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Abstract

The objective of the paper is to propose a tool for predicting intraday liquidity risks in a real time gross settlement system. To achieve this goal, we construct an intraday liquidity risk indicator (LRI) to assess intraday liquidity risks of a participant by comparing the evolution of the expected liquidity sources of the participant for settling payments with its expected liquidity requirements in the remainder of the payment day. If the participant's expected liquidity requirements are larger than its expected liquidity sources, the participant is very likely to incur a lack of intraday liquidity for settlement obligation within the remainder of the day. Otherwise, the available liquidity sources of the participant will be sufficient to cover its expected intraday liquidity requirements.

Furthermore, based on the LRI, we propose a framework that can predict the likelihood of an intraday liquidity risk event throughout the remainder of the payment day, where an intraday liquidity risk event is said to occur if the LRI rises above one. Using data from Canada's RTGS-equivalent payment system, the Large Value Transfer System, to evaluate the forecasting performance of the LRI, we find that the LRI performs reasonably well, and we obtain some new empirical findings.

Keywords: Intraday liquidity Risk; Clearing and Settlement Systems; Predicting Payment Transactions.
JEL Classification: G21, G23, C58.

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1 Introduction

Historically, interbank payments have been settled via deferred netting systems at the end of the day. As a consequence of the rapid increase in values settled in large-value payments system over the last few decades, however, policy makers of payments systems become concerned about settlement risk inherent in deferred net settlement systems. In particular, system participants are concerned about the potential for contagion effects attributable to the unwinding of net positions that would result if a participant failed to make its obligation when it is due.[1] Consequently, many countries have chosen to modify the settlement procedure employed by their interbank payment system with a view of reducing the settlement risk and delivering payments commitment effectively to meet international security and operating standards for modern payments systems (Bech and Hobijn, 2007; Bech, Preisig, and Soramaki, 2008).

Since a real time gross settlement (RTGS) system is settled continuously, individually, and irrevocably on a gross basis throughout the business day, it can reduce the settlement risk. An RTGS system can also help reduce settlement risk by facilitating payment versus payment and delivery versus payment in the settlement of forex and securities transactions, respectively. With this background, it comes as no surprise that RTGS systems have been used as the favored large-value payment systems in many countries to reduce the settlement risks inherent in clearing procedures. For example, Britain's large-value payment

[1] Unwinding is a procedure followed in certain clearing and settlement systems in which payments transfers are settled on a net basis, at the end of the processing cycle, with all transfers provisional until all participants have discharged their settlement obligations. If a participant fails to settle, some or all of the provisional transfers involving that participant are deleted from the system and the settlement obligations from the remaining transfers are then recalculated. Such a procedure has the effect of allocating liquidity pressures and losses attributable to the failure to settle to the counterparties of the participant that fails to settle (Bank for International Settlements 2003).

system, CHAPS, which previously operated under a deferred netting system, was converted to an RTGS system in April 1996. The European Monetary Union chose an RTGS system for its large-value funds transfer system, TARGET, in January 1999. Specifically, Canada is going to replace the current large value transfer system (LVTS) with Lynx, an RTGS system (Payments Canada, 2017). [2]

However, as pointed out by Allsopp et.al (2009) and Bech and Soramaki (2002), in RTGS systems, the reduction of settlement risk is traded off against an increased need for intraday liquidity requirements. As a result, participants in RTGS systems are inevitably confronted with the issue of whether there will be sufficient intraday liquidity to meet payments and settlement obligations on a timely basis. Supervisory authorities have devoted much effort to monitoring and managing the intraday liquidity risk in RTGS systems. A key issue in such supervision is that policy makers need an analytical tool to monitor intraday liquidity positions and risks (SWIFT, 2014). Under stressed conditions, such a tool can help them gauge the likely impact of distress of intraday liquidity on payments systems, while in normal times it is crucial to use such a tool to calibrate prudential instruments, such as collateral requirements, in accordance to the relative contribution of different participants to systemic risk.

In this context, Heijmans and Heuver (2014) developed monitoring indicators from large value payment systems to identify signs of liquidity stress in both individual banks and

[2] In developed countries, Canada is the only country in the Group of Ten (G-10) Countries that has decided not to implement an RTGS system. Instead, Canada opted for a hybrid system, the LVTS, which employs an advanced settlement algorithm that combines two payment streams: Tranche 1 and Tranche 2. A participant can either send a payment through the fully collateralized Tranche 1 which involves real-time settlement or through Tranche 2 in which collateral is pooled, risk is shared, and settlement takes place at the end of the payment day.

market segments. Using the data from TARGET2, they find their indicators perform well.[3] The BCBS (2009) has published "Monitoring Tools for Intraday Liquidity Management", where it explicitly includes the management of intraday liquidity risk as a principle and proposes a set of analytical tools for managing intraday liquidity risk. Leon (2012) estimated the intraday liquidity risk of financial institutions using a Monte Carlo simulation approach. Li and Perez Saiz (2018) constructed an indicator for monitoring the settlement risk at the end of day in the LVTS. These analytical tools in above-mentioned papers and references therein are very powerful for monitoring the current status of intraday liquidity risk in payments systems, but they cannot be used to predict intraday liquidity risks within an upcoming period of time in a payment day.

Taking into consideration that an effective prediction for intraday liquidity risk has substantial value to policy makers by allowing them to detect the future potential weakness and vulnerabilities in the payment systems, and possibly take pre-emptive policy actions to avoid a risk event or limit its effects, this paper aims to propose an analytical tool for predicting intraday liquidity risks in a real time gross settlement system. To achieve this goal, based on the work of Baek et. al (2014), we construct an intraday liquidity risk indicator (LRI) to assess the upcoming intraday liquidity risks of a participant by comparing the expected sources of the participant for settling payments with its expected liquidity requirements in the remainder of the day. If the participant's expected liquidity requirements are larger than its expected sources, the participant is very likely to incur a net debit position that exceeds its credit limits. Otherwise, the available sources of the participant

[3] TARGET2 is a real time gross settlement system and is used by both central banks and commercial banks to process payments in EURO. TARGET2 replaced the decentralized first-generation TARGET system.

will be sufficient to cover its expected intraday liquidity requirements within the remainder of the day. Furthermore, based on the LRI, we propose a framework that can predict the likelihood of an intraday liquidity risk event within the remainder of the payment day, where an intraday liquidity risk event is said to occur if the value of the LRI rises above one. Using the data from the LVTS to evaluate the forecasting performance of the LRI, we find that the LRI performs reasonably well, suggesting that it is a useful tool for predicting intraday liquidity risk in an RTGS system. Additionally, we find that the predicted values of the LRI are more varied in the late afternoon, which is consistent with our finding that the probabilities of an intraday liquidity risk event reach peak levels in the late afternoon. This suggests that participants need to manage their intraday liquidity well to synchronize their outgoing payments with the incoming funds that they expect to receive in the late afternoon to avoid the mismatch problem (McAndrews and Rajan, 2000).

