Over-the-Counter Search Frictions: A Case Study of the Federal Funds Market[1]

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Incomplete Draft: December 8, 2006

This paper shows how the intra-day allocation and pricing of overnight loans of federal funds reflect the decentralized inter-bank market in which these loans are traded. A would-be borrower or lender typically finds a counterparty institution by direct bilateral contact. Once in contact, say by telephone, the two counterparties to a potential trade negotiate terms that reflect their incentives for borrowing or lending, as well as the attractiveness of their respective options to forego a trade and to continue "shopping around." This over-the-counter (OTC) pricing and allocation mechanism is quite distinct from that of most centralized markets, such as an electronic limit-order-book market in which every order is anonymously exposed to every other order with a centralized order-crossing algorithm.

Among other results, we show how the likelihood that some bank i borrows from some other bank j during a particular minute t of a business day, and also how the interest rate negotiated on the loan, depend on the prior trading relationship between these two banks, the extents to which their balances at the beginning of minute t are above or below their normal respective balances for that time of day, their overall levels of trading activities, the amount of time left until their end-of-day balances are monitored for reserve-requirement purposes, and the volatility of the federal funds rate in the trailing 30 minutes.

While there is a significant body of research on the micro-structure of specialist and limit-order-book markets, most OTC markets do not have comprehensive transactions-level data available for analysis. The federal funds market is a rare exception. We go beyond a previous study by Furfine (1999) of the microstructure of the federal funds market by modeling how the

[1]We are grateful for support and data from The Federal Reserve Bank of New York and for conversations with James McAndrews, Craig Furfine, and anonymous federal funds traders. We have also benefited from comments by Andrew Metrick, Jeremy Stein, Ken French, Larry Harris, Owen Lamont, John Taylor, and Randy Westerfield. The views expressed here are not necessarily those of The Federal Reserve Bank of New York or the Federal Reserve System. Duffie is also with The National Bureau of Economic Research.

likelihood of matching a particular borrower with a particular lender, as well as the interest rate that they negotiate, depend on their respective incentives to add or reduce balances and their abilities to conduct further trading with other counterparties (proxied by the level of their past trading volumes). Our results are consistent with the thrust of search-based OTC financial market theory.[2]

1 The Federal Funds Market

A federal funds transaction is executed with an electronic request by a financial institution to the Federal Reserve Banks ("The Fed") via its Fedwire Funds Service to debit its federal funds account by a stipulated amount in favor of the account of another financial institution. Such a "send" could occur for many purposes, for example to fund or repay a loan of federal funds or as settlement of a trade for other assets. The normal terms of a federal funds loan are the amount and the interest rate, quoted on a simple overnight money-market (actual-360) basis. Loans are repaid by 6:30pm Eastern Time on the next business day. For example, a loan of \$100 million at a rate of 7.20% on a Tuesday would be executed with a send by the lender to the borrower of \$100 million on Tuesday and a send by the borrower to the lender of $100(1+0.072/360) = 100.02$ million dollars on Wednesday.[3]

Federal funds loans are not collateralized, and therefore expose the lending institution to the risk of default by the borrowing institution. Credit risk could be partly responsible for the OTC structure of the federal funds market. Not every loan is of the same quality. The willingness of the lender to expose itself to a particular borrower, and a determination of the interest rate on the loan, would be awkward to arrange in a typical centralized order-processing market of the sort that normally handles homogeneous assets. Counterparty credit risk could also explain the OTC nature of the market for interest-rate swaps, but does not account for the fact that the markets for government and corporate bonds are also OTC.

Two financial institutions can come into contact with each other by various methods in order to negotiate a loan. For example, a federal funds trader at one bank could call a federal funds trader at another bank and ask for quotes. The borrower and lender can also be placed

[2] See for example Duffie, Gârleanu, and Pedersen (2005), Lagos (2005), and Vayanos and Weill (2005).

[3] For a Friday-to-Monday loan, the repayment with three days of interest would be \$100.06 million.

in contact through a broker, although the final amount of a brokered loan is arranged by direct negotiation between the borrowing and lending bank. With our data, described in the next section, we are unable to distinguish which loans were brokered. In aggregate, approximately 27% of the volume of federal funds loans during 2005 were brokered.[4] Based on conversations with market experts, we believe that brokerage of loans is less common among the largest banks, which are the focus of our study.

