Financial Management

Credit Contagion Channels: Market Microstructure Evidence from Lehman Brothers' Bankruptcy

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Immediately after Lehman Brothers' bankruptcy, many firms disclosed their financial exposure (or lack thereof) to Lehman. This offers a clean setting to test two credit contagion channels through which a financial firm's bankruptcy can affect other firms—"counterparty risk" and "information transmission" channels. Using market microstructure variables to measure the various dimensions of contagion effects, we provide robust evidence supporting the significance of counterparty risk. Firms with exposure to Lehman suffered more severe negative effects—wider bid-ask spread, higher price impact, greater information asymmetry, and greater selling pressure—than unexposed firms. We find mixed evidence regarding the information transmission hypothesis.

On September 15, 2008, Lehman Brothers Holdings, Inc. filed a petition in the US Bankruptcy Court for the Southern District of New York seeking relief under Chapter 11 of the US Bankruptcy Code. With total debt close to \$800 billion, Lehman was the largest US bankruptcy. Lehman's share lost over 90% of its value on the announcement date and the Dow Jones Industrial index closed over 500 points down from the previous day, one of the single largest one-day point drops since September 11, 2001. Immediately in the aftermath of Lehman's bankruptcy, over a hundred firms disclosed their financial exposure (or lack thereof) to Lehman.

Lehman's collapse, in conjunction with the disclosure of these firms' financial exposure to Lehman, provides us with a unique opportunity to test two competing theories of credit contagion: 1) counterparty risk and 2) information contagion arising from the bankruptcy of a large financial institution. The counterparty risk hypothesis predicts that firms with identifiable financial exposure to the failed firm should suffer adverse consequences because of fundamental business linkages (Davis and Lo, 2001). The information transmission hypothesis argues that the failure of a firm causes investors to update their beliefs, leading to the financial distress of other firms, even if they have no direct business relationship with the failed firm (Giesecke, 2004; Collin-Dufresne, Goldstein, and Helwege, 2010).

To test these two theories of credit contagion, we manually collect information about the firms' financial exposure (or lack thereof) to Lehman.[1] We classify firms into two groups: 1) exposed firms that have some degree of exposure and 2) unexposed firms who declare (and we verify) that

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[1] The majority of the firms that made voluntary declarations after Lehman's collapse were financial firms. We use this sample of financial firms for our main analysis. In Section V, we do robustness tests by repeating our analysis with all firms (both financial and nonfinancial) that made any declarations regarding their exposure or nonexposure to Lehman.

they have no exposure to Lehman. We then examine the relative changes in a number of liquidity variables around the disclosure date for these two groups of firms. Relative change is calculated as the difference between the disclosure day liquidity of the announcing firm and its control period average, scaled by the control period average, to account for time series variations in these variables. Moreover, for each sample firm, we identify an industry and size matched firm with no financial exposure to Lehman (Industry and Size Matched [ISM] approach). This is used to control for the impact of possible confounding events on the overall market on varying disclosure dates.[2] Abnormal relative change in liquidity variables for a disclosing firm is calculated as the difference in the relative change between each disclosing firm and its matching firm.

According to the information contagion hypothesis (Giesecke, 2004; Collin-Dufresne et al., 2010), the crisis creates a greater dispersion in beliefs amongst investors leading them to rapidly update their beliefs in the postcrisis period. This should seem as abnormal trading behavior that impacts equity liquidity for all sample firms, with or without Lehman. Our full sample results indicate a dramatic increase in the bid-ask spread, the number of trades, trade size and volume, the adverse-selection component of the bid-ask spread, and the selling ratio on the announcement date relative to the nonevent period reflecting greater uncertainty and abnormal trading behavior arising from the announcement. The magnitude of abnormal relative change is smaller, but statistically significant under the ISM approach. However, when we split the sample into exposed and unexposed firms, firms without exposure to Lehman exhibit abnormal increases in volume, but decreases in Kyle's lambda under the ISM approach suggesting the price impact of trade is smaller, contrary to the information transmission hypothesis. There are no significant changes in the other liquidity variables. Abnormal equity returns are positive, albeit insignificant. Thus, we find mixed evidence for the information transmission hypothesis.

Consistent with the counterparty risk hypothesis, we find that firms with exposure to Lehman experience positive abnormal changes in the bid-ask spread, volume, Kyle's Lambda, and the adverse selection component of spread suggesting that exposed firms suffer deterioration of liquidity (e.g., higher transaction costs, greater price impact of trade, and decreased information transparency). In addition, there is significant negative order imbalance (evidenced by the higher sell ratio) and negative returns for exposed firms. This provides direct evidence that investors are more likely to sell stocks of exposed firms after their counterparty risk to Lehman is disclosed to the public. Moreover, when we compare the mean and median differences between the two groups, the exposed firms experience significantly greater increase in the price impact of trades, information asymmetry, selling pressure, and lower equity returns than the unexposed firms supporting the significance of the counterparty contagion effect.

In the financial services industry in particular, the size of institutions and the complexity of their business networks may lead to strong contagion effects by counterparty risk or information transmission channels. Identifying which contagion channel propagates the financial shock caused by a large bank failure has important policy implications. For example, Helwege (2010) argues that if information is the main contagion channel (i.e., banks with similar characteristics are likely to be adversely affected), regulators should solve the common problems of these banks (e.g., if the common problem is their investment in mortgage-backed assets, the government should support the mortgage market) rather than supporting one failing bank. Alternatively, if counterparty risk is the major contagion channel, the government should bail out the bank that is likely to cause a domino effect within the financial system.

[2] The matching sample approach is common in the microstructure literature as it is computationally prohibitive to construct microstructure variables for all firms in the market as a benchmark. We have also used the industry, size, and book-to-market matching approach as robustness checks and the results are qualitatively similar.

Although it is importantto identify whether a shock propagates through information transmission or counterparty contagion, prior studies have encountered two major problems in distinguishing between these two channels. First, very few banks file for bankruptcy. In the category of "too big to fail," Lehman is the only US case. In fact, in the days leading up to September 15, 2008, as the market learned about the extent of Lehman's financial problems, various rescue packages were publicly being discussed.[3] After the bailouts of (the much smaller financial firms) Fannie Mae and Freddie Mac earlier in the week, the expectation was that some bailout would save Lehman from imminent collapse. In addition, it is difficult to identify (and thus control for) counterparty relationships of a failed firm as such relationships are rarely disclosed to the public.[4] Lehman's bankruptcy, and the subsequent announcements by over 100 firms disclosing the extent of their exposure to Lehman, provides a unique context that allows us to explicitly disentangle the sources of contagion effects from the collapse of a large financial institution.

Apart from this advantageous setting, an innovation of our study is that we use a number of liquidity measures developed by the market microstructure literature to capture the high frequency, intraday impact of contagion effects on the liquidity of the affected firms' stocks. These measures include transaction costs, trading activity, the price impact of trade, information asymmetry, and selling pressure of the equity of disclosing firms. Although theoretical models make predictions about the specific dimensions of liquidity that may be affected because of contagion, previous empirical studies of credit contagion rely primarily on low frequency pricing data in the stock, bond, and credit default swap (CDS) markets.

Collin-Dufresne et al. (2010) use month-end bond prices and quotes to empirically test how contagion effects of a major credit event spread to a corporate bond portfolio. In examining the contagion effects of bankruptcies, Lang and Stulz (1992) measure abnormal equity returns (AR) of industry competitors after a bankruptcy filing. AR is calculated using the daily closing prices from the Center for Research in Security Prices (CRSP) database. In studying the effects of a firm's bankruptcy on the CDS spreads of its industry competitors, Jorion and Zhang (2007) use one CDS spread quote per day for a large sample of industry peer firms. In their subsequent study of counterparty risk, Jorion and Zhang (2009) examine CDS spread changes of creditors of bankrupt firms.

In contrast to these studies, we examine the liquidity measures that can only be constructed from high frequency (tick-by-tick) data, and, as such, are able to test some of the predictions of theoretical contagion models that cannot be inferred from daily/monthly observations. To cite one example, to examine sell pressure, we construct the sell ratio variable by identifying all buyer-initiated and seller-initiated trades that are executed throughout the day. Thus, our study provides more accurate tests of the contagion theory from the market microstructure perspective.

