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Abstract

We track 38,000 money market trades from execution to delivery and return to provide a first empirical analysis of settlement delays in financial markets. In line with predictions from recent models showing that financial claims are settled strategically, we document a tendency by lenders to delay delivery of loaned funds until the afternoon hours. We find that banks follow a simple strategy to manage the risk of account overdrafts—delaying the settlement of large payments relative to that of small payments. More sophisticated strategies, such as increasing settlement delays when own liquid balances are low and when dealing with small trading partners, play a marginal role. We also find evidence of strategic delay in the return of borrowed funds, although we can explain a smaller fraction of the dispersion in delays in the return than in the delivery leg of money market lending.

Key words: money market trading, settlement delay, gridlock equilibria

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1 Introduction

A common assumption in the finance literature is that agreement to trade assets in the spot market is essentially equivalent to transfer of ownership. Yet, most financial transactions "settle" (i.e., payment orders are initiated) with significant delay relative to trade time, with delays ranging from several hours for very-short-term (overnight) domestic claims to full or multiple days for transactions involving foreign exchange. These delays have significant policy implications, since they may give rise to payment congestions and increase the risk of gridlocks, which may transmit through the whole financial system and impair its efficiency.[1]

Because of the relevance of delays for the efficiency of payment systems, several recent studies have focused on the incentives that financial institutions may have to settle transactions with delay relative to trade execution (see, for instance, Angelini, 1998, Bech and Garratt, 2006, and Markose *et al.*, 2006). The key mechanism highlighted in these studies is that institutions participating in real-time gross payments systems may reduce the chance of incurring funds shortages by settling outgoing payments only upon receiving sufficient incoming payments. When sufficiently many participants follow this policy, a gridlock equilibrium may emerge, whereby most payments are withheld until late in the business day, at which point they are released in bulk (unless complete deadlock occurs, so that no payment is ever released). The resulting equilibrium may be socially suboptimal, as payment delays reduce the quality of information on cash flows to market participants and induce them to hold higher-than-optimal precautionary reserves (Angelini, 1988).[2] The possibility of gridlock equilibria also generates direct costs, as financial regulators expend considerable effort

[1] An often-cited example is the market breakdown of October 20, 1987, when a three-hour \$1.5 billion delay in payments to the accounts of two major securities firms, *Kidder, Peabody & Co.* and *Goldman Sachs*, reportedly led to a large number of systemwide payment delays that brought the system "perilously close to gridlock" (Eichenwald, 1988; see also Bernanke, 1990, for a discussion)

[2] See Bech and Soramaki (2001) and Bech and Garratt (2006) for a discussion of dead-weight losses associated with gridlock equilibria, and Bank for International Settlements (1997) for a review of the international experience with payment gridlocks.

to set up and maintain institutions to mitigate the risk of gridlocks and ease their resolution.

While theoretically intriguing, the conjecture that banks might delay settlements strategically has not yet been subject to formal empirical investigation. McAndrews and Rajan (2000), and Armantier *et al.* (2007) offer supportive evidence, showing that settlement of payments on *Fedwire Funds Service*, the Federal Reserve's large-value payments system (henceforth, *Fedwire*), tends to cluster between 4:30 and 5:30 pm daily (see also Richards, 1995). However, federal funds trades, which settle on *Fedwire*, are also concentrated in the afternoon hours (Bartolini *et al.*, 2005). Thus, concentration in settlements may well reflect concentration in trades, with little attempt by financial institutions to delay settlement deliberately. More generally, it is the lack of data on the full life cycle of financial transactions that thus far has hampered the analysis of settlement delays in financial markets.

In this paper we track 38,000 money market loans through their life-cycle stages of execution and settlement (the latter including both loan deliveries and returns), to provide a first analysis of settlement delays in financial markets. Focusing on unsecured overnight money market trades, we exploit information from two transaction-level sets of data: a set of data on money market *trades*, obtained from one of the largest U.S. money brokers; and a set of data on *settlements*, obtained from *Fedwire*, the Federal Reserve's large value payment system. The key innovation in our analysis is to overlay these two sets of data, so as to identify a set of interbank loan transactions that can be followed through their entire life. This effort allows us to uncover a number of stylized facts on settlement delays in the U.S. money market and to test the key predictions of theoretical models of strategic settlement.

Our analysis shows that both deliveries and returns of money market loans follow patterns that accord well with the hypothesis of strategic settlement of interbank loans. Senders of funds tend to cluster deliveries in the afternoon hours, even for trades executed in the morning hours. Clustering is not complete, however, as banks appear to optimize over which payments should be settled at different times of the day. Specifically, most banks appear to follow a strategy of settling relatively quickly small out-payments — which have less impact on reserve accounts and on the risk of overdraft — while leaving large out-payments for later settlement. Other strategies of optimal liquidity management, such as delaying settlement when own reserve balances are low or when dealing with smaller counterparts, are statistically significant but economically marginal. We also show that strategic behavior in the return leg of interbank lending is qualitatively similar to that in the delivery leg, but is quantitatively weaker. This finding suggests that it is mostly random operational delays that interfere with the prompt return of borrowed funds, some 23 hours after delivery.

Finally, our analysis has implications for several recent studies that have sought to proxy for difficult-to-obtain data on overnight loans by filtering data from *Fedwire* payments. This technique was pioneered by Furfine (1999) and has been used in much subsequent work, including Furfine (2001, 2003, 2006), Demiralp *et al.* (2004), Millard and Polenghi (2004), Ashcraft and Bleakley (2006), Ashcraft and Duffie (2007), and Hendry and Kamhi (2007). Our results show that settlement-based proxies cannot be relied upon for accurate representation of *intraday* patterns in trading and interest rates, since trade execution and settlement are timed too far — and too systematically — apart for the latter to proxy reliably for the former. Of course, our analysis does not invalidate the use of settlement-based proxies of interbank trades to study the behavior of money markets over the business day as a whole.

Our study is structured as follows. *Section* 2 reviews the main trading and settlement procedures in the U.S. unsecured money market, highlighting costs and benefits banks face when deciding if to settle promptly or not an executed trade. *Section* 3 describes the data and *Section* 4 presents the procedure used to identify a set of money market trades whose entire life cycle can be followed. *Section* 5 discusses summary features of settlement delays. *Sections* 6 and 7 present our main empirical results on delay behavior, for both loan deliveries and returns. *Sections* 8 and 9 investigate the robustness of our findings. *Section* 10 concludes.

2 Trade and settlement in the unsecured money market

The U.S. market for unsecured overnight loans opens daily at about 8:00 am (ET), when major New York brokers begin receiving requests from customers to match orders to lend or borrow funds with orders of opposite sign. The market effectively closes at 6:30 pm, when the Federal Reserve's electronic payments system, *Fedwire*, closes for the day, at which point it becomes impossible to trade loans of federal funds for same-day settlement, the market for Eurodollars effectively winds down, and bank reserves are tallied for regulatory purposes.[3]

In this market, money brokers play the role of establishing contact between buyers and sellers of short-term loans. While borrowers and lenders may arrange trades directly with one another, larger more sophisticated market participants tend to arrange most of their trades through brokers. A key feature of brokered trading is that trades are initiated anonymously between interested parties, as a borrower's identity is disclosed to a lender only after a match is established at an agreed-upon loan rate. After a match is established and the lender accepts to lend to the borrower (a decision usually conditioned on the presence of a predetermined credit line between the two parties), the trade is deemed "executed" by the broker and entered into a time-stamped record, normally with information on trading parties, amount traded, settlement and maturity dates, and an identifier of whether the trade was executed as a "federal funds" or a "Eurodollar" trade.[4]

The next stage in the trading process is the settlement of loans (or deliveries), whereby loaned funds are transferred from lenders to borrowers. Here the relevant distinction is whether funds are transferred in real time on a gross basis or on a delayed net basis. Federal funds loans settle exclusively on *Fedwire*, which is a real-time *gross* settlement system. *Fedwire* settlement is activated when the lending institution instructs its district's Reserve Bank to debit its reserve account and credit the reserve account of the borrowing institution.

[3] Technically, it is possible to trade and settle Eurodollars outside the United States after the closing of the New York market, although the amount of Eurodollar trading is minimal after Eurodollar settlement closes on Fedwire at 6:00 pm, until markets in East Asia open several hours later.

[4] Loosely speaking, federal funds and Eurodollars are distinguished by whether dollar deposits are held in the United States or abroad, respectively. In fact, the distinction is more subtle, in that deposit liabilities in the United States of institutions that have set up segregated sets of "foreign" accounts (so called International Banking Facilities) also qualify as Eurodollars. For a fuller discussion of differences and similarities between the markets for federal funds and Eurodollars, see Bartolini et al. (2008).