The paper is organized as follows. Section 2 outlines the effects of settlement methods on liquidity risk. In Section 3, we introduce an indicator for each participant to assess the intraday liquidity risks in the remainder of a payment day. Section 4 proposes a framework to predict the likelihood of an intraday liquidity risk event during the remainder of the day, where an intraday liquidity risk event is said to occur if the LRI rises above one. Section 5 concludes.

2 The effects of settlements methods on liquidity needs: real-time gross settlements versus netting settlements

According to the way settlement takes place, a payment system can be classified into a net settlement system or a gross settlement system. With a net settlement system, payment messages are processed continuously in real time, but settlement occurs only at the end of a clearing cycle, on a net multilateral basis. With a gross settlement system, fund transfers at the settlement stage occur on a bilateral and gross basis. A common form of gross settlement large-value payment system is the real-time gross settlement system, in which both information processing and settlement take place continuously in real time.

Under a netting settlement system with end-of-day settlement, the payment is settled only at the end of the day, at which it would have received all of the day's incoming funds, as well as having made all the outgoing transfers. The end-of-day payment implies that sending participants have no incentive to delay sending the payment messages if there are no other payment-system-imposed constraints. Hence, there should be no costly settlement delays or gridlock.[4] Also, since each participant needs to pay only the net amount at the end of a day, which usually is much smaller than the value of total outgoing payments the participant has to make during the day, it needs to hold lower clearing balances as payment liquidity relative to an RTGS system. However, if the sending participants fail during the day and cannot make their payments at the end of the day, this may result in a chain of defaults by other participants in the system. Particularly, the potential spillover of this settlement failure to other payment systems and financial markets could lead to a collapse in the financial system. Consequently, the main concern associated with a netting settlement system is the potential settlement risk.

An RTGS system reduces settlement risk in payments systems by settling transactions on

[4] Gridlock is a case of payment system illiquidity in which the failure of some transfers to be executed prevents a substantial number of other transfers from other participants from being executed (Soramaki and Bech, 2001). For example, in the case of two participants, gridlock is a situation where participant A is waiting for participant B's payment and participant B is waiting for participant A's payment, so neither can pay the other.

bilateral and gross basis, instead of netting payments at the end of the day. A sending participant, however, is faced with the issue of when to send the payment request. This decision depends on whether it has sufficient funds in its clearing account to cover the transfer, when incoming payments will arrive, and whether it needs to save the account balance for more urgent payment requests. The timing decision of each participant in this payment system may collectively slow down the speed of funds transfer or may even trigger gridlock of the whole payment system. Therefore, the main concern with an RTGS system is whether there will be sufficient liquidity to cover outgoing payments. Participants must make intraday liquidity available for settlements that could take place throughout the business day. Otherwise, the cost of a lack of liquidity would be very high, not just for the participants, but for the payment system as a whole.[5]

3 Monitoring intraday liquidity risk

3.1 An intraday liquidity risk indicator

Management of intraday liquidity risk is a key element in the overall risk management framework of a payment system. There are two main questions of managing intraday liquidity risk in a payment system: (i) what is the current status of intraday liquidity risk in a payment system? and (ii) what is the future status of intraday liquidity risk?

Among the recent contributions to answer (i) are the studies by Heijmans and Heuver (2014), Li and Perez Saiz (2018), BCBS (2013), and Leon (2012). Particularly, the BCBS

[5]Central Banks have mitigated the need for settlement liquidity in real time to an extent by providing intraday liquidity. Lending liquidity generates credit risk for the central banks and thus this lending is collateralized to remove this risk. However, the benefits from reducing the risk associated with netting settlement systems are considered to exceed the costs of greater liquidity needs (Zhou, 2000). Hence, the number of RTGS systems has grown. Recent debate has mainly concentrated on the benefits of complementing RTGS with a liquidity-saving mechanism (Willison, 2004).

(2013) has developed a set of quantitative tools to monitor participants' intraday liquidity risk and their ability to meet payment and settlement obligations on a timely basis. Relative to the literature on developing tools to monitor current status of intraday liquidity risk in payments systems, there has been relatively little effort on prediction analysis for intraday liquidity risks. However, an effective prediction of the intraday liquidity risk has substantial value to policy makers as it allows them to detect future potential weaknesses and vulnerabilities in payment systems, and possibly take pre-emptive policy actions to avoid occurrence of a risk event or limit its effects. To answer (ii), based on the work of Baek et. al (2014), we propose an intraday liquidity risk indicator by comparing the participant's expected payment capacity with its expected payment requirements, within the reminder of the payment day. [6]

The setup of our indicator is described as follows. At time t on day j, for a participant i, the intraday liquidity source consists of its net payment income up to time t on day j, denoted by $PI^i_{t,j}$, its intraday credit limits at the central banks, denoted by $CL^i_{t,j}$, and its payment incomes to be received from other participants during the remainder of day j after time t, denoted by $RPI^i_{t,j}$. Its intraday liquidity requirements during the remainder of day j are denoted by $RPD^i_{t,j}$. Its future intraday liquidity risks are managed by the following inequality,

$$PI^i_{t,j} + CL^i_{t,j} + RPI^i_{t,j} > RPD^i_{t,j}. \tag{1}$$

[6] Baek and Soramaki (2014) propose a set of tools to monitor the future status of intraday liquidity risks in the BoK-Wire system. Unlike the BoK-Wire system, the Bank of Canada does not impose any reserve requirements through which it could control interest rates and liquidity. As a result, our indicator is different from the indicator in Baek and Soramaki (2014). Furthermore, using the data from the LVTS, we find the model that we use for predicting the expected payment transactions performs better than the model that Baek and Soramaki (2014) use.