Our paper contributes to the literature in three ways. First,this study adds to the growing literature examining the impact of the bankruptcy of Lehman Brothers' that, by all accounts, was a major crisis event in recent financial history.[5] Other studies that have examined counterparty

[3] For example, two days before Lehman's bankruptcy announcement, on September 13th, Timothy Geithner, then president of the Federal Reserve Bank of New York, called a meeting on the future of Lehman, which included the possibility of an emergency liquidation of its assets (Anderson, Dash, Bajaj, and Andrews, 2008). Lehman also reported that it had separate talks with Bank of America and Barclays for a possible sale of the company (White and Anderson, 2008).

[4] Iyer and Peydro (2010) point out the two major problems in testing contagion because of interbank linkages are the dearth of large bank failures and the lack of detailed data on interbank linkages. They overcome these hurdles by using the sudden failure of a cooperative bank in India and a unique dataset that identifies exposure to study interbank contagion.

[5] Some recent studies discussing various dimensions of the crisis triggered by Lehman include Ivashina and Scharfstein (2010), Fernando, May, and Megginson (2011), Jorion and Zhang (2011) and Aragon and Strahan (2010).

contagion have examined smaller firms with limited interconnectedness. Of note is Jorion and Zhang (2009) who focus on mostly industrial firms and a small group of financial institutions that went bankrupt, with their sample period ending before 2005.[6] However, the counterparty effect could be more significant if the failed firm is a large financial firm and its counterparty relationships are complex. We find that the counterparty effect is much stronger than reported in Jorion and Zhang (2009). In a recent Financial Crisis Inquiry Report, Federal Reserve Chairman Bernanke stated that 12 of the 13 largest banks in the US "were at risk of failure" at the depth of the 2008 financial crisis.[7] Therefore, the study of Lehman should shed light on possible contagion effects arising from these large banks on the financial system had they also been allowed to fail.

Moreover, differing from Jorion and Zhang (2011), we provide a finer test of the credit contagion hypotheses using a number of market microstructure variables that allow us to directly examine the trading behavior of market participants and the liquidity conditions of affected firms. Prior studies have used microstructure variables to investigate various corporate events.[8] We extend this strand of the market microstructure literature to the study of credit contagion effects.

In addition, this is the first paper to test the information transmission hypothesis by explicitly controlling for a counterparty relationship. Prior studies that document market-wide or industry-wide contagion effects (Lang and Stulz, 1992; Collin-Dufresne et al., 2010) generally attribute their findings to information contagion where investors update their beliefs about all other firms in the market. Yet, what is identified as information contagion could be driven by firms with fundamental business linkages with the failed firm, leading to erroneous inferences because of a failure to control for a counterparty relationship. The setting in our paper allows us to identify counterparty relationships, thus disentangling these two channels. As previously mentioned, such a distinction carries important implications for government intervention policies during a financial crisis.

The remainder of the paper is organized as follows. Section I reviews related literature and develops our hypotheses. Section II describes our sample and variables. Section III tests the counterparty risk hypothesis and information transmission hypothesis. Section IV discusses some of the robustness check results, whereas Section V provides our conclusions.

I. Related Literature and Hypotheses Development

Credit contagion is the transmission of the financial distress or the downside shock of one company to other companies wherein, in some instances, it may push other companies into bankruptcy. This has been frequently observed during bankruptcy waves and during the recent financial crisis. Credit contagion is important in explaining observed clustering of default correlations (Das, Duffie, Kapadia, and Saita, 2007) and has implications for portfolio credit risk

[6] The average total assets of firms in their sample are $1.9 billion, compared to $639 billion total assets for Lehman Brothers.

[7] Report Details Wall Street Crisis, By Carrick Mollenkamp, Aaron Lucchetti and Serena Ng, Wall Street Journal, January 28, 2011. Source: http://online.wsj.com/article/SB10001424052748703399204576108461096848824.html?mod=dist_smartbrief.

[8] Examples of the market microstructure approach to study corporate events include takeover announcements on target firms (Jennings, 1994; Smith, White, Robinson, and Nason, 1997; King, 2009), stock splits (Easley, O'Hara, and Saar, 2001), stock repurchases (Ahn, Cao, and Choe, 2001), seasoned equity offering (Butler, Grullon, and Weston, 2005; Kryzanowski, Lazrak, and Rakita, 2010), firm disclosures like earnings announcements (Krinsky and Lee, 1996), insider trading (Inci, Lu, and Seyhun, 2010), and corporate misreporting and bank loan contracting (Graham, Li, and Qiu, 2008).

models (Duffie, Eckner, Horel, and Saita, 2009). We study two major credit contagion channels that have been modeled in the literature, information contagion, and counterparty risk, which have different policy implications. As Helwege (2010) points out, if counterparty contagion is the major contagion channel, government bail-out of the failed firm is perhaps a better policy response to save many other counterparty firms, whereas regulatory aid to one distressed firm is of little use to boost confidence in the entire market if information is the major channel.

The information transmission hypothesis states that investors learn from defaults and update their beliefs. For example, the failure of Enron led investors to reassess their views of the quality of the accounting information of other firms. In a theoretical framework, Collin-Dufresne et al. (2010) demonstrate that when investors have fragile beliefs, they will learn from realized default events and rapidly update their beliefs in the postcrisis period, leading to contagion risk premia. Giesecke (2004) develops a similar model based on the statistical modeling of frailty to explore learning-from-default interpretations. King and Wadhwani (1990) propose that information asymmetry leads uninformed traders to update their beliefs about the terminal payoffs of assets after idiosyncratic shocks to a single asset. Calvo (1999) and Yuan (2005) present informationally richer models that explore the consequences of insiders being financially constrained and where uninformed investors cannot tell whether the observed selling activity is because of liquidity or real shocks. As such they may misread liquidity driven sales as signaling bad fundamentals.

Empirical investigations find support for information effects. For example, Lang and Stulz (1992) find that stock market reactions of their industry peer firms to nonfinancial firm bankruptcies are often negative. They posit that this is reflective of investors' revaluations of assets in that industry. Collin-Dufresne et al. (2010) find strong reaction of the bond market index in response to large credit shocks and attribute this to information contagion. However, these studies of the industry or market-wide effects of contagion do not control for business relationships with the failed firm. It is not clear whether and how much the companies in the same industry or in the bond market index have exposures to the distressed firm. If the overall significant effect is driven by firms that have economic linkages with the distressed firms, these results may reflect counterparty risk instead of the information transmission mechanism.

Counterparty risk hypothesis states that the default of one firm causes financial distress for its creditors or other counterparties that have a direct linkage with the distressed firm. In the extreme case, this can push the counterparty toward default. Counterparty contagion should be stronger for financial institutions, given the intricate web of relationships within the banking system. Counterparty risk has been analyzed in theoretical frameworks by Davis and Lo (2001), Giesecke and Weber (2004), and Boissay (2006).

One major problem in testing counterparty contagion is that it is usually difficult to identify the counterparty of the distressed firm as such a relationship is rarely public knowledge. There are a few notable exceptions, however. Jorion and Zhang (2009) conduct a systematic test of counterparty contagion effects using bankruptcy court filing documents to identify the top 20 unsecured creditors, and find that counterparty risk is important in explaining contagion. However, their bankruptcy sample covers mostly industrial firms, because the bankruptcy of US financial institutions has been fairly infrequent until recently. Furthermore, the average number of counterparties in their sample is only three public firms per bankruptcy. Iyer and Peydro (2011) use a sudden shock caused by a large bank failure in India and identify interbank exposures with a unique data source. They find that greater interbank exposure to the failed bank leads to large deposit withdrawals. Similar to the way they overcome the data hurdle, our study exploits the largely unexpected bankruptcy of Lehman in conjunction with the disclosure of exposure to Lehman by over one hundred companies. Our focus is different from theirs in that we attempt to disentangle the information transmission from counterparty risk channels.

In gauging the negative consequences of contagion effects, prices of securities such as stocks, bonds, or CDS have been commonly used in prior studies. Although (price) return is one important metric, there are various other dimensions of the effects of an adverse shock. First, the crisis-induced information asymmetry should lead market makers to charge greater transaction costs as measured by the quoted and effective bid-ask spread. Venkatesh and Chiang (1986) empirically document the increase in spread after information events. In addition, the arrival of new information should trigger a greater dispersion in beliefs among investors, leading to more intensive trading activities. Massa and Simonov (2005) find that uncertainty induced belief dispersion increases both volume and volatility. Moreover, when trading becomes costly and each trade moves prices away from the last traded price (reduced ease of transaction), the price impact of trades should increase (Kyle, 1985). Furthermore, higher levels of information asymmetry in the market should increase the adverse-selection component of the spread. Finally, the contagion effect should manifest in increased liquidation orders by investors and lead to sell-side order imbalance. Our market microstructure variables are suited to examine these various dimensions of the contagion effects.

