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The Trade Credit Clearinghouse: Liquidity and Coordination

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Multilateralne kompenzacije: likvidnost i koordinacija

Sažetak

U ovom radu proučavamo ekonomske učinke multilateralnih kompenzacija. Multilateralne kompenzacije omogućuju velikoj mreži poduzeća da međusobno netiraju dugove u “krug” te tako smanje rizik međusobnog neplaćanja. Koristimo detaljne podatke o mreži dugovanja i financijskim izvještajima iz razmjerno velike implementacije multilateralnih kompenzacija u Republici Srpskoj, entitetu u Bosni i Hercegovini, gdje je ukupno netiranje dugova u promatranom razdoblju iznosilo 8% BDP-a. Razvijamo novu identifikacijsku strategiju koristeći algoritam netiranja, s ciljem identifikacije kauzalnih efekata multilateralnih kompenzacija. Za svako poduzeće identificirali smo varijaciju u netiranju koja proizlazi iz dalekih promjena u mreži dugova. Koristeći tu varijaciju, pokazujemo da multilateralne kompenzacije značajno smanjuju rizik neplaćanja dužnika te potiču rast i investicije poduzeća. Multilateralne kompenzacije su korisne jer omogućavaju financijski ranjivim poduzećima plaćanje dugova potencijalno nenaplativim potraživanjima. Također, centralizirano netiranje omogućuje velikoj mreži dužnika koordinaciju međusobnog plaćanja te tako pomaže sprječavati pojavu velikih “krugova” neplaćanja.

Ključne riječi: trgovački kredit, multilateralne kompenzacije, blokade, likvidnost, koordinacija, investicije

JEL: D22, G20, G30

The Trade Credit Clearinghouse: Liquidity and Coordination*

Milan Božić[†] Jurica Zrnc[‡]

Abstract

We study the economic effects of a clearinghouse that allows a large network of firms to reduce their trade credit exposures and thus potentially lower the risk stemming from interfirm financial linkages. The clearinghouse reduced the gross debt by a sizable 8% of GDP in Republika Srpska, one of the two entities that form Bosnia and Herzegovina. Exploiting unique data on the debt network and the clearinghouse algorithm, we identify plausibly exogenous variation in clearing for a particular firm that derives from changes in debts far away in the network. We find that clearing reduces the probability of default, especially for financially distressed and cash poor firms. Consistent with reductions in firm risk, clearing increases sales, while it increases investment only for cash rich firms. We argue that the clearinghouse is an exchange technology that alleviates the lack of appropriate financial contracts. Furthermore, we provide evidence that the clearinghouse solves a coordination failure arising in a complex network of debts.

Keywords: trade credit, clearinghouse, default, real effects, liquidity, coordination
JEL codes: D22, G20, G30

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Contents

1 Introduction

Trade credit is the biggest form of short term financing for firms. It is also a major source of risk that often materializes as late payment or outright default of trading partners. In this paper, we study the economic effects of a clearinghouse that allows a large network of firms to reduce their trade credit exposures and thus potentially lower the risk stemming from interfirm financial linkages. Does the clearinghouse lead to lower firm risk? Does it have real effects? To answer these questions we use the unique data on the network of debts and clearing coupled with the universe of firm financial statements.

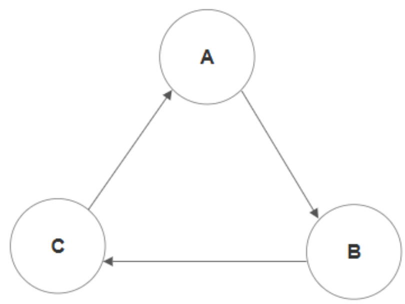
Trade credit and late payment are an important policy issue[1]. For example, the European Commission states that "Each year across Europe thousands of small and medium-sized enterprises go bankrupt waiting for their invoices to be paid"[2]. These negative effects can be compounded by input-output linkages and result in insolvencies and bankruptcies across the economy (Acemoglu et al., 2012; Jacobson and von Schedvin, 2015; Baqaee, 2018; Costello, 2020). Bankruptcies, especially liquidations, can have long-lasting negative effects on utilization of capital and the local economy (Bernstein et al., 2019b,c). All these issues have become especially salient during the COVID-19 pandemic, when policymakers enacted a plethora of policies to prevent a wave of firm bankruptcies (see e.g. Demmou et al., 2020; Didier et al., 2020). We study an alternative policy designed to tackle the issue of corporate liquidity - the trade credit clearinghouse.

We analyze the establishment of the trade credit clearinghouse in Republika Srpska, one of the two entities that constitute Bosnia and Herzegovina. In 2014, the National Assembly of Republika Srpska passed the Multilateral Compensation Law, which requires all firms and government units to report their delinquent payables to the central clearinghouse. Firms and government units are also allowed to report non delinquent payables. Based on the network structure of these payables, the clearinghouse performs gross multilateral netting. Specifically, it calculates clearing cycles of the form $A \to B \to C \to A$ such that each firm exactly offsets its payables with receivables (Figure 1). In this way the clearinghouse reduced the gross debt amount in the economy by a sizable 8% of GDP from 2015 to 2019.

[1]For the case of the European Union see European Parliament (2000, 2011) and for US see e.g. Barrot and Nanda (2016)

[2]Link: https://ec.europa.eu/growth/smes/sme-strategy/late-payment_en. Accessed on 30th of May 2022.

Figure 1: A simple cycle network



This figure represents a simple cycle network. A → B means "firm A is indebted to firm B".

In this paper, we study the real effects of clearing on individual firms. For this purpose, we combine the unique data on the network of late debts with the universe of corporate financial statements in Republika Srpska. Our novel identification strategy is based on our knowledge of the treatment assignment process, because we can run the algorithm that the clearinghouse uses to allocate clearing. We exploit the fact that the network of debts is complex and identify variation in clearing for a particular firm that comes from changes in debts far away in the network. Using the algorithm, we identify the currency value of clearing which comes from changes in the debts that are at least three edges away from firm i. We argue and provide various tests that this variation in clearing is plausibly exogenous to a particular firm. Using this identification strategy, we find that clearing reduces payment default rates, especially for financially distressed and cash poor firms. Consistent with reductions in firm risk, clearing increases sales, while it increases investment only for cash rich firms. We argue that the clearinghouse is an exchange mechanism that alleviates the lack of a market for receivables and low access to finance. Furthermore, we find evidence that the clearinghouse solves a coordination failure that arises on a complex network of debts.

We make several contributions to the literature: (1) we study a policy experiment designed to tackle late debt, which might be applied in many countries, (2) we document the pervasiveness of late debt (3) we show that clearing reduces default risk and has real effects and (4) we find evidence that the clearinghouse solves a coordination failure on a large network of debts.

Stylized facts. We use a unique dataset of around 1.5 million late debts that includes firms and government units in the period from October 2015 to December 2019. We merge this dataset with the universe of financial statements in Republika Srpska. Using this data, we find that late debt is ubiquitous. 25% of firms do not pay on time, and late payment is 16% of GDP at the beginning of the sample. The median lateness for active firms is 29 days, which is comparable to firms in countries such as Greece, Italy and Spain, where mean delays were 41, 31 and 25 days respectively, according to surveys (European Commision, 2015). There is substantial variation in late payment, many debts are very late. Firms in the 90th percentile of late payment are on average more than 165 days late. Given that usual trade credit maturity is 30 to 60 days, late payment can thus substantially increase liquidity provision by suppliers.

As expected, late payers seem to be more financially distressed as indicated by lower cash holdings, higher leverage and lower profits than firms which pay on time. While financial distress seems to be an important characteristic of late payers, it is not the only one. Firms pay late, but at the same time have positive profits of around 8% of assets. This fact suggests that firms exploit the weak enforcement of laws regarding late payment for financial gains (European Parliament, 2011).

Theoretical framework. Although the main contribution of the paper is empirical, we also develop a model to understand why clearing might have real effects. We rely on three key features in our model: zero recovery in case of default, costless late payment and limited access to finance. We argue that these assumptions reflect important features of reality and are especially pronounced in Bosnia and Herzegovina due to somewhat underdeveloped financial and legal institutions (Ristić and Rička, 2015; European Commission, 2019).

The model shows that the clearinghouse can be used as an exchange mechanism which replaces the non-existent market for receivables and alleviates the lack of access to finance. By using the clearinghouse, liquidity constrained firms can pay their payables with illiquid receivables. Firms can avoid default due to liquidity, although they have no cash.

In the model, late payment in a circle can be a result of a coordination failure which the clearinghouse solves. Due to relatively costless late payment firms might have an incentive to pay out profits and pay late at the same time, a phenomenon we document in the data. However, late payment in a cycle might leave all firms in the cycle liquidity constrained and thus prone to default. The clearinghouse is a technology that solves the coordination problem by allowing firms to coordinate on the outcome where everybody repays. The result of clearing is lower probability of default. A reduction in firm risk through clearing has many other real implications. Default is costly and might severely hinder business operations. Decreasing firm default risk increases the net present value of investment projects, so the firm might undertake projects which were previously unprofitable. Banks might be more willing to lend to firms with lower default risk, which might further spur investment.

Empirical strategy. The empirical analysis is complicated by the fact that clearing is not randomly assigned. The clearing allocation is decided by an algorithm that uses the network of debts as an input. Firm network characteristics are, in turn, systematically related to firm characteristics and are not random. Because the goal of the algorithm is to maximize the currency value of cleared debts, it favors firms which are more central to the network. Many cycles necessarily pass through central firms, and these firms also tend to be larger. They also have various distinguishing observable and potentially unobservable characteristics. To arrive at plausibly exogenous variation in clearing, we propose a novel identification strategy.

We exploit the fact that the network of late debts is complex. The network is such that in each round of clearing there is one large strongly connected component of almost one thousand participants. In the strongly connected component there is a path from every node to any other node in the component. This implies that clearing cycles can be very large and that the clearing of a particular firm can be affected by network characteristics of firms far away in the network. We replicate the clearinghouse algorithm and use the network of debts to identify changes in clearing that are caused by changes in the network far away from the firm of interest. Simply put, our identification strategy is to compare firms that did get cleared and did not get cleared because of changes far away in the network. The identification assumption is that the characteristics of firm i are not related to changes in debts and credits of participants who are at least three nodes away in the network from firm i. This assumption about exogeneity of non-neighboring nodes is similar to Bramoullé et al. (2009) and De Giorgi et al. (2010) which study peer effects in social networks. Although the identification assumption is untestable, it has testable implications which allow us to evaluate its plausibility. Specifically, we test whether the variation in clearing coming from the outer network is related to pre-treatment firm characteristics. Our tests show that the identifying variation is not related to observable firm characteristics, supporting our claim that it is exogenous to the firm.

Results. We find that clearing reduces the probability of payment defaults by $\approx 6\%$ on average. This effect is stronger for firms that are financially distressed and cash poor according to various measures. The results are consistent with our model in which clearing is an exchange mechanism which alleviates liquidity and financial constraints.

Clearing of a debt between two firms reduces the indebtedness between the two firms in the next two to three months as well. More importantly, we show that clearing also induces the firm to reduce debts towards non-cleared creditors. This suggests that clearing increases the financial strength of the firm and allows it to repay sooner to all creditors.

We also find that clearing strongly affects future firm sales. We argue and provide evidence that this reflects a reduction in default probabilities. Our measure of default is whether a firm has a blocked bank account. A creditor can block the bank account of a debtor if the debtor is late on her debts. All remaining and incoming funds are immediately transferred to the creditor. The with a debtor blocked bank account then cannot operate her bank account freely. This severely impacts business operations of the firm, thereby further reducing the firm's ability to repay. Hence, trading partners are usually reluctant to block bank accounts of other firms; it is mostly done by the state to enforce payment of taxes. Given the very inefficient court system in Bosnia and Herzegovina, most financially distressed firms do not go through formal bankruptcy procedures but end up with blocked bank accounts for a long time. We argue that clearing is especially valuable because it allows firms to avoid costs associated with blocked bank accounts. This is reminiscent of costly default present even in developed economies (see e.g. Bernstein et al., 2019c) and in our theoretical model. Blocked bank accounts are also public information, which implies that trading partners might be reluctant to trade with a firm that was blocked recently. Consistent with this, we find that clearing increases purchases of intermediates. Furthermore, we find that the effect of clearing is very large for firms that have blocked bank accounts. Clearing arguably has large effects for these firms because, on average, blocked firms clear a sizable 30% of their blocked debts. Clearing is also large relative to cash holdings for these firms. Half of firms that are both blocked and cleared had no any cash available, while for the other half clearing was 25% of their cash holdings.

Without relying on the financial sector, firms can avoid liquidity issues by saving cash, but then they might have insufficient funds for investment. We find that clearing increases investment, but only for cash rich firms, suggesting that firms reduce precautionary cash savings. Cash is especially important because most firms in our sample are small and do not have a lending relationship with a bank. In this setting, it might not be surprising that we found no effect of clearing on bank lending to the firm.

If clearing is valuable, why do not firms coordinate to offset debts without the clearinghouse? In reality, firms do communicate, and they might coordinate to offset debts without a central mechanism. Indeed, experimental results show that communication might foster cooperative outcomes in coordination games (Devetag and Ortmann, 2007). However, this communication is costly, especially if a firm has many debtors and creditors, and the cycles are large. We explore whether the effects of clearing are larger (smaller) for firms that are a part of larger (smaller) cycles, which are harder (easier) to coordinate in a decentralized fashion. We find that, for firms which form small cycles of three, the clearinghouse does not reduce the default rate. On the other hand, firms that have many trading partners and are a part of complicated networks default less after clearing. For these firms it could be very costly to gather information, communicate and coordinate on debt offsetting in the absence of the clearinghouse. We show that this result is robust even after controlling for various possible network spillovers. This evidence suggests that the clearinghouse is used as a technology that gathers information on the complex network of debts and allows participants to coordinate on repaying their debts. It also reveals that there might be coordination problems in large trade credit networks.

Discussion. The results in this paper apply only to a subset of firms which are affected by our identifying variation. We proceed to explore the possible aggregate implications of our estimates, unintended consequences of the policy and generalizability to other countries.

To illustrate the possible aggregate importance of the clearinghouse, we provide a back of the envelope calculation of the aggregate effects of clearing on default rates. The idea is to extrapolate the estimated effect of clearing to all cleared firms. We do this for financially distressed firms, since they are a group that benefits the most from clearing. Using this approach, we find that clearing reduces the aggregate default rate by 0.4 percentage points from an average of 7%. We leave for future work the estimation of network and general equilibrium effects of clearing.

A possible unintended consequence of the trade credit clearinghouse is that it incentivizes firms to increase late debts. In this paper, we study the effects of a plausibly exogenous and thus unexpected clearing shock. Firms might, however, change their behavior if they anticipate clearing, and therefore the consequences of anticipated clearing might be different than the effects of an unexpected clearing shock. In particular, the firm can increase its probability of clearing by increasing payables and receivables. Consider a firm which has a receivable that is not likely to get paid on time. Then the firm might wait and not pay its payables in order to enforce payment of its receivable through the clearinghouse. In that way the clearinghouse which mechanically reduces late debts, might actually increase late payment by changing the behavior of firms. Rostowski (1994) makes a similar argument when analyzing multilateral netting in the context of post-Soviet countries at the beginning of 1990s. Using our unique data, we show that firms did not start paying later after the establishment of the clearinghouse; if anything, lateness of debts decreased. We also study whether lateness of firm debts increases right before firms get cleared and show that there is no increase. Another scenario we explore is whether firms have increased accounts payable and receivable to increase the probability of clearing. We find no increase in accounts payable or receivable prior to clearing. All this evidence taken together suggests that clearing does not induce perverse incentives which increase late debts.

We also explore the external validity of our results by comparing the institutional and economic features of Bosnia and Herzegovina to other countries. Firms in our sample rely similarly on trade credit as other firms in the EU. This suggests that the possibility to clear trade credit is substantial in other economies as well. A case in point is Slovenia, an EU country, which is also implementing the trade credit clearinghouse. Our theory and results suggest that countries with a more developed financial system and lower bankruptcy costs might benefit less from the clearinghouse. Hence, we would expect that the benefits of clearing trade credit would be somewhat lower in high-income countries.

Contribution and related literature. First, we contribute to the literature by analyzing a policy experiment that might have sizable real effects and that could be implemented in many countries. To the best of our knowledge this kind of policy was analyzed only in Rostowski (1994), but in the context of post communist stabilization policies and using only few data points on aggregate clearing amounts. We improve on this analysis by using detailed network data on late debts, coupled with firm financial statements that allows us to study a rich set of mechanisms. We use the clearinghouse algorithm to develop a novel identification strategy and move beyond descriptive statistics to claim causality. Furthermore, we develop a simple theoretical model which offers new insights on the effects of the clearinghouse beyond the discussion in Rostowski (1994).

Second, we contribute to the literature that studies the transmission of shocks through trade credit networks (Boissay and Gropp, 2013; Jacobson and von Schedvin, 2015; Dewachter et al., 2018; Cortes et al., 2019; Reischer, 2019; Alfaro et al., 2020; Costello, 2020) by showing that a clearinghouse can reduce the risks associated with trade credit and thus have real effects.

We also contribute to the literature on the real effects of trade credit maturity (Murfin and Njoroge, 2015; Klapper et al., 2012; Barrot, 2016; Barrot and Nanda, 2016), by studying an alternative policy designed to alleviate liquidity issues arising from long payment periods. Liquidity of the corporate sector and payment terms were important issues not only in Bosnia, but also in the EU and the US during the Great Recession. In the EU, the European Parliament enacted the Late Payment Directive with the aim of curbing late payments (European Parliament, 2011). The Directive prescribed shorter payment periods and larger fines for late payment. A later evaluation of the Directive found, however, that it did not visibly change the behavior of firms (European Commision, 2015). In the US, the federal government started the Quick - Pay initiative that shortened the payment delay of the US government by 15 days. Barrot and Nanda (2016) find that this direct reduction in trade credit provided to the government had sizable real effects on firms.

Netting of gross exposures is not a novel institution in financial markets. For example, banks net out their intraday payments in order to reduce liquidity needs. After the Great Recession, the biggest change in the functioning of over the counter derivatives markets was the introduction of central clearing counterparties (CCPs) and compression trading, which reduced gross exposures by $1 quadrillion (Duffie, 2018, 2019). In addition to multilateral netting, CCPs offer insurance of net positions which the trade credit clearinghouse does not. The empirical literature on CCPs shows that they reduce liquidity and counterparty risk (Loon and Zhong, 2014; Bernstein et al., 2019a; Vuillemey, 2020). Vuillemey (2019) and Menkveld and Vuillemey (2020) argue that in the absence of close ties between market participants, a clearinghouse is unlikely to arise without government intervention. We contribute to this literature by showing empirical evidence that clearing is especially beneficial for firms in complicated networks where debt offsetting by decentralized action is very costly.

Finally, we contribute to a more broader empirical literature on reasons why trade credit arises (for a survey see Cuñat and Garcia-Appendini, 2012). For example, in Kim and Shin (2012), trade credit allows the sustaining of large production chains through payment delays. We provide evidence that payment delays, a form of trade credit, can occur as a result of a coordination failure on a complex network of debts and thus might not be efficient.

