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

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Abstract

We empirically test for the presence of two types of financial contagion across large broker-dealers and dealer banks during the crisis of 2007-2009: the type based on the idea that market illiquidity mediates the spread of distress from one dealer to others, or, "liquidity contagion", and the type based on the idea that one dealer's distress directly undermines the franchise value of others, or, "franchise value contagion". We test for the two types of contagion against the null hypothesis that correlation in dealer-distress during the crisis was only due to an observable common shock to the real estate assets that triggered the crisis. We find evidence that prior to the Federal Reserve and Treasury market interventions in the Fall of 2008, both types of contagion were present. Franchise-value contagion, however, dominates, accounting for 95% of all contagion. Furthermore, unlike liquidity contagion which disappears after the interventions are in place, franchise-value contagion remains.

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The current literature on the 2007-2009 financial crisis reminds Lo (2012) of Akira Kurosawa's classic film "Rashomon," in that no single coherent interpretation explains what actually happened. Scholars have proposed many theories about and narratives of the crisis, some of which conflict, but the task of evaluating them with formal empirical work remains unfinished. We help fill this void by formally testing different theories on a phenomenon central to financial crises: the spread of financial distress, or "contagion," from one large broker-dealer or dealer bank (henceforth, collectively, "dealers") to dealers who are healthy prior to infection.[1] Because different contagion channels imply different policy responses, a better understanding of the channels through which cross-dealer contagion spreads is of paramount importance. In this study, we test for the presence of different contagion channels during the 2007-2009 crisis period against the null hypothesis that the simultaneous financial distress of many dealers was due to a credit shock in the mortgage market rather than to contagion.[2] We also gauge the economic significance of different contagion channels.

To understand the how failure can spread across dealers, it is necessary to understand how dealers can fail. Securities dealers are at the center of a hub of financial transactions. Duffie (2011) points out that dealers derive their franchise value from providing prime brokerage services such as cash management and financing to institutional investors. They also serve as counterparties in over-the-counter derivatives and as market makers in securities. Broadly speaking, dealers provide liquidity, which involves a time-mismatch between sellers and buyers and is therefore risky. To mitigate this risk, dealers need to have easy access to funding and a high level of capital. They also need their counterparties and clients to have confidence in the knowledge that their franchise value is robust. A hint that a dealer is in trouble can cause its franchise value to deteriorate because funding providers, clients, or counterparties may cease doing business with the dealer. Such a deterioration, in turn, will lead to the departure of even more lenders, clients, and counterparties, leading ultimately to a dealer's collapse. See Duffie (2011) for a detailed description of the failure mechanism of a dealer.

[1] Bernanke (2008), Bernanke (2010), and Hart and Zingales (2011) argue that the potential for contagion is the main reason governments rescue failing financial institutions. They also argue that these rescues cause a moral hazard, which we do not take up here.

[2] A common credit shock can simultaneously drive down the fundamental value of many dealers' assets and render them insolvent. Simultaneous dealer failure from a common shock, however, cannot be classified as "contagion," because in this scenario, the failure of one dealer does not cause the failure of others.

The mechanics of dealer failure suggests two broad ways in which the failure of one dealer can spread to others. We label the first channel as the "franchise-value channel," and the second one the "liquidity channel." We discuss each in turn.

Under the franchise-value channel of contagion, distress at one dealer directly undermines the franchise value of others, causing short-term lenders, counterparties and customers to drain cash from even healthy dealers, rendering them insolvent. This can happen if market participants become concerned that otherwise healthy dealers have significant credit or counterparty exposure to the ailing dealer.[3] Alternatively, distress at one large dealer might lead markets to suspect that the financial sector is insolvent in the aggregate, even though some dealers may in fact be healthy. Goldstein and Leitner (2013) show that as long as market participants lack the information needed to distinguish healthy dealers from ailing ones, even healthy dealers will experience a cash run, and hence a fatal deterioration in franchise value.

The "liquidity channel" of contagion is based on Brunnermeier (2009) and Brunnermeier and Pedersen (2009). Distress at a single large dealer does not directly cause problems for other dealers; rather, distress spreads indirectly through the mediating effect of illiquidity. A single large dealer's failure directly causes a large, systematic negative shock liquidity. Consequently, the prices of securities used by other dealers as funding collateral drop below their fundamental value, causing secured funding providers to stop rolling over short-term debt. This could quickly render previously healthy dealers insolvent due to their heavy reliance on short-term debt, much of it overnight.

To study cross-dealer contagion, we borrow empirical methods from the literature on cross-country financial contagion.[4] For the 2007-2009 crisis period, we examine correlations in dealer credit default swap (CDS) spreads, a market measure of default probability, as well as the ways in which these correlations are related to aggregate illiquidity in the financial system. We conduct these analyses using an SUR (seemingly unrelated regression) approach, so that we can simultaneously control for each dealer's unique exposure to the securitized products at the root of the crisis, such as subprime residential mortgage-backed securities. This method enables us to determine

[3]See Allen and Gale (2000) and Zawadowski (2013) for formal models of contagion across financial institutions driven by direct credit and counterparty exposure.

[4]Forbes (2012) provides an overview of the methods commonly employed in the cross-country contagion literature. We use two of the methods described by Forbes (2012), namely analysis of correlations and a structural VAR.

whether any apparent contagion effects are really just the result of common credit shocks in the mortgage markets that drove the crisis. We also estimate an SVAR (structural vector autoregression) to gauge the economic significance of the liquidity and franchise-value contagion channels. Specifically, our SVAR explicitly models the ways in which increases in the riskiest dealers' CDS spreads impact the spreads of the safest dealers, either directly, or by first impacting illiquidity. It also allows for other indirect effects and feedback effects. This approach gives us greater statistical power when we compare the relative economic importance of the two contagion channels.

Our SUR analysis reveals that prior to the Treasury and Federal Reserve interventions begun in September 2008, the CDS spreads of the safest dealers are highly sensitive to the CDS spreads of the riskiest dealers. They are also sensitive to aggregate illiquidity. These results are consistent with the presence of both channels of contagion. Post-interventions, however, CDS spreads become less sensitive to illiquidity, suggesting the interventions reduce the potential for liquidity contagion. Individual dealers' sensitivity to the riskiest dealers' spreads, however, become even stronger after the interventions, suggesting that the interventions fail to curb franchise-value contagion. We also use our SUR analysis to quantify the importance of the liquidity contagion by estimating the extent to which distress spreads from high risk dealers to other dealers indirectly through illiquidity. Our point estimates suggest that, in the pre-intervention period, the liquidity channel accounts for approximately 6% of all contagion. This point estimate, however, is not statistically significant. We also find no such indirect liquidity effects during the post-intervention period. In addition, we find that the extent to which a dealer relies on extreme short-term debt financing affects the dealer's susceptibility to franchise-value contagion, but not to liquidity shocks.

Our SVAR confirms the presence of the liquidity channel before the interventions, but not afterward. Even then, however, our SVAR results indicate that the economic significance of the liquidity channel is smaller than that of the franchise-value contagion. In fact, a shock to the CDS spread of the dealers under distress has an effect on the safest dealers' CDS spread, but before the major interventions that followed the Lehman Brothers bankruptcy, the liquidity channel accounted for a statistically significant but economically modest 5% of the total effect.

We recognize that franchise-value contagion is a broad category, and one that encompasses several possible mechanisms. Safe dealer CDS spreads might be sensitive to those of the riskiest dealers because of counterparty exposure, or it could be that increases in the riskiest dealer CDS spreads are related to market participants' updating unfavorably about the aggregate solvency of the financial system. The perceived willingness of the government to dispense bailouts might also factor into market expectations about aggregate solvency; that is, safe dealers' CDS spreads might be sensitive to the spreads of the riskiest because the latter reflect perceptions about the government's willingness to keep the system solvent. Our methods do not allow us to pin down the relative importance these precise mechanisms driving franchise-value contagion, but there is nevertheless a fundamental difference between a single dealer's distress directly undermining safer dealers' franchise value, through whatever mechanism, versus distress spreading through liquidity shocks. Moreover, the types of interventions that address liquidity contagion are fundamentally different from those that address franchise-value contagion. Hence, there is value in determining the relative importance of liquidity contagion and franchise-value contagion, even if we cannot pin down the precise mechanisms behind the latter.

In all of our analyses, we use the Musto, Nini, and Schwarz (2011) measure of aggregate systematic illiquidity, which is based on violations of the law of one price in US Treasury notes and bonds. All of our inferences on the relative importance of the liquidity channel assume that this measure is valid. At first glance, this assumption appears doubtful. Liquidity contagion channels operate through market/funding illiquidity feedback effects in the securities that dealers hold, of which Treasuries are only a small part. However, both the theoretical and empirical literature provides strong support for the proposition that the kinds of systematic funding liquidity shocks at the heart of liquidity contagion models manifest themselves in large, unexploited arbitrage opportunities in markets where distressed dealers are important participants (e.g., Brunnermeier (2009), Brunnermeier and Pedersen (2009), Duffie (2010), Gromb and Dimitri (2010), Griffoli and Ranaldo (2011), Mitchell, Pedersen, and Pulvino (2007), Garleanu and Pedersen (2011), Musto, Nini, and Schwarz (2011), Schwarz (2014)). Since US Treasuries carry no credit risk, and all the dealers in our sample, as primary dealers, are important participants in the Treasury market, cleanly identified violations of the law of one price within this market arguably constitute the best possible measure for systematic illiquidity for our sample. In addition, Hu, Pan, and Wang (2013) and others (e.g., Barclay, Hendershott, and Kotz (2006), Goldreich, Hanke, and Nath (2005), and Vayanos and Weill (2008)) provide evidence that large discrepancies in the yields of Treasuries of similar duration, which can be associated with violations of the law of one price, are a good proxy for the kinds of systematic liquidity shocks driven by funding difficulties that are at the heart of liquidity-based contagion models. In robustness checks we use other proxies of illiquidity based on discrepancies in Treasury yields, such as the Hu, Pan, and Wang (2013) yield curve model fit error statistic and the off-the-run spread. These measures are positively correlated with the Musto, Nini, and Schwarz (2011) measure, but they are not as precise in measuring violations of the law of one price. When we use these alternative proxies for illiquidity, we fail to find evidence of liquidity contagion, though franchise value contagion remains just as strong.

Our paper is directly related to the large body of theoretical research that rapidly emerged in the wake of the 2007–2009 crisis on contagion across financial institutions.[5] This literature suggests that the channels of contagion we study were likely important during the crisis. We contribute to this literature by directly linking market expectations of a single dealer's failure to the expectations of other dealers' failures, and we gauge the economic significance of different contagion channels.