On the basis of our discussion above, we formulate the following two hypotheses:

H1: *Information Transmission Hypothesis:* The disclosure announcement creates a greater dispersion in belief amongst investors, leading them to update their expectations and require an uncertainty risk premium. Therefore, all sample firms, with or without exposure to Lehman, should have greater bid-ask spreads, increased trading activities, higher price impacts of trade, greater levels of information asymmetry, and greater sell order imbalances on the disclosure day compared to the control period.

H2: *Counterparty Risk Hypothesis*: Firms with exposure to Lehman should suffer more severe adverse consequences than unexposed firms as a result of direct credit losses or potential losses because of lost business relationships. Therefore, the exposed firms should have higher bid-ask spreads, more trading activities, greater price impact of trade, greater levels of information asymmetry, and more selling pressure than the unexposed firms.

Our study adds to the growing list of papers investigating a variety of issues in the context of Lehman Brothers' bankruptcy. For example, Ivashina and Scharfstein (2010) examine bank lending behavior during the crisis and find that after the failure of Lehman Brothers, there was a run by short-term bank creditors, making it difficult for banks to roll over their short-term debt. They also demonstrate that banks with greater cosyndication with Lehman suffered more liquidity stress, indicating that Lehman's failure put more of the funding burden on other members of the syndicate and increased the likelihood that more firms would draw on their credit lines. Fernando, May, and Megginson (2011) investigate the value of investment banking relationships by exploring the impact of Lehman's bankruptcy on clients of its underwriting business. They find that firms that employed Lehman for equity offerings suffered during Lehman's bankruptcy. Their sample excludes firms with exposure to Lehman, though. Aragon and Strahan (2010) examine the role of hedge funds as liquidity providers using evidence from the Lehman bankruptcy. They find that stocks traded by the Lehman-connected hedge funds experienced greater declines in liquidity than other stocks. More broadly, our study also relates to the assessment of contagion effects during the recent subprime crisis, as examined in the context of hedge funds by Dudley and Nimalendran (2011) and the study of the sector level contagion effect by Phylaktis and Xia (2009).

II. Sample and Variables

A. Sample

Our data come from several sources. Over 100 firms voluntarily disclosed their exposure to Lehman after its bankruptcy and provided detailed information on the type and amount of this exposure. Several of them stated that their business relationships with Lehman are not expected to have an adverse material effect on their financial condition or liquidity. This is most likely to reassure investors and reduce speculation arising from information uncertainty or information-based contagion because of imperfect information. Some other firms also made public statements at that time that they did not have any financial exposure to Lehman. We hand-collect information on all such firms that disclose their exposure (or lack thereof) to Lehman in the two weeks after Lehman's bankruptcy from various news sources and cross-check using the Lexis–Nexis news database and Securities and Exchange Commission (SEC) filings. We include those firms that declared they had exposure into the exposed sample and the ones that indicated they had (and we verified) no exposure in the unexposed group.

In addition, we gather information for firms with exposure from the bankruptcy filing documents of Lehman Brothers that disclose the top 30 unsecured claimholders on bankruptcy day including creditor names, credit types, and credit amounts extended to the bankrupt firm. Of these, four firms have returns data from CRSP and are included in our sample.[9]

We use the Lexis–Nexis database to search for news items for our initial sample of voluntarily disclosing firms and exclude several firms that experienced other significant corporate events either in our testing (event) days or in the control period (August 2008). These firms include Fannie Mae and Freddie Mac that were nationalized on September 8, 2008, Bank of America and Merrill Lynch that reached an acquisition plan on September 15, 2008, Barclays that acquired (postbankruptcy) Lehman Brothers on September 16, Goldman Sachs and Morgan Stanley that were converted into "bank holding companies" on September 22, Washington Mutual that was seized by the Federal Deposit Insurance Corporation (FDIC) on September 25, and Wachovia that was in distress and acquired by Wells Fargo in early October.[10]

Our purpose is to examine abnormal changes in liquidity for firms that disclose information on exposure to Lehman around the disclosure date relative to the nonevent control period.[11] Instead of examining the changes in the levels of liquidity variables around a firm's disclosure date, we construct the relative changes (in percentage) of liquidity variables to control for variations in liquidity variable levels across sample firms. Disclosure date is the date on which each sample firm announces publicly, for the first time, its exposure (or lack thereof) to Lehman. Disclosure dates range from September 15, 2008 to September 24, 2008. The control period, against which we compare the event period changes, is August 2008. We require these firms to have data on the NYSE's Trade and Quote (TAQ) database, stock price information in the CRSP database,

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[9] For these firms, the disclosure date is the bankruptcy filing date.

[10] Although the Wachovia takeover date falls outside our testing period, we eliminate this firm as the possibility of its takeover was already in the news by mid-September.

[11] Instead of Lehman's bankruptcy date, we use the disclosure date of each firm as its event date because the information on exposure to Lehman was not known to the public until the disclosure was made after Lehman's bankruptcy date. Thus, we cannot capture contagion because of the counterparty relationship on the bankruptcy date. Further in the manuscript, we construct a variable, *Sellratio*, which is a measure of the relative sell pressure in the market for firms disclosing their financial exposures to Lehman. We find that in the days before the disclosure announcement was made, this *Sellratio* variable is almost always close to 50% indicating that traders did not rush to sell off stocks in these firms, corroborating the fact that the exposure announcements were largely unanticipated by the market.

and company information in the Compustat database. The final sample includes 86 firms, 60 of which are financial institutions (standard industrial classification [SIC] Code 6XXX). For our main tests, we focus on this sample of 60 financial firms, of which 47 have exposure to Lehman. In later robustness tests, we replicate all of our results with the full sample of 86 firms, of which 56 have exposure to Lehman.

To control for volatile market conditions on different disclosure dates after Lehman's bankruptcy, we construct an industry-size matched sample of firms against which we compare our sample firms. To construct the matching sample, we begin with all firms that have the same two-digit SIC code as the disclosing firm. Then, we identify the firm with the closest market capitalization as the disclosing firm as its matching firm. Notably, after obtaining each match, we verify from each company's 10-K and 10-Q disclosures that they make no mention of any financial relationship with Lehman Brothers.

We calculate relative (percentage) changes in liquidity variables for this matched sample, and then measure the pure impact of exposure on the disclosing firms as the relative change in liquidity variables for the sample firms minus the corresponding relative changes of the matched firms.[12] We expect our methodology to ensure that the main driver of the difference in equity returns and microstructure variables between the disclosing firms and their matched counterparts is exposure to Lehman, rather than market conditions, industry, or size differences. Our approach should provide clean estimates of the effect of exposure to Lehman on the sample firms.

We measure a firm's exposure as credit claims, including direct exposure to Lehman's debt (i.e., commercial paper, notes, bonds, and bank loans issued by Lehman). Reported exposures, however, also include positions in preferred stock and common stock. Firms also report their exposure arising from derivatives contracts. This includes CDS protection sold on Lehman, as well as derivatives positions entered into with Lehman that have positive value and, as such, are exposed to counterparty risk.

In Panel A of Table I, we provide a breakdown of all the declaring firms into financial companies and nonfinancial companies. Among the 86 firms in our sample, 60 are in the finance, insurance, and real estate sector with 47 exposed firms and 13 unexposed firms. Panel B limits the sample to financial firms and reports the dates on which these firms voluntarily disclose their exposure to Lehman Brothers. 15 of the 60 firms announced their exposure (zero or positive) on the very day of Lehman's bankruptcy. Within the next three days, 53 of the 60 (over 88% of the sample) had made the extent of their exposure known.

B. Variables

We use the number of trades, average trade size, and trade volume aggregated at the daily frequency to measure the trading activities of disclosing firms. In addition, we use quoted and effective spread, Kyle's Lambda, adverse selection cost, and sell ratio to measure the liquidity conditions and information asymmetry of the disclosing firms. All the variables are collected intraday and averaged for each stock each day. We then average each variable for each sample stock over all sample days and report the average across stocks, in effect treating each stock as a

[12] Such a matched sample approach is common to microstructure studies because it is computationally prohibitive to construct microstructure variables for all firms in the market as a benchmark (Bessembinder, 1999, 2003; Chung, Van Ness, and Van Ness, 2001). Davies and Kim (2009) explain the advantages of the matching approach in market microstructure research. Following Eberhart, Altman, and Aggarwal (1999), we adopt the industry and size matching approach, which has been commonly used in the credit risk literature to control for industry risk. We have also used another matching approach (i.e., industry, size, and book-to-market [ISM] approach) as in Eberhart et al. (1999) to identify matching firms. The results are qualitatively similar.