With rare exception, any institution's federal funds balance must be non-negative at the close of every business day. Overnight overdrafts may be assessed large penalties. If necessary, the Discount Window is available as a backstop source of federal funds loans directly from the Fed. Loans through the Discount Window, however, are at an interest rate that is set by fiat at 100 basis points (as of this writing) above the current targeted federal funds rate. The Discount Window rate is therefore highly unattractive to a trader that might have been able to borrow directly from another market participant at rates that are typically negotiated within a few basis points of the target rate. A Discount Window loan, moreover, must be collateralized by acceptable assets that are supplied to the Fed by the borrowing financial institution. This constitutes another incentive to achieve non-negative balances without using the Discount Window.

A large bank typically targets a rather small positive balance relative to its total amount sent over Fedwire. Currently, for example, the total amount of reserves held by financial institutions is roughly $17.3 billion, whereas the total daily amount sent on Fedwire is over $2.3 trillion per business day. Banks do not have much incentive to hold reserve balances in large amounts at the close of business days because these balances do not earn interest from The Fed. Unnecessary end-of-day balances could have been exchanged for interest-bearing overnight assets, such as commercial paper. Banks therefore economize on the use of balances through the use of "sweep" accounts, in which customer funds held as demand deposits during the day are "swept" into money-market accounts at the end of each day, thereby increasing the interest earnings of customers and reducing the quantity of reserves that a bank must hold. The resulting small total amount of reserves held by banks relative to the demand for federal funds transactions may

[4]This figure comes from the Payments Studies Function of the Federal Reserve Bank of New York, and is calculated by combining several data sources.

convey some advantage to The Fed in targeting interest rates though open-market transactions, because adding or removing a relatively small amount of reserves from the system can have a significant proportionate influence on the scarcity of reserves available as a medium of exchange for intra-day transactions and for purposes of meeting reserve requirements. During the business day, financial institutions are permitted to have negative balances in their accounts up to a maximum "cap." Beyond the caps, these "daylight overdrafts" are charged a penalty fee.[5]

Motivated in part by discussions with federal funds traders, we document that federal funds trading is significantly more sensitive to balances in the last hour of the day. For example, at some large banks, federal funds traders responsible for targeting a small non-negative end-of-day balance ask other profit centers of their banks to avoid large unscheduled transactions (for example currency trades) near the end of the day. Once a federal funds trader has a reasonable estimate of the day's yet-to-be-executed send and receive transactions, he or she can adjust pricing and trading negotiations with other banks so as to push the bank's balances in the desired direction. We show evidence of this behavior, and further, find that lending is more active when federal funds rate volatility in the trailing half hour is high. Hamilton (1996) discusses the implications of the two-week monitoring cycle for daily price behavior. We do not find evidence of significant dependence of intra-day balance targeting on the number of days remaining in the current two-week monitoring period.

We do not consider behavior on days of extreme stress, such as the stock market crash of 1987 or September 11, 2001, when the events at the World Trade Center prevented the Bank of New York from being able to process payments. Access to the Discount Window and massive infusions of liquidity by The Fed and other central banks would (and did, on 9/11) mitigate adverse systemic effects, as explained by McAndrews and Potter (2002) and Lacker (2003).

[5]Because of recent increases in daylight overdrafts, there has been some discussion of the informal practice by some market participants to offer lower interest rates on loans that are for return early on the next business day. See Jennifer Johnson,"Consultation Paper on Intraday Liquidity Management and Payment System Policy," Board of Governors of the Federal Reserve System, Docket OP-1257, June 14, 2006.

2 Data

This study uses transactions-level data from Fedwire. We focus mainly on the top 100 commercial banks by transaction volume, and on the business days of 2005. Our data set permits the construction of real-time balances for each institution, and allows us to identify the sender and receiver of both payments and loans.