We also contribute to a large empirical literature related to the financial crisis. As do Afonso, Kovner, and Schoar (2011) and Duygan-Bump, Parkinson, Rosengren, Suarez, and Willen (2013), we find that the interventions that followed the Lehman bankruptcy succeeded in arresting funding-liquidity contagion. We add to these findings by focusing on the connection between market liquidity and funding liquidity. We also contribute to those papers that present evidence of illiquidity during the financial crisis. For instance, Adrian and Shin (2009) show that dealer leverage is procyclical and that a reduction in aggregate dealer REPO financing predicts increases in the VIX. Frank, Gonzalez-Hermosillo, and Hesse (2008) show that credit spreads on asset-backed commercial paper and the TED spread were highly correlated with the off-the-run spread during the crisis. Finally, Krishnamurthy (2009) and Gorton (2009) suggest that trouble at major financial institutions was

[5] See for instance Diamond and Rajan (2011), Brunnermeier (2009), Brunnermeier and Pedersen (2009), Goldstein and Leitner (2013), Martin, Skeie, and von Thadden (2010), Liu and Mello (2009), Acharya, Gale, and Yorulmazer (2011), Acharya and Skeie (2011).

associated with persistent reductions in bond market liquidity during the crisis, while Acharya and Merrouche (2012) show that UK banks hoarded liquidity after crisis events during 2007. As do the authors of these papers, we find evidence of liquidity contagion during the crisis; however, our results point out that a direct contagion channel - the franchise-value channel - had a much larger economic significance than the liquidity channel of contagion.

Our paper is also related to those which analyze the run on the "securitized-banking" system during the 2007-2009 crisis. In the traditional banking system, a financial institution makes and holds loans using funding provided by clients' deposits. In the securitized-banking system, in contrast, loans are originated, securitized, and sold to investors, some of which fund their investments with short-term loans from money market funds. Some papers have shown evidence that the 2007-2009 crisis was a run on the securitized-banking system.[6] We contribute to this literature by showing that the run on the securitized-banking system mostly happened through mechanisms similar to those in Goldstein and Leitner (2013) and Zawadowski (2013), and not through a liquidity channel.

In addition, many studies have examined financial contagion not specifically related to the 2007–2009 crisis. Our paper contributes to this literature in several ways. While many empirical contagion studies look at commercial banks,[7] we focus on dealers, including broker-dealers unaffiliated with a commercial bank. Given the central and unique role that dealers play in the modern financial system (e.g., Duffie (2010)), our paper fills an important gap in the literature. Our study also differs in its methods. Previous works on contagion across banks and nonfinancial firms utilize actual failures or defaults in their research designs.[8] Instead, we examine co-movements in credit default swaps since there are few actual dealer failures in our data period. Finally, because we focus on contagion across institutions, our study differs from those examining contagion across countries,[9] asset classes (e.g., Longstaff (2010)), or particular securities (e.g., Coval and Stafford

[6] See for instance Gorton and Metrick (2012), Acharya, Schnabl, and Suarez (2013), Krishnamurthy, Nagel, and Orlov (2013), and Copeland, Martin, and Walker (2010).

[7] Aharony and Swary (1983), Aharony and Swary (1996), Iyer and Peydro (2011), Swary (1986), Jayanti and Whyte (1996).

[8] Das, Duffie, Kapadia, and Saita (2007), Duffie, Eckner, Horel, and Saita (2009), Lang and Stulz (1992), Jorion and Zhang (2007), and Jorion and Zhang (2009) all study contagion across non-financial firms.

[9] See Kaminsky, Reinhart, and Vegh (2003) and Forbes (2012) for reviews of this literature.

(2007)).

The remainder of this study is organized as follows. In Section 1, we discuss our data and descriptive statistics. In Section 2 we present our main tests. Section 3 concludes.

1 Data and descriptive statistics

We collect data on broker dealers and dealer banks designated by the Federal Reserve as "Primary Dealers" during the crisis years (2007-2009). From the CMA CDS database, we obtain five-year CDS spreads for the 13 of 17 primary dealers for which there exists a reliable time series. We exclude HSCB, Nomura, Diawa, and Mizuho because all four have long stretches during our sample period with no actively traded CDS contracts and have either 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 the CMA. Finally, for each day, we split the dealers into quintiles and take the cross-sectional average quote for the top and bottom quintiles, which we label $HighCDS$ and $LowCDS$ respectively, and for each we construct a daily time series that covers the 2007-2009 period. Since all of our variables are very persistent, we conduct all of our analysis in first differences, rather than levels. Table 1 presents descriptive statistics for first changes in $HighCDS$ and $LowCDS$, along with the descriptive statistics for the panel of first differences in the individual CDS spreads of dealers whose spread is never in the top quintile. In our SUR analysis of individual dealer spreads, we exclude all dealers who have ever appeared in the top quintile in order to ensure that a mechanical relation between $HighCDS$ (the cross-sectional average spread for the top quintile) and individual dealer spreads does not drive our results. We include statistics for three distinct time periods: the period before the failure of Lehman Brothers, which was the period before the most significant interventions were introduced; the post-TARP period, during which the government interventions responding to the crisis were largely in place; and a transition period, consisting of the month following the failure of Lehman brothers, a period during which the interventions were being introduced.

Our main liquidity proxy is the Musto, Nini, and Schwarz (2011) yield-based measure, which measures the extent to which yields on recently issued, just off-the-run 10-year note differ from yields on a precisely duration-matched portfolio of STRIPS and old 30-year bonds which mature on approximately the same date as the 10-year note. We label this variable "Illiquidity," and we include descriptive statistics on its first differences in Table 1. In a robustness test, we also consider the pricing-error statistic of Hu, Pan, and Wang (2013) as well as the 10-year, off-the-run Treasury spread. To compute the off-the-run Treasury spread, we obtain the daily time-series closing yield-to-maturity on the Merrill Lynch 9- to 11-year off-the-run Treasury index from Datastream. We then subtract the closing yield on the on-the-run 10-year Treasury note for same day. We use the 10-year, off-the-run spread because the 10-year, on-the-run note is more liquid than both the on-the-run five-year note and the 30-year bond. We do not use a spread derived from shorter maturities because it is more likely to be distorted by Federal Reserve open market operations. Figure 1 compares the behavior of all three proxies and shows that they behaved similarly during the crisis.

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. 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.) We then compute the daily returns for the two index averages. To keep our SVAR analysis parsimonious, we take a simple average of these returns and denote this average as the variable *credit*. However, in the robustness tests in our SUR analysis, we also include the returns on the ABX and CMBX indices separately as control variables, and our results do not change. Table 1 presents descriptive statistics for the level of *credit*. In all analyses, we use the level of *credit*, not first differences, since it is a return.

To examine how a dealer's reliance on extremely short-term risky debt financing affects the sensitivity of its CDS spread to security-market liquidity, we obtain the face value of each dealer's outstanding REPO and unsecured commercial paper liabilities as of the end of 2006 from SEC filings.[10] In addition, following Acharya, Schnabl, and Suarez (2013), we obtain from Philipp Schnabl's website each dealer's liabilities related to its guarantees of asset-backed commercial paper

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

conduits as of the end of 2006, much of which are off balance sheet. In line with Acharya, Schnabl, and Suarez (2013), we normalize each dealer's funding liabilities by the book value of common equity. Also following Acharya, Schnabl, and Suarez (2013), we focus on 2006 liabilities, a time before the crisis period, 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. Hence we attempt to further minimize the confounding effects of endogenous capital structure adjustment by limiting this analysis to the early part of the crisis in 2007, as it arguably takes time to make capital structure adjustments. Table 3 presents descriptive statistics for these liability ratios, as well as their sum, which we denote as "total runnable funds."

Figure 1 suggests that dealer failure can lead to large illiquidity discounts. The figure graphs the time series of the four different illiquidity proxies over the 2006–2009 period. Note how all measures increase dramatically following the distressed sale of Bear Sterns to JP Morgan as well following the failure of Lehman Brothers.

Figure 2 charts $HighCDS$ and $LowCDS$ over the 2007-2009 period. There is considerable time-series variation among them, and large movements are not concentrated around any specific events. However, there is a large jump in all CDS around both the distressed sale of Bear Sterns in March 2008 and the Lehman Brothers bankruptcy filing in September 2008. Note further that there is a large decline in both on October 15, 2008, the day after the Treasury announced the precise form in which it would use TARP funds to stabilize the financial system, as well as the day after the FDIC declared it would guarantee the senior debt of all bank holding companies, which included all dealers at that point in time.[11]

2 Tests and Results

Our tests fall into two broad categories: analysis of co-movements in dealer CDS spreads, which we conduct with SUR analysis (see Section 2.1), and tests based on time-series SVARs (see Section 2.2). We use our SUR model to examine the sensitivity of individual dealers' CDS spreads to

[11] The two surviving pure-play investment banks, Goldman Sachs and Morgan Stanley, had reincorporated as bank holding companies shortly after Lehman's collapse.

aggregate illiquidity and other dealer CDS spreads. We simultaneously control for the individual dealers' exposure to subprime residential and commercial mortgage-backed securities, which are well-known to be the fundamental credit drivers of the financial crisis. While such analysis of co-movements is helpful, it could plausibly underestimate the importance of the liquidity channel because it does not explicitly model complex chains of causation and feedback effects. Our SVAR analysis in Section 2.2, though it relies on stronger identifying assumptions, allows us to better measure the extent to which contagion is direct versus whether it runs first through the mechanism of market liquidity.

2.1 Panel data SUR analysis

Our first set of analyses examines the extent to which, during the crisis, individual dealer CDS spreads' were sensitive to the CDS spreads of the riskiest dealers as well as to systemic liquidity. We control for each individual dealer's exposure to the markets that drove the crisis, namely residential and commercial mortgage-backed securities. To that end, we estimate the following equations using SUR analysis:

$$\Delta CDS_{i,t} = \alpha_i + \beta \Delta HighCDS_t + \gamma_i Credit_t + \epsilon_{i,t} \tag{1}$$

$$\Delta CDS_{i,t} = \alpha_i + \beta_1 \Delta HighCDS_t + \beta_2 \Delta Illiquidity_t + \gamma_i Credit_t + \epsilon_{i,t} \tag{2}$$

We run the regressions in first differences in $HighCDS_t$ and $Illiquidity_t$ for simplicity since these time series variables are non-stationary. Recall that $Credit_t$ is derived from ABX and CMBX return data, so there is no need to first-difference it.