Table I. Distribution of Firms Disclosing Exposure to Lehman Brothers

The table reports summary statistics for the firms disclosing exposures to Lehman Brothers after its bankruptcy on September 15, 2008. Panel A breaks down all 86 disclosing firms to financial and nonfinancial companies. Panel B lists the disclosure dates of 60 financial companies categorized by exposure to Lehman.

Panel A. Industry Breakdown of Disclosing Companies

Industry	All	Exposed	Unexposed
Financial	60	47	13
Nonfinancial	26	9	17
Total	86	56	30

Panel B. Breakdown of Disclosing Financial Companies by Disclosure Date

Date	All	Exposed	Unexposed
15-Sep-08	15	12	3
16-Sep-08	11	10	1
17-Sep-08	11	10	1
18-Sep-08	16	8	8
19-Sep-08	3	3	
22-Sep-08	2	2	
23-Sep-08	1	1	
24-Sep-08	1	1	
Total	60	47	13

unit of observation. Next, we describe the construction of these microstructure liquidity variables. All variable definitions are also provided in the appendix.

1. Quoted and Effective Spread

Spreads are calculated from NYSE, Arca, and NASDAQ quotes obtained from the TAQ database.[13] We use equally weighted spread measures across trades within the day to calculate measures for each stock each day.[14] The quoted spread is the difference between the best (lowest) ask price and the best (highest) bid price. Effective spread, which captures the difference between an estimate of the true value of a security (the quote midpoint) and its actual transaction price, is calculated for stock i at time k on day t as:

$$\mathit{Effective\,Spread}_{i,k,t} = 2q_{i,k,t}(p_{i,k,t} - m_{i,k,t}), \tag{1}$$

where $q_{i,k,t}$ is an indicator variable equal to one for buyer initiated trades and negative one for seller initiated trades, $p_{i,k,t}$ is the trade price, and $m_{i,k,t}$ is the prevailing quote midpoint. We

[13] We apply the following filters to clean the trade and quote data. We use trades and quotes from regular hours trading only. We use only trades for which TAQ's CORR field is equal to zero, one, or two and for which the COND field is either blank or equal to @, E, F, I, J, or K. Trades with nonpositive prices or quantities are eliminated, as are trades with prices more than (less than) 150% (50%) of the previous trade price. We use only quotes for which TAQ's MODE field is equal to 1, 2, 6, 10, 12, 21, 22, 23, 24, 25, or 26. We eliminate quotes with nonpositive price or size, with a bid price greater than the ask price, when the quoted spread is greater than 25% of the quote midpoint, or when the ask price is more than 150% of the bid price. We exclude other exchanges, which account for a very minor fraction of the overall trading volume, to avoid stale quotes.

[14] Volume-weighted measures yield qualitatively similar results.

follow the trade signing approach of Lee and Ready (1991) where a trade is classified as buyer initiated if the trade price is above the quote midpoint and as seller initiated if the trade price is below the quote midpoint. Trades occurring at the midpoint between the best bid and the best offer are classified as seller initiated (buyer initiated) if the trade price is lower (higher) than the price of the previous trade. We use contemporaneous quotes to sign trades because Chakrabarty, Moulton, and Shkilko (2011) find that daily level studies need not lag quotes when using the Lee–Ready (1991) algorithm. Greater quoted and effective spreads indicate higher transaction costs and lower stock liquidity.

2. (Kyle's) Lambda

Microstructure models predict that trading costs increase with the degree of information asymmetry in the market (Glosten and Milgrom, 1985; Kyle, 1985). The amount that a risk-neutral and competitive market maker charges to protect them against adverse selection increases with the degree of information asymmetry and decreases with the amount of noise trading. Kyle (1985) models this cost as the price impact of trade, $\Delta P = \lambda V$, where V is the number of shares traded and λ, commonly known as Kyle's Lambda, is the price impact per unit of trade. Kyle (1985) finds that λ is proportional to the standard deviation, σ, of the distribution of possible fair values of the security, and inversely proportional to the standard deviation of the distribution of trades by noise traders, σ_u: $\lambda = 2\ \sigma / \sigma_u$.

3. Glosten and Harris Adverse Selection Component of Spread

Spread decomposition models in the market microstructure literature split the bid-ask spread into three components: 1) inventory holding costs (price risk and opportunity cost of holding a suboptimal portfolio of securities), 2) order processing costs (costs of arranging trades, recording, and clearing a transaction), and 3) adverse selection costs (costs that arise if investors trade on the basis of superior information). The adverse selection cost represents the compensation that market liquidity suppliers need to be willing to trade with informed investors. Oliver and Verrecchia (1994)argue that some well informed investors possess a better ability to analyze publicly available data and convert it into private information. As the market makers are unable to differentiate between the processors and the uninformed investors, they protect themselves by charging a higher spread. Therefore, uninformed traders lose to informed traders implicitly by having to pay wider spreads induced by this adverse selection problem. The level of information asymmetry is captured in the adverse-selection component of the bid-ask spread. A higher level of the adverse selection component of the bid-ask spread indicates greater information asymmetry and more informed trading.

Trade indicator models compute spread components by regressing price changes on a trade indicator variable. One such model is the Glosten and Harris (1988) model which assumes that the different spread components have a linear relationship with trade size. Their model produces the best estimates when order processing costs are fixed and the adverse selection component cost increases with trade size.[15]

[15] In the Glosten-Harris (1988) model that we use to estimate the adverse selection component of spread, the linear regression equation can be written as: $\Delta P_t = c_0 \Delta Q_t + c_1 \Delta Q_t V_t + z_0 Q_t + z_1 Q_t V_t + \varepsilon_t$, where P_t is the trade price at time t, Q_t is a trade indicator equal to +1 (–1) if the trade is buyer (seller) initiated, V_t is the number of shares traded at time t, and ε_t is the public information arrival rate which also represents the error term. In this model, the adverse selection component is $2(z_0 + z_1 V_t)$. An alternative to the adverse selection component of spread would be the PIN, probability of informed trading, estimate. We choose to estimate the former as PIN is generally calculated over longer periods of time and, by our study design, the abnormal measures we calculate are for very short (daily) frequencies.

4. Sell Ratio

Intraday data allow us to use the Lee–Ready (1991) algorithm to classify trades into buyer and seller initiated. We use this algorithm to examine whether there is selling pressure once the sample firms disclose their degree of exposure to Lehman. To do this, we construct two measures: 1) *Sellratio* and 2) *Lagged Sellratio*. *Sellratio* is the number of seller initiated trades divided by the total trades, whereas *Lagged Sellratio* is the *Sellratio* measure computed for the previous day. This measure has also been used by Jakob and Ma (2003) to measure order imbalance on exdividend days and is better suited than the normal scaled order imbalance measure.[16]

Table II presents the descriptive characteristics of the sample. Panel A provides the control period measures for the liquidity variables, whereas Panel B reports the event window (Days [0, +1] relative to each firm's exposure disclosure date) measures. Both quoted and effective spreads increase upon exposure announcements. Mean quoted spread increases from 6.5 to 10.8 cents and mean effective spread increases from 3.3 to 6 cents. Quoted spread is higher than effective spread, indicating that some trades happen within (not at) the best quotes. Despite this increased transaction cost (spread increase), there is a huge volume surge upon disclosure. The average number of trades per day increases from 20,759 to 59,688 along with increased trade size (from 197 to 223 shares per trade). Adverse selection increases from 0.75 to 0.84, reflecting increased information asymmetry. Increased volume counterbalances increased spreads, such that the price impact variable, Kyle's lambda, indicates a modest change between the control period (0.018) and the event window (0.021).

The mean *Sellratio* in the control period (Panel A) is 50%, indicating that buy and sell pressure are generally equally balanced daily in the month of August (before the bankruptcy announcement). This confirms that the bankruptcy announcement was indeed unexpected, and there was no run-up to order flow before the exposure announcement. However, in the event window, we find an increase of the sell pressure to 52% over days (0, +1).

