful sales, we again filter out all firms for which $\frac{1}{2}(V_i^{\text{pre}} + V_i^{\text{post}}) < 30,000$ Rubles (approx. $1,000$ USD). Figure A.3 in the Appendix illustrates the data and the construction of the variables of interest.

Table 2, Panel A reports summary statistics for firm-firm payment growth $Y_{i,j}$. Its mean (median) is equal to 0.166 (0.334) with a standard deviation equal to 1.726. Table 2, Panel B reports summary statistics for Y_i. Its mean/median is equal to 0.169/0.260 with a standard deviation equal to 1.505 due to a number of outlier firms with the min/max values of $Y_i = -2/2$.

Firm-level access-to-payment shocks. We link firm-level outcomes to the firm's ability to pay upstream firms for inputs captured by access-to-payment shocks. Empirically, we construct corresponding shock variables $Z_{i/j}$ as the sender/receiver firm's i/j's loss of access-to-payment services due to the interbank loan market panic effect on all S_i/R_j banks that firms use to send/receive payments.

To construct $Z_{i/j}$, we define the exposure $\kappa_{i,s}^{\text{pre}} \in [0, 1]$ of firm i to bank s as the pre-panic share of the sender bank s in the total payments made by firm i to all of its upstream (i.e., receiver) firms.[12]

[12] As an example, consider a firm using 2 banks, $N_i = 2$, to make payments to 3 supplies with payment volumes

For each sender firm i and its sender banks $s = 1, ..., S_i$ we define i's loss of access-to-payment services, Z_i, and similar for each receiver firm j and its receiver banks $r = 1, ..., R_j$ we define j's loss of access-to-payment services, Z_j. The access-to-payment shocks are

$$\begin{aligned} Z_i &= \textstyle\sum_{s=1}^{S_i} \text{Interbank Connection Loss}_s \cdot \kappa_{i,s}^{\text{pre}}, \\ Z_j &= \textstyle\sum_{r=1}^{R_j} \text{Interbank Connection Loss}_r \cdot \kappa_{j,r}^{\text{pre}}. \end{aligned} \tag{5}$$

The firm-level shocks $Z_{i/j} \in [-2, 2]$ capture how the shock to the firm's banks affects its ability to make payments to suppliers (upstream firms) or receive payments (downstream firms).[13] Higher/lower values of $Z_{i/j}$ imply the firm is less/more able to make payments to its suppliers (receive payments from customers) due to the interbank loan market panic.

Table 2, Panel A reports summary statistics for Z_i and Z_j, respectively. Shocks to up/downstream firms are centered around zero with a mean equal to 0.059/0.045 and standard deviations equal to 0.344/0.330.

Up/downstream shocks. Testing the up/downstream propagation of access-to-payment shocks requires tracing the impact of receiver firm i's loss of access-to-payment services on all n_i^{d} downstream and n_i^{u} upstream firms that firm i receives/sends payments from/to in the pre-panic period.

Let $\zeta_{i,k}^{\text{d}} \in [0, 1]$ and $\zeta_{i,j}^{\text{u}} \in [0, 1]$ be the pre-panic shares of downstream (i.e., customer) firm k and, respectively, upstream (i.e., supplier) firm j in the total payments received and sent by firm i. For each firm i and its pre-panic downstream firms, $k = 1, ..., n_i^{\text{d}}$, we define firm i's loss of access to receiving payment services from its customers, Z_i^{d}. Similarly, for each firm i and its pre-panic upstream firms, $j = 1, ..., n_i^{\text{u}}$, we define firm i's loss of access to sending payment services to its suppliers, Z_i^{u}

$$\begin{aligned} Z_i^{\text{d}} &= \textstyle\sum_{k=1}^{n_i^{\text{d}}} \zeta_{i,k}^{\text{d}} \cdot Z_k, \\ Z_i^{\text{u}} &= \textstyle\sum_{j=1}^{n_i^{\text{u}}} \zeta_{i,j}^{\text{u}} \cdot Z_j, \end{aligned} \tag{6}$$

where Z_k and Z_j are the payment shocks hitting firm i's customers and suppliers defined in (5).

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 $\kappa_{i,2} = 3/5$.

[13]While $Z_i \in [-2, 2]$ does not match one-to-one with m_i used in the model, the proper match can be achieved using transformation $(Z_i + 2)/4 \in [0, 1]$.

The firm-level shocks $Z_i^{\mathrm{d/u}} \in [-2, 2]$ are the flow-weighted payment shocks from *all* down/upstream firms connected pre-panic to firm i. Higher/lower values of $Z_i^{\mathrm{d/u}}$ imply the firm is more/less affected by the interbank loan market panic due to its connections to down/upstream firms.

Table 2, Panel B reports summary statistics for Z_i in the cross-section of receiver firms and for the network of the receiver firm's partners $Z_i^{\mathrm{d/u}}$. All shocks have the same zero median value. The mean and volatility of the shock to downstream firms' banks, equal to 0.062 and 0.208, respectively, are larger than the mean and volatility of the shock to upstream firms' banks, equal to 0.046 and 0.175, respectively.

Identification and alternative banking channels. The access-to-payment shocks $Z_{i/j}$ have a shift-share structure at the firm level in the spirit of Bartik (1991). The share component is the pre-panic firm's exposure to banks, $\kappa_{i,s}/\kappa_{j,r}$, while the shift component is the bank's loss of connectivity on the interbank loan market, Interbank Connection $\text{Loss}_{s/r}$. Goldsmith-Pinkham, Sorkin, and Swift (2020) study identification assumptions needed for a shift-share instrument coming from the exogeneity of shares. Our case corresponds to the quasi-random assignment of banking shocks to firms that allows endogeneity between shares and payment flow outcomes (Borusyak, Hull, and Jaravel (2022)). The shocks $Z_i^{\mathrm{d/u}}$ maintain the shift-share structure where shift works through the exogenous loss of connectivity on the interbank loan market of each firm i's partners' banks, having demonstrated that (Z_k, Z_i, Z_j) are exogenous with respect to firm-firm payment flows, and the shares are the pre-panic weights $\zeta_{i,k/j}^{\mathrm{d/u}}$ of firm i's partners' flows.

In order for our firm-level shocks $Z_{i/j}$ to be valid in disentangling the exogenous variation in a firm's access to payments we show that payment outcomes of firms before the panic did not differ across strongly-hit and weakly-hit firms during the panic. This suggests that shocks $Z_{i/j}$ should be exogenous to pre-determined characteristics of firms. We establish the conditional random assignment of banking shocks to firms by conducting falsification tests in Table 4, Panel B that relate payment flows between firm pairs in 2003 ($Y_{i,j}^{2003}$) to access-to-payment shocks that hit those firms in 2004 ($Z_{i/j}^{2004}$). We show that payment flows of sender and receiver firms in 2003 did not vary systematically with banking shocks $Z_{i/j}$ that hit them in 2004. This evidence provides support for our identification assumptions. Table 5, Panel B performs the same falsification tests for the up/downstream propagation of access-to-payment shocks.

The invariance of firms' initial conditions to the interbank loan market shock of their banks leaves a concern that the shock could affect other banking channels that also influence firms' payment flows. For example, due to the sticky relationship of firms with banks, they may use the same bank for payment services and commercial loans. In this case, it is possible that the lending channel could be driving our results: banks that were hit by the interbank loan market panic could reduce the loan supply to firms which could depress their economic activity and payment flows. It is well known that this bank lending channel impacts the real activity of firms during a severe economic crisis caused by the collapse of systemically important banking institutions such as Lehman Brothers (e.g., Chodorow-Reich (2014), Alfaro, García-Santana and Moral-Benito (2021)). In the case of the liquidity crunch caused by the 2004 interbank loan market panic, the lending channel should be less important while the payment network disruption should become the primary channel affecting the firm's payment flows. In robustness tests, we check that interbank connection losses caused by the interbank loan market panic did not significantly affect either banks' lending or non-performing loans in the post-panic period.[14] This evidence goes against the alternative explanation.

Observable firm-level characteristics. We use standard firm-level characteristics as controls $\boldsymbol{X}_i$, including firm size (we use log(Assets) as its proxy), Return-on-assets (ROA), Cash-to-assets ratio, and Revenue turnover (revenue/assets ratio). We also include Days payable outstanding (DPO) and Receivables collection period (RCP) which capture the average number of days it takes for a firm to send and receive payments from its counterparties. We also geolocate firms by their address and calculate the geographical distance between all sending i and receiving j firm pairs in our sample. Vast international trade literature documents that geographical distance is a good proxy for transportation costs between upstream and downstream firm pairs (Chaney (2018)).

Summary statistics for all control variables $\boldsymbol{X}_i$ are reported in Table 3. The average/median value of sender firms' log(Assets) is equal to 14.54/14.64 with a standard deviation of 2.786. The

[14] We use the granular data on payment invoices for calculating the time period between dates when firms entered the contract for selling goods and services and when the payment was wired by firms' banks. We show that the loss of connectivity by a sender bank in the interbank loan market network causes a significant delay in the processing time of a firm's payments wired through a bank. This evidence supports our main argument that during the liquidity crunch, the exogenous shock to the bank's network connectivity has a direct effect on its ability to process the firm's payments leading to a real impact on the economy.

Table 3: Summary statistics for the firm level controls

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

	Mean	Std. Dev.	Min	Median	Max	N
Panel A: Sender firms (customers) characteristics						
log(Assets)	14.54	2.786	0	14.64	28.24	203,020
ROA	0.051	0.383	-1.391	0.029	1.151	175,794
Cash-to-assets	0.163	0.252	0.001	0.044	1	192,268
Revenue turnover	11.76	32.94	0.009	3.18	254.4	190,876
Days payable outstanding (days)	133.2	216.9	1	47	834	190,824
Receivables collection period (days)	95.24	179	0	26	713.5	190,637
Firm-firm distance (km)	577.3	1103	0	33.79	7,581	225,997
Panel B: Receiver firms (suppliers) characteristics						
log(Assets)	14.54	2.765	0	14.66	28.24	238,570
ROA	0.047	0.371	-1.328	0.026	1.175	206,758
Cash-to-assets	0.163	0.253	0.001	0.043	1	225,468
Revenue turnover	11.88	35.5	0.018	3.052	292.3	224,660
Days payable outstanding (days)	145.3	244.3	0	49.5	956	224,627
Receivables collection period (days)	98.56	182.5	0	28	727	224,417
Firm-firm distance (km)	620.3	1115	0	78.29	7,793	273,523

average/median ROA is equal to 0.051/0.029 with a standard deviation of 0.383, while the average/median cash-to-assets ratio is equal to 0.163/0.044 with a standard deviation of 0.252, indicating that the median firm in our sample is small. The average/median revenue turnover is equal to 11.76/3.18 with a standard deviation of 32.94. The average/median geographical distance between firm pairs in our sample is equal to 577.3/33.79 kilometers with a standard deviation of 1,103 and a max value of 7,581. The averages reported in Panel B of the table for observable receiver firms' characteristics are very similar to those reported in Panel A for sender firms. This indicates that on average sender and receiver firms are similar in our sample.

We now have all the necessary variables to document the set of stylized facts on the impact of payment stress on firm-firm payments and firm growth.

3.2 Impact of access-to-payment shocks on firm-firm flows

We start by exploring how access-to-payment shocks influence firm-firm payments. Intuitively, we expect payment disruptions to diminish firms' ability to make payments for goods and services to one another thus reducing the firm-firm payment growth, which we find in the data.

FACT 1: *Firm-firm payment growth $Y_{i,j}$ declines with firms' access-to-payment shocks at sender (downstream/customer) firm i, Z_i, and receiver (upstream/supplier) firm j, Z_j.*

To establish this fact in our data, we estimate the elasticity of payment growth between sender and receiver firms i, j to access-to-payment shocks, using the first-difference regression model:[15]

$$Y_{i,j} = \alpha_{F_{j/i}} + \alpha_{I_{j/i}} \times \alpha_{\mathrm{Zip}_{j/i}} + \beta_1 Z_{i/j} + \gamma' \boldsymbol{X}_{i/j} + \varepsilon_{i,j}. \tag{7}$$

Specification (7) nests several empirical models with different combinations of fixed effects. Appendix A provides a discussion of the empirical specification. The firm-level fixed effects $\alpha_{F_{j/i}}$ absorb all time-invariant unobservables such as investment opportunities of firms. Industry-location fixed effects $\alpha_{I_{j/i}} \times \alpha_{\mathrm{Zip}_{j/i}}$ control for the local shocks to costs of inputs and industry-wide demand shocks. The set of control variables $\boldsymbol{X}_{i/j}$ is listed in Table 3. In a model with the sender-firm fixed effects, α_{F_i}, coefficient β_1 captures the differential effect of the receiver firm's access-to-payment shocks Z_j on the growth of payment flows *within* the sender firm i. Similarly, in a model with receiver firm fixed effect, α_{F_j} coefficient β_1 captures the differential effect of the sender firm's access-to-payment shocks Z_i on the growth of payment flows *within* the receiver firm j. We double-cluster standard errors at the sender firm's industry location and receiver firm's industry-location levels and weight firm pairs by the inverse number of sender firms per recipient firm.

Table 4 reports our results for the interbank loan market panic period (Panel A) and for the year preceding the panic (Panel B). Effectively, Panel B reports the estimation results of the falsification test. The insignificance of coefficients across all columns of Panel B confirms the parallel trends assumption needed for establishing the exogeneity of access-to-payment shocks. Let us focus on the main results reported in Panel A of Table 4. The first notable result is that, in agreement with model prediction 1, firm-firm payment growth declines with the shocks to the firm's own banks at both ends of the payment flows. Estimated coefficients on shocks $Z_{i/j}$ are negative and highly statistically significant across all specifications.

[15] The econometrics of difference-in-differences and first-difference regression models have recently received renewed attention in de Chaisemartin and D'Haultfoeuille (2020) and Callaway, Goodman-Bacon, and Sant'Anna (2024) among others. Our specification (7) falls into the sharp design category and satisfies the stable group assumption of de Chaisemartin and D'Haultfoeuille (2020) since there are firms whose banks were unaffected by the interbank loan market panic.

We estimate specification (7) with receiver firm fixed effect (Column 1) and with firm-level controls (Column 2). The estimated coefficients in these columns are not statistically and economically different despite a considerably higher explanatory power in a specification with the firm fixed effect (R^2 is 63 percent). This suggests that the access-to-payment shocks to sender firms are exogenous to the unobserved demand of receiver firms (absorbed by a fixed effect) and observable receiver firm characteristics (following Chodorow-Reich (2014) and Altonji, Elder, and Taber (2005)). Estimation of a model with sender firm fixed effect (Column 3) and with firm-level controls (Column 4) yields qualitatively similar results.

The second notable result emanating from Panel A of Table 4 is that the firm-firm payment growth decreases more with access-to-payment shocks of the customers (downstream shock) than access-to-payment shocks of the suppliers (upstream shock). This is evident from the magnitude of the estimated coefficients: the regression coefficient in column (1) is equal to $\beta_1 = -0.079$ for shocks to the sender (downstream) firms, while the coefficient in column (3) is equal to $\beta_2 = -0.042$ for shocks hitting the receiving (upstream) firms.

