Economic Resilience: Spillovers, Courts, and Vertical Integration*

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Abstract

We investigate the impact of institutions on the transmission of shocks across firms. Using novel inter-firm wire transfer data, we find that suppliers exposed to natural disasters pass this shock to their customers particularly when the *customers'* court system is congested. Evidence suggests that congested courts amplify spillovers through potential future holdup problems: customers face frictions both in contracting with new suppliers and in obtaining bank credit. Subsequently, customers integrate the affected supplier's industry and obtain liquidity by selling their accounts receivables. Results highlight the importance of institutions in facilitating economic resilience.

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1 Introduction

Firms are profoundly interconnected. Annual firm-to-firm transactions constitute twice the size of the GDP in major economies.[1] A stream of papers in macroeconomics estimates that localized shocks transmit through input-output linkages and explain between 50 and 83 percent of aggregate fluctuations (Foerster et al., 2011; Acemoglu et al., 2012; di Giovanni et al., 2014; Atalay, 2017; Carvalho et al., 2016).[2] The recent outbreak of Covid-19 that rattled both global and domestic supply chains has put supply chain resilience at the forefront of the policymakers, academics, and practitioners alike (European Parliament, 2020; Garnett et al., 2020; Guan et al., 2020; Kearney Consulting, 2020).[3] There is a growing urgency in understanding how supply chain disruptions can be alleviated in order to minimize further economic distress.[4]

In this paper, we investigate the role of courts in this transmission. Courts are essential for firm-to-firm relationships, since they bear the ultimate authority to enforce a contract between contracting parties. While courts are an important determinant in choosing business partners (Johnson et al., 2002), the overall effect of court quality on the transmission of shocks is ambiguous. Imagine a downstream firm facing disruptions due to a sudden loss of a supplier that provides inputs and trade credit. How does the ability to enforce a contract from the customer affect the resilience of this customer?

Courts could affect the downstream firm *positively* and *negatively* through their effect on both *potential* and *existing* relationships. On one hand, strong courts should mitigate hold-up problems with *potential* contracting parties and facilitate contracting (Hart and Moore (1988), Hart (1995)), enabling the customer to recover faster by both contracting with alternative suppliers and obtaining additional funds from creditors. On the other hand, court congestion might shield this customer against lawsuits from *existing* counterparties

[1] World Input Output Database (Timmer et al., 2015).

[2] The economic effects can be sizeable. Carvalho et al. (2016) find that input-output linkages accounted for 1.2% loss of GDP after the Great Japanese earthquake.

[3] See also evidence of this recent discussion in the press: Financial Times "EU Industrial supply lines need strengthening, commissioner says" May 5th, 2020; Bloomberg "Trump White House Turns to Military for New Supply Chain Mission" April 25th, 2020. Recent evidence also suggests that firms emerging from lock-downs in Asia are focusing on building up resillience in their operations and supply chains to avoid further disruptions (Chenneveau et al., 2020).

[4] While there is ample evidence that localized shocks propagate across firms (Long and Plosser, 1987; Horvath, 1998, 2000; Atalay et al., 2011; Boehm et al., 2018), far less is known about economic factors that drive this transmission (some exceptions include, Barrot and Sauvagnat, 2016; Carvalho et al., 2016; Costello, 2020).

and give it more time to restructure its operations and replace the affected supplier (Aghion et al., 1992; Hart et al., 1997; Vig, 2013). In fact, firms quite often resort to courts to delay the fulfilment of their obligations, for instance, through filing for Chapter 11 in the US.[5] Slow courts might delay the fulfilment of these obligations even further. In the light of this literature, the goal of this paper is threefold: examine whether court quality amplifies or mitigates spillovers of localized shocks, to assess its relative importance, and to investigate the underlying channels through which courts affect spillovers.

In this paper, we use detailed wire transfer data from the Brazilian System of Payments, to construct customer-supplier relationships for manufacturing firms in Brazil.[6] We find that large and unexpected natural disasters propagate from suppliers to their customers particularly when *customers*' court system is congested. The evidence supports contracting frictions – in the form of future hold-up problems – with both suppliers and creditors. First, consistent with the difficulty in outsourcing inputs, connected customers seem to integrate the affected supplier's industry after a shock. Second, consistent with the difficulty in obtaining new bank credit, customers outsource credit risk through factoring their accounts receivables and customers with unused credit lines suffer less.

There are three fundamental challenges in establishing a link between court quality and transmission of shocks empirically. The first one relates to data. To examine the propagation along the supply chain, one needs to observe customer-supplier relationships, which is very difficult to come by. The second and third challenges relate to severe endogeneity concerns. At first, one needs to identify shocks that are randomly assigned. Otherwise, the documented propagation might be measuring a common trend such as a decline in demand for all firms in the supply chain rather than a shock to the initial supplier. Then, court quality is endogenous and correlates with various characteristics such as local firm quality. Thus, propagation might be different in areas with weaker courts due to the low quality of firms rather than courts themselves.

We start our analysis by examining the propagation of shocks, stemming from natural disasters, along the supply chain. We collect data on all large weather shocks (floods, storms, hailstorms, etc.) that are considered as emergency situations by the federal government

[5] In Brazil, about 30% of judges in Brazil argue that firms frequently use congested courts to delay obligations strategically (Pinheiro, 2003).

[6] This data records all inter-bank transfers, recording both the amount of transfer and the direction of the flow between the two firms. For more details please refer to Section 2.2.

in Brazil and that cause at least BRL 100 million in damages.[7] We use a difference-in-differences research design and analyze firms in municipalities that are *not* directly affected by these disasters. Specifically, we compare firms whose suppliers are located in a disaster-struck municipality against those firms whose suppliers are located elsewhere. A potential concern is that connected customers might be geographically closer to disaster areas than unconnected firms, and thus be directly affected by the shock. We deal with this issue by comparing connected and unconnected firms *within* the same *unaffected* municipality and industry, thereby controlling for all demand and supply shocks within each local industry.

We find that shocks propagate to downstream firms. These customers experience a drop of 9.1 percent in cash inflow in the two years after the shock relative to unconnected firms in the same local industry. Downstream firms also purchase fewer goods from their suppliers as well as sever relationships with some suppliers, since both cash outflow and number of suppliers relatively decrease by 17 percent. The propagation also impacts firms' employment. After the shock, connected customers employ 2.2 percent fewer workers relatively to unconnected firms. Altogether, results suggest that customers of affected suppliers experience a significant disruption in their manufacturing.

The propagation of shocks is particularly severe in areas with weak court enforcement. Important for our setting, court-shopping is prohibited in bankruptcy, since under the Brazilian civil law bankruptcy cases must be filed in the jurisdiction of the defendant's headquarter.[8] Therefore, our court congestion measure proxies for the credibility of current and potential future contracts that might be dishonored by the downstream firm that experienced input disruptions and needs to 'replace' the affected supplier. To measure local court quality, we follow Ponticelli and Alencar (2016) and use information on courts' congestion from National Council of Justice (CNJ). We construct a municipality-level variable of court congestion as the ratio of total backlog of cases per judge. The quality of courts is weaker when the measure of court congestion is higher. The correlation between court congestion and length of litigation is 77 percent at the state level (see Figure 3).[9] The average duration of a court case in Brazil is two years and four months. Resolution of a court case takes by

[7]Using event study approach, we find that markets did not anticipate these disasters and connected firm value declined around these disasters (see Section 4.4).

[8]While firms could move their headquarters over time, this happens seldom – only 0.2 percent of large firms do so.

[9]Since data on length of litigation is available only at the state level, we rely on the local court congestion measure in our analysis. Furthermore, using a confidential sub-sample of court cases, Ponticelli and Alencar (2016) show that results of their study are unaltered when one performs the analysis with length of litigation as a measure of court inefficiency.

about one year longer in the 75th relative to the 25th percentile of court congestion.

We find that input disruptions are more severe for downstream firms located in areas with congested courts. A one standard deviation increase in court congestion (an increase of about 8 months) results in a further drop in cash inflow by 4.8 percent relative to the mean effect of 9.1 percent. We find similar effects in other outcomes. Downstream firms' cash outflow decreases by additional 4.2 percent, the number of suppliers by 3.3 percent, and the total number of employees by 2.5 percent with a one standard deviation increase in court congestion. Overall, the results are consistent with the view that weaker courts amplify the propagation of negative shocks, since downstream firms are less likely to fully replace their affected suppliers due to contracting frictions.

The main concern with the interpretation of the results above is that endogenously determined court quality may be correlated with other local characteristics such as quality of firms. To alleviate such concerns, we strengthen the interpretation by exploiting pre-determined state laws that determine the creation of judicial districts (Ponticelli and Alencar, 2016). Brazil's over 5,500 municipalities are organized in roughly 2,500 judicial districts. The size of these districts is determined by state laws that establish the minimum requirements that a municipality must satisfy to become the seat of a judicial district. Jurisdiction over municipalities that do not meet the requirements is assigned to an adjacent municipality that is the seat of a judicial district, making existing courts more congested. Thus, our measure of potential extra-jurisdiction equals the number of neighboring municipalities that do not meet the requirements. We find that this variable strongly predicts congestion of civil courts. Municipalities with a one standard deviation higher potential extra-jurisdiction have 9.1 percent more congested civil courts. In contrast, potential extra-jurisdiction is uncorrelated with differences in observable characteristics between connected and unconnected customers prior to a shock.

The results obtained with this identification strategy are consistent with the results above. Downstream firms in municipalities with a one standard deviation higher potential extra-jurisdiction experienced a 14 percent larger drop in cash inflows in the two years after the shock. Similarly, downstream firms in these municipalities experienced a 8.6 percent additional drop in cash outflow, 5.1 percent lower number of suppliers, and employed by 5.2 percent fewer workers in the same time period.[10]

[10]These results are robust to controlling for observable differences among both firms and judicial districts. See Internet Appendix Table A.6.

We present a set of additional results that lend support to the interpretation of our estimates. First, a concern might be that firms in congested areas are connected to more specific suppliers, or suppliers more affected by the shock. To alleviate this, we compare the effect of propagation for customers connected to the *same* supplier but located in municipalities with different levels of court congestion. Thus, we control for all time-varying characteristics of this supplier, common time-varying trends among all firms connected to this supplier as well as the reasons why firms might want to connect with this supplier. We find our results remain unchanged.

Another possibility could be that municipalities with low court congestion are located nearby large economic centers, providing a lot of alternative suppliers that could replace the *same* affected supplier of the downstream firms. This would imply that the propagation is more severe in municipalities with congested courts because there are no alternative suppliers rather than the weak contract enforcement by courts. To address this, we compare the effect of propagation on the customers located in two adjacent municipalities and connected to the *same* affected supplier. In this setup, costs associated with replacing the affected supplier, for instance transportation costs, should be comparable for downstream firms. Our results remain unchanged.

There are several channels through which courts could affect the transmission of shocks. The first one relates to the classic hold-up problem that can affect contracting with both suppliers and creditors (Hart and Moore, 1988). Suppliers and banks might reduce credit supply to downstream firms facing inefficient courts in anticipation of future hold-up problems in case of a default. Alternatively, potential new suppliers might not want to contract with the downstream firm if it requires a relationship-specific investment which the supplier might be unwilling to make due to potential future hold-up problems (Grossman and Hart, 1986). Another mechanism could be through moral hazard. Downstream firms located in areas with stronger courts might have higher order incentives to replace the affected supplier, since other suppliers and customers can file a lawsuit against the connected firm for dishonouring contracts. Thus, customers in areas with weaker courts might work less to recover from the loss.

Our evidence highlights contracting frictions with both creditors and alternative suppliers. We start by examining the credit channel. Consistent with liquidity value of credit lines, we find that the propagation is less severe for connected downstream firms that have larger balances of unused credit lines just before the shock hits. Furthermore, we find important differences in how connected downstream firms in areas with weak courts contract with banks after a shock. While these customers rely less on standard working capital loans after a shock, they are more likely to factor their accounts receivables, particularly, in court congested areas. Since in factoring banks are more concerned with the creditworthiness of the borrower's customer who made the initial promise to pay, the borrower 'outsources' the credit risk to its customers. Consistent with 'outsourcing' court quality to customers with better courts, we find that downstream firms use this type of contract relatively more when the quality of their customers' courts are better in comparison to the their own courts. Overall, the evidence supports the view that congested courts amplify propagation of shocks through the credit channel.

Connected downstream firms also struggle forming new relationships with alternative suppliers when courts are weaker. To overcome this contracting friction, connected customers in weak court areas seem to integrate part of the affected input by acquiring firms and hiring workers from the affected supplier's industry. Specifically, we find that downstream firms located in areas with weak courts are more likely to hire specialist employees who used to work in the same industry as their affected supplier. This suggests that firms are acquiring human capital with experience in manufacturing the disrupted input. Furthermore, we also find that downstream firms located in areas with weak courts are more likely to acquire a firm operating in the same industry as the affected supplier. Both of these results suggest that connected downstream firms mitigate their production disruptions in part by integrating some of the previously outsourced inputs when local court quality is weak. These findings are consistent with the survey evidence by Johnson et al. (2002) who document that firms find it easier to contract with other firms when courts are effective.

The results in this paper touch on several strands of literature. The paper is most closely related to the literature assessing the propagation of shocks in production chains. While historically the dominant view was that idiosyncratic shocks should cancel out in the aggregate (Lucas, 1977), recent studies highlight that micro shocks can affect the economy at large. A stream of papers argues that shocks to central firms can affect total output (Gabaix, 2011; Carvalho and Gabaix, 2013). Others argue that shocks are transmitted in the economy through industry linkages (Long and Plosser, 1987; Jovanovic, 1987; Durlauf, 1993; Bak et al., 1993; Horvath, 1998, 2000; Conley and Dupor, 2003; Carvalho, 2010; Acemoglu et al., 2012; di Giovanni et al., 2014; Caliendo and Parro, 2015; Caselli et al., 2015; Baqaee, 2018; Bigio and La'O, 2016; Ozdagli and Weber, 2017; Costello, 2020). Our work is closest to empirical studies by Barrot and Sauvagnat (2016), Boehm et al. (2018), and Carvalho et al. (2016) who also leverage natural disasters to study the role of firm-level linkages in propagating input disruptions.[11] Barrot and Sauvagnat (2016) document that shocks propagate if the affected supplier is specific and hard to substitute. The former two papers examine supply-chain effects of the Japanese earthquake in 2011 across countries (Boehm et al., 2018) and within Japan (Carvalho et al., 2016). We contribute to these papers by documenting that the propagation of shocks is amplified in presence of weak courts.

Our results also relate to the literature examining the relationship between institutions and economic development (Djankov et al. (2003), Nunn (2007), Levchenko (2007), Acemoglu and Johnson (2005) among many others). The law and finance literature argues that better institutions such as courts reduce contracting frictions and facilitate access to finance (La Porta et al. (1997, 1998); Levine (1999); Qian and Strahan (2007); Djankov et al. (2007); Davydenko and Franks (2008); Ponticelli and Alencar (2016)). We contribute to this literature by examining how court quality affects customer-supplier relationships. Our results suggest that negative effects of losing a supplier are more severe when courts are weak. Furthermore, our back of the envelope estimates suggest that losses due to propagation can be sizable on local *unaffected* economies. This has important policy implications, since our findings point out that production networks in economies with weak courts are more fragile.