Over the course of 2008, the Treasury, the FDIC and the Federal Reserve intervened in markets numerous times in an attempt to bolster both dealer solvency and funding liquidity. These interventions likely changed the nature of both franchise value and liquidity contagion. We provide a timeline of these interventions in Table 2. In order to get a sense for how these changes may have influenced contagion, we note that the most significant interventions came in the wake of the Lehman Brothers bankruptcy on September 14, 2008, culminating in the TARP and the FDIC's guarantee of dealer senior debt. We thus define three periods for our analysis: a pre-Lehman period, during which there are few interventions; a transition period, during which the important intervention programs are being established; and the post-TARP period during which the significant interventions are already in place. The pre-Lehman period begins on January 1, 2007 and ends on the last trading day before the Lehman bankruptcy filing on September 15. Although TARP was signed into law on October 3, 2008, it was not until October 14, 2008, that the Treasury announced precisely how it would use TARP funds. As a result, on October 14, a great deal of uncertainty about both the nature and effectiveness of TARP was resolved, as is reflected in the large drop in all dealer CDS spreads on that date (see Figure 2). We also note that on October 14, the FDIC took the unprecedented step of guaranteeing senior debt issues of bank holding companies, which at that point included all the primary dealers. Hence we begin our post-TARP period on October 15, 2008, which leaves our Transition period to include all trading days between September 15 and October 14, 2008, inclusive. If the unprecedented interventions during the fall of 2008 were to have substantially reduced either franchise-value contagion or liquidity contagion, we would expect individual dealer CDS spreads to become less sensitive to $\Delta Illiquidity_t$ and $\Delta HighCDS_t$. Hence we run the following specification:

$$\begin{aligned} \Delta CDS_{i,t} &= \alpha_i + \beta_1 \Delta HighCDS_t + \gamma_i Credit_t \\ &+ \beta_3 \Delta HighCDS_t \times Transition_t + \beta_4 \Delta HighCDS_t \times PostTarp_t + \epsilon_{i,t} \end{aligned} \tag{3}$$

$$\begin{aligned} \Delta CDS_{i,t} &= \alpha_i + \beta_1 \Delta HighCDS_t + \beta_2 \Delta Illiquidity_t + \gamma_i Credit_t \\ &+ \beta_3 \Delta HighCDS_t \times Transition_t + \beta_4 \Delta HighCDS_t \times PostTarp_t + \\ &+ \beta_5 \Delta Illiquidity_t \times Transition_t + \beta_6 \Delta Illiquidity_t \times PostTarp_t + \epsilon_{i,t} \end{aligned} \tag{4}$$

Where $Transition_t$ and $PostTarp_t$ are dummy variables indicating that the observation belongs to the Transition and Post-TARP periods, as defined above.

We estimate each equation using SUR analysis, excluding dealers whose CDS spreads are in the top quintile at any time during the sample period. We exclude these dealers so as not to introduce a mechanical relation between $\Delta CDS_{i,t}$ and $\Delta HighCDS_t$. This exclusion also reduces the potential for reverse causality and feedback between $\Delta CDS_{i,t}$ and $\Delta Illiquidity_t$. We are not concerned about feedback between $\Delta CDS_{i,t}$ and $\Delta HighCDS_t$ because it is implied by the franchise value contagion channel. We allow the coefficient on $Credit_t$ to be different for each dealer. In this manner, the data tell us how exposed each dealer is to the securitized debt markets, which enables us to control for each dealer's unique exposure to the assets driving the financial crisis. For brevity, Table 4 reports only 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 $Credit_t$ and a Wald test of their joint significance.

The coefficient on $\Delta HighCDS_t$ in Equation (1) provides a measure of the total contagion effect over the entire sample period, including both the liquidity and franchise value channels, while controlling for observable credit shocks. As can be seen in Table 4, this coefficient is positive and significant. In Equation (2) we add our illiquidity proxy. Hence, in this specification, to the extent that we are accurately measuring illiquidity and common credit shocks, the coefficients on $\Delta HighCDS_t$ measures the contagion effect apart from illiquidity, namely franchise value contagion. Consistent with the hypothesis that franchise value contagion is important, the coefficient on $\Delta HighCDS_t$ is positive and significant. The coefficient on $\Delta Illiquidity_t$ measures the extent two which dealers are vulnerable to systematic liquidity shocks, a necessary (but not sufficient) condition for liquidity contagion. The positive and significant coefficient indicates that the potential for liquidity contagion is real.

Despite the statistically significant effect of $\Delta Illiquidity_t$, the magnitudes of the point estimates of both $\Delta Illiquidity_t$ and $\Delta HighCDS_t$ suggest that only franchise value contagion is economically significant. A coefficient of 0.296 on $\Delta Illiquidity_t$ (see column 2 of Table 4) indicates that a change in illiquidity equal to the standard deviation of its first difference (see Table 1) is associated with an increase of only 0.352 basis points in $CDS_{i,t}$ $[0.352 = 0.296 \times 1.19]$, an economically modest amount compared to the standard deviation in $\Delta CDS_{i,t}$ of 7.32. However, a coefficient of 0.0713 on $\Delta HighCDS_t$ implies that an increase in this variable equal to its standard deviation of 34.8 leads to a 2.48 basis points increase in $CDS_{i,t}$ $[2.48 = 0.0713 \times 34.8]$, which is significant compared to the sample standard deviation of 7.32 in $\Delta CDS_{i,t}$. In a robustness test, we replace $Illiquidity_t$ with the Hu, Pan, and Wang (2013) measure and the 10-year Treasury off-the-run spread. The results (untabulated) are qualitatively similar, with an even smaller illiquidity effect when using the Hu, Pan, and Wang (2013) measure.

Note further that a significant coefficient on $\Delta Illiquidity_t$ is not sufficient to establish liquidity contagion. A positive coefficient merely indicates that dealer default probabilities increase when aggregate illiquidity increases. It does not necessarily mean that increases in CDS spreads of the riskiest dealers lead to increase in other dealer spreads indirectly by first affecting aggregate illiquidity. To establish liquidity contagion, we must establish that we must establish that $\Delta Illiquidity_t$ is an intermediate variable through which $\Delta HighCDS_t$ affects other dealer spreads. In other words, we must establish that $\Delta Illiquidity$ is what is known in statistics as a mediating variable. By the logic demonstrated in Baron and Kenny (1986), a necessary condition for $\Delta Illiquidity_t$ to mediate the relation between $\Delta HighCDS_t$ and $\Delta CDS_{i,t}$, the coefficient on $\Delta HighCDS_t$ must decrease when $\Delta Illiquidity_t$ is added to the specification as a covariate in regressions where $\Delta CDS_{i,t}$ is the dependent variable. That is, the coefficient on $\Delta HighCDS_t$ must be greater in equation (4) than in equation (2). In fact, as can be seen in Table 4, the coefficient is the same in both specifications. Hence there is no evidence of liquidity contagion in the full sample, even though individual dealer spreads are sensitive to illiquidity.

The results from Equation (4) in Table 4 indicate that the 2008 interventions altered the patters of contagion. Notice that in column (4), when the dummies and interactions are included in the specification, the coefficient on $\Delta Illiquidity_t$ is now 0.461. This means that in the pre-Lehman period, the sensitivity of dealer spreads to illiquidity is larger than in the full sample. The value of 0.461 implies that a one standard deviation shock to $\Delta Illiquidity_t$ of 1.19 basis points increases dealer CDS spreads by 0.549 basis points [$1.19 \times 0.461 = 0.549$], which is substantially more than the effect in the full sample of 0.352 basis points, but still modest. Note further that the coefficient on the interaction of $\Delta Illiquidity_t$ with the $PostTarp$ dummy takes the value of -0.232, negative and large in absolute magnitude relative to the direct effect of 0.461. However, the standard error of this coefficient is large, so despite the coefficient's large size, the coefficient estimate is not statistically significant. On the other hand, the coefficient on the interaction of $\Delta Illiquidity$ with $Transition$ is positive, and it is statistically larger than the negative coefficient on the interaction of $\Delta Illiquidity$ with $PostTarp$ at the 1% level. Hence the sensitivity of individual dealer CDS spreads to illiquidity declined significantly once the interventions were in place relative to the period during which they were being introduced, the time of greatest illiquidity in our sample. This suggests that the interventions did reduce dealer sensitivity to illiquidity.

Simply examining how the sensitivity of dealer CDS spreads to illiquidity changed after the interventions is not enough to establish whether liquidity contagion changed. We must also examine the change in the magnitude by which $\Delta Illiquidity_t$ mediates the relation between $\Delta HighCDS_t$ and $\Delta CDS_{i,t}$. To measure the mediating effect of $\Delta Illiquidity_t$ in the pre-Lehman period, we examine the extent to which the coefficient $\Delta HighCDS_t$ is larger in Equation (3) than it is in Equation (4). The point estimate of the coefficient does in fact decrease when $\Delta Illiquidity_t$ is added as a covariate, from 0.096275 to 0.090759, and the difference of 0.005516 provides a point estimate of the magnitude illiquidity's mediating effect (e.g., Baron and Kenny (1986)). In addition, we verify that $\Delta Illiquidity_t$ has a positive partial correlation with $\Delta HighCDS_t$, another necessary condition for mediation. The point estimates, therefore, imply that, in the pre-Lehman period, about 5.7% of the total contagion was due to the liquidity channel [0.005516/0.096275 = 5.7%]. However, when we compute the standard error using them method suggested in Baron and Kenny (1986), we find this point estimate is not statistically significant. Hence, though the point estimates suggest modest liquidity contagion during the pre-Lehman period, it is not statistically significant. Furthermore, a quick glance at the coefficients on interaction terms further indicate there is no liquidity contagion during the post-TARP period. We note, however, that these tests of the liquidity channel may be biased, since we fail to model the effect of $\Delta Illiquidity_t$ on $\Delta HighCDS_t$ and $Credit_t$, as well as other possible feedback effects. We will remedy this problem with our structural VAR in the next section.

On the other hand, notice how the coefficient on the interaction of $\Delta HighCDS_t$ with the post-TARP dummy is positive, statistically significant and economically large. This suggests that dealer CDS spreads become even more sensitive to the riskiest dealers' CDS spreads after the intervention, holding constant illiquidity. Hence franchise-value contagion worsens after the interventions. Taking the sum of the coefficients on $\Delta HighCDS_t$ and the interaction term, we obtain a value of 0.1885. This implies that a one standard deviation shock of 34.8 basis points to $\Delta HighCDS_t$ tends to increase the safer dealer CDS spreads by 6.56 basis points [6.56=34.8×0.1885], which is close to the full sample standard deviation in $\Delta CDS_{i,t}$ of 7.32.

Our estimate of the importance of the two contagion channels in these specifications depends on the extent to which our credit variable measures fundamentals in the mortgage-backed securities markets. Note, however, that Stanton and Wallace (2011) argue that the AAA tranches of the ABX index did not reflect mortgage credit risk 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 are able to at least partly mitigate this issue by using BBB tranches of the ABX index rather than the AAA tranches used by Stanton and Wallace. Because BBB tranches were already known to be somewhat speculative, they were less likely to be held by institutions prone to needing credit insurance. Even if the BBB tranches at least in part reflected overall financial system distress, however, then our estimates of the coefficients on $\Delta HighCDS_t$ and $\Delta Illiquidity_t$ and their interactions will tend to be biased toward zero, assuming the true fundamentals underlying $Credit_t$ have a positive partial correlation with these variables.[12] Hence, if anything, our results understate the importance of the franchise-value channel of contagion.

In order to examine whether our results on the liquidity channel are a result of our choice of aggregate illiquidity proxy, in a robustness test, we replace $Illiquidity_t$ with the Hu, Pan, and Wang (2013) measure and the 10-year Treasury off-the-run spread. The results (untabulated) show that dealer CDS spread sensitivity to illiquidity is even smaller with these arguably less accurate proxies. We also fail to find any mediating effect of illiquidity with these proxies either during the pre-Lehman or post-TARP periods.