The intraday liquidity risk indicator is defined as,

$$LRI^i_{t,j} = \frac{RPD^i_{t,j}}{PI^i_{t,j} + CL^i_{t,j} + RPI^i_{t,j}}. \tag{2}$$

In Tranche 1 of the LVTS, to prevent a participant from incurring a situation where its net debit position is in excess of its net debit cap, the LVTS applies a real-time risk control test to each payment submitted to the system, which ensures that the submitted payment value does not exceed the summation of the participant net payment income and credit limit, i.e.,

$$PI^i_{t,j} + CL^i_{t,j} > PD^i_{t,j}, \tag{3}$$

where $PI^i_{t,j}$ and $CL^i_{t,j}$ have the same definitions as in (1) and $PD^i_{t,j}$ is the submitted payment value at time t on day j for the participant i. [7] Compared to (3), the $LRT^i_{t,j}$ is obtained from extending the risk control test by replacing $PD^i_{t,j}$ with the expected liquidity demands during the remainder of the day j ($RPD^i_{t,j}$) and increasing liquidity sources by the expected payment income during the remainder of the day j ($RPI^i_{t,j}$).

For a given participant and a time t, if the $LRI^i_{t,j}$ is greater than one, the predicted liquidity needs of the participant are larger than its available sources and thus it will possibly incur a liquidity risk event where the expected intraday liquidity requirements exceed the expected intraday liquidity sources. Otherwise, at the given time, the participant's expected liquidity sources are sufficient to cover its expected intraday liquidity requirements within

[7] In Tranche 2 of the LVTS, the payment submitted will be processed only if it passes two risk control tests: the bilateral risk control test, and multilateral risk control test. Based on the two risk control tests, we can build two indicators for predicting whether the bilateral net debit position and multilateral debit position can be covered by the bilateral credit limits and multilateral intraday line of credit, respectively, in the reminder of the payment day. This work is beyond the focus of this paper and will be pursued in our future research.

the remainder of the day.

A participant's intraday credit limits represent the maximum net debit position that the participant can incur during the remainder of the day. The participants determine the value of their credit limits and must fully secure this limit with eligible collateral. If a participant's $LRI^i_{t,j}$ at time t is greater than one, it should increase its credit limits at any time during the payments cycle by apportioning additional collateral on a dollar-for-dollar basis. If its $LRI^i_{t,j}$ is less than one, it may reduce its credit limits at any time during the payments cycle. The collateral no longer needed to cover a participant's appointment becomes part of its excess holdings.

In order to implement the intraday liquidity risk indicator, we need to predict the values of both $RPD^i_{t,j}$ and $RPI^i_{t,j}$. In the following, we outline the method to predict both $RPI^i_{t,j}$ and $RPD^i_{t,j}$. Let TPI^i_j represent the total payment income that participant i has received on day j, and $PI^i_{t,j}$ be the total payment that participant i has received up to time t on day j. We have,

$$RPI^i_{t,j} = TPI^i_j - PI^i_{t,j}. \tag{4}$$

Similarly, let TPD^i_j represent the total payment demand that participant i has spent on day j, and $PD^i_{t,j}$ be the total payment that participant i has sent up to time t on day j, we have,

$$RPD^i_{t,j} = TPD^i_j - PD^i_{t,j}. \tag{5}$$

Since $PI^i_{t,j}$ and $PD^i_{t,j}$ in both (3) and (4) are given by the data, to predict the values of $RPI^i_{t,j}$ and $RPD^i_{t,j}$, we only need to predict both TPI^i_j and TPD^i_j. In next subsection, we will introduce three models for predicting both payments sent and payments received, and evaluate their forecasting performance.

3.2 Alternative models for predicting payment transactions and their forecasting performance

3.2.1 Alternative models for predicting payment transactions

To calculate both the expected liquidity requirement and the expected liquidity source for the remainder of the day, we need to predict the total payment income and total payment demand for each participant. We examine the predicting accuracy of the following three models commonly used in this literature for predicting payment transactions. The three models are a linear regression model, an autoregressive integrated moving average model, and a lognormal diffusion model.

A. A linear regression model

We fit a linear regression model with the payment income to be received as the response variable, with the days of the week and the holiday being independent variables,

$$TPI_j^i = \alpha_i^R + \beta_i^R D_j + \gamma_i^R H_j + \varepsilon_j^i, \tag{6}$$

where α_i^R is a consistent effect on the total payment incomes on day j for participant i, D_j is the vector of the week indicators with the exception of Monday (Tuesday, Wednesday, Thursday, and Friday), and H_j is the indicator of whether day j is a Canadian holiday, and ε_j^i is an error term. Similarly, for TPD_j^i, we have,

$$TPD_j^i = \alpha_i^D + \beta^D D_j + \gamma^D H_j + \varepsilon_j^i. \tag{7}$$

Given the regression equations for participants, we can get a seemingly unrelated regression (SUR) model which consists of these linear regression equations for different participants. We use the feasible general least squared method to estimate the SUR model (Zellner, 1962).

B. An autoregressive integrated moving average model

An autoregressive integrated moving average model (ARIMA) is a popular and flexible class of predicting model that utilizes historical information to make predictions.

Let $\triangle TPI_j^i = TPI_j^i - TPI_{j-1}^i$, the $ARIMA(1,1,1)$ model for predicting payments received is specified as,

$$\triangle TPI_j^i = c_i^I + \alpha_i^I \triangle TPI_{j-1}^i + \epsilon_j^i - \beta_i^I \epsilon_{j-1}^i, \tag{8}$$

where ϵ_j^i is the random shock to bank i occurring at time j.

Similarly, let $\triangle TPD_j^i = TPD_j^i - TPD_{j-1}^i$, the $ARIMA(1,1,1)$ model for predicting payments sent is specified as,

$$\triangle TPD_j^i = c_i^D + \alpha_i^D \triangle TPD_{j-1}^i + \epsilon_j^i - \beta_i^D \epsilon_{j-1}^i, \tag{9}$$

where ϵ_j^i is the random shock to participant i on day j. The maximum likelihood estimation procedure is used to estimate the ARIMA(1, 1, 1) model.

C. A lognormal diffusion process model

The total payment income is modeled by a lognormal diffusion process,

$$dTPI_j^i / TPI_j^i = \mu_i^I dt + \sigma_i^I dw_j^i, \tag{10}$$

where w_j^i is a standard Brownian motion process, μ_i is the instantaneous growth rate of the payment value, and σ_i is the instantaneous volatility of the growth rate of the payment value.

Similarly, the total payment sent is modeled as,

$$dTPD^i_j/TPD^i_j = \mu^D_i dt + \sigma^D_i dw^i_j. \tag{11}$$

3.2.2 Performance of alternative models for forecasting payment transactions

Since any net debit position incurred by a participant must be fully collateralized in Tranche 1 of the LVTS, Tranche 1 is very similar to an RTGS system. The focus of our paper is on the Tranche 1 payment stream. The transaction and credit limit data are obtained from the Payments Canada over the period from January 4, 2016 to December 29, 2017, with the exact time of the payments sent, payments received, and collateral (credit limits) pledged by each participant.