Economically, an increase of shock Z_i by one-standard-deviation reduces the firm-firm payments growth by 2.7 percentage points (=-0.079×0.344), while a similar increase in Z_j shock reduces the firm-firm payments growth by only 1.4 percentage point (=-0.042×0.330).

3.3 Impact of access-to-payment shocks on firms' revenue growth

We now shift to testing the relationship between the firm's revenue growth and its own access-to-payment shock as well as the propagation of access-to-payment shocks to its partner firms. At the firm level, we focus on how shocks hitting firms directly and shocks to their partners impact revenue growth. Based on our tests for the first part, we establish how access-to-payment shocks to a firm's own banks affect its growth.

FACT 2: *Firm growth Y_i declines with access-to-payment shocks to firm i's own banks, Z_i.*

The next fact is about the direction of firm-firm spillovers due to payment disruptions. In a production economy with Cobb-Douglas technology, productivity/supply chain shocks propagate downstream from one sector to another, that is, from supplier to customer. Carvalho *et al.* (2015)

Table 4: Disaggregated firm-firm analysis

This table reports regression results nested in the specification (7). In columns 1 and 3 we include (sender/receiver) firm fixed effects, while in columns 2 and 4 we include observable (sender/receiver) firm controls. Column 5 reports results where the sample is restricted to firms with multiple partners on the sending and receiving side. Control variables are listed in Table 3. "-" indicates fixed effects that are absorbed by firm-level fixed effects. In all columns, the standard errors are double clustered at the sender firm's industry*postal code and receiver firm's industry*postal code levels. Panel A reports our main results for the year 2004. Panel B reports the results of the falsification test where we assign shocks that occurred in 2004 to inter-firm payment growth in the year 2003. Significance levels are * 5%, ** 1%, *** 0.1%.

	Dep. variable: *Firm-firm payment growth* $Y_{i,j}$				
	(1)	(2)	(3)	(4)	(5)
Panel A: Payment growth in year 2004					
Shock to sender firm's banks Z_i^{2004}	-0.079***	-0.087***			-0.075***
	(0.009)	(0.014)			(0.011)
Shock to receiver firm's banks Z_j^{2004}			-0.042***	-0.056**	-0.046***
			(0.012)	(0.020)	(0.007)
Sender firm controls (i)	NO	NO	NO	YES	YES
Receiver firm controls (j)	NO	YES	NO	NO	YES
Sender firm FE (i)	NO	NO	YES	NO	NO
Receiver firm FE (j)	YES	NO	NO	NO	NO
Sender firm indust.*postal code FE (i)	YES	YES	-	YES	YES
Receiver firm indust.*postal code* FE (j)	-	YES	YES	YES	YES
Adj. R^2	0.516	0.152	0.562	0.366	0.247
No. sender indust.*postal clusters	11,662	11,662	11,315	11,315	11,221
No. receiver indust.*postal clusters	11,577	11,577	12,609	12,609	11,549
Observations	3,902,139	3,902,139	4,030,264	4,030,264	3,809,678
Panel B: Falsification tests—payment growth in year 2003					
Shock to sender firm's banks Z_i^{2004}	0.010	-0.022			-0.036
	(0.007)	(0.030)			(0.024)
Shock to receiver firm's banks Z_j^{2004}			0.008	0.009	0.022
			(0.007)	(0.008)	(0.012)
Sender firm controls (i)	NO	NO	NO	YES	YES
Receiver firm controls (j)	NO	YES	NO	NO	YES
Sender firm FE (i)	NO	NO	YES	NO	NO
Receiver firm FE (j)	YES	NO	NO	NO	NO
Sender firm indust.*postal FE (i)	YES	YES	-	YES	YES
Receiver firm indust.*postal FE (j)	-	YES	YES	YES	YES
Adj. R^2	0.628	0.206	0.517	0.176	0.212
No. sender indust.*postal clusters	11,812	11,812	11,379	11,379	11,267
No. receiver indust.*postal clusters	8,378	8,378	9,425	9,425	8,342
Observations	2,746,473	2,746,473	2,838,237	2,838,237	2,636,794

extend this setting to CES technology. Shocks then propagate both upstream and downstream. However, downstream effects are almost always larger than upstream effects. For access-to-payment shocks, we establish the opposite.

FACT 3: *Access-to-payment shocks propagate upstream. Firm growth Y_i declines with access-to-payment shocks to the customers (downstream shock Z_i^d) more than access-to-payment shocks to the suppliers (upstream shock Z_i^u).*

Our empirical model to establish these facts nests several specifications where we include different combinations of access-to-payment shocks. To check the propagation of shocks from up/downstream partners, we add the supplier firms' loss of access-to-payment services due to the interbank loan market panic effect on all downstream firms the firm i receives payments from, Z_i^{d}, and all upstream firms the firm i sends payments to, Z_i^{u}, to firm's own shock Z_i and obtain the following model:

$$Y_i = \alpha_I \times \alpha_{Zip} + \beta_1 Z_i + \beta_2 Z_i^{\mathrm{d}} + \beta_3 Z_i^{\mathrm{u}} + \gamma' \boldsymbol{X}_i + \varepsilon_i, \tag{8}$$

where $\alpha_I \times \alpha_{Zip}$ are saturated industry and postal code fixed effects, respectively, Z_i is the access-to-payment shock to firm i from (5), $Z_i^{\mathrm{d/u}}$ are defined in (6) and $\boldsymbol{X}_i$ are firm-level controls, reported in Table 3.[16] Standard errors are double-clustered at the firm industry and postal code levels.

We start with our main estimation results of specification (8) at the firm level reported in Table 5. In columns (1)-(3) we test the impact of individual shocks $Z_i, Z_i^{\mathrm{d}}, Z_i^{\mathrm{u}}$ on firms revenue growth, while in columns (4)-(6) we experiment with different combinations of access-to-payment shocks. The specification tested in column (1) of Table 5 is qualitatively similar to specification (2) on disaggregated firm-firm payments in Table 4. In both cases, we test the impact of the receiver firm's access-to-payment shocks on either firm-firm or firm-level payments. Similarly, specification tested in column (2) of Table 5 is qualitatively similar to specification (1) in Table 4, while specification tested in column (4) of Table 5 is similar to specification (3) on disaggregated firm-firm payments in Table 4.

We find that firms' sales are significantly negatively affected by access-to-payment shocks to their own banks and the banks of their partners. Access-to-payment shocks hitting a firm's customers have the most pronounced effect on a firm's revenue growth. The estimate for the most satu-

[16] 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.

rated specification in Column (6) indicates that a one-standard-deviation increase in the access-to-payment shock to the firm's own banks, Z_i, leads to a 2.1 percentage-point (=-0.061×0.349) decrease in the firm's revenue growth. A one-standard-deviation increase in the access-to-payment shock to downstream firm's banks, Z_i^d, leads to a 2.7 percentage-point (=-0.127×0.208) decrease in the firm's revenue growth. A one-standard-deviation increase in the access-to-payment shock to upstream firm's banks, Z_i^u, leads to a 0.7 percentage-point (=-0.039×0.175) decrease in the firm's revenue growth.

We also find that access-to-payment shocks propagate upstream, a one-standard-deviation shock to sender firms' banks has a larger effect on the supplier firm i's revenue growth, than a one-standard-deviation shock to its own banks, and much larger than a one-standard-deviation shock to firm i's upstream firms' banks. This is because in the first case when the sender banks cannot process payments the sales 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 on internal inputs.

We now establish the conditional random assignment of access-to-payment shocks on a firm's revenue growth during the interbank loan market panic, by relating the pre-panic revenue growth measured in 2003 to access-to-payment shocks $Z_i, Z_i^{\mathrm{d}}, Z_i^{\mathrm{u}}$ measured in 2004. Panel B of Table 5 reports results for this falsification test. As can be seen, the revenue growth of receiver firms in 2003 did not vary systematically with banking shocks that hit them and their partners in 2004. This evidence provides support for our identification assumptions.

3.4 Heterogeneity in firms' resilience to access-to-payment shocks

Up until now, we have focused on the impact of access-to-payment shocks on firm-level flows and the shock propagation through the input-output network. Next, we investigate the relation between the firm's revenue growth, the firm's input-output network centrality, and the access-to-payment shocks to its own banks. We expect the *resilience* to access-to-payment shocks to differ across firms. A firm is more resilient to access-to-payment shocks if its growth is less affected which depends on the firm's input-output network position prior to the shock, which yields our last stylized fact.

Table 5: Upstream propagation of access-to-payment shocks

The table documents the growth of firms' payment inflows and access-to-payment shocks to firm's banks, and downstream and upstream firms' banks. It reports the estimates from specification (8). Panel B documents falsification tests of access-to-payment shocks. The panel documents the growth of firms' payment inflows in 2003 prior to interbank loan market panic and access-to-payment shocks to firm's banks, and downstream and upstream firms' banks in 2004. Significance levels are * 5%, ** 1%, *** 0.1%.

Panel A: Payment growth in year 2004

	Dep. variable: *Payment inflow (revenue) growth* Y_i					
	(1)	(2)	(3)	(4)	(5)	(6)
Shock to firm's own banks Z_i	-0.293***			-0.061***	-0.294***	-0.061***
	(0.015)			(0.006)	(0.015)	(0.005)
Shock to downstream firms' banks Z_i^{d}		-0.494***		-0.129***		-0.127***
		(0.010)		(0.013)		(0.014)
Shock to upstream firms' banks Z_i^{u}			-0.045***		-0.050***	-0.039***
			(0.012)		(0.013)	(0.011)
Firm controls	YES	YES	YES	YES	YES	YES
Industry*Zip FE	YES	YES	YES	YES	YES	YES
No. Industry*Postal code	10,335	10,335	10,335	10,335	10,335	10,335
Adj. R-squared	0.287	0.288	0.283	0.500	0.287	0.500
Observations	522,716	522,716	522,716	522,716	522,716	522,716

Panel B: Falsification tests—payment growth in year 2003

	Dep. variable: *Payment inflow (revenue) growth* Y_i^{2003}		
	(1)	(2)	(3)
Shock to firm's own banks Z_i^{2004}	-0.024		
	(0.017)		
Shock to downstream firms' banks $Z_i^{\mathrm{d},2004}$		0.023	
		(0.020)	
Shock to upstream firms' banks $Z_i^{\mathrm{u},2004}$			-0.003
			(0.011)
Firm controls	YES	YES	YES
Industry*Zip FE	YES	YES	YES
No. Industry*Postal code	10,053	10,053	10,053
Adj. R-squared	0.067	0.541	0.067
Observations	481,316	481,316	481,316

FACT 4: *Firms exhibit different resilience to access-to-payment shocks depending on their input-output network position. Firms with higher eigenvector centrality* δ_i^{pre} *are more sensitive to access-to-payment shocks, that is, firm growth* Y_i *declines more with higher* $Z_i \times \log \delta_i^{pre}$.

Formally, we define the pre-panic centrality of each firm i in the input-output network as the logarithm of the firm's eigenvector centrality during the six-month period prior to the interbank loan market panic, $\log \delta_i^{\text{pre}}$. In addition, we calculate the average centrality of the firm's customers and suppliers by employing the same weighting scheme we used for shocks.

$$\log \delta_i^{\text{d/u}} = \sum_{k/j=1}^{n_i^{\text{d/u}}} \zeta_{i,k/j}^{\text{d/u}} \cdot \log \delta_{k/j}^{\text{pre}}, \tag{9}$$

where $\log \delta_{k/j}^{\text{pre}}$ is the eigenvector centrality of firm i's customers k and suppliers j, respectively, and $\zeta_{i,k/j}^{\text{d/u}}$ are the weights defined in (6).

In our empirical model, we are interested in the effect of downstream and upstream partners' shocks and their centralities on the firm's revenue growth. We add the natural logarithm of firm i's pre-panic Domar weight, $\log \delta_i^{\text{pre}}$, and its interaction with the shock to firm i's own banks, $Z_i \times \log \delta_i^{\text{pre}}$. We test the following specification

$$\begin{aligned} Y_i = \alpha_I \times \alpha_{Zip} + \beta_1 Z_i + \beta_2 (Z_i \times \log \delta_i^{\text{pre}}) + \beta_3 \log \delta_i^{\text{pre}} + \beta_4 Z_i^{\text{d}} + \beta_5 (Z_i^{\text{d}} \times \log \delta_i^{\text{d}}) + \beta_6 \log \delta_i^{\text{d}} + \\ + \beta_7 Z_i^{\text{u}} + \beta_8 (Z_i^{\text{u}} \times \log \delta_i^{\text{u}}) + \beta_9 \log \delta_i^{\text{u}} + \gamma' \boldsymbol{X}_i + \varepsilon_i. \end{aligned} \tag{10}$$

In (10), we focus on the coefficients $\beta_2, \beta_5, \beta_8$ that capture the change in the firm's sensitivity to access-to-payment shocks $Z_i, Z_i^{\text{d}}, Z_i^{\text{u}}$ depending on centrality of a firm and centralities of its downstream and upstream partners. 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 6 presents results for specification (10). In columns (1)-(3) we test the impact of individual shocks $Z_i, Z_i^{\text{d}}, Z_i^{\text{u}}$ interacted with respective centralities on firms revenue growth, while in columns (4)-(6) we experiment with different combinations of these shocks and centralities. Coefficient estimates on interaction terms in columns (1)-(3) suggest that higher centrality strengthens the negative impact of access-to-payment shocks to the firm and to its partners. The sensitivity of more central firms to access-to-payment shocks is higher than the sensitivity of less central firms. In column (1), a one-standard-deviation increase in the log centrality of a firm leads to a 1.1 percentage-point (=-0.026×0.349×1.193) larger decrease in the firm's revenue growth for a one-standard-deviation shock Z_i. The estimation results reported in columns (4)-(6) suggest that the only interaction term that is robust across more saturated specifications is on the firm's own centrality, $Z_i \times \log \delta_i^{\text{pre}}$.

Table 6: Firm's network centrality and sensitivity to access-to-payment shocks

The table documents the growth of firms' payment inflow (revenue) and access-to-payment shocks to firm's banks, downstream and upstream firms' banks interacted with pre-panic centrality. It reports the estimates from specification (10). Significance levels are * 10%, ** 5%, *** 1%.

	Dep. variable: *Payment inflow (revenue) growth* Y_i					
	(1)	(2)	(3)	(4)	(5)	(6)
Shock to firm's own banks Z_i	-0.145***			-0.083**	-0.110***	-0.085***
	(0.039)			(0.033)	(0.035)	(0.032)
Firm's eig. centrality $\log \delta_i^{\text{pre}}$	-0.166***			-0.437***	-0.178***	-0.409***
	(0.014)			(0.010)	(0.009)	(0.011)
$Z_i \times \log \delta_i^{\text{pre}}$	-0.026***			-0.012	-0.021***	-0.016**
	(0.009)			(0.008)	(0.008)	(0.008)
Shock to downstream firms' banks Z_i^{d}		-0.187***		-0.107*		-0.166**
		(0.057)		(0.060)		(0.076)
Downstream firms eig. centrality $\log \delta_i^{d,\text{pre}}$		-0.033***		0.401***		0.372***
		(0.007)		(0.009)		(0.010)
$Z_i^d \times \log \delta_i^{d,\text{pre}}$		-0.026*		-0.008		-0.025
		(0.015)		(0.016)		(0.021)
Shock to upstream firms' banks Z_i^{u}			-0.154***		-0.033	0.008
			(0.053)		(0.051)	(0.051)
Upstream firms eig. centrality $\log \delta_i^{u,\text{pre}}$			0.001		0.033***	0.031***
			(0.007)		(0.007)	(0.007)
$Z_i^u \times \log \delta_i^{u,\text{pre}}$			-0.040**		-0.001	0.013
			(0.020)		(0.019)	(0.019)
Firm controls	YES	YES	YES	YES	YES	YES
Industry*Zip FE	YES	YES	YES	YES	YES	YES
No. Industry*Postal code	8,642	8,642	8,642	8,642	8,642	8,642
Adj. R-squared	0.049	0.038	0.044	0.063	0.055	0.069
Observations	295,850	295,850	225,209	295,850	225,209	225,209

Overall, access-to-payment shocks have persistent negative real effects at the firm level, but these effects are dampened for less central firms, that is firms whose centrality is less elastic to access-to-payment shocks. These results suggest that the aggregate impact of payment stress depends on the location of the access-to-payment shocks in the network of firm-firm flows and how the input-output network adjusts to these disruptions.