Outline. The remainder of the paper is organized as follows. In Section 2, we discuss the institutional details of the clearinghouse. Section 3 introduces the novel dataset that we use, and presents stylized facts. In Section 4, we discuss our theoretical framework, and in Section 5, we show our novel empirical strategy. In Section 6, we present the results and in Section 7, we discuss their application in different contexts. Section 8 concludes.

2 Institutional background

In Republika Srpska, one of the two entities that constitute Bosnia and Herzegovina, the National Assembly of Republika Srpska passed the Multilateral Compensation Law in 2014 as a response to severe liquidity issues in the economy. A similar law was also passed in an EU country - Slovenia in 2011. According to the Multilateral Compensation Law the Banja Luka Stock Exchange is the institution implementing debt clearing. By law, cycles of debt clearing need to be calculated such that total debt reduction in the network is maximized. Clearing was originally done every six months, from 2017 quarterly, and from 2019 every two months.

The clearing is implemented in the following manner. All firms and government units are required to report late debts within two days from the start of the process. Debt which is not late can also be reported for clearing. After the deadline for reporting debts has passed, the clearing allocation is calculated. At this point, firms are informed about how much and which debts and credits are cleared. Participants can withdraw selected debts. This means that firms voluntarily participate in the clearing, because they can always withdraw all of their debts. After these withdrawals, the clearing cycles are calculated again, but on the subset of debts that were not withdrawn and the clearing allocation is then final. This way the clearinghouse ensures that all firms participate voluntarily in clearing.

The clearinghouse uses the Simic and Milanovic (1992) algorithm to calculate clearing cycles. It states the problem of clearing as a minimum-cost flow problem. The clearinghouse solves the min-cost flow problem using the OR-tools Google library. Because the library is publicly available and we have all the data needed to calculate the clearing cycles, we can run the algorithm as well and use it in our identification strategy.

3 Data

We use a unique dataset of around 1.5 million late debts that includes firms and government units in the period from October 2015 to December 2019. The data originates from the Banja Luka Stock Exchange that performs the debt clearing. It contains information about debtor and creditor ID, the amount of debt, due date for payment, the amount of clearing, whether the firm opted out from clearing and amount of final clearing.

It also contains information on whether the firm is blocked. A creditor can, through a court procedure, block the bank account of a delinquent debtor. The firm is blocked if it has legally lost control of its bank account until it repays the late debt. Most of the blocked firms are blocked due to not paying income tax and social contributions. In Bosnia and Herzegovina firms pay the income tax on behalf of their workers to the state. Thus, a firm that is blocked is highly likely to be severely financially distressed. In our analysis, we will use blocked status as an indicator of default or severe financial distress. In Bosnia and Herzegovina, firms often do not undergo formal bankruptcy procedures but just stay dormant and do not repay their creditors. This is not surprising given a very inefficient and costly bankruptcy system (European Commission, 2019).

We couple the clearinghouse data with financial statements of the quasi-universe of firms in Republika Srpska. The provider of the data is the Agency for IT and Financial Services (APIF) from Banja Luka. There is a share of entries in the clearinghouse data that do not have their counterpart in the financial statements dataset, as described in Subsection C.1. APIF data contains all limited liability firms, but it excludes sole proprietors, government units, etc. In Subsection C.1, we show that this data contains the majority of employed in business entities.

Following Lopez-Garcia and Di Mauro (2015) we exclude all state owned enterprises and firms operating in sectors with major state influence such as agriculture, education, public utilities, etc. Throughout the text, we use the phrase “private market sector firms” to denote this sample of firms. It is also important to note that the timing of clearing rounds changed throughout the analysis. The first clearing happened at the end of 2015, then during 2016 it was organized every 6 months, in 2017 quarterly and from 2019 every two months. To have a more comparable frequency of data, in the main regression analysis we focus on clearing from 2017 to the end 2019, but we will also show descriptives and results using the whole sample. Given the novelty and extensive nature of the dataset, we will present the most relevant descriptives as five distinct stylized facts.

Stylized Fact 1: Late Debts are a Sizable Fraction of Economic Activity.

In any given clearing round, late debt is a sizable 9% of GDP on average (Table B.1). For private market sector firms, late debt is 7% of total firm payables. Furthermore, 20% of firms pay late, suggesting that delaying payment is ubiquitous. Late debt is a sizable fraction of economic activity, and tends to be very late. For active firms[3], the median lateness is 37 days. This is comparable to firms in countries such as Greece, Italy and Spain, where mean delays were 41, 31 and 25 days respectively, according to surveys (European Commision, 2015). Late payment distribution is very skewed, with the 90th percentile of lateness being 211 days. Given that usual trade credit maturity is 30 to 60 days, late payment can thus substantially increase the liquidity provision by suppliers. Late payment is also risky for the buyer, because a firm that is more than 60 days late is legally eligible for bankruptcy. These debts are 2% of firm payables in the aggregate.

[3]For analysis of lateness, we remove the blocked firms. They are mostly dormant firms that are not active and thus their lateness increases through time.

Table 1: Descriptive statistics - firm level

	All					Debtor		Cleared	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Mean	Std	p10	Median	p90	Mean	Median	Mean	Median
Employment	19	69	1	5	34	39.5	10.5	52.7	16
Assets	2701812	15081392	56664	473561	4951632	5805592	1323433	7562421	2147490
Profits/Assets	0.14	0.29	0.00	0.06	0.34	0.09	0.04	0.09	0.06
Receivables/Assets	0.30	0.23	0.04	0.26	0.63	0.30	0.26	0.29	0.26
Payables/Liabilities	0.46	0.29	0.07	0.45	0.89	0.47	0.45	0.47	0.45
Liabilities/Assets	0.63	0.56	0.11	0.55	1.02	0.67	0.61	0.59	0.56
Blocked	0.03	0.16	0.00	0.00	0.00	0.13	0.00	0.03	0.00
Cash/Short term debt	0.50	1.00	0.00	0.09	1.61	0.25	0.03	0.28	0.03
Clearing amount/Assets	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.00
Clearing amount/Cash	0.38	3.20	0.00	0.00	0.05	1.86	0.04	2.87	0.25
Late debt/Assets	0.01	0.07	0.00	0.00	0.02	0.06	0.02	0.05	0.02
Late credit/Assets	0.02	0.05	0.00	0.00	0.04	0.02	0.01	0.03	0.01
Number of obs			14,925			3,068		1,977	

The table reports descriptive statistics for "private market sector" firms. We include only those that reported financial statements the previous year, current year and forthcoming year, because we will be able to analyze these firms in financial statement regressions. The period is from 2016 to 2019. Debtor denotes firms that have debts in the clearinghouse. Profits are net income after taxes, Cash - cash holdings at the end of year. Sources are the Agency for Financial and IT services (APIF) and the Banja Luka Stock Exchange (BLSE). Blocked denotes firms that have blocked bank accounts due to delinquent payables. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level for the equality of means t-test, respectively.

Stylized Fact 2: Clearing is an Important Part of Economic Activity.

Firms and government units clear in an average clearing around 0.6% of yearly GDP, amounting to 1.6% of GDP cleared per year (Table B.1). For private market oriented firms, clearing is on average 2% relative to yearly cash holdings. There is also a substantial fraction of cleared debts that are more than 60 days late, but very late debts, e.g. more than 180 days late, are very rarely cleared. This reflects the fact that these firms are likely insolvent and do not have receivables with which to participate in clearing.

Stylized Fact 3: Late Payers are on Average More Financially Distressed, According to Multiple Indicators.

As expected, late payers seem to be more financially distressed. They have lower cash coverage of short term debt, higher leverage and lower profits than an average firm in our sample (Table 1). This is also partly a validation of the dataset because we would expect that firms which pay on time to be financially stronger than late payers, as is indeed the case.

Stylized Fact 4: Firms Pay Late and have Positive Profits at the Same Time.

Simultaneously while paying late, firms have positive profits of around 98% and cash holdings of 25% relative to short term debt (Table 1). This fact is not undermined by the timing of measurements as both the financial statements and late payment data are measured at the end of the year. To make sure that the timing of measurements is not driving the results in some way, we look at firms whose debts are late more than one year. These firms had positive profits during the year but decided not to repay their debts from the previous year. For firms which are more than one year late on their debts, profits are 4% of assets on average (Figure A.1). These findings suggest that enforcement of prompt payment is severely undermined in this economy and that financial distress, although important, is not the only reason why firms pay late. The European Parliament in its Late Payment Directive (European Parliament, 2011) states that late payment is financially attractive to debtors in most of the European Union because of low or zero interest rates charged on late payments and/or slow procedures for redress. Indeed, survey data also suggests that one of the most important reasons for late payment is the debtor's choice and not the inability to pay on time (Intrum Iustitia, 2018).

Stylized Fact 5: Cleared Firms are on Average Larger, More Profitable, Less Financially Distressed Than Other Late Payers.

Cleared firms are larger than the average late payer, since large firms are more central to the network and thus more likely to get cleared. They are also more profitable, less levered and only 3% of them are blocked compared to 13% of late payers. Cleared firms have also more late receivables, highlighting the nature of the clearing mechanism. Firms that do not have offsetting receivables cannot participate in the clearing cycles. Thus, heavily insolvent firms that have no receivables will not benefit from the clearinghouse.

4 Theoretical framework

We present here the theoretical framework that guides our analysis of clearing and its economic consequences. The model shows that the clearinghouse is used as an exchange mechanism that replaces the non-existent market for receivables and alleviates the lack of access to finance. Additionally, the model shows that late payment in a circle can be a result of a coordination failure which the clearinghouse solves.

First, we outline the main features of the environment that are important to understand why gross positions in accounts payable and receivable are a source of risk and spillovers. In less developed legal systems, bankruptcy is very slow and costly, making it difficult for creditors to recover their funds. Even in well functioning legal systems, trade credit is junior, and thus creditors are very unlikely to recover their claims (Cuñat and Garcia-Appendini, 2012; Jacobson and von Schedvin, 2015). Firms that have limited or costly access to finance will be especially vulnerable to settlement risk (Murfin and Njoroge, 2015), as they will not be able to draw on liquidity from financial intermediaries. Given these features, trade credit is quite expensive (Cuñat and Garcia-Appendini, 2012). However, firms have an interest in their trading partner's survival because of long-term relationships they build (Cunat, 2007; Brugués, 2020). Hence, late payment is relatively cheap and common, e.g. in many economies there are usually no interest rates charged on late payments (Giannetti et al., 2020) and procedures for redress are slow (European Parliament, 2011). Even in developed financial markets, small and medium sized enterprises have limited access to finance (Whited and Wu, 2006; Hadlock and Pierce, 2010; Buehlmaier and Whited, 2018). In the market for receivables, there is likely to be asymmetric information which can lead to market collapse.

Firms have private information about their trade partners, while the potential buyers of receivables - banks, have limited information (Smith, 1987; Mian and Smith Jr, 1992; Biais and Gollier, 1997; Burkart and Ellingsen, 2004), especially if the firms are SMEs. Bosnia and Herzegovina is a country where these features are especially pronounced, because of a lower level of financial and legal development (Ristić and Rička, 2015; European Commission, 2019).

In Subsection C.2 we build a simple model with three periods and three symmetric firms. The model contains the above features: financing constraints and costly default which leads to zero recovery in cases of default. In the model, the network of debts is formed exogenously[4] in period 0. Firms maximize consumption in period 1 and 2. They simultaneously decide in period 1 whether to pay their debts on time or delay. Motivated by the fact that firms have positive cash holdings and profits, while at the same time paying late, we allow firms to pay late and consume at the same time. In different extensions of the model, we also allow for a cash and investment decision. The source of uncertainty is an aggregate productivity shock in period 2. After observing the shock, firms make a default decision. Here we assume that the firm cannot indefinitely delay, and that it needs to repay its debts after the realization of the productivity shock or it needs to default. This might be motivated by the fact that creditors will not tolerate late payment forever. Or at an extreme, the government is likely in reality to force the firm into bankruptcy for not paying taxes after some time.

In the model, late payment serves as an alternative form of financing. For liquidity constrained firms, late payment enables the firm to wait for a future productivity realization and potentially to repay their debt in the next period. In this way late payment serves as a form of bridge financing.

There is also a different motive behind late payment in the model. Even firms which have sufficient funds to repay might choose to delay. The firm benefits by paying late because this dilutes the value of its debt. Paying late reduces the expected value of the outstanding debt. After paying late, the firm defaults in period 2 if it suffers a low productivity shock and it did not save cash from the previous period. On the other hand, the cost of paying late is that the firm loses its production value in the case of default. Given these incentives, delaying will be the dominant strategy if there is a low enough possible productivity realization and

[4]Abstracting from network formation is standard in a class of models from the network literature. For details see Jackson (2010).

the outstanding debt is big.

There are no strategic considerations for liquidity constrained firms in period 1. As they lack sufficient funds to repay outstanding debts, firms delay payment until period 2. In period 2, all firms default in the low (but positive) productivity state, although they have larger assets than liabilities. They are forced to default because their receivables are illiquid, in other words they did not receive payment from their debtors and there is no market for reselling payables.

For liquidity unconstrained firms, there are two pure strategy Nash equilibria, both characterized by late payment under the considered parameter space. In one equilibrium, all firms pay late and save no cash, and thus expose themselves to default risk. This equilibrium mirrors the one for liquidity constrained firms, because they do not have enough cash to save themselves from default. The only difference is that in this equilibrium, firms expose themselves to liquidity risk by choice. This equilibrium is a result of a coordination failure because all firms would prefer an equilibrium where everybody pays on time, but delaying is a dominant strategy. Paying late increases liquidity for debtors at the expense of creditors, but since all firms are debtors and creditors at the same time, there is no gain in liquidity by paying late in a cycle. In other words, the firm dilutes the value of its liabilities but given that all firms are symmetric, its assets shrink by the same amount because its debtor is also paying late. This results in the reduction of expected receivables by the same amount as payables. The firm is, however, worse off overall than in the equilibrium where everybody pays on time, because the default probability increases, so the expected profit is lower than in the outcome where everybody pays.

In the other pure strategy equilibrium, firms pay late and simultaneously save cash, which allows them to avoid default. This equilibrium replicates the outcome where everybody pays on time. It Pareto dominates the first equilibrium where firms intentionally expose themselves to default by reducing their cash holdings.

Hypothesis 1: *Clearing reduces default risk, especially for financially distressed firms.*

In the model, we introduce clearing at the end of period 1. This corresponds to the setting in which firms decide on late payment and then clearing is exogenously introduced. Clearing enforces the first best outcome in which everybody pays on time and thus reduces default rates. Clearing is a technology that allows firms to pay their payables with illiquid receivables.

By doing so, it alleviates the problem of the "missing" market for receivables because it allows firms to exchange payables with receivables.

The model predicts that firms which are close to bankruptcy due to liquidity will reduce their default rates through clearing. Thus, in the empirical part we will consider various measures of financial distress and check whether they are consistent with a model where liquidity risk matters for the effect of clearing on default. Simple extensions of the basic model in Subsection C.2 give rise to other hypotheses that we proceed to discuss.

Hypothesis 2: *Clearing has real effects, it increases investment, sales and bank lending.*

If clearing reduces default risk then this has other financial and real implications. Reduced default risk increases the net present value of investment projects and might spur investment. Banks are more likely to lend to a firm that has lower default risk. Indeed, banks collect data on firm payment defaults and are less likely to give loans to firms that had a payment default in the past. The central bank publishes the data on blocked bank accounts and firms consider this information when making a decision to buy or sell to a particular firm. For example, public procurement tenders often require proof that the firm did not have a blocked bank account recently. Thus, clearing might spur demand for products of the firm, by avoiding payment defaults. Furthermore, payment defaults result in blocked bank accounts which make it hard to direct cash towards maintaining production levels, such as buying intermediates. Hence, clearing might also prevent disruptions in production that come with payment defaults. These disruptions should show up in sales data, which we can observe in financial statements.

Hypothesis 3: *Clearing alleviates a coordination failure, due to costly coordination in a large network.*

In the model, late payment is a coordination failure. Why is the clearinghouse needed to coordinate the debt offsetting between firms? Experimental results show that communication can foster cooperative outcomes in coordination games (Devetag and Ortmann, 2007). Arguably, firms could communicate and agree to clear debts in a decentralized manner. However, this communication is costly, especially if a firm has many debtors and creditors, and the cycles are large. The complexity of the debt network might make the communication and information gathering in a decentralized fashion prohibitively expensive. If this is the case, the clearinghouse can be viewed as a central mechanism that collects information and allows firms to coordinate.

5 Empirical strategy

The main equation of interest can be specified in the following way:

$$Y_{it+1} = \alpha + \beta \text{Cleared}_{it} + \Gamma' X_{it} + \delta_s + \tau_t + \epsilon_{it} \tag{1}$$

where Y_{it+1} is the outcome of interest such as default, Cleared_{it} is an indicator of clearing, X_{it} is a vector of observable firm characteristics, δ_s is a 2-digit NACE sector fixed effect, and τ_t are the time fixed effects. β shows the average effect of clearing on cleared firms. If there are no real effects of clearing, this parameter will be statistically indistinguishable from zero. Instead of an indicator for clearing, we also use the log of clearing value. In the vector X_{it}, we include information about the firm such as measures of firm size, profitability, cash holdings, leverage, bank loans, default status, accounts payable, accounts receivable, late payables, late receivables and exposure to the public sector. Furthermore, we control for possible network spillovers with measures of debtor and creditor clearing, size, leverage, cash holdings and profitability. For an exhaustive list see Subsection C.3.

Identifying the effect of clearing using equation (1) is challenging, because clearing is not randomly assigned. We have shown that cleared and not cleared firms differ across many dimensions such as size and financial distress. All these stem from the nature of the clearinghouse and the algorithm that calculates clearing cycles. To participate in clearing cycles, a firm needs to have offsetting receivables. This means that heavily insolvent firms with no receivables cannot benefit from the clearinghouse. Furthermore, firms that have many links to other participants and that are more central to the network are more likely to get cleared. These are usually larger firms. The pool of cleared firms is likely to be better performing based on many measures of unobservables as well, such as manager quality, productivity, etc.