We focus primarily on assessing the forecasting performance of the above three models for five large participants which account for a significant portion of the Canadian financial sector. The results for the remaining participants are qualitatively similar to those for the five participants and available upon request. [8]

In order to evaluate both in-sample and out-of-sample forecasting performance of the three models, we divide our data into two subsamples. The first subsample, from January 4, 2016, to November 30, 2017, is used to estimate the model parameters and to evaluate the in-sample forecasting performance of the three models. The second subsample from December 1, 2017, to December 29, 2017, is used to evaluate out-of-sample forecasting performance of the three models. We use the root mean squared error (RMSE) to evaluate

[8] As of 2018, there are 17 financial institutions, including the Bank of Canada participating in the LVTS.

the in-sample and out-of-sample forecasting performance of the three models. [9]

For participant 1 (Bank1), participant 2 (Bank2), ..., and participant 5 (Bank5), the estimation results from the SUR model are reported in Tables 1-3. All coefficients of this model are statistically significant at a significance level of 5%. The estimation results of the ARIMA(1, 1, 1) model and the lognormal diffusion process model are reported in Table 4 and Table 5, respectively.

For in-sample forecasting, we have,

$$\text{RMSE} = \sqrt{\sum_{\text{j=2016 January 4}}^{\text{j=2017 November 30}} (y_j^i - \hat{y}_j^i)^2/505}, \tag{12}$$

where y_j^i is for either the total payment sent or the total payment received, and $\hat{y}_j^i$ is either the in-sample forecasting value for the total payment sent or the in-sample forecasting value for the total payment received. We have 505 observations over the period from January 4, 2016, to November 30, 2017.

For out-of-sample forecasting, we have,

$$\text{RMSE} = \sqrt{\sum_{\text{j=2017 December 1}}^{\text{j=2017 December 29}} (y_j^i - \hat{y}_j^i)^2/29} \tag{13}$$

where y_j^i is for either the total payment sent or the total payment received, and $\hat{y}_j^i$ is either the out-of-sample forecasting value of the total payment sent or the out-of-sample forecasting value of the total payment received. We have 29 observations over the out-of-

[9] In-sample analysis is important and can reveal useful information about possible sources of model misspecification. In practice, however, what matters most is the evolution of the payment transactions in the future, not in the past. A model that fits a historical data well may not forecast the future well because of unforseen structural changes or regime shifts in the data-generating process. Therefore, from both practical and theoretical standpoints, in-sample analysis alone is not adequate, and it is necessary to examine the out-of-sample predictive ability of payments transaction models (White, 2000).

sample forecasting period from December 1 , 2017, to December 29, 2017.

The RMSE values of both in-sample and out-of-sample forecasts are reported in both Table 6 and Table 7, respectively. Among all the three models, it is noticeable that the ARIMA(1, 1, 1) model consistently shows the best performance for both in-sample forecasting and out-of-sample forecasting across all participants. The ARIMA(1, 1, 1) model uses a combination of past values and past forecasting errors and therefore it offers a potential for fitting data that could not be adequately fitted by using a linear regression model or a diffusion process model.

Since the ARIMA(1, 1, 1) model has a better forecasting performance than other two models, we use the ARIMA(1, 1, 1) model to fit the data and obtain the predicted total payment transactions for each participant. The predicted total payment transactions are used to compute the values of the intraday liquidity risk indicator for each participant.

Table 1: **Estimation results of regression models for total payment transactions**

	Payments sent		Payments received	
	Coefficient	t-test statistic	Coefficient	t-test statistic
Bank 1				
Intercept	23. 37	1226	23.37	1189
Tue	-0.029	-1.636	-0.0239	-3.904
Wed	-0.017	-7.235	-0.0203	-2.781
Thu	-0.006	-2.970	-0.0046	-1.742
Fri	0.0421	1.827	0.0505	1.885
Holiday	0.0501	1.949	0.0414	1.954
Family-day	-2.819	-22.104	-2.8039	-21.723
Aug-civic	-3.286	-25.773	-3.0172	-23.375
Bank 2				
Intercept	23.98	1271	23.980	1282
Tue	-0.0129	-1.505	-0.008	-3.079
Wed	0.04863	1.916	0.046	1.847
Thu	-0.0138	-2.653	-0.010	-3.142
Fri	0.04228	1.649	0.038	1.506
Holiday	-0.0179	-2.816	-0.016	-3.427
Family-day	-3.2845	-26.026	-3.277	-26.672
Aug-civic	-4.0521	-32.108	-3.887	-31.634

The data used to estimate the models covers the period from January 4, 2016, to November 30, 2017. The number of observations is 503. The feasible general least squared method is used to estimate the SUR model. For Bank1, the model for payments sent: Adjusted R-Squared is 0.70; the model for payments received: Adjusted R-Squared is 0.68. For Bank2, the model for payments sent: Adjusted R-Squared is 0.78; the model for payments received: Adjusted R-squared is 0.79.

Table 2: **Estimation results of regression models for total payment transactions**

	Payments sent		Payments received	
	Coefficient	t-test statistic	Coefficient	t-test statistic
Bank 3				
Intercept	23.21	719	23.2119	706.10
Tue	-0.1460	-3.3552	-0.1336	-3.0182
Wed	-0.1089	-2.5106	-0.1039	-2.3498
Thu	-0.0719	-1.6553	-0.0672	-1.5178
Fri	-0.0037	-0.0769	-0.0025	-0.0549
Holiday	0.04201	0.66827	0.04727	0.73478
Family-day	-2.5549	-11.842	-2.5500	-11.896
Aug-civic	-2.8739	-13.321	-2.8641	-13.259
Bank 4				
Intercept	24.5789	1376	24.5793	1347
Tue	0.00485	0.20121	-007364	0.29968
Wed	0.06343	2.64114	0.06299	2.56661
Thu	0.05074	2.11028	0.05176	2.10645
Fri	0.07829	3.22719	0.07452	2.99338
Holiday	0.06089	1.74943	0.05692	1.59404
Family-day	-2.7173	-22.750	-2.7154	-22.650
Aug-civic	-3.2647	-27.333	-3.2348	-26.983

The data used to estimate the models covers the period from January 4, 2016, to November 30, 2017. The number of observations is 503. The feasible general least squared method is used to estimate the SUR model. For Bank3, for payment sent: Adjusted R-Squared is 0.39, for payment received: Adjusted R-Squared is 0.49. For Bank 4, Adjusted R-Squared is 0.73, for payment received : Adjusted R-Squared is 0.73.