The remaining question is the aggregate impact of payment system stress. To provide an estimate, we need to address the missing intercept problem that occurs in reduced-form analysis.[17] To

[17] https://benjaminmoll.com/wp-content/uploads/2021/02/missing_intercept.pdf.

do so, the next sections provide a model-based micro-to-macro expression for the aggregate impact on GDP of granular disruptions in firm's ability to make and receive payments.

4 Model for Aggregate Impact of Payment System Stress

This section develops an equilibrium model that is consistent with the stylized facts documented in the prior section. In this model of a multi-firm production economy subject to access-to-payment shocks, firms' input-output relations yield a network structure of real and financial links between customer and supplier firms. The model serves three purposes. First, it provides a framework to theoretically capture the propagation of access-to-payment shocks over the customer-supplier network. Second, it allows us to quantify the macroeconomic impact of the 2004 payment disruption event on the Russian economy. Finally, it allows for counterfactual analysis.

The production side of the model builds on a static multisector model in which each sector operates a constant returns-to-scale production technology subject to a sector-specific productivity shock (Acemoglu *et al.* (2012)). The sectoral technology takes outputs of other sectors as intermediate input factors thus linking all sectors to an input-output production network. We extend the static input-output production network in two key ways: by introducing an internal production factor k that is 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, originating in the financial sector unrelated to the production sector and operating through a payment-in-advance constraint, have a differential impact on external and internal factors (Bigio and La'O (2020)). Specifically, by altering firms' ability to pay for external inputs, ξ-shocks make firms more reliant on internal production factor k. Consequently, the topology of the input-output network readjusts to accommodate the new firm-firm flows of goods which, in turn, affects firm-level cash flows and aggregate output.

4.1 Setup

There are $i = 1, \ldots, N$ competitive firms in the economy. The output goods 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, denoted as y_i, given by

$$y_i = e^{\varepsilon}(\prod_{j=1}^{N} x_{ij}^{w_{ij}})^{1-\mu} k_i^{\mu}, \qquad \mu \in [0,1], \tag{11}$$

where ε is an aggregate productivity shock, x_{ij} denotes the amount of external input good produced by firm j used in the production by firm i, k_i are internal inputs, and μ is the elasticity of substitution between the external and 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. 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 a high out-degree, while downstream firms have a high in-degree.

Denote by p_i the price of the goods produced by firm i and p_k the cost of internal factors. Firm i maximizes profits $\Pi_i = p_i y_i - p_k k_i - \sum_{j=1}^{N} p_j x_{ij}$, where $p_i y_i$ are the firm's sales, $p_k k_i$ is the cost of internal inputs, and the last term captures the costs of external inputs.

The firm is subject to a payment-in-advance constraint:

$$\sum_{j=1}^{N} p_j x_{ij} \leq (1 - \xi_i) p_i y_i, \qquad \xi_i \in [0,1]. \tag{12}$$

Condition (12) controls the amount of sales the firm can spend on external inputs, which is similar to the financial constraint used in Bigio and La'O (2020). Unlike in their model, we introduce a stochastic shock ξ_i in (12) that affects the relative productivity of external and internal inputs. We assume that ξ_i shocks are independent across time but allow them to be correlated across firms at a given point in time. The access-to-payment shock ξ_i controls the "tightness" of the collateral constraint. The constraint is slack when $\xi_i \leq \mu$, and it is tight when $\mu < \xi_i \leq 1$. When the collateral constraint binds, the internal inputs generate ξ_i fraction of the sales, while the external inputs generate $1 - \xi_i$ fraction of sales. Conversely, when the collateral constraint is slack, the internal inputs generate a μ fraction of sales, while the external inputs generate a $1 - \mu$ fraction of sales. Therefore, we introduce the effective elasticity of substitution between the external and internal inputs as

$$m_i \equiv \max\{\xi_i, \mu\} \in [\mu, 1]. \tag{13}$$

The shock m_i captures payment system stress and allows for a compact representation of the model's solution and the aggregate effect of shocks ξ on the economy's GDP.

The effective access-to-payment shock Z_i is

$$Z_i \equiv m_i - \mu = \begin{cases} \xi_i - \mu, & \text{if } \mu < \xi_i \leq 1, \\ 0, & \text{otherwise.} \end{cases} \tag{14}$$

One can interpret $Z_i/m_i/\xi_i$ as access-to-payment shocks affecting firms' ability to make external payments and, hence, the sourcing of external inputs and firm-firm payments. The ξ-shocks originate in banking services and are not a direct input to production. 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 concrete, 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 than μ realization of ξ_i implies firm i is less/more able to make payments to its suppliers at time t, in which case it must rely more/less on internal production factors. These modeling assumptions allow us to study how payment disruptions originating in the financial system propagate through the real economy.

The access-to-payment shocks are responsible for generating cross-sectional variation in sales share across firms. We show later that without ξ-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 does not feature ξ_i's or, equivalently, ξ_i does 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.

To close the model, we assume financial markets are complete and there exists a stochastic discount factor η. The market value of firm i is, hence, $S_i = \mathbb{E}\left(\sum_{s=t}^{\infty} \eta_s \Pi_{is}\right)$. A representative consumer in the economy has Cobb-Douglas utility over consumption c_i: $U = \mathbb{E}\left(\sum_{t=0}^{\infty} \beta^t \prod_{i=1}^{N} c_i^{\gamma/N}\right)$, 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_i shares in firm i at time t and supplies internal input $k = \sum_{i=1}^{N} k_i$ at rate p_k. We normalize the total number of shares for each firm to one, $k = 1$. The consumer maximizes her utility subject to the standard budget constraint.

It is easily shown that the consumption shares are the same for all firms: $p_i c_i = p_j c_j, \forall(i,j)$. Together with market clearing discussed later, this also implies that the consumption shares are given by $p_i c_i = \frac{1}{N}\mathrm{GDP}, \forall(i,t)$, and GDP in the economy equals aggregate consumption:

$$\mathrm{GDP} = p_k \cdot 1 + \sum_{i=1}^{N} \Pi_i. \tag{15}$$

DEFINITION 1: *The competitive equilibrium in the economy is defined by quantities* (x_{ij}, k_i, y_i), *consumption bundle* c_i, *prices* p_i, p_k, *and* S_i *such that:*

(i) *Firms maximize profits* $\Pi_i = p_i y_i - p_k k_i - \sum_{j=1}^{N} p_j x_{ij}$.

(ii) *The representative consumer maximizes her period-by-period utility* $U = \mathbb{E}\left(\sum_{t=0}^{\infty} \beta^t \prod_{i=1}^{N} c_i^{\gamma/N}\right)$.

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

$$c_i + \sum_{j=1}^{N} x_{ji} = y_i, \forall i = 1, \ldots, N, \text{ and } \sum_{i=1}^{N} k_i = 1.$$

(iv) *The financial market clears at all times:* $q_i = 1 \quad \forall i = 1, \ldots, N$.

The next subsection outlines the solution to the model.

4.2 Model solution

To describe the equilibrium, it is useful to establish some notation. Collect the effective fraction of the output produced by internal inputs, $m_i, i = 1, ..., N$, in a diagonal matrix M and the factor input weights in an $N \times N$ matrix $W = [w_{ij}]_{N \times N}$. The composite matrix Σ with typical element

$\Sigma_{ij} = (1 - m_i)w_{ij} \geq 0$ embeds the factor weights w_{ij} and the effective fraction of the output produced by the external inputs, $1 - m_i$, with these weights by each firm:

$$\Sigma = (I - M) \cdot W = \underbrace{\begin{bmatrix} 1-m_1 & 0 & \cdots & 0 \\ 0 & 1-m_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1-m_N \end{bmatrix}}_{\text{Effective fraction of output due to external inputs}} \cdot W =$$

$$= \begin{bmatrix} w_{11}(1-m_1) & w_{12}(1-m_1) & \cdots & w_{1N}(1-m_1) \\ w_{21}(1-m_2) & w_{22}(1-m_2) & \cdots & w_{2N}(1-m_2) \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}(1-m_N) & w_{N2}(1-m_N) & \cdots & w_{NN}(1-m_N) \end{bmatrix}. \tag{16}$$

Note that the payment ξ-shocks enter Σ via matrix M.

The Leontief inverse with elements l_{ij} compounds all ξ-shocks and captures how shocks at customers propagate to suppliers:

$$L = (I - \Sigma)^{-1} = I + \underbrace{\Sigma}_{\text{Direct effect}} + \underbrace{\sum_{s=2}^{\infty} \Sigma^s}_{\text{Indirect effect}}. \tag{17}$$

The power series expansion of L (assuming the spectral radius is $\rho(L) < 1$) illustrates how the infinite sum of shock contributions get encoded. 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. Since m_i is directly affected by the payment ξ-shocks, the chain of kth order effects is encoded in the kth term of the expansion and shows how ξ-shocks propagate through the economy.

The eigenvector centrality δ_i measures firm i's Domar weight adjusted for access-to-payment shocks:

$$\delta_i = \frac{1}{N} \sum_{j=1}^{N} l_{ji}. \tag{18}$$

Accordingly, the set of firms' eigenvector centralities $\delta = \frac{1}{N} L' \mathbf{1}$ (column averages of L) capture the firms' exposures to ξ-shocks by measuring their global position in the directed network of flows between firms. The income share of the internal factors is an aggregate term and equals $\psi = m'\delta = \sum_{i=1}^{N} m_i \delta_i$.

We obtain the following characterization of the goods market equilibrium.

PROPOSITION 1: *Define ϵ as a vector of composite shocks with elements given by*

$$\epsilon_i = \varepsilon + \mu \log\left(\frac{m_i \delta_i}{\psi}\right) + (1-\mu)\sum_{j=1}^{N} w_{ij} \log\left(\Sigma_{ij}\frac{\delta_i}{\delta_j}\right). \tag{19}$$

The equilibrium vector of production equals $y = e^{L\epsilon}$, with typical element

$$y_i = e^{l_i'\epsilon} = e^{\sum_{j=1}^{N} l_{ij}\epsilon_j} = \prod_{k=1}^{N}\left\{\left(\frac{m_k \delta_k}{\psi}\right)^{l_{ik}\mu} \prod_{j=1}^{N}\left(\Sigma_{kj}\frac{\delta_k}{\delta_j}\right)^{l_{ik}(1-\mu)w_{kj}}\right\}. \tag{20}$$

Expression (20) shows that the firm i's output depends on the composite shock, ϵ_i, given by (19). The first term in (19) captures the "productivity" of the firm i's internal inputs, while the second term captures the "productivity" of the firm i's external inputs. Firms heavily relying on the payment system, that is firms with large m_i, and "downstream" firms, that is, firms with large value of $\sum_{j=1}^{N} l_{ij}\log(m_j)$, depend more strongly on the internal factors k than other firms. The output of firms with low in-degree centrality for which $l_{ij\neq i}$ is small, that is, upstream and central firms, depends mostly on their own composite shock ϵ_i. The output of firms with high in-degree centrality for which $l_{ij\neq i}$ is large, that is, downstream and peripheral firms, depends more strongly on the composite shocks of the connected firms, $\epsilon_{j\neq i}$. Nonetheless, access-to-payment shocks ξ in every firm affect its supply and, hence, the output in all other firms so long as the l_{ij} elements are non-zero.

Total sales of firm i, $Y_i = p_i y_i$, yield a sales vector, Y, that can be determined explicitly. Define the $N \times N$ augmented adjacency matrix Ω with typical element $\Omega_{ij} = \frac{1}{N}(m_i + \pi_i) + \Sigma_{ij}$. Elements Ω_{ij} depend on both the factor weights w_{ij} and payment system ξ-shocks, with the latter coming from the effective elasticity m. The following proposition summarizes the results about the firms' sales.

PROPOSITION 2: *Goods market clearing implies that firms' sales adhere to a network structure*

$Y_i = \sum_{j=1}^N \Omega_{ji} Y_j$ *or, in matrix form,* $\Omega' Y = \mathbf{1} Y$*, that depends on the factor weights* w *and* ξ*-shocks of all firms in the economy.*

This result means the equilibrium firm sales Y are equal to the vector of eigenvector centralities of the firms corresponding to the unit eigenvalue of the transformed adjacency matrix Ω that adjusts for ξ-shocks. 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_{ji}. This shows it is the out-degree—and not the in-degree—of the firm that matters for its importance in the economy.

Firm sales Y can be written as shares of GDP that depend on the size of access-to-payment shocks. Equilibrium prices, p_i, adjust to compensate for the payment system shocks. Even with fully flexible prices, they buffer the demand effects of ξ-shocks differently depending on the firms' centrality. Using the goods market clearing condition,

$$Y = \frac{1}{N}(I - \Sigma')^{-1}\mathbf{1}\text{GDP} = \frac{1}{N}L'\mathbf{1}\text{GDP} = \delta \cdot \text{GDP}. \tag{21}$$

Finally, the income share of internal factors as part of GDP is given by $K \equiv p_k k = \psi \cdot \text{GDP}$.

To determine how GDP and cash flows across firms depend on payment disruptions, we need to solve for goods prices. Normalize the ideal price index as $\frac{1}{N}\prod_{i=1}^N p_i^{-1/N} = 1$. Since $Y_i = \delta_i \cdot \text{GDP}$ from (21), this implies that $\text{GDP} = \frac{p_i y_i}{\delta_i}, \forall i$. Then GDP is given by

$$\text{GDP} = \prod_{i=1}^N \left(\frac{p_i y_i}{\delta_i}\right)^{1/N} = \frac{1}{N}\prod_{i=1}^N \left(\frac{y_i}{\delta_i}\right)^{1/N}. \tag{22}$$

Goods prices satisfy the inverse aggregate demand function $p_i = \frac{\delta_i}{\psi}\frac{1}{y_i}p_k$ and the equilibrium factor price equals $p_k = \psi \cdot \text{GDP}$. Firms' expenses on internal factors are $K_i = m_i \delta_i \text{GDP}$ and firm-firm payment flows correspond to the entries in the input-output flow table. Finally, aggregate profits equal $\sum_{i=1}^N \Pi_i = (1-\psi)\cdot\text{GDP}$.