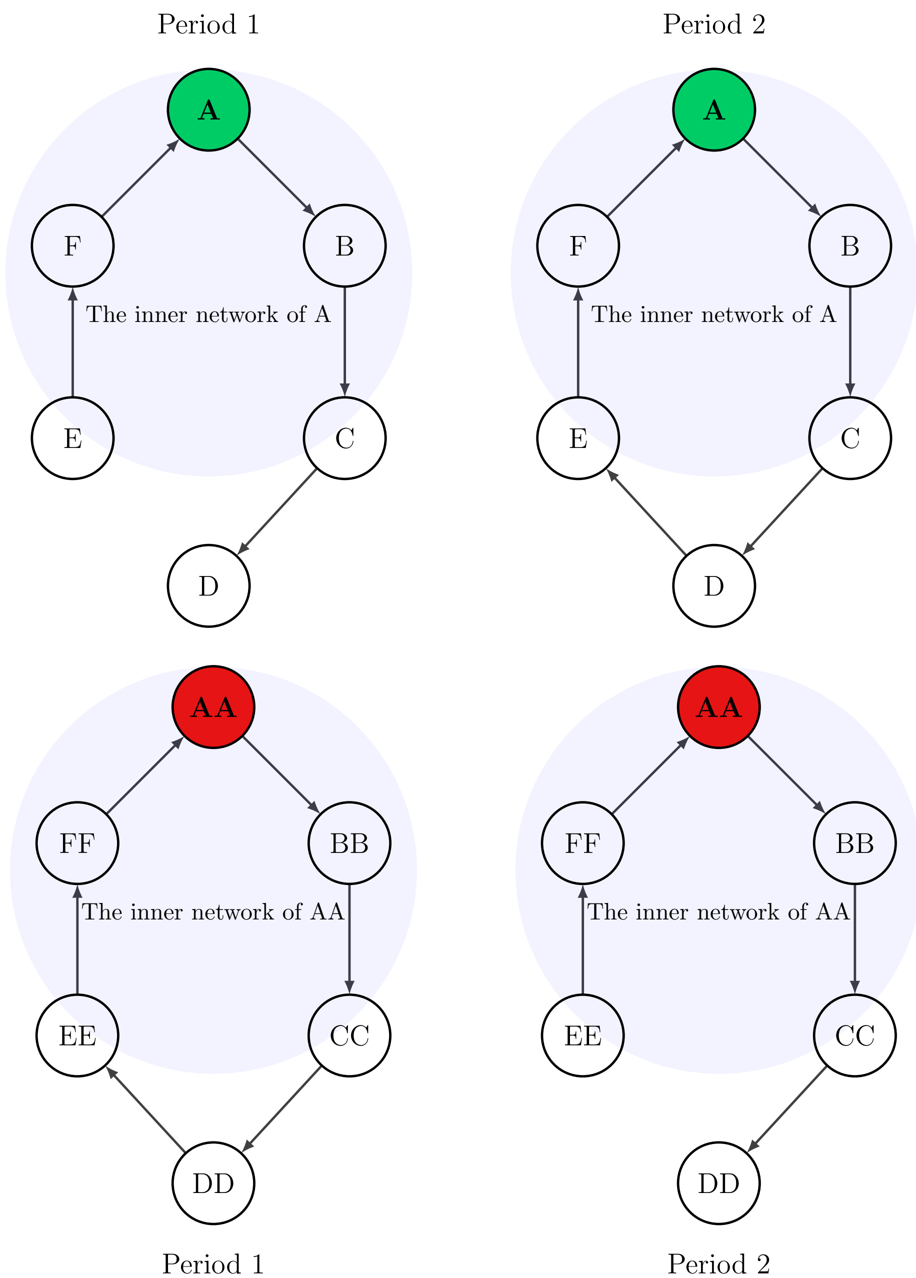
To overcome this problem, we identify variation in clearing for each firm that comes from changes in debts of other participants far away in the network. This variation is plausibly exogenous to the firm since it comes from unrelated participants in the network. The identification strategy exploits the complexity of the debt network, which results in large clearing cycles. Usually, the network forms one large connected component of approximately one thousand nodes and many disconnected nodes that cannot be cleared. In the connected component, there is a path from any node in the component to any other node in the component. We find that the median cycle length is 10 participants, using a procedure that approximates the optimal clearing allocation[5].

Figure 2 shows a simple example of our identification strategy. We wish to identify cases where clearing of a particular firm is affected by changes in connections between nodes far away in the network. In this example, firm AA gets cleared in period 1, but firm A does not get cleared. In Period 2 the outer network changes. In particular, firm DD is no longer indebted to firm EE. This action causes firm AA to not get cleared. On the other hand, firm D has a new debt towards E, a debt that it did not have before, and this causes firm A to get cleared. The identification assumption is that this action of firm D is not related to firm A's potential outcomes. In other words, the assumption is that the change in debt of firm D affects firm A's outcomes only through clearing and not in any other way. The same assumption is needed for firms DD and AA, e.g. that the change in debt of firm DD is not related to firm AA's potential outcomes. The treatment group in this natural experiment are firms that get cleared because of changes in the "outer" network (firm A), while the control group are firms who do not get cleared because of changes in the "outer" network (firm AA). In Subsection C.4 we describe the identification strategy in terms of potential outcomes.

In order to calculate this variation, we use the clearinghouse algorithm. For a particular firm i, we take its "inner" network from period t and manually change the "outer" network to the one from period $t-1$. We apply the clearing algorithm on this alternative network. The clearing amount for firm i in this alternative network is the clearing that would have occurred if the "outer" network did not change. The difference between actual clearing and

[5] The Simic and Milanovic (1992) algorithm finds the maximal clearing in a debt network but does not allow us to identify what are the elementary cycles and their length. To provide an approximation of the length of actual clearing cycles, we found all elementary non-weighted cycles using the Johnson (1975) algorithm in the clearing allocation. To get the maximum possible clearing amount in each cycle, we took the minimum debt value in each cycle and removed the cycle from the network. We applied this algorithm until there were no more cycles left in the residual network. This method, however, never achieves maximal clearing as in Simic and Milanovic (1992) algorithm. This happens because many cycles are mutually exclusive, such that clearing one cycle removes the possibility of clearing another. Since we iteratively and not optimally remove the cycles, there are always leftover cycles which never get to be cleared but should get cleared if we want maximal debt clearing.

Figure 2: Illustration of distant changes in the network and clearing



This figure is an illustration of our identification strategy. The left and right hand of the figure represent the network in Period 1 and Period 2 respectively. The shaded blue area represents the inner network according to our definition. In period 1 Firm A does not get cleared, while firm AA does get cleared. In Period 2 firm A gets cleared because firm D has a new debt to firm E. On the other hand, firm AA does not get cleared in Period 2 because firm DD is no longer indebted to firm EE, while in Period 1 it did get cleared. Our identification strategy compares firm A to firm AA.

this alternative clearing scenario is only due to the fact that we manipulated the “outer” network. Below, we describe the procedure in more detail, while in Subsection C.4 and Subsection C.5, we describe it formally.

1. Denote by l_i the set of firm i's debtors and creditors. We define the ”inner” network of firm i as all incoming and outgoing links of i and l_i. In Figure 2 these would encapsulate all debts except those pointing towards firm DD and from firm DD.

2. Define the “outer” network as all other links that are not in the inner network. We are interested in the effects of changes in the outer network on firm i clearing. These changes are considered exogenous to firm i according to our identification assumption.

3. Use the clearinghouse algorithm to calculate the alternative clearing that would occur if the outer network stayed constant as in the last period. In other words, calculate the clearing allocation with the inner network from period t and the outer network from period $t-1$. In this alternative clearing allocation, some firms might get cleared more or less relative to actual clearing.

We propose two ways of identifying the variation due to outer network changes:

1. **Switcher firms:** Identify firms that switch their clearing status between the alternative and actual clearing. These are the firms that got cleared or not cleared because of changes in the outer network. Compare firms that got cleared in reality but would not get cleared if the outer network stayed the same (firm AA) to firms that did not get cleared in reality but would get cleared if the outer network stayed the same (firm A). For both groups of firms, the clearing status is exogenous given our identification assumption.

2. **Continuous version:** Calculate the log difference between actual clearing C_{it} and counterfactual clearing C_{it}^{A}. This difference stems from changes in the outer network, as we kept the inner network constant. We call this difference - clearing due to changes in the outer network $\ln(1+\mathrm{C}_{it}^{ON}) = \ln(1+\mathrm{C}_{it}) - \ln(1+\mathrm{C}_{it}^{A})$. We add a one to the clearing amount because there are many firms with 0 clearing. To remove excess notation in the rest of the paper, we add one to all clearing amounts such that they start from one and not zero ($\mathrm{C} \in [1, +\infty), \mathrm{C}^{ON} \in [1, +\infty), \mathrm{C}_{it}^{A} \in [1, +\infty)$).

To estimate the effect of clearing due to changes in the outer network, we propose two estimation approaches: ordinary least squares and instrumental variables. In both estimation approaches, the main identification assumption is that the actions of clearinghouse participants which are more than two edges away from firm i are not related to firm i outcomes, except via clearing. While this assumption is fundamentally untestable, it has testable implications. Specifically, we can check whether firms who change clearing due to the outer network are systematically different prior to treatment. In Subsection 5.5, we present the results of these tests and discuss their plausibility.

5.1 Regression - switchers

In the regression approach, we compare firms that got cleared and did not get cleared because of changes in the outer network (firm A and AA in our example from Figure 2). We restrict the sample only to firms that reported debts to the clearinghouse, as firms that did not report cannot get cleared. Given our identification assumption, we can estimate the causal effect of clearing with the following regression:

$$Y_{it+1} = \alpha + \beta \text{Cleared}_{it} \times \text{Switcher}_{it} + \text{Switcher}_{it} + \Gamma' X_{it} + \delta_s + \tau_t + \epsilon_{it}, \tag{2}$$

where Switcher_{it} is an indicator for firms that switch clearing status because of changes in the outer network. We use this indicator to make sure that the comparison is within the group of firms that changed their clearing status. Thus, our control group are firms who did not get cleared due to changes in the outer network (firm AA in Figure 2). Another option would be to restrict the analysis only to switcher firms, but this would severely limit the sample size. There is only a small number of switcher firms ≈ 30 per period. This is also the reason why we use the continuous measures in the main analysis. Furthermore, clearing is done in two stages, where in the second round there is a participation choice by the firm. This choice might be endogenous to firm characteristics, so we restrict our analysis to firms that accepted clearing. In the continuous approach, we can also include firms that did not accept clearing.

5.2 Instrumental variables - continuous treatment version

As there are few firms that switch clearing status, we develop an empirical strategy that uses continuous variation in the clearing amount. We use the log clearing due to changes in the outer network $\mathrm{lnC}_{it}^{ON} = \mathrm{lnC}_{it} - \mathrm{lnC}_{it}^{A}$ as an instrument for actual clearing. The lnC_{it}^{ON} does not necessarily correspond to actual clearing because there is an inner network component of clearing as well, which might further increase or decrease the clearing amount (for a more detailed discussion see Subsection C.5). Another reason for the discrepancy between actual clearing and our instrument is the fact that clearing is done in two rounds as explained in Section 2[6]. On average these choices are small, around 2% of total clearing. To avoid contamination of our instrument by firm choices, our identifying variation comes from the first round.

We estimate the first stage:

$$\mathrm{Cleared}_{it} = \alpha_1 + \beta_1 \mathrm{lnC}_{it}^{ON} + X_{it}'\Gamma_1 + \delta_s + \tau_t + \epsilon_{1it}, \tag{3}$$

where β_1 is the effect of 1% change in clearing due to the outer network on the probability of clearing. We also report results for a continuous measure of clearing and a specification in first differences.

The IV research design needs additional assumptions to be valid, which we discuss in Subsection 5.5. The second stage is:

$$Y_{it+1} = \alpha_2 + \beta_2 \widehat{\mathrm{Cleared}}_{it} + X_{it}'\Gamma_2 + \delta_s + \tau_t + \epsilon_{2it}, \tag{4}$$

where $\widehat{c}_{it}$ are fitted values from the first stage. The coefficient β_2 is the local average treatment effect of clearing on our outcome of interest, e.g. default probability.

5.3 Debt level data

We can also use more detailed debt level data to shed light on how firm indebtedness changes after clearing. In particular the first stage is:

[6] As described in Section 2, the clearing allocation is offered in the first round after which firms decide whether to withdraw some debts from clearing. When the withdrawal period ends, the algorithm is run again and the second round is final.

$$\text{Cleared}_{ijt} = \beta_2 \text{lnClearing}_{ijt}^{ON} + FE + \gamma_2' X_{it} + \gamma_2' X_{jt} + \epsilon_{ijt}, \quad (5)$$

where j denotes the creditor, $textCleared_{ijt}$ is clearing of a particular debt, $\text{lnClearing}_{ijt}^{ON}$ is clearing due to the outer network for that particular debt, while FE denotes various fixed effects constellations. The second stage is then:

$$\Delta\text{lnDebt}_{ijt+1} = \beta_1 \widehat{lnClearing}_{ijt} + FE + \gamma_1' X_{it} + \gamma_1' X_{jt} + \epsilon_{ijt}. \quad (6)$$

Additionally, we use total debtor clearing $\text{lnClearing}_{it}^{ON}$ but restrict the sample only to non-cleared debts. In this way, we study the effects of firm level clearing on non-cleared debts.

5.4 Financial statements

To establish the effects of clearing on sales, investment and other real variables, we will turn to financial statements data outcomes. This data is available only on the yearly frequency. The first stage is:

$$\text{Cleared}_{iy} = \alpha_1 + \beta_1 \text{lnC}_{iy}^{ON} + X_{iy-1}' \Gamma_1 + \delta_s + \tau_t + \epsilon_{1iy}, \quad (7)$$

where y denotes the year. We adjust our variables taking into account that there are multiple clearing rounds during the year. For example, $\text{Cleared}_{iy} = 1$ if the firm got cleared in year y. lnC_{iy}^{ON} is the log of the sum of clearing due to the outer network in a given year y. To avoid bad control problems, all controls are lagged one year. The second stage estimates the effect of clearing on the outcome variable next period, e.g. investment: $Y_{iy+1} = \alpha_2 + \beta_2 \widehat{\text{Cleared}}_{iy} + X_{iy-1}' \Gamma_2 + \delta_s + \tau_y + \epsilon_{2iy}$.

5.5 Testing the validity of the research design

Clearing due to the outer network constitutes on average 13% of clearing per round (Table B.2). Approximately half of the variation in the currency value of our instrument is positive and the other half is negative. On average in any given clearing round ≈200 firms are affected negatively by changes in the outer network, and ≈200 firms are affected positively. This gives us a treatment and control group of approximately the same size. To increase the sample size, we also include firms that are not affected by the instrument in our estimation, but this does not affect our point estimates. We also graphically show the continuous variation in our instrument and its relation to changes in the log clearing amount (Figure A.2).

The first stage results in Table 2 show a positive and highly significant effect of our instrument on the probability of clearing. In particular, a one standard deviation increase in the instrument (0.7 log points) increases the probability of clearing by 4 percentage points (p.p.). The F-statistic in a model with a full set of control is very high - 830, well above usual thresholds, suggesting that the there is no issue of weak instruments (Stock and Yogo, 2002; Lee et al., 2021). In Table B.3, we also report the first stage with continuous clearing variable and change in the clearing as the treatment. The F-statistics are also very high in these cases.

In Table 2, we also indirectly test for *random assignment* of our instrument. It can be seen that as we add controls the β_1 coefficient barely changes, indicating that the instrument is not related to a plethora of observables. We also directly test this hypothesis for each of the 28 observable characteristics in Table B.4. The tables show that clearing due to changes in the outer network is not statistically related to pre-treatment default, firm size, profitability, share of receivables in total assets, share of payables in total assets, leverage, receivables $>$ 60 days late, payables $>$ 60 days late and exposure to the public sector. For the regression approach with switcher firms, we report the same regressions in Table B.5.

Another crucial element is the *exclusion restriction*, which states that the instrument affects our outcome variables only through clearing and not through other variables. Although the exclusion restriction is fundamentally untestable in this setting, we argue that it plausibly holds in our analysis. A concern here is that the variation in the outer network that causes clearing might also spill over from the outer network to the inner network and then to the firm itself. The instrument might be invalid if there are spillovers from participants three or more nodes apart. In our example in Figure 2, the fact that firm D is indebted to firm E might make the borrowing constraint of firm E tighter, spilling over to firm F and ultimately to firm A. Liquidity spillovers might increase the probability of default for the firm and could bias the coefficient of clearing upwards. Given that we estimate a negative effect of clearing on future probability of default, liquidity spillovers might bias the coeffi-

Table 2: First stage - Changes in the outer network

	(1) Cleared	(2) Cleared	(3) Cleared	(4) Cleared	(5) Cleared
$\ln C_{it}^{ON}$	0.0524***	0.0542***	0.0539***	0.0524***	0.0524***
	(0.00240)	(0.00189)	(0.00181)	(0.00182)	(0.00182)
Inner network	NO	YES	YES	YES	YES
Debt controls	NO	NO	YES	YES	YES
Debtor-creditor controls	NO	NO	NO	YES	YES
Firm controls	NO	NO	NO	NO	YES
Industry & time FE	NO	YES	YES	YES	YES
Observations	30,155	30,155	30,155	30,155	30,155
R-squared	0.584	0.841	0.842	0.848	0.848
F-stat for instrument	478	823	880	843	830

The table shows the first stage of our 2SLS estimation strategy. Standard errors in parentheses are clustered at sector level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

cient towards zero. However, if these spillovers are significant then they would also affect firm characteristics that are reported before the clearing. Given that the spillover shock might have occurred between two consecutive clearing rounds (time $t-1$ and t), there was time for it to affect the characteristics of firm at time t, which are measured one or two days before clearing takes place (in the case of clearinghouse variables such as late payables and receivables). For example, consider a firm i that gets cleared due to more late debts in the outer network. If these late debts spill over to firm i then we would see a correlation between our instrument and late debts of firm i. As shown in Table B.4, the instrument is not related to pre-treatment characteristics (at time t or $t-1$), suggesting that there are no spillovers from the outer network to firm outcomes. To further alleviate concerns about possible spillovers, we control for a plethora of debtor and creditor characteristics such as neighboring firms size, exposure to payables, receivables and liquidity measures (for a complete list, see Subsection C.3). Inclusion of these variables does not change our first and second stage estimates (Table 2 and Table 3), suggesting that third order spillovers are not biasing our results.

A potential concern is that changes in the outer network interact with the inner network to determine a clearing for each firm, which we discuss formally in Subsection C.5. The inner network is plausibly endogenous and so the exclusion restriction might be violated. The simplest example is when a firm has no receivables or payables, because then it cannot get cleared. A similar example is when its neighbors do not have receivables or payables. We control for twelve measures of inner network characteristics in our estimation and check that they do not affect our estimates (Table 2). We include measures of log amount of payables, receivables, number of debtors and creditors for the firm and its neighboring nodes. Firms with many links and a lot of debts and credits are more likely to get cleared, but this does not seem to interact with our identifying variation.

The *monotonicity* assumption might be invalid if our instrument has a negative effect on treatment for some firms. Consider a change in the outer network that causes an increase in clearing for a firm. The firm can choose to set that amount of clearing to zero, but it cannot set it to be less than zero. In this sense, it is impossible for a firm to be a defier. A possible scenario in which defiers could exist is if changes in the outer network cause the firm to set all of its clearing equal to zero, including the clearing caused by the inner network. In this way, the variation in clearing due to the outer network might cause a reduction in clearing amount. We could not think of a plausible scenario why this would happen. To test this scenario, we exclude all the firms that set all the clearing equal to zero and run the first stage regression again. In results available on request, we find that the estimate is still similar and statistically significant, suggesting that defiers are not an issue in our analysis.

Another important concern is whether *stable unit treatment value assumption* (SUTVA) holds. Our instrument is defined as a spillover of an action taken by a node far away in the network on firm i's clearing. However, this is not a problem because the instrument quantifies the clearing spillover for each firm i in the data vector. It is equal to zero for firms that caused the variation (firm D in our example in Figure 2) and takes non-zero values for firms that are affected by these actions. Thus, this network effect is quantified and does not bias our estimates. Another concern might be spillovers from outcomes and treatments of debtors and creditors on firm i, which we have discussed as a part of the exclusion restriction section above.