Fedwire provides instantaneous, irrevocable settlement as soon as the payment instruction is received by the Federal Reserve Bank of the sender's district.[5] *Fedwire* also handles the vast majority of short-term, unsecured, Eurodollar loans traded in the New York market, with the residual settling on other systems, such as the *Clearing House Interbank Payments System* (CHIPS), a private system that queues and settles transactions throughout the day using a method that economizes on balances relative to a gross settlement system.[6]

At maturity, settlement of loan returns works almost identically to that of loan deliveries, except that borrowing banks now act as "senders" and are expected to instruct the Federal Reserve to move balances out of their accounts and back into the accounts of lending banks (who now act as funds "receivers"), for an amount including both principal and interest due.

In both the delivery and return legs of loan settlement, the decision about when banks are expected to settle executed trades is essentially governed by market conventions and by banks' desire to maintain good reputations in a market in which repeated relationships play a key role. A bank that gains a reputation for late payments may face difficulty in obtaining credit and establishing sufficient credit lines. Clearly, this informal enforcement of prompt settlement leaves much scope for banks to time settlements strategically, so to as to minimize the cost of liquidity management while maintaining reputation as reliable senders of funds.

Specifically, when a bank decides whether a loan out-payment should be processed immediately or delayed, it must consider the risk that immediate settlement might leave it with a low balance in its Federal Reserve account, and hence greater risk of an account overdraft. If

[5] A *Fedwire* payment instruction is usually executed even when doing so creates or increases an overdraft in the lender's account. This is because, while banks are subject to caps on allowable overdrafts, adherence to caps is normally monitored after the fact, allowing banks to issue payment instructions that increase overdrafts above their cap.

[6] Eurodollar trades between U.S.-based entities usually settle directly on *Fedwire*, while Eurodollar trades between entities operating abroad usually settle on CHIPS. Eurodollar trades settling over CHIPS are then netted along with other dollar payments settling on CHIPS, and result in *Fedwire* payments between each CHIPS participant (or their designated settlement bank) and CHIPS. However, it is not possible to match these net transfers with any individual trades arranged between the CHIPS participants themselves.

a bank has an overdraft in its account, each additional dollar transferred out of its account incurs a charge (after an initial deductible amount) of 0.36 percent annualized, multiplied by the value of the overdraft, on a prorated full-day basis. (If the overdraft spills overnight, the fee escalates significantly; furthermore, each bank is penalized when its overdraft position exceeds a predetermined cap.) This fee is effectively the cheapest way for banks to obtain funds to meet intraday liquidity needs, and therefore represents the relevant cost for a bank to close a gap between incoming and outgoing payments. To avoid such fee, banks may try to delay out-payments until a sufficient number of in-payments has arrived. Delays may look especially appealing when a bank's account falls below zero, since that is when the bank may be charged an overdraft fee. The focus in the rest of this study is on whether these factors influence decisions about settlement time as described in this section.

3 Data

Trade data. We obtained transaction-level data on overnight interbank loans for 660 business days, from February 11, 2002, until September 24, 2004, from *BGC Brokers* (formerly *Eurobrokers*), one of the four largest interbank dollar brokers. The data we obtained include all federal funds trades arranged by *BGC Brokers* during the sample period, as well as all Eurodollar trades arranged by *BGC Brokers*' New York headquarters over the same period. For each transaction we obtained amount traded, applicable interest rate, loan delivery date, term, trade completion time (in date/hour/minute/second format), and a 'federal funds' vs. 'Eurodollar' identifier. We obtained no information on the parties involved in each trade.

With one exception (see below) the data were in excellent shape, reflecting *BGC Brokers*' real-time electronic recording of executed trades. Nevertheless, we screened the data by hand and by computer routines and discarded a few clearly mistyped or inconsistent records (about 0.25 percent of total trades). We then retained only overnight transactions (that is, loans maturing on the business day following delivery), leaving us with 174,345 trades, of which 64.8 percent were federal funds trades and 35.2 percent were Eurodollar trades.

The only significant problem we encountered with the data reflected the end-day trade reconciliation that *BGC Brokers* conducts normally over a 20-30 minute interval between 5:00 and 6:30 pm, during which the electronic recording of trades is halted, and incoming trades are queued for recording until the process is completed. We tackled this problem by assuming the correct execution times of delayed trades to be uniformly distributed during the interruption. As a result, 7.6 percent of our trades received an estimated time-stamp, which could differ by a few minutes (presumably, in random fashion) from the true one.

Settlement data. Our second main source of data was *Fedwire*, the large-value payment system operated by the U.S. Federal Reserve, on which the vast majority of money market trading between U.S. institutions settles during the open hours of the U.S. money market (8:00 am to 6:30 pm, daily). We obtained access to a set of variables for every funds transfer recorded in the *Fedwire* transactions journal, including information on senders' and receivers' identities, dollar amounts (in dollar and cents), and time stamps (in day/hour/minute/second format). Using other Federal Reserve System data sources, we also obtained information for each institution on instantaneous reserve balances and daily total assets.

4 Matching brokered trades with settlement orders

The first task in our empirical effort was to identify a subset of brokered trades that could be uniquely matched to *Fedwire* payment orders. To this end, we used the following algorithm.

For each brokered trade record, we searched for a *Fedwire* payment that:

1. involved the same dollar amount specified for the loan in the brokered trade record;

2. settled at any time after the execution time reported in the brokered trade record, but before that day's closing of *Fedwire*;

3. matched a payment order between the same two banks in the opposite direction on the following business day, for an amount equal to the sum of the principal and interest

reported in the brokered trade record;

4. was *uniquely* matched, in the sense that no other *Fedwire* order also satisfied 1, 2, and 3, between the same or any other pair of banks.

This algorithm is vulnerable to two types of problems. First, since the matched sample (for use in our subsequent analysis) includes only brokered trades that can be matched uniquely to *Fedwire* orders, a selection bias may arise if the chance of uniquely matching a given brokered trade interacts systematically with our empirical explanatory variables. To address this problem, we included in our analysis a correction for possible selectivity bias based on the standard Heckman selection model approach. As it turns out, the model correcting for selectivity bias yielded very similar results to the model *not* correcting for this bias, suggesting that sampling distortion plays a negligible role in our analysis.

Second, a brokered trade may be matched with an incorrect *Fedwire* order. The only way for this problem to occur is if the brokered trade settles on a system other than *Fedwire* (such as CHIPS), and a single, different *Fedwire* order, satisfying requirements 1-4 shows up in its place. In practice, this can only be a very rare occurrence, since federal funds trades *must* settle on *Fedwire*, and the vast majority of Eurodollar loans traded in New York also settles on *Fedwire*. So the problem may occur only for a limited number of Eurodollar trades settling outside *Fedwire*, and only if a different order matching 1-4 appears in *Fedwire*. In such a case, our brokered trade would be matched with an essentially-random order settling any time between our time of trade and the close of business. The likely effect of this mismatch would be to overestimate the delay with which these Eurodollar trades are settled, a delay that would be captured, in large part, by a fixed-effect dummy for Eurodollar trades included in our empirical model.

With these details in background, our algorithm yielded 38,385 uniquely matched records, each including information on trading, delivery, and return times, loaned amount, interest rate, a federal funds / Eurodollar identifier, and information on trading counterparts. This matched sample constitutes the input data for the empirical analysis that follows.

5 Settlement delays: Summary features

Summary features of our raw and matched brokered data are reported in *Table* 1.

Our sample of raw brokered data includes 174,345 trades.[7] Of these, 38,385 trades were matched uniquely with single *Fedwire* orders and were retained for the analysis that follows. Discarded trades included 126,276 trades matching multiple *Fedwire* orders and 9,684 unmatched trades, i.e., trades settling on systems other than *Fedwire*.[8]

Our first task was to compare the features of the raw and matched sets of trades, to assess the extent to which the latter could be viewed as representative of the former. This screening revealed negligible differences between the raw and matched samples in terms of mean trade size ($126 million and $138 million for the two samples, respectively, well within standard confidence bounds), interest paid (1.31 and 1.30 percent, respectively) and share of federal funds vs. Eurodollar trades (0.65 and 0.64, respectively).

By contrast, we found significant differences in the distribution of time of trade between our two samples. As shown in *Table* 1 and *Figure* 1, matched trades were drawn disproportionately from the late part of the day, with a mean time of trade of 1:18 pm for all trades

[7] A preliminary data question is the extent to which our *BGC Brokers* data can be viewed as representative of conditions in the brokered market as a whole. To address this issue, we compared daily transaction-weighted interest rates calculated from our federal funds *BGC Brokers* data with daily effective rates published by the Federal Reserve and calculated using data from *all* major brokers (including *BGC Brokers*). This comparison yielded a mean absolute deviation between the *BGC Brokers* and the broader series of 0.7 basis points and no evidence of serial correlation in the deviations. Specifically, a regression of the spread {*BGC Brokers rate* - *published rate*} on its own lag and a constant yielded an autoregressive coefficient of 0.011 (with a standard error of 0.039), a constant term of -0.0009 (with a standard error of 0.0005), and r^2 of 0.0007. Additional lags were small and insignificant. We view this evidence as suggesting that our data can be viewed as a random sample of price conditions in the broader market. The presumption is that representativeness should also extend to non-verifiable quantity conditions.