LEMMA 1: (i) *Firm sales* $Y_i = \delta_i \cdot \text{GDP}$ *and profits* $\Pi_i = \pi_i \delta_i \cdot \text{GDP}$ *are proportional to each firm's eigenvector centrality and the equilibrium profit margin equals* $\pi_i = (1-m_i)(1-d_i^{in})$ *which* *varies one to one with the ξ-shocks and the in-degree of the firm.*

(ii) *Firm-firm payment flows X_{ij} are proportional to the firms' ξ-shocks and the sender firm's eigenvalue centrality δ_i:*

$$\text{Firm-firm payment flows}: \quad X_{ij} \equiv p_j x_{ij} = \Sigma_{ij} \cdot \underbrace{\delta_i \cdot \text{GDP}}_{\text{Firm sales } Y_i}. \tag{23}$$

(iii) *The log* GDP *aggregates all composite access-to-payment shocks ϵ_i from (19), weighted by eigenvalue centrality δ_i and buffered by the firms' average log eigenvalue centrality according to*

$$\log \text{GDP} = \sum_{i=1}^{N} \delta_i \epsilon_i - \log N - \frac{1}{N} \sum_{i=1}^{N} \log \delta_i. \tag{24}$$

Appendix C uses a simple example to illustrate the model's inner workings. Firm sales Y and profits Π in this input-output economy are proportional to the eigenvector corresponding to the unit eigenvalue of Ω and, equivalently, to the eigenvector centrality δ. Intuitively, higher centrality δ provides pricing power because many firms rely on central inputs. This implies sales and profits tend to be larger in firms with large δ that are more central in the economy.

4.3 Access-to-payment shock propagation and payment network readjustments

Assuming firms are unconstrained before the access-to-payment shocks, $\xi_i^{\text{pre}} < \mu$ ($m_i^{\text{pre}} = \mu$), $\forall i = 1, ..., N$, the effective access-to-payment shock Z_i can be computed using expression (14). Panel B of Table 7 reports the summary statistics of ξ_i^{post} using the baseline estimate $\mu = 0.85$ for the external-internal input elasticity. The average ξ_i^{post} across all firms in our sample equals 0.068, with a large standard deviation of 0.513. As a result, the average (median) effective access-to-payment shock Z_i according to expression (14) with an elasticity estimate of 0.85 equals 0.007 (0.00) with a standard deviation of 0.029.

Access-to-payment shocks Z_i lead to adjustments in the firms' Domar weights and the input-output network structure. Lemma 1 shows that firms' equilibrium sales shares equal their eigenvector centrality: $\delta_i^{\text{pre/post}} = \frac{1}{N} \sum_{k=1}^{N} l_{ki}^{\text{pre/post}}$. Using the Leontief inverses before, L^{pre}, and after the shock, L^{post}, we can express the ξ-shocks propagation according to

$$L^{\text{post}} - L^{\text{pre}} = \sum_{s=1}^{\infty}[((I-M)W)^s - (1-\mu)^s W^s]. \tag{25}$$

The incremental change in eigenvector centrality δ is, hence,

$$\delta^{\text{post}} - \delta^{\text{pre}} = \frac{1}{N}(\sum_{s=1}^{\infty}(((I-M)W)^s - (1-\mu)^s W^s))' \cdot \mathbf{1} \leq 0. \tag{26}$$

To see the effect on each firm, expand the pre- and post-shock sales shares as:

$$\begin{aligned} \delta_i^{\text{pre}} &= \tfrac{1}{N}\left(1 + (1-\mu)\textstyle\sum_{k=1}^N w_{ki} + (1-\mu)^2 \sum_{k=1}^N \sum_{j=1}^N w_{kj}w_{ji} + ...\right), \\ \delta_i^{\text{post}} &= \tfrac{1}{N}\left(1 + \textstyle\sum_{k=1}^N (1-m_k)w_{ki} + \sum_{k=1}^N \sum_{j=1}^N (1-m_k)(1-m_j)w_{kj}w_{ji} + ...\right). \end{aligned} \tag{27}$$

The expression shows how, after access-to-payment shocks materialize, firms' eigenvector centrality readjusts to accommodate firms' inability to make timely payments to one another. The post-shock δ_i^{post} compounds all access-to-payment shocks $m_{i=1,...,N}$ and is a sufficient statistic for all routes of shock transmission through the network.

Next, we pass the Z_i shocks through relations (27) to determine eigenvector centralities δ_i^{pre} and δ_i^{post} for each firm. We generate 100 summation terms in expression (27) which captures the impact of access-to-payment shocks to firm's i neighbors and shocks to neighbors of neighbors up to chains of length 100. Panel C of Table 7 reports the summary statistics of all eigenvector centralities. Panel C shows that the average δ_i (scaled by 100,000) drops from 0.204 to 0.203 and its standard deviation across firms drops from 0.58 to 0.56.

To decompose how access-to-payment shock propagates and the input-output Domar weights readjust, define the counterfactual pre-shock sales shares δ^0 assuming $\mu = 0$, which corresponds to an economy without internal factors. With counterfactual Leontief $L^0 = (I-W)^{-1}$, $\delta^0 = \frac{1}{N}L^{0\prime}\mathbf{1}$, which can be expanded as:

$$\delta_i^0 = \frac{1}{N} + \frac{1}{N}\sum_{k=1}^{N}\left(w_{ki} + \sum_{j=1}^{N} w_{kj}w_{ji} + \sum_{j=1}^{N}\sum_{l=1}^{N} w_{kj}w_{jl}w_{li} + ...\right). \tag{28}$$

The term in parenthesis captures all direct and indirect routes from k to i. Define

$$A^0_{ki} \equiv w_{ki} + \sum_{j=1}^{N} w_{kj}w_{ji} + \sum_{j=1}^{N}\sum_{l=1}^{N} w_{kj}w_{jl}w_{li} + ... = w_{ki} + \sum_{j=1}^{N} w_{kj}A^0_{ji}. \tag{29}$$

Collect the terms in matrix A^0 and rearrange to yield: $A^0 = W + WA^0 = (I - W)^{-1}W = L^0W$. Hence, $\delta^0_i = \frac{1}{N}(1 + \sum_{k=1}^{N} A^0_{ki})$ with

$$A^0_{ki} = \sum_{j=1}^{N} l^0_{kj}w_{ji}. \tag{30}$$

The full impact of the access-to-payment shock is captured by $\delta^{\text{post}}_i - \delta^{\text{pre}}_i$. To trace out the directions of transmission, expand the term $\delta^{\text{post}}_i - \delta^{\text{pre}}_i$ by the step of propagation and the order of shock expansion. When we expand by the propagation step, one can see that access-to-payment shocks propagate upstream and that at every higher-order propagation step all shocks along the path from downstream to upstream matter and, in addition, the interactions of the shocks buffer or amplify the full impact:

$$\begin{aligned}\delta^{\text{post}}_i - \delta^{\text{pre}}_i = &-\frac{1}{N}\sum_{k=1}^{N} w_{ki}Z_k - \frac{1}{N}\sum_{k=1}^{N}\sum_{j=1}^{N} w_{kj}w_{ji}(Z_k + Z_j - Z_kZ_j) - \\ &- \frac{1}{N}\sum_{k=1}^{N}\sum_{j=1}^{N}\sum_{l=1}^{N} w_{kj}w_{jl}w_{li}(Z_k + Z_j + Z_l - Z_kZ_j - Z_jZ_l - Z_kZ_l + Z_kZ_jZ_l) - ....\end{aligned} \tag{31}$$

The first term in (31) captures the direct impact of shocks to customers of i. The second term captures the indirect impact of shocks to customers of i and the direct impact of shocks to customers of customers of i. Similarly, the third term captures additional indirect effects of shocks to customers of i, indirect effects of shocks to customers of customers of i, and the direct impact of 3rd order customers of i. We can collect all propagation steps and for each order of shock expansion determine in closed form the total impact of payment disruptions on sales shares.

PROPOSITION 3: *The Domar weights δ readjust to access-to-payment shocks Z defined in (14)* *by:*

$$\begin{aligned}
\delta_i^{\text{post}} - \delta_i^{\text{pre}} &= \sum_{s=1}^{\infty}\sum_{k=1}^{N} \mathcal{R}_{ik}^{(s)} Z_k \\
&= -\sum_{k=1}^{N} \delta_k^0 A_{ki}^0 Z_k + \sum_{k=1}^{N}\sum_{j=1}^{N} \delta_k^0 A_{kj}^0 A_{ji}^0 Z_k Z_j - \\
&\qquad - \sum_{k=1}^{N}\sum_{j=1}^{N}\sum_{l=1}^{N} \delta_k^0 A_{kj}^0 A_{jl}^0 A_{li}^0 Z_k Z_j Z_l + ... \qquad (32)
\end{aligned}$$

where $\mathcal{R}_{ik}^{(s)}$ captures the s-order resilience of firm i to an access-to-payment shock Z_k originating at customer k. The resiliences at order $s = 1, 2, ...$ equal

$$\begin{aligned}
\mathcal{R}_{ik}^{(1)} &= -\delta_k^0 A_{ki}^0, \\
\mathcal{R}_{ik}^{(2)} &= \delta_k^0 \textstyle\sum_{j=1}^{N} A_{kj}^0 A_{ji}^0 Z_j, \\
\mathcal{R}_{ik}^{(3)} &= -\delta_k^0 \textstyle\sum_{j=1}^{N}\sum_{l=1}^{N} A_{kj}^0 A_{jl}^0 A_{li}^0 Z_j Z_l, \\
&...
\end{aligned} \qquad (33)$$

Proposition 3 illustrates that how access-to-payment shocks at any order of customers affect firm i depends on the customers' counterfactual centrality δ^0 and all routes from k to i based on the input-output weights W. Only the first-order resilience $\mathcal{R}^{(1)}$ does not depend on the size of other firms' shocks along the route. Access-to-payment shocks originating at firm k hence spill over to firm i, affecting i's sales, profits, and firm-firm payment flows according to Lemma 1 with incremental change in $\delta_i, \pi_i, \Sigma_{ik}$ given by (25) and (26). Firm i is more resilient to ξ-shocks originating at firm k (Z_k), the less negative is the sensitivity of i's eigenvector centrality, $\mathcal{R}_{ik}^{(1)}$, which thus serves as firm-level measure of resilience to access-to-payment shocks.

Proposition 3 also highlights that the model is consistent with the empirical findings in Tables 4 and 5. Shocks to a firm's own banks Z_i reduce its sales $Y_i = \delta_i \cdot \text{GDP}$ and firm-firm payment flows $X_{ij} = \Sigma_{ij}\delta_i \cdot \text{GDP}$. From (32), the direct impact of shocks to the firm's own banks is negative and equals $\delta_i^{\text{post}} - \delta_i^{\text{pre}}|_{Z_{k\neq i}=0} = -\delta_i^0 A_{ii}^0 Z_i$. Expression (32) also implies that access-to-payment shocks propagate upstream. Shocks to customer k of firm i propagate according to $\delta_i^{\text{post}} - \delta_i^{\text{pre}}|_{Z_{j\neq k}=0} = -\delta_k^0 A_{ki}^0 Z_k$.

Finally, Proposition 3 shows that the network structure changes because of the propagation of access-to-payment shocks and, as a result, the network centralities of the firms readjust. This prediction is consistent with Table 6. The higher the resilience of firm i, which is equivalent to $\mathcal{R}^{(s)}$ being less negative for odd s indices and $\mathcal{R}^{(s)}$ being more positive for even s indices, the less do its sales and profits drop due to access-to-payment shocks originating at j, that is, the less affected is firm i. $\mathcal{R}^{(s)}$ are important characteristics capturing the cross-sectional response to ξ-shocks, both firm-specific and spilled over through the firm-firm network from other firms.

5 Aggregate Impact of Access-to-Payment Shocks

The main purpose of this section is to quantify the impact of access-to-payment shocks on GDP. We consider two case studies, the 2004 banking crisis for which we have 133 million transactions, and the Russia-Ukraine conflict that started in 2022 for which we perform a counterfactual policy analysis based on our data, assuming the topology of the Russian economy remained comparable to 2004.

5.1 Input elasticity

The input elasticity μ is an important determinant for the systemic importance of payment stress. To calibrate it, consider that the in-degree centrality of firm i, d_i^{in}, accounts for the input relations with suppliers in such a way that more factor-intensive firms generate lower profit margins. The average in-degree centrality $\overline{d^{in}} \equiv \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}$ accounts for the economy-wide dependence on suppliers.

Table 7, Panel A reports that the average in-degree centrality of all sample firms before May 2004 is $\overline{d^{in}} = 0.4$. Lemma 1 shows the profitability of more factor-intensive firms is less sensitive to access-to-payment shocks. Hence, average profitability, $\overline{\pi} = \frac{1}{N}\sum_{i=1}^{N}\pi_i$, declines with $\overline{d_i^{in}}$. Now consider $\xi_i \leq \mu$ and take expectations of equilibrium profits over all firms to obtain

$$\mathbb{E}[\pi_i - (1-\mu)(1-d_i^{in})] = 0.$$

This relation can be used to estimate the input elasticity μ in the data. A consistent estimator is

$$\widehat{\mu} = 1 - \frac{\overline{\pi}^{\text{pre}}}{1 - \overline{d^{in}}^{\text{pre}}}, \tag{34}$$

where the superscript indicates the pre-crisis period.

Accounting data on firm-level profitability is available only for public firms. Table 7, Panel A reports that the average return-on-assets is $\overline{\pi}^{\text{pre}} = 9.1\%$. This yields a baseline estimate for the external-internal input elasticity of $\mu = 1 - \frac{0.091}{0.59} = 0.85$. This estimate is higher than the value of 0.5 reported by Carvalho *et al.* (2021) for Japan, albeit they have used the CES technology instead of the Cobb-Douglas technology that we use.

An alternative is to use median profitability equal to 2.7% in Panel A of Table 7. In this case, we obtain an even larger input elasticity of $\mu = 1 - \frac{0.027}{0.59} = 0.95$. However, both estimates are upper bounds to the extent that private firms are more profitable than public firms. Out of 586,649 firms in our sample, 344,866 (58.8%) are public and send or receive payments and are not deep-in-distress (ROA<–100%). Based on a private profit margin of 13.6%, a lower bound in our data is $\mu = 1 - \frac{0.136}{0.59} = 0.77$.

5.2 Access-to-payment shocks in 2004

Throughout, we assume $\xi_i \leq \mu \ \forall i$ before access-to-payment shocks materialize, hence, $m = \mu\mathbf{1}$. After the realization of the access-to-payment shocks ξ, the equilibrium quantities, input-output flows, and prices readjust while productivity is unchanged in the short term. After transitioning back to equilibrium, $m \neq \mu\mathbf{1}$, and productivity ε remains otherwise the same as prior to ξ shocks. To measure the impact on GDP, we need several input parameters.

Before access-to-payment shocks materialize, firms' productivity is

$$\epsilon_i^{\text{pre}} = \varepsilon + \mu \log\left(\frac{\mu\delta_i^{\text{pre}}}{\psi^{\text{pre}}}\right) + (1-\mu)\sum_{j=1}^{N} w_{ij} \log\left((1-\mu)w_{ij}\frac{\delta_i^{\text{pre}}}{\delta_j^{\text{pre}}}\right), \tag{35}$$

where δ_i^{pre} is based on the Leontief inverse before the shock, $L^{\text{pre}} = (I - (1-\mu)W)^{-1} = I + \sum_{s=1}^{\infty}(1-\mu)^s W^s$. L^{pre} corresponds to the shock propagation mechanism in Acemoglu *et al.* (2012)

Table 7: Summary statistics of access-to-payment shocks and centralities

This table reports the summary statistics for firms that both sent and received payments in the pre-crisis period. In Panel A of the table, we report the in-degree centrality d_i^{in} and profitability π_i of all public firms where deep-in-distress firms with ROA below -100% are filtered out. Panel B reports the raw and modified payment system stress shocks. Panel C reports eigenvalue centralities after 100 iterations. Panel D reports statistics of the composite productivity shocks.