6 Results

6.1 Main results

We start by analyzing the effects of clearing on default. As explained before, we focus on blocked bank accounts as a measure of default, because bankruptcy is relatively rare and slow in Bosnia and Herzegovina. The naive estimate shows that cleared firms have on average 3.9 p.p. lower default probability in the next period (Table 3). This effect, however, shrinks to zero after controlling for an extensive set of controls that we described in the previous section (column (2)).

We showed that "switcher" cleared firms are similar to "switcher" non-cleared firms. After treatment, however, "switcher" cleared firms have lower default probabilities by ≈ 4 p.p. (Table 3). Since there is no statistically significant relationship between our identifying variation and a plethora of observables, it is not surprising that the estimate is fairly stable when we include the full set of controls in the regression. This suggests that our identifying variation is unrelated to these observables and to other possible unobservables which might be correlated to these controls (Altonji et al., 2008).

Our preferred instrumental variables specification, which uses continuous variation from changes in the outer network, shows an average reduction in the probability of default by ≈ 6 p.p. This is a large effect relative to the average default rate of 11% in the sample of firms which are both debtors and creditors in the clearinghouse and can thus potentially get cleared. The results from the "switcher" regression and IV approach are representative of slightly different subpopulations of firms. The regression with "switcher" firms uses discrete changes in clearing induced by the outer network. The IV approach exploits continuous variation in the probability of clearing. The estimates using the two approaches are nonetheless quite similar, within one standard error from each other.

These plausibly causal estimates are lower from the naive estimate with controls in column (2). We argue that this is because the subgroup of firms that is affected by our identifying variation is smaller, has lower liquidity and is more likely to benefit from the clearinghouse via reduction in default than other cleared firms. In Table B.6 we also show that the results are very similar when using the continuous clearing variable instead of a cleared dummy as the treatment.

Table 3: Results

	OLS		OLS - Switcher		IV	
	(1)	(2)	(3)	(4)	(5)	(6)
	Default_{t+1}	Default_{t+1}	Default_{t+1}	Default_{t+1}	Default_{t+1}	Default_{t+1}
Cleared_{it}	-0.0379***	-0.00988			-0.0574***	-0.0632***
	(0.00525)	(0.00872)			(0.0201)	(0.0178)
$\text{Cleared}_{it} \times \text{Switcher}_{it}$			-0.0312	-0.0449***		
			(0.0196)	(0.0167)		
Debt controls	NO	YES	NO	YES	NO	YES
Debtor-creditor controls	NO	YES	NO	YES	NO	YES
Firm controls	NO	YES	NO	YES	NO	YES
Industry & time FE	NO	YES	NO	YES	NO	YES
Observations	30,297	30,297	30,146	30,146	30,297	30,297
R-squared	0.790	0.810	0.790	0.812	-	-

The table shows the estimation results for our main variable of interest. It is estimated on the sample of debtors in the clearinghouse data. The OLS results in columns (3) and (4) have fewer observations because we need to exclude firms who were preliminary cleared but not in the final round. All regression include $Default_t$. Standard errors in parentheses are clustered at sector level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

After three periods which roughly correspond to 9 months, however, the average default risk is lower for treated firms by ≈ 2.5 p.p. (Table B.7) and is not statistically different from zero, suggesting that in the longer term the effects of clearing shrink over time. This might not be surprising because we are measuring payment defaults on short term debts. However, if a firm gets cleared every period, then the benefits of clearing might be long term. Indeed there is a lot of persistence in clearing (autocorrelation ≈ 0.7), because it depends on the network characteristics of the firm that are, in turn, related to persistent firm level features, such as size. Reassuringly, our identifying variation shows almost no persistence (autocorrelation ≈ -0.03), suggesting again that it is plausibly random.

Does clearing lead to a reduction in debts between firms? We find that clearing reduces outstanding debts between two firms and the probability that the debt exists in the next two to three months (Table 4). Column (1) shows that a 1 log point increase in clearing of a particular debt reduces that debt in the next period by 3.8 p.p. when controlling for creditor $\times$ time FE, debtor sector $\times$ year FE and debtor controls. We get a similar estimate when controlling for the heterogeneity of debtors with debtor $\times$ time FE, creditor sector $\times$ year

FE and creditor controls. Furthermore, we find that clearing reduces the extensive margin of indebtedness. Clearing reduces the probability of outstanding debt link existing between two firms by 6.3 p.p. (9.4 p.p.), when controlling for creditor (debtor) $\times$ time FE. These indicate that clearing reduces the debts between firms that had a cleared debt.

What happens to other payables of cleared firms? Clearing imposes seniority of payment to cleared creditors. This might induce the firm to increase its indebtedness to non-cleared creditors. Hence, clearing might just redistribute funds across creditors and not increase the financial strength of the firm. To investigate if this is the case, we study the effect of clearing on the average firm payables and on non-cleared payables. Column (5) in Table 4 shows that clearing of debtors reduces all of their debts on average by 3.7 p.p. The non-cleared debts decrease by a nearly identical amount - 3.8 p.p. (column (6)). These results are consistent with the interpretation that clearing increases the financial strength of debtors and allows them to decrease payables to all firms. Similarly to effects on default, the effects on debts quickly decline to zero after one period (Table B.8).

Table 4: Debt level data - effects of debtor clearing on debtor payables

					All	Not cleared	All	Not cleared
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta\text{lnDebt}_{ijt+1}$	Exists_{ijt+1}	$\Delta\text{lnDebt}_{ijt+1}$	Exists_{ijt+1}	$\Delta\text{lnDebt}_{ijt+1}$	$\Delta\text{lnDebt}_{ijt+1}$	Exists_{ijt+1}	Exists_{ijt+1}
lnClearing_{ijt}	-0.0382***		-0.0437***					
	(0.0076)		(0.0066)					
Cleared_{ijt}		-0.0634**		-0.0944***				
		(0.0254)		(0.0191)				
lnClearing_{it}					-0.0369***	-0.0377**		
					(0.0136)	(0.0158)		
Cleared_{it}							-0.0031	0.0513
							(0.0508)	(0.0553)
Creditor × Time FE	Yes	Yes			Yes	Yes	Yes	Yes
Debtor sector × Time FE	Yes	Yes			Yes	Yes	Yes	Yes
Debtor controls	Yes	Yes			Yes	Yes	Yes	Yes
Debtor × Time FE			Yes	Yes				
Creditor sector × Time FE			Yes	Yes				
Creditor controls			Yes	Yes				
Observations	58,043	90,692	61,831	101,000	57,803	49,770	90,692	75,848

Note: This table presents the effects of debtor clearing on cleared debts, all debts and on non-cleared debts specifically. All - regressions using the whole sample. Not cleared - sample restricted only to not cleared debts. Cleared_{ijt} is an indicator variable that equals 1 if the debt from i to j got cleared. Cleared_{it} is an indicator variable that equals 1 if the debtor gets cleared any of its debts, and otherwise it is zero. i denotes the debtor, j denotes the creditor. lnClearing_{it} is the log total clearing amount of the debtor. All variables in logs are one plus the actual value of the variable, to avoid issues with zeros. Exists_{ijt+1} indicates whether the debt is present in the clearinghouse data in the next period. Standard errors in parentheses are clustered at debtor and creditor level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Real effects. Clearing increases firm sales by ≈ 37 p.p. (Table 5) on average. Default and bankruptcy proceedings have large negative effects on firm operations, even if the firm goes through restructuring and does not liquidate. In our case, the measure of default is whether a firm has a blocked bank account. These have severe consequence for business operations, as the debtor cannot buy intermediate goods needed for production until it repays the creditor. Blocked bank accounts are monitored and publicly reported each month by the central bank. This is in turn an important criterion which firms and the government consider when doing business with other firms. Suppliers will be less willing to trade with firms that are signalled to be very irregular payers. Customers will be less willing to buy from firms that are at risk of not being able to deliver on the promised goods. Consistent with this, we see a large effect of clearing on intermediate goods purchases (column (2) Table 5). Clearing seems not to affect employment levels for firms, but one needs to take into account that these are not mandatory to report, so they might be of lower quality. Furthermore, a significant fraction of workers in Bosnia and Herzegovina is not formally registered in order to avoid paying taxes[7]. Arguably, it is harder to avoid paying taxes when buying buying intermediates and land or equipment. Clearing seems not to change firm investment. The majority of firms are SMEs and do not have any outstanding loans with the banks, so only firms with sufficient liquidity might invest, which we explore in the next section.

On the liabilities side of the balance sheet, not much changes Table B.9. We do not find evidence of changes in outstanding loans or accounts payable, suggesting that the firm does not use more external financing after clearing. Given that most firms in our sample are small and do not have a lending relationship with a bank, it might not be surprising that changes in default probabilities do not translate into more bank loans.

6.2 Financial distress and liquidity

One of the main predictions of our model is that financially distressed and liquidity constrained firms should especially benefit from clearing. To proxy for financial distress and liquidity issues we use multiple indicators. The most obvious indicator is whether a firm has a blocked bank account. These firms cannot operate their bank accounts until they repay their debts, often because they didn't pay taxes on wages, and are thus most likely in severe

[7]Link: https://www.ilo.org/wcmsp5/groups/public/—europe/—ro-geneva/—sro-budapest/documents/genericdocument/wcms_751314.pdf. Accessed on 30th of May 2022

Table 5: Clearing and other outcome variables

	(1)	(2)	(3)	(4)
	ΔlnPY$_{iy+1}$	ΔlnM$_{iy+1}$	ΔlnL$_{iy+1}$	ΔlnK$_{iy+1}$
Cleared$_{iy}$	0.3480***	0.5700**	-0.0049	0.0650
	(0.1235)	(0.2557)	(0.1059)	(0.0813)
Controls	Yes	Yes	Yes	Yes
Sector & Year FE	Yes	Yes	Yes	Yes
Observations	2,475	2,475	2,475	2,475

The table shows results of the second stage regression as described in Subsection 5.4. PY - sales, M - intermediate inputs, L - labor, K - plant, property and equipment. All changes are relative to the year prior to clearing: $\Delta X_{it+1} = X_{it+1} - X_{it-1}$. All regressions include the full set of controls described in Subsection C.3. The first stage coefficient of the instrument is 0.057, with a t-stat of 13.75 which amounts to an F-stat of 189. Standard errors in parentheses are clustered at sector level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

financial distress.

Second, we identify firms that are legally susceptible to starting a bankruptcy procedure. Under the Bankruptcy Law firms that are more than 60 days late on their payables can enter into the bankruptcy procedure. A similar indicator of financial distress is the 4th quartile of the debt lateness distribution[8]. These firms are later than the majority of other firms and thus are more likely to be financially distressed and liquidity constrained[9].

Next, we turn to financial statement indicators of short term liquidity. Since we are interested in defaults on short term debt due to insufficient liquidity, we focus on indicators such as cash over accounts payable. Given that these indicators do not perfectly measure liquidity constraints, we compare the 1st quartile of their respective distributions to the 4th quartile, removing the interquartile range from the distribution. In this way, we want

[8]When identifying quartiles of the distribution, we only consider firms that are debtors and creditors at the same time, because only for these firms does our instrument have any variation. These are firms that can possibly be cleared, while firms that are only debtors or creditors cannot be cleared. Hence, the number of observations decreases significantly in column (2), because we are examining only the 1st and 4th quartile of the distribution of firms that are both debtors and creditors.

[9]The 75th percentile of late debts changes from 80 days at the beginning of the sample to around 50 days at the end of the sample

to alleviate the inherent measurement error problems in identifying liquidity constrained firms[10].

Table 6: Financial distress and clearing

	(1)	(2)	(3)	(4)	(5)
			Default_{t+1}		
Cleared_{it}	0.00287	-0.00573	-0.00978	-0.0237	-0.0347
	(0.0226)	(0.0438)	(0.00981)	(0.0300)	(0.0304)
$\text{Cleared}_{it} \times \text{Late} > 60\ \text{days}_{it}$	-0.223***				
	(0.0505)				
$\text{Cleared}_{it} \times$ 4th quartile of lateness_{it}		-0.250***			
		(0.0719)			
$\text{Cleared}_{it} \times \text{Default}_{it}$			-0.447**		
			(0.179)		
$\text{Cleared}_{it} \times$ 1st quartile$\frac{Cash_{iy-1}}{AP_{iy-1}}$				-0.147**	
				(0.0574)	
$\text{Cleared}_{it} \times$ 1st quartile$\frac{Cash_{iy-1}}{STL_{iy-1}}$					-0.136**
					(0.0553)
Controls	YES	YES	YES	YES	YES
Observations	30,297	3,648	30,297	3,276	3,275
R-squared	0.798	0.801	0.796	0.626	0.627

The table shows results exploring the role of financial distress and liquidity for the effects of clearing. $\text{Late} > 60\ \text{days}_{it}$ is equal to one if the weighted lateness of firm debts in the clearinghouse is larger than 60 days. $\text{Cleared}_{it} \times$ 4th quartile of lateness_{it} is equal to one if the firm is in the 4th quartile of lateness for firms that are debtors and creditors in the same clearing round. 1st quartile$\frac{Cash_{iy-1}}{AP_{iy-1}}$ is equal to one if the firm is in the 1st quartile for the variable cash coverage over accounts payables. Analogously for 1st quartile $\frac{Cash_{iy-1}}{STL_{iy-1}}$. The sample size drops in columns (2), (4) and (6) because we drop the interquartile range of relevant variables and we focus only on firms that are both debtors and creditors. For firms that are only debtors there is no variation in our instrument. Furthermore, if the interaction variable is from firm financial statements, the sample size might drop even more, because some firms do not report financial statements, usually because of financial distress. Standard errors in parentheses are clustered at sector level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

The results in Table 6 show that late payers and financially distressed firms are less likely to default in the next period if they clear. The effect is very strong. Clearing decreases

[10] A further issue is that not all firms in the clearinghouse data report financial statements, although they are obliged to do so. Given that these are missing values we will not consider these firms when calculating the quartiles of the distribution, and thus the number of observations is lower in columns (4)-(5) than in column (2). Firms sometimes do not report by mistake or if they do not want to publicly disclose their financial situation in a particular year, although reporting is mandatory by law. Most of the financial statement data are made public through the APIF web page.

default risk by 45 p.p. for firms that are already in a payment default (column (3)), while for firms that could legally be in a bankruptcy procedure, the effect is 22 p.p. (column (1)). We find a similar effect for firms that are in the 4th quartile of lateness (column (2)). Consistent with our model, cash poor firms are those that benefit from the clearinghouse (columns (4)-(5)). For firms which have relatively low coverage of payables and short term debts with cash, clearing especially decreases the default probability. Given the missing market for receivables and lack of access to credit, these results suggest that the clearinghouse is an exchange technology that alleviates financial constraints.

In financial statements, we find that clearing disproportionately increases the sales of firms that are already in a payment default (Panel A of Table B.10). For debtors in payment default, the clearinghouse performs netting only of their blocked debts, while other debts are excluded from netting. This is done in order to preserve the seniority of creditors that blocked the firm bank account. As a consequence, clearing arguably helps the firm in default to reduce the exact debts that severely hinder its business operations. On average, cleared firms in payment default net 31% of their defaulted debts. Clearing is also large relative to the cash holdings of these firms. Half of the cleared firms in payment default did not report cash holdings in the previous year. For the median cleared blocked firm that did report, netting is 25% of it's previous end of year cash holdings. These facts suggest that clearing is very valuable for firms in payment default and is consistent with our previous result that it strongly reduces their probability of default (Table 6) and sales (Panel A of Table B.10).

On the other hand, cash rich firms seem to benefit from the clearinghouse in other ways. We find that cash rich firms increase investment after clearing (Panel B of Table B.10). In our sample, 2/3 of firms do not have any outstanding bank loans and the mean firm has 40 employees, which suggests that most of the firms do not have access to bank credit. Arguably, mostly cash rich firms are able to increase investment. But why did not cash rich firms invest before clearing? Our theoretical model shows that firms can reduce precautionary cash savings and increase investment because of clearing.

6.3 Coordination failure

We have shown that financially distressed and liquidity constrained firms are less likely to default after clearing. But why do firms not perform the debt offsetting in a decentralized manner? Why do they not coordinate without the centralized clearinghouse?

To provide evidence on the coordination hypothesis, we focus on firms that form cycles of three and on firms that are a part of very complicated networks. Clearing in a cycle of three nodes is relatively easy to coordinate even in the absence of the clearinghouse. Firms that form simple cycles might benefit less from clearing, because in the counterfactual without the clearinghouse, they would coordinate among themselves easily. Indeed, there are consulting firms in Bosnia and Herzegovina that offer mediation between firms that want to offset debts[11], but it seems to be a very small industry. This is not surprising given that a decentralized search for information about the network of debts might be very costly, inefficient and slow.

The cost of finding cycles through the decentralized gathering of information is larger if a firm has many links and/or is connected to a firm that has many links. For these firms the clearinghouse might be an especially useful way of finding cycles. We would expect that these firms will benefit more from the clearinghouse, in other words default less in the future.

We calculate whether the firm forms a simple cycle of three (a triangle), and interact this indicator variable with clearing. We also provide an alternative measure, the clustering coefficient, which is the share of triangles in all possible triangles for a given firm in the network. For ease of interpretation, we calculate the 4th quartile of the distribution with respect to this variable and compare it to the 1st quartile.

To measure the communication and information costs, we count all the links in the "inner" network of a particular firm. This means that we count all incoming and outgoing edges of a firm, as well as all the incoming and outgoing edges of neighboring nodes. To interpret the regression coefficient more easily, we compare firms in the 4th quartile of the distribution to the 1st quartile. A second measure we use comes from the HITS algorithm that was initially developed to rate web pages and provides a hub and authority score for each node (Kleinberg, 1999)[12]. In our context, a hub is a node that is indebted to many authorities, while an authority is a node that is a creditor to many hubs. We sum these two indices and identify firms in the 4th quartile according to this measure.

[11]Usually this is just one of the side services a legal consulting company offers, suggesting that it is not a large industry. See e.g. https://www.lrcbh.com/vok. Accessed on 30th of May 2022.

[12]In the context of the Internet, hubs are pages that link to many authoritative pages, but do not themselves contain any authoritative information. On the other hand, authorities are pages to which many authorities link to.

