Delay by Contagion in the Payment System

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February 28, 2023

Abstract

This paper provides empirical evidence of contagion of delay in the payment system caused by banks' unexpected liquidity outflow shock experiences. We study the system's outward and inward spillovers of delay using transaction-level data from the German interbank payment market. We find banks that have experienced shock temporarily halt settlement within payment systems unless adequate incoming payments are received. We also find significant heterogeneity in the relative importance of direct and network (indirect) effects of unexpected liquidity outflows across the interbank network. Furthermore, we pin down the role of banks acting as intermediaries in payment transactions requested by financial and non-financial institutions. Our results ensure consistency after controlling for a multiple set of control variables of unobserved characteristics of the network and bank-pair effects. This type of delay has policy implications since payment system gridlocks may happen if a considerable number of payments are settled late due to unexpected liquidity outflow shock.

Keywords: Payment system, Interbank Market, Financial Contagion, Delay Contagion
JEL classification: E44; G10; G21.

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1 Introduction

One of the fundamental principles of banking supervisory innovations is to ensure an effective and reliable payment system [Parlour et al., 2022]. The payment system is frequently subjected to unexpected outflows of liquidity. As a result, payment system members may be enticed to temporarily halt settlement within payment systems unless adequate incoming payments are received. The biggest concern is that those delayed payments might cause additional delays in the system, which will cause the entire or a large part of the connected payment network to be delayed. The main question that emerges then is how the delay contagion spreads across the payment network. Despite the importance of late payments to financial stability, there have been few empirical studies on the effects of late payments in the interbank market. This is primarily due to the lack of a robust and straightforward empirical method to track contagion in the payment system as a complex and interconnected system, as well as limited access to transaction-level data.

This paper studies the delay and dynamics of contagion processes in the payment system and addresses its ambiguity. We use novel transaction-level data from the Trans-European Automated Real-time Gross settlement Express Transfer (TARGET) payment system, which is a real-time gross settlement (RTGS) payment system. We call it a delay if the time of payment stays in the payment system until the clearing time is higher than zero. We analyze the unexpected liquidity outflow shock when a member of the payment system has an experience of receiving an order with the payment value at the top of its payment value distribution. This shock might be considered a single idiosyncratic shock affecting an individual member of the system. We define the corresponding delay to this shock as a fundamental delay in the payment system. Furthermore, we introduce a different kind of delay caused by contagion, in which the counterparty or counterparty of the counterparty experienced a delay with the idiosyncratic shocks.

We investigate the contagion effects of unexpected liquidity outflow shocks on the payment system empirically. Generally, banks have several ways of generating liquidity, such as borrowing from other banks (interbank loans) or the central bank, selling loans, and raising capital. The interbank activities of other banks in the payment system might partially influence a bank's liquidity requirements [Parlour et al., 2022]. Loss of liquidity could happen to a bank if it loses some fractions of its liquidity due to the liquidity hoarding of counterparties or unexpected liquidity outflow shock from customers. Indeed, banks that would have enough liquidity to fulfil their payments on time if the delays did not occur may encounter an unexpected lack of liquidity. Thus, banks immediately ask for available interbank liquidity to avoid experiencing liquidity problems. As a result, illiquidity spreads throughout the financial system. In this situation, the system requires large amounts of liquidity and is prone to a significant number of payment delays [Martin and McAndrews, 2008]. There is some theoretical and empirical evidence that illiquidity can lead to insolvency when banks cannot pay their debts. In theory, payment systems can be characterized by multiple equilibria involving some undue delays [Angelini, 1998, 2000, Bech and Garratt, 2003]. If the cost of delay is adequately low and the banks have unrestricted access to intraday liquidity provided by central banks, banks do not have an incentive to postpone payments. In this equilibrium, payments must be released early, and payments would not be queued. If the system charges banks for intraday liquidity, the banks have an incentive to delay payments, and the equilibrium output might not be socially optimal [Angelini, 1998]. When intraday liquidity is costly, the payment system's environment becomes more turbulent and uncertain. As a result, members of the payment system behave strategically because the situation may change because of other members' actions. Both delaying and not delaying can be characterized as equilibrium results of the system in this situation [Kobayakawa et al., 1997]. Therefore, banks must synchronize their payment with arriving payments and find the most suitable action in a coordination game with imperfect and incomplete information [McAndrews and Rajan, 2000].

Our research is based on interbank payment transaction-level data from the Deutsche Bundesbank's real-time gross settlement plus (RTGSplus) system. The transaction-level data allows us to make an accurate hourly and daily analysis of the system's response to delays. This unique dataset provides us with a deep understanding of banks' behaviour in interbank markets. This information is crucial for identifying delay contagion in the network and answering the key question of this paper. We aggregate multiple transactions on the same hour or the same day for the same bank pair to a single observation and build hourly or daily networks to assess outward and inward spillovers of delay on the system. The payment network is not constant, and the number of nodes and links changes over time. These systematic patterns have an important implication for our study. In fact, the characteristics of this dynamic network help us determine the role of bank connectivity in the risk of the contagion of delay in the system over time.

Estimating network effects of the delay of payment poses three challenges: the identification of unexpected outflow liquidity shocks, the identification of the directed impact of these shocks, and the identification of the network (indirect) impacts of the shocks. We address the first challenge by defining an indicator when a bank receives an order with a value in the top 5% of its payment distribution. To address the second challenge, we construct a simple and traceable econometric model to identify the directed impact of unexpected outflow liquidity shocks. We pin down these shocks' effects by controlling the time, bank, and bank-to-bank level fixed effects on a transaction and hourly basis. Finally, we address the third challenge by using spatial autoregression models. These spatial models help to decompose the overall effect of unexpected liquidity outflow on the payment system into direct and indirect (higher-order network) effects. These models allow us to estimate the total effect of unexpected liquidity outflow on the payment system within a small event window while adjusting for any confounding effects of potential shocks.

An essential contribution of our study thus lies in providing a tractable and structural interpretation of network effects on both high- and low-frequency basis. Using our simplified model, we can identify where the shock originates and how it travels through the network. We discuss a network view of the payment system and describe our identification strategy to study the delay and dynamics of contagion processes in the payment system. We construct our network based on the information of the senders and receivers of the payment. As is crucial for the propagation of shocks, the structure of this network is not constant and can vary from hour to hour and day to day. On a daily basis, we estimate the system's response to unexpected liquidity surprises with non-spatial and spatial panel data models.

We present the empirical results of this study in Section 5. Our specification is empirically relevant since it efficiently translates into a simple test for contagion and tracks the delay driven by the counterparty or counterparty of the counterparty. We observe that the unexpected liquidity outflow shocks resulting from the request by non-members and payment system members are significant and increase during forenoon and afternoon, respectively. Accordingly, our model allows us to pin down the role of banks acting as intermediaries in payment transactions demanded by financial and non-financial institutions. We find that the structure of the payment network is not constant and can be changed hourly and daily. At the beginning of the working day, banks create several clusters with other banks to stall their payments. At the end of the working day, the financial network structure is changed, and banks are linked in a star structure. According to our empirical analysis, banks are delaying payments in the morning on the condition that all payments must be cleared and settled by the end of the working day, which is consistent with the empirical findings of Lacker [1997], Angelini [1998], Kahn and Roberds [2001]. We observe these patterns of payment delay regularly. These patterns reveal the systematic behaviour of payment system members over time. The reason might be that a member of the payment system holds enough liquidity during the afternoon, enabling members to be resilient to counterparty and fundamental unexpected liquidity shocks. The second casual explanation is that banks primarily postpone or slow their settlement process to utilize their counterparties' resources to process their payment. Consequently, to distinguish the main delay factors derived from unexpected liquidity shortages from some systematic time-related facets, we extract the seasonality component of the payment data. Our simple tractable model lets us pin down the effects of shocks from upstream counterparties that can circulate by contagion on the transaction and hourly level. We conduct our empirical strategy with different time frequencies, and we control the seasonality patterns in payment data on an hourly and daily basis. Nonetheless, these are not the only channels through which shock can travel in the network. Since financial networks include several loops and intermediaries, the delayed shocks might move back to their origins. We, therefore, extend our baseline model to a spatial model and identify direct and higher-order network (indirect) effects of the overall effect of shocks of unexpected liquidity outflow. We then run the rolling window regression analysis to obtain the unexpected liquidity outflow shocks time variation of direct and indirect (network) effects. Our findings show several structural breaks and regime evolution of unexpected liquidity outflow shocks over time which might be explained by endogenous and exogenous factors related to the payment system.

We also document considerable heterogeneity in the comparative importance of direct and network effects of unexpected liquidity outflow across the interbank network. Banks impose fewer interbank shocks to their strategic partners in the payment system. The prime importance of direct effects of the unexpected liquidity outflows is that these shocks directly increase the time to process the payment, which gets transmitted to other system members and further upstream in the interbank network. Since the interbank network is nonlinear with cycles and loops and banks are naturally liquidity constrained, the unexpected liquidity outflow shock indirectly hits banks.

The rest of this paper is structured as follows. The section 2 describes our contributions to several strands of the banking literature on payment system delays. In section 3, we describe the data source for our empirical study and define our explanatory variables. The experimental design of our model is described in section 4. The section 5 discusses the empirical results. Section 6 provides concluding remarks.

2 Related Literature

Our paper relates to the recent and growing literature on financial contagion through the delay channel. The concept of financial contagion in the banking literature has been initiated with studies about bank runs under incomplete information [Diamond and Dybvig, 1983] or perfect information [Rochet and Tirole, 1996, Diamond and Rajan, 2005, Allen and Gale, 2000], leading to financial contagion. These studies assumed that when one member of the financial system becomes insolvent or defaults, other members become insolvent or default due to interconnections. More generally, our paper is related to the broad literature on exploiting relationships among banks [Petersen and Rajan, 1994, Detragiache et al., 2000, Wilner, 2000, Dahiya et al., 2003], between banks and customers [Petersen and Rajan, 1994, Dahiya et al., 2003], as well as between banks and firms [Sharpe, 1990]. We contribute to this literature by analyzing the interbank relationship of banks in the payment system. Our empirical strategy helps to understand the role of the relationship between banks and pin down the delay mechanism in the payment system. In this regard, our study is also similar to another strand of literature which highlights the role of financial institutions' interconnectedness in spreading shocks through the financial system. Prior studies propose various mechanisms for describing contagion in a financial system and the role of different network structures of the financial system [Gale and Kariv, 2007, Allen and Gale, 2000]. Due to the interlinked financial exposures among institutions, this distress can spread throughout the financial system in a domino fashion. The essential issue concerning the contagion mechanism of the financial networks compared to other networks is the different types of the complexity of financial systems from other social or economic systems [Jackson and Pernoud, 2020]. For instance, in the contagion of a disease or spread of an opinion, adding more interactions solely speeds up the rate of spreading. In the financial system, the contagion of stress can be effective if several counterparties are affected. Therefore, the intervention or regulation strategy for mitigating the stress in this network is not the same as other networks like social distancing strategies to stop the spread of COVID-19 or the SARS-CoV-2 virus [Stukalov et al., 2021].

This paper is closely related to empirical work on the settling process in the RTGS system by Bräuning and Fecht [2017]. They use the Furfine and Stehm [1998] algorithm to extract "unsecured overnight lending" information from transaction payment data recorded in Deutsche Bundesbank's real-time gross settlement (RTGSplus) system. Their findings indicate that partner lenders are more likely to provide liquidity to their relatively close borrowers, especially opaque borrowers who obtain finances at lower rates from their partner lenders. During the crisis, partner lenders issued more affordable loans to their relatively near depositors. We apply a similar empirical methodology but do not restrict our analysis to "unsecured overnight lending" information.

Additionally, we extend our regression model to a spatial model to decompose the overall impact of unexpected liquidity outflow on the payment system into direct and indirect (higher-order network) effects. Typically, spatial models deal with the problem related to "location, transport, and land" in economics [Proost and Thisse, 2019]. Bresnahan and Reiss [1991], Pinkse et al. [2002] apply the spatial models to study price competition between firms in the market, while Agarwal and Hauswald [2010] use these models to investigate spatial discrimination [Hollander and Verriest, 2016] in the relationship of bank-firms in the loan lending markets.

We investigate the impacts of unexpected outflow liquidity shocks on the time processing of the payments in RTGS systems. The results of a study by Kahn et al. [2003] show that large liquidity requirements could create deadlocks in the system and raise the necessity of central bank intervention [Kahn and Roberds, 2001]. Baglioni and Monticini [2008], Kraenzlin and Nellen [2010] explore the banks' intraday liquidity mechanism by utilizing RTGS payment systems in the Italian and the Swiss interbank markets. Maddaloni [2015] shows that liquidity risks in the RTGS payment systems depend on the efficiency and competence of liquidity management policy. Kahn et al. [2003] discuss other settlement risks. Similarly, Merrouche and Schanz [2010] explore the time dimension of settlement risks. Martin and McAndrews [2008] study the "liquidity-saving mechanism" in the RTGS system with implications for welfare. They show the trade-off of the expenses of delaying and postponing the payment versus the central bank liquidity borrowing approach. Freixas et al. [2000], based on the Freixas and Parigi [1998] approach, find that the liquidity from the central bank for RTGS systems is an efficient way to eliminate deadlock equilibria. In fact, central banks providing liquidity freely to members of the payment system ensure payment settlement, and preserve the liquidity and functionality of the net settlement system. To our knowledge, no prior studies have examined the payment system's response to outflow liquidity shocks in a network setting. We complement the past studies on the payment system by providing a long term study of the payment system members' behaviour in an interconnected model. In our study, we consider the liquidity risk when a member of RTGS will not acquire payment due to settlement delay, which becomes an encouragement to delay the future payment.