Table 3: Estimation results of regression models for total payment transactions

Payments sent			Payments received	
	Coefficient	t-test statistic	Coefficient	t-test statistic
Bank 5				
Intercept	23.6837	997.790	23.6813	972.343
Tue	0.01669	0.52102	0.02254	0.68707
Wed	0.07031	2.20237	0.06968	2.12706
Thu	0.05118	1.60160	0.05614	1.71173
Fri	0.07775	2.41105	0.07709	2.31986
Holiday	0.03083	0.66636	0.01812	0.38017
Family-day	-2.9705	-18.709	-2.8251	-17.653
Aug-civic	-3.2237	-20.304	-2.8466	-17.788

The data used to estimate the models covers the period from January 4, 2016, to November 30, 2017. The number of observations is 503. The feasible general least squared method is used to estimate the SUR model. For Bank 5, the model for payments sent: Adjusted R-Squared is 0.62; the model for payment received: Adjusted R-Squared is 0.58.

Table 4: **Estimation results for autoregressive integrated moving average models**

	Payments sent			Payments received		
	Intercept	α	β	Intercept	α	β
Bank1	23.3504	0.8711	-0.8351	23.3569	0.8791	-0.8410
	(0.1096)	(0.1211)	(0.0182)	(0.0183)	(0.097)	(0.1095)
Bank2	23.9640	-0.7659	0.7412	23.9650	-0.7229	0.6962
	(0.0164)	(0.4586)	(0.4776)	(0.016)	(0.4844)	(0.499)
Bank3	23.1302	-0.0762	0.1644	23.1322	-0.0737	0.1638
	(0.0184)	(0.3085)	(0.3029)	(0.0184)	(0.3077)	(0.2971)
Bank4	24.5983	-0.0083	-0.0086	24.5997	-0.0076	-0.0080
	(0.0139)	(1.4180)	(1.4244)	(0.0138)	(1.5266)	(1.5342)
Bank5	23.7044	-0.2033	0.15310	23.7093	-0.2190	0.1710
	(0.0151)	(0.5466)	(0.5509)	(0.0145)	(0.5803)	(0.5855)

The data used to estimate the models covers the period from January 4, 2016, to November 30, 2017. The number of observations is 503. The model is estimated by using the maximum likelihood estimation method. The standard errors are reported in the parentheses.

Table 5: **Estimation results for diffusion models**

	Payments sent		Payments received	
	μ	σ	μ	σ
Bank1	0.08	1175.76	1.14	1457.83
	(0.04)	(557.23)	(0.57)	(732.17)
Bank2	0.23	1957.71	1.59	2337.55
	(0.11)	(998.81)	(0.78)	(1152.12)
Bank3	1.11	3842.34	0.69	3307.82
	(0.55)	(1760.10)	(0.35)	(1679.10)
Bank4	0.66	3889.73	2.51	4027.07
	(0.39)	(1048.90)	(1.33)	(1983.71)
Bank5	0.42	1968.06	1.54	2198.07
	(0.19)	(1046.90)	(0.76)	(1163.22)

The data used to estimate the models covers the period from January 4, 2016, to November 30, 2017. Number of observations is 503. The model is estimated by using the maximum likelihood estimation method. The standard errors are reported in the parentheses.

3.3 Prediction accuracy of the intraday liquidity risk indicator

Typically, for any given time in a payment day, the LRI can predict intraday liquidity risks for the remainder of the day for each participant. To evaluate the forecasting performance of the LRI, we split the data set into an in-sample period from 2016 January 4 to 2017 November 30, used for the initial parameter estimations, and an out-of-sample period from 2017 December 1 to 2017 December 29, used to evaluate forecasting performance of the LRI. For the five participants (Bank 1, ..., Bank 5), both the actual and forecasted values of the LRI are reported in Figures 1-3 across different payment times in a payment day. 95% confidence bands are also reported in these figures to evaluate the indicator forecasting performance. Several general conclusions can be drawn from these figures. First, the actual values of the LRI for each participant is lower than one, indicating that in practice, the participants' liquidity sources during the remaining times are sufficient to cover the liquidity requirements during the period considered. This suggests that these participants managed their intraday liquidity positions well to meet payment and settlement obligations on a timely basis, which contributes to the smooth functioning of payment systems. Second, the predicted values of the LRI across different participants fall into the 95% confidence bands of the actual values of the indicator, which reflects the fact that the predictive ability of the indicator performs reasonably well. Third, both the actual and predicted values of the indicator tend to be more varied in the late afternoon. This can be explained by the fact that payment activity peaking in the late afternoon makes the indicator more volatile. [10]

[10]This pattern of payment activity, i.e., payment activity peaking in the late afternoon, can be explained partially by recognizing two factors that affect participants' payment activity. First, the timing of participants'

4 Predicting the likelihood of intraday liquidity risk events

The intraday liquidity risk indicator helps us predict whether the intraday liquidity source is enough to cover the liquidity demand. However, it can only provide the prediction for the future value of the intraday liquidity risk, which can at most convey some notion of future intraday liquidity risk, but it cannot provide the possible uncertainty of the future intraday liquidity risk. For most decision issues, there is a need to provide insights on the likelihood of occurrence of intraday liquidity risk for a given period of time (Gneiting and Ranjan, 2011). In this section, we propose an approach that can predict the likelihood of occurrence of an intraday liquidity risk event within the remainder of the day, which is defined as an episode where LRI is greater than or equal to a positive constant C.

Different values of C result in different definitions for intraday liquidity risk events. A lower value of C leads to the identification of more intraday liquidity risk events. Given the information set I_t at time t, the probability that an intraday liquidity risk event will occur during the remaining day can be expressed as,

$$P[LRI^i_{t,j} \geq C|I_t]. \tag{14}$$

Since we do not know the distribution function of $LRI^i_{t,j}$, we cannot directly calculate the probability in (14). However, we can use a bootstrap method to obtain the empirical distribution of $LRI^i_{t,j}$. The bootstrap procedure used to predict the probability in (14) consists of three steps, as described below.

payment activity reflects underlying customer demand. Settlement of financial transactions customarily takes place in the late afternoon, which tends to cause a demand for payments late in the day. Second, such timing also reflects participants' efforts to synchronize their outgoing payments with the large payment inflows they expect to receive in the late afternoon.

Step 1: Use the original sample to estimate the unknown parameters in the ARIMA(1, 1, 1) models in (7) and (8) and obtain the estimated residuals: $\{R^i_{t,j}\}_{j=1}^{29}$.