Table 7: Simple cycles, complicated networks and clearing

	(1)	(2)	(3)	(4)	(5)
			Default$_{t+1}$		
Cleared$_{it}$	-0.1404***	-0.1018**	-0.0956***	-0.0268	-0.0426**
	(0.0463)	(0.0439)	(0.0232)	(0.0335)	(0.0206)
Cleared$_{it}$ × Triangle$_{it}$	0.1172**				
	(0.0483)				
Cleared$_{it}$ × Q4Clustering$_{it}$		0.1316**			
		(0.0616)			
Cleared$_{it}$ × Clustering$_{it}$			0.2972**		
			(0.1459)		
Cleared$_{it}$ × Q4(Hubs + Authorities)$_{it}$				-0.2648***	
				(0.0902)	
Cleared$_{it}$ × Q4InnerNet$_{it}$					-0.2646
					(0.1772)
Controls	YES	YES	YES	YES	YES
Observations	30,297	3,605	30,297	3,647	3,646
R-squared	0.7977	0.7679	0.7969	0.7531	0.7821

The table shows results exploring the role of cycle size for the effect of clearing. Triangle$_{it}$ is equal to one if a firm is in a cycle of three. Clustering - clustering coefficient (share of triangles in the number of all possible triangles for a given firm), Q4 - 4th quartile, Hubs - firms that are indebted to many authorities, Authorities - firms that are creditors to many hubs, Inner net - count of all nodes in the inner network of firm i. The number of variables drops in column (2) and columns (4)-(5) because we drop firms that are not creditors and we drop the interquartile range. In these columns the number of observations varies slightly because there can be different amount observations at the 25th or 75th quintile. The sample size drops in columns (2), (5) and (6) because we drop the interquartile range of relevant variables and we focus only on firms that are both debtors and creditors. For firms that are only debtors there is no variation in our instrument. Furthermore, if the interaction variable is from firm financial statements, the sample size might drop even more, because some firms do not report financial statements, usually because of financial distress. Standard errors in parentheses are clustered at sector level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

We find that for firms which form simple "triangle" cycles clearing does not result in significantly lower default rates (Table 7). The estimates tell the same story whether we consider a continuous measure of the clustering coefficient or when we consider only the 4th quartile of the distribution.

Consistent with our hypothesis on coordination failure, we find that firms which potentially need to search through many links in their network to perform debt offsetting benefit more from the clearinghouse. Clearing reduces default rates by ≈ 30% for firms that are in the 4th quartile of the distribution for our variables that measure the complexity of the debt network.

A concern might be that measures of network complexity are measuring potential spillovers from neighboring firms and not information frictions. A firm that has many connections can be potentially very exposed to counterparty risk, and clearing might help to reduce it. If this is the case then we might not be measuring coordination frictions but reduction in spillovers. To alleviate this concern we also interact clearing with late receivables over assets and check if our estimates change significantly. We find that our estimates remain statistically significant and even increase in magnitude (Table B.11). We also use financial statements data that measures the extent to which a firm is exposed to receivables and obtain similar results.

7 Discussion

We isolated a plausibly exogenous shock of clearing, which allowed us to explore how clearing affects firm economic decisions. We also assess the possible aggregate implications, unintended consequences of clearing and the external validity of our study.

7.1 Aggregate effects

Although our empirical analysis is valid only for a subgroup of firms that are affected by our instrument, we provide a back of the envelope estimate of the effect on aggregate default rates. The goal is to explore whether our estimates imply large aggregate effects of clearing. Default rates have decreased after the establishment of the clearinghouse (Figure A.3), but it is unclear whether this due to the policy. Furthermore, it is not straightforward to apply our estimate of a 6 p.p. average reduction in default probability to the whole sample of cleared firms. There might be network and general equilibrium effects that our framework does not capture. Additionally, the effect of clearing is heterogeneous across many dimensions and might not be shared between cleared firms affected by our identifying variation and the whole sample of cleared firms. For illustrative purposes, we focus on one aspect of heterogeneity - financial distress. The main proxy for financial distress is whether the firm has debts that are more than 60 days late. We argue that these are cash poor firms, financially distressed and legally susceptible to bankruptcy. In this high-impact sample, we find that clearing decreases the probability of default by $\approx 20\%$. We extrapolate this effect to all cleared firms that are more than 60 days late and calculate the aggregate reduction in default rates for each period:

$$Reduction\ in\ default_t = \sum_i \bar{\beta} \times \mathbb{1}_{>60\text{ days late}_{it}} \times \text{Cleared}_{it}, \tag{8}$$

where $\bar{\beta} \approx 0.2$. $Reduction\ in\ default_t$ is the estimated number of firms that did not default due to clearing. The estimated reduction in default rate is then equal to $Reduction\ in\ default_t$ divided by the total number of firms. This partial equilibrium estimate suggests that clearing reduced the default rate by 0.4 percentage points on a yearly basis. Given that the majority of firms did not even participate in the clearinghouse, this is a sizable fraction of the default rate which was 7% on average in the whole sample of "private market sector" firms. The simple back of the envelope calculation implies that the clearinghouse could have sizable effects on the aggregate default rate, especially if there are additional network effects of clearing.

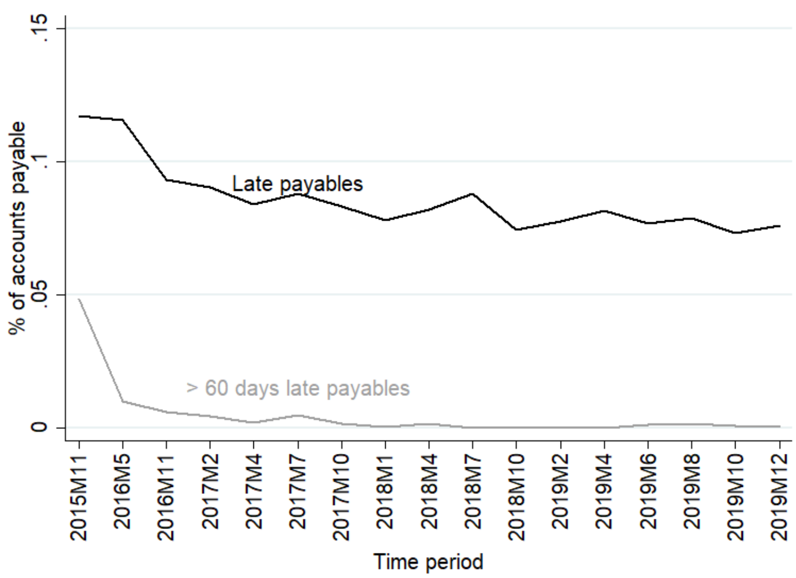
7.2 Unintended consequences

The effect of anticipated clearing might be quite different than the effect of plausibly exogenous and unanticipated clearing that we studied in previous sections. Is it possible that the establishment of the clearinghouse actually increases late debts and default? At the core of this argument is that the firm can increase its probability of clearing by increasing payables and receivables. Consider a firm which has a receivable that is not likely to get paid on time. Then the firm might wait and not pay its payables in order to enforce payment of its receivable through the clearinghouse. In this way, the clearinghouse which mechanically reduces late debts might actually increase late payment by changing the behavior of firms. Similarly, a firm that has payables that it is not likely to pay might grant additional trade credit to increase its probability of clearing and paying its debts through the clearinghouse.

Rostowski (1994) made a similar argument when he analyzed the stabilization policies in post-soviet countries at the beginning of 1990s. Multilateral netting of interfirm debt was performed as a part of stabilization policies after the collapse of communism. He argued that forced multilateral netting in a setting of rampant inflation and non-credible monetary tightening might lead to an increase in interfirm debt, and thus ultimately larger default rates. However, the context of Bosnia and Herzegovina is quite different. First, the clearing is not forced but voluntary. Second, inflation is well below 2% in the time period we analyze and the monetary regime is a currency board, with very limited power of the central bank over the money supply.

We show that late debts of private market sector firms decreased during the operation of the clearinghouse. Figure 3 illustrates the dynamics of median firm late debts after the establishment of the clearinghouse at the end of 2015. It can be seen that these are stagnating or even decreasing after the introduction of the clearinghouse. This suggests that there was no build up in late debts because of the clearinghouse.

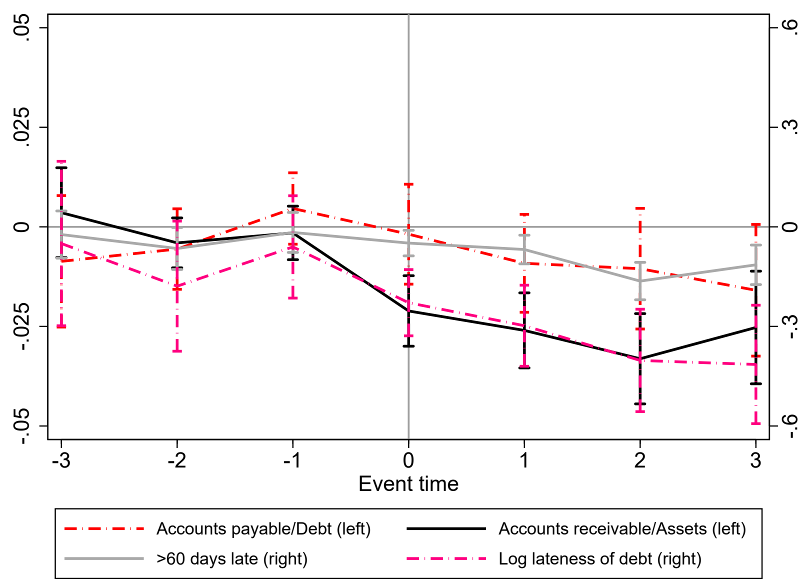
Figure 3: Dynamics of late debts after the establishment of the clearinghouse



The figure shows the evolution of late payables as a share of previous year total accounts payable for the median firm. Additionally, it shows payables that are more than 60 days late as a share of total accounts payable for the median firm. The time period is from the establishment of the clearinghouse until the end of 2019. M denotes the month.

Furthermore, we explore whether firms increase debts just before clearing. We use the De Chaisemartin and d'Haultfoeuille (2020) staggered difference in difference estimator and check for existence of pre-trends before clearing. As De Chaisemartin and d'Haultfoeuille (2020) suggest, we compare pre-trends for firms that got cleared at time t but were not cleared before, to firms that did not get cleared both at time t and before time t. We calculate whether cleared firms are more likely to have debts > 60 days late prior to clearing than not cleared firms. This should happen if the clearinghouse induces perverse incentives. Furthermore, we include a continuous measure of log lateness of debts. We also use financial statements and the same methodology to find out whether cleared firms increase payables and receivables before clearing.

Figure 4: Clearing, payables and receivables



This Figure shows the difference in differences estimates as described in De Chaisemartin and d'Haultfoeuille (2020). > 60 days late - indicator equal to one if the firm is more than 60 days late. Accounts payable/Debt and Accounts receivable/Assets estimates are from financial statements and the period is one year. On the other hand, estimates using > 60 days late and Log lateness of debt are from clearinghouse data and the period is one clearing round. We include debtor and creditor dummies in the estimation as controls. The debtor (creditor) dummy is equal to 1 if the firm is a debtor (creditor). Standard errors are clustered at firm level and computed by using 100 bootstrap replications.

We find that cleared firms are not significantly later on their debts before clearing than not cleared firms (Figure 4). Prior to clearing firms do not tend to pay later than non-cleared firms. We show this by using an indicator variable if a firm is > 60 days late and the continuous measure of log lateness of debts of a firm. It is also visible that lateness tends to decrease after clearing. Another question is, do firms extend and accept more trade credit financing in order to increase the probability of clearing? We estimate a zero effect prior to clearing and a small negative effect on receivables after clearing (Figure 4).

The anticipation effect of clearing in Figure 4 is estimated only for firms that change their clearing status. One might expect that the anticipation effects would be largest for firms that are cleared each period. These firms can expect with high probability to get cleared in every period. Hence, we also compare always cleared firms to not cleared firms. First, this comparison is immaterial for default, because always cleared firms never got a blocked bank account in our sample. Thus we use the indicator whether the firm had debts more than 60 days late, which is a formal reason to start a bankruptcy procedure. Figure A.4 shows the comparison between always cleared and never cleared firms. The share of firms that are very late on their debts decreased for always cleared, while it increased for other firms. However, this increase is largely driven by firms that most likely should have gone through liquidation, but instead remain dormant with blocked bank accounts. To have a more comparable group of firms, we add an additional criterion that the firm needs to have at least one receivable in the clearinghouse. These firms could at least potentially clear their debts and are thus a better comparison group. The share of seriously late creditor firms is constant while it decreases for always cleared firms, again indicating that clearing does not induce perverse incentives.

We turn to financial statements, and show that there was no noticeable increase in accounts payable and receivable prior to clearing for always cleared firms (Figure A.5). All this evidence taken together suggests that the clearinghouse didn't induce perverse incentives.

7.3 External validity

We place the institutional setting of Republika Srpska in an international context to discuss the potential effects of clearing trade credit in other countries. Across the world, trade credit is the main source of short term financing for firms (Cuñat and Garcia-Appendini, 2012). In an Online Appendix Subsection C.6, we show that the average usage of trade credit in Republika Srpska is similar to countries in the European Union. This suggests that multilateral netting has a potential to reduce debt levels in other economies as well. Indeed, Slovenia, an EU country, is already operating a trade credit clearinghouse. In Section 4, we argue that the clearinghouse has real effects because of financing constraints and costly default. Financing constraints are especially prominent in developing economies (Banerjee, 2001; Banerjee and Duflo, 2014), but they are also important in developed ones, especially for SMEs (Whited and Wu, 2006; Hadlock and Pierce, 2010; Buehlmaier and Whited, 2018). In Subsection C.6, we show that the bankruptcy costs in Bosnia and Herzegovina are larger than in high income countries and more similar to those in China. However, we argue that bankruptcy costs are also large in developed countries. Indeed, central clearing counterparties have been shown to reduce counterparty risk in US financial markets (Loon and Zhong, 2014; Bernstein et al., 2019a). By analogy, it is possible that a netting scheme for firm outstanding claims would also have effects even in countries where the market imperfections are not so strong as in Bosnia and Herzegovina.

7.4 Clearing trade credit in other countries

Many post-communist countries implemented multilateral compensation as a part of stabilization policies in the early 1990s (Rostowski, 1994). In communism, the payment system was centralized and firms state-owned, thus making the implementation of such a system easier for policymakers. Börner and Hatfield (2017) discuss similar netting procedures in the markets of pre-industrial fairs, where all merchants met at the same place. However, prior to the diffusion of modern information and communication technology, organizing such clearing procedures with thousands of participants on a frequent basis was arguably much more costly. In the future, we expect more of such trade credit clearinghouses emerging across the world.

7.5 Costs of clearing

The administrative cost of setting up the centralized clearinghouse is arguably negligible. Currently, the Banja Luka Stock Exchange (BLSE) is the developer and administrator of the clearinghouse. It has ten employees that perform various duties of the stock exchange, clearing of trade credit being only one of them. Clearing fees for individual firms are potentially higher. The BLSE charges a fixed fee for clearing depending on the size of the cleared debt. Large debts imply larger fees in absolute terms, but smaller in proportion to the total debt. A median (mean) firm paid a fee that was 0.34% (0.45%) of it's cleared debts. These fees are non-negligible but are below most of the estimated costs of retail payments in nine EU countries (Junius et al., 2022). Given that clearing is voluntary, participation shows that individual firms benefit more than they lose due to clearing. Our results also suggest that the benefits of clearing are much higher than its costs. Furthermore, reporting of debts might be an additional administrative burden, especially for small firms, which might not have their own accounting departments. To alleviate these concerns the BLSE allows reporting through accounting service providers. Given the ease of reporting these costs are arguably not large.

8 Conclusion

The trade credit clearinghouse is a contracting innovation which allows a large network of firms and government units to coordinate on debt offsetting. We find that the clearinghouse reduces firm default probability and increases investment. Arguably, the clearinghouse is used as an exchange mechanism that alleviates the lack of access to finance. Furthermore, we provide evidence that the clearinghouse is used to solve a coordination problem of timely debt repayment between many participants.

There are still, however, many uncertainties regarding the economic consequences of the clearinghouse. It remains to be studied how the clearinghouse affects the behavior of the government and SOEs, which are a major participant in clearing. Furthermore, does netting of debts have beneficial effects on firms that do not participate in the clearinghouse and are there any network effects of clearing? Given that participation in this policy is voluntary, it remains an open question what would be the effects of obligatory clearing and how much percent of trade credit would be cleared then.

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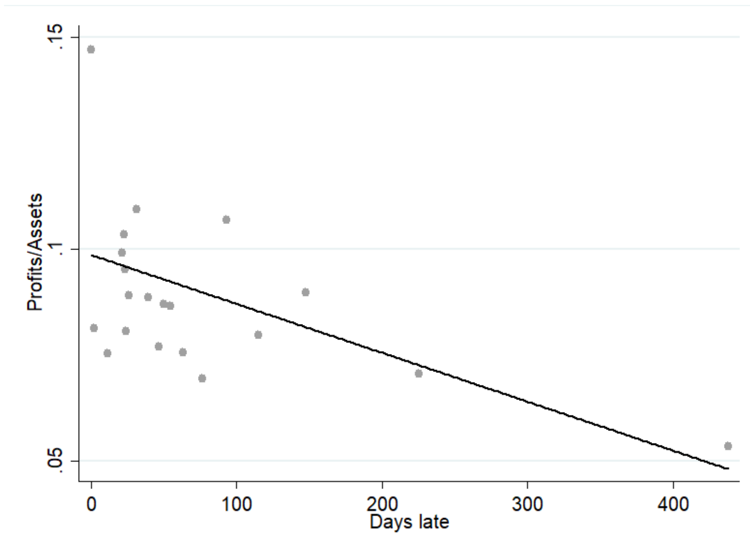
Appendices

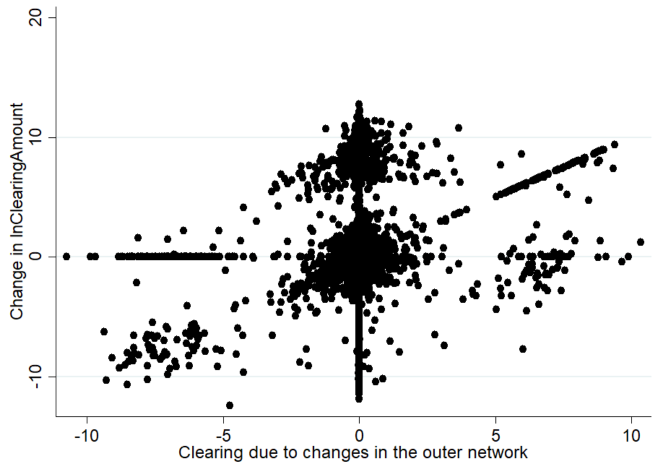
A Figures

Figure A.1: Profits and lateness of debts



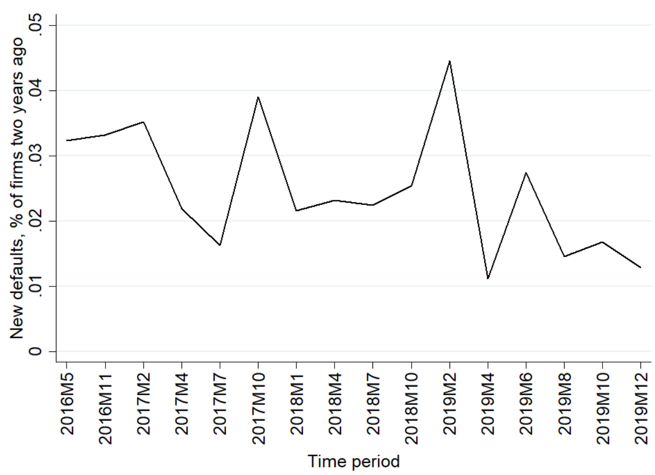
The figure shows the relationship between profitability and lateness of debts. Dots represent quantile bins. Firms that are late more than one year on their debts, still have on average positive profits. Return on assets is net income before taxes over assets. The sample is private market sector firms from 2015 to 2017. All firms with debts that are late more than 2 years are excluded, in order to remove outliers.