We start with payments data documenting every transaction sent over Fedwire during the 251 business days of 2005. These data include the date, time, amount, and account numbers involved in each transaction. We focus on transactions in the last 90 minutes of the Fedwire business day, between 5:00 pm and 6:30 pm Eastern Time. The large institutions that we study frequently have multiple accounts. We aggregate these accounts by institution, using a mapping from accounts to institutions that is updated every month. We restrict our sample to institutions that are either commercial banks or Government-Sponsored Enterprises (GSEs such as Freddie Mac, Fannie Mae, and Federal Home Loan Banks), eliminating transactions involving accounts held by central banks, federal or state governments, or other settlement systems. Using these data, we identify the top 100 institutions in each month by the total dollar volume sent, which ranges from less than \$4 billion to more than \$2 trillion. The median monthly volume of federal funds sent across the 1,200 institution-months in our sample is \$19.21 billion. The median across months of the aggregate volume sent is \$12.46 trillion. Over 80 percent of the institution-months in our sample are for commercial banks, 15 percent are for GSEs, and the remaining 5 percent are for Special Situations (non-banks that hold reserve balances at the Federal Reserve). Because our analysis is done at the institution and not the account level, we remove all transactions for which the same institution is the sender and receiver. For purposes of modeling transaction events, we aggregate transactions by date for each sender-receiver pair (of the $9900 = 100 \times 100 - 100$ pairs) for each of the minutes of the last 90 minutes of the business day. For example, if Bank i sends to Bank j twice during the minute spanning 17:45 to 17:46, we treat this as one event.

We use a data set developed by the Payments Studies Function at the Federal Reserve Bank of New York to identify as likely loans those transactions that involve a send in denominations of 1 million dollars between a pair of counterparties that is reversed the following business day with plausible federal funds interest. These data are merged with our Fedwire send data in order to seperate federal funds loans from non-loan sends. We also use a data set that documents the balance of each account at the end of every minute in which a transaction occurs. These balances are aggregated across all accounts for each institution, giving us each institution's account balance for each of the last 90 minutes of every business day in our sample. In order to deal with heterogeneity across institutions and time, we normalize each institution's account balance by the following method. From the account balance of institution i at minute t on a particular day, we subtract the median balance for institution i at minute t across all 251 business days of 2005. We then divide this difference by the total amount V_i of federal funds sent by this institution over the last 90 minutes of the day in the current month. This normalized balance, denoted $X_i(t)$, is a measure of the extent to which institution i has more or less than its normal balance for that minute, relative to the size of the institution (measured by transactions volume).

Among our other explanatory variables are measures of the volatility of the federal funds rate and of the strength of the relationship between pairs of counterparties. In order to capture the volatility of the federal funds rate, we start with a dollar-weighted average of the interest rates of all loans made in each given minute. We then measure the time-series sample standard deviation, denoted $\sigma(t)$, of these minute-by-minute average rates over the previous 30 minutes. The median federal funds rate volatility is about 3 basis points, but ranges from under 1 basis point to 87 basis points, with a sample standard deviation of 4 basis points. Our measure of sender-receiver relationship strength for a particular pair (i, j) of counterparties, denoted S_{ij}, is the dollar volume of transactions sent by i to j over the previous month, divided by the dollar volume of all transactions sent by i to the top 100 institutions. The receiver-sender relationship strength R_{ij} is the dollar volume of transactions received by i from j over the previous month, divided by the dollar volume of all transactions received by i from the top 100 institutions. Because we use a one-month lagged measure of relationship strength, we do not include transactions from the first month of 2005.

3 Analysis of Transaction Pairing Likelihood

We begin with an analysis of the determinants of the likelihood $p_{ij}(t)$ of a loan (or of a non-loan send) by institution i to institution j during minute t of a particular business day. We separately analyze loan transactions and non-loan sends. Separate logit models are estimated for each business day. The estimated probability that institution i sends (or lends) to institution j during minute t is modeled with variants of the logit model

$$p_{ij}(t) = \Lambda(V_i, V_j, X_i(t), X_j(t), S_{ij}, R_{ij}, \sigma(t), L(t); \beta), \tag{1}$$

where, for vectors x of covariates and β of coefficients, $\Lambda(x;\beta) = e^{\beta \cdot x}/(1 + e^{\beta \cdot x})$, and where $L(t)$ is the indicator variable (1 or 0) for whether t is after 17:30 Eastern Time.

Table 1 shows summary statistics for the maximum likelihood estimates $\hat{\beta}$ of the coefficients for (**??**) and for variants that include interactions of some of the explanatory variables with the late-time indicator $L(t)$. Rather than reporting the coefficients separately for each business day, Table 1 reports, for each of the models labeled (a) through (f), the mean across business days of the estimated coefficients and of the associated t-statistics, as well as the mean absolute deviation across days of the coefficient estimates and of the t-statistics. There are enough data on each business day to identify the coefficients well on most days, and we are reluctant to pool the data across business days because of non-stationarity concerns. Indeed, the estimated coefficients do vary substantially across business days, but are typically statistically significantly different than zero at standard confidence levels. The first and third rows of Model (a) of Table 1 document a strong relationship between counterparty balances and the probability of a Federal Funds loan. A high balance, relative to normal for that minute, increases the probability of being a lender to a particular potential counterparty. A low balance increases the probability of being a borrower. The second and fourth rows of Model (a) show that this relationship tends to be much stronger during the last 60 minutes of the day. Comparing the estimated coefficients for loans with those for non-loan sends in Model (d), we surmise that the likelihood of a loan is more sensitive to balances than is the likelihood of a non-loan send. For instance, a bank in need of federal funds would be more likely to increase its borrowings than to increase its sales of other assets such as treasuries or currencies.

