

How does failure spread across broker-dealers and dealer banks?

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August 31, 2012

Abstract

We empirically test for the presence of two different channels of financial contagion across large broker-dealers and dealer banks during the crisis of 2007-2009: one based on liquidity spirals of the sort modeled in Brunnermeier and Pedersen (2009), and one resulting from dealer interconnection through counterparty exposure. We test for these two forms of contagion against the null hypothesis that correlation in dealer distress during the crisis was due to only a common fundamental credit shock, not contagion. Rejecting the null, we find evidence that both the liquidity and interconnection channel were present during the financial crisis, though interconnection is the economically stronger of the two, accounting for around 86% of the total contagion effect.

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1 Introduction

The current literature on the 2007-2009 financial crisis reminds Lo (2012) of Akira Kurosawa's classic film, *Rashomon*, in that it fails to provide a single coherent interpretation of what happened. Scholars have proposed many, and sometimes conflicting theories and narratives of the crisis, but there is little formal empirical work by which to evaluate them. While the inability to provide closure can make a movie into a masterpiece, the same is not true a body of scientific literature. In this paper, we attempt to contribute to the literature by formally testing different previously-proposed theories of a phenomenon that is central to modern financial crises: the spread of financial distress from one large broker-dealer or dealer bank (henceforth, collectively, "dealers") to otherwise healthy dealers (e.g., Duffie, 2009). The potential for the spread of financial distress across dealers, called "contagion," motivated use of taxpayer funds to rescue failing dealers during the crisis of 2007-2008 (e.g., Bernanke, 2008 and 2011). Moreover, the anticipation of such rescues creates moral hazard that makes dealers more failure-prone (e.g., Hart and Zingales, 2010). Hence a better understanding of the channels by which distress spreads across dealers is fundamental not only to understanding the last crisis, but also to devising policies that can make the financial system less crisis-prone.

Cross-dealer contagion channels proposed in prior literature appear to fall into two broad categories: one based on interconnection, and the other

based on liquidity spirals. According to the interconnection channel, large dealers have thousands of financial contracts with many market participants and other dealers. As a result, the failure of a dealer may prompt a chain of cascading defaults because other dealers have significant direct or indirect counterparty exposure to the failing dealer. According to the liquidity spiral channel, the failure of a single large dealer causes a large negative systematic liquidity shock, causing prices of securities widely used by other dealers as short-term funding collateral to drop below fundamental value, in turn threatening the viability of even sound dealers. In contrast to these two potential contagion channels, the literature also suggests a third possibility: financial distress is correlated across dealers not because of contagion, but because a common fundamental credit shock impacts all dealers simultaneously. In this study, we test whether the two channels of financial contagion spread distress across dealers during the period over 2007-2009, against the null hypothesis that the appearance of contagion is due to a common fundamental credit shock. We find evidence consistent with the interconnection channel having statistically and economically significant effects, accounting for around 86% of the total contagion effect. Our evidence on the liquidity spiral channel, though statistically significant, suggests it is only of modest economic importance during the recent crisis.

Bernanke (2008), Hart and Zingales (2010), Jorion and Zhang (2009) and others describe the interconnection channel. Dealers lend to and engage in many over-the-counter derivatives transactions with one another, creating a

complex and opaque web of large inter-dealer counterparty exposures. Allen and Gale (2000) and Zawadowski (2010) present formal models in which a high degree of counterparty exposure across financial institutions arises in equilibrium. If a single dealer fails, it defaults on its contracts to other dealers, which increases the risk the latter will fail and default on their contracts to still other dealers, and so on, possibly leading to systemic collapse. Furthermore, Duffie (2009) provides reason to believe that even healthy dealers with no counterparty exposure to the failing dealer might find their solvency threatened. Since a dealer's risk exposures are unobservable to outsiders, overnight lenders, prime brokerage clients, and derivatives counterparties will run to drain cash from even an unexposed, healthy dealer (i.e. by refusing to roll over loans, closing accounts, or imposing higher margin requirements) as a prudential measure to avoid losses when a peer dealer fails.

The liquidity spiral channel is based on models by Brunnermeier and Pedersen (2009), and variations of it are described in Duffie (2009), Gorton and Metrick (2011), Krishnamurthy (2010), and others.¹ For a variety of reasons, a single large dealer failure causes a major systematic shock to market or funding liquidity, or both. The liquidity shock, in turn, causes the prices of securities used by other dealers as funding collateral to drop below fundamental value. Because all dealers are highly levered and depend heavily for funding on extreme short-term debt such as repurchase agreements

¹Diamond and Rajan (2005) construct a model for contagion across commercial banks that is very similar.

(henceforth "repos") and commercial paper, depressed securities prices curtail dealers' ability to borrow against their holdings, which, in turn, forces them to rapidly sell. Such rapid selling exacerbates the negative liquidity shock, inducing a feedback loop. The feedback loop turns into a death spiral as short-term lenders refuse to extend any credit to any dealer for fear of being stuck with illiquid collateral.

To examine the different channels of contagion between dealers, we use tests that fall into two broad categories: those based on vector autoregression (VAR) analysis, and those based upon panel data seemingly unrelated regression (SUR) models. With vector autoregressions, we examine the extent to which an increase in the least creditworthy set of dealers' CDS spreads causes an increase in the most creditworthy set of dealers' CDS spreads, and we further examine the extent to which this happens through the channel of decreased aggregate liquidity. All the while we control for the credit risk of the securitized products, namely commercial and subprime residential mortgaged-backed securities, whose impairment precipitated the crisis. To conduct this analysis we use a proxy for the illiquidity discount in the secondary bond markets and short-term funding markets uncontaminated by credit risk: the off-the-run treasury spread (e.g., Barclay, Hendershott and Kotz, 2006, Goldreich, Hanke, and Nath, 2005, Vayanos and Weill, 2008).

Our VAR analysis finds significant evidence consistent with contagion through both the liquidity and interconnection channels. Controlling for the securitized products underlying the crisis, we find that the least credit-

worthy dealers' CDS spreads impact that of the most credit-worthy dealers both through the off-the-run spread, as well as directly. However, we find that liquidity can explain only 14% of the transmission of financial contagion from the least to most creditworthy set of dealers. We attribute the remainder to the interconnection channel.

With our SUR model, we examine the extent to which individual dealers' CDS spreads are sensitive to aggregate illiquidity and the CDS spreads of their riskiest peers, while controlling for each individual dealer's unique exposure to the securitized products that precipitated the crisis. In this manner, we are more careful to isolate the effects of interconnection and liquidity from fundamental common credit shocks. Consistent with our VAR results, our SUR results indicate that, holding constant the CDS spreads of the riskiest dealer peers and securitized products, illiquidity has a statistically significant albeit economically modest relation with individual dealer CDS spreads. Namely, a one standard deviation increase to illiquidity is associated with a mere 2.6 basis point increase in an individual dealer's CDS spread. However, also consistent with our VAR results, our SUR results are consistent with a statistically and economically significant role for the direct interconnection channel. Namely, a one standard deviation increase in CDS spreads of risky peer dealers is associated with a 17.7 basis point increase in the remaining average dealer's CDS spread, holding constant illiquidity and securitized products.