Figure A.2: Instrumental variable and changes in clearing amount



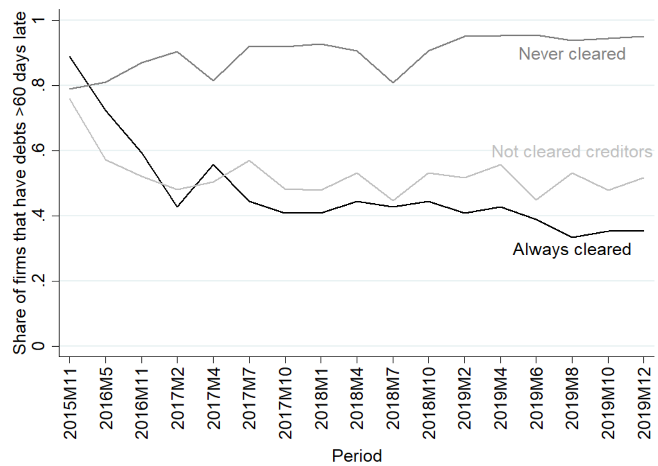
This figure shows the relation of our instrument to changes in the preliminary clearing amount. One can see that there is a robust positive relationship between the two variables. There is also a lot of variation, this is because changes in the outer network are not the only reason why clearing for the firm changes. Changes in the inner network also matter.

Figure A.3: Default dynamics after the establishment of the clearinghouse



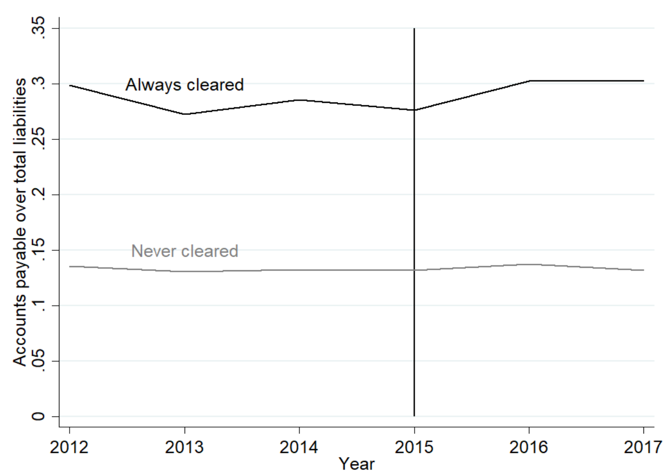
The figure shows the evolution of new blocked bank accounts as a share of number of firms. The number of firms is calculated from the APIF financial statements registry and is lagged two years, because we have APIF data until 2017, while the clearinghouse data is available until 2019.

Figure A.4: Dynamics of debts > 60 days late



This figure shows the evolution of the share of firms that are more than 60 days late on their payables for each group of firms based on their treatment status. Always cleared firms are defined as firms who got cleared each clearing round from 2015 to 2019. Never cleared are those who didn't get cleared. Not cleared creditors are firms that are debtors and creditors at the same time, but didn't get cleared at period t. M denotes the month.

Figure A.5: Dynamics of accounts payable and introduction of the clearinghouse



The figure shows the evolution of accounts payable for different groups of firms. Always cleared firms are defined as firms who got cleared each year from 2015 to 2017. Never cleared are those who didn't get cleared. The clearinghouse was established in 2015.

B Tables

Table B.1: Late debt and clearing summary statistics

Panel A: Late debt summary statistics

	All, % GDP			Firms, % Payables		
Statistic	Avg.	Oct. 2015	Dec. 2019	Avg.	Oct. 2015	Dec. 2019
Debt	9%	16%	8%	7%	8%	5%
> 60 days late	5%	7%	4%	3%	6%	2%
> 180 days late	4%	6%	3%	2%	3%	1%
Blocked	1.6%	1.4%	1.6%	0.5%	1.0%	0.3%
Days late						
-not blocked, median	37	72	16	29	81	16
-not blocked, p90	211	305	138	165	322	105
-blocked, median	1,418	993	1,747	837	473	1,069
No. of participants	13,649	12,462	15,661	2,208	2,759	2,397
No. of non-blocked	1,110	2,804	781	1020	1518	685

Panel B: Clearing summary statistics

	All, % GDP			Firms, % Cash holdings		
Statistic	Avg.	2015	2019	Avg.	2015	2019
Cleared	1.6%	1.8%	1.2%	2.0%	3.4%	3.4%
> 60 days late	0.4%	0.4%	0.3%	0.4%	0.3%	0.1%
> 180 days late	0.2%	0.2%	0.2%	0.1%	0.1%	0.0%
No. of cleared	1,185	1,351	1027	707	827	579

The table shows descriptive statistics on late debts and clearing from the clearinghouse data. Blocked denotes a firm that has a blocked bank account due to delinquent payables. For blocked entities the median of lateness is more than 1404 days and it increased from 977 days to 1744 days at the end of the sample. This shows that blocked firms stay blocked and it can take years before firms go through a bankruptcy procedure. In any given clearing round, late debts are on average 9% of GDP. This includes, however, also the debts of the government and state owned enterprises which are not the main object of our analysis. For firms, accounts payable is a better benchmark because GDP is a flow variable. For privately owned firms that operate in market oriented sectors and that are the object of our analysis, we can use an appropriate benchmark of accounts payable from financial statements. Late debts as a fraction of GDP have declined after the introduction of the clearinghouse in 2015 from 16% of GDP to 8% at the end of 2019. As a share of payables for our subset of firms, late debts have also declined from 8% of payables in 2015 to 5% in 2019.

Table B.2: The size of identifying variation relative to total clearing

	Share of IV in total clearing			Number of firms		
	Absolute	Positive	Negative	Positive	Negative	Total firms
2017Q1	0.10	0.05	-0.05	174	186	1857
2017Q2	0.09	0.05	-0.04	278	239	2155
2017Q3	0.12	0.04	-0.09	183	229	1954
2017Q4	0.14	0.03	-0.10	192	254	2149
2018Q1	0.08	0.03	-0.05	197	193	2080
2018Q2	0.30	0.26	-0.05	212	173	2135
2018Q3	0.22	0.06	-0.17	141	189	2146
2018Q4	0.18	0.16	-0.02	227	146	2105
2019P1	0.10	0.02	-0.08	154	212	2228
2019P2	0.11	0.07	-0.04	212	170	2192
2019P3	0.12	0.05	-0.07	162	173	2254
2019P4	0.10	0.06	-0.05	155	160	2234
2019P5	0.12	0.05	-0.07	146	178	2329
2019P6	0.08	0.06	-0.02	183	131	2337
Average	0.13	0.07	-0.06	187	188	2154

Absolute denotes the sum of absolute differences between actual and alternative clearing divided by total clearing. Negative denotes the sum of all negative differences and positive denotes the sum of all positive differences, both divided by total clearing. In the number of firms panel, columns correspond to the number of firms that that have negative and positive difference, respectively. Total firms column denotes all firms in sample.

Table B.3: Alternative definitions of the treatment variable

	(1)	(2)
	$\text{LnClearingAmount}_{it}$	$\Delta\text{LnClearingAmount}_{it}$
lnC_{it}^{ON}	0.419***	0.465***
	(0.0142)	(0.0323)
Inner network	YES	YES
Debt controls	YES	YES
Debtor-creditor controls	YES	YES
Firm controls	YES	YES
Industry & time FE	YES	YES
Observations	30,155	30,155
R-squared	0.875	0.171
F-stat for instrument	865	207

The table shows the first stage for other definitions of the treatment variable. $\text{LnClearingAmount}_{it}$ is the clearing amount that the firm agreed on in the final clearing round. $\Delta\text{LnClearingAmount}_{it} = \text{LnClearingAmount}_{it} - \text{LnClearingAmount}_{it-1}$. Standard errors in parentheses are clustered at sector level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.4: Randomization tests

Panel A: Randomization tests for firm level characteristics lagged two years or one clearing period

	Dependent variables lagged two years					Dependent variables lagged one clearing period								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	AR/A	AP/Lb	Lb/A	lnL	Π/A	Default	lnCR	lnCP	lnBadCR	lnBadCP	lnTimeCR	lnTimeCP	lnGovCR	lnGovCP
$\ln C_{it}^{ON}$	0.0002	0.0003	-0.0014	-0.0095	0.0001	-0.0018	-0.0347	-0.0049	0.0029	-0.0135	-0.0128	-0.0089	-0.0283	-0.0072
	(0.0014)	(0.0028)	(0.0017)	(0.0097)	(0.0005)	(0.0011)	(0.0386)	(0.0281)	(0.0271)	(0.0264)	(0.0253)	(0.0163)	(0.0346)	(0.0258)
	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297
R-squared	0.5560	0.6410	0.6515	0.7452	0.3706	0.7202	0.5100	0.0297	0.2802	0.2494	0.3963	0.3162	0.4427	0.3003

Panel B: Randomization tests for firm level characteristics lagged one years or in the clearing period

	Dependent variables lagged one year					Dependent variables in the current clearing period								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	AR/A	AP/Lb	Lb/A	lnL	Π/A	Default	lnCR	lnCP	lnBadCR	lnBadCP	lnTimeCR	lnTimeCP	lnGovCR	lnGovCP
$\ln C_{it}^{ON}$	0.0003	-0.0010	-0.0028	-0.0109	0.0002	-0.0034	-0.0408	-0.0223	-0.0323	-0.0332	-0.0229	-0.0235	0.0010	-0.0259
	(0.0014)	(0.0022)	(0.0018)	(0.0088)	(0.0005)	(0.0032)	(0.0611)	(0.0184)	(0.0490)	(0.0340)	(0.0314)	(0.0205)	(0.0477)	(0.0301)
	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297
R-squared	0.5338	0.6312	0.6199	0.7417	0.1921	0.6873	0.0582	0.0416	0.0431	0.0347	0.0527	0.0624	0.0511	0.0638

Here we present the estimates from a regression $X_{im} = \alpha + \beta \ln C_{it}^{ON} + \delta_s + \tau + \epsilon_{it}$. Where X_{im} are pre-treatment firm characteristics, t is the time of the treatment, in other words the period when clearing happend. m is the pre-treatment period, which is equal to $y-2$ for financial statements dependent variables in columns (1)-(6), where y denotes the year of clearing. $m = t-1$ for clearinghouse variables, which corresponds to one period before clearing. δ_s are sector fixed effects, and τ_t are time fixed effects. Additionally, in columns (1)-(6) we include an indicator whether the firm reported financial statements or not. Errors are clustered at sector level. Explanation of abbreviations Π - profits, A - assets, AR - accounts receivable, AP - accounts payable, Lb - total liabilities,Default - blocked bank accounts, lnCR - log receivables reported to the clearinghouse, lnCP - log payables reported to the clearinghouse, lnBadCP - log currency value of > 60 day late payables, lnBadCR - log currency value > 60 day late receivables, lnTimeCR - log weighted mean of receivables lateness, lnTimeCP - log weighted mean of payables lateness, lnGovCR - log receivables from the government, lnGovCP - log receivables from the government. Government includes SOEs and other government units. Standard errors in parentheses are clustered at sector level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.5: Randomization tests for discrete changes in clearing status

Panel A: Randomization tests for firm level characteristics lagged two years or one clearing period

	Dependent variables lagged two years					**Dependent variables lagged one clearing period**								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	AR/A	AP/Lb	Lb/A	lnL	Π/A	Default	lnCR	lnCP	lnBadCR	lnBadCP	lnTimeCR	lnTimeCP	lnGovCR	lnGovCP
Switcher Cleared$_{it}$	-0.0123	-0.0160	-0.0131	-0.0037	-0.0028	-0.0018	-0.2820	-0.0036	0.2197	-0.2202	-0.0320	-0.1642	-0.0544	-0.0668
	(0.0140)	(0.0303)	(0.0227)	(0.0982)	(0.0064)	(0.0374)	(0.4320)	(0.3216)	(0.3603)	(0.3918)	(0.2733)	(0.2065)	(0.4674)	(0.4067)
	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297
R-squared	0.5561	0.6411	0.6515	0.7452	0.3708	0.0737	0.0618	0.0254	0.0492	0.0462	0.0650	0.0682	0.0595	0.0615

Panel B: Randomization tests for firm level characteristics lagged one year or in the clearing period

	Dependent variables lagged one year					**Dependent variables in the current clearing period**								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	AR/A	AP/Lb	Lb/A	lnL	Π/A	Default	lnCR	lnCP	lnBadCR	lnBadCP	lnTimeCR	lnTimeCP	lnGovCR	lnGovCP
Switcher Cleared$_{it}$	-0.0055	-0.0319	-0.0330	-0.0227	0.0007	0.0322	-0.0733	-0.1427	-0.1858	-0.2861	-0.2414	-0.2549*	0.3729	-0.2514
	(0.0151)	(0.0225)	(0.0252)	(0.0932)	(0.0059)	(0.0315)	(0.2791)	(0.2012)	(0.5484)	(0.3680)	(0.1832)	(0.1505)	(0.5779)	(0.3334)
Observations	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297	30,297
R-squared	0.5340	0.6313	0.6200	0.7417	0.3612	0.0802	0.6533	0.1735	0.3270	0.3104	0.5212	0.4939	0.4449	0.3584

Here we present the estimates from a regression $X_{im} = \alpha + \beta\text{Switcher Cleared}_{it} + \text{Switcher}_{it} + \delta_s + \tau + \epsilon_{it}$. Where X_{im} are pre-treatment firm characteristics, t is the time of the treatment, in other words the period when clearing happend. m is the pre-treatment period, which is equal to $y-2$ for financial statements dependent variables in columns (1)-(6), where y denotes the year of clearing. $m = t-1$ for clearinghouse variables, which corresponds to one period before clearing. δ_s are sector fixed effects, and τ_t are time fixed effects. Additionally, in columns (1)-(6) we include an indicator whether the firm reported financial statements or not. Errors are clustered at sector level. Explanation of abbreviations Π - profits, A - assets, AR - accounts receivable, AP - accounts payable, Lb - total liabilities, Cash - cash holdings, Default - blocked bank accounts, lnCR - log receivables reported to the clearinghouse, lnCP - log payables reported to the clearinghouse, lnBadCP - log currency value of >60 day late payables, lnBadCR - log currency value >60 day late receivables, lnTimeCR - log weighted mean of receivables lateness, lnTimeCP - log weighted mean of payables lateness, lnGovCR - log receivables from the government, lnGovCP - log receivables from the government. Government includes SOEs and other government units. Standard errors in parentheses are clustered at sector level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.6: Continuous treatment results

	(1) Default$_{t+1}$	(2) Default$_{t+1}$	(3) Default$_{t+1}$	(4) Default$_{t+1}$
LnClearingAmount$_{it}$	-0.00349***	-0.00103	-0.00728***	-0.00794***
	(0.000484)	(0.00101)	(0.00252)	(0.00224)
Debt controls	NO	YES	NO	YES
Debtor-creditor controls	NO	YES	NO	YES
Firm controls	NO	YES	NO	YES
Industry & time FE	NO	YES	NO	YES
Observations	30,297	30,297	30,297	30,297
R-squared	0.790	0.807	0.779	0.798

The table shows the main result with a continuous treatment. Columns (1) and (2) are OLS results, while (3)-(4) are the main results with the instrumental variable. One standard deviation increase in LnClearingAmount$_{it}$ (3.3 log points) translates to a 2.5% decrease in the default probability. LnClearingAmount$_{it}$ is the clearing amount that the firm agreed on in the final clearing round. Standard errors in parentheses are clustered at sector level. All regressions include $Default_t$. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.7: Effect of clearing on default up to three periods in the future

	(1) Default$_{t+1}$	(2) Default$_{t+2}$	(3) Default$_{t+3}$
Cleared$_{it}$	-0.0632***	-0.0281	-0.0308
	(0.0178)	(0.0221)	(0.0237)
Debt controls	YES	YES	YES
Debtor-creditor controls	YES	YES	YES
Firm controls	YES	YES	YES
Industry & time FE	YES	YES	YES
Observations	30,297	30,297	30,297
R-squared	0.798	0.757	0.738

The table shows the estimation results for our main variable of interest up to three periods in the future. All regression include $Default_t$. Standard errors in parentheses are clustered at sector level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.8: Effect of clearing on debts up to three periods in the future

	(1) ΔlnDebt$_{ijt+1}$	(2) ΔlnDebt$_{ijt+2}$	(3) ΔlnDebt$_{ijt+3}$	(4) Exists$_{ijt+1}$	(5) Exists$_{ijt+2}$	(6) Exists$_{ijt+3}$
Cleared$_{it}$	-0.3241***	-0.0827	-0.0306	-0.0029	-0.0632	-0.0373
	(0.1166)	(0.1236)	(0.1386)	(0.0404)	(0.0502)	(0.0438)
Observations	57,803	51,837	48,217	90,284	90,284	90,284

Note: This table presents the effects of debtor clearing and creditor clearing on all debts up to 3 periods after clearing. These are the second stage results from the 2SLS explained in the text. It includes creditor $\times$ year FE, debtor sector $\times$ year FE and debtor controls. Cleared$_{it}$ is an indicator variable that equals to 1 if the debtor gets cleared any of its debts, and otherwise it is zero. i denotes the debtor. Variables in logs are one plus the actual value of the variable, to avoid issues with zeros. Standard errors in parentheses are clustered at debtor and creditor level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.9: Clearing and borrowing

	(1) $\Delta\frac{\text{Loans}_{it+1}}{\text{Lb}_{it+1}}$	(2) $\Delta\frac{\text{Loans}_{it+1}}{\text{A}_{it+1}}$	(3) $\Delta\frac{\text{AP}_{it+1}}{\text{Lb}_{it+1}}$	(4) $\Delta\frac{\text{AR}_{it+1}}{\text{A}_{it+1}}$	(5) $\Delta\frac{\text{Cash}_{it+1}}{\text{A}_{it+1}}$
Cleared$_{it}$	0.0349	0.0168	-0.0333	-0.0475*	-0.0003
	(0.0247)	(0.0174)	(0.0330)	(0.0282)	(0.0170)
Controls	YES	YES	YES	YES	YES
Observations	2,475	2,475	2,475	2,475	2,475

The table shows results of the second stage regression in which we explore the effect of clearing on borrowing. Loans - outstanding bank loans, Lb - total liabilities, AP - accounts payable, AR - accounts receivable, A - assets, Cash - cash holdings. All changes are relative to the year prior to clearing: $\Delta X_{it+1} = X_{it+1} - X_{it-1}$. All regressions include the full set of controls described in Subsection C.3. The first stage coefficient of the instrument is 0.057, with a t-stat of 13.75 which amounts to an F-stat of 189. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.10: Clearing, liquidity, default status and other outcome variables

Panel A: Clearing, default status and other outcome variables

	(1)	(2)	(3)	(4)
	ΔlnPY_{iy+1}	ΔlnM_{iy+1}	ΔlnL_{iy+1}	$\frac{\Delta\text{K}_{iy+1}}{A_{t-1}}$
Cleared_{iy}	0.1474	0.3479*	0.0135	0.0702
	(0.1259)	(0.1957)	(0.0770)	(0.0928)
$\text{Cleared}_{iy} \times \text{Default}_{iy}$	1.2080**	1.3063	-0.2081	-0.0417
	(0.5040)	(1.5232)	(0.3159)	(0.1384)
Controls	Yes	Yes	Yes	Yes
Observations	2,475	2,475	2,475	2,475