[8] The reason why many of our raw trades were discarded because they matched multiple *Fedwire* orders is that the *Fedwire* data includes trades arranged by all the brokers in this market, and many of the trades arranged by BGC *Brokers* share the same characteristics as trades arranged by the other brokers.

and a mean time of trade of 3:13 pm for matched trades. The reason for this difference is that it is easier to match uniquely a late trade than an early trade to a single *Fedwire* payment, since an early trade is more likely to be followed by two or more *Fedwire* orders for the same principal and interest. For the time being, this timing difference implies that useful summary statistics on settlements and delays should control for trade execution time. Thus, while *Table* 1 reports a mean settlement time of 4:50 pm and a mean settlement delay of $1^h37'$ for matched trades, we should view the former figure as being later than the actual time and the latter figure as being shorter than the actual delay. In our subsequent analysis, however, we account explicitly for the fact that the matched and original samples differ by trade time and other features, so as to assess and minimize the impact of selectivity bias.

A more useful representation of settlement patterns is offered in *Figure* 2, which breaks down the frequency distribution of settlement times into seven $1\frac{1}{2}$ hour-long intervals, from 8:00 am to 6:30 pm. The figure displays a clear tendency for settlement of trades from all trading intervals to cluster in the afternoon hours. There are clear differences across trading intervals, however. Specifically, settlement time clusters more and more around the close of business as the trading day advances, as required by the need to settle trades between trade execution and the closing of *Fedwire* at 6:30 pm.

An implication of the tendency for settlements to cluster in the afternoon hours is that settlement delays tend to be especially large for morning trades. *Figure* 3 illustrates this feature, also by breaking down the frequency distributions of delays by time intervals. The figure shows that mean delays peak at about seven hours for early-morning trades, fall to about $4\frac{1}{2}$ hours for mid-day trades, and fall to near-zero for late-day trades. The figure also shows that despite a broad tendency towards clustered settlement, there is significant residual dispersion in settlement delays, especially for early morning trades. This dispersion suggests that the clustering in settlements suggested by models of payment gridlocks may be a reasonable approximation to actual behavior, but that there is ample scope for factors other than time of trade to influence banks' decisions as to how promptly overnight trades should be settled. We explore this conjecture more rigorously in the next sections.

Another implication of the evidence summarized in *Figures* 2 and 3 is that attempts to proxy for difficult-to-obtain data on overnight loans by filtering data from *Fedwire* payments should proceed with caution. Following Furfine (1999), several recent studies have attempted to identify as federal funds loans all *Fedwire* orders that satisfy criteria such as matching bilateral payments for round dollar lots, in which return payments can be reasonably construed as including principal plus due interest.[9] The evidence from *Figures* 1 and 2, however, is that settlements do not accurately represent *intraday* patterns in trading: trade execution and settlement are timed far and systematically apart; hence, settlement time cannot proxy reliably for trading time. That said, although settlement-based proxies provide a distorted representation of intra-day trading patterns, they can be used to study the behavior of the money market over the business day as a whole.

Finally, *Figure* 4 plots the distribution of loan duration (namely, the lag between delivery and return of a loan), also broken down by trading time interval. The figure shows that duration behavior is much more uniform through the day than delivery behavior, also displaying generally smaller dispersion around its mean. Clearly, the fact that loan *deliveries* are clustered in mid-afternoon implies that loan *returns* — generally expected 23 hours later — are already clustered in mid-afternoon the next day, requiring little extra effort by borrowers to optimize settlement. However, the behavior of returns also suggests that market conventions about loan duration might be adhered to more tightly than conventions about loan delivery, and that random operational factors might largely explain the dispersion of loan durations. A possible explanation for this finding is that late returns might be frowned upon in the marketplace more seriously than late deliveries. After all, delayed *delivery* of loaned funds comes with partial compensation to borrowers, since the loan can be returned equally late the following day, some 23 hours after delivery. By contrast, delayed *return* of borrowed funds causes immediate damage to receivers (the funds' lenders). Hence it may cause greater reputational damage to borrowers and thus be more carefully eschewed.

[9] See, in particular, Furfine (2001, 2003, 2006), Demiralp *et al.*(2004), Millard and Polenghi (2004), Ashcraft and Bleakley (2006), Ashcraft and Duffie (2007), and Hendry and Kamhi (2007).

6 Delays in loan deliveries

6.1 Empirical model

To investigate the empirical determinants of settlement delays, we begin with OLS regressions explaining (log) settlement delays in the delivery leg of overnight loan contracts. (We use a log-transformation to secure the non-negativity of delays even with unbounded error terms; however, a linear model yielded very similar results.)

The choice of regressors for our model follows the discussion in *Section* 2. We begin by including a rich polynomial time structure to capture the effect of trade time on delays. In a gridlock equilibrium, where banks delay payments until a common time late in the day and later trades settle upon execution, "time of trade" should explain almost all the variability in delays: each settlement delay would equal the time elapsed from time of trade to the common settlement time. To test this hypothesis, we include regressors capturing the main costs and benefits for banks to settle trades promptly, to examine if these variables contribute to explaining the dispersion in delays observed in the data, or if such dispersion is explained almost entirely by time of trade. (We report here regressions including up to a cubic time term, but including higher order polynomials had negligible effects on results.)

Among these variables, we included each bank's reserve balance at trade time, since the most immediate cost incurred by a bank when promptly delivering loaned funds is the increased risk of a future account overdraft. Since liquidity needs and tolerance for low balances are generally bank-specific and time-varying, we normalized each bank's reserve balance relative to its recent past. (Specifically, we measured balances as quantile draws from their distribution over the previous two weeks; shorter or longer intervals yielded essentially the same results.) To investigate whether reserve balances have different effects when balances are positive or negative, we also interacted this variable with a zero-one dummy; as discussed later, only negative reserve balances had any effect on delay strategies.

Next, we included trade size as a regressor, since delaying larger out-payments relative to smaller out-payments may be a simple and effective strategy for a bank to minimize the impact of loan deliveries on the risk of an account overdraft.

Next, to investigate the effect of institutions' size on delays, we included as a regressor the relative size (measured by the difference in total financial assets) of the lending and borrowing banks. A large bank may be inclined to delay deliveries more aggressively when dealing with smaller counterparts, to exploit its bargaining position. On the other hand, a large bank may be more effective and organized than a smaller one in promptly settling payments, as well as more concerned with avoiding payment congestions later in the day.

Finally, we included as regressors controls for federal funds (vs. Eurodollar) trades, as well as a rich set of calendar dummies — for beginning of months, end of months, end of quarters, end of years, and for each day of the ten-day period over which banks are required to hold reserves against their deposit liabilities — to control for seasonalities that may affect delay patterns. The resulting empirical model is:

$$\begin{aligned} \ln(\textit{delivery delay}) \quad = \quad & \beta_0 + \sum_{i=1}^{3} \beta_i (\textit{time to closing})^i + \beta_4 (\textit{sender's balance if} < 0) \\ & + \beta_5 \textit{trade size} + \beta_6 (\textit{sender} - \textit{receiver's assets}) \\ & + \beta_7 \textit{fedfunds\_dum} + \sum_{i=8}^{20} \beta_i \textit{calendar\_dum} + \epsilon \ , \end{aligned} \tag{1}$$

where time- and bank-specific subscripts for all variables are omitted for brevity.

6.2 Results

OLS regressions of our model of delivery delays are documented in *Column* 1 of *Table* 2. Heteroskedasticity-robust (White) standard errors are reported in parenthesis.

Consider first the estimated pattern of delays as a function of time of trade, illustrated in *Figure* 5. (The pattern drawn in the figure is that implied by the cubic time polynomial in *Table* 2, with all independent variables other than time to closing set at their mean values.)

The figure illustrates two points. First, the curve's negative slope documents the larger delay with which morning trades are settled relative to afternoon trades. If all trades were settled with the same delay, up to random operational errors, the curve in *Figure* 5 should be almost horizontal, except late in the day when the need to settle trades before closing time forces the delay to zero. Contrary to that prediction, and in accord with the raw evidence of *Section* 5, estimated delays are sharply higher for earlier trades than for later trades.

Second, the figure illustrates the extent to which the data accord with the predictions of models of payment gridlocks, according to which settlements should be clustered strategically at a late time in the business day. If all trades settled at the same time, then delays would equal (*settlement time*)-(*time of trade*), and the slope of the curve in *Figure* 5 should approximate -1. This is not quite the case for the curve in *Figure* 5: its average slope is about -0.8, and late-day delays approach zero asymptotically. Yet, the curve in *Figure* 5 behaves much more in accord with the predictions of models strategic delay than with the view that delays might be driven mostly by random operational factors, which would predict a flat relationship between delay and time of trade.