Our inference that liquidity played only a minor role in transmitting con-

tagion during the last crisis assumes that the ten year off-the-run spread is a valid illiquidity proxy. At first glance, this assumption appears doubtful. The liquidity spiral channel operates through illiquidity in the securities that dealers hold, of which Treasuries are only a small part and affected least by illiquidity. However, Hu, Pan and Wang (2012), as well as Musto, Ninni and Schwarz (2012) provide evidence that large discrepancies in the yields of Treasuries of similar duration are a good proxy of the kinds of systematic liquidity shocks behind the liquidity spiral channel. Hence our proxy is appropriate. When we use the more complex Hu, Pan and Wang (2012) Treasury pricing error statistic in place of our simple measure of the off-the-run spread in robustness tests, we find an even smaller role for liquidity. On the other hand, our results do not rule out the possibility that the liquidity spiral channel has the potential of being important. It may not have played a large role during the last crisis because the many unprecedented government interventions injecting funding liquidity into the system successfully counteracted destabilizing liquidity shocks (e.g., Afonso, Kover and Schoar, 2010 and Duygan-Bump et. al , 2012).

Our finding that the riskiest dealers' CDS spreads directly impact that of all other dealers, while consistent with a strong interconnection channel of contagion, is also consistent with a frailty story.² Increases in the riskiest dealers' CDS spreads may cause investors to update their beliefs about unob-

²See Duffie, Eckner, Horel and Saitia (2009) for theory and evidence related to frailty-induced default correlations in non-financial firms.

served factors related to the fragility of the financial system, thereby causing the spreads of other dealers to change, even if the latter have no counterparty exposure. We partly address this issue by confining our analysis to years during which the main fundamental factors behind financial system fragility, namely securitized credit products, are well-known and observable. Nevertheless, we cannot with certainty rule out the existence of other unobservable common factors for which we cannot control. For example, investors might be inferring from changes in the riskiest dealers' CDS spreads that the willingness of the government to assist failing institutions is changing.

Our paper is directly related to the large theory literature on contagion across financial institutions that rapidly emerged in the wake of the crisis of 2007-2009³. While this literature makes it plausible that the channels discussed above were important during the crisis, and some anecdotal evidence has been brought to light, there is little formal empirical work examining their relative importance during the crisis.

In addition, there exists a large empirical literature on financial contagion not specifically related to the crisis 2007-2009. Our study contributes to this literature in important ways. While there are many empirical contagion studies that focus on commercial banks,⁴ we focus on dealers, including broker-dealers unaffiliated with a commercial bank. Given the central role

³See for instance Diamond and Rajan (2009), Brunnermeier (2009), Brunnermeier and Pedersen (2009), Martin, Skeie, and Thadden (2010), Liu and Mello (2010), Acharaya, Gale and Yorulmazer (2010), Acharya and Skeie (2010).

⁴Aharony and Swary (1983 and 1996), Iyer and Peydro (2011), Swary (1986), Whyte (1996).

that dealers have come to play in the modern financial system, particularly during the last crisis, and the fact their business model fundamentally differs from that of commercial banks (e.g., Duffie, 2009), our study fills an important gap in the literature. Our study also differs in its methods. Previous studies on contagion across banks and non-financial firms utilize actual failures or defaults in their research design.⁵ Instead, we utilize co-movements in credit default swaps since there are few actual dealer failures in the data. Finally, since we focus on contagion across institutions, our study differs from the empirical literature on contagion across countries,⁶ asset classes (e.g., Longstaff, 2010), and particular securities (e.g., Coval and Starfford, 2007).

Some indirect and suggestive evidence on the liquidity spiral channel has also emerged in studies not directly tied to the contagion literature. Adrian and Shin (2008) show that dealer leverage is pro-cyclical, and that reduction in aggregate dealer repo financing predicts increases in implied market volatility, as measured by the VIX. Acharya and Merrouche (2010) present evidence that UK banks hoarded liquidity after crisis events during 2007. Copeland, Martin and Walker (2010) show how repo counterparties reduced the amount of credit they were willing to extend to dealers, even with Treasury collateral, during crisis events. Frank, Gonzalez-Hermosillo, and Hesse (2008) show that stock market volatility, credit spreads on asset-backed com-

⁵Das, Duffie, Kapadia and Saitia (2007), Duffie et al. (2009), Lang and Stulz (1992), and Jorion and Zhang (2007 and 2012) all study contagion across non-financial firms.

⁶See Kaminsky, Reinhart and Vegh (2003) for a review of this literature. See Jotikasthira, Lundblad and Ramadorai (2011) for a recent example.

mercial paper, as well as the TED spread, are all highly correlated with the off-the-run spread during the crisis, providing suggestive evidence that liquidity spirals are related to system-wide default risk. Krishnamurthy (2010) and Gorton (2009) provide suggestive evidence that trouble at major financial institutions was associated with persistent reductions in bond market liquidity during the crisis. While all of the above empirical papers are valuable, none provides direct evidence that links market expectations of a single dealer's failure to the expectations of other dealer's failure through an illiquidity discount. By providing such empirical links, we establish the first direct evidence of the liquidity channel of contagion. We also believe we are the first paper to provide evidence of the interconnection channel during the crisis, as well as the first to compare the relative importance of the two channels.

Our paper is also related to those that analyze the run on the "securitized-banking" system during the 2007-2009 crisis.⁷ In the traditional banking system, a financial institution makes and holds loans with funding provided by clients' deposits. In the securitized-banking system, on the other hand, loans are originated, securitized and sold to investors, some of which fund their investments with short-term loans made by money market funds. Some papers have shown evidence that the 2007-2009 crisis was a run on the "securitized-banking" system. We contribute to this literature by analyzing the depen-

⁷See for instance Gorton and Metrick (2009), Acharya, Schnabl, and Suarez (2010), Krishnamurthy, Nagel, and Orlov(2011).

dence of dealers on short-term funding and the mechanism by which this dependence helps transmitting the failure of one dealer to other dealers.

The rest of this study is organized as follows. In Section 2, we develop our empirical hypotheses. In Section 3, we discuss our data and descriptive statistics. In Section 4 we present our main tests. Section 5 concludes.

2 Hypothesis Development

In this section, we consider hypotheses based on the two channels of contagion: liquidity and interconnection.