Panel B: Clearing, liquidity and investment

	(1)	(2)	(3)	(4)	(5)	(6)
		$\frac{\Delta\text{K}_{it+1}}{\text{A}_{it-1}}$			$\frac{\Delta\text{FA}_{it+1}}{\text{A}_{it-1}}$	
Cleared_{it}	-0.0709	-0.0264	-0.0413	-0.0774	-0.0313	-0.0474
	(0.1004)	(0.0934)	(0.0884)	(0.1020)	(0.0942)	(0.0891)
$\text{Cleared}_{it} \times \text{4th quartile}\frac{Cash_{iy-1}}{AP_{iy-1}}$	0.4773**			0.4990**		
	(0.2159)			(0.2270)		
$\text{Cleared}_{it} \times \text{4th quartile}\frac{Cash_{iy-1}}{AP_{iy-1}}$		0.3789*			0.3978*	
		(0.2132)			(0.2190)	
$\text{Cleared}_{it} \times \text{4th quartile}\frac{Cash_{iy-1}}{STL_{iy-1}}$			0.4662*			0.4913*
			(0.2365)			(0.2471)
Controls	YES	YES	YES	YES	YES	YES
Observations	2,475	2,475	2,475	2,475	2,475	2,475

The table shows results of the second stage regression in which we explore the effect of clearing on real outcomes of firms in payment default (Panel A) and the effect of clearing on investment for cash rich firms (Panel B) . PY - sales, M - intermediate inputs, L - labor, K - plant property and equipment, A - assets, FA - fixed assets, Cash - cash holdings, AP - accounts payable, STL - short term liabilities. All changes are relative to the year prior to clearing: $\Delta X_{it+1} = X_{it+1} - X_{it-1}$. All regressions include the full set of controls described in Subsection C.3. We do not exclude the interquartile range for regressions on financial statement data because of limited sample size. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.11: Coordination failure robustness

	(1) Default$_{t+1}$	(2) Default$_{t+1}$	(3) Default$_{t+1}$	(4) Default$_{t+1}$
Cleared$_{it}$	-0.0299	-0.0115	-0.0197	0.0028
	(0.0609)	(0.1181)	(0.0472)	(0.0820)
Cleared$_{it}$ × Q4(Hubs+Authorities)$_{it}$	-0.2618*	-0.5010***		
	(0.1350)	(0.1499)		
Cleared$_{it}$ × Q4InnerNet$_{it}$			-0.2991	-0.4775***
			(0.2162)	(0.1461)
Cleared$_{it}$×Q4$\frac{\mathrm{CR}_{it}}{\mathrm{A}_{iy-2}}$	0.0311		-0.0050	
	(0.0729)		(0.0655)	
Cleared$_{it}$×Q4$\frac{\mathrm{AR}_{iy-2}}{\mathrm{A}_{iy-2}}$		-0.0510		-0.0744
		(0.1526)		(0.1367)
Inner network	YES	YES	YES	YES
Debt controls	YES	YES	YES	YES
Debtor-creditor controls	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES
Industry & time FE	YES	YES	YES	YES
Observations	2,025	2,106	2,176	2,210
R-squared	0.7610	0.6737	0.7885	0.7493

The table shows the 2nd stage 2SLS robustness results for the coordination failure hypothesis by including measures of exposure to spillovers. AR - accounts receivable, A - assets, Hubs - firms that are indebted to many authorities, Authorities - firms that are creditors to many hubs, Inner net - count of all nodes in the inner network of firm *i*. The sample size is lower than in the main estimation because we drop the interquartile range of relevant variables and we focus only on firms that are both debtors and creditors. For firms that are only debtors there is no variation in our instrument. Furthermore, if the interaction variable is from firm financial statements, the sample size might drop even more, because some firms do not report financial statements, usually because of financial distress. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

C Appendix

C.1 Data

To deal with outliers, we winsorize the lower and upper 2% of the distribution for financial ratios and growth rates (e.g. future sales growth).

There is a share of entries in the clearinghouse data that do not have their counterpart in the financial statements dataset. Government organizations, such as the treasury, municipalities, hospitals and various other governmental organizations do not report financial statements to our data source APIF. Furthermore, sole proprietors such as hair stylists do not report financial statements to APIF. Another group that cannot be merged are firms that did not report their financial statements. This can occur as a result of a mistake or as a conscious decision not to report. The financial statements data are made public by APIF. Financially distressed firms might want to hide their financial status to the public by not reporting, although there are fines prescribed for such behavior. Given that financially distressed firms are important in our analysis, we include firms that didn't report financial statements in our regressions with default risk, provided that they reported late debts to the clearinghouse and financial statements previously. We control for the fact that these firms didn't report their financial statements and we set all missing values from their financial statements equal to zero. We also verify that the main results are robust to excluding these firms from the analysis.

Although all firms and government authorities in the entity of Republika Srpska are required by law to report their late debts, there are no fines for those that do not report. The law is not enforced because of the implicit decision by the policymakers that clearing should be voluntary and not forced for any party. An exception are blocked firms whose debts are automatically reported to the clearinghouse by banks. For those firms, only blocked debts are visible in the clearinghouse data, so that the creditor has ensured seniority in clearing of debts. These facts imply that our late debts data do not represent an exhaustive administrative source of all late debts in the economy, but are subject to reporting bias. This is not a major problem for our main analysis because our instrument only varies for firms that reported debts, so a comparison with firms who did not report late debts would not be possible even if we had data on their late debts from some other sources. As a consequence, most of our analysis will be constrained to firms that actually reported their late debts to the clearinghouse and only in a later section we will analyze external validity. Given the size of the data and importance of late debts in GDP, this dataset is still sizable compared to other studies in the literature (see e.g. Klapper et al. (2012); Murfin and Njoroge (2015); Giannetti et al. (2020)), which also do not use an administrative data on late payment, but usually rely on some third party information. In fact, administrative data on late debts do not exist, because they are not collected by statistical agencies nor the government. Our dataset can be thought of as a step closer to an administrative dataset of late debts, and is a lower bound on total late debts in this economy.

As noted in the main text, an important feature of the data is that many firms do not go through bankruptcy proceedings and their debts can end up in the clearinghouse data, but they are not operating anymore. For example, there are debts owed to the Tax administration reported in the clearinghouse that are late more than 5 years.

The share of the APIF dataset that we use in total corporate sector employment is constant throughout the sample period at approximately 75%. The denominator consists of total employment in business entities, which also includes sole proprietorships that are excluded from our dataset. As described in Section 3 we focus on firms not owned by the state and which do not operate in sectors heavily influenced by the government. This forms the main sample in our analysis, and represents 44% of employment in the corporate sector.

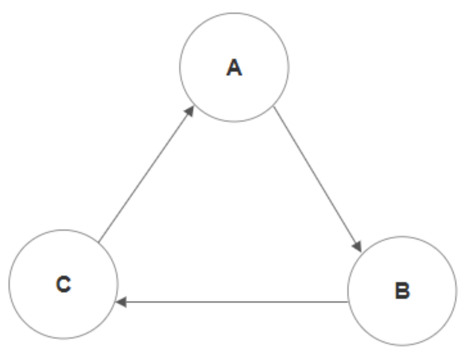
Table C.12: Description of main variables that appear in tables

Variable name	Variable description	Source
Cleared_{it}	Clearing dummy	Clearinghouse data
Default_{it}	Blocked bank account	Clearinghouse data
lnC_{it}^{ON}	Clearing due to changes in the outer network	Clearinghouse data
$\text{lnClearedAmount}_{it}$	Log clearing amount	Clearinghouse data
Switcher_{it}	Switcher indicator	Clearinghouse data
lnPY_{iy}	Log sales	Financial statements
K_{iy}	Plant, property and equipment	Financial statements
A_{iy}	Assets	Financial statements
FA_{iy}	Fixed assets	Financial statements
L_{iy}	Employment	Financial statements
M_{iy}	Purchases of intermediate inputs	
Financial statements		
AR_{iy}	Accounts receivable	Financial statements
AP_{iy}	Accounts payable	Financial statements
Cash_{iy}	Cash holdings	Financial statements
STD_{iy}	Short term debt	Financial statements
Loans_{iy}	Outstanding bank loans	Financial statements
Lb_{iy}	Liabilities	Financial statements

C.2 Theoretical model

Consider a cycle of three firms (A,B and C) that have outstanding debts to each other. There are three periods (0,1 and 2). Firm A is indebted to firm B, B to C and C to A (Figure 1). For simplicity, we assume that all firms are symmetric, so all the debts are the same and equal to b_0. These debts are a consequence of decisions made in period 0 and are due in period 1. We abstract from the reason why this network was formed, hence firms take the network as given. Each firm can consume in period 1 and period 2, so her objective function is the sum $U_i = c_{1i} + c_{2i}$. At the beginning of period 1, the firm can delay payment of its outstanding debts without paying any cost. Simultaneously, it also makes a cash decision. In a extension of the model, we include an investment decision to study the real effects of clearing. Firms play a simultaneous game of perfect information in period 1 and 2, but it will turn out that the game collapses to a one period simultaneous game. In the second period, the actions of firms will not be strategic, in other words they will not depend on the actions of other firms. Extensions to a different setup where firms play a sequential game in period 2 are also possible with no qualitative changes in the main results.

Figure C.1: A simple cycle network



This figure represents a simple cycle network. A → B means "firm A is indebted to firm B". Each debt is of the same face value b_0.

Let us consider a single firm i. The firm has an initial endowment W and outstanding debt b_0. In period 1 it can choose to delay or repay the debt due: $r_1 \in \{0, b_0\}$ and it can also choose to store value in cash M. The repayment decision is binary for exposition purposes. Subject to the choice of the other firm in the cycle, the firm can receive a payment r_1' from the other firm f'. Thus, the budget constraint in period 1 is:

$$W - M - r_1 + r_1' - c_1 \geq 0. \tag{C.1}$$

At the beginning of period 2, there is a positive observed aggregate productivity shock $a_s \in \{a_h, a_l\}$ that is happening with a known probability $\{p_h, p_l\}$. We focus on an aggregate shock for simplicity of exposition. After observing the productivity realization a_s, firms make a decision whether to repay any outstanding debts or default. If the firm paid it's debt in period 1 ($r_1 = b_0$) then there is no decision to make in period 2, it just receives the productivity realization and possible payments from other firms. If the firm didn't repay in period 1 then it has a decision to make in period 2. After observing the shock, i decides whether to repay the leftover debt from the period 1:

$$r_2 = b_0 - r_1 \tag{C.2}$$

or to default and receive a payoff 0, because of costly default. All firms decide simultaneously to pay each other or not, implying that the firm needs to use internal sources to repay it's debts:

$$r_2 \leq M + a_s. \tag{C.3}$$

This equation also implies severe financial frictions as the firm is unable to borrow against receivables r_2'. Thus consumption in period 2 is:

$$c_2 = \big(a_s - r_2 + r_2' + M\big)\mathbb{1}_{r_2 = b_0 - r_1} \tag{C.4}$$

The assumption of simultaneous repayment can be eased to a sequential repayment, where one firm is a random first mover (Jackson, 2010). With access to well functioning financial markets the firm might borrow by using the receivables as collateral, but in the economy which we study there is no lending of this form. Generally, the amount of borrowing might be limited due to financial frictions. There is evidence that this kind of lending is lacking even in developed countries, especially for small firms (Barrot, 2016; Barrot and Nanda, 2016).

In the rest of the model, we consider an interesting part of the parameter space in which default due to liquidity happens in the low productivity state.

Assumption 1: $A_h - b_0 > 0$ and $A_l - b_0 < 0$.

Assumption 1 states that productivity in the high state is enough to repay all the delayed debts. In the low state, however, firms will default if they do not hoard enough cash.

C.2.1 Equilibrium

Case 1: Clearing as an exchange mechanism. Late payment due to liquidity constraints $W < b_0$ and no bank lending.

Case 1 highlights the nature of clearing as a way to use delinquent receivables to pay outstanding debts, which is crucial in absence of a market for receivables, i.e. factoring.

If firms do not have enough cash to pay on time, then there will be no strategic considerations. The firm will not hoard cash for the next period because cash will not be sufficient to save it from default in the low productivity state. Even worse, saved cash will be lost in costly default proceedings. Firms are unable to pay each other in period 1: $r_1 = 0$ and they pay in period 2 if the high productivity materializes. In the low productivity scenario, the firm defaults because it does not have enough liquidity to repay the debt. This happens although the firm has more assets ($A_l + b_0$) than liabilities (b_0), since $A_l > 0$. Limited liability and costly default imply that the firm will default and lose the remaining value of the firm in bankruptcy proceedings. $c_2 = 0$. Furthermore, all firms in the cycle default, because of the liquidity shortage. So, the consumption value in period 2 is 0, while each firm produced the value of a_l.

Proposition 1. *For liquidity constrained firms with no access to finance, clearing reduces default risk.*

Clearing. We introduce the clearinghouse at the end of period 1, after firms chose to be delinquent on their payables, but before the default decision. This corresponds to the setting in which firms decide on late payment and then clearing is exogenously introduced. Clearing allows each firm to exactly offset payables with receivables. After clearing, firms will not have any liabilities and will not be forced to default if the low productivity state happens. Firms continue operations, and each consumes a_l in the low productivity state. Because this is a Pareto improvement and the first best efficient outcome, all firms accept to participate in clearing.

Case 2: Late payment as a choice - debt dilution and no cash decision.

If firms have enough endowment to repay in period 1, then they will make two decisions in our setting - whether to repay the debt in first period r_1 and whether to accumulate cash M.

To illustrate the debt dilution phenomenon we remove the cash decision from the model and in a later extension we include it. We solve the model by backward induction. As we have shown before, there is no strategic interaction in period 2. Firms default if they delay payment in period 1 in the case of low productivity realization, otherwise they continue operating.

Will it be optimal for the firm in period 1 to delay payment and expose itself to default? The answer is yes, because delaying dilutes the value of debt from b_0 to $p_h b_0$, which is the debt value in case of survival. Paying, on the other hand, insures against default in the low productivity state, which will yield revenues of $p_l A_l$. The firm will delay if:

$$(1 - p_h)b_0 = p_l b_0 > p_l a_l. \tag{C.5}$$

This condition holds because by Assumption 1 $A_l < b_0$ makes the firm default in the first place. Notice that the optimal decision to delay does not depend on actions of other firms, thus delaying is a dominant strategy.

Let us now construct payoffs from this game (Table C.13). All payoffs are evaluated relative to the dominant strategy equilibrium where everybody delays. We get that the outcome where all firms coordinate on repaying yields larger profits, than the late payment equilibrium. However, the allocation where everybody repays their debts is not an equilibrium, since all firms have an incentive to deviate. The structure of the game is a three player prisoners dilemma.

Proposition 2. *The clearinghouse solves a coordination failure in which everybody pays late. This results in lower default rates.*

Clearing. At the end of period 1, after everybody chose to delay, the clearinghouse offers an allocation where $r_1 = b_0 = r_1'$. This is exactly the allocation where everybody pays immediately. If somebody rejects this allocation, then firms stay in the decentralized equilibrium. Otherwise, if everybody accepts, deviation is impossible, and the debts are cleared. Since

Table C.13: The game in period 1 - three person prisoners dillema

C pays		**B** Pays	**B** Delays
A	Pays	$p_l a_l, p_l a_l, p_l a_l$	$p_l a_l, p_l b_0, -p_l b_0$
	Delays	$p_l b_0, p_l(a_l - b_0), 0$	$p_l b_0, 0, -p_l b_0$

C delays		**B** Pays	**B** Delays
A	Pays	$p_l(x_l - b_0), p_l x_l, p_l b_0$	$p_l(x_l - b_0), p_l b_0, 0$
	Delays	$0, p_l(x_l - b_0), p_l b_0$	$0, 0, 0$

All payoffs in the table are evaluated relative to the equilibrium in dominant strategies where everybody delays. The equilibrium payoff for each firm is $W + p_h a_h$, and it is substracted from each entry in the table. This is the reason why in the dominant strategy equilibrium payoffs are 0 for each firm in the table (lower left corner).

each firm weakly prefers clearing to the decentralized equilibrium, they accept to participate in the clearing.

A clearinghouse essentially enforces immediate payment of debts between firms. It solves the coordination problem that arises because firms individually have an incentive not to pay. Underlying this coordination failure is weak rule of law that allows firms to pay out profits while not repaying their debts.

Case 3: Multiple equilibria - cash decision.

Insofar, the firm could insure itself against default by paying on time but it chose not to do so. Cash is another vehicle of insuring against future default, but again the firm has the same incentive not to pay its debts on time. We will show, however, if everybody delays payment and simultaneously holds cash then the first best allocation is achieved. Cash holdings insure the firm against default risk, so late payment does not result in negative consequences for firms in the cycle.

Consider the equilibrium in which each firm delays and hoards cash s.t. $M = W, r = 0, c_1 = 0$ then the expected payoff for each firm is equal to:

$$W + p_h a_h + p_l a_l. \tag{C.6}$$

Consider a deviation from this outcome, $c_1 = W, M = 0, r_1 = 0$, then this firm defaults in the low productivity state and its expected payoff is $W + p_h a_h$. So she will not deviate. Consider another deviation $r_1 = b_0, M = 0$. Then, the firm payoff will be: $W + p_h a_h + p_l a_l$, so the firm will be indifferent between deviating and not.

On the other hand, everybody paying $r_1 = b_0$ is not an equilibrium, even if all firms have deep enough pockets, s.t. $M = W - b_0, r_1 = b_0, c = 0$ for each firm. The payment for this outcome is the first best: $W + p_h a_h + p_l a_l$. It is not an equilibrium, however. Consider a deviation where a firm does not pay and does not hoard cash: $r_1 = 0, M = 0, c = W$. The payoff is then $W + p_h(a_h - b_0) + b_0 = W + p_h a_h + p_l b_l$, which is higher than the considered candidate equilibrium.

Importantly for our analysis, there is an equilibrium where everybody pays late and does not save cash, resembling the equilibrium from the model without cash. The equilibrium is $c_1 = W, M = 0, r_1 = 0$, for each i. The payoff is the same as in Case 2: $W + p_h a_h$. Hence, if firms play this equilibrium the clearinghouse will have real effects as in the model without cash.

Insofar, the model has an implication for bankruptcy rates: clearing insures firms from default in low productivity states, if firms have insufficient liquidity. Let us now also introduce additional real effects of these financial shocks.

C.2.2 Clearing and investment

Consider a discrete investment decision in the first period $I = \{0, I_c\}$, that yields in the second period $K_s \in \{K_l, K_h\}$ with probability $p_s \in \{p_l, p_h\}$. The capital productivity is perfectly correlated with the aggregate productivity shock for simplicity. The investment has positive net expected value $p_h K_h + p_l K_l > I_c$. However, in the low investment productivity state the firm actually loses money on the investment $K_l < I_c$.

Assumption 2: $W - I_c + a_l + K_l - b_0 < 0$.

