

Federal Reserve Bank of New York
Staff Reports

The Federal Funds Market over the 2007-09 Crisis

Adam Copeland

Staff Report No. 901
November 2019
Revised March 2020



This paper presents preliminary findings and is being distributed to economists and other interested readers solely to stimulate discussion and elicit comments. The views expressed in this paper are those of the author and do not necessarily reflect the position of the Federal Reserve Bank of New York or the Federal Reserve System. Any errors or omissions are the responsibility of the author.

The Federal Funds Market over the 2007-09 Crisis

Adam Copeland

Federal Reserve Bank of New York Staff Reports, no. 901

November 2019, revised March 2020

JEL classification: D82, G01, G14

Abstract

This paper measures how the 2007-09 financial crisis affected the U.S. federal funds market. I accomplish this by developing and estimating a structural model of this market, in which intermediation plays a crucial role and borrowing banks differ in their unobserved probability of default. The estimates imply that the expected probability of default increases 0.29 percentage point at the start of the crisis in mid-2007 and then gains a further 1.91 percentage points after the bankruptcy of Lehman Brothers. These increases do not cause a market freeze, however, because simultaneously there is a shift outward in the supply of funds. The model indicates that amid the turmoil of the crisis, lenders viewed the fed funds market as a relatively attractive place to invest cash overnight.

Key words: asymmetric information, fed funds, intermediation, financial crisis

Copeland: Federal Reserve Bank of New York (email: adam.copeland@ny.frb.org). The author thanks Olivier Armantier and Brenda Samaniego de la Parra for their comments and suggestions, as well as seminar participants at the Universities of Essex and Bristol. He also thanks Philip Mulder for excellent research assistance. The views expressed in this paper are those of the author and do not necessarily represent the position of the Federal Reserve Bank of New York or the Federal Reserve System.

To view the authors' disclosure statements, visit
https://www.newyorkfed.org/research/staff_reports/sr901.html.

1 Introduction

The U.S. fed funds market is where institutions, primarily banks, borrow and lend central bank reserves with one another on an over-the-counter basis. Trades are settled the same day they are executed, even when trading takes place late in the day, enabling banks to use this market to offset unexpected liquidity shocks. The market's importance is further amplified because the Federal Open Market Committee (FOMC) targets the average fed funds rate when implementing monetary policy. Given these features, it is not surprising that this market was closely watched during the 2007-09 financial crisis, which can be viewed as a crisis of liquidity.

Interpreting changes in the rates and quantities of fed funds activity, however, is empirically challenging because in addition to the usual forces of demand and supply, the trading of fed funds, being unsecured loans, is affected by changes in the strength of asymmetric information.¹ Indeed, during normal trading periods, the effect of asymmetric information cannot be separately identified from the effect of changes in demand and supply. The arrival of the financial crisis, which strengthened the role of asymmetric information in this market, provides a chance to isolate and measure the impact of each of these three forces on fed funds activity.

Using data covering both the pre-crisis and crisis periods, I take advantage of this opportunity by developing, solving, and estimating a structural model of the fed funds market. In the model, asymmetric information manifests as a borrowing bank's unobserved probability of default. Using the estimated parameters, I leverage the model to gauge the effects of changes in demand, supply, and the probability of default on the rates and quantities of fed funds sold and purchased.

Two features of the data enable me to separately identify all three channels. First, the data reveal the rates at which market participants purchase and sell fed funds as well as the amount of funds they intermediate. Second, the data span the pre-crisis and crisis

¹Because of the unsecured nature of fed funds, banks will only lend fed funds to those banks with which they have established a line of credit (Stignum and Crescenzi (2007, p. 508)). Default has occurred in this market; a recent example is the default of Lehman Brothers on its debt to Freddie Mac, a government-sponsored enterprise (for details, see Federal Housing Finance Agency Office of Inspector General (2013)).

periods, and so I observe how both rates and quantity change with the arrival of the crisis in mid-2007 and with the deepening of the crisis in late 2008 after the bankruptcy of Lehman Brothers. Theory predicts that changes in demand, supply and the probability of default will have different effects on the rates of fed funds sold and purchased (as well as the spread between the two) and the quantity of funds intermediated. In taking the model to the data, I can then identify the relative contribution of each channel to the observed changes to rates and quantity.

The data describe the fed funds activity of three banks that were known to be large participants in the market over the sample period of 2006 to 2008.² These banks did not provide transaction level data, but rather shared the means to accurately identify the settlement legs of these trades in payments data. Having access to payments data, I construct a transaction-level data set of fed funds purchases and sales involving these three banks, from January 2006 to December 2008. For each trade, I know the principal amount, the interest rate, and, with some degree of confidence, the counterparty. I use these data to compute the average daily principal-weighted interest rate of fed funds purchased and fed funds sold by these three banks as well as the total dollar value of fed funds sold and purchased.

Befitting their intermediary status, these three banks consistently sold fed funds at rates higher than those at which they purchased them. This intermediary spread averaged 11 basis points in the pre-crisis period, from January 2006 through July 2007. Starting in August 2007, this spread jumps up to 26 basis points, a 15 basis point increase.³ Finally, the spread rockets up to 118 basis points after the bankruptcy of Lehman Brothers. Strikingly, the total amount of funds intermediated by the three

²With the Federal Reserve's introduction of paying interest on excess reserves as well as quantitative easing, the U.S. fed funds market changed dramatically after October 2008. This paper focuses on the fed funds market up until the introduction of the interest on excess reserves policy. See Federal Reserve Bank of New York (2013) and Craig and Millington (2017) for analysis of how paying interest on excess reserves changed the fed funds market.

³In this paper, the crisis period starts in August 2007 because that is the month in which the precipitous decline in asset-backed commercial paper activity began (Covitz, Liang, and Suarez, 2013). Furthermore, August saw one of the first instances of financial disruption due to sub-prime lending, when BNP Paribas suspended withdrawals from some of its hedge funds due to an inability to mark sub-prime mortgage-backed securities to market.

banks increases with the onset of the crisis, despite the increases in the intermediary's spread. Between the start of the crisis and the Lehman bankruptcy, the average total daily amount intermediated is 42 percent greater than the figure for the pre-crisis period (\$2.7 billion versus \$1.9 billion). Even after the Lehman bankruptcy and the subsequent disruptions to the overall financial system, the total amount of fed funds intermediated by the three banks is 11 percent greater than in the pre-crisis period.

To better understand the various drivers behind these movements in rates and quantities, I develop a model of the fed funds market. Reflecting the structure of the market, the model has three types of agents: borrowers, lenders, and an intermediary. Borrowers and lenders can trade directly with one another, or with the intermediary. Motivating its existence, I assume the intermediary has an informational advantage over lenders which results in the intermediary facing a lower probability of default (unconditional on borrower type). The intermediary sets the rates at which it will purchase and sell fed funds, taking into account that lenders and borrowers can trade directly. Lenders and borrowers then decide whether to trade with the intermediary and if so, how much to lend and borrow, respectively.

I estimate the structural parameters of the model using the general method of moments, where the moments are functions of the observed rates of fed funds sold and purchased as well as the change in quantity intermediated across the pre-crisis and crisis periods. The model fits the data well, and the parameters are well-estimated. The parameters imply that with the start of the crisis in August 2007, the expected probability of default by borrowing banks increases from 0.043 percent to 0.333 percent. The expected default rate then leaps up to 2.24 percent after the bankruptcy of Lehman Brothers. This progression in the estimated default rate matches the narrative of the financial crisis, where concerns about counterparty risk became elevated during the summer of 2007 and then sky-rocketed after the Lehman Brothers bankruptcy.

The parameter estimates also imply that demand of fed funds increased throughout the crisis. Perhaps more striking is that the parameter estimates also imply that the supply of fed funds shifted out over the crisis. In particular there were large increases in the supply of fed funds both starting in the summer of 2007 when the crisis first began and after the Lehman Brothers bankruptcy. This result about supply is particularly

novel because of the prevailing belief that the supply of fed funds declined over the crisis. Instead, the estimated parameters imply that banks' options of investing cash elsewhere in the financial system became increasingly less attractive over the course of the crisis. This accords with what is known about other financial markets collapsing, such as the asset-backed commercial paper market.

To better understand the economic importance of the changes to adverse selection, demand, and supply, as well as their relative importance, I conduct three counterfactuals. For each counterfactual I resolve the model and obtain predictions of rates and quantities given a change in demand or supply or adverse selection, for the period of time between the start of the crisis up until the Lehman Brothers bankruptcy. As a result, the model predicts what would have happened to the fed funds market given a change in one of these three channels, holding all other parameters at their pre-crisis levels. The counterfactuals illustrate that the increase in demand for fed funds was marginal and so had little economic effect on the market. In contrast, the increase in both supply and the probability of default were major forces at work.

The increase in expected default rates from 0.043 to 0.333 percent is significant enough that, holding all else equal, such a change would have driven down the total amount intermediated by 85.5 percent. Such a collapse in quantities illustrates that the fed funds market is quite susceptible to adverse selection, whereby small changes in expected default can create large changes to quantity. The estimated increase in supply, all else equal, also has a large effect on the fed funds market, causing the total amount intermediated to increase by 238 percent. This counterfactual reveals there is a large demand elasticity for funds, such that small changes in the price of fed funds generate large changes in quantity transacted.

Taken together, the counterfactuals demonstrate that the vitality of the fed funds market over the crisis was maintained only because of the increase in the supply of fed funds. Specifically, the fed funds market continued to operate over the crisis because banks viewed this market as an attractive place to invest cash relative to other financial markets, despite the increased probability of default. These results suggest two policy implications. First, policy makers should be aware that the fed funds market is susceptible to small changes in the expected probability of default. Hence, future adverse events

which cause banks to become more prone to default are likely to have large negative effects on this market. Furthermore, if a specific bank or group of banks were thought to become more prone to default, then the results predict that the bank or banks would not be able to borrow much in the fed funds market. Second, the fed funds market is considered to be a relatively safe place to invest cash. Given a general adverse shock to the financial system then, policy makers can expect depository institutions to shift their cash investments towards the fed funds market.

This paper contributes to the empirical literature focused on estimating the strength of asymmetric information. Given the focus on interbank markets, this paper is closest to those studying short-term debt under asymmetric information. Theoretical papers such as Flannery (1996), Bruche and Suarez (2010), and Heider, Hoerova, and Holthausen (2015) lay the ground work demonstrating how asymmetric information and counterparty risk introduce frictions into the interbank lending market.

The associated empirical literature is the body of work in corporate finance estimating the impact of asymmetric information on short-term debt markets. By and large, these works take the approach of finding empirical proxies of asymmetric information, such as financial or accounting characteristics (Abade, Sánchez-Ballesta, and Yagüe (2017)). These proxies are then used to measure the empirical relationship between changes in asymmetric information and changes in the variables of interest. This paper stands apart from this approach in that I use a structural approach to directly estimate the strength of asymmetric information (i.e. the changes in borrowing banks' probability of default). An advantage of this approach is that I can construct counterfactuals which provide predictions of market outcomes under various alternative scenarios. Indeed, using this approach I am able to parse out the relative contributions of changes in adverse selection, supply and demand on the fed funds market over the crisis.

Although the structural approach is widely used in economics, this paper's approach borrows heavily from industrial organization (IO) and as such can be grouped with the recent push to apply recent advances in empirical IO to financial topics (Kastl, 2017), including work on central bank auctions (Hortaçsu and Kastl, 2012; Cassola, Hortaçsu, and Kastl, 2013), insurance (Kojien and Yogo, 2016), and mortgages (Allen, Clark, and Houde, forthcoming).