	Mean	Std. Dev.	Min	Median	Max	N
Panel A: In-degree centrality and profitability						
d_i^{in}	0.410	0.370	0.001	0.270	1	586,649
π_i	0.091	0.324	-1	0.027	1.45	344,866
Panel B: Access-to-payment shock						
ξ_i	0.068	0.513	-2	0	2	586,649
m_i $(\mu = 0.85)$	0.857	0.029	0.85	0.85	0.99	586,649
Z_i $(\mu = 0.85)$	0.007	0.029	0.00	0.00	0.15	586,649
Panel C: Eigenvector centralities (x 100,000)						
δ_i^{pre} $(\mu = 0.85)$	0.204	0.58	0.171	0.171	349	586,649
δ_i^{post} $(\mu = 0.85)$	0.203	0.56	0.171	0.171	338	586,649
Panel D: Productivity shock						
ϵ_i^{pre}	4.90	1.16	-84.9	5.02	11.9	586,649
ϵ_i^{post}	4.89	1.18	-84.2	5.01	11.9	586,649

when $\mu = 0$. The aggregate productivity shock ε in expression (35) prior to the 2004 panic can be calibrated according to the procedure outlined in Appendix B which exploits the ideal price index. After passing the accounting data on firms' pre-shock sales to expression (A.28), we obtain aggregate productivity $\varepsilon = \frac{7.129+13.282-(-0.00002)}{1.197} = 17.04$.

After access-to-payment shocks materialize, holding productivity ε fixed, ϵ_i^{post} compounds all ξ-shocks and δ_i^{post} readjusts so that

$$\epsilon_i^{\text{post}} = \varepsilon + \mu \log\left(\frac{m_i \delta_i^{\text{post}}}{\psi^{\text{post}}}\right) + (1-\mu)\sum_{j=1}^{N} w_{ij} \log\left(\Sigma_{ij}\frac{\delta_i^{\text{post}}}{\delta_j^{\text{post}}}\right), \tag{36}$$

where δ_i^{post} is based on the Leontief inverses after the shock, $L^{\text{post}} = (I - \Sigma)^{-1} = I + \sum_{s=1}^{\infty}((I - M)W)^s$ since $\Sigma = (I-M)W$ as defined in (16). The summary statistics for ϵ_i^{pre} and ϵ_i^{post} are reported in Panel D of Table 7. The average (median) firm productivity before the access-to-payment shocks hit is 4.90 (5.02), with a standard deviation of 1.16 across firms. In the post-shock period, average (median) ϵ_i drops to 4.89 (5.01), while the standard deviation increases to 1.18.

The following Lemma summarizes the total equilibrium impact of access-to-payment shocks on GDP.

LEMMA 2: *Access-to-payment shocks reduce GDP through two channels. Define the cross-entropy measure $H^1(\delta, m)$ with $m = (m_1, ..., m_N)$ and the entropy rate $H^2(\delta)$ as*

$$\begin{aligned} H^1(\delta, m) &\equiv -\textstyle\sum_{i=1}^N \delta_i \log\left(\frac{m_i\delta_i}{\sum_{j=1}^N m_j\delta_j}\right), \\ H^2(\delta) &\equiv -\textstyle\sum_{i=1}^N \delta_i \sum_{j=1}^N w_{ij} \log\left(w_{ij}\frac{\delta_i}{\delta_j}\right). \end{aligned} \tag{37}$$

Then $\Delta \log GDP = \log GDP^{post} - \log GDP^{pre}$ can be decomposed into firms' average drop in sales and payment network readjustments that buffer the direct impact of the shocks

$$\begin{aligned} \Delta \log \mathrm{GDP} &= \underbrace{\sum_{i=1}^N (\delta_i^{\mathrm{post}}\epsilon_i^{\mathrm{post}} - \delta_i^{\mathrm{pre}}\epsilon_i^{\mathrm{pre}})}_{\text{Drop in avg. log sales}} - \underbrace{\frac{1}{N}\sum_{i=1}^N (\log\delta_i^{\mathrm{post}} - \log\delta_i^{\mathrm{pre}})}_{\text{Payment network readjustments}} \\ &= \sum_{i=1}^N (\delta_i^{\mathrm{post}} - \delta_i^{\mathrm{pre}})\varepsilon - \mu(H^1(\delta^{\mathrm{post}}, m) - H^1(\delta^{\mathrm{pre}}, 1)) - (1-\mu)(H^2(\delta^{\mathrm{post}}) - H^2(\delta^{\mathrm{pre}})) \\ &\quad + (1-\mu)\sum_{i=1}^N d_i^{in}\left(\delta_i^{\mathrm{post}}\log(1-m_i) - \delta_i^{\mathrm{pre}}\log(1-\mu)\right) + \frac{1}{N}\sum_{i=1}^N \log\left(\frac{\delta_i^{\mathrm{pre}}}{\delta_i^{\mathrm{post}}}\right). \end{aligned} \tag{38}$$

Lemma 2 provides a micro-to-macro expression for the aggregate impact on GDP of granular disruptions in a firm's ability to make payments. It can be implemented in our data without having to address the missing intercept problem that occurs in reduced-form analysis. With the data from Table 7, the predicted values for log GDP in the pre- and post-crisis periods are equal to

$$\begin{aligned} \log \mathrm{GDP}^{\mathrm{pre}} &= \textstyle\sum_{i=1}^N \delta_i^{\mathrm{pre}}\epsilon_i^{\mathrm{pre}} - \log N - \frac{1}{N}\sum_{i=1}^N \log\delta_i^{\mathrm{pre}} = 6.193 - 13.282 - (-13.189) = 6.100, \\ \log \mathrm{GDP}^{\mathrm{post}} &= \textstyle\sum_{i=1}^N \delta_i^{\mathrm{post}}\epsilon_i^{\mathrm{post}} - \log N - \frac{1}{N}\sum_{i=1}^N \log\delta_i^{\mathrm{post}} = 6.115 - 13.282 - (-13.192) = 6.025. \end{aligned} \tag{39}$$

Table 8 reports the magnitude of the composite shocks ϵ and $\Delta \log \mathrm{GDP}$. With the numbers given by expressions (39), the causal impact of access-to-payment shocks on the Russian economy in the baseline scenario is $\Delta \log \mathrm{GDP} = 6.025 - 6.100 = -0.075$, or -7.5%.

The predicted 7.5% drop in GDP attributed to the interbank loan market panic of 2004 highlights the severe economic consequences of systemic disruptions in the payment system. This substantial decline underscores the critical role of financial stability in maintaining economic activity. For reference, the reported Russian GDP growth rate was 7.3% in 2003, 7.2% in 2004, and 6.4% in 2005. The interbank loan market panic, characterized by persistent and asymmetric disruptions in firm-firm payments, led to significant impairments in economic activity, particularly affecting money-sender firms. Access-to-payment shocks propagated upstream, resulting in direct and indirect output reductions depending on the origin of the shock. Firms' resilience provided some buffering against shock transmission, yet the overall impact on GDP remained substantial. Our analysis underscores the interconnectedness of the financial sector with broader economic activity, emphasizing the need for robust payment systems to mitigate the systemic risks associated with financial disruptions.

Sensitivity of micro-to-macro estimate to input elasticity. The different input elasticities documented in Section 5.1 provide bounds on the impact of access-to-payment shocks on GDP and allow assessing the economic consequences of payment disruptions in different economic environments. We report three alternative calibrations for the input elasticity based on different measures for the firms' return-on-assets: Increasing the elasticity μ will lower the impact of access-to-payment shocks on GDP, while a lower μ will have the opposite effect. Predicted values for the impact of access-to-payment shocks on the change in GDP between the pre- and post-crisis periods for $\mu = 0.95$ is $\Delta \log \mathrm{GDP} = \log \mathrm{GDP}^{\mathrm{post}}(6.714) - \log \mathrm{GDP}^{\mathrm{pre}}(6.731) = -0.017$. This corresponds to a lower bound of 1.7% decline in GDP due to the payment crisis. At the other extreme, the predicted drop in GDP for $\mu = 0.77$ is $\Delta \log \mathrm{GDP} = \log \mathrm{GDP}^{\mathrm{post}}(5.482) - \log \mathrm{GDP}^{\mathrm{pre}}(5.613) = -0.131$. This corresponds to an upper bound of 13.1% decline in GDP due to the payment crisis.[18]

5.3 Ukraine-Russia conflict in 2022

Most Western banks have left Russia since the Russian military crossed the internationally recognized border and attacked the Ukrainian military in February 2022. In response to this, the U.S., E.U., and the allies have imposed severe economic sanctions on Russia and specifically targeted the country's financial sector by cutting it off the global financial system, freezing the Russian assets

[18]The elasticity reported in Carvalho *et al.* (2021), $\mu = 0.5$, would underestimate GDP and imply an unrealistically large decline of $\Delta \log \mathrm{GDP} = \log \mathrm{GDP}^{\mathrm{post}}(3.573) - \log \mathrm{GDP}^{\mathrm{pre}}(3.977) = -40.4\%$ due to access-to-payment shocks.

Table 8: Impact of 2004 access-to-payment shocks on GDP

This table reports statistics of the average productivity before and after the 2004 access-to-payment crisis and the impact on GDP.

	Base scenario $\mu = 0.85$	Lower bound $\mu = 0.95$	Upper bound $\mu = 0.77$	Extreme $\mu = 0.50$
Baseline avg. productivity ϵ_i^{pre}	4.90	6.33	3.84	0.867
Post-crisis avg. productivity ϵ_i^{post}	4.89	6.32	3.82	0.798
$\Delta \log \text{GDP}$ (%/100)	-0.075	-0.017	-0.131	-0.404

abroad, and excluding most of the Russian banks from the Society for Worldwide Interbank Financial Telecommunications (SWIFT).[19] The major players such as Citigroup, JPMorgan Chase, Goldman Sachs, Credit Suisse, HSBC, Deutsche Bank, Société Générale have shut down their investment banking divisions in Russia and blocked the correspondent accounts of the Russian banks that they used for making international payments. Moreover, these sanctions have made it difficult or impossible for any foreign banks to operate in Russia due to the threat of the secondary sanctions and the risks of being cut off from the dollar funding. As a result, foreign banks from other countries that did not explicitly sanction Russia also significantly scaled back their operations in dealing with Russian banks.

The exodus of foreign banks from Russia has had a significant impact on the economy. In the short run, it has made it more difficult for Russian businesses to make payments for export-import transactions. In the long run, it has made it more difficult for them to access capital markets. However, there is a growing debate about whether these unprecedented U.S.-led sanctions have worked as planned. For example, in April 2022, the International Monetary Fund (IMF) forecasted a decline in Russian GDP of minus 8.5%, which was first revised in July to minus 6% and later in October to minus 3.4%.[20] In early 2023, the IMF reported that the Russian economy shrank by a less-than-expected 2.1% in 2022 and referred to an unanticipated economic resilience. On the other hand, some politicians and academics do not believe that the official numbers are correct. They assert that the reported GDP statistics are far from the truth. They suggest that the IMF is over-reliant on official Russian data and point out that over 1,000 major multinationals have exited

[19] https://www.consilium.europa.eu/en/policies/eu-response-ukraine-invasion/

[20] https://interfax.com/newsroom/top-stories/81648/

the country, along with many Russian citizens (Sonnenfeld *et al.* 2023).

Understanding the impact of the access-to-payment shock following the Ukraine-Russia conflict is important from a policy-making perspective. Our model is designed to quantify the impact of shocks to the banking system on the Russian economy that disrupt firms' ability to make payments. As such, it provides a framework for analyzing the *payment channel* through which the conflict is affecting GDP, complementing the credit channel often analyzed in the banking literature.

Counterfactual GDP prediction. In this counterfactual exercise, we employ our 2004 granular payment data to reconstruct the structure of the Russian input-output network in 2022 and superimpose the network position of all foreign banks. Based on this structure, which assumes that firms' Domar weights are comparable between 2004 and 2022, we nowcast Russian GDP by allowing firms' sales and profits as well as aggregate productivity, to have increased significantly between 2004 and 2022. The key assumption behind this counterfactual exercise is that the input-output network has been stable over time. Within this setting, we explore the exit of all foreign banks from the Russian banking system as an exogenous access-to-payment shock.

In the first step, we generate the bank-level shocks in the interbank loan market by modifying expression (1) with the loss of interbank connectivity due to the exit of all foreign banks. Let $N_s^{Total,Pre}$ be the total number of interbank loan market links of bank s in the pre-exit period, which can be split into: $N_s^{\text{Total, Pre}} = N_s^{\text{Domestic, Pre}} + N_s^{\text{Foreign, Pre}}$, where $N_s^{\text{Domestic, Pre}}$ is the number of interbank market links of bank s with the domestic banks and $N_s^{\text{Foreign, Pre}}$ is the number of its links with foreign banks.[21]

If we allow exit of all foreign banks their links disappear in the post-exit period: $N_s^{\text{Foreign, Post}} = 0$. Assuming that after the exit of the foreign banks all connections of the domestic banks remain constant we have: $N_s^{\text{Total, Post}} = N_s^{\text{Domestic,Post}} = N_s^{\text{Domestic,Pre}}$. Using the logic of expression (1) we generate our counterfactual interbank market shock for bank s:

$$\text{Counterfactual Interbank Connection Loss}_s = -\frac{N_s^{\text{Total, Post}} - N_s^{\text{Total, Pre}}}{\frac{1}{2}(N_s^{\text{Total, Post}} + N_s^{\text{Total, Pre}})} \in [-2, 2]. \tag{40}$$

[21] We identify foreign banks operating in Russia by using the dataset from Karas and Verninov (2019).

Table 9: Pre-shock interbank loan market centrality for the 2004 vs. 2022 events

This table provides comparisons in pre-shock interbank loan market centrality for the 2004 vs. 2022 events. The columns report average daily interbank centrality measures in the pre-panic period (January 1–April 15, 2004) for the collapsed Credittrust bank, the major foreign UniCredit bank, and the sample average foreign bank. One can see that Credittrust was by far more central in the interbank loan market in comparison with the average and major foreign banks.

	Credittrust	UniCredit	Ave. foreign bank
Degree centrality	0.0567	0.0210	0.0067
Eigenvector centrality	0.1224	0.0309	0.0105
Betweennes centrality	0.0213	0.0090	0.0012

In the second step, we employ expression (5) and replace the actual interbank panic-based shock with the counterfactual foreign banks' exodus shock. This allows us to construct the firm-level instrument as follows:

$$\xi_i^{\mathrm{C}} = \sum_{s=1}^{S_i} \text{Counterfactual Interbank Connection Loss}_s \cdot \kappa_{i,s}^{\mathrm{pre}}, \tag{41}$$

This expression weighs the banks' connection losses in the interbank loan market due to the exodus of the foreign banks with the importance of these banks for the firms, $\kappa_{i,s}^{\mathrm{pre}}$, which we extrapolate from 2004. The ξ-shocks originate in banking services due to the exit of foreign banks and affect firms' ability to pay for externally sourced production factors. This shock will be more severe for firms that are clients of foreign banks or clients of domestic Russian banks that had high exposure to foreign banks on the interbank loan market.