Interpreting empirical results through the lens of theory helps understand the payment system's mechanism in response to delay. Koeppl et al. [2008] theoretically study the role of settlement in a dynamic model; Koeppl et al. [2012] use this model to investigate the optimal mechanism of clearing across markets. From a theoretical perspective, Bech and Garratt [2003] propose a model to analyze the "liquidity management game". Banks play the "stag-hunt" and "prisoner's dilemma" games as coordination type games in their model. This research indicates that banks might have incentives to delay their payments;

accordingly, there are two Nash equilibria for early and late settlement of payments. Our empirical study demonstrates how illiquidity in the interbank payment system following unexpected outflow liquidity shocks causes a series of delays in the system.

We study the timing of payments a policy of liquidity management [Kahn and Roberds, 2009]. Bartolini et al. [2010] show that in the Fedwire and the US RTGS systems, most payment transactions of money market loans are executed and settled at the end of business hours. A study by Baglioni and Monticini [2008] shows that for the period 2003-2004, trading was more costly in the morning than in the afternoon in the intraday money market. We observe similar patterns in the RTGS payment system. Several studies in the banking literature have shown that the member of the RTGS payment system delays their settlement due to the high cost of the needed liquidity [Angelini, 1998, 2000, Bech and Garratt, 2003]. Delay in the payment system might expose private and social costs [Bech and Garratt, 2012]. The former type of cost is related to the creation of uncertainty for counterparties and other payment system participants who might face credit risk exposures directly or indirectly [Kahn et al., 2003]. On a larger scale and for a longer duration, this disruption may cause counterparties to become more insecure, causing them to halt temporary activities such as investing and recruitment [Bloom, 2009]. The latter type of cost is concerned with increasing the risk of interruption in the functioning of the payment system [Bech and Garratt, 2012]. This type of delay has policy implications because payment system gridlocks may happen if a considerable number of outgoing payments are settled late in the working day.

In the present paper, we focus on the delay in the payment system due to unexpected liquidity outflow shocks. However, there are other factors that can disturb the functioning of the payment system. Some regulation policies such as bilateral or multilateral limits or other externalities can delay the processing of the payment system. Bech and Garratt [2012], Lacker [2004] investigate the consequences of financial disruptions Weill [2007] like terrorist attacks on the payment and settlement systems. Bernanke [1990] investigate the clearing and settlement of the payments during other financial disruptions, such as the stock market crash in 1987. Another important factor in delaying payment processing is the behavioural characteristics of the payment system's members. Based on available information, we cannot directly observe the tendency of the bank to delay the payment. In fact, we cannot identify banks' behaviour in response to the unexpected shock due to their prior decisions and planned choices [Barberis, 2012] or actual (natural) choices to delay the payments. Bartolini et al. [2010] investigate settlement delays empirically in the overnight interbank loans market and provide evidence of strategic delay in this market.

Armantier et al. [2008], McAndrews and Rajan [2000] show that it is possible that banks strategically postpone their settlement to anticipate an adequate number of inbound payments. However, identifying strategic behaviour banks in the settlement system is not straightforward. Bech et al. [2010] apply a Markov model to estimate the propensity of banks to delay the payment settlement. Foote [2014] extend this literature to study the strategic behaviour of a bank in delaying the payments functioning across multiple systems. In our study, we focus on one payment system. However, the competition between payment systems causes externalities and the potential of spillover effects across the whole financial system [Rochet and Tirole, 1996].

We apply our analysis to the RTGS system. In an RTGS system, payments are settled at the transaction time, while the requests of payments are netted, and the payments are then settled in a net settlement system. Kahn and Roberds [1998] compare net and gross settlement payment systems in terms of moral hazard problems, investment incentives and probability of default of banks. Our analysis is also relevant to the decentralized payment system as a new netting settlement system environment. Recent academic evidence supports the view that a decentralized finance system can solve some critical issues of a centralized payment system [Harvey et al., 2021]. Thakor [2020] reviews some innovations in payment systems such as cryptocurrencies and peer-to-peer payment systems with interactions to fintech. These new structures of payment systems aim to facilitate clearing and settlement of the payments in the decentralized finance climate [Thakor, 2020] while also reducing settlement costs [Parlour et al., 2022]. However, in this environment, the blockchain network might experience peak traffic and payment delays as well.

3 Data and variable definitions

This section will describe the data source of the payment system and provide statistical description information about the network view of data. We define the delay in a system and identify unexpected outflow liquidity shocks in the payment system. We continue the section by explaining the mechanism of delay contagions and how a delay by one institution may impact other institutions directly and indirectly.

Our analysis of this study relies on novel transaction-level data of interbank payment records taken from the Deutsche Bundesbank's real-time gross settlement plus (RTGSplus) system. One such real-time gross settlement (RTGS) system for settling large-value payments active in Europe is TARGET. This payment system was integrated into the European markets. This system has a strong influence on the financial stability of European markets. Therefore, any interruption of low performance has an immediate negative impact on other markets. Accordingly, the availability of this system with a very high performing level of payments in a short time is vital for the financial stability of the Eurosystem. The overall availability of TARGET was 99.90% in 2007, compared to 99.87% in 2006 [ECB, 2006, 2007].

The German banking system, which utilizes the TARGET system, is the largest banking system in the Euro area and one of the earliest banking systems affected by the Subprime mortgage crisis that began in 2007. Therefore, this payment system provides a novel platform to analyze the impacts of delay in the interbank system. For each transactional observation, there is information about the senders and receivers of the payment, who are members of the payment system. There is also information available about a bank or firm that orders the payment and the ultimate receiver of the payment, which may not include the members of the payment system. The sending and receiving banks recognized in the payment data are not necessarily the main participants in the transaction. These banks might be operating as dealers or intermediaries in the operation of transactions.

Our sample data starts from March 1, 2006, to November 15, 2007. The period of the study covers the beginning of the sub-prime crisis in 2008. Our data sample includes 72,851,656 payment transactions of 1,079 unique pairs of large German banks as well as some small banks. The dataset includes the transaction level of interbank payments, unsecured overnight loans, and payments on behalf of the customers. The TARGET payment system was an active real-time gross settlement system at the national level until the "TARGET2" payment system replaced it on November 19, 2007. The TARGET2 payment system is an international level payment system which covers European countries. There are transaction data from banks from other countries. However, these banks are associated with German banks' subsidiaries.

Our database contains detailed information on the Bank Identifier Code (BIC) of institutions that issue and receive the credit, as well as the amount of the credit in Euro. For each transaction data, we have information on the sender and receiver of the payment message. We also have information about the entry and clearing time and the volume of each payment. In this database, there are two types of payment transactions. The first type of payment is related to the transfer of credits between two banks as interbank payment. It might be that an RTGS member bank sends credit as the main beneficiary or on behalf of another bank. The second type of payment transaction is related to the transferring of credit by an RTGS member on behalf of an external customer. A bank or firm must request the payment to a member of the TARGET system to make the payment. The payment beneficiary receives the credited amount of payment. It is possible that several parties involved in a payment transaction are not directly members of the TARGET system.

The delay in a system is defined as the changing of the response time of the system caused by exogenous factors. These factors, which might have different contributions to changing the response time of the system, can influence the input of the system at the initial stage of the process or during the process. Consequently, the system can strategically react to exogenous shocks and adapt its behaviour to maximize its objective functions. To measure the delay in the payment system, we define the Time to Process of Payment (TPP) as follows.

Definition 3.1. *Time to Process of Payment (TPP)*

The Time to Process of Payment (TPP) is defined as the difference between the time of receipt of the payment message in RTGS ($Time^{Entry}$) and the time of clearing the payment message from RTGS ($Time^{Final}$),

$$TPP = Time^{Entry} - Time^{Final}.$$

In this study, we call it a delay when the time of payment stays in the payment system until the clearing time is higher than zero. It is a strict way of expressing delay in the RTGS system. In the following section, we present a comprehensive account of the mechanism that causes contagion within the payment system. The contagion mechanism of delay can be described as follows. When a single member of the payment system faces a delay due to unexpected liquidity experiences or strategic business of its counterparty, it creates challenges for other members waiting to receive payments from the bank to meet their liquidity obligations on time. As a result, this liquidity shock can spread throughout the system due to the payment network's structure and interconnectivity.

The delay in the payment system can be loosely categorized into two forms. The first is "fundamental delay", which includes delays caused by exogenous factors. A large payment on behalf of a customer or another bank can create an unexpected liquidity shock and cause a delay in clearing the upcoming payments. The shock is the sole knock-on effect of the idiosyncratic risk that targets the bank, causing a delay in the payment transaction. The second type of delay is "delay by contagion", which is the consequence of shocks initiated by fundamental delays or delays as a consequence of the business strategy of the payment system's member. These shocks propagate throughout the whole or a part of the system. If the shocks transmit throughout the system, it will create a channel for delay contagion; the delay of one system member may trigger a domino effect in the payment system. The delayed payments cause the bank to delay its future payments, eventually causing the whole connected network to be delayed. A delay cascade is a systemic phenomenon that occurs when a stressed member of the system hoards liquidity as a result of a large-scale unexpected liquidity shock. In this cascade, shocks are spread upstream, sending banks to their counterparties as they act to delay their payment lending. When a bank's liquidity drops below the threshold of liquidity constraint, as is expected, the bank will also delay its upcoming lending. This explains the origin of a cascade mechanism transmitted through the system, from senders to receivers. This cascade can be interpreted as a basic model of funding liquidity cascades of the interbank network.

We define Unexpected Liquidity OutFlow (ULOF) as a branch of the fundamental delay as follows:

Definition 3.2. *Unexpected Liquidity OutFlow (ULOF)*

Unexpected Liquidity OutFlow (ULOF) as an indicator when a member of the system has an experience of receiving an order from non-member which the value of the payment in the top α% of the member's payment amount distribution:

$$ULOF := \begin{cases} 1 & V(P) > F_{V(P_{q_\alpha})}, \\ 0 & otherwise, \end{cases}$$

where $V(P)$ is the amount of payment P with density function F and α percentile of the history of payments.

In our study, we choose α as 0.05, and we calculate the 95% percentile of each bank's customer and interbank amount payments, and we create a dummy that indicates the payment amounts are above this threshold or not. We use the following notations $ULOF^{Cust}$ and $ULOF^{Inter}$ for $ULOF$ shocks of a non-member of the payment system, i.e. a customer and a bank, respectively.

Next, we turn into the former type of delay, delay by contagion when a payment sender counterpart experienced with ULOF shocks which caused an expected delay. The following indicator expresses this type of delay.

Definition 3.3. *Counterparty's Liquidity OutFlow (CLOF)*

Counterparty Liquidity OutFlow is defined as as unexpected shocks as a consequence of a delay of receiving a payment by a counterparty who had an experience of $ULOF$ shocks.

$$CLOF := \begin{cases} 1 & \text{a payment by a counterparty with an experience of ULOF}, \\ 0 & otherwise. \end{cases}$$

The indicator $CLOF$ shows the delay of a payment as a consequence of a delay of a counterparty. The counterparty can have experiences of either $ULOF^{Cust}$ or $ULOF^{Inter}$ shocks. It measures the possibility of contagion of a delay from one member of RTGC to another. We use the same notation as before: $C1LOF^{Cust}$ and $C1LOF^{Inter}$ indicators present shocks by the first counterparty who had an experience of $ULOF^{Cust}$ or $ULOF^{Inter}$

shocks, respectively. We apply similar terminology for a shock by the counterparty of the counterparty, i.e., $C2LOF$ shocks. It means that the counterparty of the counterparty had an experience of $ULOF$ shocks, and it might cause a contagion to settle the current payment.

It is well-known that the time-varying global and domestic exogenous shocks can influence payments. To address these issues, we include bank and time fixed effects to control for unobserved characteristics of bank senders and bank receivers of payments. By having bank-to-bank fixed effects in the model, we can control the interbank system's unobserved characteristics with a bank-to-bank level variation. It helps us capture the endogenous and heterogeneous types of shocks in the system and identify heterogeneous effects across bank pairs. Additionally, we include the Euro OverNight Index Average (EONIA) rate and volatility of the DAX index to capture these impacts. By controlling these factors, we can isolate the pure effect of factors that cause a delay in the payment system and pin down the outward and inward spillovers of delay on the interbank system.

Since we aim to assess the risk of contagion of delay in the payment system, we need to consider the interconnectivity of banks in the payment system. In doing so, we construct a network of members of the TARGET payment system involved in a payment transaction. Alternatively, we can build a network of issuing credit institutions and final beneficiary credit institutions. However, in our study, a network of members of the TARGET system with the directional link is more relevant since it allows us to follow the flow of the credited payment amount from the sender to the receiver. In this network configuration, the nodes are banks and links representing a payment incoming to the receiver and outgoing from the sender. The network approach plays a central role in modelling the transmission of the information and determining how it spreads. Network modelling provides a better scope for analyzing the dynamic progress of the financial structure and explains how financial information flow passes through the system.

3.1 Sample Statistics

Equipped with the lager and rich payment dataset and our defined indicators, we run an algorithm to identify the unexpected liquidity shocks in the payment system. By doing so, we check information of the sender and receiver of each delayed payment transaction for detecting unexpected liquidity exprrices. We move on to check information on counterparties and counterparties of counterparties of senders and receivers to detect all related liquidity shocks.

Equipped with the larger and rich transaction-level payment dataset and our defined indicators, we run an algorithm to identify the unexpected liquidity shocks in the payment system. We check the information of the sender and receiver of each delayed payment transaction to detect unexpected liquidity experiences. Additionally, we investigate information on the several levels of counterparties of senders and receivers to detect all related liquidity shocks. Our algorithm creates several dummy variables on whether the payment system members involved in each transaction face any liquidity shocks. For visualization purposes, we aggregate all liquidity shocks on an hourly and daily basis. Table 8 presents the total number of unexpected interbank and customer liquidity shocks on an hourly basis. The information about variables are given in Table 3. The official starting time of the payment system is 8:00; however, members can send a payment message before 8:00 to be processed later [ECB, 2006, 2007]. The last two columns present the average value of time and volume amount (in Euro) of the payments. We observe that most of the unexpected liquidity shocks are in the morning. At the end of the working day, there is a large number of unexpected interbank liquidity shocks $ULOF^{Inter}$ and a few unexpected customer liquidity shocks $ULOF^{Inter}$. The number of the counterparties who had the experience of both unexpected liquidity interbank shocks $C1LOF^{Inter}$ and customer shocks $C1LOF^{Cust}$ decreases over time. Essentially, shocks appear in the morning transactions, while the higher average volume of payments value is transferred during the afternoon and near the end of the working day.