Row 5 of Table 1 indicates that the probabilities of loans and of non-loan of sends decline as the business day comes to a close. Rows 6 and 7 are evidence of the unsurprising fact that larger institutions are much more likely to be counterparties on all types of transactions. The coefficient estimates of Rows 8 and 9 indicate that an increase in funds rate volatility increases the probability of lending and reduces the probability of borrowing, but has little effect on the probability of sending or receiving. From Row 10, higher funds rate volatility tends to depress lending and sending, although it seems to have a larger impact on the latter. Finally, Rows 10 and 11 document that relationship strength has a significant impact on lending or sending, although this effect is much larger for lending than for sending.

4 Determinants of the Rate

We are interested in determinants of the cross-sectional variation, at a given minute t, of the rate $r_{ij}(t)$ negotiated by a particular lender i and borrower j, net of the current-minute dollar-weighted average rate $R(t)$ negotiated elsewhere in the market. Our rate data are those for all federal funds loans made between our top 100 institutions during 2005. As explanatory variables, we consider the cross-sectional deciles d_i^b and d_j^b of the lender's and borrower's normalized balance $X_i(t)$ and $X_j(t)$ respectively, relative to the population at minute t. The highest-decile institutions (with $d_i^b = 90$) are likely to be among those whose incentive to lend is greatest, other effects equal. In a centralized market, any market order is assigned the best available price. In an OTC market, however, theory suggests that the price negotiated is increasing in the reservation prices of the buyer and the seller. Our explanatory variable for this effect in the federal funds market is the sum $d_i^b + d_j^b$ of the percentile balances of the lender and the borrower. We anticipate that $r_{ij}(t) - R(t)$ decreases, on average, with $d_i^b + d_j^b$.

A significant number of loans in our data are made by lenders in the lower deciles by relative balances. Many of these lenders are presumably themselves in relative need of funds but agree to lend at a sufficiently high rate, planning to borrow later in the day at a lower rate. In an OTC market, the borrower does not generally know the most attractive rates available from other counterparties, nor which counterparties are offering them, and may have an incentive to accept the rate offered by such a lender. More active institutions are in a better position to offer loans when in need of funds themselves, because they are in a better position to "lay off" their positions later. An analogous effect applies to institutions who are willing to borrow, despite having excess balances. We estimate the impact of these effects on the rate negotiated by including as an explanatory variable the difference $d_i^v - d_j^v$ between the cross-sectional decile d_i^v of the lender's transaction volume V_i and the corresponding decile d_j^v of the borrower. By theory, we expect that $r_{ij}(t) - R(t)$ increases on average with $d_i^v - d_j^v$.

In order to account for the fact that institutions may be able to forecast their non-loan sends and receipts for the remainder of the day, we also construct a proxy for the conditional expectation at time t of the end-of-day balance of a given institution in the absence of any additional borrowing and lending after time t. This proxy is the current balance plus all net non-loan sends for the remainder of the day. The true conditional expectation differs from this outcome proxy by an amount uncorrelated with information available at the forecast time. The regressor that we use is the sum of the cross-sectional percentiles of this balance-outcome proxy for the lender i and borrower j, again labeled $d_i^b + d_j^b$. We also include as a regressor the interaction of $d_i^b + d_j^b$ with the dummy variable $L(t)$ for the last hour of the business day.

Table 2 documents the estimated coefficients, above the standard errors, for each of Models (a) through (h), whose dependent variable is $r_{ij}(t) - R(t)$, and whose regressors are indicated. Models (a)-(d) use actual balances to determine d_i^b, whereas Models (e)-(h) use our outcome proxies for conditional expected balances. For Models (a), (c), (e), and (g), the market rate $R(t)$ is the dollar-weighted average rates on all other loans at the same minute t. For Models (b), (d), (f), and (h), the market rate $R(t)$ is measured by regressing the actual rates negotiated on date and time-of-day dummies.