Finally, we examine the ways in which the channels of contagion are related to dealers' dependence on extreme short-term debt financing. As discussed in Section 1, we obtain data on the face

[12] See Greene (1993), p. 440.

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 use pre-crisis data 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, Schnabl, and Suarez (2013), we normalize our liability numbers by total common equity. We sum up the three types of short-term, runnable debt and denote the sum *Runnable*. We then interact *Runnable* with $\Delta Illiquidity_t$ and $\Delta HighCDS$. Table 3 displays these various ratios of liabilities to equity for each dealer, along with summary statistics. Because dealers likely adjusted their capital structure as the crisis unfolded, we expect that the 2006 liability ratios are valid only in periods close to the end of 2006. Hence, we limit the sample period for this analysis through September, 2007, since evidence in Acharya, Schnabl, and Suarez (2013) suggests that dealers and banks began to drastically alter their capital structures during August and September of 2007, shortly after troubles in the subprime markets began.

We run panel data SUR models similar to Equation (4), except we also include the runnable debt ratio in one specification, and interaction terms in the other. 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 $\Delta Illiquidity_t$, $\Delta HighCDS_t$, the runnable liability ratio, and the interaction terms. Table 5 shows the results. Notice that the interaction with $\Delta Illiquidity_t$ is not statistically significant at conventional levels, but the interaction with $\Delta HighCDS$ is. This result suggests that greater reliance on short term, "runnable" debt makes a dealer more susceptible to franchise-value contagion but not to liquidity contagion. To make sure our results are not sensitive to ending the sample in September of 2007, we also run the same specifications ending in August of 2007. The results (shown in the last two columns of this table) are qualitatively unchanged. In addition, in an untabulated robustness check, we find our results do not qualitatively change if we end the sample at the end of 2007.

2.2 VAR tests

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. Markets anticipate dealer failure, causing a large negative liquidity shock. An increase in the illiquidity discount should, in turn, cause the default probability of even the safest dealers to rise. That is, an increase to the likelihood of default of some dealers causes an increase in the likelihood of default of even the safest dealers through an increase in the illiquidity discount. The challenges of testing causal relations between two variables are well known and we do not aim to test whether the default of one dealer causes an increase in the likelihood of default of another dealer. We do, however, analyze the extent to which the relation between the likelihood of default of different dealers is explained by illiquidity. A necessary condition for the liquidity channel is that the relation between $HighCDS$ and $LowCDS$ is driven by $Illiquidity$.

Specifically, the liquidity channel of contagion implies that $Illiquidity$ is a mediating variable between $HighCDS$ and $LowCDS$.[13] We analyze the extent to which $Illiquidity$ mediates the relation between $HighCDS$ and $LowCDS$ in two ways. First, we use a reduced-form VAR to test whether $HighCDS$ Granger causes $Illiquidity$ as well as $LowCDS$ and whether $Illiquidity$ Granger causes $LowCDS$. These Granger causality tests are simple tests of the liquidity channel because a mediating relation implies that the independent variable ($HighCDS$) is related to the mediator variable ($Illiquidity$) as well as to the dependent variable ($LowCDS$), and that the mediator variable ($Illiquidity$) is related to the dependent variable ($LowCDS$). Naturally, these Granger-causality tests are excessively stringent, and consequently have low power, because they do not account for the contemporaneous relation between the variables. We will therefore later estimate a structural VAR that allows for contemporaneous effects of $Illiquidity$ on dealer CDS spreads and vice-versa.

The estimated reduced-form VAR is represented by the following system of equations:

$$y_t = \alpha + \beta \times y_{t-1} + \varepsilon_t \tag{5}$$

where $y_t = [\Delta Illiquidity_t,\, \Delta HighCDS_t,\, \Delta LowCDS_t,\, Credit_t]'$, α is a 4×1 vector, β is a 4×4 matrix and ε_t is a 4×1 vector of serially uncorrelated model disturbances. The number of lags is set

[13] In statistics, a mediating variable is an intermediate variable in the relation between two variables. See Baron and Kenny (1986).

equal to 1, the optimum based on the Schwarz criteria. We estimate the model in first differences because the time series variables are non-stationary in levels.

We present coefficient estimates in Table 6. Panel A presents the results of the VAR estimated over the entire sample period. Panel B presents the results of the VAR estimated over the sample period that ends before the Lehman Brothers bankruptcy (Sep 15, 2008), while Panel C presents the results of the VAR estimate with the sample that starts after the month of intense intervention that followed the Lehman Bankruptcy (Oct 15, 2008). The estimates in Panel A are somewhat inconsistent with the liquidity channel because $\Delta HighCDS$ does not Granger-cause $\Delta Illiquidity$. On the other hand, the Granger causality tests indicate that $\Delta HighCDS$ Granger causes $\Delta LowCDS$, which is consistent with the franchise value channel of contagion. Moreover, Panel B and C results indicate that *Illiquidity* Granger causes $\Delta LowCDS$ before the Lehman bankruptcy, while neither $\Delta HighCDS$ nor $\Delta Illiquidity$ Granger causes $\Delta LowCDS$ in the period after Oct 15, 2008. This may be a consequence of the fact that the safest dealers were insulated from contagion effects once the market intervention mechanisms created by the Fed as a response to the Lehman Brothers failure were in place. Overall, the results do not indicate the presence of an *Illiquidity* channel in the Post-TARP period. They also indicate that there was a regime shift in contagion effects after the Lehman Brothers failure.

The above reduced-form VAR analysis can be misleading in that although the effect of $\Delta HighCDS$, $\Delta Illiquidity$, $\Delta LowCDS$ and $Credit$ on one another is in all likelihood instantaneous, 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 estimate the following structural vector autoregression (SVAR):

$$\begin{bmatrix} 1 & -\beta^*_{1,2} & 0 & 0 \\ -\beta^*_{2,1} & 1 & 0 & -\beta^*_{2,4} \\ -\beta^*_{3,1} & -\beta^*_{3,2} & 1 & -\beta^*_{3,4} \\ -\beta^*_{4,1} & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta Illiquidity_t \\ \Delta HighCDS_t \\ \Delta LowCDS_t \\ Credit_t \end{bmatrix} = \alpha^* + \gamma^* \begin{bmatrix} \Delta Illiquidity_{t-1} \\ \Delta HighCDS_{t-1} \\ \Delta LowCDS_{t-1} \\ Credit_{t-1} \end{bmatrix} + u_t \qquad (6)$$

where u_t is a vector of serially uncorrelated model disturbances, $E[u_t u_t^{'}] = D$ is a diagonal matrix. The matrix β^* on the left-hand-side of Equation 6 parameterizes the contemporaneous relations between our VAR variables. The restrictions in this matrix imply that $\Delta HighCDS_t$ can affect both $\Delta Illiquidity_t$ and $\Delta LowCDS_t$. Thus an adverse shock to the credit quality of the riskiest dealers affects the liquidity premium and the credit quality of the safest dealers. $\Delta LowCDS_t$ does not contemporaneously affect any other variable in the system. In other words, shocks to the safest dealers' credit quality do not affect liquidity or the market assessment of the riskiest dealer, consistent with the notion, common to all contagion theories, that distress spreads from the riskiest to the safest institutions, not the other way around. $Credit_t$ is affected by $\Delta Illiquidity_t$. This is consistent with the idea that the price of real estate assets was affected by an illiquidity premium during the crisis. Moreover, $\Delta Illiquidity_t$ can affect both $\Delta HighCDS_t$ and $\Delta LowCDS_t$; that is, liquidity shocks can affect the CDS spreads of all types of dealers, which is consistent with the liquidity channel. For identification purposes, we add the restriction $\beta^*_{2,1} = \beta^*_{3,1}$, which implies that the coefficient of $\Delta Illiquidity_t$ in the $\Delta HighCDS_t$ and $\Delta LowCDS_t$ equations is the same. However, as we show below, our results are not sensitive to altering this restriction so that the coefficient on $\Delta Illiquidity_t$ is greater in the $\Delta HighCDS_t$ equation. As a result of the restrictions in β^*, the system above is quasi-identified (see Hamilton (1994)). We estimate this system of four equations jointly using full-information maximum likelihood.

Naturally, the assumptions in the SVAR above are debatable. It is not our intention, however, to take a strong stand on the assumptions of this SVAR; instead, we mean to use this SVAR to analyze the relative importance of liquidity and franchise-value contagion. The SVAR above is suitable for this analysis because both of these channels are present in the specification of the SVAR in Equation (6). Indeed, the liquidity channel works through the coefficients $\beta^*_{1,2}$, $\beta^*_{2,1}$, $\beta^*_{4,1}$ and $\beta^*_{3,4}$. That is, a shock to $HighCDS$ can affect $LowCDS$ because $HighCDS$ can affect illiquidity ($\beta^*_{1,2}$) which in turn affects $LowCDS$ ($\beta^*_{2,1}$). The same shock can also affect $Credit$ ($\beta^*_{4,1}$), which in turn affects $LowCDS$ ($\beta^*_{3,4}$). On the other hand, franchise-value contagion works through the direct effect on $LowCDS$ of a shock to $HighCDS$ ($\beta^*_{3,2}$). Therefore any of the restrictions that we impose in this SVAR are relevant for us only to the extent that they can bias the relative importance of the illiquidity and the franchise-value contagion. It is not immediately obvious to us why any of the restrictions of this SVAR would bias the results of the relative importance of either one of the contagion channels.

Table 7 shows our estimates of β^* and D.[14] Panel A presents the results based on the entire sample period, Panel B presents the results based on the pre-Lehman bankruptcy period, while Panel C presents the results based on the sample starting on Oct 15, 2008. The results suggest a clear distinction in the importance of the liquidity channel between the pre-Lehman bankruptcy and the post-TARP periods. Indeed, the results in Panel B indicate that a shock to $HighCDS$ leads to a shock to $Illiquidity$, which in turn leads to a shock to $LowCDS$. The results in Panel C are not consistent with the same chain of events. In fact, the sign of the point estimate of $\beta^*_{1,2}$ suggests that a positive shock on $HighCDS$ increases liquidity, which is the opposite of what the presence of the liquidity channel implies. Moreover, the estimates of the coefficient on $Illiquidity$ in the $HighCDS$ and $LowCDS$ equations are statistically indistinguishable from zero. The results in Panel D indicate that the month between Sep 15, 2008 and Oct 15, 2008 is in fact much more volatile than either the pre-Lehman or post-TARP periods. In fact, notice that the variance of the $HighCDS$ disturbances in the entire sample period (1063.98) is about three times higher than the variance of $HighCDS$ disturbances in the pre-Lehman and post-TARP samples. This large difference in variance is driven only by the period between Sep 15, 2008 and Oct 15, 2008.