Insert Table 8 here.

These patterns show the systematic behaviour of members of the payment system on an hourly basis. Two additional pieces of evidence reveal the dynamic of the payment system. First, the top panel of Figure 4 plots the hourly average of volume amount and time to process the payment (TPP). We can observe the negative correlation between the time series of the hourly average of time and the volume of payments. This might be due to one member of the payment system holding enough liquidity during the afternoon, thus, helping other members be resilient to counterparties and fundamentally unexpected liquidity shocks. The second explanation is that banks mostly postpone or delay their settlement to use their counterparties' resources to process their payment. In relative, the peak time of transferring payments is between 18:00 to 19:00; however, the average time to process payments reduces until 13:00. These patterns have important implications for understanding the evolution of liquidity distribution in the payment system over time. Second, the bottom panel of Figure 4 plots the hourly average of $ULOF^{Inter}$, $C1LOF^{Cust}$ and $C1LOF^{Inter}$ shocks. We can observe several shocks hitting the payment system at the early working time of the payment system. The unexpected liquidity customer shocks of the first counterparty $C1LOF^{Cust}$ are significant and increase until noon to reach their peak. This figure also shows another peak for unexpected interbank liquidity shocks $ULOF^{Inter}$ around 17:00.

Insert Figure 4 here.

Insert Figure 5 here.

Insert Figure 6 here.

Figures 5 and 6 depict the hourly networks of the payment system with and without delay. We apply the same layout for plotting all figures the nodes and links present bank and hourly interbank payment transactions. For illustration purposes, we remove the links related to less than 50% frequency of interbank transactions between two banks. By applying this restriction, we observe an interesting change in the structure of the network. During the early morning, some banks only act as the sender in the network, and later, they receive payment messages for their counterparties. During the afternoon, some banks create a small sub-network isolated from the rest of the system. In the evening, some banks only act as receivers in the network. To build these graphs, we consider all the days of our study period and aggregate the result. Therefore, this pattern is stable over time.

One takeaway from the above tables and figures is the existence of strong hourly seasonality patterns in the payment system. This implies that we should take these aspects of the payment system into account when specifying an appreciative econometric model.

Insert Figure 7 here.

Figure 7 illustrates the daily average of volume amount and processing time of payments (top panel) and the daily average of unexpected liquidity shocks (bottom panel) computed from our data. We apply a smooth function to the data, which allows us to remove the noise from the data and illustrate the fluctuation over time better. The first significant finding is that during times of crisis, all-time series spatial tendencies increase (starting from August 9, 2007). The payment market responded to shock during the early stages of the global financial crisis. To compare the evolution of processing time and volume of payment with the market fluctuation, we plot the Euro OverNight Index Average (EONIA) rate and volatility of the DAX index (VDAX) over our study period. We can see the co-movement behaviour between the shocks in the systems and the EONIA index. The VDAX index correlates to the volume of payment rather than the TPP variable.

Table 9 presents the summary statistics of the payment system's network characteristics for both senders and receivers of payments. The summary definitions of variables in this table are given in Table 2. There is heterogeneity in the types of banks in terms of sending and receiving payment messages. Generally, a bank can be a sender bank as well as a receiver bank. On average, the centrality measure of sender banks is higher than the receiver banks. The minimum number of directed links to a bank (measured by in_degree) is zero, and the maximum is 142. This means that there is a bank (or several banks) which is not receiving payment, and at the same time, there is a bank (or several banks) receiving payment from all banks. We can observe the same patterns for the number of links directed away from the given node, measured by the out_degree.

We briefly explain the network centrality indicators. The primary and simple network indicator is degree. The degree is the number of relations of network nodes. According to this centrality, the network member with the most significant number of relations is the most crucial. Another measure of centrality is closeness. According to this centrality measurement, a network member is vital if it is comparatively nearer all other network members. This centrality measures the closeness centrality of a node concerning the inverse of the node's distance to other nodes in the network. Betweenness is another centrality index that is based on information flow; a network member who lies on transmission paths can control information flow. The betweenness centrality of a network member is calculated as the number of shortest paths between all other members that the member resides on. The betweenness centrality, in this context, relates to how often a network member acts as a bridge of the shortest distance between two other members. The highest variation in network centrality properties is the betweenness centrality, and the lowest variation is the closeness centrality. Both of these centrality properties measure the level of position of nodes in the network. They present how many levels (here, number of payment transactions) are needed to reach a bank from other banks or to reach other banks from a bank. This information is crucial to understanding how shocks travel in an interconnected system.

The centrality indicators, Hub score, Authority score, and PageRank, are fundamental network properties that present the importance of a node or the virtual nodes connected to it. By measuring these network centrality indicators, we can identify the prestige or reputation of the payment system members and rank them. Based on these indexes, we can argue that a bank is important because it connects to other important banks. One general way to estimate the ranking of a node is to exploit the added information integrated into the network due to its link formation. The link structure of the network is an essential factor in determining the PageRank of a node. The PageRank method relies on a Markov chain constructed from the network [Berkhout and Heidergott, 2019, Litvak and Ejov, 2009]. In a direct network, the PageRank of a node depends on two factors: first, the in_degree and out_degree of the node, and second, the PageRank of the nodes that have out-linking to the node. The second factor is more critical because links from high-ranking nodes are more valuable than those from low-ranking ones. The most intuitive sentiment of centrality is degree centrality. We should emphasize that none of these centrality degrees can solely indicate important nodes in the network. Therefore, we need to consider all relations between centrality degrees to understand the node's importance in the network.

Insert Table 9 here.

Insert Table 10 here.

Table 10 presents the summary statistics of network centrality indexes for senders and receivers of the payment system. Network properties size, out-degree, in-degree, betweenness, and closeness have right-skewed non-symmetric distributions. The number of receivers is more than the number of senders. On average, the centrality values of senders are higher than the centrality values of receivers. The standard deviation of the betweenness centrality index is high. It means there is heterogeneity in the intermediary roles of the payment members. Some banks are located in the flow of information in the financial system. These banks can control the flow of information in the system and mitigate or amplify the systemic risk in the financial system. In the appendix, Table 1 presents the maximum of network properties for senders and receivers of the payment system on an hourly basis. On average, the maximum values of the network properties decrease from morning to afternoon exponentially. At the end of the working day, the financial network structure changes, and banks are connected in a star structure. In a star network, nodes are connected with the central node. All paths from peripheral nodes go through the core node, and the maximum possible value for betweenness and closeness decreases to the smallest value.

4 Empirical Identification

The following section explains empirical analysis of the delay contagion in a financial network. We use regression analysis to investigate the fundamental and contagion effects of unexpected shocks from liquidity outflow on the processing time of payments. The definitions of $ULOF$, $C1LOF$ shocks are empirically applicable since it easily translates into a simple test for contagion. Our variable of interest is time to process the payment (TPP) on a transaction, transaction, hourly and daily basis. In our empirical analysis, we control other factors that affect interbank market participation.

Baseline Model: we apply the following specification as the base-line econometric model on the transaction level. The base-line model is given by

$$TPP_{ijt} = \beta_0 + \beta_1 C1LOF_{ijt} + \beta_2 ULOF_{ijt}^{Cust} + \beta_3 ULOF_{ijt}^{Inter} + \alpha_{ij} + \gamma_t, \tag{1}$$

where α_{ij} and γ_t are fixed effects for payments' sender and receiver and time fixed effect, respectively. We include some specifications of bank-pair fixed effects to control unobserved effects of banks' relationships. This specification allows us to pin down the role of banks acting intermediaries in payment transactions requested by financial and none financial institutes. We can efficiently isolate the directed ($ULOF$) and in-directed ($C1LOF$) factors, potentially disturbing the payment system and creating liquidity shortages in this specification. To detect the delay cascade in the payment system, we add higher order of in-directed factors like $C2LOF$, $C3LOF$ to the model. It helps to track the delay caused by the counterparty of counterparty or counterparty's counterparty of the counterparty. Using the transaction-level data enables us to study the structure of the payment system for analysing delay contagion in this system. However, the weakness of transaction-level data is that it is impossible to control the endogeneity problems caused by common factors like market or economic conditions or caused by interbanks' specifications factors like banks delay each other. It is because the transaction data is high-frequency and unregulated data. Therefore, we need to aggregate the transaction data into higher-levels like hourly or daily level data.

In order to distinguish the main delay factors derived from unexpected liquidity shortages from some systematic time-related factors, we remove the seasonality component of time to process the payment data. We try the seasonal-trend decomposition procedure proposed by Cleveland et al. [1990]. The estimated de-seasonal time to process the payment contains negative values, producing biases in our analysis. Next, we apply the seasonal adjustment procedure based on the regression analysis proposed by Lovell [1963]. The result of the statistical test shows that the hourly seasonal pattern has been removed successfully. We then aggregate seasonal-adjusted data and note hourly information from the payment transaction data. For simplicity, we do not change our notation and continue to use the TPP variable as the seasonally adjusted time to process the payment.

Given the aggregated level information on hourly transaction payments in our dataset, we construct an hourly network of the payment system. These hourly-level networks are based on the number and value of transactions between two payment system members during a given hour h of the day t. The centrality information of these networks is the primary source of understanding banks' strategic behaviour and positions in the payment system. Unobserved information about banks' strategic behaviour, such as netting or intentional delay of payments, can impact the estimation of the effects of delay caused by liquidity shortages. To alleviate endogeneity problems raised by these banks' strategic behaviour, we employ instrumental regression models. Coordinately, we design a set of instruments to satisfy the isolation condition when bank one decides to delay payment to bank two and bank two delays payment to bank one simultaneously. These instruments impact the payment transaction through the network, reflecting the network centrality information. We evaluate the exogeneity of the instruments by applying overidentifying restrictions test [Hwang, 1980] and testing for weak instruments [Staiger and Stock, 1994]. Since our interest variable, the time to process the payment, which is jointly estimated for both banks in a transaction, might be endogenous, suitable instruments for these regressors must be determined. The network centrality indexes might be appropriate candidates for instrument variables. The payment receiver's network centrality indexes (right-hand side) are commonly employed as instrumental variables. These network centrality indexes locally measure the position and ranking of banks in the payment system. Pinkse et al. [2002] apply a restriction to have non-symmetric observation and use the information of the sender as instrument variables. In our study, we apply the network centrality indexes of the receiver bank of the payment as instrument variables.

Next, we aggregate multiple de-seasonal transaction data for the same bank pair on the same day to a single observation and build associated daily networks. The aggregated data contains daily seasonal patterns and other systemic patterns, such as the end-of maintenance period and end-of-day and end-of-month effects. We apply the same technique to remove these systemic patterns from the daily data. Based on this information, we employ daily analysis of the payment system's response to delays due to unexpected liquidity shocks.

Spatial Autoregression Model: The network structure of the payment system might amplify the effects of unexpected outflow liquidity. By applying the conventional regression models, this effect can be confounded and under-identified. We address this challenge by using spatial autoregressions. We decompose the overall effect of the shocks of unexpected liquidity outflow into direct and higher-order network (indirect) effects. With several features and extensions, the spatial econometric models can measure the implicit effects of the delay caused by unexpected liquidity outflow shock experienced by counterparties. We successively extend the baseline model with the spatial characteristics of pairs of banks. We employ methods from spatial econometrics to decompose the overall payment system reaction to a liquidity outflow surprise into direct and indirect (higher-order network) effects.

The spatial models allow us to estimate the total effect of unexpected liquidity outflow on the payment system within a small event window to control any extra shocks' confounding effects. On a daily level, the spatial regression model helps us determine the upstream propagation by estimating the network's high-order feedback. While in our baseline models, at the transaction and hourly level, we focus on upstream propagation of liquidity shocks, i.e., those shocks arising from a bank's customers. The spatial econometric techniques apply to geographical information in which the data are not independent but spatially correlated. Indeed, the levels of a bank's TPP spatially depend on the levels of TPP of its counterparties. Therefore, the spatial autoregressive model can determine the different contributions of each bank to network effects.

As we stated before, that payment processing time depends on the time to process payments in neighbouring counterparties. It is thus an origination of the concept of a spatial spillover. The primary spatial econometric model is the spatial autoregressive model (SAR). The formal model is defined as

$$TPP_{ijt} = \beta_0 + \lambda W(TPP_{ijt}) + \beta_1 C1LOF + \beta_2 ULOF^{Cust} + \beta_3 ULOF^{Inter} + \alpha_{ij} + \gamma_t, \quad (2)$$

where matrix W is a row-normalized spatial-weighting matrix in which the sum of the rows is unity. The interpretation of the spatial auto-regression model coefficients is not straightforward since these coefficients incorporate information from related counterparties. Hence, we use the decomposition method by LeSage and Pace [2009] to decompose the total effect into direct and indirect effects. Direct effect determines the average point of how a change in a bank's time to process is a dependent variable when one of the independent variables, $ULOF$ or $C1LOF$, is related to the counterparty changes. The indirect effect (the spatial spillover effect) explains the dependent variable (the time taken to process the payment) and the change in independent variables $ULOF$ or $C1LOF$, such as shocks related to counterparties.

5 Empirical Results

This section explains the empirical results of our analysis on the transaction, hourly and daily levels. Later we will discuss the robustness of our findings concerning several specifications and controlling for borrower heterogeneity. Our variable of interest in all regression models is the time to process the payment (TPP).