Finally, our paper contributes to the literature on firms' boundaries and determinants of industry structure (most notably, Coase, 1937; Williamson, 1975, 1985; Klein et al., 1978; Grossman and Hart, 1986). Some previous empirical studies have shown that asset ownership creates incentives to preserve asset value (Baker and Hubbard, 2004) and that vertical integration can lead to economies of scale (Hortacsu and Syverson, 2007) and facilitate intra-firm transfer of intangible assets (Atalay et al., 2014).[12] Nunn (2007) argues that countries with strong contract enforcement specialize in manufacturing inputs that require relationship-specific investments. Our paper is closest to Boehm and Oberfield (2020). While they analyze how court quality affects industry structure, we document how quality of local courts affects propagation of shocks. Our evidence that firms in areas with weak courts seem to replace their distressed suppliers by integrating the production input is consistent with

[11] Other notable contributions include Horvath (2000), Foerster et al. (2011), Jones (2011), Atalay (2017), di Giovanni et al. (2014)

[12] Breza and Liberman (2017) document that a retailer integrates its suppliers when the set of permissible trade credit contracts is limited by the government. Skrastins (2020) argues that lenders in Brazil reduce credit and insurance frictions in farming by integrating grain warehouses, particularly, in areas with weak courts.

their prediction that firms would vertically integrate their suppliers if contract enforcement is weak.

2 Institutional Background and Data

2.1 The Brazilian Judiciary

In Brazil, firm-to-firm disputes are handled by state civil courts. The state-level judicial system is organized in geographical areas known as judicial districts or *comarcas*. These districts comprise one or several municipalities, depending on whether a municipality meets the requirements to become a seat of their own judicial district. These requirements are defined by state laws and are usually based on criteria such as the minimum level of population, number of voters, number of judicial cases distributed, and tax revenues.[13] If a municipality does not meet the requirements, jurisdiction of its cases is assigned to an adjacent judicial district, which would be responsible for cases from this municipality in addition to its own.

Brazil is an ideal laboratory to study how the quality of the judicial system affects the transmission of shocks in the economy for two main reasons. First, Brazilian laws establish that bankruptcy cases must be filed in the civil court that serves the area where the defendant's headquarter is located. In other words, when a supplier files a bankruptcy case against a customer for a missed payment, this case is handled by the courts in the judicial district of the customer. Similarly, when a customer files a bankruptcy case against a supplier for not delivering on a contract, such a case would be handled by the judicial district of the supplier. Thus, shopping for the most favorable court is not an option in bankruptcy. Second, Brazil offers vast cross-sectional variation in the quality of its judiciary (see section 4.2 for more details).[14] The average insolvency proceedings last for two years and four months.[15] Resolution of a court case takes by about one year longer in the 75th relative to the 25th percentile of court congestion.

[13]These requirements can be found in Table A1 of Ponticelli and Alencar (2016).

[14]Furthermore, the Brazilian legal system follows the first-in-first-out approach in resolving cases (see law 13,105), making the congestion rate particularly important.

[15]We take this number from National Justice Council's (CNJ) *Justiça em Números* survey in 2015. Doing Business Database, World Bank reports a slightly higher duration of four years. This is because they only consider courts in Rio de Janeiro and São Paulo.

2.2 Data

We use transaction-level data from the Brazilian Payment Systems, more specifically *Sistema de Transferência de Reservas* (STR) and *Sistema de Transferência de Fundos* (CIP-Sitraf), to construct our supplier-customer network. Both STR and CIP-Sitraf are real time gross settlement payment systems that record all electronic interbank transactions in Brazil. This data also provides information on the exact time of the transaction, and identifiers of creditors and debtors. There are about 1.1 billion transactions with a total transaction volume of R$ 76 trillion among individuals and firms between January 2007 and June 2016. We focus on all firm-to-firm transactions (excluding all financial sector firms). This leaves us with approximately 530 million transactions among more than 2 million firms with total amount traded of about R$ 67 trillion.[16]

With this firm-to-firm wire transfer data, we classify firms into suppliers and customers by following the direction of money transfers. Suppliers are the firms that receive the money, while customers are those that send the money. Since we are interested in production networks, we consider only manufacturing firms in defining the network. We also use this dataset to construct firm specific measures of total cash inflow and cash outflow.

Information on disasters comes from the Brazilian Integration Ministry, which is the federal entity responsible for declaring emergency situations after natural disasters. These natural disasters include events such as storms, droughts, fires, or landslides in which public and private losses are at least 2.77% and 8.33% of the current municipality revenue, respectively. We focus on the 13 largest emergency situations from 2008 to 2015. These natural disasters each caused damages greater than R$ 100 mln. These shocks constitute floods, storms, and hailstorms and they directly affected 70 different municipalities during our study.[17]

Data on local courts comes from *Justiça Aberta*, a public dataset made available by National Justice Council (CNJ). The CNJ collects data on court productivity through monthly reports filled by each court in Brazil. These reports contain information on location and productivity of all Brazilian courts, such as the number pending, new and sentenced cases, as well as the number of judges in each court. As noted above, we focus on civil courts, since

[16] To give an idea of how large this amount is, we divided the total amount transferred per quarter by the quarterly nominal GDP and found out the total amount transacted is on average 131% of the GDP.

[17] Using event study approach, we find that connected customer's value declined abnrmally around the natural disaster (see Section 4.4). This further suggests that these events were not predictable.

these are responsible for judging cases involving firms.

To track employment, we use data from RAIS (*Relação Anual de Informações Sociais*), a large restricted-access matched employee-employer administrative dataset from Brazil. The RAIS database records information on all formally employed workers in a given year and is maintained by the Ministry of Economics of Brazil. All formally-registered firms in Brazil are legally required to report annual information on each worker that the firm employs. RAIS includes detailed information on the employer (tax number, sector of activity, establishment size, geographical location), the employee (social security number, age, gender, education), and the employment relationship (wage, tenure, type of employment, hiring date, layout date, reason for layout, etc.). We use data from RAIS for the period from 2006 to 2015. By the end of 2014, the database covers about 50 million formal employees. We focus on all manufacturing firms that employed at least 100 workers in the year before each shock, which are officially classified as large firms in Brazil.[18] Additionally, we use information on the location of the firm (municipality), its two-digit industry classification (National Classification of Economic Activities).[19]

Finally, we utilize firms' cross ownership data from *Receita Federal* (the analogue of the IRS in the US). All firms in Brazil, including those held privately, are required to report ownership stakes in other firms. This data includes information such as the acquired stake, position held, and the date of acquisition.

2.3 Summary Statistics

In Table 1, we report our main variables that we employ in our analysis. In the top panel we report statistics on connected and unconnected firms separately. In the bottom panel, we report statistics on connected customers in judicial districts with high and low court congestion separately. All variables are measured in the year before shocks hit suppliers.

There are 3,957 connected and 119,402 unconnected firms in our sample. Connected firms are larger, which is common in the network literature (e.g., Barrot and Sauvagnat, 2016). The average annual cash inflows and outflows for connected customers are 125 and

[18] These firms constitute around 80 percent of manufacturing output in Brazil.

[19] The standard industry classification in Brazil is given by *Classificação Nacional das Atividades Econômicas* (CNAE). This classification consists of 673 groups at the 4 digit level, 285 at the 3 digit level, 87 at the 2 digit level, and 21 economic sectors.

165 million reais, respectively.[20] In contrast, unconnected firms cash inflows and outflows are circa 31 and 28.9 million reais, respectively. Connected customers have, on average, about 321 suppliers[21] and 992 employees. Unconnected firms have about 79 suppliers and 355 employees.

In the bottom panel we report the summary statistics of downstream firms in high and low congestion districts. Our measure of court congestion is the backlog of cases per judge in a judicial district (see for more details in Section 4.2). The average congestion rate in Brazil is 3,326 cases outstanding per judge. The connected customers in high congestion judicial districts are similar in size and, if anything, slightly larger than connected customers located in low court congestion municipalities. These firms on average have cash inflows and outflows of 129 and 171 million reais, they have about 337 suppliers and employ 1,008 workers. In the same time, connected customers in low congestion areas have cash inflows and outflows at 117 and 152 million reais, about 291 suppliers and 954 employees.

3 Empirical Strategy

3.1 Propagation of Shocks

This section presents our main empirical strategy to identify the effect of a supply disruption on firm performance along the supply chain. To begin, we employ 13 largest natural disasters declared as emergency situations and directly affecting firms located in 70 municipalities between 2008 and 2015 as shocks to our production network. The production network is constructed using the wire transfer data from the Brazilian System of Payments. We define a firm as connected if we observe that it transferred funds to (purchased inputs from) a supplier that is located in a directly affected municipality in the two-year window before the shock. Since we are interested in the transmission of the natural disaster along the supply chain, we focus *only* on firms located in unaffected areas by comparing firms that have a supplier in disaster-struck areas against those that have suppliers elsewhere. We classify connected and unconnected firms for each shock separately, thereby creating a shock-firm-year panel.

[20] Cash inflows tend to be smaller than outflows, since some firms sell also to retail customers. Most of retail payments are done through credit/debit card transactions, which fall outside the inter-bank payment system.

[21] The number of suppliers is measured as the distinct connections that a firm is transferring money through the inter-bank payment system.

To illustrate our identification strategy, consider Figure 1. Imagine municipality A is hit by a natural disaster. For our analysis, we would consider all firms in municipalities that were not directly affected by the shock, e.g., municipality B. In municipality B, connected customers are defined as those that had a supplier from the affected municipality A before the shock. To assess the extent of propagation, we compare the performance of connected customers in municipality B after the shock with the performance of these firms before the shock. However, other things, such as the economic environment, may have affected the performance of firms in municipality B. Unconnected firms in municipality B, as a control group, would help to account for changing economic conditions and all other time-series variation in municipality B. The difference between those two differences would then serve as our estimate of the effect of propagation through the supply chain. Similar reasoning would apply for all other natural disasters.

As the example illustrates, we use a difference-in-differences (DiD) empirical design where we compare connected against unconnected firms in unaffected areas within each shock by estimating the following model:

$$\ln(\text{Cash Inflow}_{ist}) = \alpha_{is} + \alpha_{mkst} + \delta \cdot \text{Connected}_{is} \cdot \text{Post}_{st} + e_{ist} \tag{1}$$

where *ln(Cash Inflow$_{ist}$)* is log of cash inflows for firm i in year t around the natural disaster s. The variable $Connected_{is}$ is a dummy equal to one if firm i was a direct customer of a supplier located in an area hit by the natural disaster s in a two-year window prior to the shock, and zero otherwise. The dummy variable $Post_{st}$ takes the value of one for the two years after the natural disaster s and zero for the two years before. The firm-shock fixed effect (α_{is}) controls for all firm-specific time invariant characteristics and ensures our estimated effect is measured within a firm. The time fixed effect (α_{mkst}) warrants that we compare firms within the *same* unaffected municipality m and industry k within each shock s, controlling for aggregate changes in the supply and demand within each local industry. This fixed effect also ensures that we compare firms within similar geographical proximity to the shocked area, alleviating the concern that the propagation is driven by a geographical proximity to the shock (e.g., due to co-agglomeration as in Ellison et al. (2010)).

The parameter δ measures the extent of propagation of natural disasters to connected customers. A negative value of δ implies that the total cash inflow after the shock declines for connected customers relative to unconnected firms, implying that shocks propagate along the supply chain. Similar interpretation applies to other outcome variables: total cash outflow, number of suppliers, and total employment.

3.2 Court Congestion and the Propagation of Shocks

To examine whether court quality affects the propagation of shocks, we begin by exploiting cross-sectional variation in the congestion of civil courts across Brazil. As in Ponticelli and Alencar (2016), we use data from National Justice Council and measure the local court congestion as the ratio between the backlog of outstanding cases and the number of judges in each judicial district. The lower the ratio, the stronger the local court is. We modify specification (1), by interacting the treatment effect with our measure of court quality:

$$\begin{aligned} \ln(\text{Cash Inflow}_{its}) &= \alpha_{is} + \alpha_{mkst} + \gamma \cdot \text{Connected}_{is} \cdot \text{Post}_{st} \\ &\quad + \delta \cdot \text{Connected}_{is} \cdot \text{Post}_{st} \cdot \text{Court Congestion}_{m} + e_{ist} \end{aligned} \tag{2}$$

where *Court Congestion*$_m$ is equal to the log of the ratio between backlog cases and the number of judges in municipality m where firm i is located. A negative value of δ implies that the propagation is more severe for connected customers located in areas with weaker courts. The main concern with the specification above is that court congestion is endogenous and could, for instance, correlate with the quality of local firms. We discuss this in detail in Section 4.3 where we propose another empirical strategy to address this concern exploiting a set of pre-determined rules in the allocation of courts.

4 Results

4.1 Propagation of Shocks

We start by depicting the time series evolution of firm-level outcomes in the two-year window around the natural disasters in Figure 2. The solid lines represent the evolution of outcomes for downstream firms, while the dashed lines depict the values for unconnected firms. Year 0 is measured one month before the occurrence of each natural disaster for both connected and unconnected firms.

Cash inflows drop significantly for connected relative to unconnected firms after the disaster hits (top left panel in Figure 2).[22] Importantly, before the disaster both types of firms follow a similar trend, mitigating concerns that our results might be driven by differential trends between connected and unconnected firms. Other outcomes – cash outflow (top right panel), number of suppliers (bottom left panel), and total employment (bottom right panel)[23] – follow a similar pattern. Trends are similar between connected and unconnected firms before the shock, but after the shock all outcomes relatively decline for connected customers.[24] This evidence is consistent with the propagation of natural disasters to the firms that are located in unaffected areas but connected to suppliers located in disaster-struck areas.

We also confirm the propagation statistically by estimating equation (1). Table 2 presents the results. We find that cash inflow declines by 9.1 percent for connected customers relative to unconnected firms in the same unaffected local industry (Column I). We find similar patterns in other variables. The total cash outflow and the number of suppliers relatively decline by about 17 percent for connected customers (Columns II and III).[25] Employment shrinks by 2.2 percent for connected relative to unconnected firms (Column IV).[26] The statistical evidence is consistent with the graphical evidence from Figure 2 that localized natural disasters propagate to downstream firms.[27]

4.2 Court Congestion and the Propagation of Shocks

The previous section documents that shocks propagate through the production network. This section tests whether court congestion affects the intensity of the propagation. Since

[22] Cash inflow is defined as the sum of all payments received by firm i in the years around the shock s from the Brazilian System of Payments.

[23] Cash outflow is defined as the sum of all cash payments made by firm i in the years around the shock s from the Brazilian System of Payments. Using the same data, the number of suppliers measures the total number of firms that firm i made payments to in the years around the shock s. Total employment captures the stock of employees that firm i employs in the years around the shock s.

[24] A dynamic regression model gives the same results - parallel trends before the shock with propagation to connected customers appearing just after a shock (Internet Appendix Table A.1).

[25] Results are virtually unchanged when we exclude the affected supplier from this analysis (Internet Appendix Table A.2).

[26] Our results are robust to controlling for whether or not firms were also shocked through a customer relationship (Internet Appendix Table A.3). Furthermore, results are robust also to firm size (Internet Appendix Table A.4).