A large body of the banking literature demonstrates that foreign banks engage in "cherry-picking" of the largest clients (e.g., Detragiache *et al.*, 2008; Gormley, 2010). Table 9 reports average daily interbank centrality measures in the pre-panic period (January 1–April 15, 2004) for the collapsed Credittrust bank, the major foreign UniCredit bank, and the sample average foreign bank. One can see that Credittrust was by far more central in the interbank loan market in comparison with the average and major foreign banks. This difference in the centrality of the main culprits behind the actual and counterfactual shocks will produce different predictions of the GDP decline. We expect the lower centrality of foreign banks to generate a lower counterfactual GDP decline compared to the actual 2004 banking panic case.

We pass access-to-payment shocks ξ_i^{C} trough formula (13) to obtain the effective access-to-payment shocks m_i^{C} used for generating the firms' eigenvector centrailities in formula (27). Table 10 provides summary statistics of our counterfactual access-to-payment shocks $\xi_i^{\mathrm{C}}/m_i^{\mathrm{C}}$ (Panel A) and eigenvector centralities δ_i (Panel B) for the exodus of all foreign banks scenario. With $\mu = 0.85$, the average ξ shock equals 9.2% with 14.1% standard deviation. This results in an m_i^{C} distribution with a mean of 0.851 and a standard deviation of 0.010. Panel B reports eigenvalue centralities computed using 100 iterations. The firms' average eigenvector centrality both before and after the exodus of foreign banks equals 0.204, with a standard deviation of 0.58 (pre) and 0.57 (post).

In the third step, we extrapolate firms' sales and profits to 2022 by nowcasting their productivity. The aggregate productivity shock ε in expression (35) prior to the 2022 exit can be calibrated by matching the growth in GDP between 2004 and 2022. We obtain based on Lemma 1 that aggregate productivity equals

$$\varepsilon^{2022} = \varepsilon^{2004} + \frac{\log \mathrm{GDP}^{2022} - \log \mathrm{GDP}^{2004}}{\sum_{i=1}^{N} \delta_i^{\mathrm{pre}}}. \tag{42}$$

According to the official statistics the real (nominal) GDP growth of the Russian economy between 2004 and 2022 amounted to 56% (812%). Using these values we get the following results for productivity shocks: $\varepsilon^{2022} = 17.04 + \frac{0.56}{1.2} = 17.507$. This leads to nowcasted 2022 firm-level productivities $\epsilon_i^{\mathrm{pre}}$ for all firms $i = 1, ..., N$ that differ from the 2004 numbers and reflect the larger size of the Russian economy before the 2022 exodus (Panel C of Table 10).

There are some limitations associated with this counterfactual policy analysis, including that the input-output network calibration is based on historical data, and it may not accurately reflect the impact of the current conflict. Also, the model does not take into account the full range of factors that could have affected the Russian economy, such as the Western sanctions, changes in energy prices, labor market conditions, and the overall political situation in Russia. In addition, the Russian government has tried to mitigate the impact of the sanctions by nationalizing some of the banks that have left the country. Finally, we use a three-month window in the post-panic period for studying the 2004 events. This takes into account multiple rounds of re-matching by banks in the interbank loan market network. In the 2022 exercise, these multiple rounds are not captured, since we can only use the pre-exit links of foreign banks as a one-shot shock.

Table 10: Counterfactual data for 2022 Russia-Ukraine conflict

Panel A reports the counterfactual raw and effective access-to-payment shocks under exodus of all foreign banks scenario. Panel B reports eigenvalue centralities after 100 iterations. Panel C provides nowcasted firms' productivity shocks calibrated with Russia's GDP growth between 2004 and 2022. Panel D reports the impact of the 2022 Russia-Ukraine conflict on GDP.

	Mean	Std. Dev.	Min	Median	Max	N
			Panel A: Access-to-payment shock			
ξ_i^{C}	0.092	0.141	0	0	2	586,649
m_i^{C} ($\mu = 0.85$)	0.851	0.010	0.85	0.85	0.99	586,649
			Panel B: Eigenvector centralities (x 100,000)			
δ_i^{pre} ($\mu = 0.85$)	0.204	0.58	0.171	0.171	349	586,649
δ_i^{post} ($\mu = 0.85$)	0.204	0.57	0.171	0.171	348	586,649
			Panel C: Productivity shocks			
$\epsilon_i^{\mathrm{pre}}$	5.369	1.161	-84.410	5.488	12.402	586,649
$\epsilon_i^{\mathrm{post}}$	5.367	1.174	-84.329	5.487	12.401	586,649
			Panel D: Impact of counterfactual access-to-payment shocks on GDP			
		Predicted GDP decline			Official 2022-23 GDP decline	
$\Delta \log \mathrm{GDP}$ (%/100)		-0.0107			-0.0210	

After applying Lemma 2, we report the predicted GDP decline in our counterfactual experiment in Panel D of Table 10 along with the official GDP statistics. The predicted 1.1% drop in GDP attributed to the exodus of foreign banks from Russia in the wake of the Ukraine-Russia conflict highlights the impact of geopolitical events on economic stability. The calibration of (42) to real GDP growth may underestimate the size of the Russian economy in 2022. If we use the nominal GDP growth to calibrate the rise in productivity, $\Delta \log \mathrm{GDP} = -1.9\%$, which accounts for almost all of the reported GDP decline for 2022-23. In both cases, this decline reflects the interconnectedness between the financial sector and broader economic activity, highlighting that foreign banks play a significant but not systemically important in facilitating financial transactions for businesses in Russia. As foreign banks retreat from the Russian market due to sanctions and heightened risks, the resulting disruption in payment systems (and credit availability) hampered economic productivity and growth to a limited extent.

As expected, the predicted decline in GDP is lower for our counterfactual exercise compared to the actual 2004 banking panic. This is due to the lower centrality of foreign banks whose counterfactual exit results in interbank loan market adjustments occurring at the *intensive* margin in formula (40). On the opposite, the high centrality of Credittrust Bank combined with the regulator's missteps resulted in the hollowing out of the interbank market at the *extensive* margin after the actual banking panic.

Still, the magnitude of the GDP decline underscores the relevance of the shock to the economy. An important difference between the 2004 access-to-payment shocks and the counterfactual 2022 exercise is that here we have only foreign banks leave the Russian interbank loan market and these banks were more peripheral. As a result, fewer domestic banks got completely disconnected from the interbank loan market during the Ukraine-Russia conflict.

Overall, the analysis stresses the vulnerability of the economy to payment stress depending on the network positions of the banks being affected and how they are intertwined with firms through the payment system, which highlights the importance of robust financial infrastructures in fostering resilience.

6 Conclusion

If money is the "blood" that makes the heart of any economy beat, then the payment system is the network of veins directing the money flows to the economy's vital organs. What happens to the economy when this flow turns into a trickle? This paper quantifies the answer to this question in the context of the 2004 interbank loan market panic in Russia as an exogenous shock resulting in temporary payment system stress. The withdrawal of licenses from two banks using the Russian interbank loan market for money laundering made banks with transaction histories with the guilty banks potential suspects, or toxic. This, in turn, led to the breakup of many bank-bank connections including those used to service transactions between their client firms. Relying on unique granular transaction-level data from the Moscow branch of the Central Bank of Russia (CBR), we exploit the heterogeneous exposure of Russian banks and their client firms to toxic banks to measure the firm-level access-to-payment shocks. We then combine this information with the CBR's firm-firm transaction data to trace and quantify the propagation of access-to-payment shocks along the customer-supplier network.

At the firm level, we document that a large number of firms have not been able to either receive or send payments after the 2004 interbank loan market panic. As a consequence, firms' input-output centrality declined and firm growth got depressed. Firms' growth declined with their own loss of access to payment services. Economically, a one-standard-deviation increase in the access-to-payment shock resulted in a 2.1% reduction in revenue growth. Not only firms' own shocks but other firms' shocks in the firm-firm customer-supplier network impacted revenue growth via the upstream propagation of access-to-payment shocks, that is, firm growth declined with the shocks of its customers more than with the shocks of its suppliers. This is quite different from the natural disaster shocks propagating either downstream as in Barrot and Sauvagnat (2016) or both down- and upstream as in Carvalho *et al.* (2021). Additionally, more eigen-central firms were more sensitive to access-to-payment shocks.

At the macro level, we demonstrate that payment system stress interacts with the customer-supplier network and leads to a significant aggregate effect. The payment disruptions in 2004 caused a 7.5% decline in Russian GDP, driven by a large drop in average sales but partially offset by endogenous payment network readjustments. To perform this analysis, we develop an equilibrium model in which access-to-payment shocks disrupt firms' access to bank-intermediated payment services. We modify the static input-output production model (Acemoglu *et al.* (2012)) by introducing an internal factor independent of outside factors into the production technology and allowing for access-to-payment shocks. Firms' Domar weights are stochastic in our setting and capture the pass-through rate of access-to-payment shocks to GDP.

In a counterfactual exercise, we use our estimated input-output linkages between customers and suppliers and banks' position in the interbank loan market to obtain equilibrium forecasts for the macroeconomic impact of geopolitical tensions. As an exogenous shock, we study how the exodus of major foreign banks at the onset of the Russia-Ukraine conflict spilled into the payment system and disrupted the Russian economy in 2022. We find that the causal impact of access-to-payment shocks on the Russian economy during the 2022 Russia-Ukraine conflict is estimated to be -1.1%. This decline highlights that geopolitical tensions can deteriorate economic stability. Overall, our analysis stresses the vulnerability of the economy to payment stress depending on how firms and banks are intertwined which highlights the importance of robust financial infrastructures in fostering economic resilience.

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Online Appendix

Appendix A Discussion of empirical specifications

We control for unobserved heterogeneity in the cross-section with receiver firm fixed effects to avoid potential bias due to the non-random matching of sender and receiver firms. This approach was first employed by Khwaja and Mian (2008) and in our case exploits the fact that receiver firms have multiple sender firm partners that are differently hit by access-to-payment shocks, Z_i. As a result, the estimation compares variation in payment flows from differently hit sender firms *within* a receiver firm, independently of its own idiosyncratic demand.

This empirical strategy does not allow estimating the impact of shocks Z_i on payment flows for receiver firms with only one sender firm partner, potentially leading to a sample selection bias. Because we work on the upstream-downstream production network of firms this problem is insignificant. As can be seen from Table 2, there are on average around 300 sender firms-partners per one receiver firm. There are only 5.8 percent of receiver firms that have one sender firm partner and 2.5 percent of sender firms that have one receiver firm partner in our sample.

The identification assumption of the *within-firm* estimator in Khwaja and Mian (2008) could still be violated if there are unaccounted shocks that, for example, hit the receiver firm and are correlated with the access-to-payment shocks hitting the sender firms, Z_i. In order to test the validity of the identifying assumptions, Khwaja and Mian (2008) and Chodorow-Reich (2014) suggest removing the receiver firm's fixed effect that controls for unobserved characteristics of the receiver firm and using a set of observable receiver firm's characteristics in order to explicitly control for unaccounted shocks to these firms. The difference of the estimated coefficients on access-to-payment shocks hitting the sender firms, Z_i, in specifications with receiver firm-fixed effects versus specifications with observable receiver firm controls captures the amount of bias implied by the not as-good-as random assignment of sender and receiver firms determined by unobservable receiver firm's characteristics.

We double-cluster standard errors at the sender firm's industry location and receiver firm's industry-location levels and weight firm pairs by the inverse number of sender firms per recipient firm. Double clustering accounts for possible residual serial correlation across firms within industries and geographical locations. Weighting accounts for the unequal selection probability of sender firms per recipient firm in the production network. As can be seen from Table 2 on average there are three times more sender firms-partners per one receiver firm than receiver firm partners per sender firm. We apply higher weights to the observations that are less represented in our sample, and lower weights to relatively more represented ones.

Appendix B Proofs

Proof of Propositions 1 and 2: The firm solves a constrained profit maximization problem summarized by the following Lagrangian with a multiplier λ_i^{CC} on the collateral constraint:

$$\mathcal{L}^{CC} = p_i y_i - p_k k_i - \sum_{j=1}^{N} p_j x_{ij} - \lambda_i^{CC} \left[\sum_{j=1}^{N} p_j x_{ij} - (1 - \xi_i) p_i y_i \right]. \tag{A.1}$$

The FOCs for problem (A.1) can be written as:

$$\begin{array}{rcl} (x_{ij}) & : & (1-\mu)(1+\lambda_i^{CC}(1-\xi_i))w_{ij}p_i y_i = (1+\lambda_i^{CC})p_j x_{ij}, \\ (k_i) & : & \mu(1+\lambda_i^{CC}(1-\xi_i))p_i y_i = p_k k_i, \\ (\lambda_i^{CC}) & : & \sum_{j=1}^N p_j x_{ij} = (1-\xi_i)p_i y_i. \end{array} \tag{A.2}$$

Summing FOC for x_{ij} with respect to the index j and using the FOC for λ_i^{CC} leads to:

$$(1-\mu)(1+\lambda_i^{CC}(1-\xi_i)) = (1+\lambda_i^{CC})(1-\xi_i), \tag{A.3}$$

which immediately yields the expression for λ_i^{CC}:

$$\lambda_i^{CC} = \max\left\{\frac{\xi_i-\mu}{\mu(1-\xi_i)}, 0\right\}. \tag{A.4}$$

It is clear from (A.4) that the collateral constraint binds for $\xi_i \in (\mu, 1]$. When the collateral constraint is slack $\xi_i \in [0, \mu]$ FOCs take the following form:

$$\begin{array}{rcl} (x_{ij}) & : & p_j x_{ij} = (1-\mu)w_{ij}p_i y_i, \\ (k_i) & : & p_k k_i = \mu p_i y_i. \end{array} \tag{A.5}$$

When the collateral constraint binds, we can substitute condition (A.3) back into the FOC for x_{ij} and then substitute condition (A.3) back into the FOC for k_i to obtain:

$$\begin{array}{rcl} (x_{ij}) & : & p_j x_{ij} = (1-\xi_i)w_{ij}p_i y_i, \\ (k_i) & : & p_k k_i = \xi_i p_i y_i. \end{array} \tag{A.6}$$

We can then combine solutions for unconstrained and constrained problems by introducing the net access-to-payment shock $m_i = \max\{\xi_i, \mu\}$ so that we have the following optimal external inputs x_{ij}:

$$x_{ij} = (1-m_i)w_{ij}y_i\left(\frac{p_i}{p_j}\right), \tag{A.7}$$

and internal inputs k_i:

$$p_k k_i = m_i p_i y_i. \tag{A.8}$$

Using the optimal inputs (A.7) and (A.8) in the expression for the firm's profit results in

$$\begin{aligned} \Pi_i = p_i y_i - p_k k_i - \sum_{j=1}^N p_j x_{ij} = \\ = p_i y_i(1-m_i)\left[1-\sum_{j=1}^N w_{ij}\right], \end{aligned} \tag{A.9}$$

thus yielding the following expression for the marginal profit function

$$\pi_i = \frac{\Pi_i}{p_i y_i} = (1-m_i)\left[1-\sum_{j=1}^N w_{ij}\right]. \tag{A.10}$$

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

$$\mathcal{L}_{ct} = \beta^t \prod_{i=1}^{N} c_i^{\gamma/N} - \lambda \left[\sum_{i=1}^{N} p_i c_i - p_k k + \sum_{i=1}^{N} S_i (q_i - q_{it-1}) - \sum_{i=1}^{N} \Pi_i q_{it-1} \right] \tag{A.11}$$

Then the FOCs with respect to consumption c_i yield:

$$\frac{\gamma \beta^t}{N} \prod_{i=1}^{N} c_i^{\gamma/N} = \lambda p_i c_i. \tag{A.12}$$

Market clearing: Market clearing yields that the equilibrium price p_k satisfies

$$p_k k = \sum_{i=1}^{N} m_i p_i y_i. \tag{A.13}$$

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

$$\text{GDP} = \sum_{i=1}^{N} (m_i + \pi_i) p_i y_i. \tag{A.14}$$

The goods market clearing implies

$$\begin{aligned}
& p_i c_i + \sum_{j=1}^{N} p_i x_{ji} = p_i y_i, \\
\Leftrightarrow \quad & \frac{1}{N}\text{GDP} + \sum_{j=1}^{N} (1 - m_j) w_{ji} p_j y_j = p_i y_i, \\
\Leftrightarrow \quad & \sum_{j=1}^{N} \left[m_j \frac{1}{N} + \pi_j \frac{1}{N} + (1 - m_j) w_{ji} \right] p_j x_j = p_i y_i.
\end{aligned} \tag{A.15}$$

Implications: It is useful to define some additional notation at this stage. Collect the factor input weights in the $N \times N$ matrix Σ with elements $\Sigma_{ij} = (1 - m_i) w_{ij} \geq 0$. Define $L = (I - \Sigma)^{-1}$ with elements L_{ij}. Also define a $N \times N$ adjacency matrix Ω with elements $\Omega_{ij} = (m_i + \pi_i)/N + \Sigma_{ij}$.