This implies that firms do not have sufficient funds to completely insure themselves against bankruptcy by investing and saving cash at the same time. We introduce this assumption, so that there is a trade off between investing and saving cash. Saving cash reduces the default probability, while investing increases the expected return. Without Assumption 2, firms with sufficient funds would always invest and save cash to avoid default because investment has positive NPV.

Assumption 3: $p_l(W + a_l) > p_h(K_h - I_c)$.

Assumption 3 states that investment is sufficiently unproductive and costly so that firms would rather save cash and avoid bankruptcy than invest. This allows us to study an interesting equilibrium in which firms hoard cash and do not invest.

Proposition 3: *Clearing induces everybody to repay their debts and invest. Default rates decrease.*

Equilibrium Consider a symmetric equilibrium where $I = 0, r_1 = 0, M = W$. Firms save cash to avoid default, they pay late and they do not invest. As in Case 3, the firm is indifferent between paying on time and delaying. However, investing is not a profitable deviation. By investing the firm pays the investment cost I_c and loses expected productivity in the low state $p_l a_l$ because of default. The benefit is only the productivity of capital in the high state $p_h^K K_h$. Because of Assumption 3, this will not be an optimal deviation.

Clearing. We introduce clearing at the end of period 1. Furthermore, we allow firms to optimize again their investment and cash decisions after the clearing allocation is decided. This is done, again, for simplicity of exposition, to avoid adding another period. The results go through if we add an additional period in which the firm has all the decisions as in period 1. After clearing, the firm does not have an incentive to hoard cash anymore, given that it cleared its debts and cannot default. Since the precautionary savings motive is gone and the investment project has positive NPV, the firm decides to invest. Clearing implements the first best allocation.

C.3 Description of control variables

In order to increase the precision of our estimates, we we include many controls in the regression. We also indirectly test the exogeneity of the variation in clearing by including many controls.

Financial statement controls. We include the following financial statement controls: net income over assets, cash over assets, accounts receivable over assets, accounts payable over liabilities, cash over short term liabilities, loans over liabilities, log assets and whether a firm reported their financial statement.

Late receivables and payables controls. We control for log late payables and receivables, log payables and receivables that are late more than 60 days. We also control for log late payables towards the state and receivables from the state, as well as log payables and receivables from the state that are late more than 60 days. We control also for log weighted lateness of payables and receivables, measured in days.

Network spillovers controls. To check whether network spillovers matter, we control for various weighted measures of exposure to spillovers.

We calculate Exposure DC_{it}, an indicator of firm i's exposure to debtors clearing as follows:

$$\text{Exposure to debtors } \text{X}_i = \sum_l X_l \frac{\text{Receivables}_{il}}{\text{Receivables}_i}, \tag{C.1}$$

where by l we have denoted firm i's debtors, X is a measure of debtors financial strength such as debt over assets, $Receivables_{il}$ are i's late receivables from l, and $Receivables_i$ are all late receivables of firm i. We use only receivables from the clearinghouse data, because for other receivables we do not have network information. $\frac{Receivables_{il}}{Receivables_i}$ tells as the exposure of firm i through receivables to a firm l that has a particular indicator of financial strength X. We control for possible clearing spillovers from cleared debtors with $X_l = \frac{\text{Clearing amount}_l}{\text{Payables}_l}$.

For spillovers from creditors, we calculate:

$$\text{Exposure to creditors } \text{X}_i = \sum_j X_j \frac{\text{Payables}_{ij}}{\text{Payables}_i}, \tag{C.2}$$

where j denotes firm i creditors, Payables_{ij} is the debt from firm i to firm j and Payables_i is the sum of all payables of firm i. As with receivables, we include only payables in the clearinghouse data. We control for possible clearing spillovers from cleared creditors with $X_j = \frac{\text{Clearing amount}_j}{\text{Payables}_j}$.

We consider the following characteristics of debtors and creditors: clearing amount over late payables, cash over assets, cash over total liabilities, accounts receivable over assets, accounts payable over total liabilities, log liabilities over assets and log employment.

Inner network controls. As before, denote by l and j the debtors and creditors of firm i. Similarly, denote by l_l and l_j the debtors and creditors of firm l. Also, denote by j_l and j_j the debtors and creditors of firm j. We include the following clearinghouse variables as inner network controls: log payables, log receivables, log number of debtors, log number of creditors, log value of debtors payables - $log \sum_l \sum_{l_j} Payables_{ll_j}$, log value of debtors receivables - $log \sum_l \sum_{l_l} Receivables_{ll_l}$, log number of debtors creditors - $log \sum_l \sum_{l_j} \mathbb{1}(Payables_{ll_j} > 0)$, log number of debtors debtors - $log \sum_l \sum_{l_l} \mathbb{1}(Receivables_{ll_l} > 0)$, log value of creditors payables - $log \sum_j \sum_{j_j} Payablesjj_j$, log value of creditors receivables - $log \sum_j \sum_{j_l} Receivables_{jj_l}$, log number of creditors creditors - $log \sum_j \sum_{j_j} \mathbb{1}(Payables_{jj_j} > 0)$, log number of creditors debtors - $log \sum_j \sum_{j_l} \mathbb{1}(Receivables_{jj_l} > 0)$.

C.4 Empirical strategy in potential outcomes

In this section, we explain our identification strategy using a binary treatment and potential outcomes framework. Let Ω_t be a $n \times n$ adjacency matrix whose ij-th element is debt from a clearinghouse participant i to another participant j at time t, and n is the total number of participants. Thus, the ith row of Ω_t represents i's payables at time t, while the ith column consists of it's receivables. $F(\cdot)$ is the algorithm that outputs the vector of clearing D, an $1 \times n$ vector. Define I_i an $n \times 1$ vector whose ith entry is equal to one, and other entries are equal to zero. Let $F_i(\Omega_t) = F(\Omega_t) * I_i, F_i(\Omega_t) \in \{0, 1\}$, so $F_i(\cdot)$ tells us whether the firm i gets cleared given an adjacency matrix Ω_t. The effect of clearing on an outcome of interest (e.g. default) can be modeled using the potential outcomes framework: $Y_{it+1} = Y_{0it+1} + F_i(\Omega_t)\beta$, where β is the causal effect of clearing and Y_{it+1} is an outcome of interest. Y_{0it+1} is the outcome if the firm does not get cleared.

Denote by IN^{it} the set of debtors and creditors of firm i at time t and add to this set firm i as well. Equate to zero all entries of Ω except rows and columns that are indexed by the elements of IN^{it}. Now we have an $n * n$ matrix of debts and credits of all firms in IN^{it}, which we call Ω^{IN}_{it} - the "inner" network of i.

The "outer network" of i is defined as the complement of the inner network: $\Omega^{O}_{it} = \Omega_t - \Omega^{IN}_{it}$. Our identification assumption is that changes in the outer network $\Delta\Omega^{O}_{it} = \Omega^{O}_{it} - \Omega^{O}_{it-1}$ are exogenous to potential outcomes for firm i: $(Y_{i1t+1}, Y_{i0t+1}) \perp \Delta\Omega^{O}_{it}$. An issue is that we do not have a low dimensional representation of $\Delta\Omega^{O}_{it}$ which would allow us to exploit this variation directly in a regression framework. Hence, we rely on our knowledge of the algorithm and proceed as follows.

Define the alternative network at time t as $\Omega^{A}_{it} = \Omega^{O}_{it-1} + \Omega^{IN}_{it}$. This is an alternative adjacency matrix in which the outer network is the same as in the previous period. The alternative clearing for firm i is $\text{Cleared}^{A}_{it} = F_i(\Omega^{A}_{it})$, which gives us the clearing for firm i if the outer network stayed the same as in the previous period.

Let us define two sets of firms that can identify the causal effect of interest in the binary case.

- Define the set Cleared_t^+ as $i \in \text{Cleared}_t^+$ if $F_i(\Omega_{it}) = 1 \neq F_i(\Omega_{it}^A) = 0$. These are the firms that got cleared, but wouldn't get cleared if the outer network stayed constant.

- Define the set Cleared^- as $i \in \text{Cleared}^-$ if $F_i(\Omega) = 0 \neq F_i(\Omega_{it}^A) = 1$. These are the firms that didn't cleared, but would get cleared if the outer network stayed constant.

We change the identifying assumption $(Y_{i1t+1}, Y_{i0t+1}) \perp \Delta\Omega_{it}^O$ to a new assumption $(Y_{i1t+1}, Y_{i0t+1}) \perp \text{Cleared}_{it}$ if $i \in \text{Cleared}_t^+ \cup \text{Cleared}_t^-$. It states that the treatment is unrelated to potential outcomes for a subset of firms that switch clearing status due to the outer network.

Then a simple mean comparison between these two groups will reveal the causal effect of clearing: $\mathrm{E}(Y_{t+1}|\text{Cleared}_t^+) - \mathrm{E}(Y_{t+1}|\text{Cleared}_t^-) = \mathrm{E}(Y_{0t+1}|\text{Cleared}_t^+) - \mathrm{E}(Y_{0t+1}|\text{Cleared}_t^-) + \mathrm{E}(\beta F_i(\Omega_t)|\text{Cleared}^+) - \mathrm{E}(\beta F_i(\Omega_t)|\text{Cleared}_t^-) = \mathrm{E}(\beta|\text{Cleared}_t^+)$. Given that our identifying assumption implies $\mathrm{E}(Y_{0t+1}|\text{Cleared}_t^+) - \mathrm{E}(Y_{0t+1}|\text{Cleared}_t^-) = 0$.

We use $F(\cdot)$ to find firms that switch the clearing status due to changes in the outer network. A complicating fact is that $F(\cdot)$ is a nonlinear function and the inner network interacts with the outer network to generate a clearing allocation. The inner network is endogenous to firm i outcomes and might thus generate bias in our estimates. We further develop this argument in Subsection C.5. To see if this interaction is creating bias in our results, we control for firm inner network characteristics and we check whether these controls affect our estimates substantially.

C.5 The exclusion restriction

To clearly state the assumptions needed for the exclusion restriction to hold, we assume that the clearing algorithm can be represented as a function of network measures. Specifically, we assume that clearing for the firm i can be represented as a polynomial of inner IN_{it} and outer ON_{it} network measures:

$$lnC_{it} = F(IN_{it}, ON_{it}) + \epsilon_{it}, \tag{C.1}$$

where C_{it} is one plus the cleared amount for firm i, ϵ_{it} comes from the polynomial approximation and ordering of the data that is unobservable but determines a small part of the clearing. For simplicity of exposition assume a simple form: $F(IN_{it}, ON_{it}) = \alpha IN_{it} + \beta IN_{it}ON_{it} + \gamma ON_{it}$.

We define alternative clearing as the clearing that would have occurred if the outer network stayed constant:

$$lnC_{it}^{A} = \alpha IN_{it} + \beta IN_{it}ON_{it-1} + \gamma ON_{it-1} + \epsilon_{it}^{C}. \tag{C.2}$$

Our instrument is the difference between actual clearing and alternative clearing:

$$lnC_{it} - lnC_{it}^{A} = \beta IN_{it}\Delta ON_{it} + \gamma \Delta ON_{it} + \epsilon_{it} - \epsilon_{it}^{C}. \tag{C.3}$$

Notice that because of the interaction term, the difference between actual and alternative clearing still contains the inner network measures. A potential issue is that inner network measures are not exogenous to the firm.

Using this as an instrument yields the first stage:

$$lnC_{it} = \alpha_1 + \beta_1(lnC_{it} - lnC_{it}^{A}) + \epsilon_{1it}, \tag{C.4}$$

where we exclude the vector of controls for brevity. The second stage is:

$$Y_{it+1} = \alpha_2 + \beta_2\widehat{lnC_{it}} + \epsilon_{2it}, \tag{C.5}$$

where $\epsilon_{2it} = \lambda_1 IN_{it} + \lambda_2 Z_{it} + \nu_{it}$ is the source of identification concerns. This definition of ϵ_{2it} explicitly assumes that the outer network does not determine firm outcomes after taking into account the inner network measures. ν_{it} is also not a source of concern, it is a pure random component left over after taking into account all non-random aspects of our outcome variable. The inner network, however, is a possible determinant of the outcome variable and it is also a part of the variation in our instrument. Z_{it} are the unobservable characteristics that partly determine the outcome variable and may also be correlated with the inner network measures.

The exclusion restriction is:

$$\text{Cov}(\lambda_1 IN_{it} + \lambda_2 Z_{it}, lnC_{it} - lnC^A_{it}) = 0. \tag{C.6}$$

Decompose Z_{it} into a part that is correlated with IN_{it} and one that is not: $Z_{it} = \gamma IN_{it} + Z^r_{it}$, where Z^r_{it} is the residual part of unobservables that is not correlated to IN_{it}. Thus, the "problematic" part of Equation C.6 is $(\lambda_1 + \gamma)IN_{it}$, because $\text{Cov}(Z^r_{it}, lnC_{it} - lnC^A_{it}) = 0$ given our identification assumption that changes in the outer network are exogenous. To reduce notation define $\lambda_3 = (\lambda_1 + \gamma)$.

After taking into account our original identification assumption, we are left with the term:

$$\text{Cov}(\lambda_3 IN_{it}, lnC_{it} - lnC^A_{it}) = \text{Cov}(\lambda_3 IN_{it}, \beta IN_{it}\Delta ON_{it} + \gamma \Delta ON_{it} + \epsilon_{it} - \epsilon^C_{it}), \tag{C.7}$$

where $\text{Cov}(\lambda_3 IN_{it}, \Delta ON_{it}) = 0$ and $\text{Cov}(\lambda_3 IN_{it}, \epsilon_{it} - \epsilon^C_{it}) = 0$ by the identification assumption. The interaction term between inner and outer network measures induces possible violations of the exclusion restriction:

$$\text{Cov}(\lambda_3 IN_{it}, \beta IN_{it}\Delta ON_{it}) \neq 0. \tag{C.8}$$

However, if we can control for the inner network measures the bias disappears:

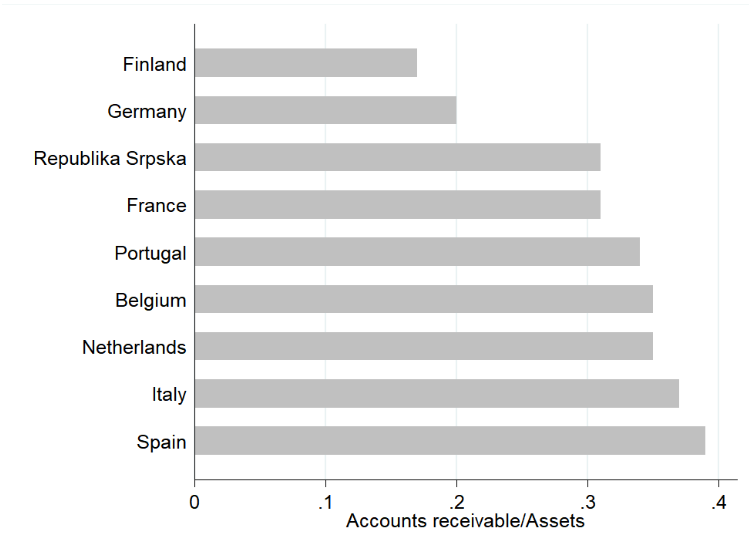
$$\text{Cov}(\lambda_3 IN_{it}, \beta IN_{it}\Delta ON_{it}|IN_{it}) = \lambda_3 \beta IN^2_{it}\text{E}(\Delta ON_{it}|IN_{it}) - \lambda_3 \beta IN^2_{it}\text{E}(\Delta ON_{it}|IN_{it}) = 0. \tag{C.9}$$

This means that if the inner network measures determine the outcome variable of our interest and there is an interaction between inner and outer network measures in the algorithm, then we must control for the inner network. Otherwise, the exclusion restriction is violated. We control for a plethora of inner network measures, and the estimates barely change suggesting that they are not biasing our estimates.

C.6 External Validity

Compared to a group of EU countries the average trade credit over total assets for Republika Srpska is not unusually high or low (Figure C.2). This suggests that the amount of clearing should be sizeable also in other countries.

Figure C.2: Accounts receivable over assets



Source: Ferrando and Mulier (2013) and own calculations.

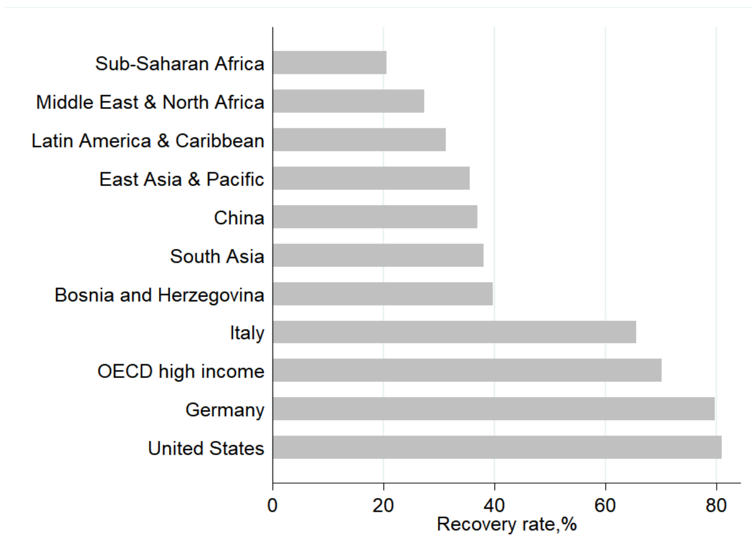
Slovenia, a high income EU country, has an operating trade credit clearinghouse system. Parallel with the government organized clearinghouse there is also a privately owned one, which is performing clearing at a similar scale[13]. In 2020, these clearinghouses cleared $\approx 0.8\%$ of GDP combined, which is lower than in the case of Republika Srpska (1.5% of GDP). In Slovenia, the government is not an active participant in clearing and thus there are less clearing cycles. In both economies, clearing is voluntary, except for firms with blocked bank accounts. If clearing would be mandatory, then the cleared amounts could be much higher. It is not evident, however, whether mandatory clearing would be beneficial given possible perverse incentives discussed in Rostowski (1994) and in Subsection 7.2. Since multilateral netting is performed only for trade credit issued to domestic counterparties, relatively closed economies like the US, EU, China and India might clear a substantially larger share of trade credit than in small open economies of Republika Srpska and Slovenia.

In Section 4 we argue that the clearinghouse has real effects because of financing constraints and costly default. Financing constraints are especially prominent in developing

[13]See https://www.ekompenzacije.com/. Accessed on 30th of May 2022.

economies (Banerjee, 2001; Banerjee and Duflo, 2014), but they are also important in developed ones, especially for SMEs (Whited and Wu, 2006; Hadlock and Pierce, 2010; Buehlmaier and Whited, 2018). It is hard to measure the cost of bankruptcy, especially across countries. We use the recovery rate for secured creditors measured by the World Bank. While the court system in Bosnia and Herzegovina is especially inefficient, there are many countries that have the same or lower recovery rate (Figure C.3). There is evidence that bankruptcy is quite costly even in the US (Glover, 2016), although by international standards it has a high recovery rate.

Figure C.3: Recovery rate, %



Source: World Bank Doing Business. Recovery rate represents cents on the dollar recovered by secured creditors through reorganization, liquidation or debt enforcement (foreclosure or receivership) proceedings.

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