[27] It is worth noting that by using inter-bank wire transfer data we observe only part of the total network of all firm-to-firm connections. For instance, some firms might pay in cash rather than use wire-transfer. Thus, some firms that might be connected to the affected areas are classified as unconnected. This, however, would create a bias against finding our results, since our control group would also respond to the shock and, therefore, introduce the classic attenuation bias due to more noisy estimates.

the Brazilian civil process determines that lawsuits involving bankruptcy proceedings must take place in courts located in the area of the defendant's headquarters, this paper focuses on the court quality at connected customers firm's headquarters. Thus, we examine how the credibility to enforce contracts of the connected customer affects the propagation of shocks. As described earlier, the ex-ante prediction is ambiguous. Weak courts might protect against inefficient liquidation, therefore, mitigating propagation. In contrast, such courts might also deter future contracting due to anticipated hold-up problems such as ex-post inefficient renegotiations (Hart and Moore, 1988).

Our proxy of court quality is the log of backlog cases divided by the number of judges, at the location of connected customers' headquarters.[28] Higher values of court congestion mean that it takes more time for a case to be sentenced in that particular location, i.e. courts are weaker. The average congestion rate in Brazil is 3,326 cases outstanding per judge with a standard deviation of 5,069. The correlation between court congestion and length of litigation is 77 percent at the state level (see Figure 3).[29] The average duration of a court case in Brazil is two years and four months. Resolution of a court case takes by about one year longer in the 75th relative to the 25th percentile of court congestion. Figure 4 plots the cross-sectional variation in court congestion sorted into deciles. As the figure shows, there is considerable variation in court quality across the country.

We find that connected customers, located in judicial districts where courts are more congested, suffer more from the propagation. Figure 5 depicts the time-series evolution of the treatment effect on cash inflow (top left panel), cash outflow (top right panel), number of suppliers (bottom left panel), and employment (bottom right panel) separately for firms located areas in the upper tercile of court congestion (solid lines) and lower tercile (dashed lines). The plots depict the difference in cash inflow for connected versus unconnected firms in the same local industry in the two-year window around the shock. For example, the top left plot shows that while cash inflows of connected customers seem to decrease relative to unconnected firms in all areas, the relative decline is stronger for connected customers located in judicial districts with weaker courts. Overall, the evidence in Figure 5 is consistent with propagation being more severe for connected customers located areas with weaker courts.

[28]We use the average congestion rate between 2009 and 2014. Since congestion rate is persistent over time, the results are robust to alternative time definitions.

[29]Since data on length of litigation is available only at the state level, we rely on the local court congestion measure in our analysis. Furthermore, using a confidential sub-sample of court cases, Ponticelli and Alencar (2016) show that results of their study are unaltered when one performs the analysis with length of litigation as a measure of court inefficiency.

We confirm that connected customers facing congested courts suffer more by estimating equation (2). Table 3 presents the results. In Column I, we compare the relative changes in the cash inflow for connected customers located in areas with different court congestion levels. Specifically, a one standard deviation increase in court congestion leads to a 4.8 percent lower cash inflow for connected customers located in more court congested areas.[30] This effect represents an increase of more than 50% over the average effect of propagation of 9.1 percent. We observe similar patterns with other outcome variables. Compared to the average connected firm, a one standard deviation increase in court congestion leads to a 4.2 percent lower cash outflow, decreases the number of suppliers by additional 3.3 percent and reduces the employment by further 2.5 percent (Columns II, III, and IV respectively). All in all, court congestion appears to amplify the propagation of shocks in supplier-customer chains.

4.3 Potential Extra-Jurisdiction and Propagation of Shocks

The main concern with the interpretation of the results above is that endogenously determined court quality may be correlated with other local characteristics such as quality of firms. To the extent that these differences are equal for all firms in the same local industry, our empirical approach takes care of this by comparing connected against unconnected firms within the same municipality and industry. Thus, the remaining concern is that congestion is correlated with connected firm characteristics in a way that could explain why propagation is stronger for firms in areas where local courts are weak. For instance, connected firms located in areas with higher court congestion might be riskier and more vulnerable to shocks.

To alleviate concerns with endogenous court congestion, we adopt an empirical strategy, proposed by Ponticelli and Alencar (2016). Their strategy exploits pre-determined rules that affect the quality of local courts through potential extra-jurisdiction. Brazil's over 5,500 municipalities are organized in roughly 2,500 judicial districts, where a judicial district is at least as large as a municipality. The size of these districts is determined by state laws that establish the minimum requirements that a municipality has to satisfy to become the seat of a judicial district. These requirements are expressed in such municipality characteristics as the population, the number of voters in the last election, the number of judicial cases originated in a municipality, the amount of tax revenues, or a combination of the above.

[30] In all columns, Court Congestion is normalized to mean zero and standard deviation of one, to interpret the magnitudes of our estimates in terms of changes in the standard deviation of court congestion.

Jurisdiction over municipalities that do not meet the requirements is assigned to an adjacent municipality that is the seat of a judicial district. Thus, courts in the municipalities that are the seats of judicial districts are the potential recipients of cases originated in the neighboring municipalities that are not the seats of judicial districts, potentially, making these courts more congested.

To proxy for court congestion, we exploit the cross-sectional variation in the potential extra-jurisdiction of courts. This measure is equal to the number of adjacent municipalities that do not meet the requirements to become a judicial district. This empirical strategy rests on two assumptions. First, the number of judges and other resources do not adjust accordingly to the additional workload of cases originated in neighboring municipalities. If true, court congestion should increase with the potential extra-jurisdiction. We confirm that potential extra-jurisdiction is strongly correlated with court congestion in Table 4.[31] Specifically, one additional standard deviation in the number of adjacent municipalities that do not meet the requirements to be the seat of a judicial district is associated with a 9.1% increase in court congestion, or 12.5% of its standard deviation (Column I). In this specification, we also control for the total number of adjacent municipalities to account for geographical characteristics such as coastal areas, which might have fewer adjacent municipalities. Overall, the results suggest that judicial districts do not adjust adequately resources to the extra jurisdiction assigned to courts. Thus, the measure of potential extra-jurisdiction is a good predictor of local court congestion.

The second assumption is that potential extra-jurisdiction is exogenous with respect to the quality of local firms. By comparing connected and unconnected firms in the same municipality and industry, our empirical setting already controls for any characteristic at the local industry level that affects both connected and unconnected firms similarly. Thus, the remaining concern is that the quality of connected customers is correlated differentially with our measure of potential extra-jurisdiction relative to unconnected firms in the same municipality and industry. To assess this concern, we examine whether potential extra-jurisdiction explains differences in firm characteristics between connected and unconnected firms within a municipality and industry *just before* each shock. We estimate the following

[31] The F-statistic of this specification is 101, that is significantly over the required minimum of 10.

regression:

$$\begin{aligned}\ln(\text{Cash Inflow}_{is}) &= \alpha_{mkst} + \gamma \cdot \text{Connected}_{is} + \delta \cdot \text{Connected}_{is} \cdot \text{Potential Extra-Jur}_m \\ &\quad + \beta \cdot \text{Connected}_{is} \cdot \text{Nr Adjacent Munis}_m + e_{is} \qquad (3)\end{aligned}$$

The coefficient of interest is δ, capturing whether or not there is a correlation between potential extra-jurisdiction and differences in characteristics between connected and unconnected firms. As Table 5 shows, the difference in outcome variables of connected and unconnected firms in municipality-industry cells is not correlated with potential extra-jurisdiction. This provides support to our identification assumption that potential extra-jurisdiction is uncorrelated with differences in observable characteristics between connected and unconnected customers within a local industry prior to the shock.[32] In what follows, we examine how court congestion affects the propagation of shocks along the supply chains where court quality is measured as the number of adjacent municipalities that do not meet the requirements to become a judicial district. Specifically, we augment our main specification (2) by replacing *Court Congestion*$_m$ with *Potential Extra-Jur*$_m$. In this specification, we also control for the number of total adjacent municipalities. The coefficient on *Potential Extra-Jur*$_m$ measures the differential effect of propagation in connected customers located in municipalities with different potential extra-jurisdiction.

Confirming our previous results, we find that the propagation of shocks is more severe in areas with more potential-extra jurisdiction. Specifically, a one standard deviation increase in potential extra-jurisdiction leads to a 14 percent higher decrease in total cash inflows for connected customers (Column I in Table 6). We find similar patterns for all other outcome variables. Total cash outflow declines by further 8.6 percent (Column II), number of suppliers by additional 5.1 percent (Column III), the number of employees shrinks by 5.2 percent more (Column IV) for connected customers located in areas with a one standard deviation higher potential extra-jurisdiction.[33] In the Internet Appendix, we show that the results are robust to controlling for several characteristics at the municipality and neighboring municipality

[32] Please refer to the original paper by Ponticelli and Alencar (2016) for additional details and robustness tests for this empirical design.

[33] The results using an IV estimate are almost identical (see Internet Appendix Table A.5). Consider two municipalities that are one standard deviation apart in terms of potential extra-jurisdiction. The municipality with a one standard deviation higher potential extra-jurisdiction has 12.5% of a standard deviation more congested courts. This implies that connected customers in such a municipality experience by 13.7%(=0.125*1.1) steeper decline in cash inflow, 8% in cash outflow, 4.3% in number of suppliers, and 5.4% in number of employees.

levels (Table A.6) and that results are stronger for customers that are more exposed to the shock (Table A.7).[34]

Overall, the results are consistent with the view that congested courts amplify the propagation of negative shocks. In Section 6 we analyze the potential mechanisms, delivering these results.

4.4 Propagation of Shocks, Courts Quality and Firm Value

We examine whether the propagation of supply-side shocks affects the value of connected customers. We exploit the exact date of the natural disaster and perform an event study comparing stock returns of connected and unconnected firms around that date. We estimate the following model:

$$\text{CAR(-1,+5)}_{is} = \alpha_{mks} + \beta \cdot \text{Connected}_{is} + e_{is} \tag{4}$$

where CAR is the cumulative abnormal return of firm i estimated from a market model using the Brazilian stock market index IBOVESPA as the benchmark in a seven-day event window (-1, + 5) around each disaster. Similarly as before, to assess whether firm value declines more in areas with weaker courts, we add interactions between the connected dummy and our measure of court congestion or potential extra-jurisdiction.

We find that propagation negatively affects connected customer value and even more so in areas with more congested courts. Table 7 presents the results. Column I shows that connected customers experience a drop of 2.4% in the stock return in the seven day window around the disaster date. This effect is stronger when firms are located in municipalities with weaker courts. Column II shows that a one standard deviation increase in court congestion is associated with a further 1.4 percent drop in cumulative returns. Similarly, a one standard deviation increase in potential extra-jurisdiction decreases firm value by additional 2.8 percent (column III). Furthermore, negative abnormal returns also suggest that markets could not predict these disasters. In sum, these results suggest that propagation of shocks affects not only performance of connected firms but also their valuation. It also highlights that these natural disasters appear to be unpredictable.

[34] We measure exposure as the fraction of payments to affected suppliers in the two years prior to the shock.

4.5 Identifying Assumptions

Examining how court congestion affects the transmission of shocks among firms rests on the assumption that connected and unconnected firms would have trended the same both in congested and uncongested court districts. While it is not possible to directly test this assumption, several pieces of evidence support its the validity.

First, our evidence on firm value suggests that natural disasters were unpredictable, hence, randomly assigned. Second, we observe parallel trends in all outcome variables for connected and unconnected firms prior to natural disasters (see Figures 2 and 5, and Table A.1). Third, trends in firm outcomes immediately diverge after a shock hits connected firms' suppliers. Thus, any confounding factor would need to coincide precisely with the shock. Fourth, the results are robust to instrumenting for court congestion through potential extra-jurisdiction, which mitigates concerns about confounding factors correlated with court quality (Tables 6 and A.5). Fifth, potential extra-jurisdiction is uncorrelated with connected vis-a-vis unconnected firm characteristics (as shown in Table 5). Sixth, controlling for observable differences among both firms and judicial districts does not affect the results (see Internet Appendix Table A.6). Seventh, firms do not usually sort themselves across districts based on court congestion. For instance, findings from a number of studies show that, in general, entrepreneurs locate their new firms near where they were previously living and working rather than through some optimization process over all possible locations (Cooper and Folta, 2000).

5 Robustness Tests

5.1 Competitive Effects on Unconnected Firms

In Section 4.1, we document that shocks propagate along the supply chain. To document this, we use a control group of unconnected firms from the same local industry as the connected customers. A concern might be that our control group – unconnected firms in the same local industry – is positively affected by shocks. Specifically, unconnected firms might increase their market share and market power, since these firms would be able to take away some business from the connected customers. This would lead to an overestimation of the propagation, since we would double-count the negative effect from propagation on the connected customers also as a positive effect on the unconnected firms. On the other hand, there could also be a contagion effect. For instance, a sizable shock to firms in the local industry might affect all firms in that industry, since firms in the local industry could be trading with each other. This channel, however, would lead to an underestimation of our results, which is less of a concern.

To assess whether our control group experiences a positive competitive effect, we use local industries that are not connected to these shocks. By comparing unconnected firms in industries that are not connected to these shocks relative to unconnected firms in industries that are connected to these shocks (both located in the same municipality) would allow us to examine the extent of within industry spillovers. Specifically, we amend our main econometric model as follows:

$$\begin{aligned} \ln(\text{Cash Inflow}_{ist}) &= \alpha_{is} + \alpha_{mst} + \delta \cdot \text{Connected}_{is} \cdot \text{Post}_{st} \\ &\quad + \gamma \cdot \text{Local Competitors}_{is} \cdot \text{Post}_{st} + e_{ist} \end{aligned} \tag{5}$$

where *Local Competitors*$_{is}$ is a dummy variable equal to one for unconnected firms operating in the same local industry[35] as the connected customer i, and zero otherwise. The second important amendment relates to the time fixed effects (α_{mts}), which control for all time-series variation in municipality m within each shock s. Other variables are defined as before. Coefficient δ estimates the effect of propagation to connected relative to unconnected firms from local industries where at least one firm is connected to the shock s. In this specification, γ is the coefficient of interest. It captures the effect on unconnected firms from industries where at least one firm is connected to shock s relative to unconnected firms from industries where no firm is connected to the same shock. A positive value would imply that unconnected firms from the same local industry as the connected firms experience a positive shock when their competitors suffer.

Our results remain robust. Unconnected firms do not seem to benefit from negative shocks to connected firms in the same local industry. Table 8 reports the results. Coefficients on *Local Competitors*$_{is}$ in columns I to III are statistically insignificant, suggesting that local competitors are no different from other unconnected firms in the same municipality or industry. As a consequence, the estimated effect on connected firms is either similar in both magnitude and statistical power to our main estimates on Table 2. In column IV, local

[35] Local industry is defined as firms in the same municipality and industry (2-digit CNAE code), as explained in the data section.

competitors experience a 2.6% drop in the number of employees when compared to other firms in the same municipality or industry. The estimated coefficient on connected firms, therefore, is slightly higher: -4.1% when compared to -2.2% in our main estimates. This further alleviates the concern that we might be over-estimating the propagation effect on connected firms.