Transaction Level Results

We perform our analysis on 72,851,656 payment transactions from March 1, 2006, to November 15, 2007. Table 11 reports the baseline results. This table shows the result of regression analysis of time to process the payment (TPP) as the dependent variable on index variables about unexpected shock by the customer and interbank payments and index variables indicating when the counterparty experienced unexpected liquidity shocks. We add several rigorous time fixed effects based on the daily and hourly information of the payment. We also control the individual characteristics of the sender and receiver of payments. Finally, to control the payment size, we add the payment volume to all regression models. This set of forceful fixed effects enables us to pin down the real effect of unexpected liquidity shocks on the payment system at the transaction level. Other necessary control variables like economic conditions can be considered in the higher-order levels, such as hourly or daily levels. Standard errors are double-clustered at the sender and receiver levels.

Insert Table 11 here.

Insert Table 12 here.

Table 11 presents the unexpected liquidity outflow ($ULOF$) shocks that occur when a member of the system receives an order from a non-member with a payment amount of more than 5% of the history of payment transactions. This has a significant influence on the time it takes to execute the payment. The estimated impact of an unexpected liquidity outflow by a customer is about a four-minute delay. However, the same type of effect by an interbank transaction has a bigger impact, i.e., almost a thirteen-minute delay. Another finding from this analysis is that the unexpected shocks as a consequence of a delay in receiving payment by a counterparty who has an experience of $ULOF$ shocks have a significant impact on the payment system. On average, a counterparty liquidity outflow connected to interbank payment produces a 28-minute delay, whereas a counterparty liquidity outflow related to customer payment causes a nine-minute delay. The coefficients are stable across specifications and controlled by fixed variables. We replicate our analysis by applying a restriction to payments not related to customers or non-financial firms. In the appendix, Table 12 presents the results. The findings of this table show a similar systemic pattern to the results of Table 11. Our analysis provides insights into this systemic delay in the payment system in payments initiated by financial firms (interbank) and non-financial firms (customer). We next examine the robustness of our base results by applying logarithm transformation of the TPP variable. Table 4, in the appendix, presents the results of the robustness test.

Hourly Level Results

On the transnational level, we add some variables to control for market and bank-to-bank levels. This identification strategy can partially control the endogeneity problems caused by common factors, such as the market or economic conditions. However, other endogeneity problems caused by interbanks' activities, such as when banks delay each other, should be addressed carefully. In the baseline model, we also control for hourly seasonal patterns. In the next step, to reduce bias in our analysis and control the endogeneity problems better, we construct the hourly-based data by calculating the hourly average of senders and receivers of the payments. We apply the seasonal adjustment procedure [Lovell, 1963] to the historical information of each bank pair to remove hourly seasonality patterns from the data. We test our fitted data by some statistical tests to check if the seasonality component of the data has been removed correctly. We calculate the hourly summation of Unexpected Liquidity OutFlow ($ULOF$) and Counterparty Liquidity OutFlow ($CLOF$) for each pair of banks.

We apply instrumental regression models at the hourly level of the baseline model. As discussed in the previous section, choosing the appropriate instruments is very important. We choose the first-lag of in-degree centrality of receivers as instruments, and we evaluate the exogeneity of our instruments. Table 13 reports the results of applying the instrumental regression model on time to process payment (TPP) on an hourly basis. The dependent variable is the hourly summation of TPP of each pair of banks. The results indicate that after controlling for the market- and bank-specific characteristics, both independent variables, $ULOF$ and $CLOF$, impact the time to process the payments and create a vital delay in the system. The results are statistically significant and economically meaningful.

Insert Table 13 here.

Our identification strategy relies on exploiting how network formation interacts with other possible sources of contagion of the delay of paymentsour baseline empirical analysis is based on classic theoretical workhorse models of bank interactions in the payment system. Mainly, the theoretical models discuss how the network properties relate to other potential origins of contagion and whether it serves to magnify or dampen the shocks. In this respect, we need to control the position or role of banks in the network. If a bank has several in-going or out-going connections or is relatively close to other banks, it might receive liquidity shocks from the network. We add several network centrality measure indexes, such as in-degree, out-degree, in- and out-closeness and PageRank to the baseline model. Each network measure index shows the different local and global roles a bank has in the payment system. The results reveal that both main independent variables are statistically significant when network factors are included in the model. One takeaway from the hourly-based results is that unexpected liquidity shocks have a strong influence on creating delays in the system. However, we need to understand the mechanism behind these delays better.

Daily Level Results

Our findings from the transnational and hourly baseline models show a substantial delay in the payment system, mainly because upstream counterparties experience unexpected liquidity outflows. This simple tractable model lets us pin down the effects of shocks from upstream counterparties that can spread by contagion. However, these are not the only channels through which shock can travel in the network; since financial networks contain several loops and intermediaries, the delay shocks might go back to their sources. We, therefore, extend our baseline model to capture these loopback shocks. First, we apply the seasonality adjusted method on a given bank pair (a given sender and receiver) to remove the daily seasonal effect of data and aggregate data to create daily data. Next, we use spatial econometrics methods to decompose the overall daily payment system reaction to a liquidity outflow surprise into direct and indirect (higher-order) delay effects.

Theoretical banking models commonly acknowledge the existence of spatial spillovers, which rise as business interactions of banks increase and coordinately decrease as the working distance of banks increases. Empirically, we can apply a panel data model to determine the spillover dynamics. The spatial econometrics methods apply to the payment data since the observations are dependent and spatially correlated. These methods help us assess outward and inward spillovers of unexpected liquidity shocks on time to process the payment.

On a daily basis, we regress the daily average of TPP of bank i on the past daily average of TPP of bank j and a weighted average of the bank j's unexpected shocks with the weights determined by the average volume of payment. The results of spatial econometrics depend on the spatial-weighting matrix, which can be ad-hoc. A natural choice for the weighting matrix in our study is a volume-weighted matrix since the structure of spillover can be interpretable.

Introducing spatial effects to the panel data models to determine spatial spillovers requires testing spatial interdependence relations between individual observations. We need to distinguish fixed effects from random effects, which show that individual effects are constant or random over time by taking spatial dependence between observations into account. We apply a standard spatial econometrics model, which deals with balanced panel data in which the payment transaction of n pairs banks are observed rigorously for T

periods. To compare fixed and random models with accounting for spatial autocorrelation, we employ the spatial Hausman test [Mutl and Pfaffermayr, 2011], which might be robust to heteroskedasticity. The results of the test show that specific individual effects are constant over time. We use the bias-corrected maximum likelihood method explained by Yu et al. [2008] to estimate the spatial autoregressive effects.

Table 14 shows the results of spatial analysis of delays in the payment system; the definitions of variables in the models are provided in Table 3. Columns 1 and 2 present the basic models: Pooled regression and Fixed effect models. The basic models are required to be developed and take spatial autocorrelation into account. Column 3 comprises the results of spatial models for all banks in the payment system. The number of pairs of banks is No_links. The dependent variable TPP is seasonality adjusted for given bank pairs (borrowers and lenders). We control the payment amount in Euro, the "EONIA" rate (Euro OverNight Index Average) and $VDAX$ (Volatility of DAX). We also control the possible seasonality patterns of weekly variation of the payment system. The variable λ is defined in Equation 2, which determines the endogenous interaction effect in the spatial model. We restrict our attention to the strategic relationships of banks and their partners in the payment system. Columns 47 illustrate the outcomes of spatial analysis for four quantiles of strategic partnership of banks. The last column (column 8) shows the results for banks with 100% partnership, i.e., active bank partners with daily businesses. To identify the strategic partners of banks, we look at the number of daily transactions between banks. We estimate the probability that a bank might be a partner in the payment system for sending or receiving the payment. A probability with a value close to one means the pair of banks have payment transactions almost every day (see Figure 1). The results of the daily level arrive at the same general conclusion, i.e., some contagion occurred. The results show a significant network effect, even at low frequency (daily level).

$\boxed{\text{Insert Table 14 here.}}$

To facilitate the interpretation of coefficients of spatial models, given in Table 14, and to drive a meaningful economic insight into the real effects of main factors, we can estimate the marginal effects of the explanatory variables. Due to the significant spatial interactions between observations of the payment system, shown by the parameter λ, the unexpected liquidity of one member of the payment system might impact its payment transaction and other members' transactions. In doing so, we can decompose the direct and indirect impacts of main factors along with the marginal effects of the explanatory variables. Table 15 presents the results of the decomposition of total effects of the explanatory variables into direct and indirect impacts. It helps to facilitate the understanding of coefficients in the estimated spatial models given in Table 14. The direct and indirect impacts are calculated based on a method proposed by LeSage and Pace [2009]. The estimated direct and indirect impacts in Table 15 correspond to results of spatial models presented in Table 14, columns 38. The top panel illustrates the effects of $C1LOF^{Cust}$ shock, and the bottom panel shows the effects of $C1LOF^{Inter}$ shock. The results show that due to spatial interactions, unexpected liquidity outflow $C1LOF^{Cust}$ and $C1LOF^{Inter}$ shocks directly affect the time to process payment of the bank and indirectly affect the time to process of all other banks.

Insert Table 15 here.

The indirect impact is the average network effects captured by the spatial model. We run the rolling window regression analysis to obtain the time variation of the unexpected liquidity outflows' direct and indirect (network) effects on TPP. This analysis helps to evaluate the stability of direct and indirect (network) effects over time. We apply the exact specifications of the spatial model, given in Table 14 column 3, and use a time window of thirty days to determine the dynamic interbank networks. Figure 8 depicts the time-varying measure of direct and indirect (network) effects of $C1LOF^{Cust}$ and $C1LOF^{Inter}$ variables. Figure 3 in the appendix presents the time series of the characteristics of the interbank networks. The rolling regression approach provides a comprehensive and detailed view to analyze the relationship between indirect and direct effects of $C1LOF^{Cust}$ and $C1LOF^{Inter}$ shocks on TPP, and it helps in determining the structural breaks and regime evolution over time.

Insert Figure 8 here.

6 Conclusion

Our identification strategy relies on exploiting the heterogeneity in banks' network characteristics in our data set. This strategy allows us to use the information on bank-to-bank and time-varying as time fixed effects to control for unobserved characteristics of the network of individual banks thoroughly. Our definitions of unexpected outflow liquidity shocks are empirically applicable for tracking contagion because they conveniently translate into a simple contagion test. The conventional regression model results may be confounded and under-identified. As a result, we use spatial econometrics methods to decompose the overall payment system response to a liquidity outflow surprise into direct and indirect (higher-order network) effects. This straightforward and tractable model enables us to pinpoint the effects of upstream counterparty shocks that can spread through contagion. Nonetheless, these are not the only channels through which a shock can transit in the network; because financial networks consist of multiple loops and intermediaries, delayed shocks can return to their origins. Accordingly, we expand our baseline model to the spatial model to comprise these loopback shocks.

Thus, this study advances our understanding of the delay contagion in the RTGS; however, our research question is relevant to the new netting settlement system environment. As a building block of a decentralized financial system, Blockchain technology facilitates payment settlement [Chiu and Koeppl, 2019]. This technology may allow market participants to shorten the length of settlement and create smaller blocks to take advantage of settling the payment early. This settlement strategy may cause blockchain congestion, resulting in system delays and unexpected liquidity outflow shocks for counterparties. This phenomenon impacts the supply side, raising transaction fees and possibly transmitting through the whole network. This is an excellent starting point for further discussion and research on delays in the decentralized payment system.

Even though some of these issues are difficult to address without simplifying other aspects of the model, we believe that future studies will address them empirically. The tree regression models differ significantly from conventional regression models [Bianchi et al., 2021] and might be an appropriate alternative model. These models can identify groups of payment observations that respond similarly to unexpected liquidity outflow shocks. More research is needed to confirm the potential of the data mining methods in tracking the delay cascade in the network.

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Appendix

A Network information

Table 1: **Hourly maximum values of network characteristics**

Hour	In-degrees	Out-degrees	In-closeness	Out-closeness	Closeness	Betweenness	PageRank
8-9	66	130	.0001185	.005848	.0065789	4918.998	.0603645
9-10	77	129	.0001665	.0055866	.0069444	5927.437	.0567214
10-11	86	128	.0001976	.0055866	.0063694	5285.841	.075504
11-12	91	124	.0002539	.0052632	.0068966	5321.749	.0680252
12-13	84	121	.0002014	.0054945	.0072993	5236.01	.0837007
13-14	79	109	.0002019	.0034602	.0073529	5463.204	.0854721
14-15	82	124	.0002356	.0035842	.0065359	5710.174	.0818129
15-16	83	130	.000248	.004902	.0078125	6232.231	.0842297
16-17	72	117	.0002421	.0039683	.0095238	6548.135	.105638
17-18	36	55	.001996	.0046296	.0208333	2469.167	.2286291
18-19	124	10	.5	1	1	375	.5744681
19-20	124	1	1	.5	1	125	.6491228
Max	124	130	1	1	1	6548.135	.6491228

This table presents the maximum hourly value of network characteristics of the payment system. We consider working hours of payment system between 8:00 to 20:00. These are the maximum value of network characteristics for the period from March 1, 2006, to November 15, 2007. The last row is the maximum values for the whole study period. The definitions of variables are given in Table 2.

Table 2: **Definitions of network variables**

Variable	Definition
Sender	The bank which is the sender of the payment transaction.
Receiver	The bank which is the receiver of the payment transaction.
Sender-Receiver	The pair of banks which are sender and receiver of the payment transaction.
In-degrees	A network centrality measure indicates the number of links directed incident to the given node.
Out-degrees	A network centrality measure indicates the number of links directed away from the given node.
Closeness	A network centrality measure indicates how many levels are required to reach every other node from a given node.
In-closeness	A network centrality measure indicates how many levels are required to reach a given node from every other nodes.
Out-closeness	A network centrality measure indicates how many levels are required to reach every other nodes from a given node.
Betweenness	A network centrality measure indicates the number of geodesics (shortest paths) passing through a node or a link.
PageRank	A network centrality measure indicates the importance of nodes.
Hub score	A network centrality measure indicates Kleinberg's hub centrality scores.
Authority score	A network centrality measure indicates Kleinberg's authority centrality scores.
Neighbourhood	A network centrality measure indicates how many nodes are at different distances from the given node.
Eigen_ central_	A network centrality measure indicates the prestige of the given node is associated with the prestige of its neighbours

This table describes the network variables used in this study.