Step 2: Use the nonparametric bootstrapping method by resampling the residuals in (7) and (8) to obtain the bootstrapping residuals $\{R^i_{t,j^*}\}_{j=1}^{29}$. Use (7) and (8), and the bootstrapping residuals to calculate the predicted payments sent and payments received, from which we can build up the bootstrapping intraday liquidity risk indicator: LRI^i_{t,j^*}.

Step 3: Repeat step 1 and step 2 R times, at time t the predicted probability of an intraday liquidity risk event within the reminder of a payment day is computed as,

$$\frac{1}{R}\sum_{j=1}^{R} I(LRI^i_{t,j^*} \geq C). \tag{15}$$

Using the sample period from January 4, 2016, to November 30, 2017, to update the model parameters and taking $R = 100$, we obtain the out-of-sample predicted probabilities of an intraday liquidity risk event from 2017 December 1 to December 29 for the five participants, which are reported in Tables 4-6, respectively. As we can see from the figures the probabilities of an intraday liquidity risk event reach a peak in the late afternoon, which is consistent with the result that the indicator tends to be more variations during that period. Thus, participants face more uncertainty of potential settlement failure if they do not have sufficient funds to cover the transfer, for example, if the income funds that they are expecting cannot arrive. The potential of whether there will be sufficient liquidity to cover outgoing payments demand may raise probability of an intraday liquidity risk event in the late afternoon.

Table 6: **In-sample predictive ability for payments from alternative models**

	Bank1	Bank2	Bank3	Bank4	Bank5
Payments sent from alternative models					
Linear regression model					
	3.0853	1.9665	4.3291	0.7104	1.9920
Autoregressive integrated moving average					
	0.0002	0.0523	0.0002	0.0252	0.0721
Log normal diffusion process					
	3.4374	2.4511	4.6129	1.1509	2.6783
Payments received from alternative models					
Linear regression model					
	0.6638	0.5340	0.9494	0.3966	0.6844
Autoregressive integrated moving average					
	0.0211	0.0167	0.0008	0.0008	0.0143
Log normal diffusion process					
	0.6867	0.5894	0.9826	0.4510	0.7019

The data used to evaluate the in-sample forecasting performance covers the period from January 4, 2016, to November 30, 2017.

Table 7: **Out-of-sample predictive ability for payments from alternative models**

	Bank1	Bank2	Bank3	Bank4	Bank5
Payments sent from alternative models					
Linear regression model					
	3.0853	1.9665	4.3291	0.7104	1.9922
Autoregressive integrated moving average					
	1.5305	0.7014	1.3405	0.3309	0.4819
Log normal diffusion process					
	1.7137	0.8954	1.4632	0.4202	0.8832
Payments received from alternative models					
Linear regression model					
	0.6532	0.5454	0.6849	0.4011	0.4667
Autoregressive integrated moving average					
	0.5463	0.3974	0.5680	0.2856	0.8955
Log normal diffusion process					
	0.6494	0.5409	0.6715	0.4145	0.6589

The data is divided into two subsamples. The first subsample from January 4, 2016, to November 30, 2017, is used to update the model parameters. The second subsample from December 1, 2017, to December 29, 2017, is used to evaluate the out-of-sample forecasting performance.

Figure 1: **Intraday Liquidity Risk Indicators for Bank 1 and Bank 2**

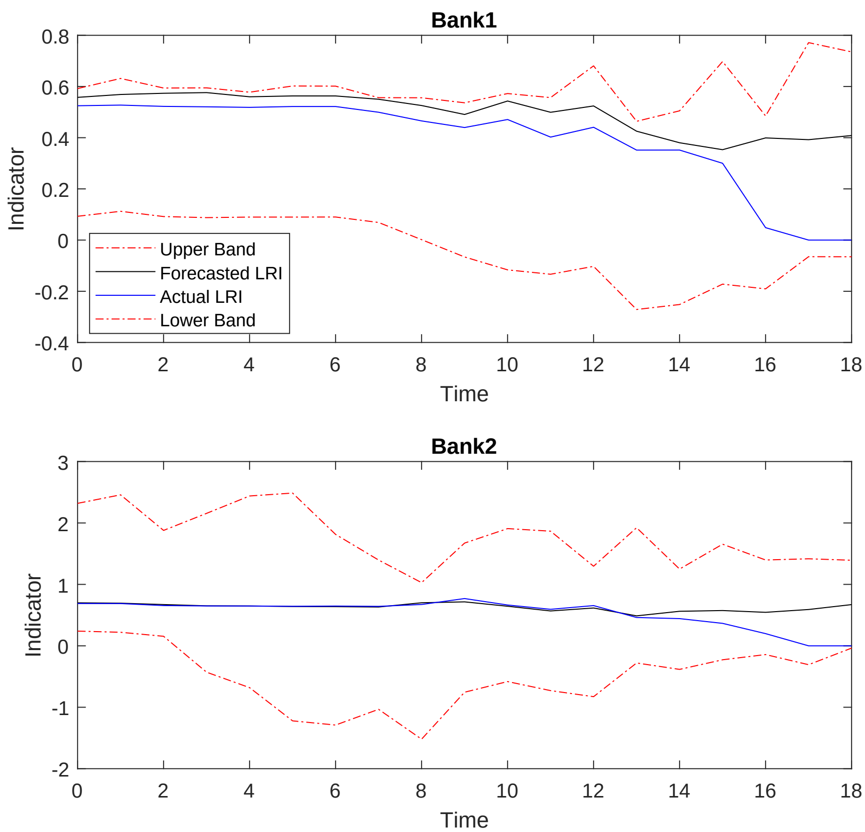

Figure 1 reports the average values of intraday liquidity indicators over the sample period from 2017 December 1 to December 29 for both Bank 1 and Bank 2 across different payment times in a payment day. The data over the sample period from January 4, 2016, to November 30, 2017, is used to estimate the model parameters, while the data over the sample period from 2017 December 1 to December 29 is used to estimate the values of the intraday liquidity risk indicators for Bank 1 and Bank 2. The intraday liquidity risk indicator is defined in (2).