Define the sales of firm i as $Y_i = p_i y_i$ and collect these in vector Y. It is easy to see that Y is an eigenvector corresponding to the unit eigenvalue of the transformed adjacency matrix Ω. Equation (A.15) amounts to $Y_i = \sum_{j=1}^{N} \Omega_{ji} Y_j$ or, in matrix form, $\Omega' Y = \mathbf{1} Y$. That is, the equilibrium sales Y are equal to the vector of eigenvector centralities of the firms. Note also the switch of indices in the adjacency weight Ω_{ji}. 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 Y can be determined explicitly from the second line in equation (A.15) which amounts to

$$Y_i = \frac{1}{N}\text{GDP} + \sum_{j=1}^{N} \Sigma_{ji} Y_j. \tag{A.16}$$

In matrix form, this can be rewritten as $Y = \frac{1}{N}\mathbf{1}\text{GDP} + \Sigma' Y$, the solution of which is given by

$$Y = \frac{1}{N}(I - \Sigma')^{-1}\mathbf{1}\text{GDP} = \frac{1}{N}L'\mathbf{1}\text{GDP}. \tag{A.17}$$

We can, thus, write sales as $Y_i = \delta_i \text{GDP}$ with $\delta_i = \frac{1}{N}\sum_{j=1}^{N} L_{ji}$ and $\sum_{i=1}^{N}(m_i + \pi_i)\delta_i = 1$. Define $\psi = \sum_{i=1}^{N} m_i \delta_i$. The internal-factor income share of the GDP is given by

$$K \equiv p_k k = p_k = \psi \cdot \text{GDP}, \tag{A.18}$$

where we have used normalization $k = 1$. Correspondingly, profits (and thus dividends) are proportional to each firm's eigenvector centrality:

$$\Pi_i = \pi_i \delta_i \text{GDP}. \tag{A.19}$$

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

$$\sum_{i=1}^{N} \Pi_i = \sum_{i=1}^{N}(1 - m_i)\left(1 - \sum_{j=1}^{N} w_{ij}\right)\delta_i \text{GDP} = (1 - \psi)\text{GDP}. \tag{A.20}$$

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

$$\begin{aligned} p_j x_{ij} &= \Sigma_{ij} Y_i = \Sigma_{ij}\delta_i \text{GDP}, \\ p_k k_i &= m_i Y_i = m_i \delta_i \text{GDP}. \end{aligned} \tag{A.21}$$

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

$$\frac{p_i}{p_k} = \frac{\delta_i}{\psi}\frac{1}{y_i}, \tag{A.22}$$

and $p_k = \psi \cdot \text{GDP}$. The equilibrium output of each firm is given by

$$y_i = e^{\varepsilon}\left(\frac{m_i \delta_i}{\psi}\right)^{\mu} \prod_{j=1}^{N}\left[\Sigma_{ij}\frac{\delta_i}{\delta_j} y_j\right]^{(1-\mu)w_{ij}}. \tag{A.23}$$

Taking logs,

$$\log y_i = \varepsilon + \mu \log\left(\frac{m_i \delta_i}{\psi}\right) + (1 - \mu)\sum_{j=1}^{N} w_{ij} \log\left[\Sigma_{ij}\frac{\delta_i}{\delta_j}\right] + (1 - \mu)\sum_{j=1}^{N} w_{ij}\log(y_j). \tag{A.24}$$

We can thus write the output in matrix form as $\log y = \epsilon + \Sigma \log y$.

Proof of Proposition 3: We can collect all terms for each order of customer and rearrange the summation in (31), ignoring the shock interactions for now

$$\begin{aligned}\delta_i^{post} - \delta_i^{pre} = -\frac{1}{N}\sum_{k=1}^{N}\left(1+\sum_{j=1}^{N} w_{jk} + \sum_{j=1}^{N}\sum_{l=1}^{N} w_{lj}w_{jk} + ...\right) w_{ki}Z_k \\ -\frac{1}{N}\sum_{j=1}^{N}\sum_{k=1}^{N}\left(1+\sum_{l=1}^{N} w_{lj} + ...\right) w_{jk}w_{ki}Z_j \\ -\frac{1}{N}\sum_{l=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N}\left(1+...\right) w_{lj}w_{jk}w_{ki}Z_l - ...\end{aligned} \quad (A.25)$$

Replacing the terms in parentheses by the eigenvector centrality for all orders of customers,

$$\begin{aligned}\delta_i^{post} - \delta_i^{pre} &= -\sum_{k=1}^{N}\delta_k^0 w_{ki}Z_k && \text{(shocks to customers of } i\text{)} \\ &\quad -\sum_{j=1}^{N}\sum_{k=1}^{N}\delta_j^0 w_{jk}w_{ki}Z_j && \text{(shocks to 2nd order customers of } i\text{)} \\ &\quad -\sum_{l=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N}\delta_l^0 w_{lj}w_{jk}w_{ki}Z_l - ... && \text{(shocks to 3rd order customers of } i\text{)} \\ &= -\sum_{k=1}^{N}\delta_k^0 A_{ki}^0 Z_k. && \text{(A.26)}\end{aligned}$$

Hence, how access-to-payment shocks at any order of customer affect firm i depends on the input-output weights w weighted by the customers' counterfactual centrality δ^0.

We can also expand highlighting the order of the shock interactions:

$$\begin{aligned}&\delta_i^{post} - \delta_i^{pre} = \\ &-\frac{1}{N}\sum_{k=1}^{N}\left(w_{ki} + \sum_{j=1}^{N}(w_{kj}w_{ji} + w_{jk}w_{ki}) + \sum_{j=1}^{N}\sum_{l=1}^{N}(w_{kj}w_{jl}w_{li} + w_{jk}w_{kl}w_{li} + w_{lj}w_{jk}w_{ki}) + ...\right) Z_k \\ &+\frac{1}{N}\sum_{k=1}^{N}\sum_{j=1}^{N}\left(w_{kj}w_{ji} + + \sum_{l=1}^{N}(w_{kj}w_{jl}w_{li} + w_{lk}w_{kj}w_{ji} + w_{kl}w_{lj}w_{ji}) + ...\right) Z_k Z_j \\ &-\frac{1}{N}\sum_{k=1}^{N}\sum_{j=1}^{N}\sum_{l=1}^{N}(w_{kj}w_{jl}w_{li} + ...) Z_k Z_j Z_l + ...\end{aligned} \quad (A.27)$$

The first term in (A.27) captures the 1st order of how shocks matter which is the direct impact of shock Z_k on firm i through all network paths. It is the same as expression (31). The remaining terms are new. The second term, now with a positive sign, captures the 2nd order of how shocks matter through shock interactions. The third term, again with a negative sign, captures the 3rd order of shock interactions, and so forth.

Derivation of ε: The ideal price index yields

$$\frac{1}{N}\sum_{i=1}^{N} -\log p_i = \log N.$$

We have

$$-\log p_i = \log y_i - \log Y_i = \sum_{j=1}^{N} l_{ij}\epsilon_j - \log Y_i,$$

with

$$\begin{aligned}
\log y_i &= \sum_{j=1}^{N} l_{ij}\epsilon_j = \varepsilon\sum_{j=1}^{N} l_{ij} + \sum_{j=1}^{N} l_{ij}\left(\mu\log\left(\frac{m_i\delta_i}{\psi}\right) + (1-\mu)\sum_{j=1}^{N} w_{ij}\log\left(\Sigma_{ij}\frac{\delta_i}{\delta_j}\right)\right),\\
\log Y_i &= \log p_i + \varepsilon\sum_{j=1}^{N} l_{ij} + \sum_{j=1}^{N} l_{ij}\left(\mu\log\left(\frac{m_i\delta_i}{\psi}\right) + (1-\mu)\sum_{j=1}^{N} w_{ij}\log\left(\Sigma_{ij}\frac{\delta_i}{\delta_j}\right)\right).
\end{aligned}$$

Hence

$$\frac{1}{N}\sum_{i=1}^{N}(\log y_i - \log Y_i) = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{N} l_{ij}\epsilon_j - \frac{1}{N}\sum_{i=1}^{N}\log Y_i = \log N.$$

With $m_i^{\text{pre}} = \mu$ and $\Sigma_{ij}^{\text{pre}} = (1-\mu)w_{ij}$,

$$\varepsilon = \frac{\frac{1}{N}\sum_{i=1}^{N}\log Y_i^{\text{pre}} + \log N - \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{N} l_{ij}^{\text{pre}}\left(\mu\log\left(\frac{m_i^{\text{pre}}\delta_i^{\text{pre}}}{\psi^{\text{pre}}}\right) + (1-\mu)\sum_{j=1}^{N} w_{ij}\log\left(\Sigma_{ij}^{\text{pre}}\frac{\delta_i^{\text{pre}}}{\delta_j^{\text{pre}}}\right)\right)}{\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{N} l_{ij}^{\text{pre}}}. \tag{A.28}$$

Appendix C Model illustration

We use a simple 2-firm economy with

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

to illustrate the inner workings of the model. We drop the time subscript for the sake of clarity for this example. The Leontief inverse $L = (I-\Sigma)^{-1}$ can be calculated to yield

$$L = \frac{1}{1-w_{12}w_{21}(1-m_1)(1-m_2)}\begin{bmatrix} 1 & w_{12}(1-m_2) \\ w_{21}(1-m_1) & 1 \end{bmatrix},$$

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

$$\begin{aligned}
\delta_1 &= \tfrac{1}{2}\tfrac{1+w_{12}(1-m_1)}{1-w_{12}w_{21}(1-m_1)(1-m_2)},\\
\delta_2 &= \tfrac{1}{2}\tfrac{1+w_{21}(1-m_2)}{1-w_{12}w_{21}(1-m_1)(1-m_2)}.
\end{aligned}$$

The expressions illustrate that δ_1 and δ_2 depend on both m_1 and m_2. The resilience matrix equals

$$\begin{aligned}\mathcal{R}^1 &= -\frac{1}{2}\left(\frac{1}{1-w_{12}w_{21}(1-m_1)(1-m_2)}\right)^2 \\ &\times \begin{bmatrix} w_{12}(1+w_{21}(1-m_2)) & w_{12}w_{21}(1+w_{12}(1-m_1))(1-m_1) \\ w_{12}w_{21}(1+w_{21}(1-m_2))(1-m_2) & w_{21}(1+w_{12}(1-m_1)) \end{bmatrix} \leq 0.\end{aligned}$$

When $w_{21}=0$ and $w_{12}\neq 0$, firm 1 is the customer, and firm 2 is the supplier. In this case, m_1 shocks affect firm 2's sales and profits. That is, shocks propagate upstream from customer to supplier. By contrast, firm 1 is insulated from m_2 shocks so long as $w_{21}=0$. When $w_{21}\neq 0$, m_2 shocks alter the network centrality of firm 1 and, hence, its sales and profitability. In turn, firm 2 is insulated from m_1 shocks only if $w_{12}=0$.

Figures A.1 and A.2 illustrate the effect of access-to-payment shocks on both firms when only one of them is affected by access-to-payment shocks of different magnitudes. Figure A.1 graphs the profitability, π_i, sales scaled by the GDP, $Y_i/C=\delta_i$, profit flow multipliers, $\Pi_i/C=\pi_i\delta_i$, and payment flow multipliers, $X_{ij}/(w_{ij}C)=(1-m_i)\delta_i$, for both firms as functions of m_1 and m_2. Figure A.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 sales, shown for each firm by a red circle with the area proportional to Y_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 $m_2=0$ for this exercise leading to

$$\begin{aligned}&\pi_1=\tfrac{1}{2}(1-m_1), \delta_1=\tfrac{3}{3+m_1}, \tfrac{\Pi_1}{C}=\tfrac{3(1-m_1)}{2(3+m_1)}, \tfrac{X_{12}}{w_{12}C}=\tfrac{3(1-m_1)}{3+m_1}, \mathcal{R}_{11}=-\tfrac{3}{(3+m_1)^2},\\ &\pi_2=\tfrac{1}{2}, \delta_2=\tfrac{6}{3+m_1}-1, \tfrac{\Pi_2}{C}=\tfrac{3-m_1}{2(3+m_1)}, \tfrac{X_{21}}{w_{21}C}=\tfrac{3-m_1}{3+m_1}, \mathcal{R}_{21}=-\tfrac{6}{(3+m_1)^2}.\end{aligned}$$

Panel A of Figure A.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 Lemma 1, the profit margin, π_i, declines with m_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 m_1 than the Domar weight of the affected firm 1, δ_1. This is because the access-to-payment shock m_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 m_1. Therefore, the affected firm's sales are greater than the unaffected firm's sales, $Y_1=\delta_1 C>Y_2=\delta_2 C$, for $m_1\in(0,1]$. However, since the unaffected firm 2 has a 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 access-to-payment shocks affect symmetric firms asymmetrically mainly due to their asymmetric impact on the input-output network.

Panel A of Figure A.2 further illustrates the impact of ξ-shocks on this two-firm network. We set m_1 to 0 (left subplot), 0.5 (middle subplot), and 1 (right subplot). Panel A of Figure A.1 shows that sales of the unaffected firm decline faster relative to sales 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 m_1 increases, firm-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 access-to-payment shock makes the symmetric economy asymmetric by tilting a greater share of the equilibrium sales 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.