5.2 Within-Affected Supplier Analysis

Evidence from previous sections suggests that the propagation is amplified for connected customers located in municipalities with weak courts. A concern might be that firms in areas with congested courts might be connected to a different set of affected suppliers than firms in less congested areas. For instance, firms in high court congestion areas might be connected to more vulnerable suppliers. It could also be that the inputs provided by suppliers of connected firms located in municipalities with weak courts are more specific and harder to replace (Barrot and Sauvagnat, 2016). While our empirical strategy using potential extra-jurisdiction should control for this type of selection among connected firms with respect to court quality, we address this concern directly. Specifically, we examine how shocks propagate to firms connected to the *same* affected supplier. This enables us to control for why firms would wish to connect to this supplier, all time-varying suppliers' characteristics such as vulnerability to the natural disasters or the quality of their local courts as well as all time varying aggregate changes in supply and demand for all firms connected to the same supplier.

We construct the test as follows. For each affected supplier, we take all firms that are its direct customers in unaffected areas. To control for local trends, we also consider all firms that are not connected to this shock but are located in the same municipality and industry as connected downstream firms. Thus, we create a shock-affected supplier-firm-year panel. With this sample, we run the following regression specification:

$$\begin{aligned} \ln(\text{Cash Inflow}_{isjt}) &= \alpha_{isj} + \alpha_{mksjt} + \alpha_{sjt} \\ &\quad + \delta \cdot \text{Connected}_{isj} \cdot \text{Post}_{st} \cdot \text{Court Congestion}_m + e_{isjt} \end{aligned} \tag{6}$$

where j refers to an affected supplier in shock s. All other subscripts are defined as before. The important addition in comparison to equation (2) is the α_{sjt} fixed effect that controls for all time-varying changes for all firms connected to the same supplier j within shock

s. To the extent that firms in congested areas connect to, for instance, weaker or more specific suppliers, this fixed effect controls for it. Thus, our cross-sectional test of court congestion compares firms connected to the *same affected supplier* but located in different municipalities. The other two fixed effects are defined similarly as before. The firm-shock fixed effect (α_{isj}) controls for all firm-specific time invariant characteristics and ensures our estimated effect is measured within a firm. The time fixed effect (α_{mksjt}) warrants that we compare firms within the *same* unaffected municipality m and industry k within each affected supplier j in shock s, controlling for aggregate changes in the supply and demand within each local industry.

Results remain robust. The propagation is more severe for connected firms located in municipalities with weaker courts, even when comparing firms connected to the same affected supplier. Table 9 reports the results. A one standard deviation increase in court congestion is associated with a 4.2 percent decrease in cash inflow for firms connected to the same supplier but located in judicial districts with different congestion of local courts (Column I). Results are similar with our previous approach. A one standard deviation increase in potential extra-jurisdiction leads to about 9.2 percent lower cash inflow for connected firms (Column II). Results are similar for all other outcome variables: a one standard deviation increase in court congestion leads to 2 to 9 percent lower cash outflow, number of suppliers, and employment. Overall, the results are robust to comparing firms connected to the same affected supplier.

5.3 Firms in Adjacent Municipalities

Besides suppliers' characteristics, the location of connected firms might also be correlated with how easy it is for them to substitute affected suppliers. One possibility is that the number of alternative suppliers available nearby is lower where courts are weaker. Again, this type of selection should be accounted for with our potential extra-jurisdiction approach. Nevertheless, to control for such possibility more directly, we compare firms connected to the same affected supplier *and* located in municipalities that share a border with each other. In the adjacent municipality setting, costs associated with replacing the same affected supplier such as the distance to the next alternative should be similar for all connected firms wishing to replace the same affected supplier.

We construct the test as follows. Similarly as above, for each affected supplier, we take all firms that are its direct customers in unaffected areas. To control for local trends, we also consider all firms that are not connected to this shock but are located in the same municipality and industry as connected downstream firms. Then we create all possible adjacent municipality-shock-affected supplier pairs where both municipalities in the pair have at least one firm connected to the same affected supplier in a shock. Thus, we create an adjacent municipality pair-shock-affected supplier-firm-year panel. With this sample, we run the following regression specification:

$$\begin{aligned} \ln(\text{Cash Inflow}_{isjpt}) &= \alpha_{isjp} + \alpha_{mksjpt} + \alpha_{sjpt} \\ &\quad + \delta \cdot \text{Connected}_{isjp} \cdot \text{Post}_{st} \cdot \text{Court Congestion}_m + e_{isjpt} \end{aligned} \tag{7}$$

where p refers to an adjacent municipality pair. All other subscripts are defined as above. The important addition is the α_{sjpt} fixed effect, which controls for all time-varying changes for all firms connected to the same supplier j within shock s and are located in two adjacent municipalities p. Thus, our cross-sectional test of court congestion compares firms connected to the same affected supplier and located in two adjacent municipalities. The other two fixed effects are defined similarly as before. The firm-shock fixed effect (α_{isjp}) controls for all firm-specific time invariant characteristics and ensures our estimated effect is measured within a firm. The time fixed effect (α_{mksjpt}) controls for all aggregate changes in the supply and demand within each local industry within a municipality pair p and affected supplier j.

Our results are robust to comparing connected customers in close geographical proximity and connected to the same affected supplier. Results are reported in Table 10.[36] Connected customers in a municipality with a one standard deviation higher court congestion experience a drop of 7.8 percent in cash inflow (Column I), 4.8 percent in cash outflow (Column III), 2.6 percent in the number of suppliers (Column V), and 1.2 percent in number of employees (Column VII). The results are similar for the interaction with potential extra-jurisdiction. A one standard deviation increase in potential extra-jurisdiction lowers all outcomes by further 2 to 8 percent. All in all, our results are robust even if we compare firms in adjacent municipalities and, therefore, unlikely to be driven by inability to replace a supplier due to geographical characteristics.

[36] The number of observations increases significantly, since one municipality has several adjacent municipalities. Thus, one affected supplier can be connected to various adjacent municipality pairs.

6 Mechanism

So far the paper provides evidence that court quality affects the propagation of shocks through production networks. Due to the institutional design of the judicial system in Brazil, we examine how the ability to enforce contracts from the connected customer – the potential defendant – affects the transmission of shocks along the supply chain.

These findings could be consistent with two broad channels. The first one relates to the moral hazard on behalf of connected firms. Since connected firms experience a disruption in their supply chain, this could lead to a breach of contract on their behalf. Dishonoring a contract might be costlier in areas with stronger courts, since the plaintiff could credibly enforce the contract through legal institutions. To prevent this from happening, connected firms located in areas with efficient courts could be exerting more effort to resolve the manufacturing disruption and to avoid costly litigation.

The second channel relates to the credibility of connected firms' contracts. Strong courts ensure that connected firms commit to honor contracts, thereby mitigating the classic hold-up problem (Hart and Moore, 1988). Creditors, both banks and suppliers, might not be willing to extend credit due to increased credit risk concerns. Similarly, connected firms might find it difficult to contract with alternative suppliers even if no credit is required. To the extent that some relationships are long-term where suppliers need to make relationship-specific investments, effective contract enforcement should facilitate such contracting in the market. Otherwise, firms might need to develop those inputs internally.

In what follows next, we find evidence consistent with a credit supply channel as well as inability to contract with alternative suppliers.

6.1 Credit Supply

Affected suppliers might have provided trade credit to connected firms prior to a shock. These suppliers, however, might not be able to extend trade credit after they are hit by a shock. At the same time, banks and other trade creditors might be unwilling to extend credit to connected customers, whose credit risk might have increased considerably. There are several alternative ways how connected customers can borrow from banks. Here we examine the role of unused credit lines and factoring of account receivables in alleviating this credit shock.

Lines of Credit

We start by examining lines of credit. A prominent role of credit lines is their insurance against negative liquidity shocks. If banks or suppliers are unable or unwilling to provide credit after the shock, firms with unused credit lines are in much better position since they can access the available liquidity. This effect should be particularly strong in areas with congested courts where making new credit contracts might be more difficult, so firms have to rely more on pre-committed capital provided by lines of credit.

Consistent with the insurance role of lines of credit, we find that firms with a larger fraction of unused credit lines, measured as the ratio between unused credit lines and total credit, suffer less in congested areas (see Table 11). In our strictest specification (7), where we compare propagation on firms connected to the same affected supplier and located in adjacent municipalities, we add the fraction of unused credit lines for connected firms, measured just before shocks hit their suppliers, and all of their interactions with other independent variables. The coefficient of interest is the quadruple difference-in-differences estimate on $Connected_{is} \cdot Post_{st} \cdot Potential\ Extra_{m} \cdot Unused\ CL_{i}$. Overall we find that having a larger fraction of unused credit lines alleviates the propagation of the negative shock across all four measures: cash inflow and outflow and the number of suppliers and employees.

Working Capital Financing

Firms could borrow from banks, for instance, via a standard working capital loan or by factoring their accounts receivables. The main difference between the two is that in factoring banks are primarily concerned with the credit risk of the borrower's customer who made the initial promise to pay rather than the risk of the borrower itself. This effectively provides connected firms a way to outsource both credit and court enforcement risk to their customers. Hence, this form of financing should be more important in areas with congested courts. Furthermore, the ability to outsource credit risk should be more relevant for connected firms facing congested courts and whose customers have relatively better courts. This would allow them to overcome frictions with local courts and exploit the relatively better customer courts. Overall, increased usage of factoring contracts would be consistent with court induced credit frictions on access to credit.

Our evidence is consistent with connected customers relying more on factoring after a shock (see Table 12). We examine the effect on log of factoring plus one (columns I and II) and the probability of factoring (columns III and IV). Similarly, we do the same for the traditional working capital financing in columns V through VIII. In our strictest specification, where we compare propagation on firms connected to the same affected supplier and located in adjacent municipalities, we find that connected customers in more congested areas increase their borrowing through factoring transactions relative to less congested areas (columns I and III). We do not observe changes in the traditional working capital financing (columns V and VII), suggesting that firms overcome the liquidity shock through factoring contracts.

Furthermore, a connected customer whose customers, on average, are located in areas with less congested courts than the connected customer itself, is more inclined to rely on factoring (columns II and IV). In contrast, we observe the opposite for working capital loans. Connected firms in more congested areas and with customers that are located in less congested judicial districts are less likely to use standard working capital financing. This suggests that these firms move from standard working capital loans to factoring after a shock by taking advantage of their customers' court quality. Overall, results are consistent with the view that connected firms face a negative credit supply shock and that this is driven by court congestion.

6.2 Vertical Integration

The literature on firm boundaries and industry structure argues that firms should produce an input in-house when transacting in the market is costly (most notably, Coase (1937), Williamson (1975, 1985), Klein et al. (1978)). Since weaker courts increase the cost of signaling the quality of future contracts, this predicts that connected firms located in areas with congested courts should be more likely to vertically integrate the input produced by the affected supplier.

Our evidence is consistent with this theoretical prediction. Connected firms located in areas with congested courts vertically integrate the input manufactured by the affected supplier. To show this, we examine two dimensions. First, using data from the Brazilian IRS, we examine whether connected firms located in areas with weak contract enforcement are more likely to acquire firms from the same industry as their affected supplier. Second, using a more indirect approach, we assess whether connected firms are more likely to hire 'specialists' from the same industry as their affected supplier.[37] Hiring specialists suggests that connected firms might be replicating in-house the manufacturing of the affected input.

Table 13 present the results, estimated in the most stringent specification (7) where we compare the propagation within the same affected supplier and pair of adjacent municipalities. Connected customers located in municipalities with high potential extra-jurisdiction tend to hire more specialists with past experience in the same industry of the affected supplier (Column I). The same firms are also more likely to acquire firms from the same industry as the affected supplier (Column II). This result is consistent with Boehm and Oberfield (2020) who show that supply chains located in areas with more congested courts are vertically more integrated in India. Overall, the results are consistent with difficulties in establishing new relationships due to court-induced contracting fictions and potential future hold-up problems.

7 Discussion and Real Effects

This section summarizes the key insights and provides back of the envelope calculations for the real effects. The main insight from this paper is that court congestion affects the propagation of local shocks in production networks. In Section 4, we document that employment in customers of affected firms falls by 2.2 percent due to propagation (Table 2, Column IV). We also find that the decline in employment is by 2.5 percent higher for one standard deviation increase in court congestion (Table 3, Column IV). In our sample, manufacturing firms constitute on average 14 percent of a municipality's GDP. Furthermore, connected customers on average employ 15 percent of all manufacturing workers in a municipality. This suggests that propagation leads, on average, to a 0.05 percent fall in local GDP of unaffected but connected municipalities ($15\% \cdot 14\% \cdot (-2.2\%)$).[38] A one standard deviation increase in court congestion is associated with a further fall of 0.05 percent in the local GDP of unaffected but connected municipalities ($15\% \cdot 14\% \cdot (-2.5\%)$). Using cash inflows to proxy for fall in the local GDP would lead to a higher estimate of 0.15 percent loss of GDP for one standard

[37] Specialists are defined as professionals from the classification of skilled occupations by the International Standard Classification of Occupations. See, for instance, Acemoglu and Autor (2011).

[38] These estimates are likely to be conservative, since in this calculation we implicitly assume no effect on firms outside our sample, i.e. all non-manufacturing firms and manufacturing firms with less than 100 employees.

deviation increase in court congestion.[39]

A one standard deviation in court congestion corresponds to a workload of roughly 7 judges in an average judicial district. Thus, reducing court congestion by adding one more judge to an average judicial district would reduce the cost of propagation by 0.007 (= 0.05%/7) to 0.02 (= 0.15%/7) percent of GDP in unaffected municipalities that are connected to the shock through supply-chain linkages. Since the average GDP of a municipality is 700 million reais, this corresponds to roughly 50,000 to 150,000 reais, which is about a one-seventh to a half of an annual salary of an entry level judge in Brazil.[40]

Since it is impossible to anticipate neither which areas are going to be shocked nor which are connected ex ante, it is important to consider the effects (savings) of adding one more judge to all judicial districts in expectation.[41] The GDP of Brazil was about 6,559 trillion reais in 2017. In an average shock in our sample, 718 out of total of 5,570 municipalities were connected to a shocked area through supply chain linkages. In other words, an average shock indirectly affected 13 percent of municipalities. Thus, adding one judge to each judicial district (2,662 in total) would generate expected savings between 22,900 (=$0.007\% \cdot 6.559 \cdot 13\%/2662$) and 45,400 (=$0.02\% \cdot 6.559 \cdot 13\%/2662$) reais per judge in terms of GDP in an average shock of our sample. These savings estimates are likely conservative since, besides the natural disasters that we examine, there are other shocks affecting supply chains (e.g., Wu, 2016; Costello, 2020). To estimate the overall effect of courts on propagation across supply chains, one would need to aggregate all these. Overall, our results suggest that losses associated with propagation of shocks due to congested courts could be sizable.

8 Conclusion

This paper presents novel empirical evidence on the propagation of local shocks through production networks. Using data on the Brazilian Payments system, we create a supplier-

[39]We chose employment, since we can observe information on all firms and workers, while for cash-flows we observe the inter-bank transfers. Using cash inflow we would get the following estimates: the propagation of shocks is associated with a 0.28 percent drop in GDP ($22\% \cdot 14\% \cdot (-9.1\%)$). A one standard deviation increase in court congestion is associated with a decrease in 0.15 percent in GDP ($22\% \cdot 14\% \cdot (-4.8\%)$).