Figure 2: **Intraday Liquidity Risk Indicators for Bank 3 and Bank 4**

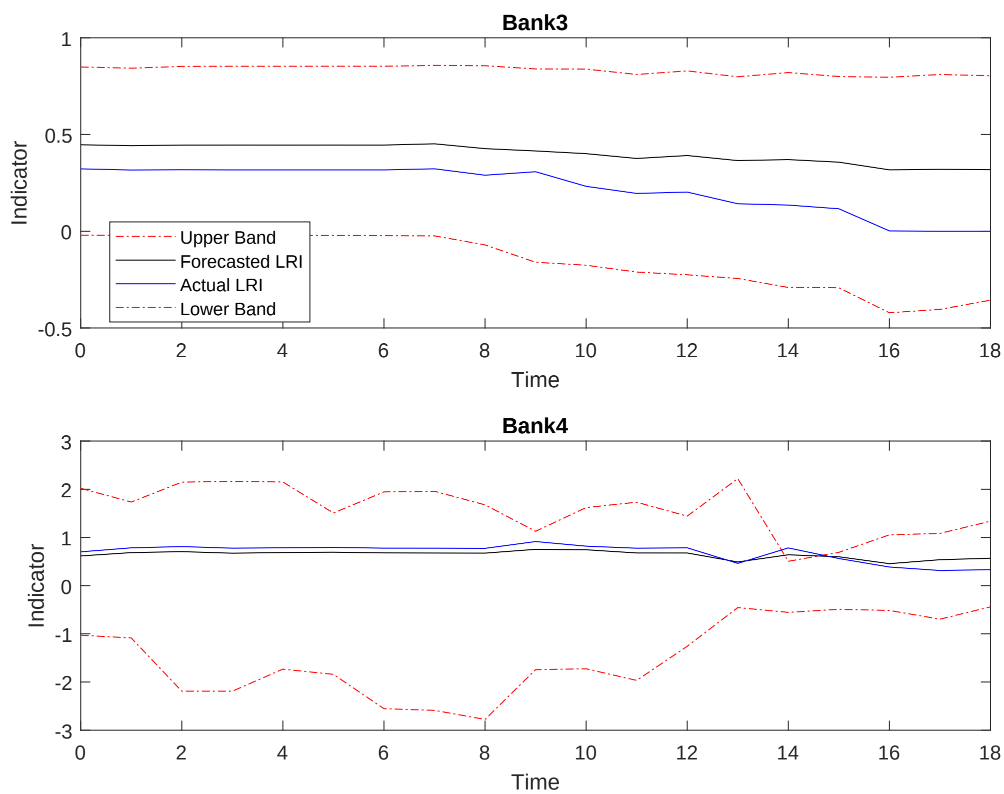

Figure 2 reports the average values of intraday liquidity indicators over the sample period from 2017 December 1 to December 29 for both Bank 3 and Bank 4 across different payment times in a payment day. The data over the sample period from January 4, 2016, to November 30, 2017, is used to estimate the model parameters, while the data over the sample period from 2017 December 1 to December 29 is used to estimate the values of the intraday liquidity risk indicators for Bank 3 and Bank 3. The intraday liquidity risk indicator is defined in (2).

Figure 3: **Intraday Liquidity Risk Indicator for Bank 5**

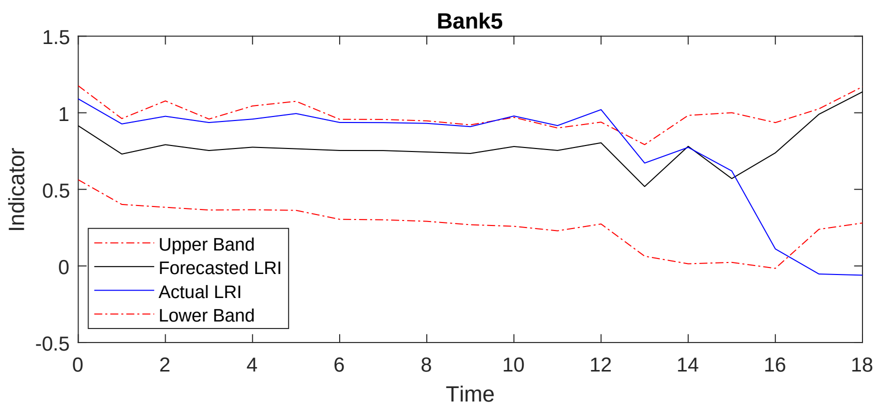

Figure 3 reports the average values of intraday liquidity indicators over the sample period from 2017 December 1 to December 29 for Bank 5 across different payment times in a payment day. The data over the sample period from January 4, 2016, to November 30, 2017, is used to estimate the model parameters, while the data over the period from 2017 December 1 to December 29 is used to estimate the values of the intraday liquidity risk indicators for Bank 5. The intraday liquidity risk indicator is defined in (2).

Figure 4: **Predicted Probability of an Intraday Liquidity Risk Event**

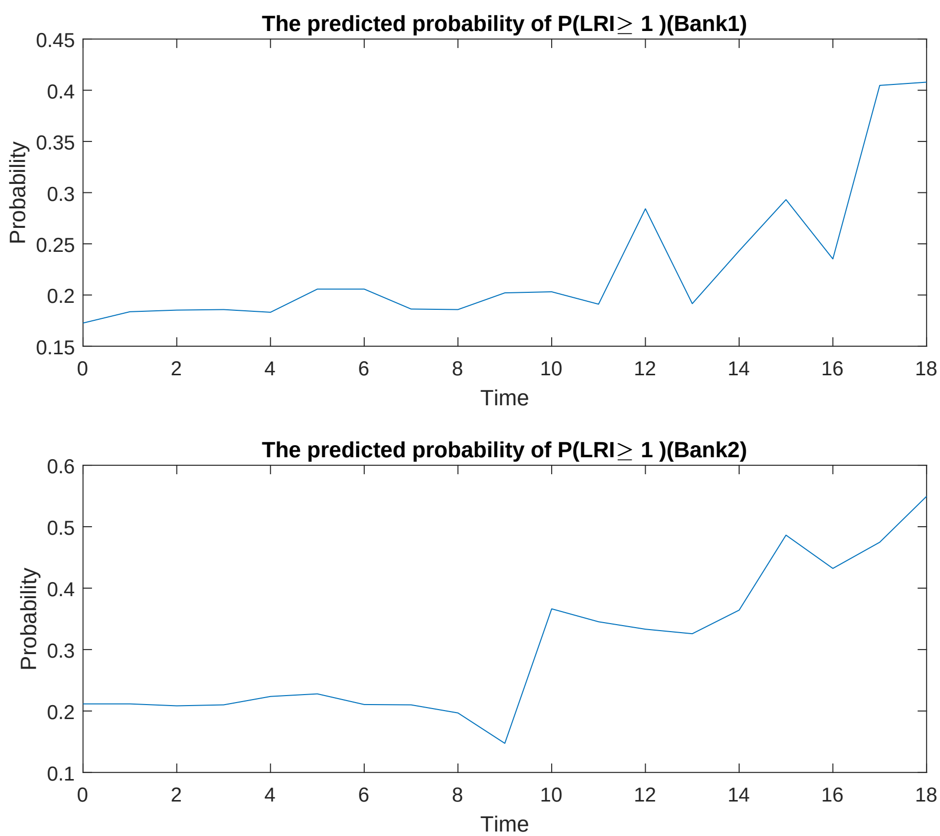

Figure 4 reports the predicted probability of an intraday liquidity risk event over the sample period from 2017 December 1 to December 30 for both Bank 1 and Bank 2 across different payment times in a payment day. The data over the sample period from January 4, 2016, to November 30, 2017, is used to estimate the model parameters, while the data over the sample period from 2017 December 1 to December 29 is used to predict the probability of an intraday liquidity risk event.