Next, we consider the asymmetric economy with $w_{12} = 0.5$ $w_{21} = 0$. In this economy, we study the upstream, that is, an access-to-payment shock originates in the supplier $m_1 \in [0, 1]$ and $m_2 = 0$, and the downstream, that is, an access-to-payment shock originates in the producer $m_1 = 0$ and $m_2 \in [0, 1]$, propagation of the access-to-payment shock.

We start with the upstream shock propagation for which we have

$$\pi_1 = \tfrac{1}{2}(1 - m_1), \delta_1 = \tfrac{1}{2}, \tfrac{\Pi_1}{C} = \tfrac{1-m_1}{4}, \tfrac{X_{12}}{w_{12}C} = \tfrac{1-m_1}{2}, \mathcal{R}_{11} = 0,$$
$$\pi_2 = 1, \delta_2 = \tfrac{3-m_1}{4}, \tfrac{\Pi_2}{C} = \tfrac{3-m_1}{4}, X_{21} = 0, \mathcal{R}_{21} = -\tfrac{1}{4}.$$

Panel B of Figure A.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 m_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 m_1 to the value of the Domar weight of the affected downstream firm 1, $\delta_1 = 0.5$ when $m_1 = 1$ and firms are no longer connected to each other. Therefore, the unaffected firm's sales and profits are never less than the affected firm's sales, $Y_2 = \delta_2 C \geq Y_1 = \delta_1 C$, and profits, $\Pi_2 = \pi_2\delta_2 C > \Pi_1 = \pi_1\delta_1 C$, for all values of $m_1 \in [0, 1]$. Finally, $m_1 = 1$ reduces the asymmetry in this case and the asymmetric economy becomes symmetric when $m_1 = 1$ and $m_2 = 0$. This can be seen in the rightmost plot where $\frac{X_{12}}{w_{12}C} = 0$ when $m_1 = 0$.

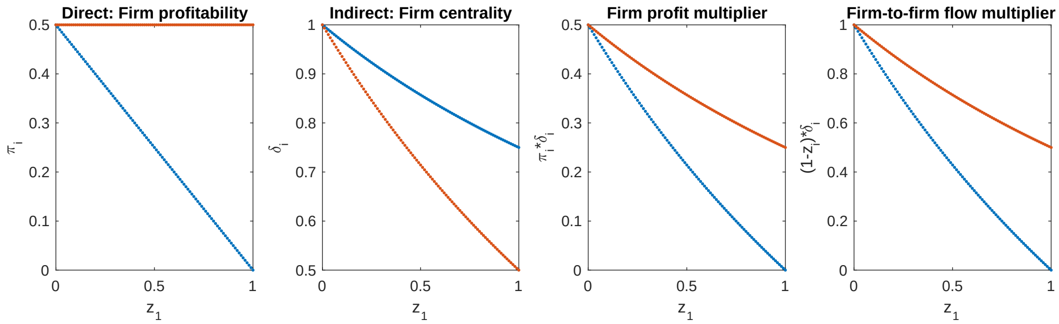
Panel B of Figure A.2 further illustrates the effects of the upstream propagation of the access-to-payment shock. Going from left to right, the unaffected firm starts as more central among the two firms, then its centrality declines with m_1, and both firms have the same centrality when $m_1 = 1$. Correspondingly, 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 m_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 A.1, the upstream access-to-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.

Next, we consider the downstream propagation for which we have

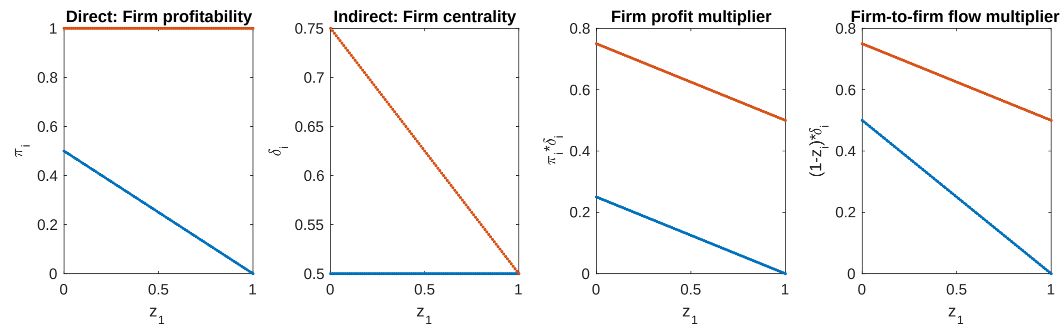
$$\pi_1 = \tfrac{1}{2}, \delta_1 = \tfrac{1}{2}, \tfrac{\Pi_1}{C} = \tfrac{1}{4}, \tfrac{X_{12}}{w_{12}C} = \tfrac{1}{2}, \mathcal{R}_{11} = 0,$$
$$\pi_2 = 1 - m_2, \delta_2 = \tfrac{3}{4}, \tfrac{\Pi_2}{C} = \tfrac{1-m_2}{4}, X_{21} = 0, \mathcal{R}_{21} = 0.$$

Panel C of Figure A.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 $1 - m_2$ 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 $m_2 \in [0, 0.5)/(0.5, 1]$. 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 weights do not depend on the shock m_2. Thus, Panel C of Figure A.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 m_2, as can be seen from the right-most subplot of Panel C, as well as from Panel C of Figure A.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 m_1 does not affect the network.

Panel A: Symmetric economy with propagation of access-to-payment



Panel B: Downstream access-to-payment with upstream propagation



Panel C: Upstream access-to-payment without downstream propagation

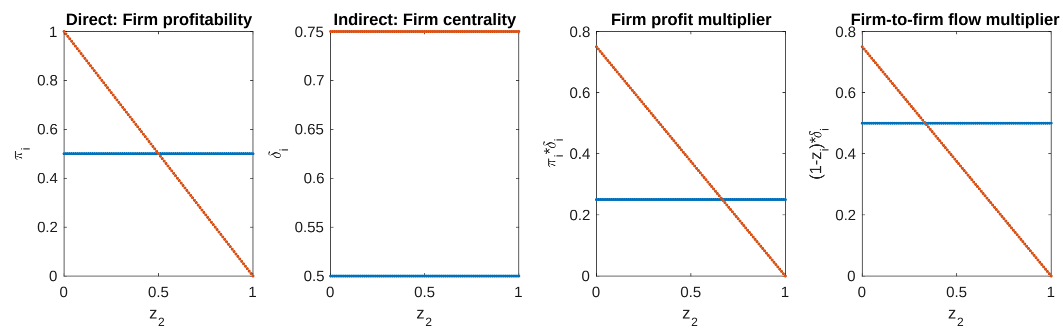
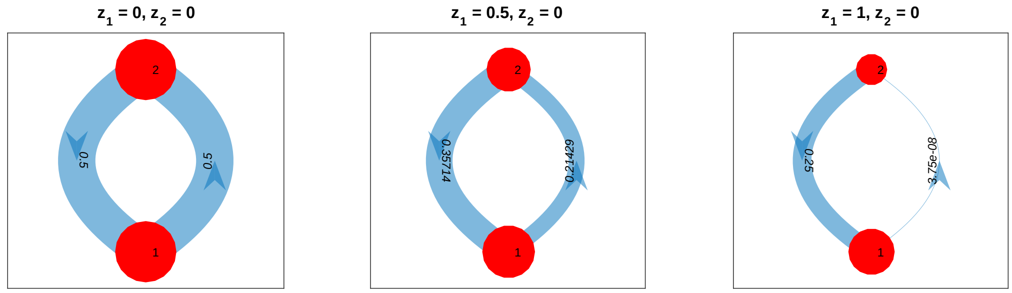


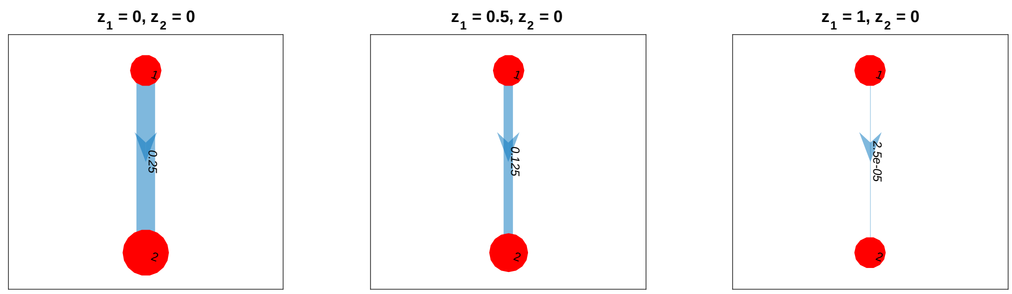
Figure A.1: Direct and indirect impact of access-to-payment shocks

This picture shows the impact of ξ-shocks on input-output networks for three types of network structures. The first graph plots firms' profitability π_i as a function of ξ-shocks. The second graph plots firms' eigenvector centrality δ_i as a function of ξ-shocks. The third graph plots firms' profit multiplier $\Pi_i/C = \pi_i * \delta_i$ as a function of ξ-shocks. The forth graph plots the firm-firm flow multiplier $X_{ij}/(w_{ij}C) = (1 - m_i) * \delta_i$ as a function of ξ-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 an access-to-payment shock originating at a customer. In Panel C, we model an access-to-payment shock originating at a supplier. The blue line corresponds to Firm 1, and the red line to Firm 2.

Panel A: Symmetric economy becomes asymmetric and source of access-to-payment impacted less



Panel B: Upstream propagation is asymmetric—Access-to-payment originates at customer 1 and propagates to supplier 2



Panel C: Downstream propagation is symmetric—Access-to-payment shock originates at supplier 2 and affects customer 1 and supplier 2 symmetrically

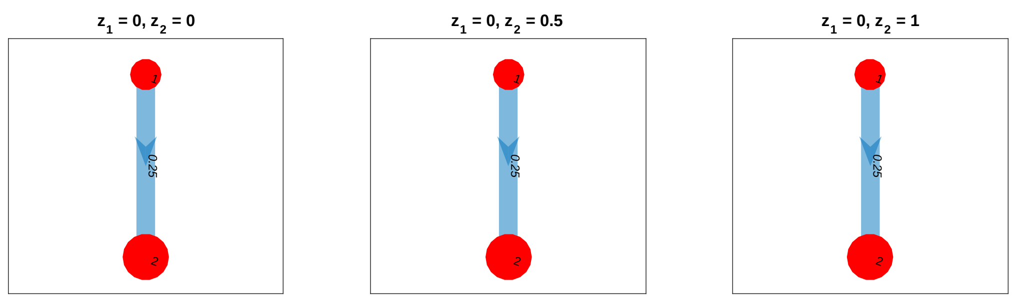


Figure A.2: Impact of access-to-payment shocks in input-output networks

This picture shows the impact of ξ-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 Y_i. The blue edges indicate the magnitude of the firm-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 an access-to-payment originating at a customer. In Panel C, we model an access-to-payment shock originating at a supplier.

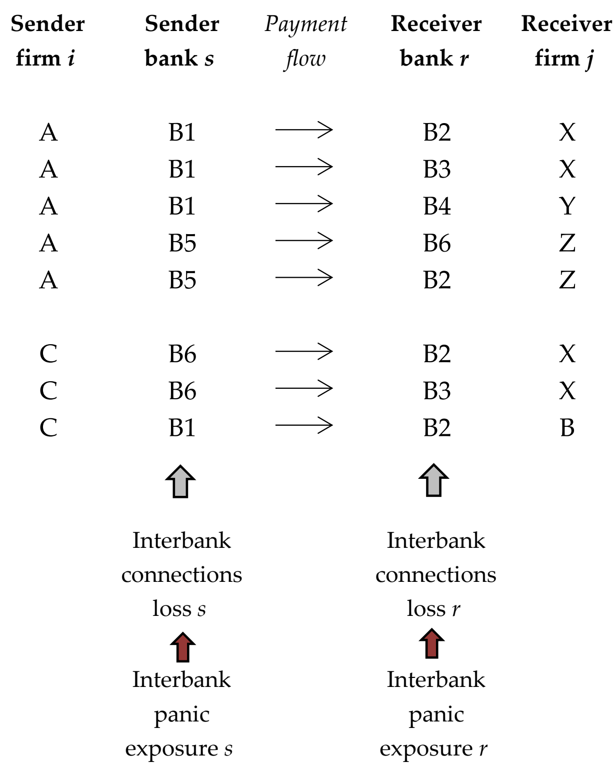


Figure A.3: Structure of the raw payment data

This picture illustrates a hypothetical example of our 4-dimensional payment data between sender and receiver 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.

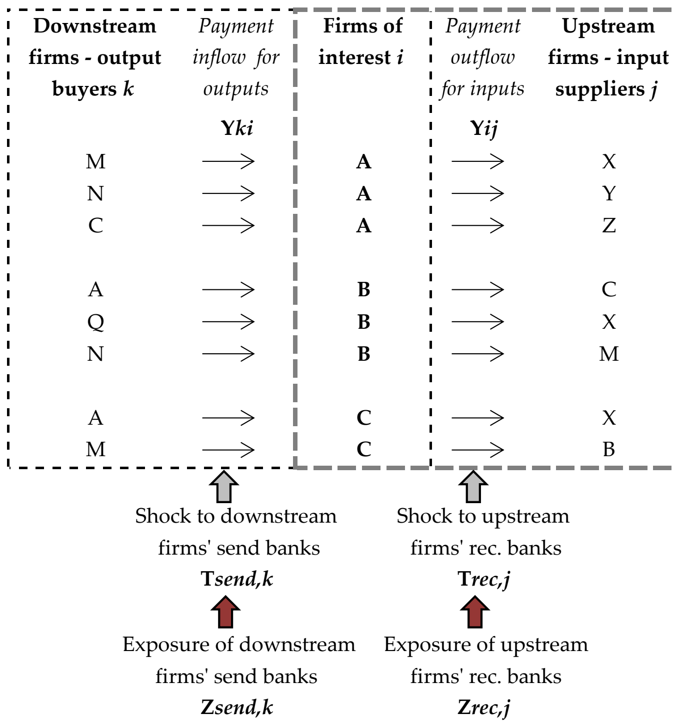


Figure A.4: Structure of firm-firm data

This picture illustrates a hypothetical example of the firm-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.

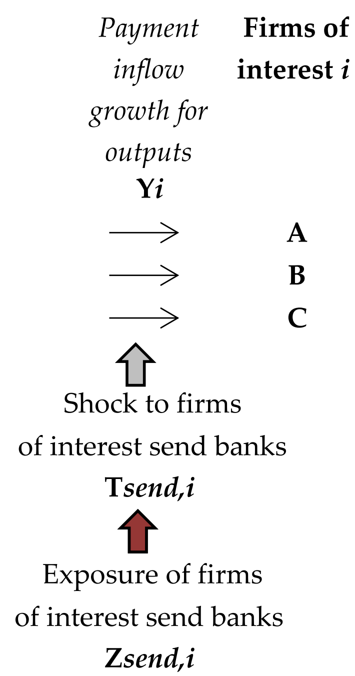


Figure A.5: Structure of the cross-sectional payment data

This picture illustrates a hypothetical example of the cross-sectional payment data which we have obtained after collapsing the firm-firm panel data circled by the black dotted line in Figure A.4. 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 t shock to the firm's 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.