Furthermore, this paper is unusual in that it studies a funding market during a

crisis period. There is only a small empirical literature that examines how the 2007-09 financial crisis has impacted unsecured interbank markets, largely because disaggregate data are often difficult to obtain.⁴ Within this literature, the most similar paper to this one in terms of question is arguably Perignon, Thesmar, and Vuillemeys (2018), which examines the unsecured interbank lending market in Europe over the recent financial crisis. The authors find evidence in favor of theories highlighting heterogeneity among lenders, as opposed to models of adverse selection.⁵ The difference in results between that work and this paper stems from a difference in focus. Perignon, Thesmar, and Vuillemeys consider market participants that lose funding altogether and test which theories best predict these “funding dry-ups.” In contrast, this paper examines large intermediaries that continue to participate in the market during the crisis, with a focus on measuring what are the drivers of change to rates and quantities.

Given the aforementioned general lack of disaggregate data on interbank loans, researchers have used algorithms to identify the settlement legs of these trades in payments data. The algorithm’s parameters were typically based on anecdotal knowledge of trade terms (such as minimum amounts lent) as well as restrictions that the implied interest rates of any two matched payments legs must be close to a published aggregate average. The algorithm labels pairs of payments as interbank loans, which are then analyzed by researchers. Examples of such papers are Afonso, Kovner, and Schoar (2011) and Acharya and Merrouche (2013). There is, however, a debate about the performance of these algorithms when applied to U.S. payments data (see the competing analysis of Kovner and Skeie (2013) and Armantier and Copeland (2015)). In contrast to this approach, the constructed data set of fed funds trades in this paper is based on bank-specific identifiers used by the banks themselves to automate the processing of payments received from others. This extra information is crucial in that it results in a more accurate picture of fed funds activity; given that I already know one settlement leg of a fed funds trade,

⁴There is an Italian online interbank market (e-MID) that makes detailed transaction-level data available. For more information on these data, see Kobayashi and Takaguchi (2018) and references therein. The Federal Reserve began collecting transaction-level data on U.S. fed funds purchases in April 2014 using the FR 2420 survey.

⁵See Gorton and Pennacchi (1990), Calomiris and Kahn (1991), and Dang, Gorton, and Holmstrom (2012) for theories focused on markets with informed and uninformed lenders.

finding the other matching leg is straightforward (details on methodology are provided in Section 2 and Appendix A).

Within the empirical asymmetric information fields, this paper is also novel in how draws upon the market microstructure literature. In particular, the market microstructure theoretical literature lays out the connections between market-makers bid-ask spreads and three sources of frictions: order-handling costs, inventory costs, and adverse selection (for a survey of the literature, see Biais, Glosten, and Spatt (2002)). The associated empirical work then uses information on observed bid-ask spreads and quantities (typically information about the central limit order book) to identify and measure the importance of these three frictions in the market. In the same manner, this paper uses a model of intermediation in the fed funds market to generate an intuitive relationship between the intermediary's bid-ask spread, quantity intermediated, and adverse selection, while accounting for the usual forces of supply and demand.⁶

Other related papers include those that analyze the interaction of a crisis with relationship lending (for example, see Cocco, Gomes, and Martins (2009) and Bolton et al. (2016)) and network formation (for example, see Craig and Ma (2018) and Kim (2017)). Although the intermediary-based lending arrangements studied in this paper can be interpreted as relationship lending, the focus here is not on comparing interbank lending done via relationships to interbank lending of a more transactional nature. Similarly, although the model in this paper involves a simple network, the focus of the paper is not on network formation in interbank markets.

Finally, this paper builds upon a rich literature focused on the functioning of the fed funds market in pre-crisis times. For example, a number of papers focus on the pricing of fed funds in the pre-crisis environment, when reserves were scarce (before the Federal Reserve created copious amounts of reserves through its quantitative easing programs). In that era of scarce reserves, banks bought and sold fed funds in order to manage their stock of reserves with an eye towards meeting regulation-mandated targets (see,

⁶That said, there are substantial differences between this paper and the usual market microstructure paper. One such instance is that market microstructure research often focuses on the buying and selling of financial assets, and so the adverse selection is about the future value of the asset. In contrast this paper focuses on short-term funding where the adverse selection is about the borrowing bank and its ability to repay its loan.

for example, Ho and Saunders (1984) and Erzurumlu and Kotomin (2010)). In contrast, this paper abstracts from this high-frequency reserve-management problem, and focuses on explaining the determinants of longer-run average rates and quantities.

The rest of the paper is organized as follows. Section 2 describes the data, and Section 3 describes the model. Section 4 lays out the empirical work, including goodness-of-fit statistics. Section 5 presents several counterfactuals and discusses the results and Section 6 presents conclusions.

2 Background and Data

This section begins with a brief introduction to the fed funds market, followed by a description and basic analysis of the data.

2.1 Background on the Fed Funds Market

As mentioned in the introduction, the fed funds market is an over-the-counter market, in which banks look to lend central bank reserves to one another on an unsecured basis.⁷ Especially because of the unsecured nature of fed funds, banks typically lend to banks which have been through some credit check process and are actively monitored. Brokers play an important role in this market by helping to match borrowers and lenders, and so reduce banks' search costs. Because of the decentralized nature of the market, historically it has been difficult to obtain disaggregate fed funds data that are representative of the market. Nevertheless, some stylized facts have emerged about this market —that the vast majority of trades have an overnight maturity, for instance, or that small banks have tended to lend reserves to large banks (see Lucas, Jones, and Thurston (1977) and Bartolini et al. (2005)).

The fed funds market plays a central role in the U.S. financial system. This market is a main source of immediate liquidity, enabling banks to execute and settle trades on the same day, even if execution occurs late in the day. Further, the FOMC targets

⁷Under the characterization of fed funds provided by Regulation D, only depository institutions can enter into fed funds trades, with few exceptions. A well-known exception is government-sponsored enterprises, such as Fannie Mae, Freddie Mac, and the Federal Home Loan Banks.

the average fed funds rate when setting monetary policy, and historically, the Federal Reserve adjusted aggregate reserves in the financial system with the goal of increasing or decreasing the fed funds rate. During the financial crisis, the Federal Reserve changed how it implemented monetary policy with the introduction of interest on excess reserves (IOER) on October 8, 2008. Because this paper focuses on the period of time before the introduction of IOER, its impact on this market is left to future research.⁸

2.2 Data Description

The data are the fed funds sales and purchases of three large banks that are considered major players in the market for fed funds over the sample period from January 2006 to December 2008. These banks did not provide transaction-level data on fed funds activity. Instead, from conversations with banks' back offices, I learned that each of these three banks require its counterparties to use a unique identifier in the payment message when sending a fed funds-related payment *to* the bank.⁹ Every fed funds trade has two settlement legs, the initial leg where the principal amount is sent to the borrower from the lender on date t , and the return leg where the principal is returned to the lender along with the agreed upon interest, at some future date. The operational system set up by these three banks means that for every sale of fed funds, the return leg has an identifier embedded in the payment message field that allows the bank's back office to identify and label that payment as being related to fed funds activity. Similarly, for each fed funds purchase by these three banks, the initial payment leg has a unique identifier embedded in the payment's message fields. These identifiers are used so that these banks, which process tens of thousands payments a day, can automate the back-office processing of fed funds payments.¹⁰

⁸Armenter and Lester (2017) and Afonso, Armenter, and Lester (2019) study the current state of the fed funds market.

⁹Supporting the claim about the use of these identifiers, the back office of another bank (not one of the three large banks) verified that it used the identifiers when sending fed funds related payments to these banks.

¹⁰From discussions with various banks' back offices, I learned that banks with smaller payments volumes tended to use a manual process to identify fed funds payments from the flow of incoming payments. In addition, some banks used identifiers that were not specific to fed funds trades, but rather

I am able to leverage the knowledge about fed funds payment identifiers because I have access to detailed data from the Fedwire[®] Funds Service (Fedwire), the payment system used by banks to settle their fed funds obligations.¹¹ I observe all the payments flowing into and out of these banks over Fedwire as well as the messaging attached to them. By combing through the message fields on payments received by these three banks, I observe one of the settlement legs of each bank’s fed funds trades.

Observing a settlement leg provides information on the amount of fed funds activity entered into by a bank, as well as information about the counterparty to the trade. Both legs of the trade, however, are needed to compute interest rates. To find the other settlement leg in the payments data, I use an algorithm. The details are described in Appendix A, but the algorithm essentially finds a payment between the same two counterparties with the correct timing and where the amount transferred implies a reasonable interest rate. Because one payment leg of the fed funds trade is already identified from the payments flow, finding the matching payment is fairly straightforward. Indeed, in the vast majority of cases there was a unique payment in the data satisfying these constraints. In Appendix A, I report the various ways in which I verified the performance of the algorithm.

The output from the algorithm is pairs of payments, or trades, that describe the rates and quantities of fed funds sold and purchased by the three large banks from January 2006 to December 2008. For each fed funds trade, I know the principal amount, the interest rate, and, with some degree of confidence, the counterparty to the three banks.¹²

The sample contains 128,677 trades, whose principal amounts sum to more than \$10

incorporated payments related to a broader set of financial activity. Such identifiers are not useful for the analysis presented in this paper, which focuses exclusively on fed funds.

¹¹Fedwire is a large-value real-time payments settlement service operated by the Federal Reserve. There is another high-value payments system in the U.S., the Clearing House Interbank Payments System (CHIPS). In discussion with the back office employees of these three banks, each stated that the Fedwire Funds payment system was almost exclusively used to transfer fed funds-related payments.

¹²The output analyzed is similar to that used in Armantier and Copeland (2015). Differences are that this paper includes fed funds trades from two banks used in Armantier and Copeland as well as a third bank. Further, this paper implements a slightly more sophisticated algorithm to find the matching payment and considers a different period of time.

Table 1: Summary Statistics on Principal and Rates

Variable		Mean	SD	Percentiles		
				25th	50th	75th
Principal	(\$ millions)	82.8	20.9	6	16.0	50
Spread of fed funds sold	(basis points)	10.5	33.5	0.0	12.5	25
Spread of fed funds purchased	(basis points)	-12.6	30.1	-12	-6.2	-2

Note: SD is standard deviation and the spreads are computed relative to the FOMC target rate.

Source: Fedwire Funds Service and author’s calculations.

trillion. The median principal amount is \$16 million, and the 25th and 75th percentiles of the distribution are \$6 and \$50 million, respectively (see the summary statistics in Table 1). The distribution of principal amounts is heavily skewed by some large transactions, evidenced by the mean principal amount of \$82.8 million. Because fed funds rates closely track the FOMC target rate, which increased in the beginning of the sample and then decreased at the end, it is useful to report fed funds rates as a spread to the FOMC target rate.¹³ In the sample, the median rate of the spread of fed funds sold is 12.5 basis points and the median rate of the spread of fed funds purchased rate is -6.2 basis points. Illustrating the intermediary role played by these banks, three-quarters of the rates of fed funds sold are above the FOMC target rate and more than three-quarters of the spread of fed funds are below the target rate.

2.3 Data Analysis

I begin with an analysis of rates on fed funds sold and purchased by the three large banks. To more clearly differentiate these banks from their counterparties, for the remainder of the paper I will refer to the three banks as intermediaries. To preserve their anonymity, I analyze the data at a daily frequency and aggregate across all three in-

¹³Starting on December 16, 2008, the FOMC switched from announcing a rate as a target, to a range of rates. The range from December 16 to the end of the sample is [0,25] basis points. I use 25 basis points as the target rate in the spread calculations.

intermediaries.¹⁴ I plot the principal-weighted average daily rate for fed funds sold and purchased by the intermediaries in Figure 1.

As expected, these rates closely track the target rate announced by the FOMC. Further, the intermediaries earn a spread in that the average daily rate of fed funds purchased is below the target rate whereas the daily average rate for fed funds sold is above the target, in general. Strikingly, this spread is a fairly constant 11 basis points until the start of the 2007-09 financial crisis, independent of the level of the FOMC's target rate. With the start of the crisis (August 1, 2007) this spread jumps up by 15 basis points to 26 basis points. This increase in the difference between fed funds sold and purchased is illustrated in Figure 2, which is a scatterplot of the rates as a spread from the FOMC's target rate and includes a smoothed line. A further increase in the difference between the rates of fed funds sold and purchased occurs after the bankruptcy of Lehman Brothers on September 15, 2008. In the period from September 15 to October 7, the average spread is an astounding 118 basis points. Finally, the introduction of IOER on October 8, leads to a dramatic fall in this spread, mainly driven by an increase in the rate of fed funds purchased, which rapidly ticks up to zero at the close of 2008.