The first two rows of Table 2 document that, on average during the last hour of the day, increasing the balances of the lender and borrower does indeed significantly reduce the loan interest rate that they negotiate relative to rates negotiated elsewhere in the market during the same minute. The third row shows that, on average, the rate negotiated is significantly higher for lenders who are more active in the federal funds market relative to the borrower. Likewise, if the borrower is more active in the market than the lender, the rate negotiated is lower, other things equal. The fourth row documents that this effect is stronger during the last hour of the day.

In order to mitigate concerns that size is a proxy for credit risk, Models (c), (d), (f), and (h) include the lender and borrower size deciles as separate regressors. The results show that most of the impact of size on rate is associated with the lender size, which has no direct bearing on the credit quality of the borrower.[6]

[6]For empirical models of how credit quality affects interbank loan rates, see Cocco, Gomes, and Martins (2005) and Furfine (2001).

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Table 1: Logit Models of Transaction Likelihood[a]

	Federal Funds Loans (a)-(c)						Non-Loan Sends (d)-(f)					
	(a)		(b)		(c)		(d)		(e)		(f)	
	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat
1. $X_s(t)$	16.73	7.98	-2.46	0.66	16.32	6.01	-1.46	-2.28	-4.04	-0.90	-0.93	-1.52
	(9.36)	(4.75)	(31.60)	(3.83)	(7.87)	(3.02)	(7.23)	(11.27)	(14.60)	(3.58)	(6.44)	(9.42)
2. $X_s(t)L(t)$	26.77	7.33	23.95	4.89	28.07	6.07	1.27	1.39	1.18	1.05	1.27	1.19
	(12.54)	(3.11)	(14.71)	(2.85)	(13.46)	(2.53)	(12.08)	(6.06)	(10.18)	(4.66)	(11.98)	(5.67)
3. $X_r(t)$	-9.37	-3.32	15.61	0.91	-7.09	-2.32	-2.15	-3.69	-1.71	-0.59	-1.50	-2.64
	(9.57)	(3.85)	(37.89)	(2.60)	(8.21)	(2.73)	(6.57)	(10.91)	(11.42)	(3.16)	(5.45)	(8.71)
4. $X_r(t)L(t)$	-26.69	-4.37	-21.55	-3.06	-24.72	-3.89	-0.86	-0.59	-0.54	-0.30	-0.54	-0.36
	(16.34)	(2.56)	(18.54)	(2.55)	(15.16)	(2.27)	(9.72)	(5.37)	(8.30)	(4.10)	(8.81)	(4.84)
5. $L(t)$	-0.87	-10.54	-0.66	-7.10	-0.85	-9.67	-1.44	-64.71	-1.11	-45.06	-1.45	-63.57
	(0.15)	(1.69)	(0.29)	(3.40)	(0.14)	(1.50)	(0.08)	(3.18)	(0.40)	(19.01)	(0.08)	(3.08)
6. V_s	0.92	32.98	0.92	33.00	0.68	21.45	0.71	114.52	0.71	114.33	0.51	68.99
	(0.05)	(2.04)	(0.05)	(2.06)	(0.05)	(1.78)	(0.02)	(5.96)	(0.02)	(5.90)	(0.03)	(4.31)
7. V_r	0.87	33.79	0.87	33.87	0.58	21.46	0.62	103.18	0.62	103.19	0.43	62.47
	(0.04)	(2.35)	(0.04)	(2.31)	(0.04)	(1.75)	(0.02)	(5.28)	(0.02)	(5.22)	(0.02)	(3.61)
8. $X_s(t)\sigma(t)$			8.45	2.68					1.34	0.77		
			(12.82)	(3.69)					(6.00)	(3.62)		
9. $X_r(t)\sigma(t)$			-10.73	-2.22					-0.32	0.02		
			(15.52)	(2.74)					(4.56)	(2.81)		
10. $\sigma(t)$			-0.27	-5.01					-0.44	-25.92		
			(0.25)	(3.08)					(0.40)	(17.61)		
11. S_{sr}					3.13	19.86					1.70	24.32
					(0.24)	(1.80)					(0.09)	(1.35)
12. R_{rs}					2.76	20.93					1.93	22.73
					(0.20)	(2.12)					(0.13)	(2.16)
13. constant	-52.08	-43.35	-51.60	-42.87	-38.80	-33.66	-36.79	-150.92	-35.95	-143.84	-26.93	-92.74
	(2.29)	(2.47)	(2.24)	(2.55)	(1.78)	(2.23)	(1.10)	(7.00)	(1.30)	(7.88)	(1.12)	(4.96)