Panel C presents the firm level characteristics of the sample. The sample is comprised of mostly large capitalization firms. The average market value of equity for the sample firms preceding the Lehman Brothers' bankruptcy (September 12, 2008) is just under $20 billion and the average stock price is about $37. *Volatility*, the average daily stock return volatility for the disclosing firm over the preceding year is 3.32%, ranging from 0.80% to 12.40%. *Leverage*, the average leverage ratio of the disclosing firm over four quarters during the preceding year, is 0.79. The leverage ratio is defined as the ratio of the book value of debt over the market value of assets, taken as the market value of equity plus the book value of debt. As expected, because the sample firms all belong to the financial sector, they have a high degree of correlation (0.45) between their equity returns and Lehman's equity returns over the preceding year.

III. Testing Information Transmission and Counterparty Risk Hypotheses

A. Univariate Analysis of Relative Changes and Abnormal Changes in Liquidity Measures

To examine the market reaction to the sample firms' disclosure regarding their exposure to Lehman, we use the event study methodology described in Corwin and Lipson (2000). This

[16] Raw order imbalance is measured as the difference between the number of buyer initiated orders and the number of seller initiated orders. To scale this, we cannot use the average control period imbalance as the denominator because a control period, when it is appropriately chosen and is free of unusual events, has extremely low (zero) order imbalance. When the denominator is close to zero, the abnormal percentage changes can tend to infinity.

Table II. Descriptive Statistics for Firms Disclosing Exposure to Lehman Brothers

This table presents the cross sectional descriptive statistics for microstructure liquidity variables of the sample of firms that disclosed their exposure to Lehman Brothers Inc. after its bankruptcy. Panel A presents the results for the control period (August 2008), whereas Panel B reports results for the event window (event Date 0 is the disclosure date of each sample firm). Panel C provides the other (control) variables. All variables are as defined in the Appendix.

Measures	Mean	Standard deviation	Minimum	Median	Maximum
Panel A. Control Period Liquidity Measures (N = 60)					
Quoted spread	0.0646	0.1133	0.0101	0.0255	1.0918
Effective spread	0.0330	0.0652	0.0086	0.0153	1.0000
Number of trades	20,759	40,012	1	4,756	242,484
Trade size	197.23	90.58	105.82	171.24	785.14
Volume	4,896	11,184	0	913	87,913.45
Lambda	0.0178	0.0395	0	0.0057	0.4807
Adverse selection	0.7567	4.4354	0	0.1596	62.6012
Sell ratio	0.50	0.08	0	0.50	1.00
Panel B. Event Window (Day [0, + 1]) Liquidity Measures (N = 60)					
Quoted spread	0.1083	0.1630	0.0105	0.0459	0.9106
Effective spread	0.0597	0.0900	0.0097	0.0298	0.5210
Number of trades	59,688	133,802	7	13,796	894,500
Trade size	223.01	104.48	106.06	197.66	887.03
Volume	14,869	37,039	4	3,098	253,472.84
Lambda	0.0214	0.0387	0	0.0060	0.2454
Adverse selection	0.8438	5.8927	0.0002	0.2320	50.0771
Sell ratio	0.52	0.08	0.27	0.51	1.00
Panel C. Other Variables (N = 60)					
Price ($)	36.92	46.42	4.03	25.92	357.18
Mveq ($ millions)	19,900	40,362	30	3,624	240,148
Volatility (%)	3.32	1.71	0.80	2.96	12.40
Leverage	0.79	0.20	0.19	0.87	1.00
Correlation	0.45	0.12	0.07	0.47	0.68

measure uses the past history of each firm as a control to examine event period reaction. We compute relative changes (in percentage) for the liquidity variables of interest described earlier. The event window is defined in two ways: 1) the disclosure date only, Day 0, and Day 2) Days 0 and 1. Event window statistics are compared to a control period that spans all trading days in the month of August. A relative change in liquidity variables for stock i is defined as:

$$\Delta LiqVar_i = \frac{Event\,Day\,Value_i - Mean\,Control\,Period\,Value_i}{Mean\,Control\,Period\,Value_i} \times 100. \tag{2}$$

In addition to the statistical tests for these measures, we also report the proportion of positive relative changes of these variables.

Table III presents the univariate analysis results. In Panel A, we report the Day 0 relative changes in liquidity variables, whereas in Panel B, we provide the averages of Days 0 and 1.

Table III. Relative Changes in Microstructure Liquidity Variables of Disclosing Firms

This table presents relative changes (%) in microstructure liquidity variables during the event window for firms that disclose exposure to Lehman Brothers. Relative changes (ΔLiquidity variable) are calculated as (the value of variable in event window–the average value of variable over the control period)/the average value of variable over the control period, multiplied by 100. The control period is August 2008. The *t*-statistics for the mean relative changes are reported. The "% (+)" entry indicates the percentage of observations with positive values.

Panel A. Relative Changes (%) in Liquidity Variables on Day 0

Measures	All Disclosing firms (N = 60)			
Day 0	**Mean (%)**	**Median (%)**	***t*-statistics**	**% (+)**
ΔQuoted spread	58.03***	40.26	5.83	88.33
ΔEffective spread	73.07***	52.83	7.44	98.33
ΔNumber of trades	178.50***	170.72	9.97	93.33
ΔTrade size	10.88***	4.65	3.15	61.67
ΔVolume	202.31***	187.59	10.07	90.00
ΔLambda	21.41**	–1.66	2.15	48.33
ΔAdverse selection	46.21**	–17.22	2.39	46.67
ΔSell ratio	7.09***	2.92	3.67	65.00

Panel B. Relative Changes (%) in Liquidity Variables on Days (0, +1)

Measures	All Disclosing firms (N = 60)			
Day (0, +1) average	**Mean (%)**	**Median (%)**	***t*-statistics**	**% (+)**
ΔQuoted spread	84.99***	63.58	7.29	93.33
ΔEffective spread	89.24***	64.99	8.62	98.33
ΔNumber of trades	168.93***	163.32	9.69	93.33
ΔTrade size	14.91***	10.36	4.59	65.00
ΔVolume	198.11***	182.23	10.58	90.00
ΔLambda	18.13**	9.11	2.27	58.33
ΔAdverse selection	55.02***	13.47	2.95	56.67
ΔSell ratio	6.04***	2.66	3.79	68.33

***Significant at the 0.01 level.
**Significant at the 0.05 level.

Both quoted and effective spreads demonstrate a dramatic increase on the announcement date (Panel A), and more so on the day after (Panel B). For example, the effective spread (the actual round trip transaction cost paid by a trader) increases by 73.07% on Day 0 compared to its predisclosure normal levels in the entire sample. More importantly, this increase is evident in over 98% of the sample. Along with increased transaction costs, there is higher trading volume in the market (an increase of 202.31% when compared to the control period), reflected in the increase in trade size, as well as the number of trades. Although there is a volume surge on the disclosure date, it seems that this increased volume does not completely cancel out the effect of higher spreads; the price impact of trade shows a significant increase relative to the control period.

The adverse selection component of spread increases by 46.21% (t = 2.39), indicating that there is greater information asymmetry in the market in the immediate aftermath of the firms' announcements. It is interesting to note that the disclosure of exposure (if any) to Lehman already reflects the fact that the disclosing companies anticipated they might face some repercussions from the bankruptcy announcement. These public disclosures were a way of reducing information asymmetry to preempt precipitate reaction from traders. The relative change in the sell ratio is 7.09% ($t = 3.67$) indicating greater sell pressure after the exposure announcements.

Lehman's bankruptcy was a huge event that caused a severe reaction in the financial markets. To control for market movement on the disclosure dates that may impact the liquidity of the sample firms, we employ a matched sample treatment, as described earlier. Table IV presents the abnormal relative change in the liquidity variables in excess of the relative changes in the same variables for the industry and size matched sample. The ARand cumulative AR (CAR) are calculated using the market model methodology following MacKinlay (1997), with parameters estimated over a window ranging from one year before the event date to three months before the event date relative to the returns for a portfolio of firms in the same industry as the disclosing firm. This industry index is constructed as a portfolio of value-weighed industry equity returns for all other firms with the same three-digit SIC code.