Figure 5: **Predicted Probability of an Intraday Liquidity Risk Event**

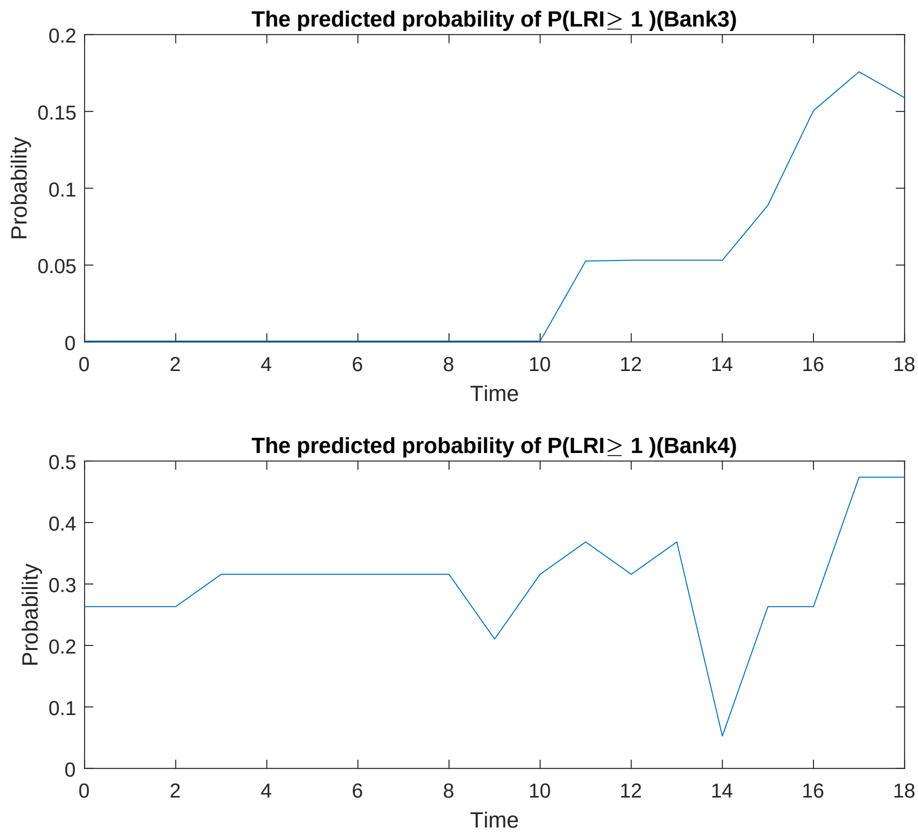

Figure 5 reports the predicted probability of an intraday liquidity risk event over the sample period from 2017 December 1 to December 30 for both Bank 3 and Bank 4 across different payment times in a payment day. The data over the sample period from January 4, 2016, to November 30, 2017, is used to estimate the model parameters, while the data over the sample period from 2017 December 1 to December 29 is used to predict the probability of an intraday liquidity risk event.

Figure 6: **Predicted Probability of an Intraday Liquidity Risk Event**

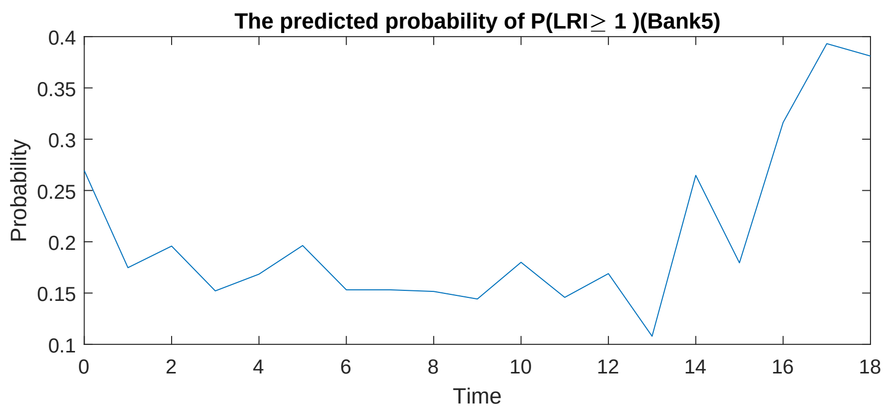

Figure 6 reports the predicted probability of an intraday liquidity risk event over the sample period from 2017 December 1 to December 30 for both Bank 5 across different payment times in a payment day. The data over the sample period from January 4, 2016, to November 30, 2017, is used to estimate the model parameters, while the data over the sample period from 2017 December 1 to December 29 is used to predict the probability of an intraday liquidity risk event.

5 Conclusion

In this paper, we construct an intraday liquidity risk indicator for monitoring whether a participant's expected liquidity sources for settling payments in the remainder of the day is sufficient to cover its expected liquidity requirements. Using data from the LVTS to evaluate the forecasting performance of the intraday liquidity risk indicator, we find that the intraday liquidity risk indicator performs reasonably well, suggesting that this indicator is a useful tool for assessing intraday liquidity risk in an RTGS system.

Based on this indicator, we propose a framework to predict the likelihood of occurrence of an intraday liquidity risk event throughout the remainder of the payment day. Using data over the period from 2017 January to December 29, we find that an intraday liquidity risk event is more likely in the late afternoon, suggesting that participants need to manage their intraday liquidity in order to synchronize their outgoing payments with the payments inflows they expect to receive in the late afternoon to avoid the occurrence of intraday liquidity risk events.

In future work, this intraday liquidity indicator can be used as a metric to conduct liquidity stress testing for an RTGS system, like Lynx, to inform a comprehensive assessment of whether participants' internal sources are sufficient to withstand adverse shocks in the payment system. This kind of stress testing could provide insights for monitoring participants' intraday liquidity risks under stressed scenarios.

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