[a] The table summarizes the fit of six logit models, labeled (a)-(f), for the probability of a loan (Models (a)-(c)) or of a non-loan send (Models (d)-(f)) in minute t. Each model is estimated separately for each of the business days of the last 11 months of 2005. Each day has $891,000 = (100 \times 100 - 100) \times 90)$ observations, one for each sender-receiver-minute combination for the top 100 institutions over the last 90 minutes of the business day. For each covariate, the table reports the mean across days of the maximum likelihood estimate of the coefficients and of the corresponding t-statistics. The second row, for each covariate, shows in parentheses the mean absolute deviation across all business days of the estimated coefficients and of the t-statistics.

Table 2: OLS Models of the Loan Rates[a]

	Actual Balance (a)-(d)				Expected Balance (e)-(h)			
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
1. $d_s^b + d_r^b$	0.0024**	0.0040***	0.0027***	0.0044***	0.0017	0.0021	0.0021*	0.0025
	(0.0010)	(0.0011)	(0.0010)	(0.0011)	(0.0012)	(0.0017)	(0.0012)	(0.0018)
2. $(d_s^b + d_r^b)L(t)$	-0.0260***	-0.1049***	-0.0266***	-0.1061***	-0.0011	-0.0086**	-0.0016	-0.0094**
	(0.0053)	(0.0068)	(0.0053)	(0.0068)	(0.0031)	(0.0043)	(0.0030)	(0.0043)
3. $d_s^v - d_r^v$	0.0137**	0.0205***			0.0136**	0.0202***		
	(0.0066)	(0.0076)			(0.0066)	(0.0077)		
4. $(d_s^v - d_r^v)L(t)$	0.0691***	0.0696***			0.0742***	0.0907***		
	(0.0085)	(0.0079)			(0.0085)	(0.0085)		
5. S_{sr}	0.3548	0.9753	0.2092	0.7839	0.3667	0.9496	0.2235	0.7621
	(1.5936)	(1.5033)	(1.5191)	(1.4122)	(1.5924)	(1.5118)	(1.5179)	(1.4206)
6. R_{sr}	3.1219**	2.5496**	2.8965**	2.3494**	3.1021**	2.4962*	2.8730**	2.2831**
	(1.3213)	(1.2897)	(1.1907)	(1.1171)	(1.3232)	(1.3090)	(1.1925)	(1.1348)
7. d_s^v			0.0212***	0.0293***			0.0211***	0.0291***
			(0.0073)	(0.0086)			(0.0073)	(0.0086)
8. d_r^v			0.0063	0.0039			0.0064	0.0043
			(0.0077)	(0.0081)			(0.0077)	(0.0082)
9. $d_s^v L(t)$			0.0750***	0.0870***			0.0799***	0.1066***
			(0.0103)	(0.0112)			(0.0103)	(0.0117)
10. $d_r^v L(t)$			-0.0653***	-0.0470***			-0.0711***	-0.0711***
			(0.0122)	(0.0159)			(0.0123)	(0.0166)
No. Obs.	121,189	123,236	121,189	123,236	121,189	123,236	121,189	123,236
R^2	0.02	0.03	0.02	0.04	0.02	0.02	0.02	0.02

[a] The table summarizes the OLS estimates of the coefficients of various models of the funds rate, labeled (a)-(h) by column. The underlying data include all federal funds loans made in 2005 between top 100 institutions defined by total send volume each month. Regressors include the decile d_s^b of the balance of the lender at the time of the loan plus decile d_r^b of the balance of the borrower at the time of the loan; the interaction of the previous variable with $L(t)$; the deciles d_s^v and d_r^v of the gross federal funds transactions of the lender and borrower in the previous month, respectively; the interaction of the previous variables with $L(t)$; and a full set of time of day fixed effects. Models (a)-(d) are based on the actual balance of the counterparties; Models (e)-(h) are based on the forecasted balances of the counterparties. For each regressor of each model, the table reports the estimated coefficient above the standard error, which has been corrected for heteroskedasticity and clustering at the sender-receiver level using the Stata robust cluster options. A coefficient estimate marked with three, two, or one asterisk, is estimated to be statistically significantly larger than zero at the 99%, 95%, and 90% confidence levels, respectively, under the usual distributional assumptions.