[40]In 2017, the yearly entry level salary of a judge was 357,500. This number does not consider other benefits, such as accommodation allowance, health insurance, among others.

[41]One could design a more sophisticated allocation by assessing the level of congestion in each district separately. And then adding judges selectively.

customer network for all manufacturing firms and follow how natural disasters propagate from an affected supplier to its customer located in an unaffected area. We document that connected customers experience a significant drop in their performance as measured by cash inflows, outflows, and number of employees relative to unconnected firms in the same local industry as the connected customers.

The propagation is stronger for connected customers located in municipalities with weak courts. When courts are more congested, customers faced by input disruption experience a further reduction in their cash inflows and outflows, number of suppliers, and number of employees relative to customers facing less congested courts. We alleviate the concerns with endogenous court quality by exploiting a set of pre-determined rules in the allocation of courts.

Our evidence is consistent with two mechanisms: difficulty both to outsource inputs and to borrow. We find that connected customers in areas with more congested courts seem to face difficulties in forming relationships with new suppliers. Instead, they appear to integrate affected suppliers' industry through acquisitions and hiring. This suggests that connected customers replicate the manufacturing of the input internally. We also find evidence consistent with credit frictions. Connected customers with unused credit lines suffer less, highlighting the insurance role of credit lines. Connected customers are also more likely to factor their accounts receivables. These contracts outsource credit and court enforcement risk to their customers, enabling connected customers to overcome congested local courts. Our results have important policy implications, since our findings point out that economies with weak courts are more fragile.

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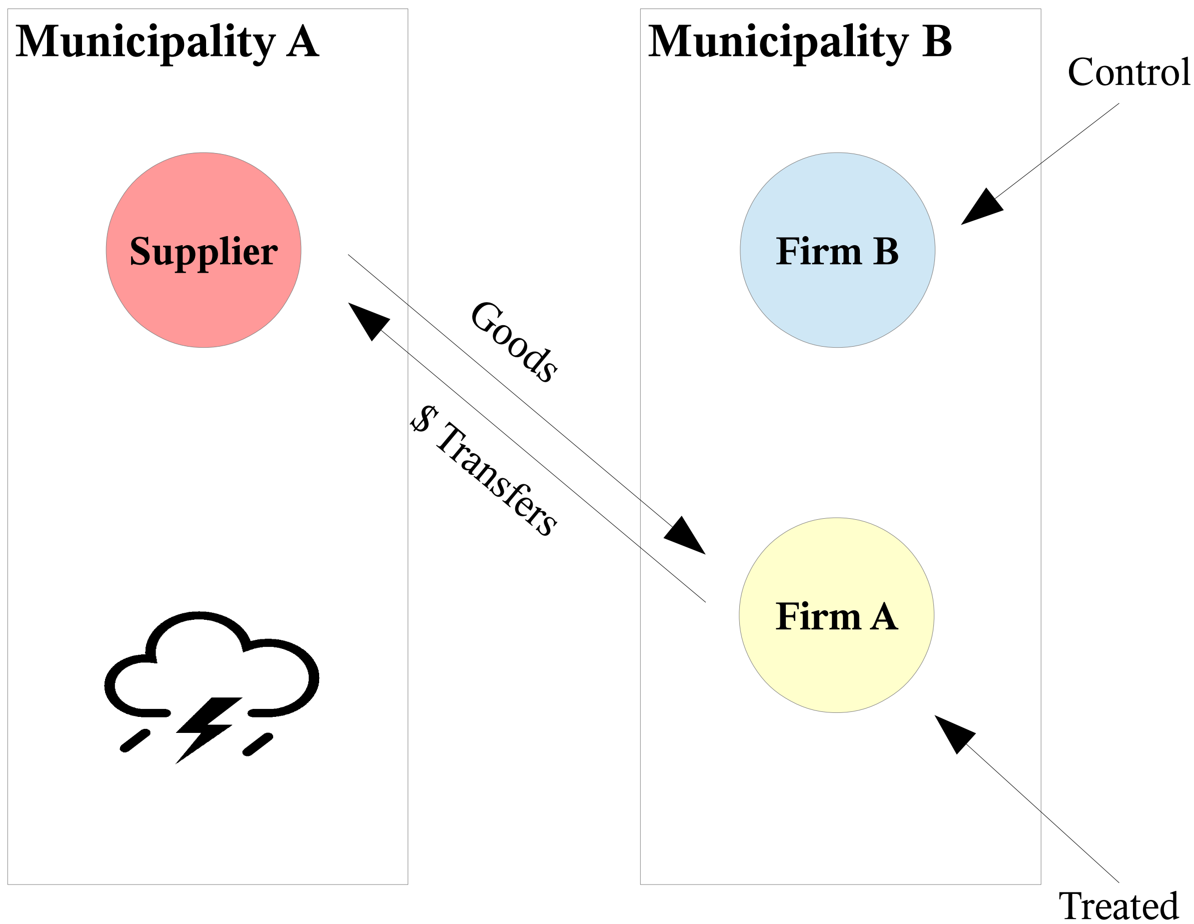
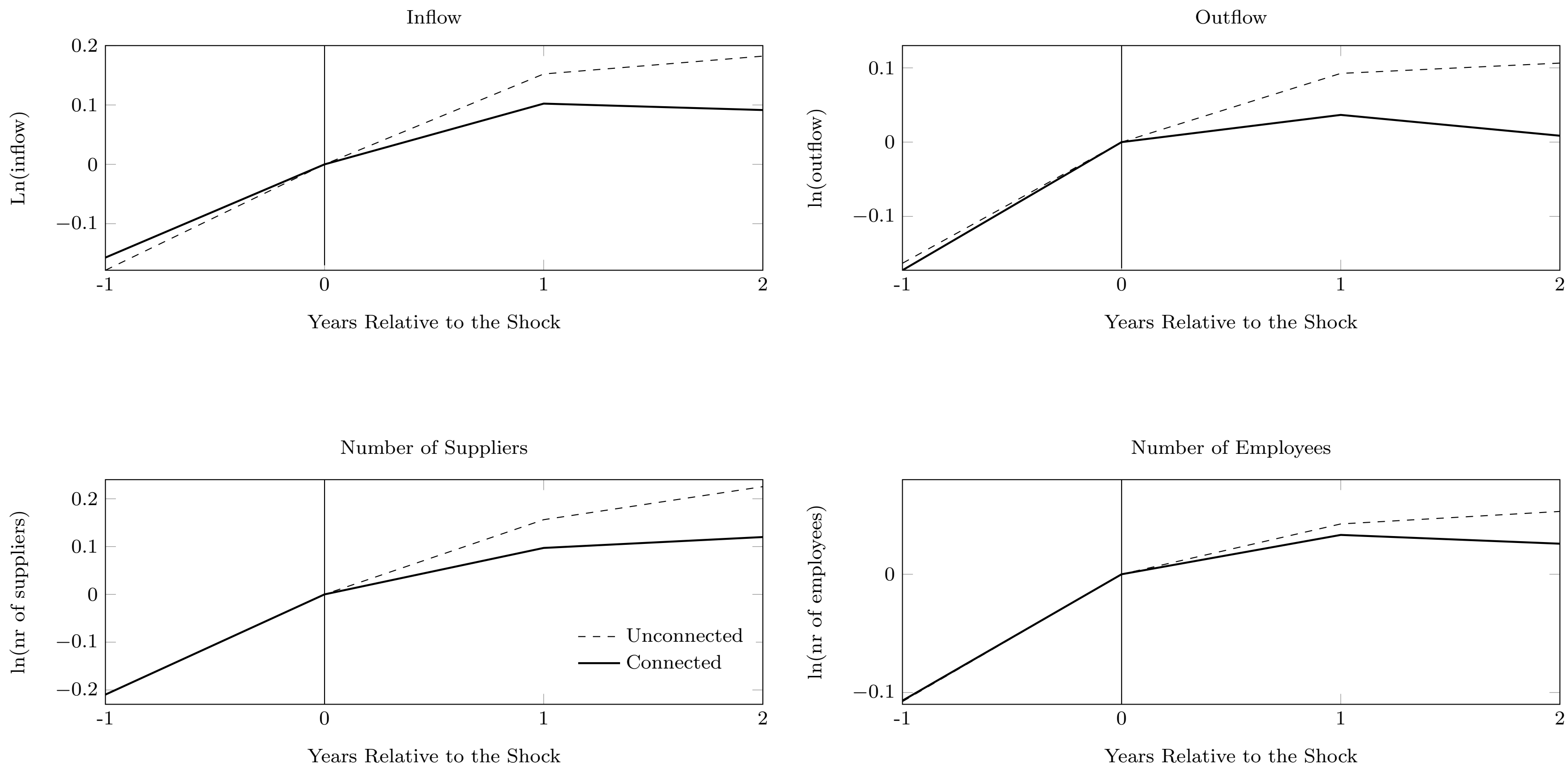
Figure 1: **Identification Strategy**



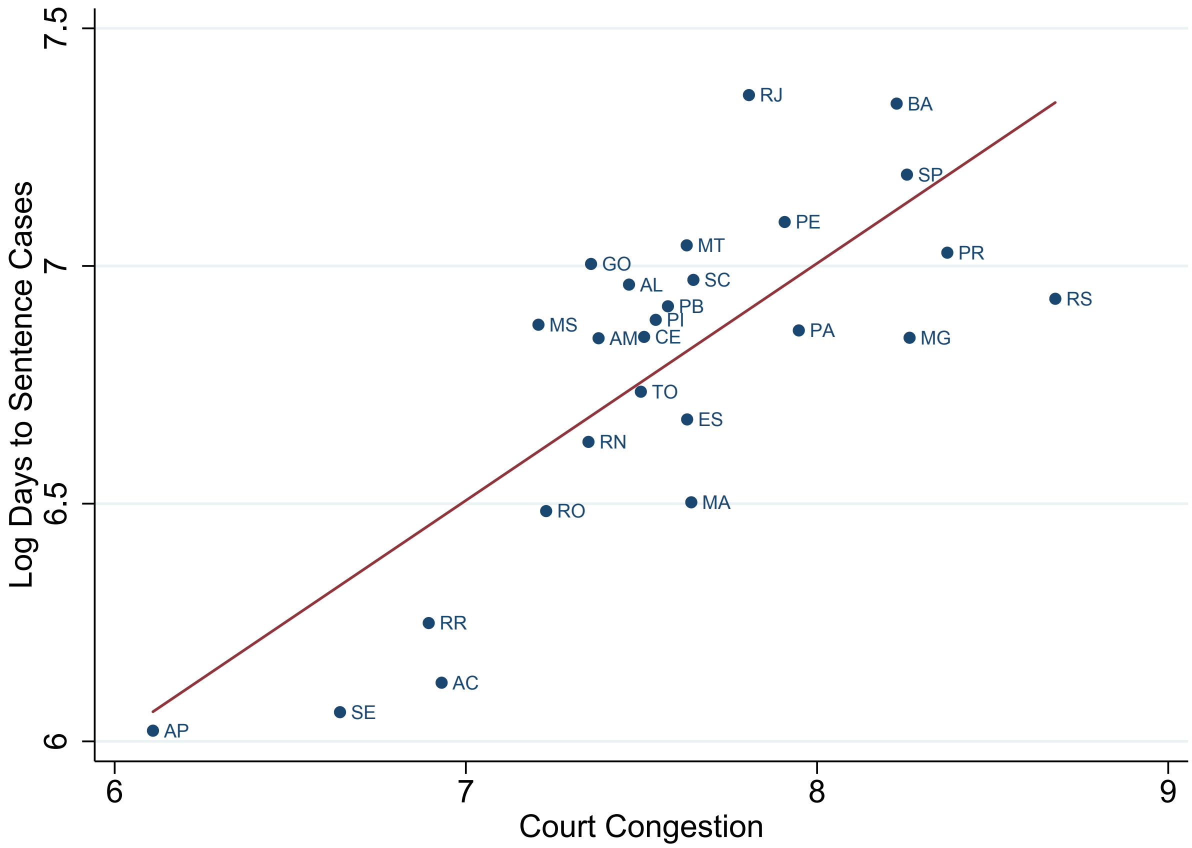
This figure explains our identification strategy. We define our pre-shock supplier-customer relationships using wire transfers from the Brazilian System of Payments in the two years before the disaster. Firm A transfers cash to Supplier and in exchange is given goods to be used as inputs. Suppose a natural disaster occurs in Municipality A. Supplier is then directly affected by the shock. Firm A is the customer of this affected supplier but it is not directly affected by the shock, since it is located in Municipality B. Firm B, located in Municipality B, is not affected by the shock both directly nor through the Supplier. Our empirical strategy compares Firm A and Firm B, located in the same unaffected municipality and industry, before and after the shock.

Figure 2: **Propagation around Natural Disasters**



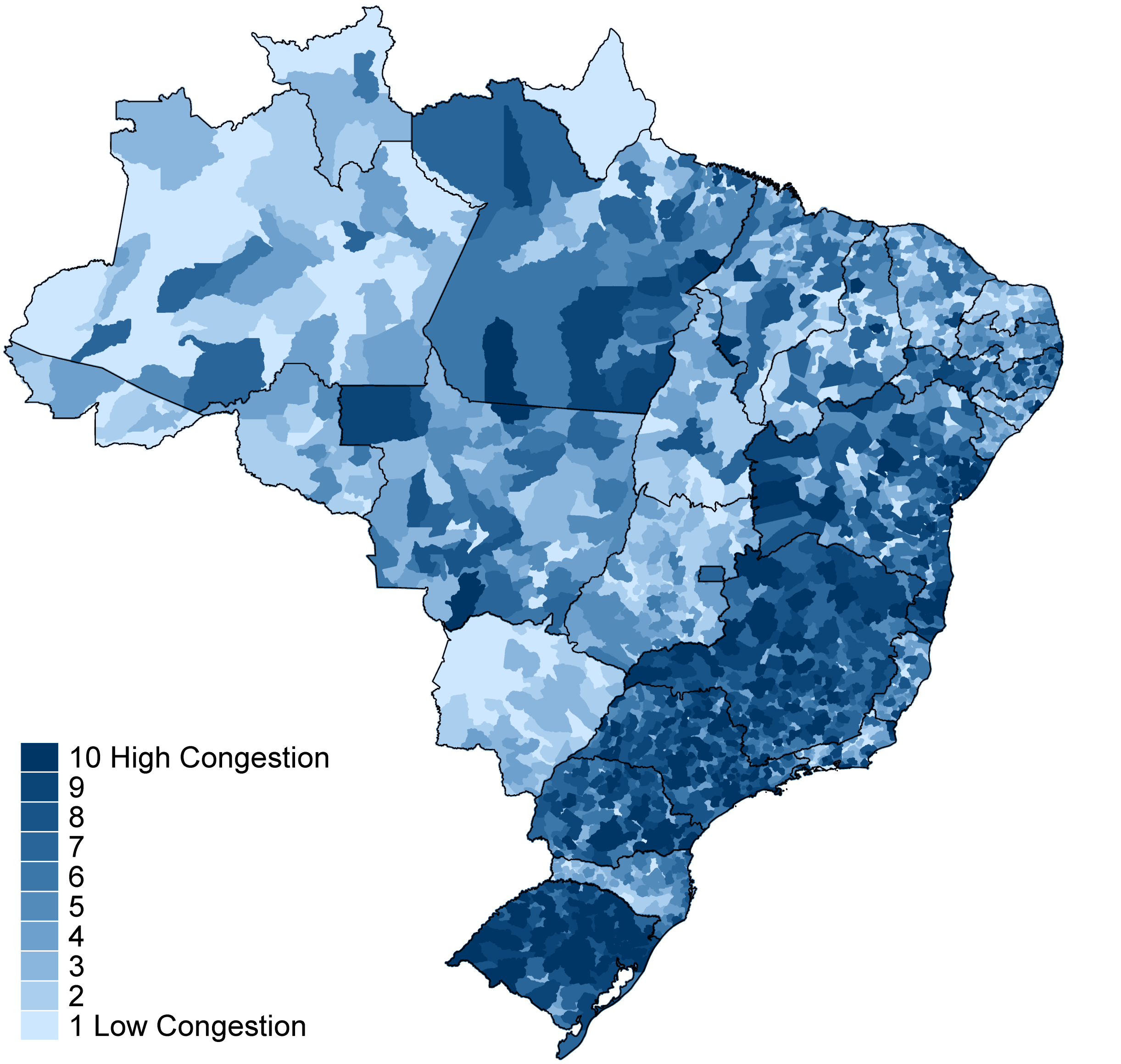
This figure presents the evolution of average log of cash inflow (top left) and outflow (top right), log of number of suppliers (bottom left), and of log of employees (bottom right) for connected (solid lines) and unconnected firms (dashed lines). Cash inflows and outflows are defined as the total amount of money received and paid out by each firm. The number of suppliers is calculated as the number of distinct firms that a firm pays to through inter-bank transfers. The number of employees is defined as the total number of workers employed at the end of each twelve month window. On the X-axis, period 0 refers to the twelve months immediately prior to a shock, while period 1 refers to the twelve months immediately after a natural disaster. Lines are normalized to zero in period 0. All plots are adjusted for municipality, industry, shock and time averages.