To get a sense of economic significance, we plot the impulse response functions implied by the parameters of our structural VAR in Figures 3, 4 and 5. These figures show how shocks in $\Delta HighCDS$, $\Delta Illiquidity$, and $Credit$ affect $\Delta LowCDS$ for each of the considered sample periods. It is interesting to note the differences in the Pre-Lehman and Post-TARP impulse responses. The Pre-Lehman impulse responses show that the $\Delta LowCDS$ response to a shock in $\Delta HighCDS$, $\Delta Illiquidity$, and $Credit$ increases between the day of the shock (time zero) and one day after the shock. On the other hand, the Post-TARP impulse responses do not show the same increasing patterns in the impulse response. It is also interesting to note that a Post-TARP shock to $\Delta Illiquidity$ has a null effect on $\Delta LowCDS$. Overall, we interpret these findings as evidence that the interven-

[14]The point estimates of α^* and γ^* are not displayed in Table 7. They are equal to $\beta^* \times \alpha$, $\beta^* \times \beta$.

tions initiated during the Fall of 2008 insulated the safest dealers from shocks to $\Delta Illiquidity$.

To understand the extent to which $\Delta HighCDS$ affects $\Delta LowCDS$ either directly (through the franchise-value channel) or indirectly, through its impact on $\Delta Illiquidity$ (liquidity channel), we further decompose the impact of $\Delta HighCDS$ on $\Delta LowCDS$ into two components. The portion of the impact that acts through $\Delta Illiquidity$ is an estimate of the portion of contagion attributable only to the liquidity channel. We can calculate this portion by setting $\beta^*_{3,2}$ equal to zero in the SVAR in Equation (6) and setting $\beta_{2,2}$, $\beta_{2,3}$, and $\beta_{2,4}$ equal to zero in the reduced-form VAR in Equation (5). To see this note that the response of $\Delta LowCDS$ at time $t+s$ to a one standard deviation shock on $\Delta HighCDS$ is:

$$\frac{\beta^*_{1,2}\beta^s_{3,1} + \beta^s_{3,2} + (\beta^*_{1,2}\beta^*_{2,1} + \beta^*_{3,2} + \beta^*_{1,2}\beta^*_{4,1}\beta^*_{3,4})\beta^s_{3,3} + \beta^*_{1,2}\beta^*_{4,1}\beta^s_{3,4}}{1 - \beta^*_{1,2}\beta^*_{2,1} - \beta^*_{1,2}\beta^*_{2,4}\beta^*_{4,1}} \times \sqrt{D_{2,2}} \tag{7}$$

where β^s is the matrix β exponentiated to s and the term $\sqrt{D_{2,2}}$ is one standard deviation in the innovation of $\Delta HighCDS_t$. The first term in the numerator, $\beta^*_{1,2}\beta^s_{3,1}$, measures the extent to which a shock to $\Delta HighCDS_t$ indirectly impacts $\Delta LowCDS_{t+s}$ by first impacting the mediating variable $\Delta Illiquidity_t$. The second term measures the extent to which a shock to $\Delta HighCDS_t$ directly impacts future values of $\Delta LowCDS_{t+s}$ without mediation. The third term mixes the franchise value channel and the liquidity channel and measures the response of $\Delta LowCDS_{t+s}$ to a change in $\Delta LowCDS_t$ that results from a shock to $\Delta HighCDS_t$, both mediated and unmediated. This term has three components. The first component ($\beta^*_{1,2}\beta^*_{2,1}$) and third component ($\beta^*_{1,2}\beta^*_{4,1}\beta^*_{3,4}$) measure illiquidity-mediated effects, while the second component measures a direct effect with no mediation ($\beta^*_{3,2}$). The fourth term ($\beta^*_{1,2}\beta^*_{4,1}\beta^s_{3,4}$) in the numerator measures the response of $\Delta LowCDS_{t+s}$ to a change in $Credit_t$ that results from a shock to $\Delta HighCDS_t$, mediated though illiquidity. The denominator is related to a feedback effect in $\Delta HighCDS_t$; that is, it measures how a shock to $\Delta HighCDS_t$ impacts $\Delta Illiquidity_t$, which in turn affects $\Delta HighCDS_t$. Consequently, by setting $\beta^*_{3,2}$, $\beta_{2,2}$, $\beta_{2,3}$, and $\beta_{2,4}$ equal to zero, we eliminate any direct effect that a shock to $\Delta HighCDS_t$ has on $\Delta LowCDS_{t+s}$ that is not mediated by illiquidity.

Figure 6, Panel A plots the cumulative impulse response of $\Delta LowCDS_{t+s}$ to a shock to $\Delta HighCDS_t$ mediated through illiquidity, ignoring any direct effect. It plots the results based on the VAR estimate over the entire sample period, the pre-Lehman period and the post-TARP period. It also plots two standard deviation bands under the null hypothesis that the parameters are as those estimated under the entire sample period. This figure clearly indicates that the liquidity channel in the pre-Lehman period was significantly different from the one in the entire sample. Overall, our results clearly show that the liquidity channel of contagion was statistically significant in the pre-Lehman period, but not in the post-TARP period.

Figure 6, Panel B plots the total cumulative response of $\Delta LowCDS_{t+s}$ to a shock to $\Delta HighCDS_t$, including both the direct response and the portion mediated through illiquidity. This figure indicates that a one standard deviation shock to $\Delta HighCDS$ ($\sqrt{325.93} \sim 18$ basis points) has a long term effect of about 3 basis points in $\Delta LowCDS$. This effect is economically significant and it is about 0.75 of a standard deviation of $\Delta LowCDS$.

A comparison of Panel A and B reveals that the economic significance of the liquidity channel is small even in the pre-Lehman period. Indeed, the liquidity channel accounts for about 5% (0.15/3) of the total response of $\Delta LowCDS$ to a shock to $\Delta HighCDS$. We see two possible conclusions from these results: Either most of the contagion between dealers is caused by something other than liquidity, namely franchise-value contagion, or, if our proxy for liquidity is poor, $\Delta HighCDS$ captures both contagion channels.

The restriction, $\beta^*_{2,1} = \beta^*_{3,1}$, which implies that $\Delta Illiquidity_t$ has the same direct effect on both $\Delta HighCDS_t$ and $\Delta LowCDS_t$, is admittedly questionable, and so we presently examine its importance. Theory suggests that adverse liquidity shocks should impact dealers closer to default more than those further from default. Hence we consider alternative restrictions, wherein the direct effect of $\Delta Illiquidity_t$ on $\Delta HighCDS_t$ is many times greater than its effect on $\Delta LowCDS_t$. That is, we consider the restriction $\beta^*_{3,1} = m\beta^*_{2,1}$ for different values of $m > 1$. Specifically, we consider values of m equal to five or ten. It turns out that our estimates of the total contagion effect are not sensitive to m and the fraction attributable to the liquidity channel decreases modestly with large values of m.[15] That is, the restriction that $\beta^*_{2,1} = \beta^*_{3,1}$ does not drive our conclusion that the

[15] Intuitively, any restriction on $\beta^*_{3,1}$ that causes us to underestimate the direct effect of $\Delta Illiquidity$ on $\Delta HighCDS$ also causes us to overestimate the indirect effect $\Delta Illiquidity$ on $\Delta HighCDS$ that is mediated though $Credit$. Hence, though different values of m change the estimated relative magnitudes of the direct and indirect effects of $\Delta Illiquidity$ on $\Delta HighCDS$, the estimated total effect does not vary much with m.

economic importance of the liquidity channel is small.

As a robustness check we run a similar specification to Equation (6), except we replace the Musto, Nini, and Schwarz (2011) measure of illiquidity with either the Hu, Pan, and Wang (2013) yield curve goodness-of-fit statistic or the off-the-run spread. In both cases, we fail to find a significant liquidity channel.[16] To explain our findings, we therefore need to conclude either that different measures of systematic liquidity mostly fail to capture the illiquidity channel, or that the most economically important channel of contagion by far during the financial crisis was the franchise channel. Moreover, the possibility that different measures of systematic liquidity fail to capture the illiquidity channel is at the odds with the fact that the illiquidity channel is statistically significant in the pre-Lehman period, while it is not significant in the post-TARP period. Therefore, all of our results together seem to indicate that illiquidity is indeed a contagion channel, but its economic magnitude is small compared with direct contagion channels.

3 Conclusion

Primary dealers are central to the operation 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 the notion that one dealer's distress directly impacts other dealers' franchise value. We test these possible contagion channels against the null hypothesis that there is no contagion and that correlated dealer distress is due merely to observable common fundamental credit shocks.

Our results indicate that financial contagion of both forms is real. Prior to the interventions in the Fall of 2008, we find individual dealer CDS spreads are sensitive to both the CDS spreads of the riskiest dealers, as well as illiquidity, even as we control for each dealer's unique exposure to the real estate assets driving the crisis. We also estimate structural vector autoregressions, which explicitly model the ways in which distress at one dealer can impact other dealers both directly and indirectly,

[16] The results are available upon request.

through the mediating effect of illiquidity. Prior to the interventions, we find that illiquidity does indeed increase in response to a positive shock to the riskiest dealers' CDS spreads, and that even the safest dealers' CDS spreads then respond to this increase in illiquidity. However, we also find that a shock to the riskiest dealers' CDS spreads also directly impacts the safest dealers' spreads, and this direct contagion effect dominates. We find that only 5% of the total contagion effect is mediated through illiquidity prior to the interventions. Furthermore, after the interventions of Fall of 2008 are in place, we fail to find evidence that illiquidity serves as a mediating mechanism transmitting shocks from the riskiest dealers to the safest. On the other hand, we also find that even after the interventions, even the safest dealer CDS spreads continue to be sensitive to the CDS spreads of the riskiest dealers, and if anything, this sensitivity increases. We infer that while the interventions succeeded in arresting liquidity contagion, franchise-value contagion remained.

While we find evidence of franchise-value contagion, we are not able to pin down its specific mechanism. A high probability of distress at one dealer might undermine the franchise value of others because of counterparty exposure; alternatively, high CDS spreads at one dealer might also be related to increased market expectations that the system is insolvent, which turn undermines the franchise value of even safe dealers, causing all spreads to rise. The perceived likelihood of government bailouts might also factor into market expectations of system solvency, and hence, induce a correlation between risky and relatively safe dealer spreads. Regardless, there is a fundamental difference between distress at one dealer directly undermining the franchise value of others and the indirect spread of financial distress through the mediating effect of illiquidity. Hence, determining the relative economic importance of liquidity contagion and franchise-value contagion is important, even if we cannot pin down its precise mechanism. We leave the latter task to future research.

Overall, our results suggest that policies cushioning the fixed-income markets and dealers against negative liquidity shocks, as well as policies aimed at bolstering confidence in surviving dealers' franchise value after the onset of a crisis, play a role in stabilizing the financial system, even when policies incentivizing cautious underwriting are in place. Furthermore, since regulators were only successful at alleviating liquidity contagion, it would seem appropriate to place a greater emphasis on devising new policies aimed at alleviating franchise-value contagion.