The increase in the difference between the rates of fed funds sold and purchased with the crisis was not symmetric relative to the FOMC target rate. Rather, this increase is driven largely by an increase in the absolute difference between the rates of fed funds purchased and the FOMC target rate. This difference averages -4 basis points in the pre-crisis period and -19 basis points in the emerging crisis period (see Table 2). In contrast, the difference between the rate of fed funds sold and the FOMC target rate is 7 basis points in both the pre-crisis and the emerging crisis periods. Similarly, in the post-Lehman crisis period, the fed funds purchased rate is much farther from the FOMC target rate relative to the rate of fed funds sold.

I also observe the quantities of fed funds sold and purchased by the intermediaries. These three banks conducted a substantial amount of fed funds purchases and sales in

¹⁴Throughout the sample, each intermediary was active on both sides of the fed funds market. In addition, there were not substantial differences across the intermediaries in terms of rates. There are fed funds trades among the three bank intermediaries, but these account for less than 0.1 percent of total value. Because the rates of these trades are close to the rates of fed funds sold, I classify these trades as fed funds sold.

Figure 1: Fed Funds Rates for Sales and Purchases

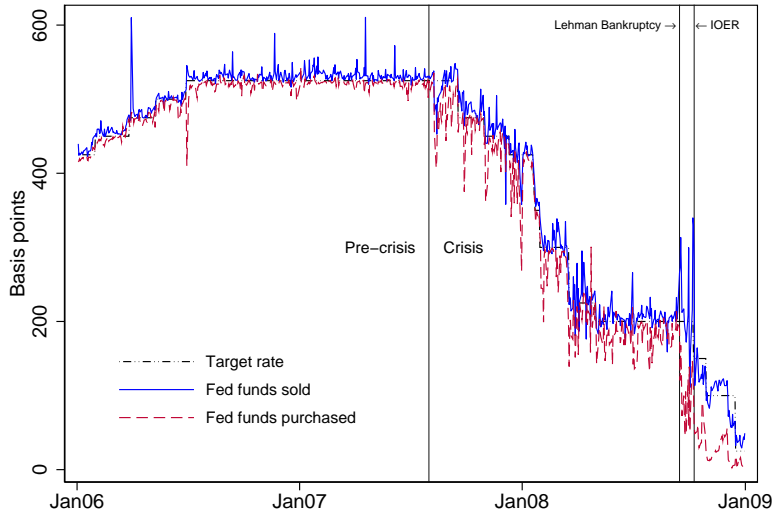
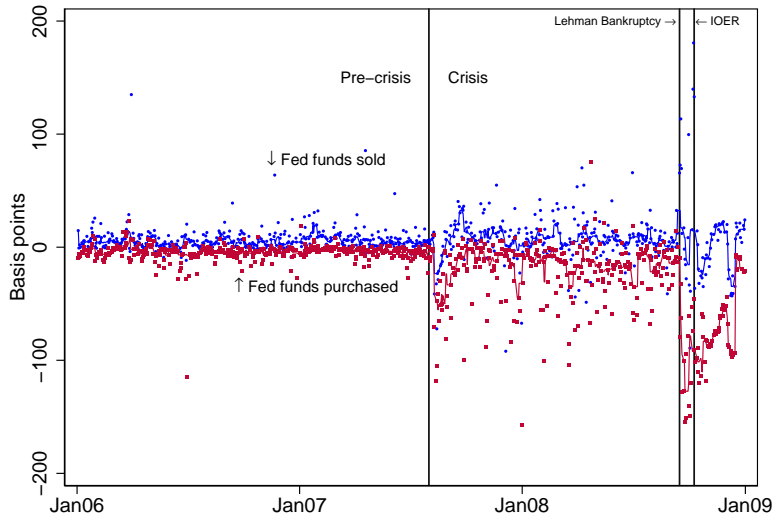


Figure 2: Fed Funds Rate Spreads for Sales and Purchases



Note: In Figure 2, the spreads are calculated with respect to the target rate announced by the Federal Open Market Committee. The vertical lines are set at: August 1, 2007, to denote the start of the crisis; September 15, 2008, the day Lehman Brothers declared bankruptcy; and October 8, 2008, when the Federal Reserve implemented its interest on excess reserves policy.

Source: Fedwire Funds Service and author's calculations.

Table 2: Fed Funds Rates Relative to the FOMC Target Rate, (basis points)

Rates	Pre-crisis period	Crisis period	
		Emerging	Post-Lehman
Fed funds sold	7	7	23
Fed funds purchased	-4	-19	-95
Difference	11	26	118

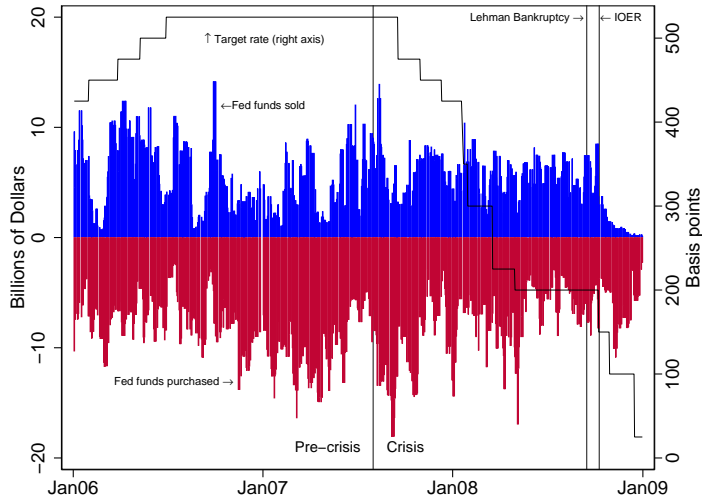
Note: FOMC is the Federal Open Market Committee, “Fed funds sold” is the rate of fed funds sold minus the FOMC target rate, “Fed funds purchased” is the rate of fed funds purchased minus the FOMC target rate. The pre-crisis period is from January 1, 2006 to July 31, 2007 and the crisis period is from August 1, 2007 to October 7, 2008. September 15, 2008 marks the end of the emerging crisis period and the beginning of the post-Lehman crisis period begins on September 15, 2008.

Source: Fedwire Funds Service and author’s calculations.

both the pre-crisis and crisis periods. With the introduction of IOER on October 8, 2008, the total value purchased and (especially) sold began trailing off (see Figure 3), reflecting a major change in the functioning of this market. Fed funds purchases do not equal sales for the three banks (either individually or collectively), because each is trading on its own position as well as acting as an intermediary. To arrive at a measure of activity intermediated, for each intermediary and each day, I compute the minimum of the total value of fed funds sold and fed funds purchased. Aggregating this value across all three banks each day provides me with a measure of the total intermediation activity. Strikingly, I find that this activity substantially increases with the arrival of the crisis. The average daily amount intermediated rises from \$1.9 billion in the pre-crisis period to \$2.7 billion in the emerging crisis period, an increase of 42 percent. After the Lehman Brothers bankruptcy, the average daily amount intermediated falls to \$2.1 billion, still above the level of activity measured in the pre-crisis period. As discussed in greater detail later in the paper, this increase in value is surprising given the fact that financial markets generally deteriorated during the financial crisis and so often exhibited less trading activity.

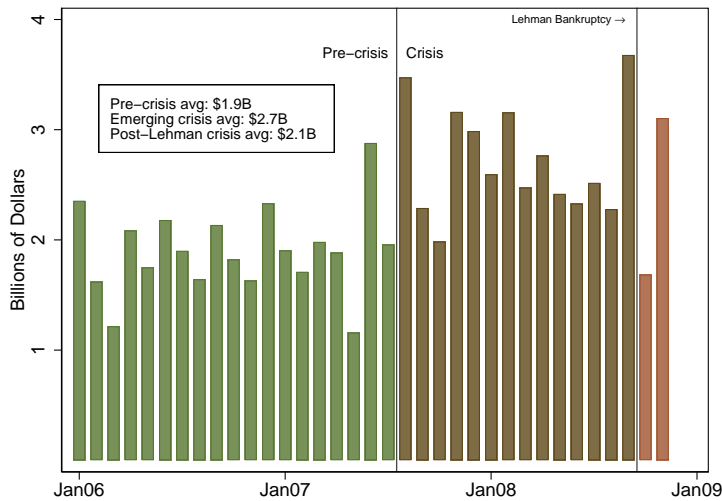
Finally, I analyze the counterparties of each of the intermediaries. The method I used to identify trades relies upon payments data and as a result the identity of the fed funds

Figure 3: Quantities of Fed Funds Sold and Purchased by Intermediaries



Note: For illustrative purposes, fed funds purchased are negative numbers. The scale for the Federal Open Market Committee target rate is on the right axis. The vertical lines are set at: August 1, 2007, to denote the start of the crisis; September 15, 2008, the day Lehman Brothers declared bankruptcy; and October 8, 2008, when the Federal Reserve implemented its interest on excess reserves policy. Source: Fedwire Funds Service and author’s calculations.

Figure 4: Average Daily Quantity Intermediated by Period and Month



Note: The vertical lines are set at August 1, 2007, to denote as the start of the crisis and September 15, 2008, the day Lehman Brothers declared bankruptcy. The numbers in the box are the average daily amounts intermediated by period. Source: Fedwire Funds Service and author’s calculations.

counterparty can be obscured. This is because a bank can use another bank to settle its fed funds obligations. Consequently, observing a payment flow from bank A to bank B does not necessarily mean that either bank is the true counterparty to the transfer; rather, customers of either bank could be the true counterparties. Because of the unique identifiers, I know one of the three intermediaries is a counterparty—but I cannot be sure whether the other bank is indeed the true counterparty or is instead acting as a correspondent bank for another bank.¹⁵ Based on conversations with banks' back-office employees however, if a bank decides to use another bank to settle its fed funds activity, it will use only that bank to ensure operational efficiency and simplicity. In the analysis below, I assume that banks will only use one correspondent bank.

I first consider how concentrated are the counterparties to which the intermediaries purchase and sell fed funds. There are a total of 515 banks selling and purchasing fed funds from the three intermediaries and on neither side of the market is there much concentration in counterparties.¹⁶ The largest counterparty for fed funds purchased accounts for 11.1 percent of total activity and for fed funds sold the largest counterparty has a share of 11.4 percent of total activity. The top five counterparties account for 27.8 and 39.3 percent of fed funds purchased and sold, respectively. Further, these concentration measures are likely inflated because the largest counterparties are large banks themselves, and so likely to be settling fed funds trades on behalf of a number of other banks.¹⁷

I then measure whether the counterparties to the intermediaries both sell and purchase fed funds. Over the whole sample counterparties shift between buying and selling fed funds. Only 15 percent of total fed funds activity involves counterparties that only sell or only purchase fed funds over the entire sample. This result lines up with the perception that banks' liquidity needs change from day to day depending on the rest of

¹⁵In general, my understanding is that small banks and foreign banking organizations are more likely to use a correspondent bank for fed funds activity.

¹⁶515 is a lower bound because this count includes correspondent banks that may be settling fed funds on behalf of multiple banks.

¹⁷If bank A settles fed funds trades on behalf of clients, then bank A's role is limited to settlement. In particular, bank A is not involved in negotiating the terms of trade. Being a large correspondent bank, then, does not imply that the bank has market power.

their business (Allen and Gale, 2000). That said, on a given day the vast majority of counterparties only show up on one side of the market. Specifically, 88 percent of total value involves counterparties that either only sell or only purchase fed funds on a given day. Further, this result could be considered a lower bound, since of the 12 percent of banks that are on both sides of the market on the same day, 70 percent are accounted for by several large banks that are known to settle payments activity on behalf of other banks. However, this result should be considered with caution, because banks may be entering into fed funds trades with entities that are outside the limited sample of trades analyzed in this paper.