Figure 3: **Court Congestion and Length of Litigation**



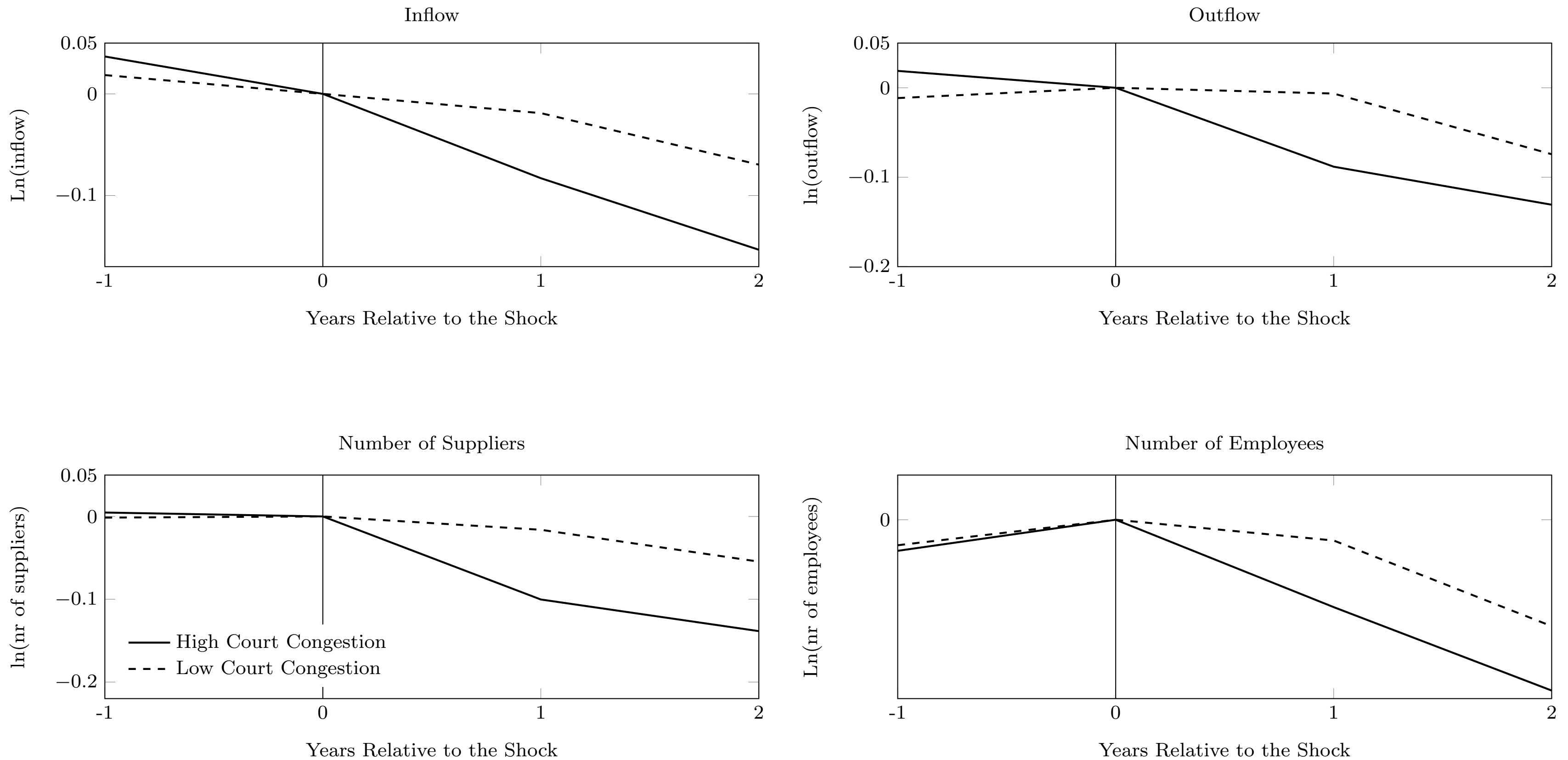
This figure presents a scatterplot of the log of average days to sentence civil cases (in the y-axis) against court congestion (in the x-axis) at the state-level. Court congestion is the log of the average number of pending cases per judge at the state-level.

Figure 4: **Geographical Distribution of Court Congestion**



This figure presents the distribution of court congestion across Brazilian municipalities. Court congestion is defined as the number of backlog cases divided by the number of judges in each judicial district. The measure is sorted into deciles. Darker areas correspond to municipalities with higher court congestion.

Figure 5: **Propagation and Court Quality**



This figure presents the evolution of the propagation on average log of cash inflow (top left) and outflow (top right), log of number of suppliers (bottom left), and log of number of employees (bottom right) for firms in municipalities in the upper (solid lines) and lower (dashed lines) tercile court congestion. The plots report the average difference between connected and unconnected firms in each local industry. Cash inflows and outflows are defined as the total amount of money received and paid out by each firm. The number of suppliers is calculated as the number of distinct firms that a firm pays to through inter-bank transfers. The number of employees is defined as the total number of workers employed at the end of each twelve month window. On the X-axis, period 0 refers to the twelve months immediately prior to a shock, while period 1 refers to the twelve months immediately after a natural disaster. Lines are normalized to zero in period 0. All plots are adjusted we control for municipality, industry, shock and time avverages.

Table 1: **Summary Statistics**

	Connected Customers			Unconnected Firms			Diff	
	Average	Std Dev.	Nr Firms	Average	Std Dev.	Nr Firms		
Inflow (R$ mil)	125	193	3,957	31	87.6	119,402	94	***
Outflow (R$ mil)	165	266		28.9	105		136.1	***
Nr Empl	992.1	1217.5		355.0	583.1		637.1	***
Nr Suppliers	321.3	359.8		79.0	162.8		242.3	***

	Connected Customers						Diff	
	High Court Congestion			Low Court Congestion				
	Average	Std Dev	Nr Firms	Average	Std Dev	Nr Firms		
Inflow (R$ mil)	129	194	2,730	117	190	1,183	12	*
Outflow (R$ mil)	171	270		152	258		19	**
Nr Empl	1,008.3	1218.6		954.6	1214.7		53.7	
Nr Suppliers	337.1	369.7		291.0	337		46.1	***

This table presents summary statistics of firm-specific variables in the year immediately before the natural disaster. Cash inflow is the total amount of transfers received by a firm, as recorded in the Brazilian System of Payments. Cash outflow is the total amount originated by the firm. The number of suppliers is the number of distinct firms that each firms pays to. The upper panel compares these variables for connected and unconnected firms. The bottom panel, compares connected customers located in municipalities in the upper vs lower median of court congestion. Court congestion is measured as the number of pending cases divided by total number of judges.

Table 2: **Propagation of Supply Side Shocks**

	ln(inflow)	ln(outflow)	ln(# sup)	ln(# empl)
	I	II	III	IV
$\text{Connected}_{is} \cdot \text{Post}_{st}$	-0.091***	-0.169***	-0.170***	-0.022**
	(0.021)	(0.020)	(0.013)	(0.010)
Firm*Shock FE	Yes	Yes	Yes	Yes
Muni*Ind*Shock*Time FE	Yes	Yes	Yes	Yes
Nr Obs	336,829	316,808	316,808	322,134
R^2	0.93	0.934	0.942	0.925

This table reports changes in firm level variables in the two-year window around a natural disaster. The dependent variables, log of cash inflow (column I) and cash outflow (column II), are calculated by summing all payments received and originated by firm i in year t around shock s, respectively. The number of distinct suppliers (column III) of firm i is the log of firms that receive a payment from firm i in year t. The log of employees (column IV) is the total number of employees in firm i and year t. Connected_{is} is a dummy equal to one if at least one of firm i's supplier is located in the area of natural disaster s, and zero otherwise. Post_{st} is a dummy equal to one in the 2 years after the shock, and zero otherwise. The bottom part of the table reports information on fixed effects. Standard errors, clustered by firm and shock, are presented in parentheses. *, **, and *** denote significance of 10%, 5% and 1%, respectively.

Table 3: **Court Congestion and Propagation of Shocks**

	ln(inflow)	ln(outflow)	ln(# sup)	ln(# empl)
	I	II	III	IV
$\text{Connected}_{is} \cdot \text{Post}_{st}$	-0.091***	-0.169***	-0.170***	-0.022**
	(0.021)	(0.019)	(0.013)	(0.010)
$\text{Connected}_{is} \cdot \text{Post}_{st}$ $\cdot$ Court Congestion_m	-0.048**	-0.042**	-0.033**	-0.025**
	(0.024)	(0.021)	(0.014)	(0.013)
Firm*Shock FE	Yes	Yes	Yes	Yes
Muni*Ind*Shock*Time FE	Yes	Yes	Yes	Yes
Nr Obs	336,829	316,808	316,808	322,134
R^2	0.930	0.934	0.942	0.925

This table reports changes in firm level variables in the two-year window around a natural disaster. The dependent variables, log of cash inflow (column I) and cash outflow (column II), are calculated by summing all payments received and originated by firm i in year t around shock s, respectively. The number of distinct suppliers (column III) of firm i is the log of firms that receive a payment from firm i in year t. The log of employees (column IV) is the total number of employees in firm i and year t. Connected_{is} is a dummy equal to one if at least one of firm i's supplier is located in the area of natural disaster s, and zero otherwise. Post_{st} is a dummy equal to one in the 2 years after the shock, and zero otherwise. Court Congestion_m is the log of the ratio between the average number of backlog cases divided by the average number of judges in municipality m where firm i is located. We standardize this variable to mean zero and standard deviation of one. The bottom part of the table reports information on fixed effects. Standard errors, clustered by firm and shock, are presented in parentheses. *, **, and *** denote significance of 10%, 5% and 1%, respectively.

Table 4: **Court Congestion and Potential Extra-Jurisdiction**

	Court Congestion	
	I	II
Potential Extra$_m$	0.091***	0.081***
	(0.013)	(0.018)
Nr Adjacent Munis$_m$	0.060***	0.028**
	(0.013)	(0.013)
MicroRegion FE		Yes
Nr Obs	5,481	5,479
F-stat	101	46.1
R^2	0.035	0.596

This table presents the first stage results of a cross-municipality regression of Court Congestion on Potential Extra-Jurisdiction. Court Congestion$_m$ is the log of the ratio between the average number of backlog cases and the average number of judges in municipality m where firm i is located. Potential Extra$_m$ is the number of adjacent municipalities that do not meet the requirements to become seats of their own judicial district. Nr of Adjacent Munis is the number of municipalities that shares a border with the seat of the judicial district. The bottom part of the table reports information on fixed effects. Robust standard errors are presented in parentheses *, **, and *** denote significance of 10%, 5% and 1%, respectively.

Table 5: **Potential Extra-jurisdiction and Firm Characteristics**

	ln(inflow)	ln(outflow)	ln(# sup)	ln(# empl)
	I	II	III	IV
Connected$_{is}$	1.741***	2.332***	1.715***	1.056***
	(0.053)	(0.054)	(0.036)	(0.033)
Connected$_{is}$ $\cdot$ Potential Extra$_m$	0.002	-0.013	-0.004	-0.010
	(0.017)	(0.019)	(0.012)	(0.011)
Connected$_{is}$ $\cdot$ Nr Adjacent Munis$_m$	0.040***	0.044***	0.030***	0.022***
	(0.008)	(0.007)	(0.005)	(0.004)
Nr Obs	169,282	158,442	158,442	168,006
Muni*ind*Shock*Time FE	Yes	Yes	Yes	Yes
R^2	0.468	0.438	0.448	0.350

This table reports the relationship between connected customer's observable characteristics and the potential extra-jurisdiction in the two years prior to a natural disaster. The dependent variables, log of cash inflow (column I) and cash outflow (column II), are calculated by summing all payments received and originated by firm i in the year prior to shock s, respectively. The number of distinct suppliers (column III) of firm i is the log of firms that receive a payment from firm i in the year prior to shock s. The log of employees (column IV) is the total number of employees in firm i and the year prior to shock s. Connected$_{is}$ is a dummy equal to one if at least one of firm i's supplier is located in the area of natural disaster s, and zero otherwise. Potential Extra$_m$ is the number of adjacent municipalities of municipality m where firm i is located that do not meet the requirement to become seats of their own judicial district. *Nr Adjacent Munis* is the number of municipalities that shares a border with the seat of the judicial district. The bottom part of the table reports information on fixed effects. Standard errors, clustered by firm and shock, are presented in parentheses. *, **, and *** denote significance of 10%, 5% and 1%, respectively.