Under the liquidity channel of contagion, the default of a single dealer triggers a large negative liquidity shock that depresses prices of assets upon which other dealers depend for short-term collateralized debt financing. The depressed prices, in turn, curtail other dealers' access to credit, which potentially threatens their solvency. The failure of a single large dealer can plausibly cause a negative liquidity shock to markets for at least four reasons. First, upon the dealer's default, its repo counterparties receive immediate title to the collateral, which generally consists of relatively illiquid, long-maturity fixed income securities that many dealers' short-term lenders, such as money market funds, are contractually prohibited from holding. Hence default triggers fire sales in fixed income securities markets (e.g., Gorton and Metrick, 2011, Krishnamurthy, 2010), causing a liquidity discount. Second, the dealer's prime brokerage clients will likely find their accounts temporarily

frozen, worsening the liquidity shock (e.g., Duffie, 2010)⁸. Third, liquidity suffers from the sudden disappearance of a major market maker. Fourth, the contagion model of Goldstein and Pauzner (2004), if applied to dealers, suggests that the failing dealer's lenders, after experiencing losses, would provide less funding liquidity to other market participants, thereby forcing the latter to supply less market liquidity. Independently of the reason why the failure of a single dealer causes a liquidity shock, the liquidity channel of contagion implies a chain of causation: one dealer's default causes liquidity to be reduced, which in turn causes other dealers to fail. Hence if markets anticipate this chain of events, we would expect an increase in the riskiest dealer's probability of default to cause an increase in the illiquidity discount, which in turn will cause other dealers' probability of default to increase. Using dealers' CDS spreads as a proxy for probability of default, as well as the off-the-run treasury spread as a measure of illiquidity uncontaminated by credit risk (e.g., Barclay, Hendershott and Kotz, 2006, Goldreich, Hanke, and Nath, 2005, Vayanos and Weill, 2008), the liquidity channel of contagion leads to the following empirical hypotheses:

H1: An increase in the CDS spread of the riskiest dealers should cause an increase in the off-the-run spread.

H2: An increase in the off-the-run spread should cause an increase in the CDS spread of even the safest large dealers.

⁸Aragon and Strahan (2009) find that the freezing of hedge fund prime brokerage accounts at the London office of Lehman Brothers significantly impacted liquidity in the stock market.

The interconnection channel postulates that contagion spreads through contracts and counterparty dealings across dealers, not through liquidity, nor investor revaluation of mortgaged-backed securities. Hence the interconnection channel implies the following empirical hypothesis:

H3: An increase in the CDS spread of the riskiest dealers should directly cause an increase in the CDS of the safest dealers, apart from its effect on liquidity, and controlling for the value of crisis-precipitating mortgage-backed securities.

Returning to the liquidity channel, if liquidity shocks can bring down even fundamentally sound dealers, we would expect the illiquidity discount to impact a dealer's probability of default even after controlling for the fundamental soundness of the dealer's assets. Hence our fourth hypothesis:

H4: During the crisis period, a dealer's CDS spread should be positively related to the off-the-run spread even after controlling for the dealer's exposure to subprime residential and commercial mortgaged-backed securities.

If the interconnection channel is effective, then an individual dealer's CDS spread should be sensitive to the weakest dealer spreads, even after controlling for liquidity, as well as its unique exposure to the structured products that precipitated the crisis:

H5: During the crisis period, a dealer's CDS spread should be positively related to the riskiest dealer's CDS spread, even after controlling for liquidity and the dealer's unique exposure to subprime residential and commercial mortgaged-backed securities.

We consider how the sensitivity of the dealer’s CDS spread to illiquidity is related to the dealer’s balance sheet. The liquidity channel functions because dealers finance their holdings of relatively illiquid, long-maturity assets with extremely short-term liabilities such as repos, commercial paper and asset-backed commercial paper. When a liquidity shock hits the secondary markets for dealer-held assets, dealer solvency is threatened because they cannot sell their assets at fair value to pay creditors who are refusing to roll over their extremely short-term debt instruments. Hence we come to our final hypothesis:

H6: The sensitivity of a dealer’s CDS spread to the off-the-run spread increases as the dealer relies more heavily on repo, unsecured commercial paper and asset-backed commercial paper financing.

3 Data and descriptive statistics

We obtain data on CDS spreads from CMA. Specifically, we use the daily mid quote of the spread on the five year CDS contract for the 17 Primary Dealers, as designated by the Federal Reserve. However, we only use data from the 13 dealers for whom we have reliable data. This leads us to exclude HSCB, Nomura, Diawa, and Mizuho, since all four have long stretches during our sample period with no actively traded contracts and only derived, rather than active, quotes, or no quotes at all. We use the five year CDS contracts because they are the most liquid and most likely to have active quotes in a

given day, as indicated by CMA. Finally, for each day, we split the dealers into quintiles and take the cross-sectional average quote for the top and bottom quintiles, labeling them *HighCDS* and *LowCDS*, respectively.

To compute the off-the-run Treasury spread (*OTRSpread*), from Datas-tream we obtain the daily time series closing yield-to-maturity on the Merrill Lynch 9-11 year off-the-run Treasury index. We then subtract the closing yield on the on-the-run 10 year Treasury note for same day. We use the ten-year off-the-run spread because the ten year on-the-run note is more liquid than the on-the-run five year note and 30 year bond. We do not use a spread derived from shorter maturities because they are more likely to be distorted by Federal Reserve open market operations. In addition, we expect dealer default primarily to affect liquidity in long-term bonds because of the maturity restrictions faced by money market funds and other repo counterparties.

For *LowCDS*, *HighCDS* and *OTRspread*, we construct a daily time series that covers the 2007-2009 period.

For our tests that require controlling for dealer exposure to the subprime market, we obtain Markit's *ABX* and *CMBX* indices for BBB tranche residential subprime and commercial mortgage backed securities, respectively. In both cases, for each day, we take the average of the index levels for the two 2006 vintage indices. We use the two 2006 vintages, rather than later vintages, so that we can have a full year of observations for 2007. Since changes in these indices may be related to liquidity, and we need a clean proxy for the fundamental credit assessment of real estate-related securities,

we build a variable that we call *Credit* using a two step procedure. First, we regress the return of the *ABX* and *CMBX* indices on changes in the *OTRSpread* using OLS. We also attempted various non-linear specifications to allow for the possibility that these real-estate-backed markets are more sensitive to systematic illiquidity shocks than are Treasuries, but we could not reject the simple linear specification. Second, we obtain the first principal component of the residuals obtained in the OLS regressions run in the first step. We construct *Credit* in such a way that it is positively correlated *ABX* and *CMBX* spread, hence an increase in *Credit* is equivalent to a decrease in the credit quality of real estate assets. Descriptive statistics for all of the above variables are in Table 1.

In order to examine how a dealer’s reliance on extremely short-term risky debt financing impacts the sensitivity of its CDS spread to security market liquidity, we obtain from SEC filings⁹ the face value of each dealer’s outstanding repo and unsecured commercial paper liabilities as of the end of 2006. In addition, we obtain from Philipp Schnable’s website each dealer’s liabilities related to its guarantees of asset-backed commercial paper conduits as of the end of 2006, much of which are off balance sheet. These asset-backed commercial paper liability data are the same as used in Acharya, Schnabl and Suarez (2011) . We follow Acharya et al. and normalize each dealer’s funding liabilities by the book value of common equity. Also following Acharya et al., we focus on the 2006 liabilities, from a time before the crisis hit, in order

⁹Form 10K for domestic dealers and form 20F for foreign.

to avoid endogeneity problems. Once the crisis hit, a dealer's susceptibility to liquidity spirals and other channels of contagion arguably influenced its capital structure choice. Descriptive statistics for these liability ratios are in Table 2.

Figure 1 contains suggestive evidence that dealer failure can lead to large illiquidity discounts. The figure presents a graph of the time series of the 10 year off-the-run spread over the 2006-2009 period. Note how the spread increases dramatically following J.P. Morgan's acquisition of Bear Sterns, as well as in the weeks following the failure of Lehman brothers. In the latter case, it jumped by nearly a factor of seven, from five basis points to nearly 35!