To investigate this hypothesis further, *Table* 2 documents the role of reserve balances and of the gap between senders' and receivers' size. Qualitatively, the impact of reserve balances accords with theoretical predictions. Low reserve balances lead banks to delay delivery of loaned funds, in accord with the fact that the lower is a bank's balance, the higher is the risk that promptly settling an out-payment may leave the bank with insufficient funds to execute other out-payments, hence in need to incur an overdraft. In background regressions (omitted for brevity, but available upon request), we found no impact of reserve balances on delays when balances are positive, indicating that balances matter for settlement behavior only when the risk of overdraft is acute. Delays decline, instead, when larger banks are to deliver funds to smaller banks, suggesting that operational factors (namely, large banks' more effective handling of payments, and their greater concern with avoiding late-day congestions) empirically outweigh market power effects. However, the statistical significance of the latter two variables masks their small economic impact. There is only a 6.1 percent difference in delay between banks in the $5th$ and $95th$ percentiles of their reserve balances; and only a 6.0 percent difference in delay between banks in the $5th$ and $95th$ percentiles of their relative asset position. Evidently, these channels play a secondary role in banks' delay strategy.

A different picture emerges when considering the impact of trade size, which plays, statistically and economically, a more significant role: on average, trades in the $95th$ percentile of the size distribution are delayed 17.6 percent longer than trades in the $5th$ percentile of the size distribution. Given the small reserve balance and market power effects discussed above, this finding suggests that banks optimize over delays mostly by a following a simple strategy of delaying large out-payments relative to small ones. Delaying large-value payments economizes on overdraft fees, while making many small payments early in the day avoids the operational costs and risks of attempting to settle a large number of payments within a short time, later in the day. This finding accords well with informal evidence we gathered through conversations with banks, suggesting that many large orders are routinely set aside and queued for settlement until the arrival of sufficient in-payments. It also accords well with results of studies showing that banks systematically make smaller-valued payments relatively early in the day, while their larger-valued payments are clustered in the late afternoon (see, for instance, McAndrews and Rajan, 2000).

Other effects documented in *Table* 2 include small and often insignificant calendar effects, and a sizable delay in settling Eurodollars relative to federal funds. The latter effect may reflect the greater operational complexity of settling Eurodollars relative to federal funds for many non-banking institutions that do not have direct access to *Fedwire* and are active lenders in the Eurodollar market. After arranging a trade, these institutions must communicate trade details to their correspondent bank, which will then issue the necessary payment instruction over *Fedwire*, introducing an additional source of settlement delay. Of course, institutions with direct access to *Fedwire* can bypass this step.

Altogether, our analysis shows that banks' loan delivery behavior accords qualitatively well with theoretical predictions and practical considerations. However, several estimated effects tend to be small. Only a simple strategy of settling large payments later than small payments explains systematic deviations from a gridlock equilibrium, in which delivery of borrowed funds is delayed until mid-afternoon, when most loans are delivered in a burst, in accord with the predictions of models of strategic settlement delays.

7 Delays in loan returns

7.1 Empirical model

Our model explaining delays in the return leg of overnight loans is very similar to that explaining delays in the delivery leg. The differences are the following.

First, the relevant time variable explaining delays is no longer the time at which a trade is executed, which is a bygone by the time the loan must be returned. Rather, it is the time at which the loaned funds were delivered. Market participants often describe the return on borrowed funds as conforming to a 23 hour convention, according to which funds are to be returned to lenders about 23 hours after they were first delivered to borrowers.

Similarly, the reserve balance variable that is relevant for banks' decision in the return leg is the balance measured some time on return day, when the borrower must decide whether to return timely the funds it borrowed. Since the actual return time is endogenous, however, we cannot measure borrowers' reserve balances at return time. In the regressions reported here we measured balances at the opening of the business day, but balances measured at various other *fixed* times of the day gave very similar results.

Finally, we included delays in loan delivery as a possible explanatory variable of delays in loan returns, to investigate if banks punish a delay in receiving funds with a delay in returning them. The other independent variables are the same as in our model of delivery delays, so that our model of return delays is:

$$\begin{aligned} \ln(return\ delay) \ =\ & \beta_0 + \sum_{i=1}^{3} \beta_i (time\ of\ delivery)^i + \beta_4 (sender\text{'}s\ balance\ if < 0) \\ & + \beta_5 trade\ size + \beta_6 (sender\text{'}s - receiver\text{'}s\ assets) + \beta_7 fedfunds\_dum \\ & +\ \beta_8 delivery\ delay + \sum_{i=9}^{21} \beta_i calendar\_dum + \epsilon\ . \qquad (2) \end{aligned}$$

7.2 Results

Our analysis of delays in the return leg of interbank loan contracts, documented in *Column* 3 of *Table* 2, delivers results qualitatively similar to those for the delivery leg, discussed above.

We begin by illustrating patterns in return delays by plotting the estimated duration of loans as a function of time in *Figure* 6. (The pattern in the figure is that implied by the cubic time polynomial in *Table* 2, with all other regressors set at their mean values.)

Once more, the negatively-sloped curve implied by our estimates captures the larger return delay of loans delivered in the morning relative to loans delivered in the afternoon. Interestingly, the average slope of the link between duration and delivery time is now close to -1, showing that borrowed funds tend to be returned mostly around a fixed time in the afternoon, irrespective of when they are due. However, the fit of our return regression is much worse than that of delivery regression: evidently, noise plays a much greater role in the return than in the delivery leg of overnight loans. A possible explanation of this finding is that since initial deliveries on the settlement date are already clustered in the late afternoon, the expected time of returns on the maturity date, normally 23 hours later, is already clustered in the next day's late afternoon. This implies that delivery time is less helpful in explaining the dispersion of delays, lowering the ratio of explained to sample variance. An alternative explanation, which we are unable to disentangle given our data, was discussed in *Section* 5: banks may be more wary of returning borrowed funds late than of delivering loaned funds late, as a late return may be viewed as a more serious breach of market conventions.

The role of reserve balances and of relative asset size is also similar in the return and delivery legs of our loan contracts. Both a low reserve balance and a smaller size of senders relative to receivers induce longer delays. And, even more so than for loan deliveries, these variables, while statistically significant, are economically marginal: there is only a 0.3 percent difference in return delay between banks in the $5th$ and $95th$ percentile of their reserve balances; and only a 3.7 percent difference in return delay between banks in the $5th$ and $95th$ percentile of their relative asset position. And while larger trades and Eurodollar trades settle with greater delay (relative to smaller and federal funds trades, respectively) the role of these factors is also much smaller than in the delivery leg.

Finally, we found little evidence of retribution by borrowers against lenders who delivered loaned funds late after trade, with statistically significant but economically insignificant effects: a one-hour delay in delivery is punished with an extra delay of only 55 seconds at return. It is difficult to judge whether lack of punishment indicates that delays in deliveries are largely expected (and accepted), or whether concern for reputation leads borrowers to abstain from retribution.

Altogether, these results point to few incentives for banks to deviate from the habit of returning borrowed funds late in the afternoon of maturity day. Deviations from this norm appear as mostly random, likely reflecting operational noise more than strategic behavior. However, our results raise questions about the strength and origin of the market convention for a 23 hour delay between the delivery and the return of borrowed funds. Further study is needed to determine whether the fact that funds are mostly delivered on the afternoon of trade day drives the tendency for those funds to be returned in the afternoon on maturity day; or, vice versa, if it is the expectation that loaned funds will be returned in the afternoon on maturity day that leads lenders to deliver those funds late in the afternoon on delivery day, some 23 hours before the expected return. Both lines of causation are likely to work in practice: our analysis should be viewed as merely documenting features of the equilibrium settlement behavior, rather than the forces that bring such equilibrium into existence.

8 Sample selectivity in trade-settlement matching

In principle, the OLS estimates discussed in the previous two sections are vulnerable to a sample selectivity bias, as our sample of matched trade-settlement records is constructed as a subset of the universe of brokered transactions obtained from *BGC Brokers*. If our matching algorithm distorts the selection of matched observations in systematic fashion, then our estimated slope coefficients may be biased and inconsistent.

To assess the significance of this problem, we specified a Heckman-style selection model capturing the key determinants of whether a given brokered trade is likely to be included in our sample of matched trades. To begin with, our model recognizes that a brokered trade is more likely to match uniquely a *Fedwire* order, the closer it is executed to the end of the business day: for late trades, there are fewer potential trades that could display the same characteristics and prevent unambiguous matching with a settlement order. To capture this feature, we allowed for a rich parametrization of the role of time of trade in the selection model, including linear, quadratic and cubic terms in our selection equation. (Including higher order terms caused insignificant changes in results.)