Table 6: **Potential Extra-jurisdiction and the Propagation of Shocks**

	ln(inflow)	ln(outflow)	ln(# sup)	ln(# empl)
	I	II	III	IV
$\text{Connected}_{is} \cdot \text{Post}_{st}$	-0.141***	-0.202***	-0.185***	-0.043***
	(0.023)	(0.024)	(0.016)	(0.011)
$\text{Connected}_{is} \cdot \text{Post}_{st}$ $\cdot$ Potential Extra_m	-0.140***	-0.086***	-0.051***	-0.052***
	(0.025)	(0.029)	(0.019)	(0.013)
$\text{Connected}_{is} \cdot \text{Post}_{st}$ $\cdot$ Nr Adjacent Munis_m	-0.009	-0.002	-0.014	0.004
	(0.014)	(0.014)	(0.010)	(0.008)
Firm*Shock FE	Yes	Yes	Yes	Yes
Muni*Ind*Shock*Time FE	Yes	Yes	Yes	Yes
Nr Obs	336,829	316,808	316,808	322,134
R^2	0.930	0.934	0.942	0.925

This table reports changes in firm level variables in the two-year window around a natural disaster. The dependent variables, log of cash inflow (column I) and cash outflow (column II), are calculated by summing all payments received and originated by firm i in year t around shock s, respectively. The number of distinct suppliers (column III) of firm i is the log of firms that receive a payment from firm i in year t. The log of employees (column IV) is the total number of employees in firm i and year t. Connected_{is} is a dummy equal to one if at least one of firm i's supplier is located in the area of natural disaster s, and zero otherwise. Post_{st} is a dummy equal to one in the 2 years after the shock, and zero otherwise. Potential Extra_m is the number of adjacent municipalities of municipality m where firm i is located that do not meet the requirement to become seats of their own judicial district. *Nr Adjacent Munis* is the number of municipalities that shares a border with the seat of the judicial district. Both variables are standardized to mean zero and standard deviation one. The bottom part of the table reports information on fixed effects. Standard errors, clustered by firm and shock, are presented in parentheses. *, **, and *** denote significance of 10%, 5% and 1%, respectively.

Table 7: **Propagation of Shocks, Court Congestion, and Firm Value**

	CAR(-1, +5)		
	I	II	III
Connected_{is}	-0.024***	-0.024***	-0.0422***
	(0.009)	(0.008)	(0.009)
$\text{Connected}_{is} \cdot \text{Court Congestion}_m$		-0.014***	
		(0.005)	
$\text{Connected}_{is} \cdot \text{Potential Extra}_m$			-0.028***
			(0.014)
$\text{Connected}_{is} \cdot \text{Nr Adjacent Munis}_m$			0.014
			(0.006)
Municipality*Ind*Shock FE	Yes	Yes	Yes
Nr Obs	764	764	764
R^2	0.667	0.673	0.684

This Table reports the propagation effect on firm value. The dependent variable is the cumulative abnormal return on the listed firms in the [-1;+5] window around the disaster date. The benchmark index is IBOVESPA. Connected_{is} is a dummy equal to one if at least one of firm i's supplier is located in the area of natural disaster s, and zero otherwise. $\text{Court Congestion}_m$ is the log of the ratio between the average number of backlog cases divided by the average number of judges in municipality m where firm i is located. Potential Extra_m is the number of adjacent municipalities of municipality m where firm i is located that do not meet the requirement to become seats of their own judicial district. *Nr Adjacent Munis* is the number of municipalities that shares a border with the seat of the judicial district. The latter three variables are standardized to mean zero and standard deviation one. Robust standard errors are presented in parentheses *, **, and *** denote significance of 10%, 5% and 1%, respectively.

Table 8: **Propagation of Shocks and Spillovers to Local Competitors**

	ln(inflow)	ln(outflow)	ln(# sup)	ln(# empl)
	I	II	III	IV
$\text{Connected}_{is} \cdot \text{Post}_{st}$	-0.086***	-0.169***	-0.189***	-0.041***
	(0.018)	(0.017)	(0.017)	(0.009)
$\text{Local Competitors}_{is} \cdot \text{Post}_{st}$	-0.009	0.012	-0.011	-0.026***
	(0.014)	(0.014)	(0.010)	(0.007)
Firm*Shock FE	Yes	Yes	Yes	Yes
Muni*Shock*Time FE	Yes	Yes	Yes	Yes
Ind*Shock*Time FE	Yes	Yes	Yes	Yes
Nr Obs	448,011	425,527	425,527	429,331
R^2	0.917	0.920	0.929	0.928

This table reports changes in firm level variables in the two-year window around a natural disaster. The dependent variables, log of cash inflow (column I) and cash outflow (column II), are calculated by summing all payments received and originated by firm i in year t around shock s, respectively. The number of distinct suppliers (column III) of firm i is the log of firms that receive a payment from firm i in year t. The log of employees (column IV) is the total number of employees in firm i and year t. Connected_{is} is a dummy equal to one if at least one of firm i's supplier is located in the area of natural disaster s, and zero otherwise. Post_{st} is a dummy equal to one in the 2 years after the shock, and zero otherwise. $\text{Local Competitors}_{is}$ equals one for unconnected firms that are located in an industry where at least one firm is connected to a supplier hit by a shock s. The bottom part of the table reports information on fixed effects. Standard errors, clustered by firm and shock, are presented in parentheses. *, **, and *** denote significance of 10%, 5% and 1%, respectively.

Table 9: **Within-Affected Supplier Analysis**

	ln(inflow)		ln(outflow)		ln(# sup)		ln(# empl)	
	I	II	III	IV	V	VI	VII	VIII
$\text{Connected}_{is} \cdot \text{Post}_{st}$ $\cdot$ Court Congestion_m	-0.042*** (0.013)		-0.044*** (0.011)		-0.038*** (0.008)		-0.015*** (0.005)	
$\text{Connected}_{is} \cdot \text{Post}_{st}$ $\cdot$ Potential Extra_m		-0.092*** (0.012)		-0.095*** (0.014)		-0.057*** (0.010)		-0.025*** (0.005)
$\text{Connected}_{is} \cdot \text{Post}_{st}$ $\cdot$ Nr Adjacent Munis_m		-0.003 (0.018)		0.008 (0.016)		-0.006 (0.012)		0.021*** (0.008)
Firm*Sup FE	Yes		Yes		Yes		Yes	
Connected*Sup*Time FE	Yes		Yes		Yes		Yes	
Muni*Ind*Sup*Time FE	Yes		Yes		Yes		Yes	
Nr Obs	310,127		294,819		298,520		312,691	
R^2	0.93	0.93	0.94	0.94	0.942	0.942	0.94	0.94

This table reports changes in firm level variables for firms connected to the same supplier in the two-year window around a natural disaster. The dependent variables, log of cash inflow (column I) and cash outflow (column II), are calculated by summing all payments received and originated by firm i in year t around shock s, respectively. The number of distinct suppliers (column III) of firm i is the log of firms that receive a payment from firm i in year t. The log of employees (column IV) is the total number of employees in firm i and year t. Connected_{is} is a dummy equal to one if at least one of firm i's supplier is located in the area of natural disaster s, and zero otherwise. Post_{st} is a dummy equal to one in the 2 years after the shock, and zero otherwise. Potential Extra_m is the number of adjacent municipalities of municipality m where firm i is located that do not meet the requirement to become seats of their own judicial district. *Nr Adjacent Munis* is the number of municipalities that shares a border with the seat of the judicial district. The latter three variables are standardized to mean zero and standard deviation one. The bottom part of the table reports information on fixed effects. To abbreviate notation, Sup stands for interacted affected supplier and shock fixed effects. Standard errors, clustered by firm and shock, are presented in parentheses. *, **, and *** denote significance of 10%, 5% and 1%, respectively.

Table 10: **Firms in Adjacent Municipalities**

	ln(inflow)		ln(outflow)		ln(# sup)		ln(# empl)	
	I	II	III	IV	V	VI	VII	VIII
Connected$_{is}$ · Post$_{st}$ · Court Congestion$_m$	-0.078*** (0.026)		-0.048** (0.021)		-0.026* (0.015)		-0.012* (0.007)	
Connected$_{is}$ · Post$_{st}$ · Potential Extra$_m$		-0.064*** (0.031)		-0.084*** (0.032)		-0.053** (0.021)		-0.022* (0.011)
Connected$_{is}$ · Post$_{st}$ · Nr Adjacent Munis$_m$		0.019 (0.018)		-0.0072 (0.016)		0.010 (0.011)		0.012** (0.006)
Pair*Firm*Sup FE	Yes		Yes		Yes		Yes	
Pair*Connected*Sup*Time FE	Yes		Yes		Yes		Yes	
Pair*Muni*Ind*Sup*Time FE	Yes		Yes		Yes		Yes	
Nr Obs	5,215,821		4,922,428		4,922,428		5,212,197	
R^2	0.93	0.93	0.939	0.939	0.941	0.941	0.949	0.949

This table reports changes in firm level variables for firms both connected to the same supplier and located in adjacent municipalities in the two-year window around a natural disaster. The dependent variables, log of cash inflow (column I) and cash outflow (column II), are calculated by summing all payments received and originated by firm i in year t around shock s, respectively. The number of distinct suppliers (column III) of firm i is the log of firms that receive a payment from firm i in year t. The log of employees (column IV) is the total number of employees in firm i and year t. Connected$_{is}$ is a dummy equal to one if at least one of firm i's supplier is located in the area of natural disaster s, and zero otherwise. Post$_{st}$ is a dummy equal to one in the 2 years after the shock, and zero otherwise. Potential Extra$_m$ is the number of adjacent municipalities of municipality m where firm i is located that do not meet the requirement to become seats of their own judicial district. *Nr Adjacent Munis* is the number of municipalities that shares a border with the seat of the judicial district. The latter three variables are standardized to mean zero and standard deviation one. The bottom part of the table reports information on fixed effects. To abbreviate notation, Sup stands for interacted affected supplier and shock fixed effects. Standard errors, clustered by firm and shock, are presented in parentheses. *, **, and *** denote significance of 10%, 5% and 1%, respectively.

Table 11: **Propagation and Unused Credit Lines**

	ln(inflow)	ln(outflow)	ln(# sup)	ln(# empl)
	I	II	III	IV
Unused $\text{Limit}_{is} \cdot \text{Post}_{st}$	0.009***	-0.013***	-0.034***	0.024***
	(0.001)	(0.001)	(0.001)	(0.000)
$\text{Connected}_{is} \cdot \text{Post}_{st}$ $\cdot$ Unused Limit_{is}	0.057***	0.079***	0.074***	-0.025***
	(0.006)	(0.005)	(0.004)	(0.003)
Unused $\text{Limit}_{is} \cdot \text{Post}_{st}$ $\cdot$ Potential Extra_m	0.008***	-0.008***	-0.007***	-0.004***
	(0.001)	(0.002)	(0.001)	(0.001)
$\text{Connected}_{is} \cdot \text{Post}_{st} \cdot$ Potential Extra_m	-0.102***	-0.159***	-0.077***	-0.062***
	(0.038)	(0.038)	(0.022)	(0.016)
$\text{Connected}_{is} \cdot \text{Post}_{st} \cdot$ Potential Extra_m $\cdot$ Unused Limit_{is}	0.026***	0.023***	0.014***	0.011***
	(0.007)	(0.005)	(0.003)	(0.003)
Pair*Firm*Sup FE	yes	yes	yes	yes
Pair*Connected*Sup*Time FE	yes	yes	yes	yes
Pair*Muni*Ind*Sup*Time FE	yes	yes	yes	yes
Nr Obs	4,422,030	4,160,528	4,160,528	4,369,645
R^2	0.941	0.957	0.962	0.959

This table examines the effect of available credit line balances on firm level variables for firms both connected to the same supplier and located in adjacent municipalities in the two-year window around a natural disaster. The dependent variables, log of cash inflow (column I) and cash outflow (column II), are calculated by summing all payments received and originated by firm i in year t around shock s, respectively. The number of distinct suppliers (column III) of firm i is the log of firms that receive a payment from firm i in year t. The log of employees (column IV) is the total number of employees in firm i and year t. Unused CL_i is the fraction of credit line that is not yet used by firm i just before the shock sorted into quartiles. Connected_{is} is a dummy equal to one if at least one of firm i's supplier is located in the area of natural disaster s, and zero otherwise. Post_{st} is a dummy equal to one in the 2 years after the shock, and zero otherwise. Potential Extra_m is the number of adjacent municipalities of municipality m where firm i is located that do not meet the requirement to become seats of their own judicial district. *Nr Adjacent Munis* is the number of municipalities that shares a border with the seat of the judicial district. The latter three variables are standardized to mean zero and standard deviation one. The bottom part of the table reports information on fixed effects. To abbreviate notation, Sup stands for interacted supplier and shock fixed effects. Standard errors, clustered by firm and shock, are presented in parentheses. *, **, and *** denote significance of 10%, 5% and 1%, respectively.

Table 12: **Factoring and Connected Firms Customers' Congestion**

	ln(factoring)		P(factoring)		ln(work cap)		P(work cap)	
	I	II	III	IV	V	VI	VII	VIII
$\text{Connected}_{is} \cdot \text{Post}_{st}$ $\cdot$ Potential Extra_m	0.213* (0.123)	0.142 (0.125)	0.021** (0.009)	0.018** (0.009)	0.010 (0.014)	0.033** (0.014)	0.150 (0.213)	0.507** (0.221)
Good Customer $\text{Courts}_{is} \cdot \text{Post}_{st}$		0.033 (0.029)		0.003 (0.002)		0.127*** (0.005)		2.006*** (0.073)
$\text{Connected}_{is} \cdot \text{Post}_{st}$ $\cdot$ Good Customer Courts_{is}		0.376** (0.164)		0.029** (0.011)		0.243*** (0.019)		3.890*** (0.305)
Good $\text{Customer}_{is} \cdot \text{Post}_{st}$ $\cdot$ Potential Extra_m		0.086*** (0.008)		0.007*** (0.001)		-0.010*** (0.002)		-0.248*** (0.023)
$\text{Connected}_{is} \cdot \text{Post}_{st} \cdot$ Potential Extra_m $\cdot$ Good Customer Courts_{is}		0.290*** (0.068)		0.013*** (0.005)		-0.033*** (0.007)		-0.466*** (0.111)
Pair*Firm*Sup FE	Yes		Yes		Yes		Yes	
Pair*Connected*Sup*Time FE	Yes		Yes		Yes		Yes	
Pair*Muni*Ind*Sup*Time FE	Yes		Yes		Yes		Yes	
Nrr Obs	5,996,764		5,996,764		5,996,764		5,996,764	
R^2	0.702		0.685		0.747		0.765	

This table examines the effect on factoring and standard WC loans for firms both connected to the same supplier and located in adjacent municipalities in the two-year window around a natural disaster. The dependent variables are log of factoring plus one (columns I and II), probability of factoring (columns III and IV), log of working capital loans plus one (columns V and VI), and probability of working capital loans (columns VII and VIII). Connected_{is} is a dummy equal to one if at least one of firm i's supplier is located in the area of natural disaster s, and zero otherwise. Post_{st} is a dummy equal to one in the 2 years after the shock, and zero otherwise. *Good Customer* $Courts_i$ is a dummy variable that takes the value of 1 if courts at the connected customer's i location are more congested than this firm's customers' courts (i.e., customers of connected customers). Potential Extra_m is the number of adjacent municipalities of municipality m where firm i is located that do not meet the requirement to become seats of their own judicial district. *Nr Adjacent Munis* is the number of municipalities that shares a border with the seat of the judicial district. The latter two variables are standardized to mean zero and standard deviation one. The bottom part of the table reports information on fixed effects. To abbreviate notation, Sup stands for interacted supplier and shock fixed effects. Standard errors, clustered by firm and shock, are presented in parentheses. *, **, and *** denote significance of 10%, 5% and 1%, respectively.