Table 3: **Definition of explanatory variables**

Variable	Definition
ULOF6^{Cust}	Dummy indicating a payment transaction with top of 5% quntile of payment volume ordered by the customer.
ULOF^{Inter}	Dummy indicating a payment transaction with top of 5% quntile of payment volume ordered by interbank.
C1LOF^{Cust}	Dummy indicating a payment transaction with unexpected liquidity shock from the customer in the pervious step.
C1LOF^{Inter}	Dummy indicating a payment transaction with unexpected liquidity shock from nterbank in the pervious step (sender is not equal to ordering).
C2LOF^{Cust}	Dummy indicating a payment transaction with unexpected liquidity shock from the customer in two previous steps.
C2LOF^{Inter}	Dummy indicating a payment transaction with unexpected liquidity shock from interbank in two pervious steps (sender is not equal to ordering).
TPP	Time to process of the payment.
Volume	Amount of the payement.
VOL_DAX	Volatility of DAX index.
EONIA	Euro OverNight Index Average.
Hour	Categorical data of hours 8:00-20:00.
Day	Data information of calender.
Weekly_day	Categorical data of weekly day 1(Monday):5(Friday).
Crisis	Dummy variable is one from 9 August 2007 onwards, otherwise zero.

This table describes the explanatory variables used in this study.

Table 4: **Interbank Transaction Level: Logarithm Transformation of TPP**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ULOF^{Inter}$	0.569***	0.544***	0.334***	0.538***	0.512***	0.299***	0.333***	0.535***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$C1LOF^{Cust}$	3.064***	3.270***	3.923***				2.601***	2.132***
	(0.004)	(0.004)	(0.004)				(0.004)	(0.004)
$C1LOF^{Inter}$				3.497***	3.591***	4.220***	3.333***	2.868***
				(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
FE: Hour	YES	YES		YES	YES		YES	YES
FE: Day	YES			YES			YES	
Volume (control)	YES	YES	YES	YES	YES	YES	YES	YES
FE: Sender	YES	YES	YES	YES	YES	YES	YES	YES
FE: Receiver	YES	YES	YES	YES	YES	YES	YES	YES
FE: Sender* Receiver	YES	YES	YES	YES	YES	YES	YES	YES
adj. R^2	0.157	0.149	0.119	0.160	0.152	0.124	0.133	0.161

This table presents the spatial analysis of delay in the payment system. The dependent variable is log(TPP). To check robustness of our model, we replicate models shown in Table 12 with logarithm transformation of TPP variable. All models include a constant. The robust standard errors are clustered at the Receiver bank level. Standard errors are in parentheses; Note, the symbols *, **, *** denote significance at the 10 percent, 5 percent, and 1 percent level. The definitions of variables are given in Table 3.

Internet Appendix
Delay by Contagion in Payment System

(not to be included for publication)

A Crisis Period

This paper uses a novel and comprehensive payment dataset to analyze whether unexpected liquidity shocks might interrupt the payment process, both before and during the financial crisis. In the past, during crisis times, banks have had the right to delay their payment [Allen and Gale, 1998]. The German banking system are heavily active in this payment system and made significant investments in mortgage-backed securities in the United States market; therefore, the German banking market was among the first and most affected by the subprime crisis in the United States [Fecht et al., 2015]; even the Association of German Savings Banks assisted some important banks with emergency liquidity. We define the crisis index as a dummy variable equal to one for days after August 9, 2007, and otherwise zero. First, we analyze the statistical descriptions of variables for after and during crisis time. Table 5 presents the comparison of daily variables TPP, $C1LOF^{Cust}$ and $C1LOF^{Inter}$ during and after crisis time. The t-value, z-value, and Chi-squared values correspond to t-statistic, Wilcoxon-Mann-Whitney and Kruskal-Walli tests, respectively. Figure plots the density plots of $C1LOF^{Cust}$ and $C1LOF^{Inter}$ variables before and during crisis.

Insert Table 5 here.

Insert Table 6 here.

Insert Figure 9 here.

According to crisis-contingent theories [Forbes and Rigobon, 2001], the contingent mechanism might change during a crisis time. Next, We try to test this hypothesis by interacting the crisis index variable with unexpected liquidity outflows $C1LOF^{Cust}$ and $C1LOF^{Inter}$

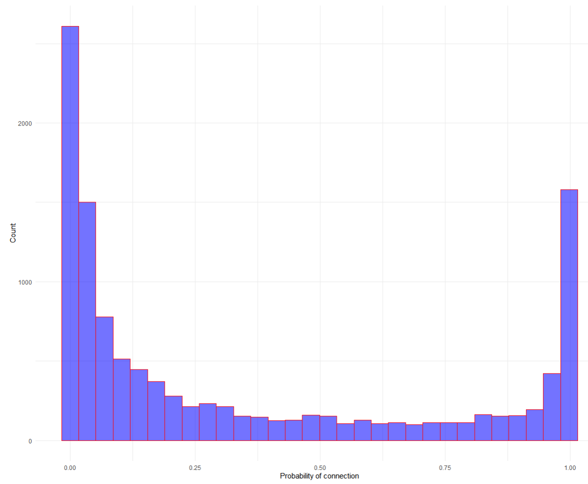
variables. Table 6 presents the spatial analysis of delay in the payment system before and during crisis time. The dependent variable is TPP which is measured in second. We replicate models shown in columns 3-8 of Table 14 including crisis interaction terms. The models, including fixed effects, are indicated with YES. The coefficients of interaction terms in the spatial model with considering neighbourhood relationships between payment observations are statistically meaningful. The interaction terms related to unexpected liquidity outflows $C1LOF^{Cust}$ has the highest variation to explain the dynamics of unexpected liquidity outflows during crisis time. Taken together, results from this analysis provide some pieces of evidence about the transmission of delay shocks during crises time.

B Reserve maintenance period

We look at banks' abnormal payment processing behaviour during the reserve maintenance period. The minimum reserve regulation for banks operating in the euro region is another component of monetary operations and liquidity management [Hartmann et al., 2001]. Banks carefully manage their minimum reserves to maintain a specific level of reserves in Eurosystem accounts. Any unanticipated liquidity shocks during the maintenance period might cause the payment process to behave differently on such days. The interbank market is commonly more active at the end of the maintenance period [Iori et al., 2008]; therefore, we consider the final days of the minimum reserve maintenance period. We collect information on open market operations from the European Central Bank (ECB) website. We estimate the two-day and three-day windows cumulative abnormal value of the time to payment process on the last day of the minimum reserve maintenance period. Table 7 provides the results event study with two-day and three-day windows. The substantial variations on the last day of the maintenance can be seen by looking at the average cumulative anomalous value Figure 2. It is mainly because the market activity is generally higher at the end of the maintenance period. The plots also imply that the series behaved differently in 2006 and 2007, starting the financial crisis.

Insert Table 7 here.

Figure 1: **Probability of partnership in the payment**



This graph depicts an estimate of the likelihood that a bank will participate in the payment system as a sender or receiver of funds. The strategic partnership, i.e., active bank partners who do business on a daily basis.

Insert Figure 2 here.

Table 5: **Mean comparison tests of daily variables pre and during crisis time.**

	Variable	Mean	Standard Deviation	N	Min	25th	50th Percentile	75th	Max
No Crisis	$T\bar{P}P$	624.7574	34.40522	307	490.166	603.2842	624.9822	649.1967	700.3903
	$C1LOF^{Cust}$	.0724458	.0048414	307	.057986	.0689879	.0721622	.0760481	.0841807
	$C1LOF^{Inter}$	.0559209	.0037896	307	.0415452	.0535472	.0560416	.0586355	.0656781
Crisis	$T\bar{P}P$	633.1637	33.61739	70	508.9829	612.0081	640.7895	650.7979	692.7079
	$C1LOF^{Cust}$	.0739919	.004573	70	.0616942	.0714932	.0742017	.0767578	.0838631
	$C1LOF^{Inter}$	.0575891	.003542	70	.0451775	.0559207	.0576306	.0598024	.0648445
Total	$T\bar{P}P$	626.3182	34.37222	377	490.166	605.9032	627.5402	649.3076	700.3903
	$C1LOF^{Cust}$	.0727329	.0048245	377	.057986	.0693696	.0728133	.0761953	.0841807
	$C1LOF^{Inter}$	.0562307	.0037963	377	.0415452	.0540217	.0563884	.0588475	.0656781

Variable	t-test t-value	Wilcoxon-Mann-Whitney test z-value	Kruskal-Wallis chi-squared
$T\bar{P}P$	-1.8524	-2.263	5.122
$C1LOF^{Cust}$	-2.4354	-2.618	6.854
$C1LOF^{Inter}$	-3.3629	-3.667	13.446

This table presents the comparison of daily variables TPP, $C1LOF^{Cust}$ and $C1LOF^{Inter}$ during and after crisis time. The crisis time is defined by a dummy variable equal to days after August 9, 2007, and otherwise zero. The number of observations depends on number days before and during the crisis time. We have statistical descriptions of variables for after and during crisis time. The t-value, z-value and Chi-squared values correspond to t-statistic, Wilcoxon-Mann-Whitney and Kruskal-Walli tests, respectively. The definitions of variables are given in Table 3.

Table 6: **Crisis time: spatial analysis of delay in payment system pre and during crisis**

	(All))	(4 (Q1))	(5 (Q2))	(6 (Q3))	(7 (Q4))	(8 (100%))
$C1LOF^{Cust}$	5443.617***	940.465 ***	1242.626***	771.086 ***	987.398 ***	987.398 ***
	(15.859)	(77.701)	(80.437)	(79.151)	(52.307)	(52.307)
$C1LOF^{Inter}$	466.406 ***	189.597	-480.966***	24.242	286.201***	286.201***
	(0.007)	(0.018)	(0.019)	(0.019)	(0.018)	(0.018)
$C1LOF^{Cust}$ *crisis	123.695 ***	-439.805*	379.992 *	21.823	26.648	26.648
	(23.720)	(188.557)	(192.861)	(187.391)	(106.670)	106.670)
$C1LOF^{Inter}$ * crisis	-216.047***	568.570*	134.963	253.992	-170.660	-170.660
	(37.362)	(264.635)	(263.745)	(265.032)	(159.940)	(159.940
λ	0.038***	0.067***	0.047*	0.051**0	0.061***	0.061***
	(0.007)	(0.018)	(0.019)	(0.019)	(0.018)	(0.018)
EONIA	0.169	-398.260	-392.141	-401.622	-416.442	-416.442
	(0.517)	(6.044)	(6.073)	(6.093)	(5.869)	(5.869)
VOL_DAX	-0.017	0.382	-0.858	0.002	2.161	2.161
	(0.086)	(1.718)	(1.719)	(1.728)	(1.676)	(1.676)
Weekly Day	Yes	Yes	Yes	Yes	Yes	Yes
Amount	Yes	Yes	Yes	Yes	Yes	Yes

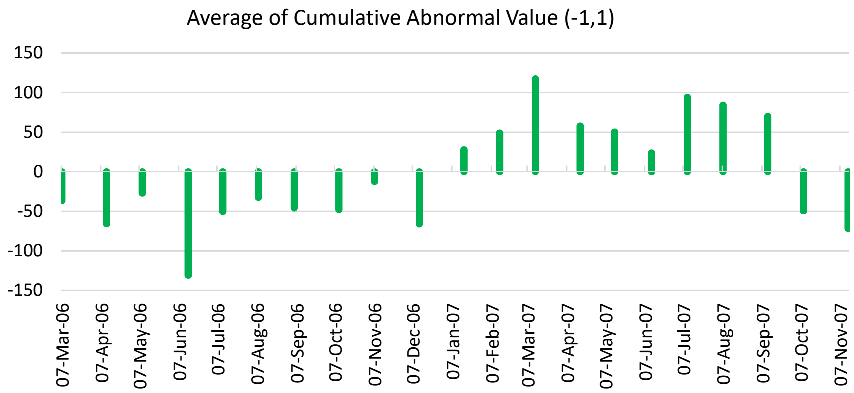
This table presents the spatial analysis of delay in the payment system before and during crisis time. The dependent variable is TPP which is measured in second. The crisis time is defined by a dummy variable equal to days after August 9, 2007, and otherwise zero. We replicate models shown in columns 3-8 of Table 14 including crisis interaction terms. The models, including fixed effects, are indicated with YES. All models include a constant. The robust standard errors are clustered at the Receiver bank level. Standard errors are in parentheses; Note, the symbols *, **, *** denote significance at the 10 percent, 5 percent, and 1 percent level. The definitions of variables are given in Table 3.