Second, a trade is more likely to be matched uniquely if it is executed at an "odd" rate, that is, at a rate that is not a round multiple of 0.25%; or if it involves an "odd" lot size, that is, an amount that is not a round multiple of \$10 million. To capture these conjectures, we included dummies identifying trades executed at round rates (multiples of 0.25%) and round amounts (multiples of \$10 million).[10] Finally, we included as a regressor in the selection model the absolute difference between the trading rate and the current federal funds target rate, since a trade executed at an extreme (high or low) rate is more likely to be matched to a unique payment order. The resulting selection equation is:

$$\begin{aligned} match\_dum &= \beta_0 + \sum_{i=1}^{3} \beta_i (time\ of\ trade)^i + \beta_4 (round\ rate\_dum) \\ &\quad + \beta_5 (round\ amount\_dum) + \beta_6 \left| rate - fed\ funds\ target\ rate \right| + \eta \ . \quad (3) \end{aligned}$$

We estimated our two-equation Heckman model (the selection equation (3) with either (1) or (2) as outcome equation) by maximum likelihood. The results are reported in columns 2 and 4 of *Table* 2.

Two features emerge from these estimates. First, our explanatory variables in the selection equation are all statistically significant, with intuitively signed coefficients. Second, properly accounting for the selection process changes minimally the coefficients in the outcome equations. The only coefficient that changes sign is that capturing retribution effects in the return leg of loan contracts, but this coefficient is in either case nearly nil. These results suggest that our matching algorithm is not vulnerable to significant selectivity bias.

[10] We experimented with different round values for both rates and quantities. The regression presented here is the one giving the best fit for the selection model; different round values gave a worse fits for the selection equation but virtually identical slope coefficients for the outcome equation.

9 Predicting trade and settlement time

Finally, while our study's focus is on settlement *delays*, a useful perspective on our analysis — as well as a check of robustness — can be gained by investigating the predictability of trade *times* (given settlement times) and of settlement *times* (given trade times) separately. This task appears especially relevant since our evidence above was supportive of a near-gridlock equilibrium with a cluster of trades delayed for settlement until late afternoon.

To illustrate the issue at stake, consider the extreme case of a gridlock, with all trades settled at business close. In this case, settlement delays can be predicted exactly from time of trade: *delay=close of business-time of trade*. Then, a regression explaining settlement time with time of trade should yield an insignificant coefficient for time of trade; the reverse regression explaining time of trade with settlement time should have no explanatory power.

Results of these paired regressions are presented in *Table* 3. Contrary to the implications of a complete gridlock equilibrium, time of trade is a significant predictor of settlement time, with a large and significant coefficient (0.344); this regression also explains a large share (0.56) of the variance in settlement time, indicating that dispersion in settlement times is not just noise around a strict gridlock equilibrium. (These results are of course expected, given our previous investigation of settlement delays.) Conversely, the coefficient for settlement time in the reverse regression (that explaining time of trade) is large (1.599) and statistically significant, with the same (0.56) ratio of explained variance.[11]

Altogether, these regressions accord well with our previous results. The data that we investigate conform broadly to the predictions of theoretical models that predict a tendency for payments to be delayed and clustered late in the afternoon. However, a gridlock equilibrium does not hold strictly: settlement time does, on average, reveal some information regarding the probable time of trade execution.

[11] The interpretation of the remaining coefficients is marginal to our study. Trade size has a negative effect on time of trade (suggesting that large trades tend to be executed later in the day) and a positive effect on time of settlement (large trades tend to settle later); similarly, federal funds trades tend to be executed later in the day, but tend to settle sooner, after controlling for time of trade.

10 Concluding remarks

Analysis of 38,000 money market trades provides unique insight on the life of interbank loans and on the functioning of the U.S. money market which — with more than $400 billion in loans exchanged daily — is one of the largest financial markets in existence. This market's efficiency is key to the smooth operation of the banking system and it would be troubling if loans in this market were delayed randomly between the times of their execution and settlement.

Our results help mitigate concern with the potentially random nature of settlement delays, but also point to areas of concern. On the one hand, our study finds that delays in settling U.S. money market loans are far from random manifestations of operational frictions. Delays are to a large extent predictable and are thus likely to be expected by the parties to the trade, who can then plan accordingly their own settlements and other high-frequency liquidity management decisions.

However, this reassuring view is tempered by evidence that money market delays are predictable mostly because payments are clustered in time, in a way that heightens the risk of potential gridlocks, and in accord with the predictions of recent models of strategic delay of payment settlements. Our study shows that early trades are delayed systematically and settled mostly during the late afternoon. The residual dispersion in delays around this broad pattern can be traced mostly to a simple strategy whereby large trades are delayed relative to small trades, so as to limit the chances of daylight overdraft fees while minimizing the risk of congestion when settling a large number of trades late in the day. More sophisticated liquidity management strategies, such as delaying settlement when own liquid balances are low, play a smaller role. We find similar patterns in both the delivery and return legs of money market lending, though our ability to explain the dispersion of delays is weaker for the return leg than for the delivery leg. Ancillary findings include evidence that Eurodollar settlements are delayed relative to federal funds settlements and lack of evidence that borrowers who were delivered funds late on trade day may punish their lenders by delaying the return of borrowed funds.

Our results suggest that future theoretical research on the microstucture of the money market may benefit from incorporating a more complete description of the life cycle of money market trades, including execution, delivery, and return of loaned funds. An important question these models could help address is whether a payment system in which all settlements are scheduled to occur at a particular time would dominate, on welfare grounds, the current mechanism in which payments are settled at banks' discretion and enforcement of timely delivery is left mostly to the force of reputation.