Figure 2 contains a chart of all 13 primary dealers' five year CDS spreads over the 2007-2009 period. We note that there is considerable time series variation in all of them, and large movements are not concentrated around any specific events, though there certainly is a large jump in all of them around both the distressed sale of Bear Sterns in March of 2008 and the Lehman Brothers bankruptcy filing in September of 2008.

4 Tests and Results

Our tests fall into two broad categories: tests based on time series vector autoregressions (VAR), which we discuss in Section 4.1, and tests based upon panel data seemingly unrelated regression models (SUR), discussed in Sec-

tion 4.2. With our VAR tests, we examine how an increase in the riskiest dealers' probability of default leads to an increase in even the safest dealers' probability of default, and examine how much of this occurs through the mechanism of aggregate liquidity. With our SUR model, we examine the sensitivity of individual dealers' CDS spreads to aggregate illiquidity and other dealer CDS spreads, while simultaneously controlling for the individual dealer's exposure to subprime residential and commercial mortgage-backed securities, which are well-known to be the fundamental credit drivers of the financial crisis.

4.1 VAR tests

Recall that the liquidity channel of contagion implies the following chain of causation: a single or small subset of dealers becomes likely to default, which causes the illiquidity discount to increase, as markets anticipate dealer failure to cause a large negative liquidity shock. An increase in the illiquidity discount should, in turn, cause even the safest dealers' default probability to rise. We test this chain of causation in two ways. First, we conduct simple tests of Granger causality using a reduced-form VAR. We then run a structural VAR to get a sense of the contemporaneous effects of liquidity on dealer CDS spreads and vice-versa.

To conduct granger causality tests, we jointly estimate the vector autore-

gression represented by the following system of equations:

$$y_t = \alpha + \sum_{j=1}^2 \beta_j y_{t-j} + \varepsilon_t \quad (1)$$

where $y_t = [OTRSpread_t, HighCDS_t, LowCDS_t, Credit_t]'$, α is a 4×1 vector and β_j are 4×4 matrices, and ε_t is a vector of serially uncorrelated model disturbances. The number of lags is set equal to 2, the optimum based on a Lagrange multiplier test. We present coefficient estimates in Table 3, and results from Granger causality tests in Table 4. Consistent with the liquidity hypotheses, *HighCDS* Granger-causes the *OTRSpread*, and the *OTRSpread*, in turn, Granger-causes *LowCDS*.

The above reduced-form VAR analysis can be misleading. In all likelihood, the effect of *HighCDS*, *OTRSpread*, *LowCDS* and *Credit* on each other is instantaneous, whereas the above specification only allows for a lagged effect. To get a sense of the true instantaneous effects and build impulse response functions that are motivated by the theory we follow Bernanke (1986) and we estimate following structural vector-autoregression:

$$y_t = \alpha^* + \sum_{j=0}^2 \beta_j^* y_{t-j} + u_t \quad (2)$$

Where u_t is vector of serially uncorrelated model disturbances and $E[u_t u_t'] = \Sigma$, a diagonal matrix. We impose the following restrictions on the matrix β_0^* ,

which controls the contemporaneous relations between our VAR variables.

$$\begin{bmatrix} 0 & \beta_{1,2}^* & 0 & 0 \\ \beta_{2,1}^* & 0 & 0 & \beta_{2,4}^* \\ \beta_{3,1}^* & \beta_{3,2}^* & 0 & \beta_{3,4}^* \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad (3)$$

These restrictions imply that *OTRSpread* can affect both *HighCDS* and *LowCDS*, that is liquidity shocks can affect the CDS spreads of all types of dealers. *HighCDS* can affect both *OTRSpread* and *LowCDS*, that is an adverse shock to the credit quality of the riskiest dealers impacts the liquidity premium and the credit quality of the safest dealers. *LowCDS* does not contemporaneously affect any other variable in the system, while *Credit* is not affected by any other variable in the system. That is, shocks to the safest dealers' credit quality do not affect liquidity or the market assessment of the riskiest dealer, an assumption consistent with all theories of contagion, while the fundamental credit quality of real estate assets is an exogenous state variable.

The system above is quasi-identified (see Hamilton [1994]). We estimate the above system of three equations jointly using full-information maximum likelihood. Our estimates of β_0^* are in Table 5 below.¹⁰ To get a sense of economic significance, we plot the impulse response functions implied by the

¹⁰The point estimate of α^* , β_1^* , and β_2^* are linear transformations of α , β_1 , and β_2 and are not displayed herein.

parameters of our structural VAR in Figure 3. This figure along with the point estimates in Table 5 reveal that shocks in *HighCDS*, *OTRSpread*, and *Credit* have a long-lasting effect on *LowCDS*.

We further decompose the impact of *HighCDS* on *LowCDS* into three pieces to understand the extent to which *HighCDS* impacts *LowCDS* through its impact on the off-the-run spread. The proportion of the impact that acts through the off-the-run spread is an estimate of the fraction of contagion attributable to the liquidity channel. The fraction is given in Figure 4. Specifically, Figure 4 plots a series of impulse responses in which some of the parameters in the matrices β_j^* are set equal to zero. For instance, to understand the proportion of a shock on *HighCDS* that is transmitted to *LowCDS* through changes in the off-the-run spread, we set all the coefficients in the *LowCDS* equation equal to zero with exception of those that are multiplying $OTRSpread_{t-j}$ as well as $LowCDS_{t-j}$, $j = 0$ to 2 and we estimate the impulse response, which is labeled as "Liquidity" in Figure 4. As can be seen in this figure, the liquidity channel is responsible for only a small fraction of the shock of *HighCDS* on *LowCDS*. In fact, the second panel of Figure 4 reveals that only 14% of the long-term cumulative impact of a shock in *HighCDS* onto *LowCDS* is related to liquidity. On the other hand, the direct effect of a shock in *HighCDS* onto *LowCDS* accounts for the largest fraction of the contagion between dealers. We see two possible conclusions from these results. Either most of the contagion between dealers is due to an interconnection channel, or *HighCDS* captures both contagion

channels if our proxy for liquidity is poor.

As a robustness check we run a similar specification to Equation (2), except we use first differences of all the variables. In untabulated results, we find that the liquidity-spiral channel of contagion is even weaker than what we find with our levels specification, but the interconnection channel is qualitatively just as strong. We also run a specification in which we replace *OTRS*spread with the Hu, Pan and Wang (2012) more general summary statistic for discrepancies in yields in Treasuries with similar duration. The fraction of contagion due to of illiquidity effects in these (untabulated) results is even smaller. Hence, if anything, our main results overstate the importance of illiquidity in transmitting financial contagion.