Table 7: **Event study: Maintenance days**

Event-date	CAV (-1,1)	t-test	CAV (-1,2)	t-test
07-Mar-06	-36.66777	-3.346197	-54.68601	-4.924118
11-Apr-06	-65.63953	-5.990078	-111.9596	-10.08123
09-May-06	-27.1776	-2.480151	-34.45176	-3.102156
14-Jun-06	-130.9386	-11.94909	-166.4989	-14.99214
11-Jul-06	-50.28384	-4.588761	-62.36251	-5.615336
08-Aug-06	-32.64518	-2.979106	-31.14013	-2.803965
05-Sep-06	-45.89175	-4.187951	-53.36576	-4.805238
10-Oct-06	-47.92884	-4.37385	-36.30954	-3.269437
07-Nov-06	-12.47908	-1.138805	-18.33081	-1.65057
12-Dec-06	-65.89801	-6.013666	-66.95754	-6.029089
16-Jan-07	27.88137	2.544375	63.65109	5.731364
13-Feb-07	49.12924	4.483395	74.86757	6.741335
13-Mar-07	117.6066	10.73244	136.257	12.26905
17-Apr-07	57.77664	5.272533	111.028	9.997342
14-May-07	50.19954	4.581068	78.00123	7.0235
12-Jun-07	23.77619	2.169748	45.93153	4.135834
10-Jul-07	94.14919	8.591788	141.2629	12.7198
07-Aug-07	84.19337	7.683248	104.7685	9.433714
11-Sep-07	70.03156	6.390882	110.2469	9.927014
09-Oct-07	-49.56339	-4.523015	-32.60976	-2.936296
13-Nov-07	-71.75803	-6.548435	-102.7142	-9.248746

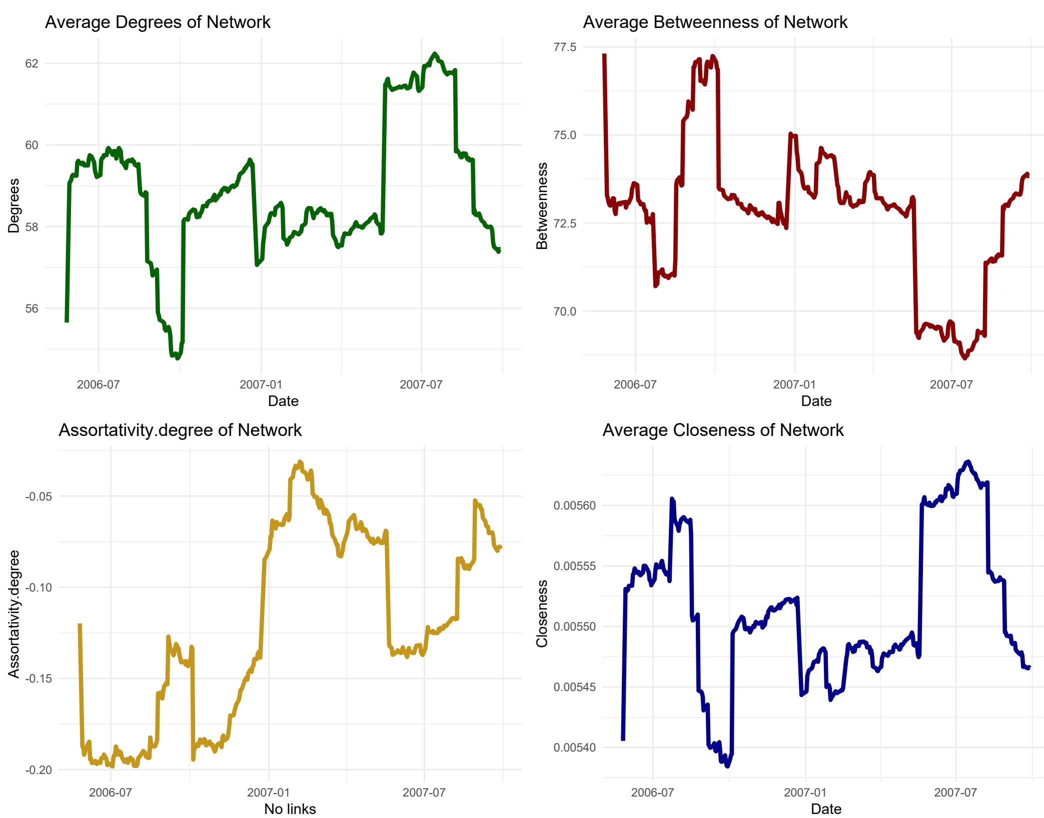
The findings of the event analysis with two-day and three-day periods are shown in this table. On the last day of the minimum reserve maintenance period, we compute the cumulative abnormal value of the time to payment process for the two-day and three-day windows.

Figure 2: **Event study: maintenance days**



This figure depicts fluctuation in the average cumulative anomalous value on the maintenance's final day. We compute the cumulative abnormal value of the time to payment process for the two-day and three-day windows on the last day of the minimum reserve maintenance period.

Figure 3: **Daily average of network characteristics**



This figure plot the time series of network characteristics. We apply a rolling window approach and estimate each network information. The definitions of variables are given in Table 2.

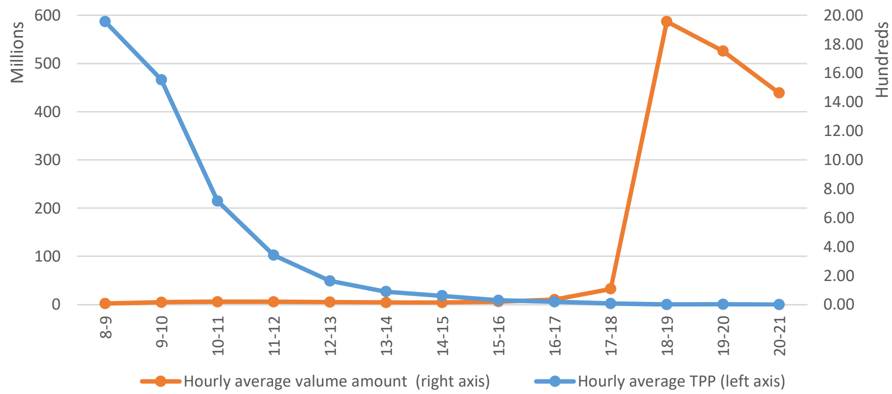
Table 8: **Hourly Total Number of Unexpected Liquidity Shocks and Hourly Average of TPP and Volume**.

Hour	$ULOF^{Cust}$ (Total)	$ULOF^{Inter}$ (Total)	$C1LOF^{Cust}$ (Total)	$C1LOF^{Inter}$ (Total)	$C2LOF^{Cust}$ (Total)	$C2LOF^{Inter}$ (Total)	TPP (Average)	Volume (Average)
8-9	214872	134316	155513	176364	17647	18990	1695.09	2424610
9-10	258381	166011	45389	54335	8269	13258	1446.29	4645385
10-11	259849	116013	17826	18318	4879	5356	634.69	5188215
11-12	292937	117315	14907	13009	4155	4152	279.26	5695822
12-13	295789	89936	4213	2656	621	254	139.36	4741604
13-14	234103	73102	1341	558	63	36	78.04	4254045
14-15	239222	93153	1507	669	163	72	53.72	4214545
15-16	209983	168773	2517	3441	215	163	26.67	6323789
16-17	117472	156227	920	1664	49	146	8.62	10800000
17-18	8246	33055	0	6	0	0	2.75	40200000
18-19	5	32913	0	0	0	0	0.25	534000000
19-20	0	690	0	0	0	0	0.00	524000000

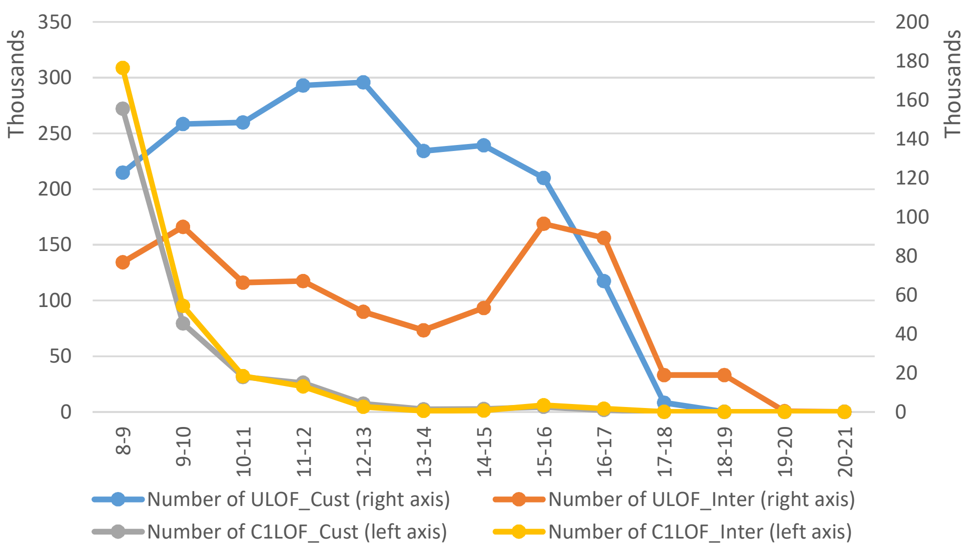
This table presents the total number of unexpected interbank and customer liquidity shocks in the hourly basis. The last two columns present the average value of the total time of process and volume of the payments. We consider 8:00 as the starting time of the payment system. It is possible to submit a payment message early morning which it should be processed later. The information about variables are given in Table 3

Figure 4: **Hourly Average of Volume, TPP and Unexpected Liquidity Shocks**

(a) **Hourly Average of Volume, TPP**

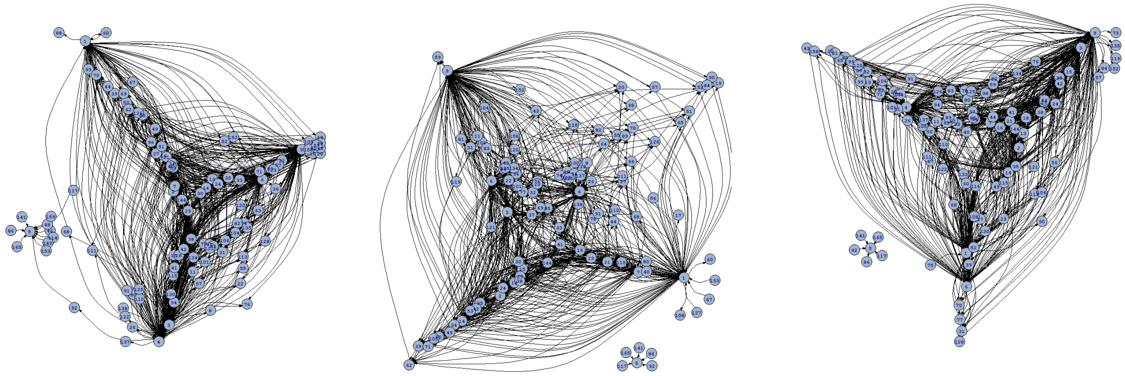


(b) **Hourly Average of $ULOF^{Inter}$, $C1LOF^{Cust}$ and $C1LOF^{Inter}$**

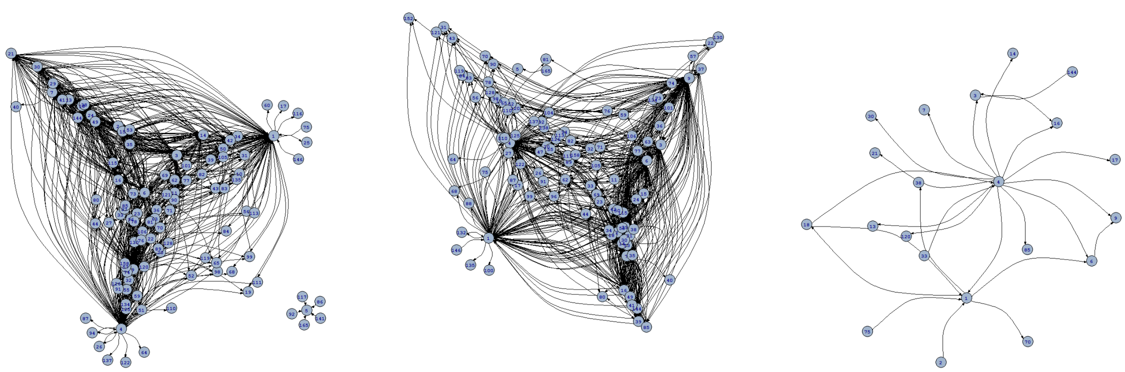


The top panel plots the hourly average of volume, TPP. The bottom panel plots hourly average of $ULOF^{Inter}$, $C1LOF^{Cust}$ and $C1LOF^{Inter}$. We consider transaction payment from 8:00 to 20:00. The definitions of variables are given in Table 3.

Figure 5: **Hourly Network of Payment System with delay**



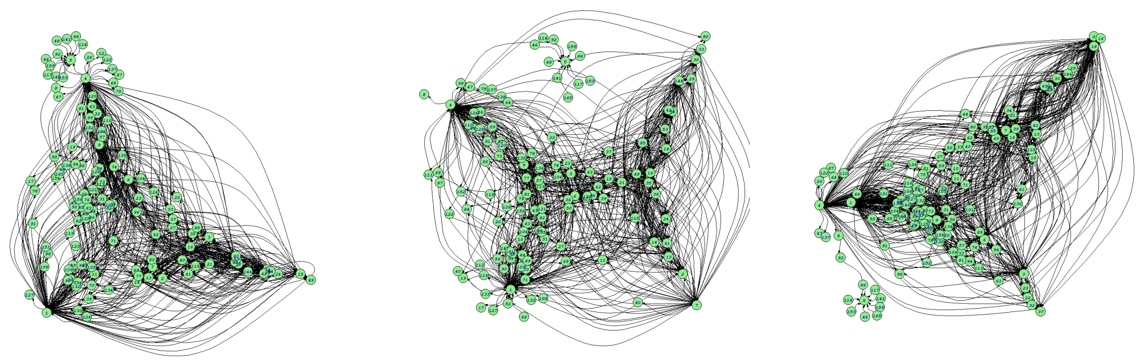
(a) From 8:00 to 10:00 (left), From 10:00 to 12:00 (middle), From 12:00 to 14:00 (right)



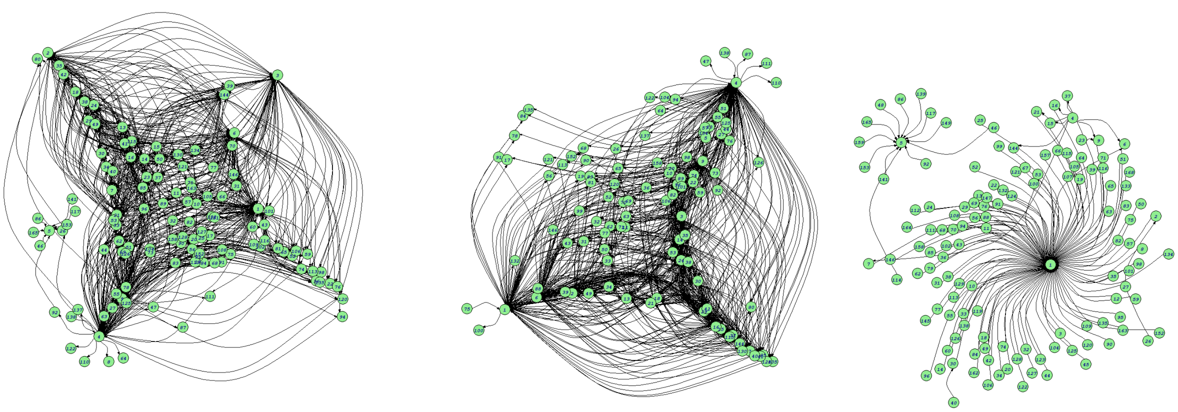
(b) From 14:00 to 16:00 (left), From 16:00 to 18:00 (middle), From 18:00 to 20:00 (right)

These figures depict the hourly networks of the payment system. The nodes and links present bank and hourly interbank payment transaction, respectively. To better illustrate the interconnections in the network, we delete links related to less 50 % frequency of interbank transaction between two banks. We apply the same layoout for plotting all figures. The structure of network is changing over time. Source: Authors calculations.