Figure 1
Frequency distribution of brokered and matched trades

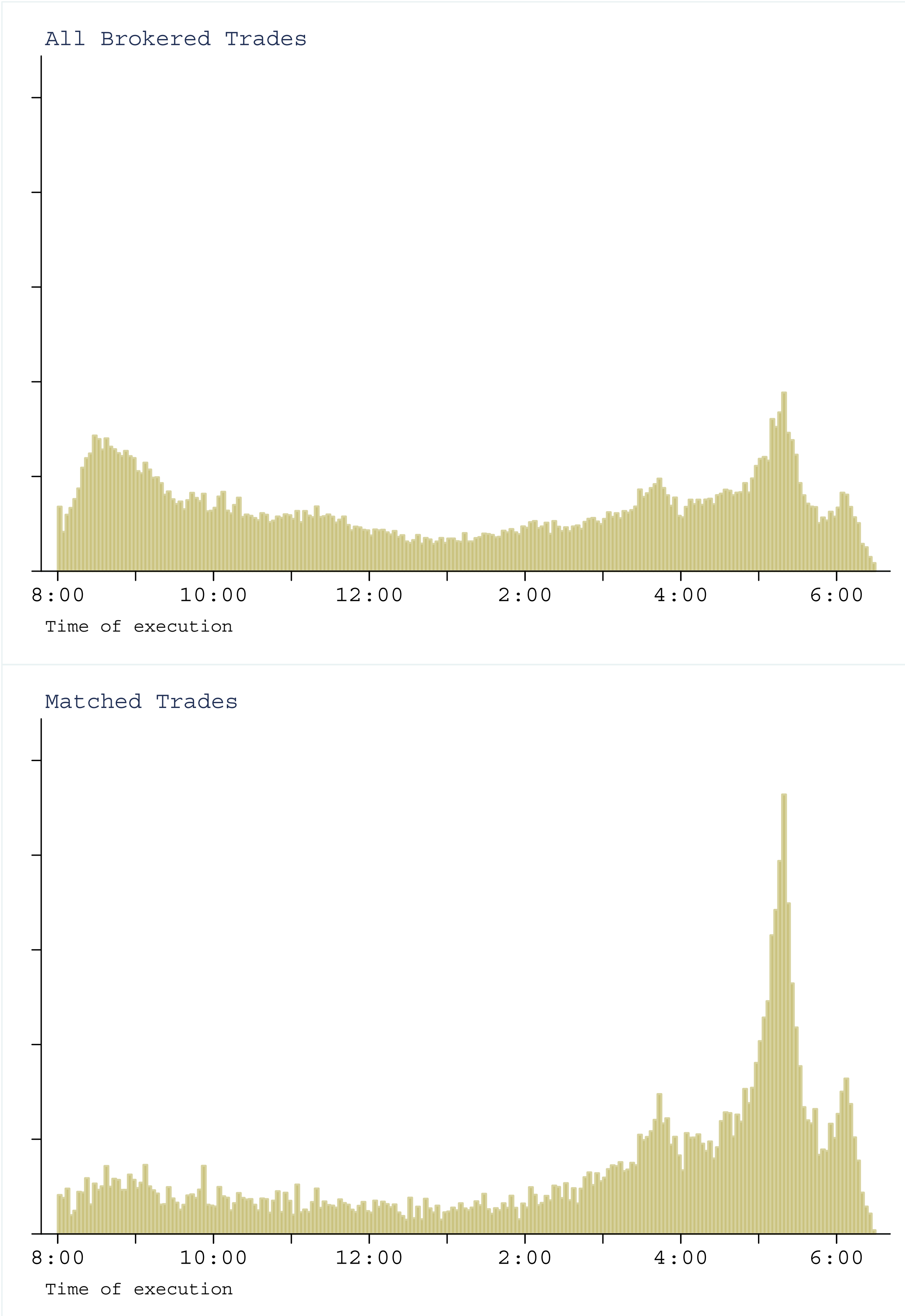

Figure 2
Frequency distribution of delivery times, by time of trade

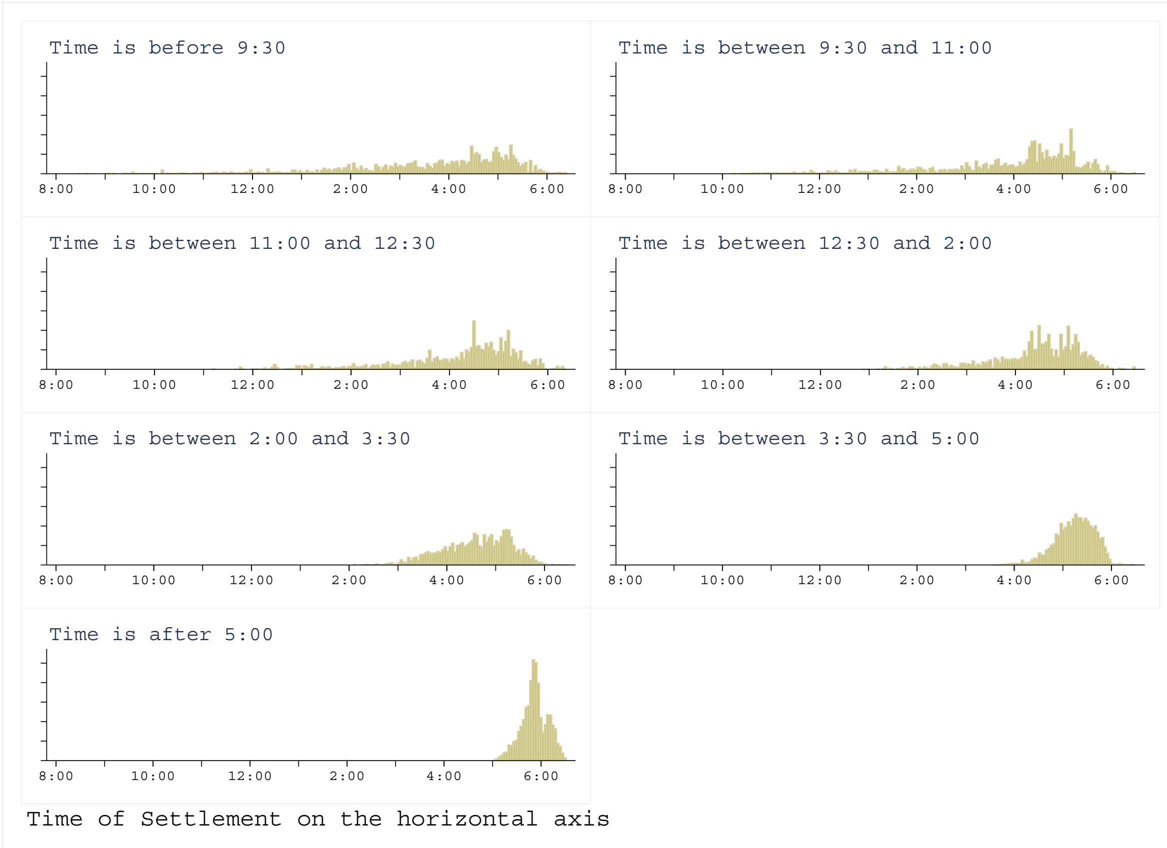

Figure 3
Frequency distribution of delivery delays, by time of trade

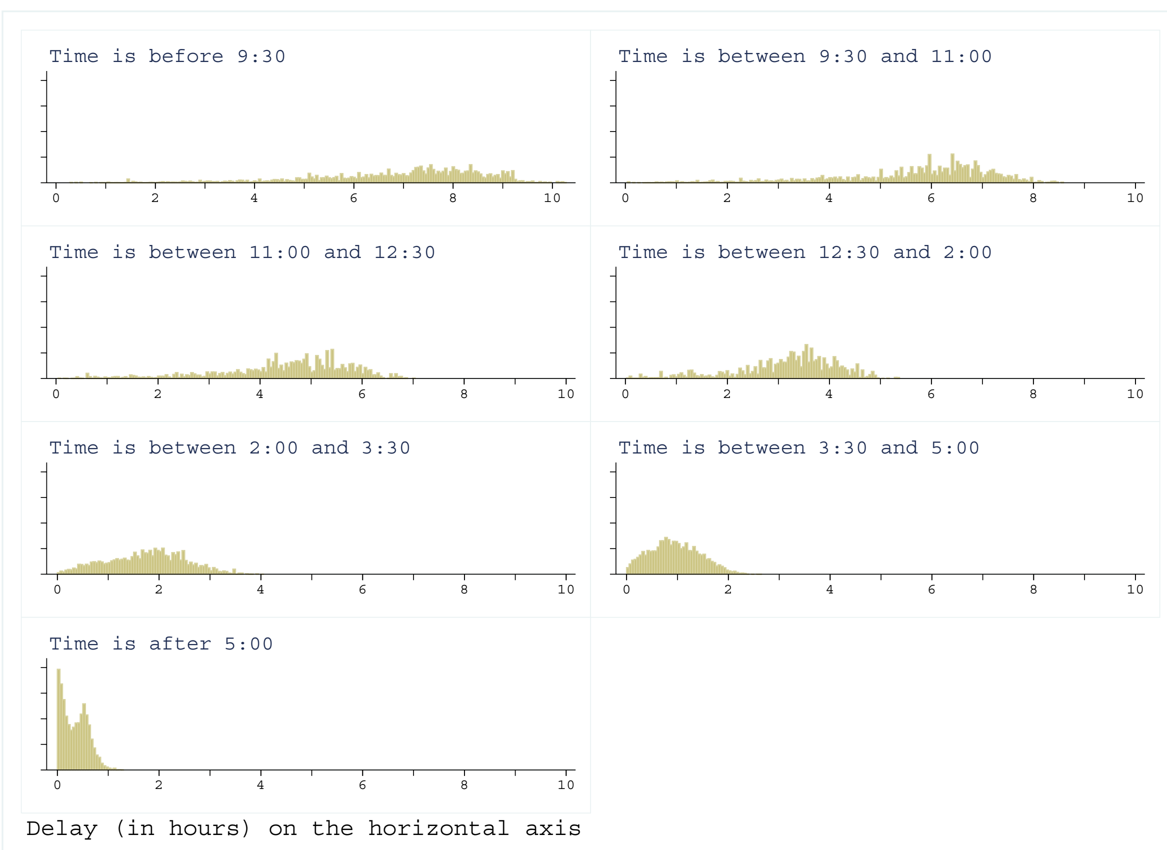

Figure 4
Frequency distribution of loan durations, by time of trade

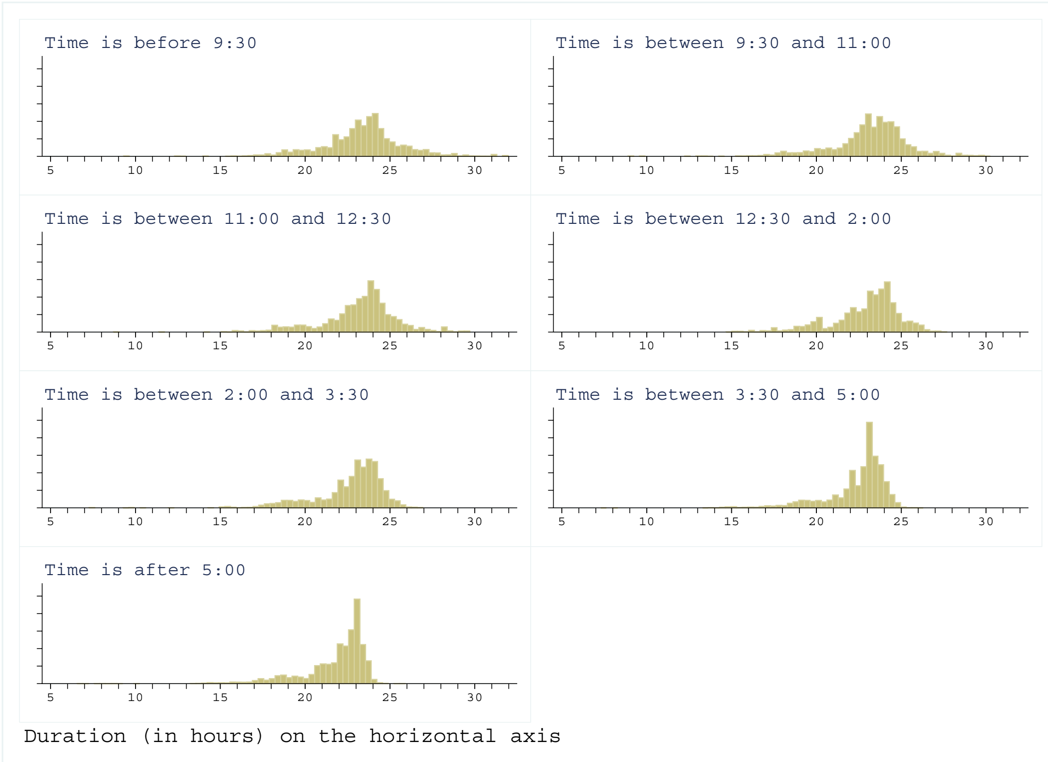

Figure 5
Estimated delay in delivery, by time of trade

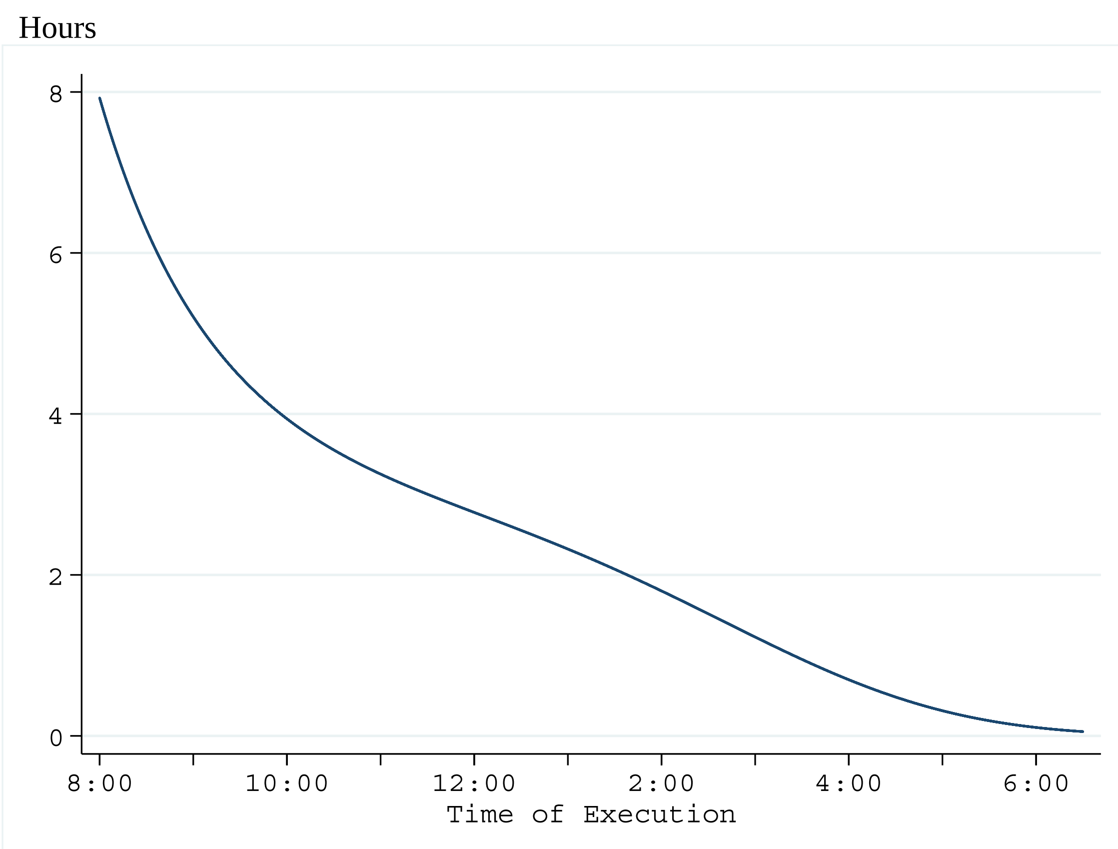

Figure 6
Estimated duration of loans, by time of delivery

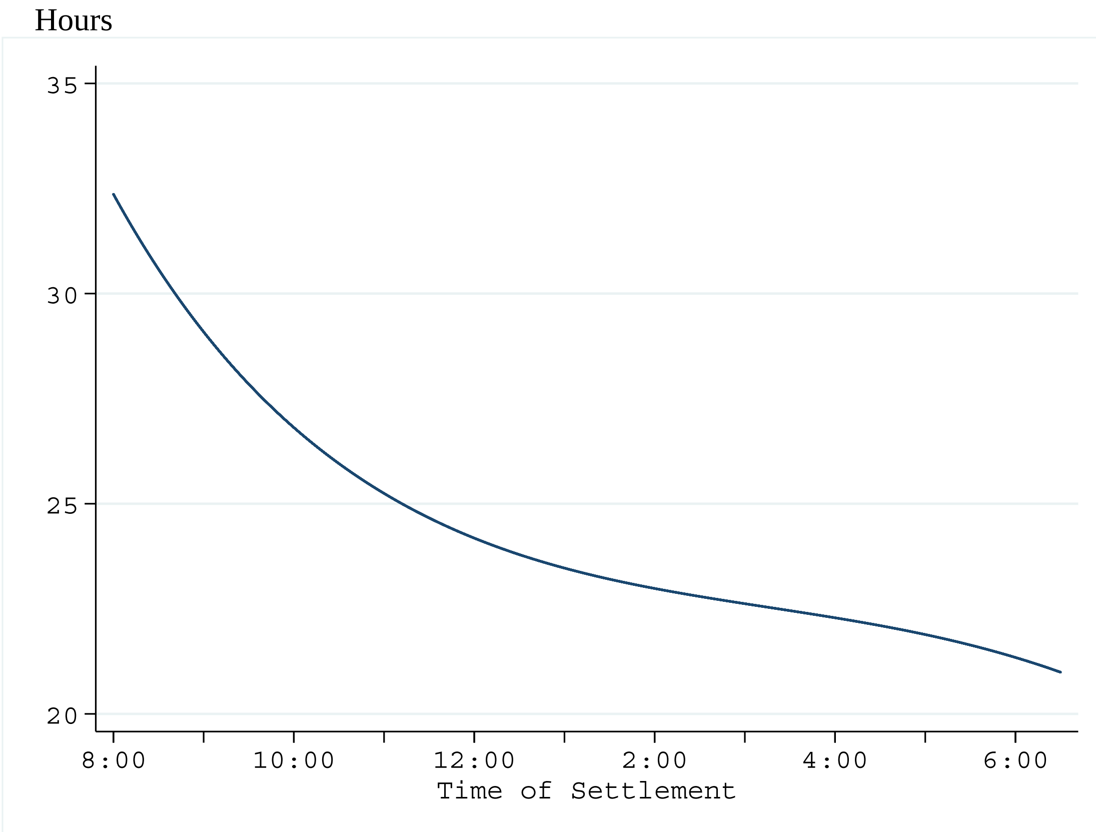

Table 1
Brokered money market data: Summary statistics

	All trades	Matched trades
Number of trades	174,345	38,385
Mean transaction size, in million of $	126 (163)	138 (203)
Mean interest rate, volume weighted	1.31% (0.31%)	1.30 % (0.31%)
Share of federal funds trades	0.648	0.642
Mean trade time	1:18 pm (3^h19’)	3:13 pm (2^h44’)
Mean time of delivery		4:50 pm (1^h16’)
Mean delivery delay		1^h37’ (2^h02’)
Mean loan duration		21^h52’ (2^h13’)

Notes: The table reports summary information on the complete set of overnight loan data obtained from *BGC Brokers* and on the subset of trades that were uniquely matched with *Fedwire* trade orders. Clock times are on U.S. Eastern Time basis. Standard deviations are reported in parentheses.