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Table 1: Descriptive statistics

This table presents summary statistics of our main variables in different sample periods. We present the number of observations (N), the mean, standard deviation and the percentiles of each variable.

Panel A: Full Sample

	N	Mean	Stdev	1st pctl	25th pctl	50th pctl	75th pctl	99th pctl
ΔHighCDS	751	0.168	34.8	-96.9	-5.30	0.000	6.30	91.5
ΔLowCDS	751	0.0647	4.80	-13.7	-1.35	0.0500	1.60	12.4
ΔIlliquidity	751	0.00121	1.19	-3.45	-0.345	0.000	0.330	0.349
Credit	751	-0.261	2.25	-5.91	-1.43	-0.152	0.683	7.95
ΔCDS	4506	0.0822	7.32	-23.3	-1.74	0.000	2.10	23.2

Panel B: Jan. 1, 2007-Sept. 14, 2008 (Pre-Lehman Period)

	N	Mean	Stdev	1st pctl	25th pctl	50th pctl	75th pctl	99th pctl
ΔHighCDS	427	1.31	19.3	-52.9	3.25	0.167	5.20	56
ΔLowCDS	427	0.161	3.91	-12.3	-0.500	0.050	1.35	10.5
ΔIlliquidity	427	0.0326	0.625	-1.938	-0.206	0.0150	0.262	1.78
Credit	427	-0.433	1.93	-5.99	-1.33	-0.205	0.352	4.52
ΔCDS	2562	0.243	4.88	-13.9	-0.800	0.000	1.60	14.2

Panel C: Sept. 15 - Oct. 15, 2008 (Transition Period)

	N	Mean	Stdev	1st pctl	25th pctl	50th pctl	75th pctl	99th pctl
ΔHighCDS	21	-12.8	178	606	54.8	1.05	84.4	203
ΔLowCDS	21	-0.824	17.0	-28.9	-12.7	-2.00	7.85	34.0
ΔIlliquidity	21	0.147	3.32	-11.6	-0.470	0.965	1.81	3.88
Credit	21	0.481	2.93	-3.56	-1.57	0.482	0.970	7.95
ΔCDS	126	-1.83	23.8	-74.5	-10.7	0.350	10.0	45.5

Panel D: Oct. 16, 2008-Dec. 31, 2009 (Post-TARP Period)

	N	Mean	Stdev	1st pctl	25th pctl	50th pctl	75th pctl	99th pctl
ΔHighCDS	303	-0.546	19.2	-41.7	-8.85	-1.31	6.47	58.9
ΔLowCDS	303	-0.00887	4.06	-11.7	-2.07	-0.0900	2.05	10.6
ΔIlliquidity	303	-0.0532	1.50	-3.96	-0.658	-0.074	0.442	5.796
Credit	303	-0.0704	2.58	-5.69	-1.48	-0.006	0.958	9.91
ΔCDS	1818	-0.0111	7.76	-22.9	-3.10	-0.070	2.50	26.5

Table 2: Timeline of selected major interventions directly impacting dealers

The data source is Source: Federal Reserve Bank of St. Louis Financial Crisis Timeline at http://timeline.stlouisfed.org/index.cfm?p=timeline#

12/7/2007	Fed creates the Term Auciton Facility (TAF), which makes available collateralized short-term loans, $20 billion in aggerate every two weeks, to depository instutions
3/5/2008	Fed increases TAF from $20 to $50 billion; makes term repos available to primary dealers, up to $100 billion in aggregate.
3/11/2008	Fed creates the Term Securities Lending Facility (TSLF), lending Treasuries to primary dealers against AAA MBS or agency securities
3/16/2008	Fed establishes Prime Dealer Credit Facility (PRCF): loans to primary dealers, at primary credit rate, collateralized by investment grade securites
3/24/2008	Fed finances distressed sale of Bear Sterns to J.P. Morgan
5/2/2008	Fed modifies TSLF to accept AAA asset-backed securities as collateral; TAF incrased to $75 billion
7/30/2008	Fed extends TSLF & PDCF and increases maximum term of TAF loans to 84 days
9/14/2008	PDCF modified to accept below-investment grade collateral; all investment-grade collateral accepted for FSLF
9/15/2008	Lehman Brothers files for bankruptcy; Bank of America purchases Merrill Lynch in distressed transaction backed by Fed.
9/16/2008	Prime Reserve Money Market Fund NAV drops below $1 per share
9/19/2008	Treasury guarantees money market funds; Fed creates Asset-Backed Commercial Paper Facility to finance bank purchases of asset-backed commercial paper from dealers; Program to purchase agency notes from primary dealers announced.
9/21/2008	Goldman Sachs and Morgan Stanley allowed to reincoporate as bank holding companies and thus gain access the discount window
10/3/2008	TARP Signed into law
10/6/2008	Fed starts to pay interest on reserves
10/7/2008	Commercial Paper Funding Facility (CPFF) created; Fed buys CP directly form issuers.
10/7/2008	FDIC deposit insurance limits increased to $250,000
10/14/2008	Treasury announces it will invest in financial institution preferred stock under TARP; FDIC guarantees senior debt issued by bank holding companies.
10/21/2008	Fed creates Money Market Investor Funding Facility (MMFF), lending to SIVs established to buy financial institution commercial paper from money market funds
10/28/2008	Treasury makes first TARP investment in financial institution preferred stock
11/23/2008	TARP, FDIC and Fed do joint bailout of Citigroup
11/25/2008	Fed creates Term Asset-Backed Securities Lending Facility (TALF), providing loans collateralized by AAA asset backed securities
12/2/2008	Fed extends its major liquidity facilities
1/16/2009	Tarp, Fed and FDIC do joint bailout of Bank of America
2/10/2009	TALF expanded and now accepts AAA rated CMBS and RMBS
3/20/2009	Collateral accepted for TALF expanded again

Table 3: Short-term liability ratios

This table presents the 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. "Total Runnable Debt" in the last column is defined as the sum of the first three columns.

	Repos	Unsecured Commercial Paper (cp)	Asset-backed Commercial Paper (abcp)	Total Runable Debt
Bank of America	1.64	0.23	0.35	2.22
Barclays	2.55	0.49	0.62	3.66
Bnp Paribas	4.96	0.00	0.19	5.15
Citigroup	2.79	0.37	0.78	3.93
Credit Suisse	6.20	0.32	0.10	6.62
Deutschebank	4.31	0.12	0.89	5.32
Goldman Sachs	4.51	0.05	0.00	4.56
JP Morgan	1.24	0.13	0.37	1.74
Morgan Stanley	7.81	0.66	0.00	8.47
Bear Sterns	5.75	1.71	1.14	8.60
RBS	0.78	0.06	0.21	1.05
Lehman Brothers	6.96	0.09	0.11	7.15
Merrill Lynch	5.70	0.16	0.18	6.04
Mean	4.25	0.34	0.38	4.96
Median	4.51	0.16	0.21	5.15
Stdev	2.27	0.45	0.37	2.42

Table 4: SUR results

This table presents results from a seemingly unrelated regression analysis of the first difference of each dealer's own CDS spread on the first difference in *HighCDS* (the average CDS of the riskiest quintile of dealers) and *Illiquidity*, the level of *Credit*, and interactions with period dummies. The sample period is all trading days over the 2007-2009 period. Only dealers whose spreads are never in the riskiest quintile are included in the sample. The *PostTarp* period constitutes all trading days in the sample after Oct 14, 2008, and the *Transition* period is all trading days between Sep 15 - Oct 14, 2008. *Credit* is constructed by taking the average daily return on the ABX and CMBX indices. The coefficients on *ΔHighCDS*, *ΔIlliquidity* and interactions are constrained to be equal for all dealers, and their estimates along with their standard errors (in parentheses) are given below. Each dealer is allowed to have a different coefficient on the credit variable. The mean of these dealer-specific coefficients are reported, along with the chi-square statistic of their joint significance. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% level.

	(1)	(2)	(4)	(4)
ΔHighCDS	0.0713***	0.0713***	0.0963***	0.0908***
	(0.00381)	(0.00384)	(0.00783)	(0.00808)
ΔIlliquidity		0.296***		0.461*
		(0.104)		(0.247)
ΔHighCDS*Transition			-0.0226***	-0.0187**
			(0.00867)	(0.00900)
ΔHighCDS*PostTarp			0.0903***	0.0977***
			(0.0121)	(0.0124)
Δilliquidity*Transition				0.408
				(0.329)
Δilliquidity*PostTarp				-0.232
				(0.274)
Mean of Coefs on Credit	-0.5415***	-0.5341***	-0.3643***	-0.3571***
Joint χ^2 test statistic	576.52	567.11	287.87	252
N	4506	4506	4506	4506

Table 5 - Results of SUR with interactions

This table presents results from a seemingly unrelated regression analysis of the first difference of each dealer's own CDS spread on the first difference in *HighCDS* (the average CDS of the riskiest quintile of dealers) and *Illiquidity*, the level of *Credit*, and their interactions with *Runable*, our proxy for total runnable funds. We define *Runable* as the sum of a dealer's REPO, commercial paper, and asset-backed commercial paper liabilities (both on and off balance sheet), scaled by total book common equity, as of the end of fiscal 2006. In columns (1) and (2) the sample is from Jan 1 – Aug 31, 2007, and in columns (3) and (4) is from Jan 1 – Sep 30, 2007. Only dealers whose spreads are never the riskiest quintile during these periods are included in the sample. The coefficients on *ΔHighCDS*, *ΔIlliquidity*, *Runnable* and interactions are constrained to be equal for all dealers, and their estimates along with their standard errors (in parentheses) are given below. Each dealer is allowed to have a different coefficient on the credit variable, but these coefficients are not reported. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)
ΔHighCDS	0.162***	0.133***	0.148***	0.126***
	(0.011)	(0.015)	(0.012)	(0.015)
ΔIlliquidity	0.308	0.086	0.311	0.036
	(0.203)	(0.278)	(0.219)	(0.291)
Runnable	0.001	0.001	0.009	0.007
	(0.013)	(0.014)	(0.012)	(0.013)
Runnable*ΔIlliquidity		0.055		0.073
		(0.047)		(0.050)
Runnable*ΔHighCDS		0.007***		0.005**
		(0.003)		(0.003)
N	1692	1692	1521	1521

Table 6: Reduced form VAR

This table presents parameter estimates (and standard errors) for a reduced-form vector autoregression that includes a credit variable constructed from the ABX and CMBX indices (*Credit*) and the first differences in the following variables: the Musto-Nini-Schwartz illiquidity measure (Illiquidity), 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. Panel A displays results for the sample period that includes all trading days over 2007-2009. Panel B displays results for the sample period that ends before Lehman Brothers bankruptcy (Sep 15, 2008). Panel C displays results for the sample period that starts on Oct 15, 2008 (post-TARP).