Figure 6: **Hourly Network of Payment System without delay**



(a) From 8:00 to 10:00 (left), From 10:00 to 12:00 (middle), From 12:00 to 14:00 (right)

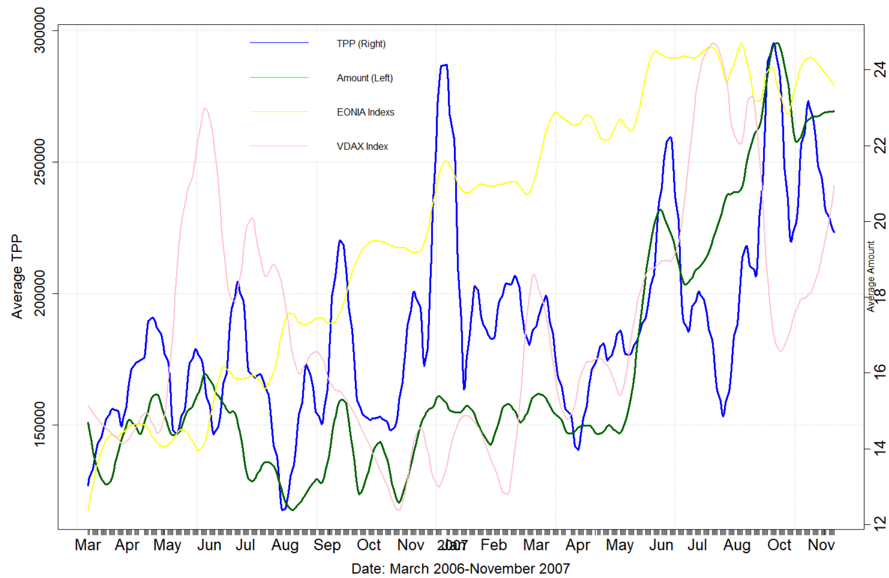


(b) From 14:00 to 16:00 (left), From 16:00 to 18:00 (middle), From 18:00 to 20:00 (right)

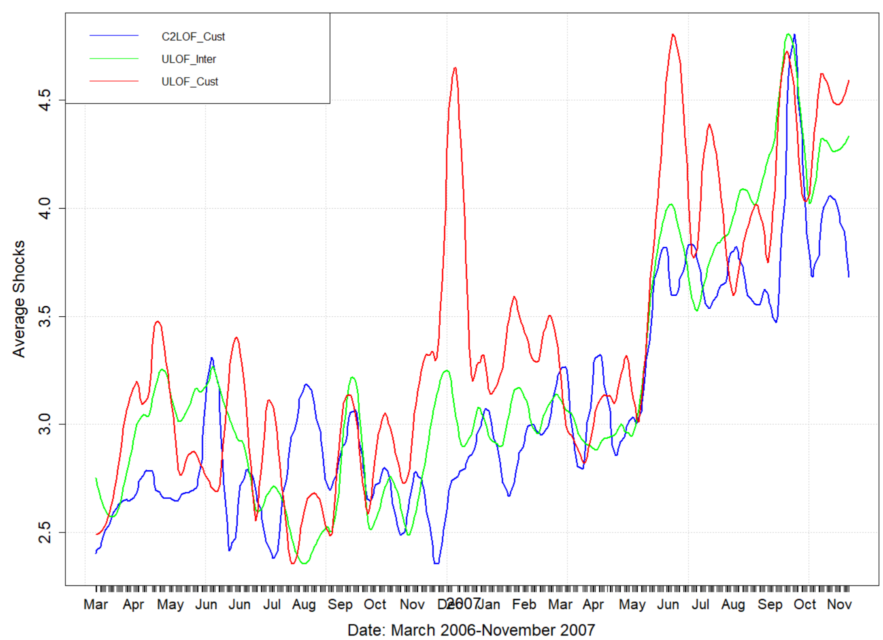
These figures depict the hourly networks of the payment system. The nodes and links present bank and hourly interbank payment transaction, respectively. To better illustrate the interconnections in the network, we delete links related to less 50 % frequency of interbank transaction between two banks. We apply the same layoout for plotting all figures. The structure of network is changing over time.

Figure 7: **Daily Average of Volume, TPP and Unexpected Liquidity Shocks**

(a) **Daily Average of Volume, TPP**

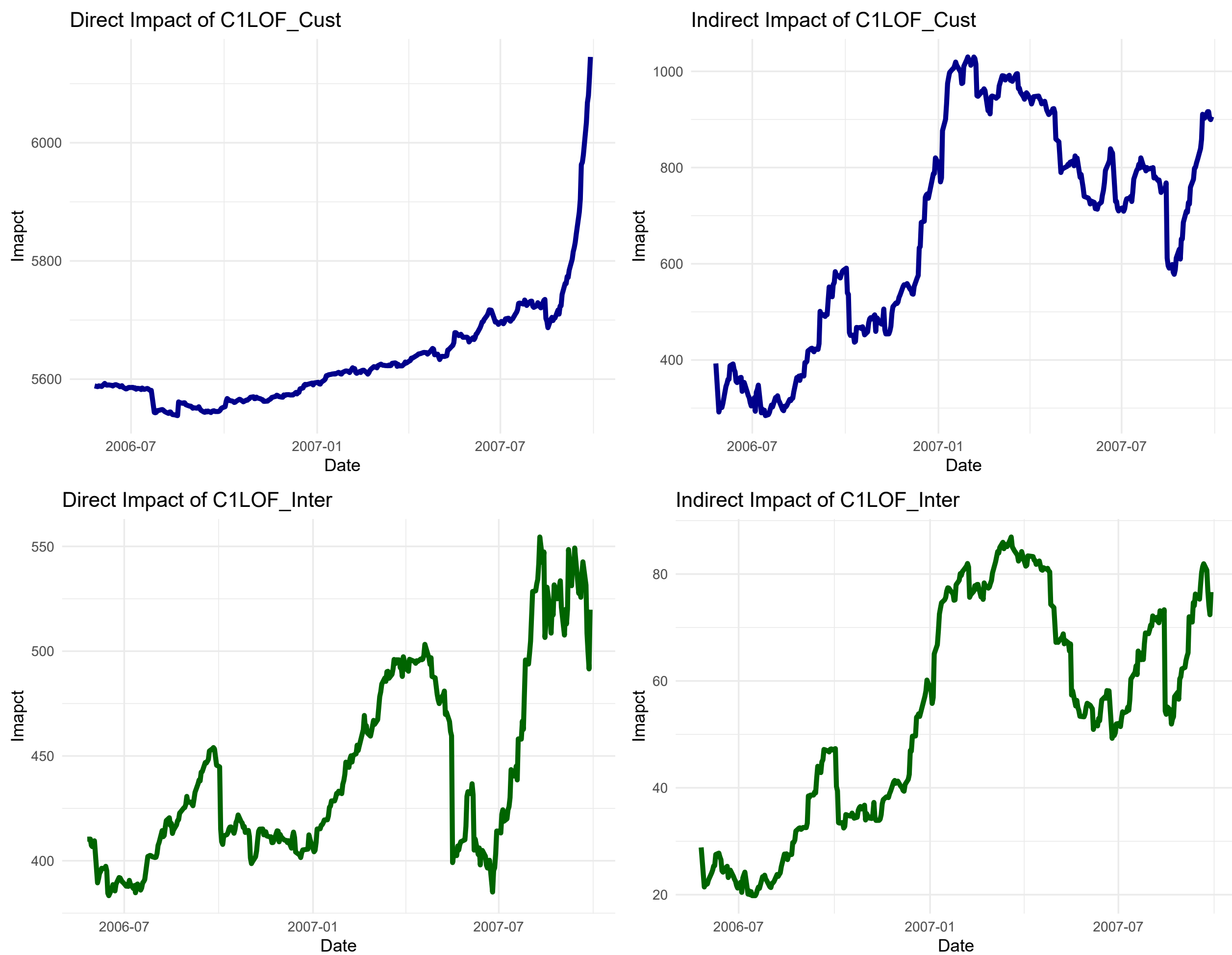


(b) **Daily Average of $ULOF^{Inter}$, $C1LOF^{Cust}$ and $C1LOF^{Inter}$**



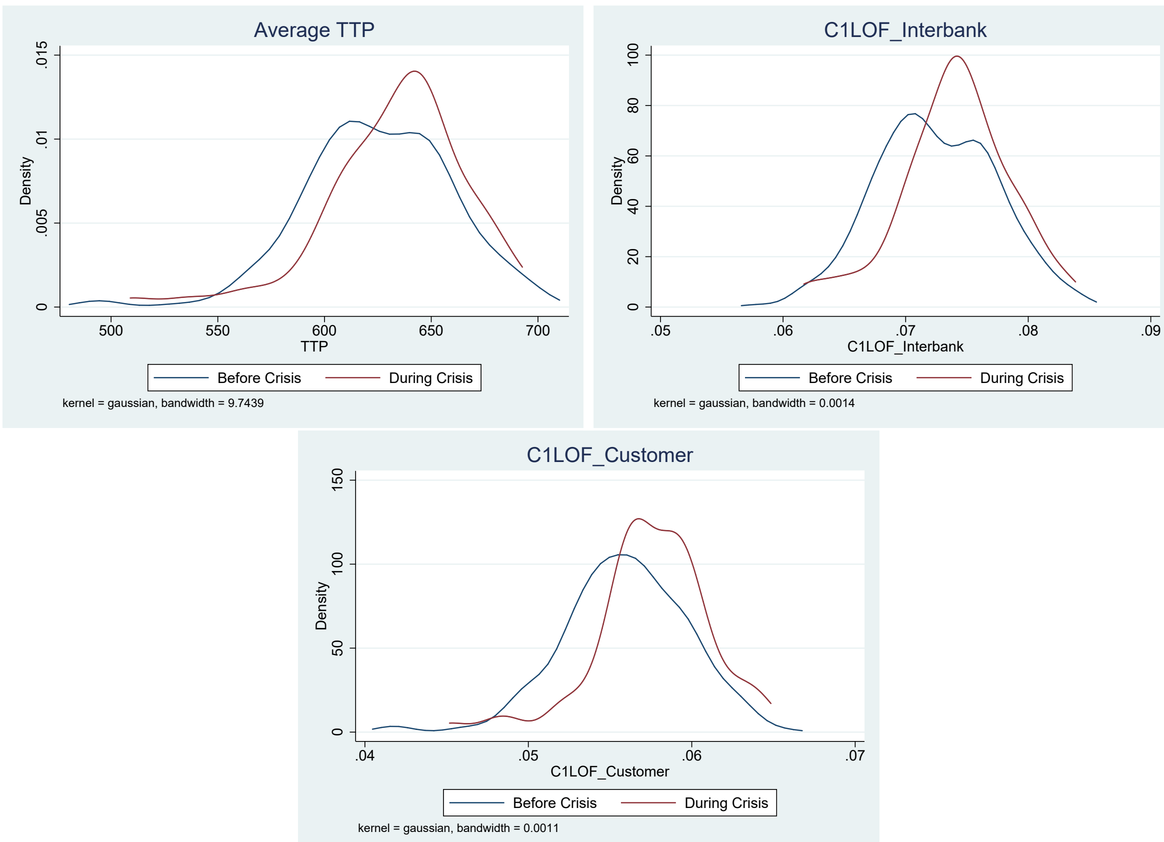
The top panel plots the daily average of volume, TPP. For comparison, we also add the EONIA rate (Euro OverNight Index Average) and VDAX (Volatility of DAX). The bottom panel plots daily average of $ULOF^{Inter}$, $C1LOF^{Cust}$ and $C1LOF^{Inter}$. Our dataset covers the period from March 1, 2006 to November 15, 2007. The definitions of variables are given in Table 3.

Figure 8: **Rolling window Spatial Effects**



This figure plots the time series of direct and indirect effects of spatial analysis of delay in the payment system. We apply the same model presented in Tables 14 and 15 in a rolling window framework. Top panel plots the direct and indirect effects of unexpected liquidity shock by customer order $C1LOF^{Cust}$ and bottom panel plots direct and indirect effects of unexpected liquidity shock by interbank order $C1LOF^{Inter}$.

Figure 9: **Density Plots of Unexpected Liquidity Shocks Before and During Crisis**



These figures plot the density plots of variables before and during crisis. The crisis time is defined by a dummy variable equal to days after August 9, 2007, and otherwise zero.