Finally, I consider whether the change in the fed funds market associated with the start of the crisis can be traced to a change in the composition of the intermediaries' counterparties. I find that the composition of counterparties is little changed from pre-crisis to crisis. Indeed, 88 percent of the counterparties active in the crisis period are also active in the year before the start of the crisis period.¹⁸

With these stylized facts in mind, let us turn to describing the empirical model.

3 Empirical Model

In this section I describe the model of the fed funds market. After describing the environment, I detail the lenders', borrowers', and intermediary's problem, and define an equilibrium.

3.1 Environment

There is a single period and three types of agents: borrowers, lenders, and an intermediary. There are two markets—an over-the-counter market with search where lenders and borrowers trade, and an intermediated market where lenders and borrowers trade with the intermediary.

There is a set B of borrowers, where borrowers are defined as banks that have a project that requires funding. Borrowers default on their obligations with an exogenous

¹⁸Using crisis period activity as a weight raises this statistic to 98 percent.

probability, where the default probability depends on a borrower's type. A borrower can be normal (N) or risky (R), where a normal borrower's default probability is π_N and a risky one's is π_R , such that $0 < \pi_N < \pi_R < 1$. To avoid questions about whether borrowers can signal their type, I assume that borrowers do not know their type when contracting with lenders or the intermediary.¹⁹

There is a set L of lenders, where each lender can invest an amount $Q > 0$. A lender can either invest in a borrower or invest in the intermediary. A lender does not observe a borrower's type, but knows the distribution of types. The lender, then, faces a classic adverse selection problem when directly facing a borrower in the over-the-counter market. In contrast, the intermediary will not default on the lender. Finally, a lender $l \in L$ earns a deterministic lender-specific rate of return $r_{l0} > 0$ on cash not invested in a borrowing bank or the intermediary, an option that captures investors' outside investment opportunities. This return has two parts, $r_{l0} = r_0 + \varepsilon_l$, where r_0 is a component common to all lenders and ε_l is an idiosyncratic component. Let ε_l be a random variable distributed on \mathbb{R}_+ so that $r_{l0} > r_0 \forall l$. This differentiation in the lender's outside return is motivated by the heterogeneity across banks in outside investment opportunities. Because lenders only differ in this outside return, l indexes both lenders and their outside option.

The intermediary seeks to purchase funds from lenders and sell funds to borrowers. The intermediary has access to additional information that enables it to better distinguish between the two types of borrowers, albeit not perfectly. As a consequence, the set of borrowers the intermediary faces is a subset of all borrowers, $\bar{B} \subset B$, where the proportion of risky borrowers in this subset is less than the proportion in B . As a result, the intermediary, relative to lenders, faces a less severe degree of adverse selection when investing with borrowers.²⁰ (This informational advantage provides motivation for the existence of the intermediary.) I assume the intermediary's business model is such that there is no default risk to the lenders. The intermediary, like lenders, can invest in an outside option where its return is equal to r_0 , the common component of lenders' outside option.

¹⁹Prescott and Townsend (1984) details how signaling opportunities can lead to a problems related to nonoptimality of an equilibrium, multiple equilibria, or nonexistence.

²⁰ \bar{B} can be interpreted as a network of borrowers maintained by the intermediary.

The timing of the model is that the intermediary announces a rate r_p at which it will borrow from lenders and a rate r_s at which it will invest in borrowers. Lenders and borrowers observe this pair of rates and decide to either directly trade with one another or with the intermediary.

3.2 Lenders

Lenders have the choice of investing in the intermediary or directly lending to borrowers. Given r_p and the outside option r_{l0} , a lender's profits from investing in the intermediary are given by

$$p_i(r_{l0}, r_p) = \max_{q_p} \{r_p q_p + (Q - q_p)r_{l0}\}, \quad (1)$$

where $Q - q_p \geq 0$ and the subscript i denotes that this is the case of lending to the intermediary. This problem is linear and therefore lenders will decide to invest either Q or 0 with the intermediary.

If a lender chooses not to invest with the intermediary, the lender is matched with a borrower with probability $m_l(r_p, r_s)$ and faces the expected probability of default $\pi_d(r_p, r_s)$. (The l subscript denotes that this is the matching probability of the lender and the d subscript denotes that this is the direct lending case.) Both the matching function and beliefs about default depend upon the intermediary's pricing, because those rates determine the set of lenders and borrowers that are active in the direct lending case. Let $L(r_p, r_s) \subseteq L$ and $B(r_p, r_s) \subseteq \bar{B}$ denote the set of lenders and borrowers respectively, that chose to trade with the intermediary given the pair of rates (r_p, r_s) . The complements of these sets then define the lenders and borrowers that trade directly with one another in the over-the-counter market.

The lenders' matching function is based on the relative proportion of borrowers to lenders that chose the direct lending route,

$$m_l(r_p, r_s) = \min \left(\frac{\int_{b \in B \setminus B(r_p, r_s)} g(b) db}{\int_{l \in L \setminus L(r_p, r_s)} f(l) dl}, 1 \right), \quad (2)$$

where g and f denote the distribution of borrowers' types and lenders, respectively. The

expected default risk faced by lenders is

$$\pi_d(r_p, r_s) = \pi_R \int_{b \in B \setminus B(r_p, r_s)} \mathbf{1}_{\{\theta(b)=R\}} g(b) db + \pi_N \int_{b \in B \setminus B(r_p, r_s)} \mathbf{1}_{\{\theta(b)=N\}} g(b) db, \quad (3)$$

where $\theta(b) \in \{N, R\}$ denotes the borrower's type and $\mathbf{1}_{x=y}$ is an indicator function equal to 1 if $x = y$.

If the lender chooses the direct route and is matched with a borrower, the lender offers a rate r_d and the borrower chooses how much to borrow. Hence, for a pair (r_p, r_s) , a lender l expects profits from the direct case to be

$$p_d(r_{l0}; r_p, r_s) = (1 - m_l(r_p, r_s)) \cdot Q r_{l0} + m_l(r_p, r_s) \cdot \max_{r_d} \left\{ (1 - \pi_d(r_p, r_s)) r_d q_d(r_d) - \pi_d(r_p, r_s) q_d(r_d) + (Q - q_d(r_d)) r_{l0} \right\}, \quad (4)$$

where $q_d(r_d)$ denotes a borrower's demand for funds given a rate r_d and $Q - q_d(r_d) \geq 0$. The first term in the above problem shows the return to the lender when there is no match with a borrower, and as a result the lender invests Q in his outside option. The second term describes the return when there is a match with a borrower. The borrower's demand for funds given a rate r_d does not depend on the borrower's (unobserved) type, a result shown in the next subsection. To simplify the analysis and rule out corner solutions to the direct lending case, I assume that Q is large enough such that $Q > q_d$. Turning to the first order condition for the direct lending case, we have,

$$\frac{dq_d}{dr_d} [(1 - \pi_d(r_p, r_s)) r_d - \pi_d(r_p, r_s) - r_{l0}] + q_d(r_d) (1 - \pi_d(r_p, r_s)) = 0.$$

Because the lenders have different outside options, the interest rate offered by a lender will depend upon r_{l0} . Furthermore, a lender's expected profit in the direct lending case is increasing in r_{l0} , a result driven by the assumption that Q is large enough such that lenders invest some of their cash in the safe asset and earn r_{l0} .

Putting the intermediary and direct lending cases together, the lender's profit maximization problem is, given (r_p, r_s) and r_{l0} ,

$$\Pi_l(r_{l0}; r_p, r_s) = \max \{ p_i(r_{l0}, r_p), p_d(r_{l0}; r_p, r_s) \}. \quad (5)$$

3.3 Borrowers

Borrowers are banks with projects that require funding. Denoting $q > 0$ as the amount borrowed, the return on the borrower's project is given by $Y(q)$, where Y is increasing and concave. In addition to being either a risky or safe type, borrowers differ in whether or not they are in \bar{B} (i.e., the intermediary's network). Borrowers in \bar{B} have the choice of borrowing from the intermediary or borrowing directly from a lender, whereas borrowers in the complement of \bar{B} can only borrow directly from lenders. If a borrower chooses to try to borrow directly from a lender, the borrower will be matched with a lender with probability $m_b(r_p, r_s)$ and knows that the set of lenders choosing the direct route is $L \setminus L(r_p, r_s)$. (The subscript b denotes that the matching function is for borrowers.) The matching function for borrowers is driven by the relative proportion of borrowers and lenders active in the direct lending route, and so is defined as

$$m_b(r_p, r_s) = \min \left(\frac{\int_{l \in L \setminus L(r_p, r_s)} f(l) dl}{\int_{b \in B \setminus B(r_p, r_s)} g(b) db}, 1 \right). \quad (6)$$

We begin by describing the profit maximization problem for those borrowers in \bar{B} . If the borrower of type $\theta \in \{N, R\}$ chooses to borrow from the intermediary, then given a r_s , she maximizes expected profits by choosing a quantity to borrow:

$$h(r_s, \theta) = \max_q \{(1 - \pi_\theta) (Y(q) - r_s q)\}. \quad (7)$$

Note that upon default the borrower earns zero profit. The resulting first order condition is

$$\frac{dY}{dq} - r_s = 0. \quad (8)$$

Because the first order condition does not depend on the borrower's default probability, a borrower's demand for funds is independent of type.

If a borrower eschews the intermediary and chooses to borrow directly from a lender, then she is matched with a lender with probability $m_b(r_p, r_s)$ and that lender is drawn from $L \setminus L(r_p, r_s)$. If the borrower is not matched with a lender, then she earns zero profits. As a result, expected profits are given by

$$h_d(r_p, r_s; \theta) = (1 - m_b(r_p, r_s)) \cdot 0 + m_b(r_p, r_s) E_{l \in L \setminus L(r_p, r_s)} [h(r_d(r_{l0}), \theta)], \quad (9)$$

where $r_d(r_{l0})$ is the rate a lender r_{l0} will offer in the direct lending case. Putting this together, a borrower $b \in \bar{B}$ has expected profits of

$$\Pi_{b \in \bar{B}}(r_p, r_s, \theta) = \max \{h(r_s; \theta), h_d(r_p, r_s; \theta)\}. \quad (10)$$

A borrower in the complement of \bar{B} can only borrow directly from lenders, and as a result her expected profit is

$$\Pi_{b \in B \setminus \bar{B}}(r_p, r_s, \theta) = h_d(r_p, r_s; \theta). \quad (11)$$

3.4 Intermediary

Last, we turn to the intermediary's problem. As mentioned above, the intermediary offers all lenders a rate r_p at which the intermediary will purchase fed funds and offers borrowers $b \in \bar{B}$ a rate r_s at which the intermediary will sell fed funds. The expected probability of default faced by the intermediary is given by

$$\pi_i(r_p, r_s) = \theta_R \int_{b \in B(r_p, r_s)} 1_{\{\theta(b)=R\}} g(b) db + \theta_N \int_{b \in B(r_p, r_s)} 1_{\{\theta(b)=N\}} g(b) db, \quad (12)$$

and note that by assumption $0 < \pi_i(r_p, r_s) < \pi_d(r_p, r_s) < 1$ for all (r_p, r_s) where $B(r_p, r_s) \neq \emptyset$.

The intermediary's problem is

$$\begin{aligned} \max_{r_s, r_p} \int_{b \in B(r_p, r_s)} & [(1 - \pi_i(r_p, r_s)) r_s q_s(r_s) - \pi_i(r_p, r_s) q_s(r_s)] g(b) db \\ & - \int_{l \in L} r_p q_p(r_p, l) f(l) dl \\ & + r_0 \left(\int_{l \in L} q_p(r_p, l) f(l) dl - \int_{b \in B(r_p, r_s)} q_s(r_s) g(b) db \right), \quad (13) \end{aligned}$$

where it must be the case that $\int_{l \in L} q_p(r_p, l) f(l) dl - \int_{b \in B(r_p, r_s)} q_s(r_s) g(b) db \geq 0$, or the intermediary borrows at least as much as it lends in aggregate.