4.2 Panel data SUR analysis

Using SUR analysis, we more carefully control for common credit shocks in order to ensure that our estimates of the relative importance of the two channels of contagion are truly valid. We estimate the following three SUR models using a panel of dealer-day observations:

$$CDS_{i,t} = \alpha_i + \sum_{j=0}^2 \beta_j HighCDS_{t-j} + \sum_{j=1}^2 \gamma_{i,j} CDS_{i,t-j} + \epsilon_t \quad (4)$$

$$\begin{aligned}
CDS_{i,t} = & \alpha_i + \sum_{j=0}^2 (\beta_j HighCDS_{t-j} + \delta_j OTRSpread_{t-j}) \quad (5) \\
& + \sum_{j=1}^2 \gamma_{i,j} CDS_{i,t-j} + \epsilon_t
\end{aligned}$$

$$\begin{aligned}
CDS_{i,t} = & \alpha_i + \sum_{j=0}^2 (\beta_j HighCDS_{t-j} + \delta_j OTRSpread_{t-j} + a_{i,j} Credit) \quad (6) \\
& + \sum_{j=1}^2 \gamma_{i,j} CDS_{i,t-j} + \epsilon_t
\end{aligned}$$

Where $CDS_{i,t}$ is the CDS spread for dealer i at time t . $OTRSpread_t$, $HighCDS_t$ and $Credit_t$ are defined as before. The coefficient on $OTRSpread_t$ measures how an individual dealer's CDS spread is related to illiquidity, holding fixed the credit quality of its riskiest peers. Likewise, the coefficient on $HighCDS_t$ measures the extent to which an individual dealer's CDS spread is related to the credit quality of its riskiest peers, holding fixed illiquidity. The liquidity channel of contagion predicts a positive and significant coefficient on $OTRSpread_t$, whereas the interconnection channel predicts a positive and significant coefficient on $MaxCDS_t$. We include two lags of all variables to be consistent with our VAR analysis, but our results are not sensitive to the number of lags. We estimate each equation for all the dealers

jointly, excluding those dealers whose CDS spread is within the top quintile at any time during the sample period. We exclude these dealers so as not to induce a mechanical relation between $CDS_{i,t}$ and $HighCDS_t$. The exclusion also reduces the potential for reverse causality and feedback between $CDS_{i,t}$ and $OTRSpread_t$, since the results from our VAR suggest that only deterioration in the riskiest dealers credit quality has a causal impact on the off-the-run spread. We are not concerned about feedback between $CDS_{i,t}$ and $HighCDS_t$ because it is implied by the interconnection contagion channel. In Equation (6) we allow the coefficient on $Credit_t$ and its lags to be different for each dealer. In this manner, we allow the data to tell us how exposed each dealer is to the securitized debt markets, thereby allowing us to control for each dealer's unique exposure to the assets driving the financial crisis.

We estimate each equation using seemingly-unrelated regression analysis. The results are in Table 6, where for brevity we only report the coefficients and standard errors of coefficients that we force to be the same across dealers. We also report the mean of the dealer-specific coefficients on $Credit_t$ in Equation (6), as well as a Wald test of their joint significance. The coefficient on $HighCDS_t$ in Equation (4) provides a measure of the total contagion effect, including liquidity and interconnection channels, but ignoring the possibility that a fundamental credit shock is driving the result. As can be seen in Table 6, it is positive and significant. In Equation (5), we add our illiquidity proxy, but we do not control for the individual dealer's exposure to the

securities that precipitated the crisis. Hence the coefficients on $HighCDS_t$ and $OTRSpread_t$ in this specification, though both statistically significant, might plausibly be contaminated by a common fundamental credit shock. Finally, in Equation (6), by adding our $Credit_t$ variable and allowing the coefficients on this variable and its lag be different across all dealers, we can isolate the liquidity and interconnection contagion channels from the null hypothesis of a fundamental credit shock. The coefficients on $OTRSpread_t$ and $HighCDS_t$ continue to be individually positive and significant when we control for dealer-specific exposure to common credit shocks, consistent with hypotheses H4 and H5. Furthermore, these coefficients are virtually unchanged from their values estimated in Equation (5), implying that not only are the interconnection and liquidity channels real, but their effect is largely orthogonal to our measure of the dealers' fundamental common credit factor.

Though the statistical significance of our estimated parameters of Equation (6) suggests both channels of contagion are present, the magnitudes of the point estimates suggest that only the interconnection channel is economically large. A coefficient of 0.325 on $OTRSpread_t$ (see Table 6) suggests that a one standard deviation increase in this variable (see Table 1) is associated with an increase of only 2.62 basis points in $CDS_{i,t}$, an economically modest amount compared to the mean and median values of CDS_t of 116 and 92.5, respectively. However, a coefficient of 0.113 on $HighCDS_t$ implies that a one standard deviation increase in this variable is associated with 17.7 basis

point increase in $CDS_{i,t}$, indicating a substantially larger effect than that of $OTRSpread_t$. In a robustness test, we run a specification similar to Equations (4) to (6), except we use first differences of all variables (and no lags). Our results, untabulated, are qualitatively similar. We also run a specification in which we replace $OTRSpread_t$ with the Hu, Pan and Wang (2012) summary statistic for all yield discrepancies in Treasuries of similar duration. The results (untabulated) indicate an even smaller illiquidity effect.

Our estimate of the importance of interconnection in these specifications depends on the extent to which our credit variable measures fundamentals in the mortgage-backed securities markets. However, Stanton and Wallace (2011) argue that the AAA tranches of the ABX index did not reflect fundamentals during the crisis, but rather implied impossibly high expected mortgage loan loss rates. They attribute this apparent mispricing to high demand for credit insurance, along with capital constraints on the suppliers of insurance. We at least partly mitigate this issue by using BBB tranches of the ABX index, rather than the AAA tranches Stanton and Wallace study. Since BBB tranches were already known to be somewhat speculative, they were less likely to be held by institutions prone to need credit insurance. However, even if the BBB tranches, at least in part, reflected overall financial system distress, then our estimate of the coefficient on $HighCDS_t$ is biased downward, assuming the true fundamentals underlying $Credit_t$ have a positive partial correlation with $HighCDS_t$.¹¹ Hence, if anything, our

¹¹See Green (1997), p. 440.

results understate the importance of the interconnection channel.

Finally, we present some evidence on how the liquidity channel of contagion is related to the dependence of dealers on extreme short-term debt financing. As discussed in Section 3, we obtain data on the face value of each dealer's liabilities related to repurchase agreements, unsecured commercial paper and asset backed commercial paper. We obtain these data as of the end of fiscal 2006, the last available annual filing before the onset of the crisis. We wish to use pre-crisis data in order to avoid a potential endogeneity problem: a dealer's ability to finance itself with short-term debt during the crisis might be related to its susceptibility to contagion. Following Acharya et al., we normalize our liability numbers by total common equity. We then interact each liability ratio with the off-the-run spread. We present these various ratios of liabilities to equity for each dealer, along with summary statistics, in Table 2. Furthermore, since dealers likely adjusted their capital structure as the crisis, the 2006 balance sheet ratios are likely only in periods close to the end of 2006. Hence we limit the sample period for this analysis to the trading days of 2007.