Increases in both abnormal quoted and effective spreads are significant on Day 0 and the [0, +1] event window, but the magnitudes is smaller than that reported in Table III. The adverse selection component of spread reports a large abnormal increase (41.22% on Day 0 and 45.67% on the two-day event window). The abnormal increase in the sell ratio is 8.72% ($t = 4.01$) on Day 0. We find a lower abnormal selling ratio on the [0, 1] event window (7.75%) when compared to Day 0. This is expected, given that the order imbalance measure has been found to be contrarian in the literature. Chordia, Roll, and Subrahmanyam (2002) find that buying activity is more pronounced after market crashes, whereas selling activity is more pronounced after market rises. The abnormal returns on the disclosure date and the [0, 1] event window are both negative and significant at the 95% level of confidence.[17]

The results in Tables III and IV provide some support for the information transmission hypothesis. Upon disclosure, the average disclosing firm experiences declines in liquidity conditions, increased information asymmetry, greater selling pressure, and lower abnormal returns. This does not happen for all firms, however, as demonstrated by the percentage of positive changes. The full sample result may be driven by firms with actual exposure to Lehman. Next, we split the sample into two groups: 1) those with financial exposure to Lehman and 2) those without and compare the abnormal liquidity measures across the two groups. Difference in means (medians) across these groups is tested using *t*-statistics (Wilcoxon statistics).

Table V presents the results of the abnormal relative changes in liquidity variables and abnormal equity returns after subtracting relative changes for the matched sample firms. There are significant increases in both the abnormal quoted spreads (31.49%) and the effective spreads (26.98%) for the exposed firms, whereas the changes in these measures for the unexposed firms are statistically insignificant. Likewise, although the exposed firms face significantly higher price impacts as measured by lambda (excess abnormal increase of 32.87%) and adverse selection costs (increase of 70.95%), the unexposed firms actually experience lower price impacts (decrease of 26.46%) and insignificant changes in adverse selection.

The declarations by the unexposed firms seem to have had their intended consequences. The exposed firms have a significantly higher adverse selection component of spread than the

[17] In Tables III and IV, we demonstrate that: a) the matching approach leads to the same conclusions as the unadjusted sample, and b) the inferences are the same whether we consider a Day 0 event date or Day (0, +1) event window. All subsequent analyses we have done have been repeated using both variants in (a) and (b), but for reporting purposes, we present all the results later in the manuscript under the matching approach and using a Day 0 event date.

Table IV. Abnormal Relative Changes in Microstructure Liquidity Variables of Disclosing Firms (Industry and Size Matching Approach)

This table presents abnormal relative changes in microstructure liquidity variables during the event window for firms that disclose exposure to Lehman Brothers using the industry and size matching approach. We proceed in two steps. First, for both the disclosing firms and the ISM matching firms, relative changes in liquidity variables are calculated as (the value of variable in event window − the average value of variable over the control period)/the average value of variable over the control period, multiplied by 100. Next, abnormal relative changes in liquidity variables for the disclosing firm are calculated as relative changes in liquidity variables in excess of relative changes of the ISM matching firm. The matching firm is in the same two-digit industry and has the closest market value of equity as the disclosing firm. AR (CAR) is the industry-adjusted abnormal (cumulative abnormal) return (in percentage) of the disclosing firm on the event window defined from an industry market model estimated over the period of one year to three months before the disclosure date. The industry index is constructed from a portfolio of value-weighted industry equity returns for all firms in the same three-digit SIC code as the disclosing firm. The *t*-statistics for the mean abnormal relative changes are reported. The "% (+)" entry indicates the fraction of observations with positive values.

Panel A. Abnormal Changes (%) in Liquidity Variables on Day 0

Measures	All disclosing firms ($N = 60$)			
Day 0	**Mean (%)**	**Median (%)**	***t*-statistics**	**% (+)**
Abnormal Δquoted spread	29.88***	16.29	2.96	65.00
Abnormal Δeffective spread	26.09**	10.96	2.12	58.33
Abnormal Δnumber of trades	39.26*	26.19	1.88	60.00
Abnormal Δtrade size	5.95*	3.41	1.77	55.00
Abnormal Δvolume	62.82***	54.05	2.83	68.33
Abnormal Δlambda	20.01*	–0.50	1.91	51.67
Abnormal Δadverse selection	41.22	2.16	1.58	51.67
Abnormal Δsell ratio	8.72***	3.65	4.01	65.00
AR	−3.54***	−1.56	−2.75	40.00

Panel B. Abnormal Changes (%) in Liquidity Variables on Day (0, +1)

Measures	All disclosing firms ($N = 60$)			
Day (0, +1) average	**Mean (%)**	**Median (%)**	***t*-statistics**	**% (+)**
Abnormal Δquoted spread	54.09***	32.11	4.55	68.33
Abnormal Δeffective spread	37.81***	21.92	3.03	60.00
Abnormal Δnumber of trades	29.69	24.84	1.24	58.33
Abnormal Δtrade size	9.97***	5.43	2.99	61.67
Abnormal Δvolume	58.62**	34.94	2.38	61.67
Abnormal Δlambda	20.04**	1.15	2.23	53.33
Abnormal Δadverse selection	45.67*	25.21	1.93	60.00
Abnormal Δsell ratio	7.74***	3.04	4.19	66.67
CAR	−3.42*	−2.97	−1.82	40.00

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

Table V. Abnormal Changes in Microstructure Liquidity Variables Classified by Exposure (Industry and Size Matching Approach)

This table compares abnormal relative change in microstructure liquidity variables on Day 0 between firms with exposure (47) and firms without exposure (13) to Lehman Brothers using the industry and size matching approach. First, for both the disclosing firms and the ISM matching firms, relative changes in liquidity variables are calculated as (the value of variable in event window − the average value of variable over the control period)/the average value of variable over the control period, multiplied by 100. Next, abnormal relative changes in liquidity variables for the disclosing firm are calculated as relative changes in liquidity variables in excess of relative changes of the ISM matching firm. The control period is August 2008. The matching firm is in the same two-digit industry and has the closest market value of equity as the disclosing firm. AR is the industry-adjusted abnormal equity return (in percentage) of the disclosing firm on the event window defined from an industry market model estimated over the period of one year to three months prior to the disclosure date. The industry index is constructed from a portfolio of value-weighted industry equity returns for all firms in the same three-digit SIC code as the disclosing firm. In the "Exposed Firms" and "Unexposed Firms" panels, the mean and median of the abnormal relative changes, and the t-statistics for the mean abnormal relative changes are reported. The "% (+)" entry indicates the percentage of observations with positive values. In the "Comparison" panel, the mean differences and the t-test statistics for mean differences between two groups are reported. The median differences and the Wilcoxon statistics for median differences are also reported.

	Exposed Firms				Unexposed Firms				Comparison			
Measures Day 0	Mean (%)	Median (%)	t-statistics	% (+)	Mean (%)	Median (%)	t-statistics	% (+)	Mean difference	t-statistics	Median difference	Wilcoxon statistics
Abnormal Δquoted spread	31.49**	9.48	2.57	63.83	24.08	19.24	1.56	69.23	−7.41	−0.38	9.76	0.45
Abnormal Δeffective spread	26.98*	7.56	1.84	59.57	22.90	16.66	1.08	53.85	−4.09	−0.16	9.10	0.02
Abnormal Δnumber of trades	42.15**	22.99	1.97	59.57	28.83	29.39	0.49	61.54	−13.32	−0.21	6.40	−0.32
Abnormal Δtrade size	6.56	0.45	1.56	51.06	3.79	3.97	1.09	69.23	−2.77	−0.51	3.53	0.47
Abnormal Δvolume	69.07***	55.82	3.19	68.09	40.22	22.72	0.59	69.23	−28.85	−0.4	−33.10	−0.27
Abnormal Δlambda	32.87***	13.50	2.60	61.70	−26.46**	−25.40	−2.31	23.08	−59.33**	−2.43	−38.89***	−2.58
Abnormal Δadverse selection	70.94**	20.78	2.36	57.45	−66.24	−67.97	−1.63	30.77	−137.18**	−2.24	−88.75**	−2.33
Abnormal Δsell ratio	11.44***	9.40	4.42	70.21	−1.11	−1.31	−0.53	46.15	−12.55**	−2.48	−10.71**	−2.40
AR	−4.78***	−2.77	−3.11	36.17	0.92	1.30	0.55	53.85	5.71**	2.51	4.06*	1.83

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

unexposed firms, reflecting higher information asymmetry. Not surprisingly, higher levels of information asymmetry for exposed firms could be because of the fact that evaluating the exact amount and implication of a positive exposure is more complex than evaluating a disclosure that states nonexposure. For the exposed firms, traders have to interpret the significance of their exposure. For the unexposed firms, the news is much easier to interpret.

Notably, although the exposed firms face an abnormal increase in sell pressure of 11.44% ($t = 4.42$), the unexposed firms do not experience any increase in sell pressure. Higher sell pressure leads to negative returns. Exposed firms face significant negative (–4.78%) one-day industry-adjusted abnormal returns. In contrast, the unexposed firms show positive (0.92), but insignificant abnormal returns relative to their industry peers.