Panel A - Sample period includes all trading days over 2007-2009

	Dependent Variable			
	ΔIlliquidity	ΔHighCDS	ΔLowCDS	Credit
Lag1 ΔIlliquidity	0.1123***	-2.3490**	-0.0893	0.0003
	(0.0368)	(1.0522)	(0.1445)	(0.0006)
Lag1 ΔHighCDS	0.0001	-0.1870***	0.0205***	0.00003
	(0.0014)	(0.0410)	(0.0056)	(0.00002)
Lag1 ΔLowCDS	-0.0002	1.0121***	-0.0132	-0.0002
	(0.0103)	(0.2958)	(0.0406)	(0.00017)
Lag1 Credit	0.2370	-164.3453***	-33.5185***	0.3736***
	(2.1262)	(60.8537)	(8.3545)	(0.03592)
Constant	0.0011	-0.2471	-0.0166	-0.0015**
	(0.0436)	(1.2486)	(0.1714)	(0.00074)
N	750	750	750	750

Panel B - Pre-Lehman sample period.

	Dependent Variable			
	ΔIlliquidity	ΔHighCDS	ΔLowCDS	Credit
Lag1 ΔIlliquidity	-0.0477	-4.6113***	0.5325**	-0.0004
	(0.0503)	(1.5260)	(0.2587)	(0.0014)
Lag1 ΔHighCDS	0.0004	0.1462**	0.1213***	-0.0001**
	(0.0019)	(0.0584)	(0.0099)	(0.00005)
Lag1 ΔLowCDS	-0.0193**	-0.0583	-0.1789***	0.0002***
	(0.0084)	(0.2545)	(0.0431)	(0.00023)
Lag1 Credit	-1.3650	-128.3583**	-23.5929**	0.2665***
	(1.8638)	(56.4968)	(9.5774)	(0.05040)
Constant	0.0307	0.8107	-0.0372	-0.0029***
	(0.0309)	(0.9354)	(0.1586)	(0.00083)
N	426	426	426	426

Table 6: Reduced form VAR (contd.)

Panel C - Post-TARP sample period

	Dependent Variable			
	ΔIlliquidity	ΔHighCDS	ΔLowCDS	Credit
Lag1 ΔIlliquidity	0.2519***	-0.3099	-0.0583	-0.0001
	(0.0550)	(0.7111)	(0.1500)	(0.0009)
Lag1 ΔHighCDS	-0.0046*	-0.0872***	-0.0089	0.0001*
	(0.0026)	(0.0330)	(0.0070)	(0.00004)
Lag1 ΔLowCDS	0.0354	0.3088	0.0619	-0.0005
	(0.0235)	(0.3037)	(0.0640)	(0.00038)
Lag1 Credit	0.0031	-138.2628***	-34.9925***	0.4169***
	(3.4071)	(44.0158)	(9.2825)	(0.05508)
Constant	-0.0446	-0.8015	-0.0404	-0.0002
	(0.0833)	(1.0755)	(0.2268)	(0.00135)
N	303	303	303	303

Table 7 - Structural VAR results

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. Panel A displays results for the sample period that includes all trading days over 2007-2009. Panel B displays results for the sample period that ends before Lehman Brothers bankruptcy (Sep 15, 2008). Panel C displays results for the sample period that starts on Oct 15, 2008. Panel D presents the estimation of the variances of the disturbances in the structural VAR model.

Panel A - Sample period includes all trading days over 2007-2009

	Independent Variable			
	ΔIlliquidity	ΔHighCDS	ΔLowCDS	Credit
ΔIlliquidity		0.0047***		
		(0.0013)		
ΔHighCDS	0.2483			-463.8000***
	(0.1918)			(60.1314)
ΔLowCDS	0.2483	0.0608***		-25.2274***
	(0.1918)	(0.0047)		(7.6711)
Credit	-0.0005			
	(0.0006)			

Panel B - Pre-Lehman sample period

	Independent Variable			
	ΔIlliquidity	ΔHighCDS	ΔLowCDS	Credit
ΔIlliquidity		0.0072***		
		(0.0016)		
ΔHighCDS	0.4617*			-266.0971**
	(0.2450)			(53.5826)
ΔLowCDS	0.4617*	0.0448***		-19.6473**
	(0.2450)	(0.0082)		(9.0753)
Credit	-0.0045***			
	(0.0013)			

Panel C - Post-TARP sample period

	Independent Variable			
	ΔIlliquidity	ΔHighCDS	ΔLowCDS	Credit
ΔIlliquidity		-0.0038		
		(0.0114)		
ΔHighCDS	0.1058			-264.8736***
	(1.6663)			(53.2082)
ΔLowCDS	0.1058	0.0918		-15.3914
	(1.6663)	(0.0821)		(9.4541)
Credit	0.00003			
	(0.0012)			

Table 7: Structural VAR results (contd.)

Panel D - Variances of disturbances

	Sample period		
	2007-2009	Pre-Lehman	Post-TARP
ΔIlliquidity	1.38	0.36	2.10
	(0.07)	(0.02)	(0.21)
ΔHighCDS	1,063.98	325.93	305.06
	(55.51)	(22.36)	(47.95)
ΔLowCDS	16.38	8.96	11.03
	(10.47)	(0.61)	(127.35)
Credit	0.00040	0.00027	0.00055
	(0.00002)	(0.00002)	(0.00005)