We run a panel data SUR models similar to Equation (6) above, except we also include the liability ratios mentioned above, as well as their interaction with the off-the-run spread and its lags. We run four specifications, one for each of our three liability ratios, and then a fourth that includes all three ratios and their interaction with the off-the-run spread and its lags. As before, we allow the coefficient on $Credit_t$ to differ for each dealer, but we

force all dealers to have the same coefficient on the off-the-run spread, the liability ratios, and the interaction terms. Since our liability ratio variables have no time series variation in our sample, we do not include dealer fixed effects in order to avoid perfect colinearity. The results are in Table 7. The interactions of $OTRSpread_t$ with the ratio of repos and unsecured commercial paper to equity are statistically significant in the predicted direction in all specifications where they appear, suggesting that the liquidity channel of contagion is related to dealer reliance on repo and unsecured commercial paper for funding, consistent with hypothesis H6. However, our finding that the interaction of illiquidity with the ratio of asset-backed commercial paper liabilities to common equity is not significant in any specification suggests that asset-backed commercial paper does not play a role in the liquidity channel.

5 Conclusion

Primary dealers are central to the operations of financial markets and the shadow banking system. Consequently, it is important for policy makers, regulators and risk managers to understand how the increase in default risk for one or a subset of primary dealers affects other primary dealers. In this paper, we empirically study two possible contagion mechanisms of dealer failures, one based on illiquidity and another based on direct interconnection through counterparty exposure, against the null hypothesis that there is no contagion, and correlated dealer failure is due merely to observable common

fundamental credit shocks.

Our results provide evidence that financial contagion of both forms is real. Specifically, we find that an increase in the riskiness of any large dealer causes market liquidity to decline, which then in turn causes even the safest dealers to become riskier, supporting the liquidity channel. However, we find that the vast majority of contagion operates apart from liquidity. We also run tests showing individual dealer CDS spreads during the crisis are sensitive to other dealer spreads, as well as market illiquidity, even when we control for the individual dealer's unique exposure to subprime residential and commercial mortgage-backed securities, the assets that precipitated the crisis. Since the effect of other dealer spreads is stronger, our evidence is consistent with interconnection being the dominant channel of contagion during the last crisis, though it is also consistent with a fragility story in which investors use increases in the riskiest dealers' default probabilities to learn about observed factors related to the fragility of the financial system. Overall, our results suggest that policies cushioning the fixed income markets against negative liquidity shocks, as well as encouraging greater and more timely transparency about dealer risk exposures, as well as greater policy maker transparency, all play a role in stabilizing the financial system even when policies incentivizing cautious underwriting are in place.

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Table 1
Descriptive Statistics

	N	Mean	Stdev	1st pctl	25th pctl	50th pctl	75th pctl	99th pctl
HighCDS	751	228	157	22.5	125	196	335	715
LowCDS	751	58.1	34.9	4.95	30.3	60.5	82.8	136
OTRSpread	751	9.82	8.09	0.100	3.90	7.50	12.50	33.80
ABX	751	-0.004	0.026	-0.082	-0.014	0.000	0.007	0.066
CMBX	751	-0.001	0.032	-0.085	-0.011	0.000	0.007	0.113
Credit	751	0.000187	0.0318	-0.106	-0.00931	-0.000486	0.0124	0.0808
CDS	9245	116	105	5.70	44.5	92.5	105	476

Table 2 - Ratios of repo, commercial paper, and asset-backed commercial paper liabilities (both on and off balance sheet) to total common book equity as of the end of fiscal 2006.

	Repos	Unsecured Commercial Paper (cp)	Asset-backed Commercial Paper (abcp)
Bank of America	1.64	0.23	0.35
Barclays	2.55	0.49	0.62
Bnp Paribas	4.96	0.00	0.19
Citigroup	2.79	0.37	0.78
Credit Suisse	6.20	0.32	0.10
Deutschebank	4.31	0.12	0.89
Goldman Sachs	4.51	0.05	0.00
JP Morgan	1.24	0.13	0.37
Morgan Stanley	7.81	0.66	0.00
Bear Sterns	5.75	1.71	1.14
RBS	0.78	0.06	0.21
Lehman Brothers	6.96	0.09	0.11
Merrill Lynch	5.70	0.16	0.18
Mean	4.25	0.34	0.38
Median	4.51	0.16	0.21
Stdev	2.27	0.45	0.37

Table 3 - This table presents parameter estimates (and standard errors) for a reduced-form vector autoregression that includes the following variables: the off-the-run spread (*OTRSpread*), the average CDS spread for dealers in the riskiest quintile in a given day (*HighCDS*), and the average CDS spread for dealers in the safest quintile in a given day (*LowCDS*). The symbols ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively. The sample period includes all trading days over 2007-2009.

	Dependent Variable			
	OTRspread	HighCDS	LowCDS	Credit
Lag1 OTRspread	0.6644*** (0.0345)	3.0305*** (0.6333)	0.2840*** (0.0884)	0.00077 0.00057
Lag2 OTRspread	0.3025*** (0.0346)	-2.7488*** (0.6366)	-0.2265** (0.0888)	(0.00030) 0.00057
Lag1 HighCDS	-0.0063*** (0.0022)	0.7694*** (0.0409)	0.0205*** (0.0057)	(0.00003) (0.00004)
Lag2 HighCDS	0.0080*** (0.0022)	0.1341*** (0.0408)	-0.0232*** (0.0057)	0.00002 (0.00004)
Lag1 LowCDS	-0.0252 (0.0160)	1.0433** (0.2935)	0.9702*** (0.0409)	0.00004 (0.00026)
Lag2 LowCDS	0.0225 (0.0161)	-0.7261** (0.2954)	0.0210 (0.0412)	(0.00012) (0.00026)
Lag1 RE Credit	3.4196 (2.3520)	132.6211*** (43.2153)	23.8535*** (6.0299)	0.41129 (0.03857)
Lag2 RE Credit	-2.9235 (2.2311)	-56.2014 (40.9950)	-6.8221 (5.7201)	0.01539 (0.03659)
Constant	0.0818 (0.1289)	0.9782 (2.3680)	0.6427** (0.3304)	0.00145 (0.00211)
N	749	749	749	749

Table 4 - Granger causality tests using results from the estimated reduced form VAR model.

Dependent Variable	Independent Variable	Chi-Square Statistic	P-value for Granger Causality
OTRspread	HichCDS	13.87	0.001
	LowCDS	2.65	0.266
	RE Credit	2.77	0.251
HighCDS	OTRspread	23.39	0.000
	LowCDS	23.39	0.000
	RE Credit	9.45	0.009
LowCDS	OTRspread	12.83	0.002
	HighCDS	16.62	0.000
	RE Credit	15.79	0.000
RE Credit	OTRspread	7.71	0.021
	HighCDS	0.60	0.740
	LowCDS	1.26	0.531

Table 5-This table presents the results of the structural VAR estimation. The corresponding standard errors are reported in parentheses below each estimated coefficient. The symbols ***,**, and * indicate a significance level of one, five and the percent, respectively.