Overall, the higher spread, price impact of trade, adverse selection costs, selling pressure, and negative equity returns for the exposed firms, when compared to the unexposed firms, demonstrate that the Lehman bankruptcy had substantially greater consequences for this group. This supports the theory that the counterparty contagion is a major contagion channel when a large financial institution fails. In addition, the subsample results confirm that the full sample results are indeed driven by the exposed firm. This suggests that it is important to control for counterparty relationships to test contagion channels.

B. Multivariate Tests of Counterparty Risk and the Information Transmission Hypotheses

In this section, we test the information transmission and counterparty contagion effects after controlling for firm, industry, and market characteristics. Our dependent variables are abnormal relative changes in the liquidity variables ($Abn\Delta liqVar$) using the ISM approach and abnormal equity returns using the industry market model. Our basic regression equation is:

$$Abn\Delta liqVar = \alpha + \beta_1 ExpDm + \beta_2 LnPrice + \beta_3 LnMveq + \beta_4 LnVolume + \beta_5 Volatility + \beta_6 Leverage + \beta_7 Correlation + \varepsilon. \quad (3)$$

The major variable of interest is *ExpDm*, the exposure dummy variable. If the information transmission hypothesis dominates, liquidity deterioration and equity returns should not be related to the firm's exposure to Lehman. Therefore, *ExpDm* should be insignificant in all regression specifications. If the counterparty contagion hypothesis holds, a disclosing firm with greater exposure to Lehman is more likely to experience more liquidity deterioration. Therefore, we hypothesize the coefficient on *ExpDm* to be positive when the dependent variables are abnormal changes in microstructure liquidity measures, and negative when the dependent variable is abnormal equity returns.

Prior studies (Bollen, Smith, and Whaley, 2004) have demonstrated that equity price, firm size, and trading volume are factors driving equity liquidity conditions. Thus, we add *LnPrice* (logarithm of share price), *LnMveq* (logarithm of the market value of equity), and *LnVolume* (logarithm of daily trading volume) as control variables. In addition, we use two variables, *Volatility* and *Leverage*, to proxy for the future default probability of the disclosing firm. Merton-type structural models suggest that companies with higher equity return volatility and greater leverage are associated with a higher default probability. We expect the liquidity conditions of such firms to be more vulnerable to the negative shock from the collapse of Lehman.

Also included in the regression is *Correlation*, defined as the correlation of equity returns between the disclosing firm and Lehman Brothers over the preceding year, to control for cash flow similarities between the disclosing firm and Lehman. Contagion effects on firms' liquidity conditions are expected to be greater for a disclosing firm that has a higher equity correlation with Lehman, because of commonality in cash flows.

In models where the dependent variable is *Sellratio*, we add an additional variable, *Lagged Sell Ratio* (one day lagged *Sellratio*) to account for the order imbalance of the previous day because Chordia et al. (2002) find that lagged order imbalance is significantly positively related to current order imbalance. In addition, we include disclosure date dummies in the regressions to account for overall market conditions that are known to influence liquidity conditions.[18]

Table VI presents the correlations between our abnormal liquidity measures (dependent variables) and the independent variables used in the regression framework. Coefficients that are significant at the 95% confidence level or higher are boldfaced. As expected, the liquidity variables display a high degree of correlation amongst them. For example, abnormal trading volume and number of trades have a correlation of greater than 80%, whereas higher trading volume reduces the price impact of trade, leading to a significant negative correlation between volume and lambda.

The relationships between the explanatory variables are also as expected. For example, high priced stocks are usually from high market capitalization firms (correlation coefficient = 0.54 and significant). The correlation of the equity returns of sample firms with Lehman's equity return is higher for the higher market capitalization firms (correlation coefficient = 0.49 and significant).

Because Table VI demonstrates a fair degree of correlation amongst the explanatory variables, we test for potential multicollinearity issues using the variance inflation factor (VIF). All VIFs are below four, suggesting that multicollinearity is not a serious concern for our models.

To address whether a two stage least squares (2SLS) estimation is preferable to the ordinary least squares (OLS) procedure, we perform a Hausman test and find no basis to reject the null hypothesis that OLS is superior to a 2SLS estimation.[19] Therefore, we estimate OLS regressions, where the *t*-statistics for the regression coefficients are based on robust standard errors adjusted for events clustering. The results are presented in Table VII.

Although the exposure dummy is insignificant in Models 1, 2, 3, and 5, in the other four regression models (6, 7, 8, and 9), this variable is significant and has the right sign. Like the univariate results presented earlier, these results also bear mixed support for the information transmission hypothesis. Consistent with the counterparty contagion hypothesis, the exposure dummy is positively associated with abnormal changes in lambda, adverse selection, and sell ratio, all of which are statistically significant at 5% or above. In Model 9, where the abnormal equity return is the dependent variable, *ExpDm* is negative and statistically significant. Taken together, the univariate and multivariate results provide strong support for the significance of counterparty contagion risk because exposed firms experience significantly more negative consequences from Lehman's bankruptcy, as evidenced by the greater price impact of trade, more information asymmetry, greater selling order imbalance, and considerably lower equity returns than unexposed firms.

IV. Robustness Checks

As detailed in the sample selection procedures, our results are based on the sample of financial firms (SIC Code 6XXX) that should have the strongest ties to Lehman Brothers. However, Table I

[18] To save space, the coefficients on these variables are not reported, but we verify that the estimates have the expected signs.

[19] In addition, we also check for autocorrelation in the dependent variables by doing a Durbin–Watson (DW) test. All the DW test statistics are close to two, indicating no concerns for autocorrelation. The results of the Hausman test and the DW test are available upon request.

Table VI. Correlation Table

This table reports pairwise correlations of major variables in the multivariate regression. The correlation with a p-value of 0.05 or lower is indicated in bold.

Pairwise Correlation	Abnormal ΔQuoted Spread	Abnormal ΔEffective Spread	Abnormal ΔNumber of Trades	Abnormal ΔTrade Size	Abnormal ΔVolume	Abnormal ΔLambda	Abnormal ΔAdverse Selection	Abnormal ΔSell Ratio	AR	ExpDm	LnPrc	LnMveq	LnVolume	Volatility	Leverage
Abnormal ΔEffective Spread	0.6930	1													
Abnormal ΔNumber of Trades	−0.1676	−0.0152	1												
Abnormal ΔTrade Size	0.2818	0.2692	0.2715	1											
Abnormal ΔVolume	−0.1429	0.0826	0.8132	0.3890	1										
Abnormal ΔLambda	0.3462	0.4132	−0.1825	−0.3023	−0.2966	1									
Abnormal ΔAdverse Selection	0.3791	0.2701	−0.2408	−0.1378	−0.3160	0.5374	1								
Abnormal ΔSell ratio	0.2077	0.3151	−0.0250	0.3066	0.1274	0.0690	0.1190	1							
AR	−0.0622	−0.0453	−0.3806	−0.3985	−0.3993	−0.0447	0.0095	−0.2256	1						
ExpDm	0.0394	0.0178	0.0342	0.0442	0.0698	0.3038	0.3202	0.3737	−0.2373	1					
LnPrc	0.1083	0.0174	−0.2396	−0.1943	−0.2684	0.0231	0.1045	−0.1981	0.3299	−0.0450	1				
LnMveq	−0.0596	−0.1842	−0.1023	−0.3503	−0.0617	−0.2382	−0.1416	−0.3445	0.3111	−0.2766	0.5431	1			
LnVolume	−0.1714	−0.1614	0.1483	−0.1962	0.1476	−0.3923	−0.3390	−0.3358	0.1026	−0.4248	−0.0628	0.6492	1		
Volatility	−0.0184	−0.0457	0.1131	0.1075	0.2005	−0.1081	−0.1543	0.0572	−0.3686	−0.1995	−0.3561	−0.0498	0.3064	1	
Leverage	0.0599	0.1439	0.2487	0.1846	0.3281	−0.1155	−0.1201	−0.0024	−0.0505	0.0148	−0.1692	0.0484	0.2889	0.1728	1
Correlation	0.1286	0.0197	0.0237	−0.2285	−0.0225	0.0131	−0.0413	−0.2180	−0.0278	−0.1072	0.3199	0.4975	0.4514	0.0337	0.0753

Table VII. Cross-Sectional Analysis of Abnormal Changes of Market Microstructure Measures (Industry and Size Matching Approach)

This table presents coefficient estimates of the cross-sectional regression and its variations:

$$Abn\Delta liqVar = \alpha + \beta_1 ExpDm + \beta_2 LnPrice + \beta_3 LnMveq + \beta_4 LnVolume + \beta_5 Volatility + \beta_6 Leverage + \beta_7 Correlation + \varepsilon.$$

The dependent variables for Model 1–Model 8 are the abnormal relative change of each market microstructure variable for disclosing firms on the disclosure date (Day 0) using the industry and size matching approach. Model 8 includes an additional explanatory variable, Lagged *Sellratio*. In Model 9, the dependent variable is AR, the industry-adjusted abnormal equity return (in percentage) of the disclosing firm on the event day. Other variables are defined in the appendix. In addition to the reported variables, disclosure date dummies are also included in the regressions. The regression is based on the sample of 60 financial companies. The t-statistics reported beneath the coefficients are based on robust standard errors adjusted for events clustering.