Table 2
Delivery and Return Delay Regressions

	Delivery regressions Dependent variable = log(delivery delay)				Return regressions Dependent variable = log(return delay)			
	OLS		MLE with selection		OLS		MLE with selection	
Time to closing	1.435***	(0.018)	1.442***	(0.018)				
(Time to closing)^2	-0.186***	(0.004)	-0.188***	(0.005)				
(Time to closing)^3	0.009***	(0.000)	0.009***	(0.000)				
Time of delivery					-0.486***	(0.058)	-0.513***	(0.058)
(Time of delivery)^2					0.031***	(0.004)	0.033***	(0.004)
(Time of delivery)^3					-0.001***	(0.000)	-0.001***	(0.000)
Sender's balance*(balance<0)	0.066***	(0.018)	0.066***	(0.018)	0.004**	(0.002)	0.004*	(0.002)
Sender's-receiver's assets ($ trillion)	- 0.032**	(0.010)	-0.032**	(0.010)	-0.020**	(0.001)	-0.020**	(0.001)
Trade size ($ billion)	0.329***	(0.027)	0.307***	(0.029)	0.084***	(0.003)	0.077***	(0.003)
Fed funds (vs. Eurodollar)	-0.656***	(0.012)	-0.658***	(0.012)	-0.032***	(0.001)	-0.033***	(0.001)
Delivery delay					0.001*	(0.000)	-0.001*	(0.000)
constant	-2.576***	(0.028)	-2.607***	(0.031)	5.735***	(0.283)	5.833***	(0.283)
Day 2	-0.041	(0.024)	-0.041	(0.024)	-0.001	(0.002)	-0.001	(0.002)
Day 3	0.047*	(0.024)	0.047*	(0.024)	0.001	(0.002)	0.001	(0.002)
Day 4	0.016	(0.023)	0.017	(0.023)	-0.005*	(0.002)	-0.005*	(0.002)
Day 5	0.022	(0.023)	0.022	(0.023)	-0.009***	(0.002)	-0.009***	(0.002)
Day 6	0.007	(0.023)	0.007	(0.023)	-0.003	(0.002)	-0.003	(0.002)
Day 7	-0.062**	(0.023)	-0.061**	(0.023)	-0.008***	(0.002)	-0.008***	(0.002)
Day 8	0.038	(0.025)	0.038	(0.025)	0.001	(0.003)	0.001	(0.003)
Day 9	0.029	(0.023)	0.030	(0.023)	-0.004	(0.002)	-0.004	(0.002)
Day 10	0.046*	(0.023)	0.046*	(0.023)	-0.004	(0.002)	-0.003	(0.002)
First day of month	0.120***	(0.026)	0.120***	(0.026)	0.006*	(0.003)	0.006*	(0.003)
Last day of month	0.031	(0.026)	0.031	(0.026)	-0.003	(0.003)	-0.003	(0.003)
Last three days of quarter	0.118***	(0.028)	0.118***	(0.028)	0.001	(0.003)	-0.001	(0.003)
Last five days of year	-0.249***	(0.043)	-0.250***	(0.043)	-0.012**	(0.004)	-0.013**	(0.004)
Sample selection model								
Time of trade			-0.067***	(0.013)				
(Time of trade)^2			-0.025***	(0.003)				
(Time of trade)^3			0.002***	(0.000)				
Time of delivery							-1.128***	(0.106)
(Time of delivery)^2							0.090***	(0.008)
(Time of delivery)^3							-0.002***	(0.000)
Rate = multiple of 0.25%			-0.242***	(0.010)			-0.237***	(0.010)
Amount = multiple of $10 million			-1.162***	(0.008)			-1.163***	(0.008)
$\lvert$rate – fed funds target rate$\rvert$			0.416***	(0.063)			0.442***	(0.062)
Constant			0.345***	(0.017)			3.576***	(0.450)
R^2	0.63				0.11			

Notes: The table reports OLS and MLE selection-corrected regressions, with (log) delay between time of trade and time of delivery as dependent variable in the delivery regression, and (log) delay between time of return and expected time of return (the latter set at 23 hours from delivery) as dependent variable in the return regression. Heteroskedasticity-robust (White) standard errors are shown in parenthesis. The sample period is February 11, 2002 - September 24, 2004. *, **, and *** indicate significance at the 0.05, 0.01, and 0.001 levels respectively. The sender's balance is computed at the time of trade in the delivery regression and at 8:30 in the morning of the return day in the return regression.

Table 3
Trade and Delivery Time Regressions

Dependent variable	Time of trade		Time of delivery	
Time of trading			0.344***	(0.002)
Time of delivery	1.599***	(0.007)		
Trade size ($ billion)	-1.550***	(0.048)	0.791***	(0.002)
Fed funds (vs. Eurodollar)	0.945***	(0.020)	-0.389***	(0.009)
Constant	-12.035***	(0.129)	11.716***	(0.028)
Day 1	-0.049	(0.042)	0.005	(0.019)
Day 2	0.045	(0.042)	-0.060**	(0.019)
Day 3	-0.064	(0.042)	0.074***	(0.019)
Day 4	0.025	(0.041)	-0.022	(0.019)
Day 5				
Day 6	-0.052	(0.041)	0.013	(0.019)
Day 7	0.007	(0.041)	-0.045*	(0.019)
Day 8	-0.042	(0.044)	0.040*	(0.020)
Day 9	-0.038	(0.041)	0.013	(0.019)
Day 10	-0.130**	(0.041)	0.056**	(0.019)
First day of month	-0.133**	(0.046)	0.031	(0.021)
Last day of month	-0.188**	(0.046)	0.063**	(0.021)
Last three days of quarter	-0.024**	(0.050)	0.162***	(0.023)
Last five days of year	0.335**	(0.076)	-0.283***	(0.035)
R^2	0.56		0.56	

Notes: The table reports OLS regressions with time of trade and time of delivery as dependent variables. Heteroskedasticity-robust (White) standard errors are shown in parenthesis. The sample period is February 11, 2002 - September 24, 2004. *, **, and *** indicate significance at the 0.05, 0.01, and 0.001 levels respectively.

References

Angelini, Paolo (1998), "An Analysis of Competitive Externalities in Gross Settlement Systems," *Journal of Banking and Finance* 22, pp. 1-18.

Armantier, Olivier, Jeffrey Arnold, and James McAndrews (2008), "Changes in the Tiiming Distribution of Fedwire Funds Transfers," *Economic Policy Review*, Federal Reserve Bank of New York, forthcoming.

Ashcraft, Adam, and Hoyt Bleakley (2006), "On the Market Discipline of Informationally-Opaque Firms: Evidence from Bank Borrowers in the Federal Funds Market" manuscript, University of Chicago.

Ashcraft, Adam, and Darrell Duffie (2007), "Systemic Illiquidity in the Federal Funds Market," *American Economic Review, Papers and Proceedings* 97:2, pp. 221-225.

Bank for International Settlements (1997), *Real Time Gross Settlement Systems*, prepared by the Committee on Payment and Settlement Systems of the Central Banks of the Group of Ten Countries, Basle.

Bartolini, Leonardo, Svenja Gudell, Spence Hilton, and Krista Schwarz (2005), "Intraday Trading in the Overnight Federal Funds Market," *Current Issues in Economics and Finance* 11:11, Federal Reserve Bank of New York.

Bartolini, Leonardo, Spence Hilton, and Alessandro Prati (2008), "Money Market Integration," *Journal of Money, Credit, and Banking* 40:1, pp. 193-213.

Bech, Morten L., and Rod Garratt (2003), "The Intraday Liquidity Management Game," *Journal of Economic Theory* 109, pp. 198-209.

Bernanke, Ben S. (1990), "Clearing and Settlement During the Crash," *The Review of Financial Studies* 3:1, pp. 133-151.

Demiralp, Selva, Brian Preslopsky, and William Whitesell (2004), "Overnight Interbank Loan Markets," manuscript, Board of Governors of the Federal Reserve.

Eichenwald, Kurt (1988), "The Day the Nation's Cash Pipeline Almost Ran Dry," T*he New York Times*, October 2.

Furfine, Craig (1999), "The Microstructure of the Federal Funds Market," *Financial Markets, Institutions & Instruments* 8:5, pp. 24-44.

Furfine, Craig (2001), "Banks as Monitors of Other Banks: Evidence from the Overnight Federal Funds Market," *Journal of Business* 74, pp. 33-55.

Furfine, Craig (2003), "Interbank Exposures: Quantifying the Risk of Contagion," *Journal of Money, Credit and Banking* 35, pp. 111-128.

Furfine, Craig (2006), "The Costs and Benefits of Moral Suasion: Evidence from the Rescue of Long-Term Capital Management," *Journal of Business* 79:2, pp. 593-622.

Hendry, Scott, and Nadja Kamhi (2007), "Uncollateralized Overnight Loans Settled in LVTS," Bank of Canada, Working Paper No. 2007-11.

Kahn, Charles and William Roberds (1998), "Payment System Settlement and Bank Incentives," *The Review of Financial Studies* 11, pp. 845-870.

Makrose, Sheri, Amadeo Alentorn, Stephen Millard, and Jing Yang (2006), "Designing Large Value Payment Systems: An Agent-Based Approach," Bank of England, working paper.

McAndrews, James and Samira Rajan (2000), "The Timing and Funding of *Fedwire* funds transfers," *Economic Policy Review* 6:2, pp. 17-32.

Millard, Stephen, and Marco Polenghi (2004), "The Relationship Between the Overnight Interbank Unsecured Loan Market and the CHAPS Sterling System," Bank of England Quarterly Bulletin, Spring, pp. 42-47.

Richards, H. W. (1995), "Daylight Overdraft Fees and the Federal Reserve's Payment System Risk Policy," *Federal Reserve Bulletin* 81, pp. 1065-77.