	Dependent Variable		
	OTRspread	HighCDS	LowCDS
OTRspread		-0.2907 (2.1877)	0.1594** (0.0812)
HighCDS	0.0003 (0.0068)		0.0602*** (0.0046)
LowCDS			
RE Credit		319.2551*** (39.1519)	25.2649*** (5.1597)

Table 6 - This Table presents results from a seemingly unrelated regression analysis of each dealer's own CDS spread on two lags of the dependent variable, *HighCDS*, the off-the-run spread, and a credit variable constructed from the ABX and CMBX indices, as well as two lags of all independent variables. The coefficients on *HighCDS* and the off-the-run spread (and their lags) are constrained to be equal for all dealers, but each dealer is allowed to have a different coefficient on the credit variable (and its lags). Only dealers whose spreads are never in the top quintile are included in the sample. Coefficients and standard errors (in parentheses) on the off-the-run spread and *HighCDS* as well as their lags, are reported. In addition, the mean of the dealer-specific coefficients on the contemporaneous credit variable is reported, along with the chi-square statistic of their joint significance. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% level. The sample period includes trading days over 2007-2009.

	(1)	(2)	(3)
HighCDS	0.124*** (0.00442)	0.125*** (0.00445)	0.113*** (0.00449)
Lag1 HighCDS	-0.0801*** (0.00612)	-0.0784*** (0.00618)	-0.0695*** (0.00609)
Lag2 HighCDS	-0.0368*** (0.00491)	-0.0403*** (0.00495)	-0.0375*** (0.00491)
OTRspread		0.350*** (0.0831)	0.325*** (0.0802)
Lag1 OTRspread		-0.0668 (0.0973)	-0.0556 (0.0936)
Lag2 OTRspread		-0.232*** (0.0836)	-0.232*** (0.0806)
Mean of Coefs on Credit			53.21
Joint χ^2 test statistic			145.03***
N	5243	5243	5243

Table 7 - This Table presents results from a seemingly unrelated regression analysis of each dealer's own CDS spread on two lags of the dependent variable, *HighCDS*, the off-the-run spread, and credit, which is constructed from the ABX and CMBX, as well as two lags of all independent variables. The coefficients on HighCDS and the off-the-run spread (and their lags) are constrained to be equal for all dealers, whereas each dealer is allowed to have a different coefficient on the credit variable. Finally, we interact the off-the-run spread with the ratio of dealer repo, unsecured commercial paper (cp), and asset-backed commercial paper (abcp) liabilities to total equity. Only dealers whose spreads are never in the top quintile are included in the sample. Only coefficients (and standard errors) for interactions of OTRSpread with repo liabilities are reported.. The sample period includes all trading days over 2007. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)
repos*OTRspread	0.0381** (0.0157)			0.0406** (0.0166)
Lag1 repos*OTRspread	-0.0156 (0.0159)			-0.0109 (0.0168)
Lag2 repos*OTRspread	-0.0140 (0.0159)			-0.0220 (0.0167)
abcp*OTRspread		-0.0211 (0.0742)		-0.00813 (0.0840)
Lag1 abcp*OTRspread		0.0825 (0.0750)		0.0696 (0.0849)
Lag2 abcp*OTRspread		-0.0839 (0.0749)		-0.105 (0.0849)
cp*OTRspread			0.268* (0.152)	0.310* (0.164)
Lag1 cp*OTRspread			0.0429 (0.153)	-0.0207 (0.166)
Lag2 cp*OTRspread			-0.151 (0.152)	-0.0839 (0.165)
N	2480	2480	2480	2480