Table 13: **Vertical Integration: Hiring and Acquisition of Upstream Firms**

	ln(# hires)	P[Acquisition]
	I	II
$\text{Connected}_{is} \cdot \text{Post}_{st} \cdot \text{Potential Extra}_m$	0.041***	0.002**
	(0.014)	(0.001)
$\text{Connected}_{is} \cdot \text{Post}_{st} \cdot \text{Nr Adjacent Munis}_m$	0.008	0.003***
	(0.010)	(0.001)
Pair*Firm*Sup FE	Yes	
Pair*Connected*Sup*Time FE	Yes	Yes
Pair*Muni*Ind*Sup*Time FE	Yes	Yes
Nr Obs	5,401,788	5,401,788
R^2	0.745	0.05

This table presents the results on worker hiring and firm acquisition for firms both connected to the same supplier and located in adjacent municipalities in the two-year window around a natural disaster. The dependent variable in column I is defined as the log of hired skilled employees with prior work experience in firm's i affected suppliers j' industry. The pendent variable in column II, is a dummy variable equal to one if firm i acquired a stake in a firm from the same industry as the affected supplier j. Connected_{is} is a dummy equal to one if at least one of firm i's supplier is located in the area of natural disaster s, and zero otherwise. Post_{st} is a dummy equal to one in the 2 years after the shock, and zero otherwise. Potential Extra_m is the number of adjacent municipalities of municipality m where firm i is located that do not meet the requirement to become seats of their own judicial district. *Nr Adjacent Munis* is the number of municipalities that shares a border with the seat of the judicial district. The latter three variables are standardized to mean zero and standard deviation one. The bottom part of the table reports information on fixed effects. To abbreviate notation, Sup stands for interacted supplier and shock fixed effects. Standard errors, clustered by firm and shock, are presented in parentheses. *, **, and *** denote significance of 10%, 5% and 1%, respectively.

Appendix A. Additional Figures and Tables

Table A.1: **Dynamic Specification**

	ln(inflow)	ln(outflow)	ln(# sup)	ln(# empl)
	I	II	III	IV
Connected$_{is}$ · Year $(0)_{st}$	0.0338	-0.029	-0.008	-0.016
	(0.021)	(0.018)	(0.010)	(0.010)
Connected$_{is}$ · Year $(+1)_{st}$	-0.040**	-0.140***	-0.117***	-0.026**
	(0.019)	(0.024)	(0.013)	(0.015)
Connected$_{is}$ · Year $(+2)_{st}$	-0.088***	-0.228***	-0.192***	-0.032**
	(0.025)	(0.028)	(0.016)	(0.014)
Firm*Shock FE	Yes	Yes	Yes	Yes
Size*Muni*Ind*Shock*Time FE	Yes	Yes	Yes	Yes
Nr Obs	336,829	316,808	316,808	322,134
R^2	0.929	0.934	0.942	0.925

This table reports the evolution of the changes in firm level variables in the years around a natural disaster. The dependent variables, log of cash inflow (column I) and cash outflow (column II), are calculated by summing all payments received and originated by firm i in year t around shock s, respectively. The number of distinct suppliers (column III) of firm i is the log of firms that receive a payment from firm i in year t. The log of employees (column IV) is the total number of employees in firm i and year t. Connected$_{is}$ is a dummy variable equal to one if at least one of firm i's supplier is located in the area of natural disaster s, and zero otherwise. The dynamics is measured relatively to the values two years prior to a shock (omitted category). Year (0) equals one in the twelve months prior to shock, and zero otherwise. Year (+1) equals to one in the twelve months after the shock, and zero otherwise. Year (+2) equals one in in the twelve months exactly after the first year of the shock, and zero otherwise. The bottom part of the table reports information on fixed effects. Standard errors, clustered by firm and shock, are presented in parentheses. *, **, and *** denote significance of 10%, 5% and 1%, respectively.

Table A.2: **Propagation of Supply Side Shocks and Unaffected Firms**

	ln(unaffected inflow)	ln(unaffected outflow)	ln(unaffected # sup)
	I	II	III
$\text{Connected}_{is} \cdot \text{Post}_{st}$	-0.086***	-0.164***	-0.163***
	(0.021)	(0.020)	(0.013)
Firm*Shock FE	Yes	Yes	Yes
Muni*Ind*Shock*Time FE	Yes	Yes	Yes
Nr Obs	336,783	316,761	316,761
R^2	0.930	0.938	0.942

This table reports changes in firm level variables in the two-year window around a natural disaster. The dependent variables, log of cash inflow (column I) and cash outflow (column II), are calculated by summing all payments, *excluding to and from firms located in disaster area* s, received and originated by firm i in year t around shock s, respectively. The number of distinct suppliers, *excluding those located in disaster area* s, (column III) of firm i is the log of firms that receive a payment from firm i in year t. Connected_{is} is a dummy variable equal to one if at least one of firm i's supplier is located in the area of natural disaster s, and zero otherwise, respectively. Post_{st} is a dummy equal to one in the 2 years after the shock, and zero otherwise. The bottom part of the table reports information on fixed effects. Standard errors, clustered by firm and shock, are presented in parentheses. *, **, and *** denote significance of 10%, 5% and 1%, respectively.

Table A.3: **Propagation of Supply and Demand Sided Shocks**

	ln(inflow)	ln(outflow)	ln(# sup)	ln(# empl)
	I	II	III	IV
Connected to Aff $\text{Sup}_{is} \cdot \text{Post}_{st}$	-0.083***	-0.161***	-0.165***	-0.022**
	(0.021)	(0.020)	(0.013)	(0.007)
Connected to Aff $\text{Cust}_{is} \cdot \text{Post}_{st}$	-0.064***	-0.061***	-0.037***	-0.033***
	(0.018)	(0.020)	(0.013)	(0.006)
Firm*Shock FE	Yes	Yes	Yes	Yes
Muni*Ind*Shock*Time FE	Yes	Yes	Yes	Yes
Nr Obs	336,829	316,808	316,808	322,134
R^2	0.930	0.941	0.941	0.955

This table reports changes in firm level variables in the two-year window around a natural disaster. The dependent variables, log of cash inflow (column I) and cash outflow (column II), are calculated by summing all payments received and originated by firm i in year t around shock s, respectively. The number of distinct suppliers (column III) of firm i is the log of firms that receive a payment from firm i in year t. The log of employees (column IV) is the total number of employees in firm i and year t. Connected to Aff Sup_{is} and Connected to Aff Cust_{is} are dummy variables equal to one if at least one of firm i's suppliers or customers is located in the area of natural disaster s, and zero otherwise, respectively. Post_{st} is a dummy equal to one in the 2 years after the shock, and zero otherwise. The bottom part of the table reports information on fixed effects. Standard errors, clustered by firm and shock, are presented in parentheses. *, **, and *** denote significance of 10%, 5% and 1%, respectively.

Table A.4: **Propagation of Supply Side Shocks and Firm Size**

	ln(inflow)	ln(outflow)	ln(# sup)	ln(# empl)
	I	II	III	IV
$\text{Connected}_{is} \cdot \text{Post}_{st}$	-0.057**	-0.151***	-0.142***	-0.020*
	(0.027)	(0.024)	(0.017)	(0.012)
Firm*Shock FE	Yes	Yes	Yes	Yes
Size*Muni*Ind*Shock*Time FE	Yes	Yes	Yes	Yes
Nr Obs	230,739	216,270	216,270	220,309
R^2	0.938	0.943	0.949	0.943

This table reports changes in firm level variables in the two-year window around a natural disaster, controlling for firm size. The dependent variables, log of cash inflow (column I) and cash outflow (column II), are calculated by summing all payments received and originated by firm i in year t around shock s, respectively. The number of distinct suppliers (column III) of firm i is the log of firms that receive a payment from firm i in year t. The log of employees (column IV) is the total number of employees in firm i and year t. Connected_{is} is a dummy variable equal to one if at least one of firm i's supplier is located in the area of natural disaster s, and zero otherwise, respectively. Post_{st} is a dummy equal to one in the 2 years after the shock, and zero otherwise. The bottom part of the table reports information on fixed effects. Standard errors, clustered by firm and shock, are presented in parentheses. *, **, and *** denote significance of 10%, 5% and 1%, respectively.

Table A.5: **Court Congestion and Propagation - IV Estimates**

	ln(inflow)	ln(outflow)	ln(# sup)	ln(# empl)
	I	II	III	IV
Connected$_{is}$ · Post$_{st}$	-0.102***	-0.173***	-0.174***	-0.027**
	(0.028)	(0.021)	(0.015)	(0.013)
Connected$_{is}$ · Post$_{st}$	-1.110***	-0.646***	-0.349***	-0.436***
· Court Congestion$_m$	(0.266)	(0.216)	(0.149)	(0.129)
Firm*Shock FE	Yes	Yes	Yes	Yes
Muni*Ind*Shock*Time FE	Yes	Yes	Yes	Yes
Model	IV	IV	IV	IV
Nr Obs	336,829	61,466	316,808	322,134
R^2	0.929	0.937	0.942	0.924

This table reports the relationship between changes in firm level variables and court congestion in the two-year window around a natural disaster, using an instrumental variable approach (2SLS). The dependent variables, log of cash inflow (column I) and cash outflow (column II), are calculated by summing all payments received and originated by firm i in year t around shock s, respectively. The number of distinct suppliers (column III) of firm i is the log of firms that receive a payment from firm i in year t. The log of employees (column IV) is the total number of employees in firm i and year t. Connected$_{is}$ is a dummy equal to one if at least one of firm i's supplier is located in the area of natural disaster s, and zero otherwise. Post$_{st}$ is a dummy equal to one in the 2 years after the shock, and zero otherwise. Court Congestion$_m$ is instrumented through Potential Extra$_m$, which is the number of adjacent municipalities of municipality m where firm i is located that do not meet the requirement to become seats of their own judicial district, and *Nr Adjacent Munis*, which is the number of municipalities that shares a border with the seat of the judicial district. Cross-sectional variables are standardized to mean zero and standard deviation one. The bottom part of the table reports information on fixed effects. Standard errors, clustered by firm and shock, are presented in parentheses. *, **, and *** denote significance of 10%, 5% and 1%, respectively.

Table A.6: **Potential Extra-jurisdiction and Propagation: Adding Controls**

	ln(inflow)	ln(outflow)	ln(# sup)	ln(# empl)
	I	II	III	IV
$\text{Connected}_{is} \cdot \text{Post}_{st}$	-0.229***	-0.248***	-0.211***	-0.062***
	(0.034)	(0.035)	(0.023)	(0.017)
$\text{Connected}_{is} \cdot \text{Post}_{st}$	-0.083**	-0.077*	-0.048*	-0.045***
$\cdot$ Potential Extra_m	(0.041)	(0.046)	(0.025)	(0.021)
$\text{Connected}_{is} \cdot \text{Post}_{st}$	-0.050	-0.059*	-0.045*	-0.016
$\cdot$ Nr Adjacent Munis_m	(0.037)	(0.035)	(0.024)	(0.019)
Firm*Shock FE	Yes	Yes	Yes	Yes
Muni*Ind*Shock*Time FE	Yes	Yes	Yes	Yes
Nr Obs	336,829	316,808	316,808	322,078
R^2	0.93	0.934	0.942	0.925

This table compares outcomes of firms connected to suppliers located in disaster struck areas with unconnected firms in the two years window around the natural disaster cross-sectionally. Connected_{is} is a dummy equal to one if at least one of firm i's supplier is located in the area of natural disaster s, and zero otherwise. Post_{st} is a dummy equal to one in the 2 years after the shock, and zero otherwise. Potential $\text{Extra-jurisdiction}_m$ is the number of adjacent municipalities that do not meet the requirement to become seats of their own judicial district. *Nr Adjacent Munis* is the number of municipalities that shares a border with the seat of the judicial district. We also add interactions between Connected $\cdot$ Post with a series of control variables: (a) the log of the average income per capita of municipality m; (b) the log of the geographical area of the municipality; (c) the number of firms to population ratio of each municipality; (d) the averages of the last 3 variables for the neighboring municipalities of municipality m; and (e) a dummy equal to one if there is a bankruptcy court in the municipality m, and zero otherwise. We standardize the continuous variables by demeaning them and dividing by its standard deviation to facilitate the interpretation of the results. Log of cash inflow (column I) and cash outflow (column II) are calculated by summing all the payments received and originated by each firm i in year t around shock s, respectively. The number of distinct suppliers (column III) of firm i is calculated by counting the firms that receive a payment. we construct the number of employees (column IV) using data on labor contracts in firm i and year t. The first set of fixed effects controls for any time invariant factor within the firm and shock event. The second set of fixed effects controls for any time-varying factor at the local industry within each shock. Standard errors, clustered by firm and shock, are presented in parenthesis. *, **, and *** denote significance of 10%, 5% and 1%, respectively.

Table A.7: **Exposure, Potential Extra-Jurisdiction and the Propagation of Shocks**

	ln(inflow)	ln(outflow)	ln(# sup)	ln(# empl)
	I	II	III	IV
Connected$_{is}$ · Post$_{st}$	-0.061	-0.089*	-0.086**	0.001
	(0.052)	(0.050)	(0.034)	(0.018)
Connected$_{is}$ · Post$_{st}$ · Quart Exposure$_i$	-0.033*	-0.046**	-0.040***	-0.013*
	(0.019)	(0.019)	(0.013)	(0.007)
Connected$_{is}$ · Post$_{st}$ · Potential Extra$_m$	-0.021	0.045	0.017	0.005
	(0.056)	(0.059)	(0.040)	(0.020)
Connected$_{is}$ · Post$_{st}$ · Potential Extra$_m$ · Quart Exposure$_i$	-0.049**	-0.054**	-0.028*	-0.013*
	(0.021)	(0.025)	(0.017)	(0.008)
Firm*Shock FE	Yes	Yes	Yes	Yes
Muni*Ind*Shock*Time FE	Yes	Yes	Yes	Yes
Nr Obs	336,829	316,808	316,808	322,134
R^2	0.93	0.934	0.942	0.954

This table reports the effect of exposure to suppliers located in disaster struck areas and the quality of courts on changes in connected firm level variables in the two-year window around the natural disasters. Connected$_{is}$ is a dummy equal to one if at least one of firm i's supplier is located in the area of natural disaster s, and zero otherwise. Post$_{st}$ is a dummy equal to one in the 2 years after the shock, and zero otherwise. Potential Extra-jurisdiction$_m$ is the number of adjacent municipalities that do not meet the requirement to become seats of their own judicial district. We standardize this variable by demeaning it and dividing by its standard deviation to facilitate the interpretation of the results. We sort connected firms into quartiles of exposure ($Quart\ Exposure_i$), which is calculated as the ratio between the cash outflow to affected suppliers and the total cash outflow of firm i in the two years before the natural disaster. Log of cash inflow (column I) and cash outflow (column II) are calculated by summing all the payments received and originated by each firm i in year t around shock s, respectively. The number of distinct suppliers (column III) of firm i is calculated by counting the firms that receive a payment. we construct the number of employees (column IV) using data on labor contracts in firm i and year t. The first set of fixed effects controls for any time invariant factor within the firm and shock event. The second set of fixed effects controls for any time-varying factor at the local industry within each shock. Standard errors, clustered by firm and shock, are presented in parenthesis. *, **, and *** denote significance of 10%, 5% and 1%, respectively.