The first term in the intermediary's problem is the expected return to investing in the borrowing banks, where the intermediary forms expectations over the default rate. The second term is the cost of raising funds from the lending banks, which differ in the value of their outside investment options. Finally, the third term captures the fact that any funds that the intermediary borrows but does not lend will earn r_0 .

3.5 Equilibrium and Solving the Model

An equilibrium is given by the interest rates (r_p^*, r_s^*) and quantities $(\{q_p^*(l)\}_{l \in L(r_p^*, r_s^*)}, q_s^*)$ in the intermediated market as well as the expected interest rates and quantities, $\{r_d^*(r_{l0}), q_d^*(l)\}_{l \in L \setminus L(r_p^*, r_s^*)}$ in the over-the-counter market such that

- The intermediary's profit is maximized,
- All lenders and borrowers maximize their expected profits,
- The market clearing condition is satisfied, such that the intermediary purchases at least as much funds as it sells, and
- Both lenders' and borrowers' beliefs about matching probabilities and default rates are rational.

Solving the model can be simplified by reducing the number of control variables in the intermediary's problem from two to one. Because lenders require a rate of return greater than r_0 to invest with the intermediary, whereas the intermediary can only earn r_0 on any excess cash it holds, the intermediary will always choose a pair of rates such that the market clearing condition holds exactly. This implies r_p can be written as a function of r_s , where r_p is chosen so that the intermediary borrows an amount exactly equal to what it lends. In addition, borrowers are homogenous in their actions and so either all the borrowers in \bar{B} will trade with the intermediary or none will. I focus on the interesting case where the intermediary is active and so consider parameters whereby $B(r_p, r_s) = \bar{B}$ and so $\pi_i(r_p, r_s)$ is a constant, denoted as $\tilde{\pi}_i$. Folding these results into the intermediary's problem gives us

$$\max_{r_s} \left\{ \tilde{\pi}_i r_s q_s(r_s) - \tilde{\pi}_i q_s(r_s) - \int_{l \in L} \tilde{r}_p(r_s) q_p(\tilde{r}_p(r_s), l) f(l) dl \right\},$$

where r_p is now explicitly a function of r_s .

The problem is further simplified by using the result that lenders only invest Q or 0 with the intermediary and that expected profits from directly lending are increasing in l (recall that f has support on \mathbb{R}_+). As a result, for a given (r_p, r_s) there is a cutoff lender \hat{l} that is exactly indifferent between investing in the intermediary and investing

directly with a borrower. Lenders whose $l < \hat{l}$ (and so $r_{l0} < r_{i0}$) will invest Q in the intermediary, whereas all other lenders eschew the intermediary and lend directly with borrowers. Letting \hat{l} depend directly upon r_s , these results imply that the set $L(\tilde{r}_p(r_s), r_s)$ is equal to the interval $[0, \hat{l}(r_s)]$, and so the intermediary's problem further simplifies to

$$\max_{r_s} \left\{ \tilde{\pi}_i r_s q_s(r_s) - \tilde{\pi}_i q_s(r_s) - \tilde{r}_p(r_s) Q \int_0^{\hat{l}(r_s)} f(l) dl \right\}.$$

4 Empirical Work

In this section I detail how the model is taken to the data. The model's focus is to explain the observed rates of fed funds sold and purchased over time as well as the change in the total amount intermediated, as described earlier in Section 2. I then present and discuss the results.

4.1 Specification

To estimate the model, I need to make functional form assumptions about the return to borrowing and the distribution of lenders' outside option. In addition, parameters need to be time-varying to allow the model to capture the rise and fall in rates. As illustrated in the data section, a main driver of rates appears to be monetary policy and so I incorporate the target rate announced by the FOMC, denoted as \hat{r}_{ft} , into the model.²¹

I assume that the return to borrowing at date t is given by

$$Y_t(q) = \beta_t q^\alpha, \tag{14}$$

where $\alpha \in (0, 1)$, $\beta_t = \hat{r}_{ft} \cdot \beta$, and $\beta > 0$. The borrower's return, then, is a function of the FOMC's target rate. Turning to lenders, I assume that f , the distribution of the idiosyncratic portion of their outside option, is uniformly distributed between 0 and μ . I also assume that the common component of the lender's outside option can vary over time, denoting $r_{0t} = \hat{r}_{ft} - \gamma$. The parameter γ measures the discount to the target rate

²¹The $\hat{}$ accent over a variable indicates it is exogenous to the model.

that lenders receive on their outside option. The total return of the outside option of lender l at date t is given by

$$r_{l0t} = \hat{r}_{ft} - \gamma + \varepsilon_{lt}, \quad (15)$$

where $\varepsilon \sim U(0, \mu)$. With these specification choices, I have both the lender's outside option and the borrower's return varying with the FOMC's target rate.²²

Although the model has four parameters related to the probability of default, what matters when solving the model is the unconditional probability of default in the over-the-counter direct lending case and in the intermediary's case. The data however, cover only the market with an intermediary and so I cannot identify both default rates. As a result, I estimate π_d , the unconditional default rate in the direct case, and assume that the intermediary's informational advantage halves the unconditional probability of default, or that $\pi_i = \frac{1}{2}\pi_d$. More significantly, I assume that this informational advantage does not change over the crisis. This assumption seems reasonable, as it is not clear why the intermediary banks's informational advantage over other banks in the fed funds market would be stronger or weaker in a financial crisis.

I allow three parameters to differ across the pre-crisis, emerging crisis, and post-Lehman crisis periods, to capture the three channels through which fed funds rates and quantities can change. The first channel is a change in the strength of asymmetric information, modelled as allowing π_d to vary across the three periods. A change in this parameter reflects changes to the proportion of risky borrowers among all borrowers with the arrival of the crisis. The second channel is a change to the supply of fed funds, which is captured by allowing the common component of the value of lenders' outside option (γ) to vary across the three periods. Finally, the third channel is a change in the demand for funds, captured by allowing variation to the linear return to borrowing, β . Consequently, I estimate $\{\bar{\pi}^P, \bar{\pi}^E, \bar{\pi}^L, \gamma^P, \gamma^E, \gamma^L, \beta^P, \beta^E, \beta^L, \alpha\}$, where the superscripts, $\{P, E, L\}$ denote the pre-crisis, emerging crisis and post-Lehman crisis periods, respectively.

²²This specification captures the results of more general models where the Federal Reserve changes aggregate reserves through open market operations, and as a consequence both fed funds rates and other interest rates in the economy rise or fall through the usual monetary policy channels.

Four other parameters in the model are fixed. The total mass of borrowers, \mathbb{B} , is 2 and the mass of borrowers eligible to borrow from the intermediary, \bar{B} is 1. The maximum amount a lender has available to invest, Q , is 2 and the parameter denoting the right endpoint of the uniform distribution characterizing lender types, μ , is fixed to 0.001. These parameters were chosen with the aim of ensuring that there is an interior solution to the borrower’s and lender’s problem in the over-the-counter direct case and that market clearing was feasible.

4.2 Estimation Method and Identification

The estimation approach is generalized method of moments. I choose this approach because the time-series variation in the model is driven by changes to the FOMC’s target rate and as a result, the model is suited to explaining moments of the data conditional on a target rate. In the pre-crisis period there are four changes to the FOMC target rate (see Figure 1), and, because the target rate only increases over this time, five interest rate regimes. In the crisis period, the FOMC target rate declines and there are nine interest rate regimes (eight regimes in the emerging period and one in the post-Lehman period).

The moments used are average interest rates in each regime in the pre-crisis period and the two crisis periods. For each interest rate regime, I compute (i) the value-weighted average rate of fed funds sold, (ii) the value-weighted average rate of fed funds purchased, and (iii) the difference between the value-weighted average rates of fed funds sold and purchased. In addition to these rate-focused statistics, I compute the average quantity of fed funds intermediated in each period and use the percent change in this amount between (a) the pre-crisis and emerging crisis period and (b) the pre-crisis and post-Lehman period as another 2 moments (see Figure 4 for average daily quantities intermediated in each period). Denote these data moments $\hat{\omega}$.

For a given parameter vector ζ and vector of FOMC target rates $\{\hat{r}_{ft}\}_{t=1}^{14}$, the model will generate interest rates of fed funds sold and purchased for the intermediary case as well as the total amount intermediated. I use these predicted rates and the change in the quantity intermediated across the periods to construct a vector of model moments, $\omega(\zeta)$. My estimation strategy is then to choose ζ so as to minimize the distance between

$\hat{\omega}$ and $\omega(\zeta)$. Formally, I minimize $\Lambda(\zeta)$, defined as

$$\Lambda(\zeta) = (\omega(\zeta) - \hat{\omega})'W(\omega(\zeta) - \hat{\omega}), \quad (16)$$

where W is a weighting matrix.²³

The parameters from both the lenders' and the borrowers' problem are identified because of the availability of data from before and during the crisis, on the rates of fed funds sold and purchased, as well as the total quantity intermediated. Whereas the parameters of the lenders' problem primarily impact the rate of fed funds purchased and the parameters of the borrowers' problem primarily impact the rate of fed funds sold, in equilibrium these parameters affect both the rates and the total quantity intermediated. Identifying these parameters is difficult then, when limited to using data where rates and quantities are fairly constant. Fortunately, the data used in the paper incorporate the arrival of the crisis, whereupon there were significant changes to rates and quantities. This allows for identification, because the theory predicts that changes to each parameter has different effects on rates and quantities. For example, a decrease in the lender's outside option both lowers the rates of fed funds sold and purchased and increases the quantity intermediated, whereas an increase in the default probability increases the spread between the rates of fed funds sold and purchased and decreases the quantity intermediated. These differences in how changes in the parameters affect rates and quantities allows for identification.

4.3 Goodness of Fit

Before reporting the parameter results, I consider the model's goodness of fit. Averages of the data moments by period are listed in the upper panel of table 3. The corresponding averages predicted by the model given the estimated parameters are listed in the lower panel of the same table. Comparing the results across the panels, we observe

²³I use the standard two-step approach to estimate the model's parameters. In the first step W is set to the identity matrix and a consistent estimate of the parameters, ζ^1 is obtained. In the second step, I first use ζ^1 to construct a new weighting matrix, which is an diagonal matrix where the diagonal elements are equal to the inverse of $(\omega(\zeta^1) - \hat{\omega})^2$. Using this new weighting matrix, I obtain new estimates of the parameters and calculate their associated standard errors.

Table 3: Goodness-of-Fit Statistics

Variable		Pre-Crisis Period	Crisis Periods	
			Emerging	Post-Lehman
Data	Fed funds sales (basis points)	6.7	7.3	23.3
	Fed funds purchases (basis points)	-4.0	-19.0	-95.1
	Intermediary's spread (basis points)	10.7	26.3	118.4
	Change in quantity (percent)	–	41.7	11.0
Model	Fed funds sales (basis points)	7.7	7.9	20.8
	Fed funds purchases (basis points)	-3.5	-17.5	-98.7
	Intermediary's spread (basis points)	11.2	25.5	119.5
	Change in quantity (percent)	–	41.0	8.5

Note: Data means the reported statistics are based on data, whereas Model means the reported statistics are based on predictions from the model given the estimated parameters. Rates are reported as a spread to the FOMC target rate. Change in quantity is the percent change in quantity intermediated relative to the pre-crisis period.

Source: Fedwire Funds Service and author's calculations.

that the model's rate predictions are quite close to those observed in the data. This is exemplified by the fact that the average intermediary's predicted spread for each period is only 0.5, 0.8, and 1.1 basis points away from the observed averages. The model's goodness-of-fit is illustrated in more detail in Appendix C, with charts showing the predicted and observed rates by interest rate regime for the pre-crisis and crisis periods.