Figure 1
10-Yr T Notes on-the-run off-the-run Spread

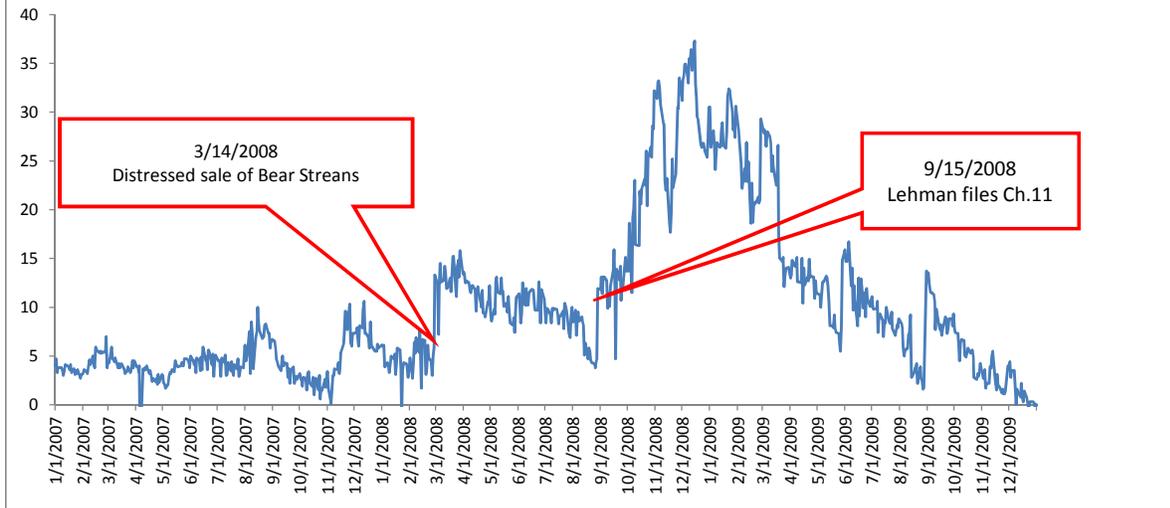


Figure 2: Individual Dealer CDS Spreads

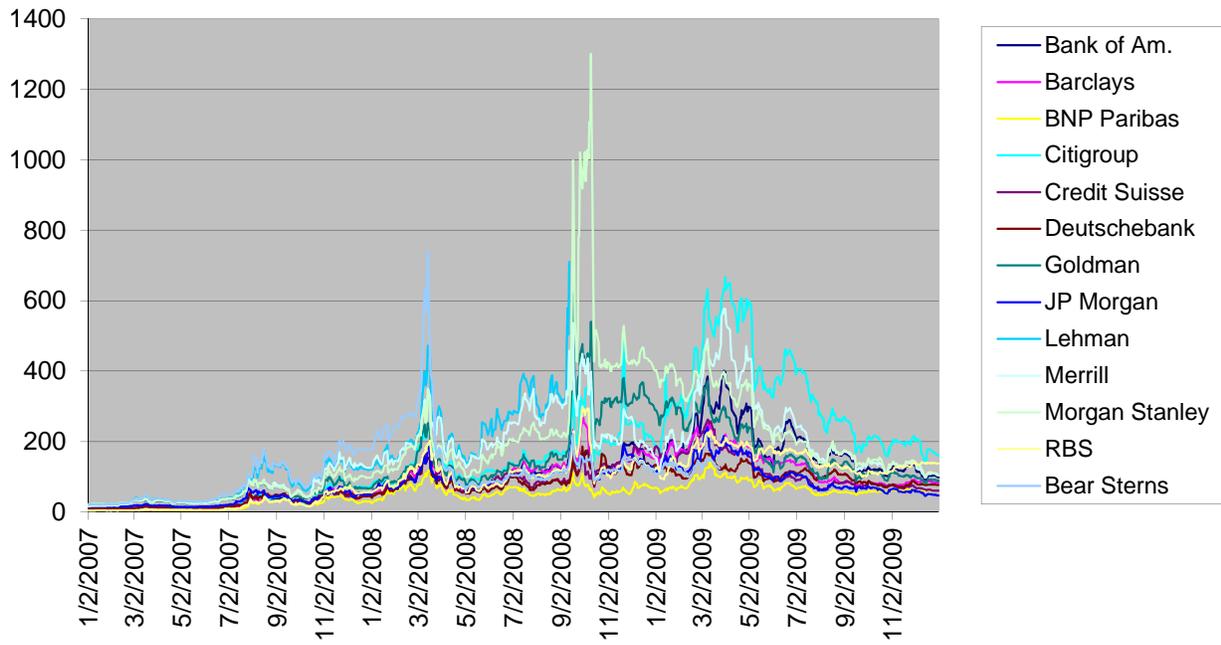
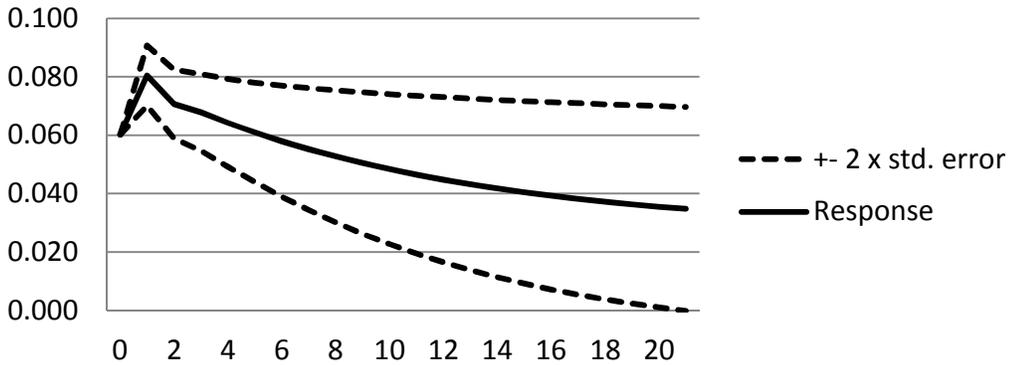
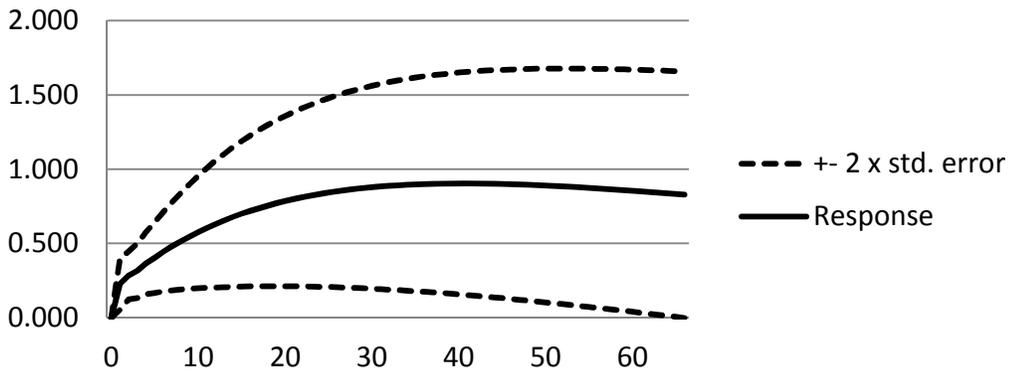


Figure 3 - This figure presents different impulse response functions implied by the estimated structural VAR parameters.

Response of One Basis Point Impulse on HighCDS onto LowCDS



Response of One Basis Point Impulse on OTRSpread onto LowCDS



Response of One Basis Point Impulse on RE Credit onto LowCDS

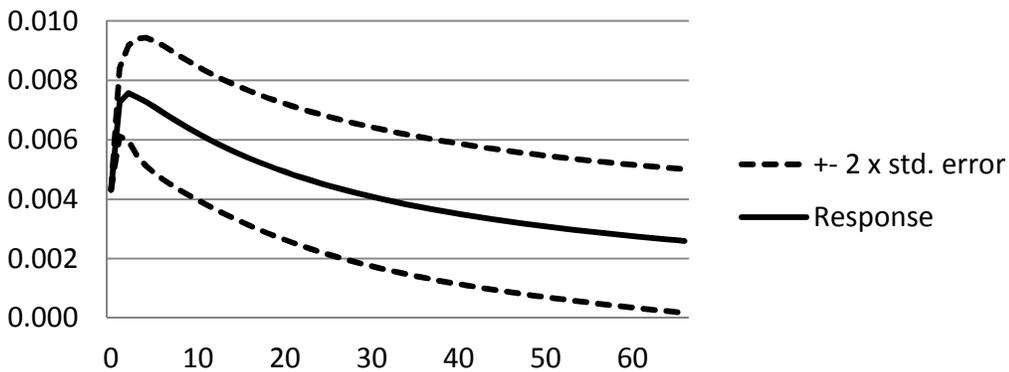
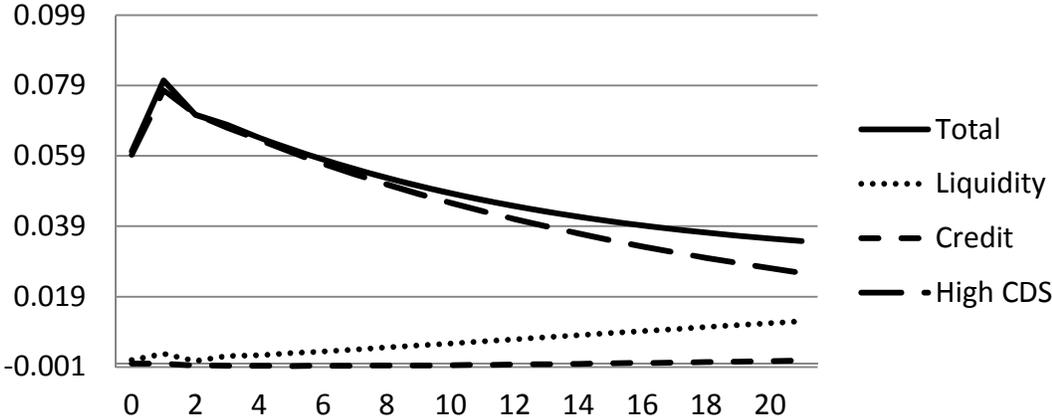


Figure 4 – This figure presents the response on LowCDS to a shock of one basis points in HighCDS. The top panel presents response per day while the bottom panel presents the cumulative response. These functions are calculated with the parameters estimated for the structural VAR. The curves labeled “Total” consider the effect of MaxCDS onto MinCDS through all the contagion mechanisms implied by the estimated structural VAR. The curves labeled “Liquidity only” assume that the impulse response is through the off-the-run spread variable only. That is, the “Liquidity channel” assumes that the coefficients of HighCDS, RE Credit and their lags in the LowCDS-VAR equation are equal to zero. The curves labeled “Credit Only” and “High CDS only” assume that the impulse response is through the RE Credit and the High CDS variables respectively.

Response of One Basis Point Impulse on HighCDS onto LowCDS



Cummulative Response of One Basis Point Impulse on HighCDS onto LowCDS