Table 9: **Summary Statistics of Network Characteristics of Payment System**

Variable	No	Mean	Standard Deviation	Min	25th Percentile	50th Percentile	75th Percentile	Max
(Sender)								
In-degree	6853303	17.4083	17.3753	0	4	10	26	124
Out-degree	6853303	23.8623	27.1668	0	4	13	34	142
Closeness	6853303	0.0035	0.0012	0	0.0031	0.0034	0.0038	1
Betweenness	6853303	287.8890	669.3148	0	0.2222	13.9319	202.6324	6548.1348
PageRank	6853303	0.0106	0.0113	0.0011	0.0039	0.0062	0.0127	0.6491
Hub	6853303	0.3543	0.3051	0	0.0770	0.2872	0.5720	1
Authority	6853303	0.4076	0.3146	0	0.1309	0.3282	0.6888	1
Neighborhood	6853303	31.9919	29.5609	1	10	21	46	143
Eigenvalue	6853303	0.3852	0.2968	0	0.1315	0.3009	0.6133	1
(Receiver)								
In-degree	6853303	15.2505	16.4754	0	3	8	21	123
Out-degree	6853303	18.5628	23.6736	0	2	9	27	142
Closeness	6853303	0.0034	0.0010	0	0.0031	0.0033	0.0037	1
Betweenness	6853303	225.7321	598.5791	0	0	5.0274	127.6854	6548.1348
PageRank	6853303	0.0094	0.0100	0.0011	0.0037	0.0054	0.0106	0.6491
Hub	6853303	0.2935	0.2911	0	0.0304	0.2048	0.4966	1
Authority	6853303	0.3694	0.3015	0	0.1126	0.2772	0.5848	1
Neighborhood	6853303	26.4375	26.5564	1	8	16	37	143
Eigenvalue	6853303	0.3269	0.2791	0	0.0986	0.2338	0.5214	1

The summary statistics of network characteristics for senders of payment massages are presented in panel 1, and the same information for receivers of payment messages are shown in panel 2. A bank can be the sender and receiver of the payment. Some banks are mostly a receiver of the payment message. The information about network characteristics are given in Table 2

Table 10: **Hourly Average of Network Characteristics of Payment System**

Hour	In-degree	Out-degree	Clossne_	Between_	PageRa_	Hub	Author_	Neighbou_	Eigen_
				(Sender)					
8-9	17.2802	26.8675	0.0037	264.0477	0.0104	0.3536	0.4844	34.9287	0.4329
9-10	18.3344	23.1018	0.0035	279.7642	0.0101	0.3359	0.3923	31.9839	0.3678
10-11	18.6461	21.9228	0.0034	297.8770	0.0101	0.3411	0.3730	30.8059	0.3658
11-12	19.1395	22.1512	0.0034	293.8874	0.0100	0.3501	0.3642	31.0467	0.3624
12-13	18.2383	21.8240	0.0034	298.7520	0.0105	0.3471	0.3838	30.1692	0.3702
13-14	17.3942	21.0249	0.0034	302.7983	0.0107	0.3495	0.3836	29.1949	0.3704
14-15	17.4553	20.8195	0.0034	308.2865	0.0106	0.3448	0.3729	29.1077	0.3637
15-16	17.5007	20.9518	0.0035	333.7210	0.0108	0.3359	0.3672	29.2432	0.3631
16-17	13.9876	17.0200	0.0036	322.3087	0.0123	0.3145	0.3571	24.3872	0.3455
17-18	5.0531	8.3560	0.0066	246.0794	0.0293	0.2668	0.3499	11.9574	0.3242
18-19	1.0053	0.9874	0.0005	0.0543	0.0074	0.8716	0.0085	2.9918	0.0879
19-20	1.0000	0.9853	0.0013	0.1265	0.0078	0.8767	0.0073	2.9837	0.0881
				(Receiver)					
8-9	13.9696	18.9222	0.0035	174.0712	0.0087	0.2561	0.4074	26.6342	0.3372
9-10	16.3486	20.0523	0.0034	226.8860	0.0091	0.2986	0.3574	28.4577	0.3311
10-11	17.0517	19.7711	0.0034	255.6895	0.0094	0.3132	0.3465	28.2186	0.3380
11-12	17.6550	20.2192	0.0033	256.6656	0.0093	0.3247	0.3407	28.7061	0.3377
12-13	16.3374	19.1394	0.0034	248.0784	0.0095	0.3109	0.3507	27.0274	0.3350
13-14	15.6426	18.4258	0.0034	252.0299	0.0097	0.3124	0.3512	26.1802	0.3351
14-15	15.8406	18.5092	0.0034	255.8291	0.0097	0.3135	0.3453	26.4106	0.3338
15-16	15.7959	18.4746	0.0034	272.4378	0.0098	0.3040	0.3390	26.3683	0.3319
16-17	12.5388	14.9189	0.0036	258.7586	0.0110	0.2843	0.3286	21.8794	0.3151
17-18	3.7971	5.4015	0.0062	147.6636	0.0224	0.1862	0.3075	8.5507	0.2531
18-19	0.2742	1.0082	0.0005	0.8076	0.0050	0.8590	0.0031	2.2757	0.0813
19-20	0.0000	1.0000	0.0012	0.0000	0.0039	0.6906	0.0008	2.0000	0.0635

This table presents the average hourly value of network characteristics of the payment system. The top panel gives network information of senders, and the bottom panel shows network information of receivers.

Table 11: **Transaction Level: All Transaction**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ULOF^{Inter}$	873.493***	863.363***	744.966***	851.532***	841.545***	719.927***	728.644***	849.228***
	(2.962)	(2.977)	(3.033)	(2.961)	(2.976)	(3.031)	(3.015)	(2.961)
$ULOF^{Cust}$	272.738***	273.112***	142.369***	275.633***	275.854***	146.068***	150.232***	276.740***
	(2.043)	(2.053)	(2.091)	(2.042)	(2.051)	(2.089)	(2.079)	(2.042)
$C1LOF^{Cust}$	1145.908***	1202.677***	1768.872***				963.790***	553.060***
	(5.878)	(5.903)	(6.009)				(6.332)	(6.216)
$C1LOF^{Inter}$				1897.010***	1915.339***	2464.849***	2138.783***	1724.497***
				(5.595)	(5.621)	(5.720)	(6.032)	(5.921)
FE: Hour	YES	YES		YES	YES		YES	YES
FE: Day	YES			YES			YES	
FE: Sender	YES	YES	YES	YES	YES	YES	YES	YES
FE: Receiver	YES	YES	YES	YES	YES	YES	YES	YES
FE: Sender * Receiver	YES	YES	YES	YES	YES	YES	YES	YES
Volume (control)	YES	YES	YES	YES	YES	YES	YES	YES
N	51635246	51635246	51635246	51635246	51635246	51635246	51635246	51635246
adj. R^2	0.240	0.232	0.201	0.241	0.234	0.202	0.211	0.242

This table presets the estimation result of regression model on transaction level. The dependent variable is TPP. The models, including fixed effects, are indicated with YES. All models include a constant. The robust standard errors are clustered at the Receiver bank level. Standard errors are in parentheses; Note, the symbols *, **, *** denote significance at the 10 percent, 5 percent, and 1 percent level. The definitions of variables are given in Table 3.

Table 12: **Transaction level: interbank payment transactions**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ULOF^{Inter}$	901.132***	888.086***	737.744***	881.301***	868.049***	716.916***	734.588***	880.408***
	(3.061)	(3.074)	(3.117)	(3.055)	(3.068)	(3.109)	(3.093)	(3.054)
$C1LOF^{Cust}$	1150.661***	1222.553***	1690.629***				925.288***	589.705***
	(5.927)	(5.939)	(6.008)				(6.300)	(6.218)
$C1LOF^{Inter}$				1901.597***	1925.688***	2379.219***	2071.680***	1727.629***
				(5.637)	(5.654)	(5.716)	(6.004)	(5.927)
FE: Hour	YES	YES		YES	YES		YES	YES
FE: Day	YES			YES			YES	
FE: Sender	YES	YES	YES	YES	YES	YES	YES	YES
FE: Receiver	YES	YES	YES	YES	YES	YES	YES	YES
FE: Sender * Receiver	YES	YES	YES	YES	YES	YES	YES	YES
Volume (control)	YES	YES	YES	YES	YES	YES	YES	YES
N	17195335	17195335	17195335	17195335	17195335	17195335	17195335	17195335
adj. R^2	0.157	0.149	0.119	0.160	0.152	0.124	0.133	0.161

This table presets the estimation result of regression model on transaction level. The dependent variable is TPP. We restrict our sample dataset when the order of payment is a member of interbank network. The models, including fixed effects, are indicated with YES. All models include a constant. The robust standard errors are clustered at the Receiver bank level. Standard errors are in parentheses; Note, the symbols *, **, *** denote significance at the 10 percent, 5 percent, and 1 percent level. The definitions of variables are given in Table 3.

Table 13: **Hourly Level: (IV Lag receiver In Degree)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8) : Q3	(9): Q4
$ULOF^{Inter}$	1.031***	1.031***	1.030***	1.030***	1.038***	1.031***	1.030***	0.004*	1.355***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.002)	(0.051)
$C1LOF^{Inter}$	0.956***	0.956***	0.956***	0.956***	0.952***	0.956***	0.956***	0.253***	0.639***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.006)	(0.023)
$C1LOF^{Cust}$	1.271***	1.271***	1.269***	1.270***	1.261***	1.271***	1.270***	0.491***	1.180***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.007)	(0.029)
In-degrees		0.004***							
		(0.001)							
Out-degrees			0.019***						
			(0.001)						
In-closeness				-666.267***					
				(62.175)					
Out-closeness					2388.510***				
					(32.649)				
PageRank							-14.552***		
							(1.528)		
Volume (control)	YES	YES	YES	YES	YES	YES	YES	YES	YES
FE: Hour	YES	YES	YES	YES	YES	YES	YES	YES	YES
FE: Bank to Bank	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj. R^2	0.021	0.021	0.022	0.021	0.023	0.021	0.021	0.007	0.007

This table presents the estimation of IV-regression models on an hourly base. The dependent variable is the seasonally adjusted hourly average of TPP (it is measured in hour). The models, including fixed effects, are indicated with YES. All models include a constant. The robust standard errors are clustered at the bank to bank level. Standard errors are in parentheses; Note, the symbols *, **, *** denote significance at the 10 percent, 5 percent, and 1 percent level. The definitions of variables are given in Table 3.

Table 14: **Daily level: spatial analysis of delay in payment system**

	(1)	(2)	(3 (All))	(4 (Q1))	(5 (Q2))	(6 (Q3))	(7 (Q4))	(8 (100%))
$C1LOF^{Cust}$	4380.420***	429.768 ***	5463.957***	874.290***	1261.104***	760.282***	992.460 ***	638.641***
	(25.206)	(20.508)	(15.377)	(72.186)	(74.316)	(73.205)	(49.395)	(87.639)
$C1LOF^{Inter}$	1818.843***	0.168***	429.142 ***	278.380**	-401.375***	87.356	258.143 ***	164.535
	(19.228)	(0.001)	(20.517)	(103.288)	(105.909)	(106.225)	70.675)	(124.474)
λ			0.038***	0.066***	0.045*	0.050**	0.061***	0.062***
			(0.007)	(0.018)	(0.019)	(0.019)	(0.018)	(0.019)
EONIA	0.988	0.018	-0.018	0.358	-0.757	0.009	2.195	0.917
	(0.707)	(0.086)	(0.086)	(1.718)	(1.720)	(1.728)	(1.676)	(1.734)
VOL_DAX	4.525	3.359	1.013	0.006	0.007	0.030	-0.138	0.011
	(1.198)	(0.862)	(0.872)	(0.286)	(0.286)	(0.288)	(0.279)	0.289)
L1.TPP	-0.019***	2.002***						
	(0.119)	(0.862)						
Weekly Day	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No_send banks			131	131	131	127	131	131
No_ receive banks			191	190	176	161	161	118
No_links			9528	3974	1564	1080	3042	981

This table presents the spatial analysis of delay in the payment system. The dependent variable is TPP which is measured in second. Columns 1 and 2 present the Pooled regression model (2) Fixed effect model, respectively. Column 3 contains the results of spatial analysis for all banks. Columns 4-7 show the results of spatial analysis for four quantiles of strategic partnership of banks. The last column (column 8) shows the results of banks with 100 % partnership. The robust standard errors are clustered at the Receiver bank level. The number of observations in each model is No_links and depends on the size of the network. Standard errors are in parentheses; Note, the symbols *, **, *** denote significance at the 10 percent, 5 percent, and 1 percent level. The definitions of variables are given in Table 3

Table 15: **Direct and indirect effect of spatial analysis**

		(3 (All))	(4 (Q1))	(5 (Q2))	(6 (Q3))	(7 (Q4))	(8 (100%))
$C1LOF^{Cust}$							
	(Direct Effect)	5466.65***	875.974***	1263.261*	756.661**	993.679 ***	637.370 ***
		(15.309)	(71.584)	(75.282)	(74.140)	(50.073)	(85.967)
	(Indirect Effect)	212.831***	61.662***	59.407*	39.541**	64.139***	41.913***
		(40.697)	(18.113)	(26.008	(16.019)	(20.289)	(14.500)
	(TOTAL Effect)	5679.481***	937.636***	1322.668*	796.202**	1057.818***	679.284***
		(44.400)	(78.574)	(83.176)	(80.276)	(56.923	(92.670)
$C1LOF^{Inter}$							
	(Direct Effect)	427.744***	276.201 ***	-403.159*	92.413	257.638 ***	167.759
		(20.262)	(103.823)	(108.003)	(106.504)	(70.682)	(123.849)
	(Indirect Effect)	16.648***	19.466***	-19.000*	4.715	16.655***	11.016
		(3.261)	(9.470)	(9.870)	(6.194)	(7.133)	(9.201)
	(TOTAL Effect)	444.392 ***	295.668***	-422.159*	97.128	274.293 ***	178.775
		(21.198)	(111.352)	(113.536)	(111.980)	(75.476)	(132.065)

This table presents the direct, indirect and total effects of spatial analysis, shown in Table 14. Columns show the effects corresponding to columns 3- 8 of Table 14. The top panel shows the effects of $C1LOF^{Cust}$, and the bottom panel shows the effects of $C1LOF^{Inter}$ variable. Robust standard errors are clustered at the Receiver bank level. Standard errors are in parentheses; Note, the symbols *, **, *** denote significance at the 10 percent, 5 percent, and 1 percent level. The definitions of variables are given in Table. 3.