With regard to quantity, the model accurately predicts a substantial 41 percent increase in the quantity of funds intermediated from the pre-crisis period to the emerging crisis period. The model slightly under-predicts the amount intermediated in the post-Lehman period, reporting an 8.5 percent increase relative to the pre-crisis period, below the observed 11.0 percent increase.

Table 4: Parameter Estimates

Parameter		Estimate	SE	Confidence Interval	
<i>Lenders</i>					
Return to outside option (basis points)					
	Pre-crisis	γ^P	6.28	0.31	(5.68, 6.88)
	Emerging crisis	γ^E	19.88	0.51	(18.88, 20.89)
	Post-Lehman crisis	γ^L	100.43	0.04	(100.36, 100.51)
<i>Borrowers</i>					
Nonlinear return to borrowing		α	0.9843	0.0007	(0.9828, 0.9857)
Linear return to borrowing					
	Pre-crisis	β^P	1.0139	0.0004	(1.0130, 1.0147)
	Emerging crisis	β^E	1.0248	0.0012	(1.0225, 1.0272)
	Post-Lehman crisis	β^L	1.1029	0.0002	(1.1025, 1.1033)
Probability of default (percent)					
	Pre-crisis	$\bar{\pi}^P$	0.0430	0.0029	(0.0374, 0.0486)
	Emerging crisis	$\bar{\pi}^E$	0.3334	0.0044	(0.3249, 0.3420)
	Post-Lehman crisis	$\bar{\pi}^L$	2.2401	0.0009	(2.2383, 2.2419)

Note: SE is standard error. Confidence Interval is a 95 percent confidence interval.

Source: Author's calculations.

4.4 Results

Now that we have confidence in the model's goodness of fit, I report the parameter estimates in Table 4, all of which are precisely estimated. Starting with the lenders' problem, the estimates imply that the common component of the return on the lender's outside option is decreasing over the three periods. Recall that γ captures the discount to the FOMC target rate that lenders earn ($r_{0t} = \hat{r}_{ft} - \gamma$) and is the main parameter driving the model's prediction of the rate of fed funds sold. In the pre-crisis period, this return is estimated to be 6.3 basis points below the target rate. This discount more than triples to 19.9 basis points in the emerging crisis period and then rockets up to 100 basis

points in the post-Lehman crisis period. These estimates imply that lenders' alternative to lending cash in the fed funds market became increasingly unattractive, reflecting the turmoil found in other financial markets over this time.

Turning to borrowers, I estimate that the nonlinear return to borrowing is quite close to 1. The estimates of the linear return to borrowing imply there is an increase to borrowing fed funds with the crisis. The increase in this return from the pre-crisis to emerging crisis period is small, at 1.1 percent. However, the return jumps up in the post-Lehman period to 1.103, an 8.8 percent increase from the pre-crisis period. This change reflects a rise in demand for fed funds, a natural response given the fall in funding liquidity available in financial markets shortly after the bankruptcy of Lehman Brothers.

Finally, the estimates imply that the unconditional probability of default dramatically increases with the crisis. In the pre-crisis period, the estimate implies that the default probability is a tiny 0.04 percent.²⁴ In the emerging crisis period, the default probability increases almost 0.3 percentage point, to 0.33 percent. Finally, in the post-Lehman period the default probability jumps up to 2.24 percent, a massive increase relative to the pre-crisis period.

5 Analysis

In this section I present several counterfactuals that illustrate the quantitative importance of the estimated parameter changes, and then discuss the importance of these results.

5.1 Counterfactuals

The estimated parameters imply that with the arrival of the crisis, there were three fundamental changes in the fed funds market: the return to lenders' outside option decreased, borrowers' return to purchasing fed funds increased, and the default probability

²⁴This is the unconditional probability of default that a lender faces in the direct lending case. The intermediary, because of superior information, faces a set of borrowers where the unconditional probability of default is one-half of the value faced by lenders. Therefore, in the pre-crisis period the default probability faced by the intermediary is 0.02 percent.

increased. To gauge how each of these changes affected rates and quantities in the fed funds market, I conduct four counterfactual exercises focused on the emerging crisis period. The first exercise, “No Change”, considers what would happen to prices and quantities in the emerging crisis period if parameters remained at their pre-crisis levels (and the FOMC target rate decreased as it did in the data), and so serves as a point of reference. The second, third, and fourth counterfactuals explore how changes in lenders’ outside option (a.k.a. supply), in borrowers’ return to purchasing fed funds (a.k.a. demand) and the unconditional default probability (a.k.a. adverse selection), respectively, affect rates and quantities holding all other parameters at their pre-crisis level.²⁵

Beginning with the “No Change” counterfactual, the model predicts that with parameters at their pre-crisis levels, the fall in the FOMC rate would result in the spread between the rates of fed funds sold and purchased narrowing to 9.6 basis points, relative to the pre-crisis period when the spread was 11.2 basis points. Further, there is an uptick in quantity traded of 1.2 percent relative to the pre-crisis period (see the third column of Table 5).

The “Supply” counterfactual demonstrates how a 13.6 basis point decrease in the return to lenders’ outside option, holding all over parameters at their pre-crisis levels, affects fed funds rates and quantities. Under this positive supply shock scenario, the rates for both fed funds sold and purchased shift down and the quantity of funds intermediated skyrockets up. The rates of fed funds sold and purchased decrease by roughly the same amount, leading to only a small contraction in the intermediary’s spread relative to the spread predicted in the “No Change” exercise (8.1 versus 9.6 basis points).

The rate of fed funds purchased decreases because the intermediary recognizes that lenders’ return on their outside option has decreased, so lenders are willing to lend the same amount of fed funds at a lower rate. The intermediary lowers the rate of fed funds sold both because of the lower rates of fed funds purchased (i.e., the intermediary’s cost of acquiring funds has fallen) and because borrowers’ have the option of bypassing the intermediary and borrowing directly from lenders (which now have lower outside options) in the direct lending market. Perhaps the most telling result from this exercise is the

²⁵For each counterfactual, I solve the model given the average FOMC rate in the emerging crisis period.

Table 5: Counterfactual Results for the Emerging Crisis Period

Predicted Variables	Benchmark		Counterfactuals			
	Pre-Crisis	Crisis	No Change Crisis	Supply Crisis	Demand Crisis	Adv. Sel. Crisis
Fed funds sold (basis points)	7.7	7.9	5.9	-1.1	7.5	17.5
Fed funds purchased (basis points)	-3.5	-17.5	-3.7	-9.2	-2.2	-6.0
Intermediary's spread (basis points)	11.2	25.4	9.6	8.1	9.7	23.5
Change in quantity (percent)	-	41.0	1.2	237.8	53.6	-85.5

Note: The rates of fed funds sold and purchased are reported as a spread to the FOMC target rate. The intermediary's spread is equal to fed funds sold minus fed funds purchased and the change in quantity row shows the percent change in total quantity intermediated from the pre-crisis to the emerging crisis period. Benchmark columns shows the average of the predicted variable over the interest regimes in the pre-crisis and the emerging crisis periods, given the estimated parameters (the same numbers are reported in the first two columns on Table 3). The four counterfactuals show the same average for the emerging crisis period. In the No Change counterfactual all of the parameters are set to their pre-crisis levels; In the Supply counterfactual only the return to the lending bank's outside option changes from its pre-crisis level; in the Demand counterfactual only the linear return to borrowing changes from its pre-crisis level; and similarly, in the Adverse Selection counterfactual only the probability of default changes.
Source: Author's calculations.

large quantity change of 237.8 percent, a result demonstrating that lenders are willing to dramatically increase fed funds purchased given moderate changes to rates.

The “Demand” counterfactual illustrates the sensitivity of rates and quantities to a 1 percent increase in the linear return to borrowing. The impact of rates is subtle: relative to the “No Change” exercise, rates of fed funds sold and purchased are about 1.5 basis points higher. More striking is the 53.6 percent increase in quantity intermediated, which highlights an elastic supply of fed funds. This is most clearly seen by comparing the “Demand” and “No Change” exercises, two counterfactuals where the parameters of the lenders’ problem are the same. In the latter exercise, a fed funds purchased rate of -3.7 basis points (as a spread to the FOMC target rate) is associated with a 1.2 percent increase in quantity intermediated, whereas in the former exercise the rate is -2.2 basis points and the quantity intermediated is 53.6 percent. As a result, lenders are willing to vastly increase how much they lend, a 52.4 percentage point increase, given an increase of 1.5 basis points in rates.

Finally, in the “Adverse Selection” counterfactual the only parameter change is the estimated increase in the unconditional default probability to 0.33 percent (a 0.29 percentage point increase), and so focuses on the quantitative importance of the default probability. Under this scenario, the spread between the two fed funds rates widens to 23.6 basis points, driven mainly by an increase in the rate of fed funds sold. The intermediary increases the spread to offset the losses associated with the greater probability of default. In line with the increase in rates, the amount of quantity intermediated plummets to a level that is 85.5 percent smaller than the pre-crisis amount, a contraction that would likely be labelled a market freeze in practice.

The counterfactual exercises highlight that the changes to the supply of funds and the default rate are the main drivers of the changes to rates from the pre-crisis to the emerging crisis periods. The increase in the default rate is revealed to be the main force behind the observed widening of the intermediary’s spread. In contrast, the observed level of rates of fed funds sold and purchased are the result of offsetting forces from the increase in default probabilities and the supply of fed funds. Finally, the observed quantity intermediated in the emerging crisis period is driven by changes to all three channels, but the dominant force is the shifting out of the supply of fed funds.

5.2 Discussion

The predictions from the model fit the narrative of the crisis. With the start of the crisis in August 2007, market participants became more worried about the solvency of other participants, which in the fed funds markets materializes as an increase in the expected probability of default. Strikingly, if the increase in default had been the only change, the model predicts that the fed funds market would have experienced a severe contraction in quantity traded, perhaps even a market freeze. However, the data indicate that the market remained functional, and in fact the amount intermediated even expanded, a result that the model attributes to lenders finding other investment opportunities in the financial system to be less palatable.

The model predicts that these dynamics play out again in the post-Lehman period, but much more dramatically. Lenders become even more willing to sell fed funds, accepting a rate that is almost 100 basis points below the FOMC target rate, even while the expected default rate reaches 2.24 percent —a combination of forces that results in the intermediary earning a rate spread of over 119 basis points while still intermediating a greater quantity of funds than in the pre-crisis period.

Through the lens of the model, a crucial feature of the fed funds markets is that in times of stress, it is a relatively attractive place to invest cash overnight. Because of this, the market remains well-functioning even during the height of the 2007-09 crisis, the period of time right after the Lehman Brothers bankruptcy, when the model estimates there are sizeable increases in the expected default probability. This result on the relative attractiveness of fed funds has the flavor of those results that the banking system is a safe harbor for depositors during periods of market stress, given the protections of deposit insurances as well as the Federal Reserve's role as a lender of last resort.²⁶ The nuance here, is the model's prediction that banks were more willing to lend to one another in the fed funds market relative to other investment opportunities, such as, perhaps,

²⁶For example, Saidenberg and Strahan (1999), Gatev and Strahan (2006), and Gatev, Schuermann, and Strahan (2009) report that during periods of market stress, investors often deposited their funds within the banking system because it was viewed as a safe haven. Acharya and Mora (2015) examine whether banks continued to fulfill this role in the 2007-09 financial crisis, when banks were arguably at the center of the crisis. They report that investors did not see banks as a safe haven until the government implemented a number of interventions in the fall of 2008.

commercial paper or asset-backed commercial paper.

Since the model's results are based on a sample of three banks, these findings may not be generalizable to the entire fed funds market. It is possible that the actions of these three large banks, which continued to purchase and sell fed funds during the crisis are not representative of general activity in the fed funds market.

6 Conclusion

During the 2007-09 financial crisis, the U.S. fed funds market was closely watched because of its central role in the financial system. Interpreting changes to the rates and quantities of fed funds being traded, however, is empirically challenging because in addition to the usual forces of demand and supply, fed funds trades, being unsecured loans, are affected by changes in adverse selection.