Dependent variable	Model 1 Abnormal ΔQuoted spread	Model 2 Abnormal ΔEffective spread	Model 3 Abnormal ΔNumber of trade	Model 4 Abnormal ΔTrade size	Model 5 Abnormal ΔVolume	Model 6 Abnormal ΔLambda	Model 7 Abnormal ΔAdverse selection	Model 8 Abnormal ΔSellratio	Model 9 AR
Constant	143.59	116.63	−230.24	39.93	−182.69	222.77**	83.64	9.07	−8.71
	(1.81)	(0.76)	(−0.77)	(0.65)	(−0.91)	(2.07)	(0.35)	(0.72)	(−0.53)
ExpDm	−16.56	−3.37	−35.77	−6.96**	31.05	57.78***	101.78**	8.95**	−3.38**
	(−0.59)	(−0.09)	(−0.38)	(−1.97)	(0.35)	(3.44)	(2.12)	(2.33)	(−2.03)
LnPrice	2.5	10.74	−24.64	0.91	−45.88	−4.8	−3.24	−1.66	2.11
	(0.25)	(0.41)	(−0.58)	(0.12)	(−1.27)	(−0.36)	(−0.1)	(−0.6)	(0.66)
LnMveq	−6.46	−12.17	−13.18	−4.84	10.66	−1.35	5.99	−0.74	1.15
	(−0.83)	(−1.03)	(−0.47)	(−1.16)	(0.66)	(−0.21)	(0.27)	(−0.37)	(0.54)
LnVolume	−3.58	−8.34	17.25	−0.33		−14.2***	−0.59	0.24	0.04
	(−1.07)	(−0.8)	(0.67)	(−0.11)		(−5.7)	(−0.03)	(0.17)	(0.03)
Volatility	−0.98	−5.48	−0.53	1.18	11.12	−0.56	−13.16	−0.12	−2.02**
	(−0.38)	(−1.33)	(−0.06)	(0.39)	(0.47)	(−0.06)	(−0.96)	(−0.09)	(−2.22)
Leverage	−4.42	50	202.43	26.67	259.11	−48.64	−117.51	−8.23	0.27
	(−0.12)	(1.38)	(1.35)	(1.36)	(1.13)	(−0.81)	(−1.27)	(−0.69)	(0.05)
Correlation	73.47	84.02	100.32	−11.85	50.37	118.05	−82.62	19.27*	−15.51
	(0.93)	(0.86)	(0.4)	(−0.18)	(0.23)	(1.08)	(−0.47)	(1.65)	(−1.16)
Lagged sell ratio								0.47***	
								(6.81)	
R^2 Adjusted (%)	49.68	44.18	5.4	1.46	3.94	11.93	2.43	23.34	31.88
p-value for F-statistic	< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.0004	< 0.0001	< 0.0001	< 0.0001	< 0.0001

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

reports that several (26) nonfinancial firms also made voluntary declarations about their exposure (or lack thereof) to Lehman in the immediate aftermath of its bankruptcy. As a robustness check, we rerun all of our tests using both the financial and nonfinancial firms. We do this because most theories of financial contagion relate the effects of a shock (in our case the collapse of Lehman Brothers) to other firms in the economy (not limited to the same industry).

The counterparty hypothesis predicts that the shock from the collapse of a big firm should impact firms that have a direct counterparty relationship with it. The hypothesis makes no distinction whether such counterparty firms should belong to the same industry. For example, Dynegy, an electric energy production company (SIC Code 1311), had a $70 million Lehman Brothers Commercial Paper commitment under a $1.15 billion revolving credit facility and another $850 million letter of credit facility. The stock price of Dynegy plunged by over 10% upon its announcement of exposure to Lehman. Although Dynegy is not in the same industry as Lehman, its stock price decline reflects a potential loss from having to reestablish these contracts with other financial institutions.

Likewise, the information transmission hypothesis posits that the collapse induces a belief revision by all traders, leading to greater trading activities that should impact all firms in the economy. Although it is true that the policy implications of the contagion effect pertains to predominantly financial firms, the theoretical predictions (that we test) do not limit contagion effects to financial firms only. Therefore, the robustness tests should help to relate our work more broadly to the literature on contagion.

All our conclusions hold in this larger sample. We find mixed support for the information transmission hypothesis and strong support for the counterparty risk hypothesis. The univariate results indicate that although there is liquidity deterioration for both groups, the exposed firms suffer far worse effects than the unexposed firms. Multivariate results confirm that the exposure dummy variable is significant in four of the nine models. We also run the tests by matching on industry, market capitalization, and book-to-market (instead of the ISM), and all our results hold in this set of tests, as well.[20]

V. Conclusion

Lehman was the only large financial institution that filed for bankruptcy during the recent financial crisis. Immediately after Lehman's bankruptcy, over a hundred companies disclosed their financial exposure to Lehman. This allows us to test the significance of credit contagion effects arising from the collapse of a large financial institution and distinguish two contagion channels by explicitly controlling for a counterparty relationship. Prior empirical evidence supporting information contagion theory does not account for possible counterparty relationships.

A novelty of this study is that we construct microstructure liquidity variables using high frequency intraday data to provide a finer test of contagion theories. Specifically, our investigation focuses on the adverse impact on market liquidity, trading activity, information asymmetry, and order imbalance of other companies because of the financial distress of Lehman Brothers. Our analysis contributes to the credit contagion literature by testing contagion effects from a market microstructure perspective.

After controlling for counterparty relationships, we find that the disclosing firms in our sample experience liquidity deterioration in some dimensions, providing mixed support for the information transmission theory. However, our results demonstrate robust evidence for the counterparty

[20] All robustness test results are available upon request.

contagion hypothesis. Firms that have exposure to Lehman experience greater decreases in liquidity, higher price impacts of trade, and greater increases in information asymmetry. They also face greater sell pressure and lower abnormal equity returns than unexposed firms. Therefore, what we might attribute to information-based contagion in the full sample results seems to be driven mainly by counterparty exposure.

Proper identification of the channels of credit contagion is important from a policy perspective. As argued previously, policy response to financial crises should differ if the channel of contagion is identified as counterparty risk (in which case a bailout of failing financial institutions may be recommended) versus information transmission (in which case supporting the distressed sector may be a better option). By studying the sources of contagion effects after Lehman's collapse, our study also contributes to the policy debate on government response to the failure of large financial institutions during a financial crisis.

Appendix: Variable Definitions

Name	Definition
Microstructure liquidity variables	
Quoted Spread	Equally weighted quoted bid-ask spread
Effective Spread	Equally weighted effective bid-ask spread
Number of Trades	Daily average number of trades
Trade Size	Average trade size
Volume	Average daily trading volume in ('000)
LnVolume	Natural logarithm of trading volume
Lambda (in '000)	Kyle's Lambda
Adverse Selection (in '000)	Adverse selection component of bid-ask spread
Sellratio (%)	Selling ratio (number of seller initiated trades divided by total trade)
Lagged sellratio (%)	Lagged selling ratio (number of seller initiated trades divided by total trade) for the previous day
Control Variables	
Price	The average stock price in control period (August 2008)
LnPrice	Natural logarithm of stock price
Mveq (in millions)	Market value of equity preceding the event
LnMveq	Natural logarithm of market value of equity
Volatility	Daily stock return volatility over the previous year
Leverage	The average leverage ratio over four quarters during the preceding year, defined as the ratio of book value of debt over the market value of assets, taken as the market value of equity plus the book value of debt
Correlation	The correlation of equity returns between the sample firm and Lehman Brothers over the preceding year
ExpDm	Dummy variable equal to one if the firm has exposure to Lehman and zero otherwise

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