To quantify the effect of each of these channels on the trading of fed funds, I develop, solve, and estimate a model of the market for fed funds, in which borrowers have an unobserved probability of default. The model estimates imply that with the arrival of the 2007-09 crisis, two major forces were at play: the expected default probability increased and lenders' supply of funds shifted outward. The model predicts that by itself, the increase in expected default would have caused severe disruptions to the fed funds market. However, the simultaneous increase in supply, perhaps reflecting lenders' perception that banks are relatively safe counterparties during the crisis, offset the adverse effects of the rise in expected default.

The results suggest two policy implications. First, policy makers should be aware that the fed funds market is susceptible to small changes in the expected probability of default. Hence, future adverse events which cause banks to become more prone to default are likely to have large negative effects on this market. Second, the fed funds market is considered to be a relatively safe place to invest cash by banks. Given a general adverse shock to the financial system then, policy markers can expect depository institutions to shift their cash investments towards the fed funds market.

References

- Abade, David, Juan Pedro Sánchez-Ballesta, and José Yagüe (2017), “The short-term debt choice under asymmetric information.” *SERIEs*, 8, 261–285.
- Acharya, Viral V. and Ouarda Merrouche (2013), “Precautionary hoarding of liquidity and inter-bank markets: Evidence from the sub-prime crisis.” *Review of Finance*, 17(1), 107–160.
- Acharya, Viral V. and Nada Mora (2015), “A crisis of banks as liquidity providers.” *Journal of Finance*, 70(1), 1–42.
- Afonso, Gara, Roc Armenter, and Benjamin Lester (2019), “A model of the federal funds market: Yesterday, today, and tomorrow.” *Review of Economic Dynamics; special issue on Fragmented Financial Markets*, 33, 177–204.
- Afonso, Gara, Anna Kovner, and Antoinette Schoar (2011), “Stressed, not frozen: The federal funds market in the financial crisis.” *Journal of Finance*, 66(4), 1109–1139.
- Allen, Franklin and Douglas Gale (2000), “Financial contagion.” *Journal of Political Economy*, 108(1), 1–33.
- Allen, Jason, Rob Clark, and Jean-François Houde (forthcoming), “Search frictions and market power in negotiated price markets.” *Journal of Political Economy*.
- Armantier, Olivier and Adam Copeland (2015), “Challenges in identifying interbank loans.” *Economic Policy Review*, 21(1), 1–18. Federal Reserve Bank of New York.
- Armenter, Roc and Benjamin Lester (2017), “Excess reserves and monetary policy implementation.” *Review of Economic Dynamics*, 23, 212–235.
- 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), 1–7.
- Biais, Bruno, Lawrence Glosten, and Chester Spatt (2002), “The microstructure of stock markets.” CEPR Discussion Paper No. 3288.

- Bolton, Patrick, Xavier Freixas, Leonardo Gambacorta, and Paolo Mistrulli (2016), “Relationship and transaction lending in a crisis.” *Review of Financial Studies*, 29(10), 2643–2676.
- Bruche, Max and Javier Suarez (2010), “Deposit insurance and money market freezes.” *Journal of Monetary Economics*, 57(1), 45–61.
- Calomiris, Charles and Charles Kahn (1991), “The role of demandable debt in structuring optimal banking arrangements.” *American Economic Review*, 81, 497–513.
- Cassola, Nuno, Ali Hortaçsu, and Jakub Kastl (2013), “The 2007 subprime market crisis through the lens of european central bank auctions for short-term funds.” *Econometrica*, 81(4), 1309–1345.
- Cocco, Joao, Francisco Gomes, and Nuno Martins (2009), “Lending relationships in the interbank market.” *Journal of Financial Intermediation*, 18(1), 24–48.
- Covitz, Daniel, Nellie Liang, and Gustavo Suarez (2013), “The evolution of a financial crisis: Collapse of the asset-backed commercial paper market.” *Journal of Finance*, 68(3), 815–848.
- Craig, Ben R. and Yiming Ma (2018), “Intermediation in the interbank lending market.” Working Paper, Columbia Business School.
- Craig, Ben R. and Sara Millington (2017), “The federal funds market since the financial crisis.” *Economic Commentary*. Federal Reserve Bank of Cleveland.
- Dang, Tri Vi, Gary Gorton, and Bengt Holmstrom (2012), “Ignorance, debt, and financial crisis.” Working Paper, Yale University.
- Erzurumlu, Yaman Omer and Vladimir Kotomin (2010), “Inventory management effects, isolated: Evidence from the federal funds market.” *Quarterly Review of Economics and Finance*, 50, 61–66.
- Federal Housing Finance Agency Office of Inspector General (2013), “Case study: Freddie Mac’s unsecured lending to Lehman Brothers prior to Lehman Brothers’ bankruptcy.” https://www.fhfaoig.gov/Content/Files/EVL-2013-03_1.pdf.

- Federal Reserve Bank of New York (2013), “Fedpoint: Federal funds and interest of reserves.” <https://www.newyorkfed.org/aboutthefed/fedpoint/fed15.html>.
- Flannery, Mark (1996), “Financial crisis, payment system problems, and discount window lending.” *Journal of Money, Credit, and Banking*, 28(4), 804–824.
- Gatev, Evan, Til Schuermann, and Philip Strahan (2009), “Managing bank liquidity risk: How deposit-loan synergies vary with market conditions.” *Review of Financial Studies*, 22, 995–1020.
- Gatev, Evan and Philip Strahan (2006), “Banks’ advantage in hedging liquidity risk: Theory and evidence from the commercial paper market.” *Journal of Finance*, 61, 867–892.
- Gorton, Gary and George Pennacchi (1990), “Financial intermediaries and liquidity creation.” *Journal of Finance*, 45, 49–71.
- Heider, Florian, Marie Hoerova, and Cornelia Holthausen (2015), “Liquidity hoarding and interbank market spreads: The role of counterparty risk.” *Journal of Financial Economics*, 118, 336–354.
- Ho, Thomas and Anthony Saunders (1984), “A micro model of the federal funds market.” *Journal of Finance*, 40(3), 977–988.
- Hortaçsu, Ali and Jakub Kastl (2012), “Valuing dealers’ informational advantage: A study of canadian treasury auctions.” *Econometrica*, 80(6), 2511–2542.
- Kastl, Jakub (2017), “Recent advances in empirical analysis of financial markets: Industrial organization meets finance.” In *Advances in Economics and Econometrics: Eleventh World Congress, Econometric Society Monographs* (Bo Honoré, Ariel Pakes, Monika Piazzesi, and Larry Samuelson, eds.), 231–270, Cambridge University Press, Cambridge, U.S.
- Kim, Kyungmin (2017), “A price-differentiation model of the interbank market and its application to a financial crisis.” Finance and Economics Discussion Series 2017-065.

- Kobayashi, Teruyoshi and Taro Takaguchi (2018), “Identifying relationship lending in the interbank market: A network approach.” *Journal of Banking and Finance*, 97, 20–36.
- Koijen, Ralph and Motohiro Yogo (2016), “Shadow insurance.” *Econometrica*, 84(3), 1265–1287.
- Kovner, Anna and David Skeie (2013), “Evaluating the quality of fed funds lending estimates produced from fedwire payments data.” FRBNY Staff Report No. 629.
- Lucas, Charles M., Marcos T. Jones, and Thom B. Thurston (1977), “Federal funds and repurchase agreements.” *Quarterly Review*, 1, 33–48. Federal Reserve Bank of New York.
- Perignon, Christophe, David Thesmar, and Guillaume Vuillemeys (2018), “Wholesale funding dry-ups.” *Journal of Finance*, 73(2), 575–617.
- Prescott, Edward and Robert Townsend (1984), “Pareto optima and competitive equilibria with adverse selection and moral hazard.” *Econometrica*, 52(1), 21–46.
- Saidenberg, Marc R. and Philip Strahan (1999), “Are banks still important for financing large businesses?” *Current Issues in Economics and Finance*, 5(12), 1–6. Federal Reserve Bank of New York.
- Stignum, Marcia and Anthony Crescenzi (2007), *Stignum’s Money Market, fourth edition*. McGraw-Hill Companies., New York, U.S.

A The Algorithm and Its Performance

In this section I describe the algorithm used to find the payment leg that matches the identified fed funds payment transfer to the three large intermediary banks. I then present several measures that document the algorithm's performance.

A.1 Algorithm Description

I begin by describing how the set of fed funds related payments are constructed, and then provide details on the algorithm used to match these payments with other payment transfers.

As stated in the body of the paper, the three banks require their fed funds counterparties to place a unique identifier in the message field of payment transfers to the bank. Since I have access to payments' messages fields, I scan all payments messages associated with payment transfers to the three large banks for their unique identifiers. The resulting set of payments, F , is the known settlement legs of fed funds trades over our sample period of January 1, 2006 to December 31, 2008. The distribution of payment amounts in F revealed that fed funds trades typically involve large principal amounts. However I also observe a tiny number of transfers that were small enough to be interest payments. Upon discussion with the three banks' back offices about these small-value payments, I learned that standard practice is to return the principal and interest of a fed funds trade in one transfer. This occurs even if the two parties to the trade agree to another fed funds trade. However, some of the banks' counterparties, on occasion, settled their principal and interest obligation with two transfers, where one transfer is the principal amount and the other is the interest payment. This practice is quite infrequent; the three large banks discouraged this practice because it increases the operational complexity on their end as it usually requires manual intervention to process the payment.

To account for this (rare) behavior, I implement a process that determines whether two payments from a counterparty to one of the three large banks could in fact be combined into one principal plus interest payment. To describe this process, I introduce some notation. Let the three banks be designated as b_i where $i = 1, 2, 3$ and let a counterparty to these banks be $c \in C$. A payment from c to b_i on date t is denoted as

$y_{c,b_i,t}$, where the order of c and b_i denotes the direction of the transfer. Let $F_{c,b_i,t}$ denote all the fed funds identified payments from c to b_i on date t . For every t , $c \in C$ and $\{b_i\}_{i=1}^3$, I consider whether any possible pair of payments $(x, y) \in F_{c,b_i,t}$ could in fact, when combined, be a principal and interest payment. The criterion is that the interest portion implies a reasonable interest rate, which I compute as

$$r(x, y) = x * 360 / y, \tag{17}$$

where the 360 reflects the convention used to annualize rates in the fed funds market. As evidenced here and throughout the algorithm, I am only considering overnight fed funds transactions.²⁷ Reasonable interest rates are defined to be those that fall into a range (\underline{r}, \bar{r}) . Let r_t^{min}, r_t^{max} be the minimum and maximum fed funds rates published by the Federal Reserve on date t .²⁸ Then $\underline{r} = \max(0.9, r_t^{min} - 50)$ where rates are in basis points and $\bar{r} = r_t^{max} + 50$.²⁹ If $y \in F_{c,b_i,t}$ meets the reasonable interest rate criterion when paired with only one other payment in $F_{c,b_i,t}$, then I combine these two payments into one.

But if y meets this criterion with more than one payment in $F_{c,b_i,t}$, I use a median interest rule to select a pair of payments to combine. I do this by ranking the candidate payments to y by the implied interest rate and computing the median interest rate across these candidates. The candidate payment that is closest to the median rate is selected to be combined with y , with tie-breakers going to the candidate which implies the larger interest rate. In practice, there were very few instances of payments being combined over our sample period, with fewer than 80 overall.

²⁷If date t occurs on a Friday and the following Monday is a regular business day, then I replace 360 with 360/3 to reflect the three day tenor of the fed funds trade. In a similar fashion, I adjust the tenor to account for holidays.

²⁸Over our sample period, the Federal Reserve collected daily confidential data on rates from brokers in the fed funds market. Moments from these data are published at <https://apps.newyorkfed.org/markets/autorates/fed%20funds>. This process was replaced in 2014 when the Federal Reserve established a collection of trade level information on fed funds purchases. For details see information on FR 2420 published by the Federal Reserve Board.

²⁹For the period analyzed in this paper, my understanding of the market is that rates on fed funds trades were always positive. Therefore, I set a minimum of 0.9 basis points on \underline{r} . This constraint binds because in the sample period the minimum fed funds rate published by the Federal Reserve falls below 50 basis points.

Given the resulting set of identified fed funds payments, the first step of the algorithm is to divide the payments into principal and principal plus interest payments. I make this division based on whether the amount transferred is a round number, or has a factor of 1,000. Rounded amounts are assumed to be the principal amount and non-rounded amounts are assumed to be principal plus interest amounts.³⁰ Let the resulting set of principal payments be denoted as P and the set of principal and interest payments be I , where $P \cup I = F$. Further, let $P_{c,b_i,t} \subseteq F_{c,b_i,t}$ denote the known principal amounts from c to b_i on date t . Similarly, let $I_{c,b_i,t} \subseteq F_{c,b_i,t}$ denote a set of known principal and interest payments from c to b_i on date t . Finally, let $M_{b_i,c,t+1}$ denote all payment flows from b_i to c on date $t + 1$ observed over Fedwire.

The second step is to search for the matching settlement leg among all the payments flows. The algorithm begins with finding matches to known principal payments. Recall that all payments are received by the three large banks, and therefore principal payments necessarily reflect the initial settlement leg of a fed funds purchased trade. For a given $y \in P_{c,b_i,t}$, the algorithm considers whether any payment $x \in M_{b_i,c,t+1}$ is a successful match, where the criterion for success is whether x , as a principal plus interest payment, implies a reasonable implied interest rate (as defined above). If there are no successful matches, then the algorithm moves on to another principal payment amount in $P_{c,b_i,t}$. If there is a single successful match, then the payments pair (y, x) is recorded in a final data set used for analysis. Further, the payment x is removed from $M_{b_i,c,t+1}$, so that it cannot be paired with another known fed funds principal payment.³¹ If there are multiple successful matches, then I select a payment pair based on the median interest rate rule discussed above, record it in a final data set, and remove the selected payment from $M_{b_i,c,t+1}$.³²

The algorithm's final step is to find matches for the known principal and interest

³⁰Given the market practice of negotiating interest rates either to the nearest basis point or to the nearest sixteenths of an interest rate, it would be extraordinary for the principal and interest amount of an actual fed funds trade to be equal to a number with a factor of \$1,000.

³¹For the unusual case where c is one of the three large banks, say, $c = b_k$ for $k \neq i$, I also check if x is in $I_{b_k,b_i,t+1}$. If so, I remove it from this set of payments, to avoid double counting.

³²For the unusual case where c is one of the 3 large banks, say $c = b_k$ for $k \neq i$, and there are multiple successful payment matches, I given priority to $x \in I_{b_k,b_i,t+1}$.

payments in I . For a given $y \in I_{c,b_i,t}$, the algorithm considers whether any payment $x \in M_{b_i,c,t-1}$ is a successful match. The algorithm uses the same criterion described above of a reasonable implied interest rate to define a successful match and in addition requires that x be a rounded amount (i.e. has a factor of 1,000), because x is considered the principal amount. Similar to what I described above, if a given payment y has multiple successful matches, a median interest rate rule is used to select a single pair (y, x) , which is recorded in a final data set.

A.2 Algorithm Performance

Over the sample period of January 1, 2006 to December 31, 2008, I found 132,709 Fedwire payments to the three large banks that included the unique fed funds identifiers. The algorithm found matching payments for 97.0 percent of these fed funds payments (128,677 out of 132,709). Although I cannot say for sure, a likely reason for the algorithm not finding a match is that the term of the fed funds trade was longer than overnight.³³ For the cases when the algorithm found a matching payment, the vast majority were unique matches, or there was only one candidate payment. Weighting all payments equally, I find that 95 percent of matches were unique, and more than 98 percent had two or less candidate payments (see the first two columns of Table 6). Weighting payments by their principal amount, I find that 82 percent of value is uniquely matched and more than 92 percent had two or less candidate payments (see the last two columns of Table 6).

I interpret these results as strong support for the algorithm's performance. My understanding of this market is that the vast majority of trades are overnight, and so the algorithm should nearly always find at least one candidate payment. If the algorithm finds more than one candidate, then issues arise of whether the algorithm's median interest rate rule is selecting the correct matching payment leg. Fortunately, given the high incidence of unique matches, the concern of how to choose one payment from among multiple candidates is at best a minor issue. I also informally checked the results of the final data set with two of the three banks. With each bank, there was a discussion about the algorithm's output, focusing on the total quantities sold and purchased, rates nego-

³³Recall that I restricted the algorithm to only look for matching payments on the next business day.

Table 6: Algorithm’s Matching Performance

Number of candidate matches	Volume weighted		Value weighted	
	(frequency)	(percent)	(\$ billion)	(percent)
1	122,026	94.83	8,786	82.42
2	4,203	3.27	1,091	10.24
3	1,266	0.98	405	3.8
4+	1,182	0.92	378	3.54
Total	128,677	100	10,660	100

Note: Volume weighted means all transactions are equally weighted whereas value weighted means transactions are weighted by principal. '4+' means four or more candidate payments, where the largest number of candidate matches was 76.

Source: Fedwire Funds Service and author’s calculations.

tiated and number of counterparties in recent weeks, in addition to the larger patterns observed over the recent financial crisis. The result from these discussions is that the algorithm’s output matched each bank’s understanding of its fed funds activity.

B Direct Lending Case

In this section, I present the details behind solving the direct lending case for a particular functional form of Y given a match has occurred between a borrower and lender. Assume that

$$Y(q) = \beta q^\alpha. \tag{18}$$

From the borrower's first order condition, we have

$$\begin{aligned}\frac{dY}{dq} &= r_d \\ \alpha\beta q^{\alpha-1} &= r_d \\ \frac{\alpha\beta}{q^{1-\alpha}} &= r_d \\ \left(\frac{\alpha\beta}{r_d}\right)^{1/(1-\alpha)} &= q_d\end{aligned}$$

Consequently,

$$\begin{aligned}\frac{dq}{dr} &= \frac{1}{1-\alpha} \left(\frac{\alpha\beta}{r_d}\right)^{1/(1-\alpha)-1} \frac{-\alpha\beta}{r_d^2} \\ &= q \frac{-\alpha\beta}{1-\alpha} \frac{r_d}{\alpha\beta} \frac{1}{r_d^2} \\ &= \frac{-q}{r_d(1-\alpha)}\end{aligned}$$

Turning now to the lender's FOC, I can solve for r_d ,

$$\begin{aligned}\frac{dq}{dr}(1-\bar{\pi})r_d + (1-\bar{\pi})q_d - \bar{\pi}\frac{dq}{dr} - r_0^l\frac{dq}{dr} &= 0 \\ \frac{-q}{r_d(1-\alpha)} [(1-\bar{\pi})r_d - \bar{\pi} - r_0^l] + (1-\bar{\pi})q_d &= 0 \\ -\frac{1-\bar{\pi}}{1-\alpha} + \frac{\bar{\pi} + r_0^l}{(1-\alpha)r_d} + (1-\bar{\pi}) &= 0 \\ \frac{\bar{\pi} + r_0^l}{(1-\alpha)r_d} &= \frac{1-\bar{\pi}}{1-\alpha} - (1-\bar{\pi}) \\ \frac{\bar{\pi} + r_0^l}{(1-\alpha)r_d} &= (1-\bar{\pi})\frac{\alpha}{1-\alpha} \\ \frac{\bar{\pi} + r_0^l}{\alpha(1-\bar{\pi})} &= r_d.\end{aligned}$$

This allows us to solve for quantity. In the end, given a match between a borrower and lender in the direct case, we have

$$r_d^* = \frac{\bar{\pi} + r_0^l}{\alpha(1 - \bar{\pi})}, \quad (19)$$

$$q_d^* = \left[\frac{\alpha^2 \beta (1 - \bar{\pi})}{\bar{\pi} + r_0^l} \right]^{1/(1-\alpha)}, \quad (20)$$

The lender's expected profit is then

$$(1 - \bar{\pi})r_d^*q_d^* - \bar{\pi}q_d^* + (Q - q_d^*)r_0^l, \quad (21)$$

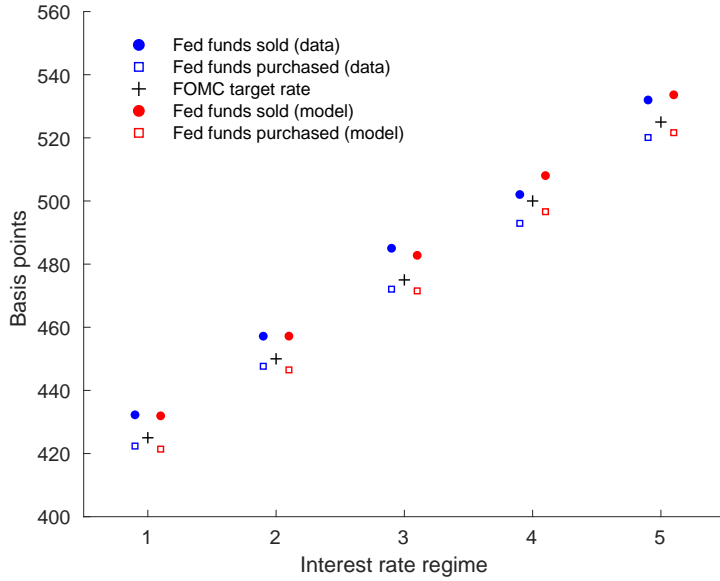
and the borrower's expected profit, for $\theta \in \{N, R\}$ is

$$(1 - \pi_\theta) (\beta(q_d^*)^\alpha - r_d^*q_d^*). \quad (22)$$

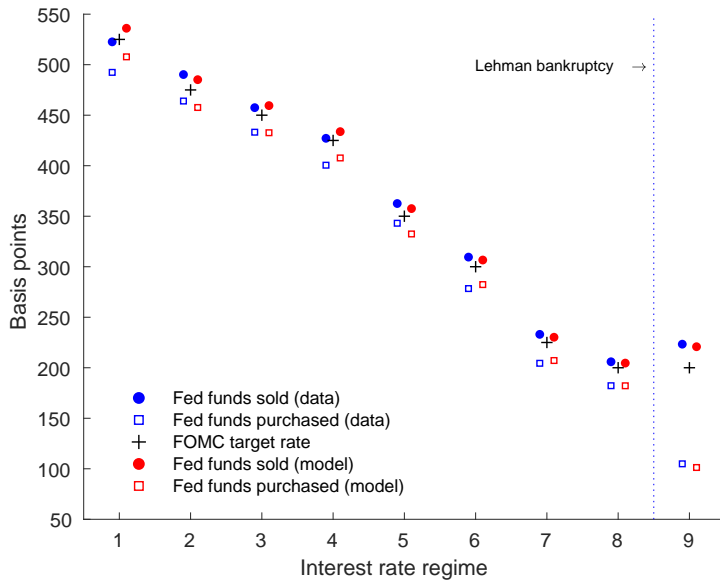
C Goodness-of-Fit Charts

This section presents Figure 5, which illustrates how the observed average fed funds rates and the corresponding model predictions line up given the estimated parameters. Figure 5a shows the observed and predicted rates of fed funds sold and purchased in the pre-crisis period alongside the FOMC target rate. Similarly, Figure 5b plots the observed and predicted interest rates in the emerging and the post-Lehman crisis periods. Overall, these figures demonstrate that the model's predictions of fed funds rates are quite close to the data.

Figure 5: Predicted and Actual Interest Rates



(a) Pre-Crisis Period



(b) Crisis Period

Note: The interest rate regimes are periods of time when the FOMC target rate was unchanged. The vertical line in the lower panel denotes the separation between the emerging and post-Lehman crisis periods.