Figure 1: Comparison of Illiquidity Measures

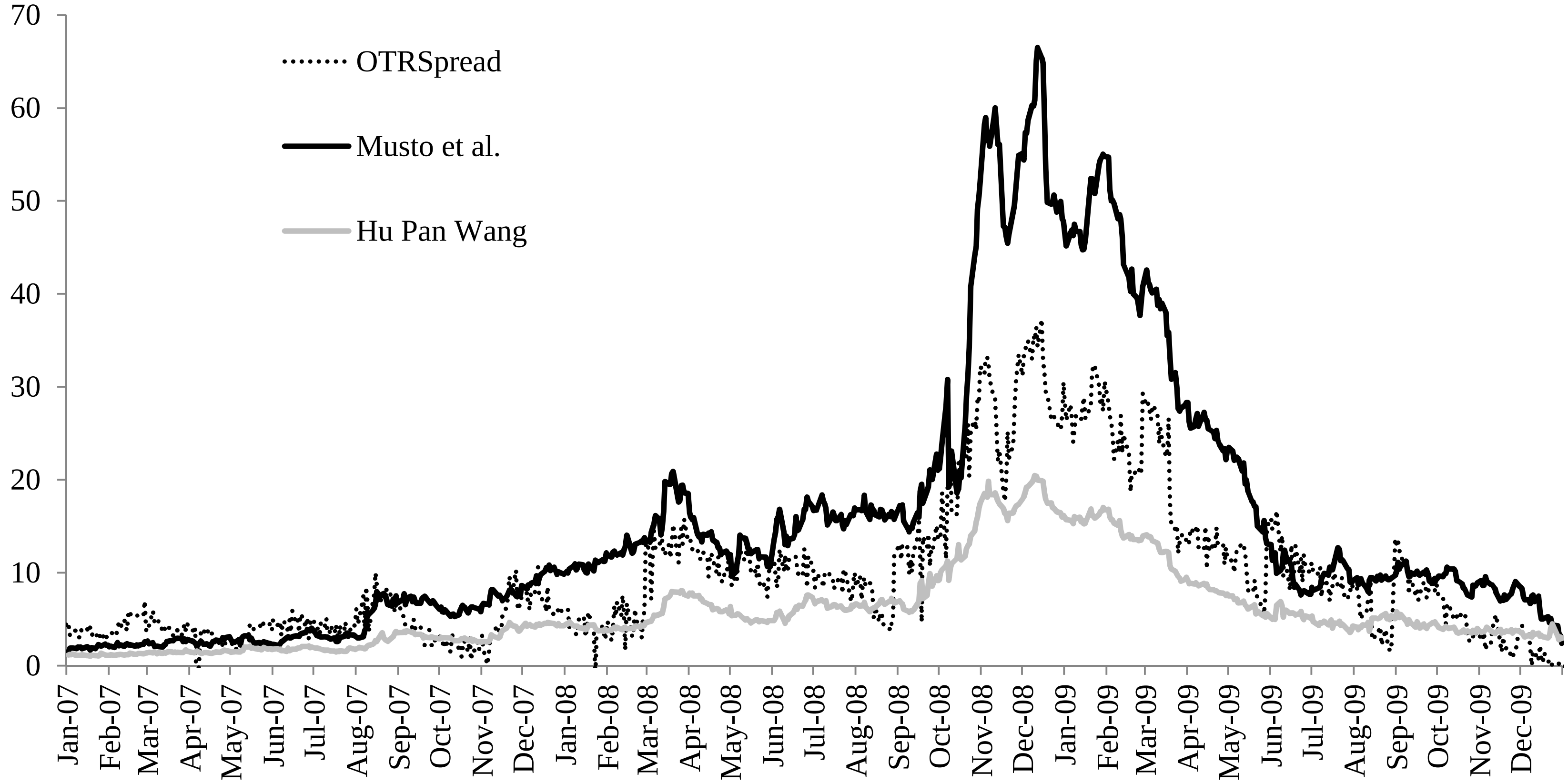


Figure 2: Time series of CDS spreads

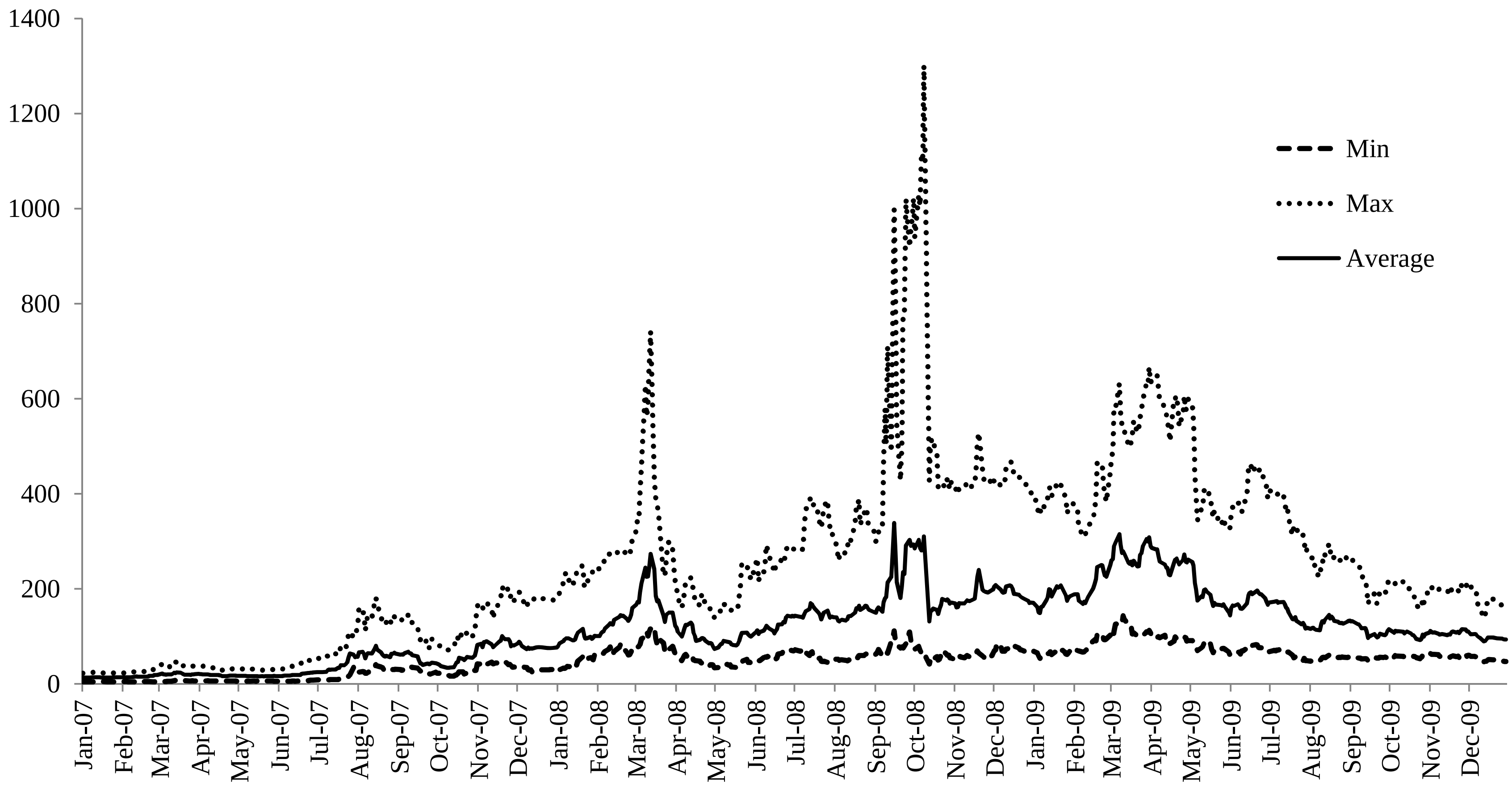
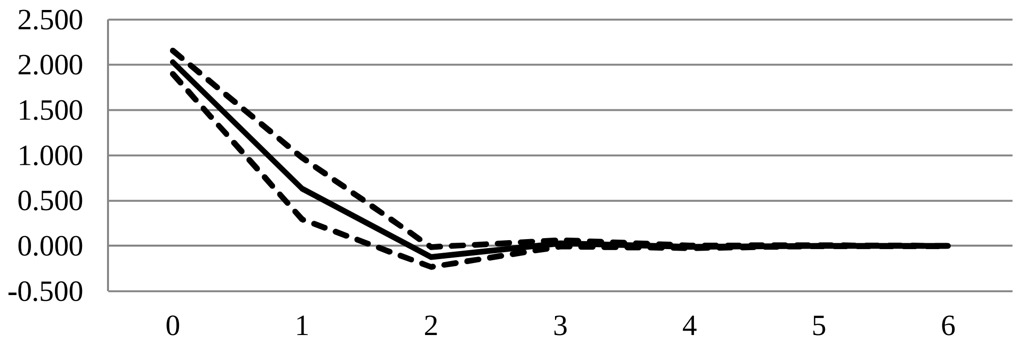


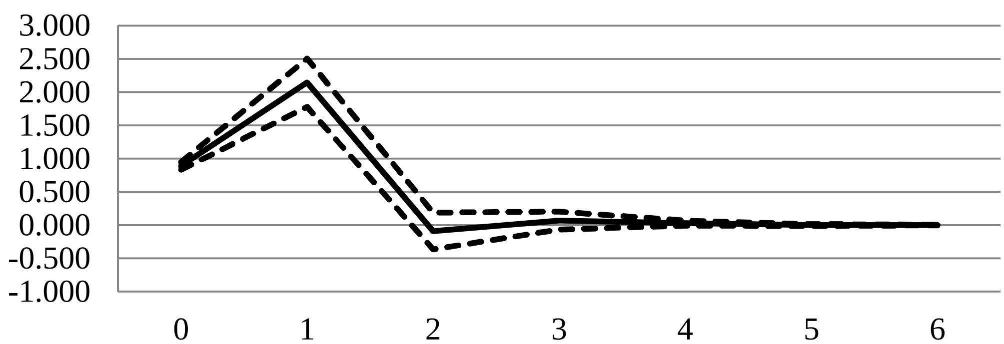
Figure 3 - Response of ΔLowCDS to a ΔHighCDS shock

This figure presents the daily response on ΔLowCDS to a shock of one standard deviation on the ΔLowCDS. The impulse responses are implied by the estimated structural VAR model. The dashed lines represent plus or minus two standard errors from the impulse response. The first panel is for the sample period that includes all trading days over 2007-2009. The second panel uses the sample period that ends before Lehman Brothers bankruptcy (Sep 15, 2008). The third panel is related to the sample period that starts on Oct 15, 2008.

Sample 2007 to 2009



Pre-Lehman sample



Post-TARP sample

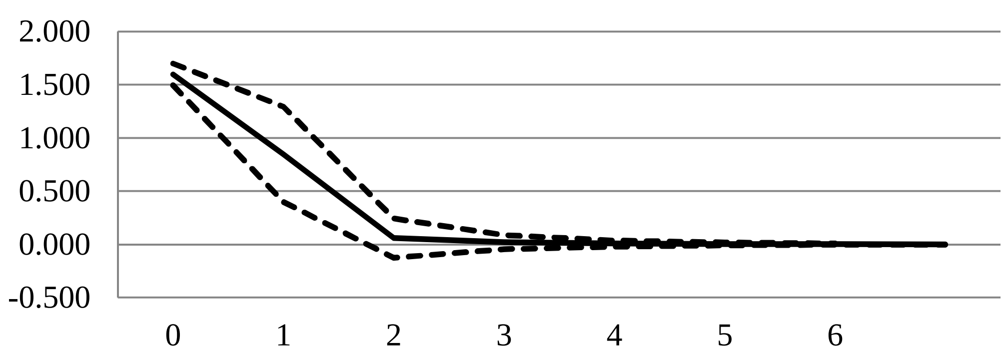


Figure 4 - Response of ΔLowCDS to a Illiquidity shock

This figure presents the daily response on ΔLowCDS to a shock of one standard deviation on the Illiquidity. The impulse responses are implied by the estimated structural VAR model. The dashed lines represent plus or minus two standard errors from the impulse response. The first panel is for the sample period that includes all trading days over 2007-2009. The second panel uses the sample period that ends before Lehman Brothers bankruptcy (Sep 15, 2008). The third panel is related to the sample period that starts on Oct 15, 2008.

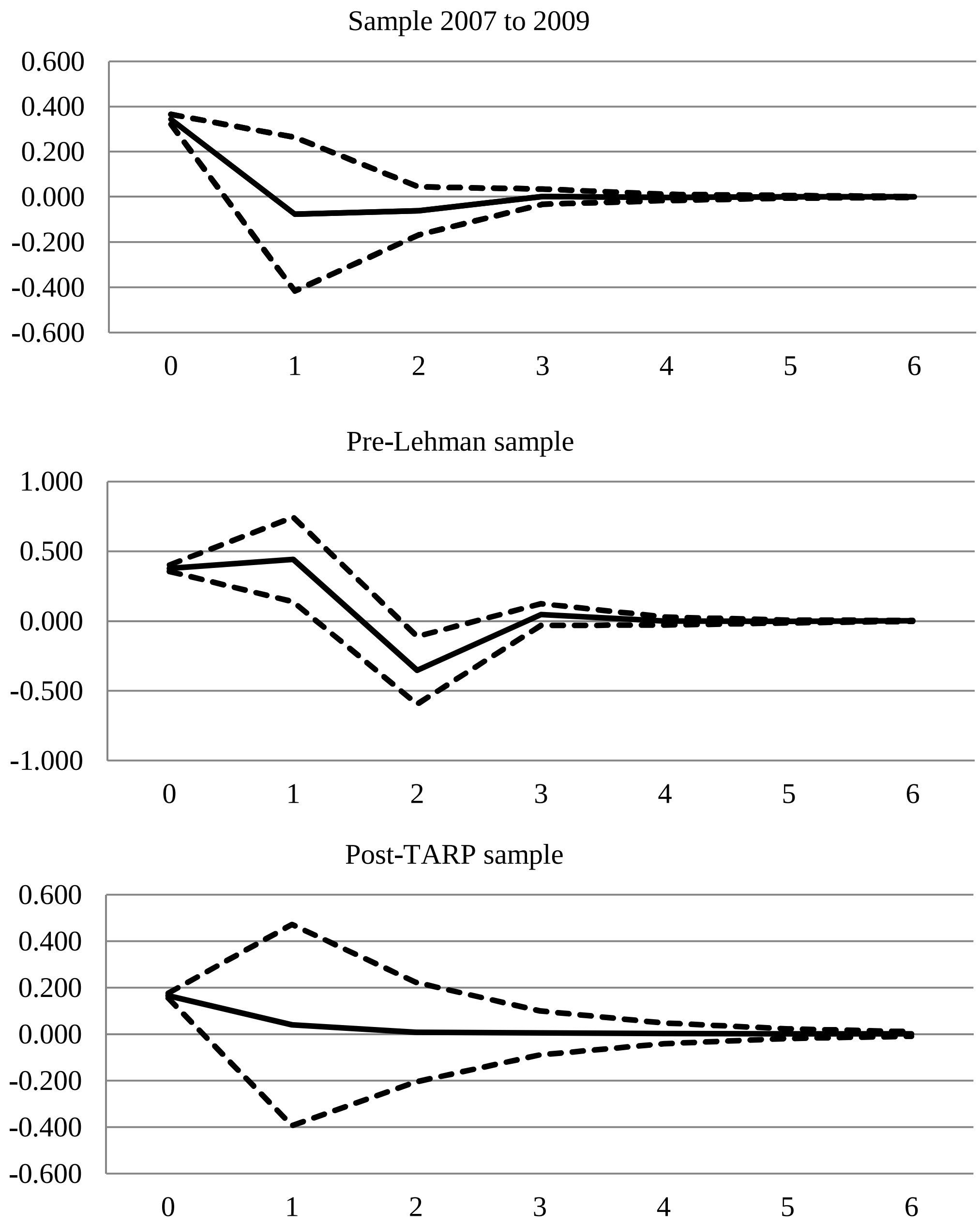


Figure 5 - Response of ΔLowCDS to a Credit shock

This figure presents the daily response on ΔLowCDS to a shock of one standard deviation on Credit. The impulse responses are implied by the estimated structural VAR model. The dashed lines represent plus or minus two standard errors from the impulse response. The first panel is for the sample period that includes all trading days over 2007-2009. The second panel uses the sample period that ends before Lehman Brothers bankruptcy (Sep 15, 2008). The third panel is related to the sample period that starts on Oct 15, 2008.

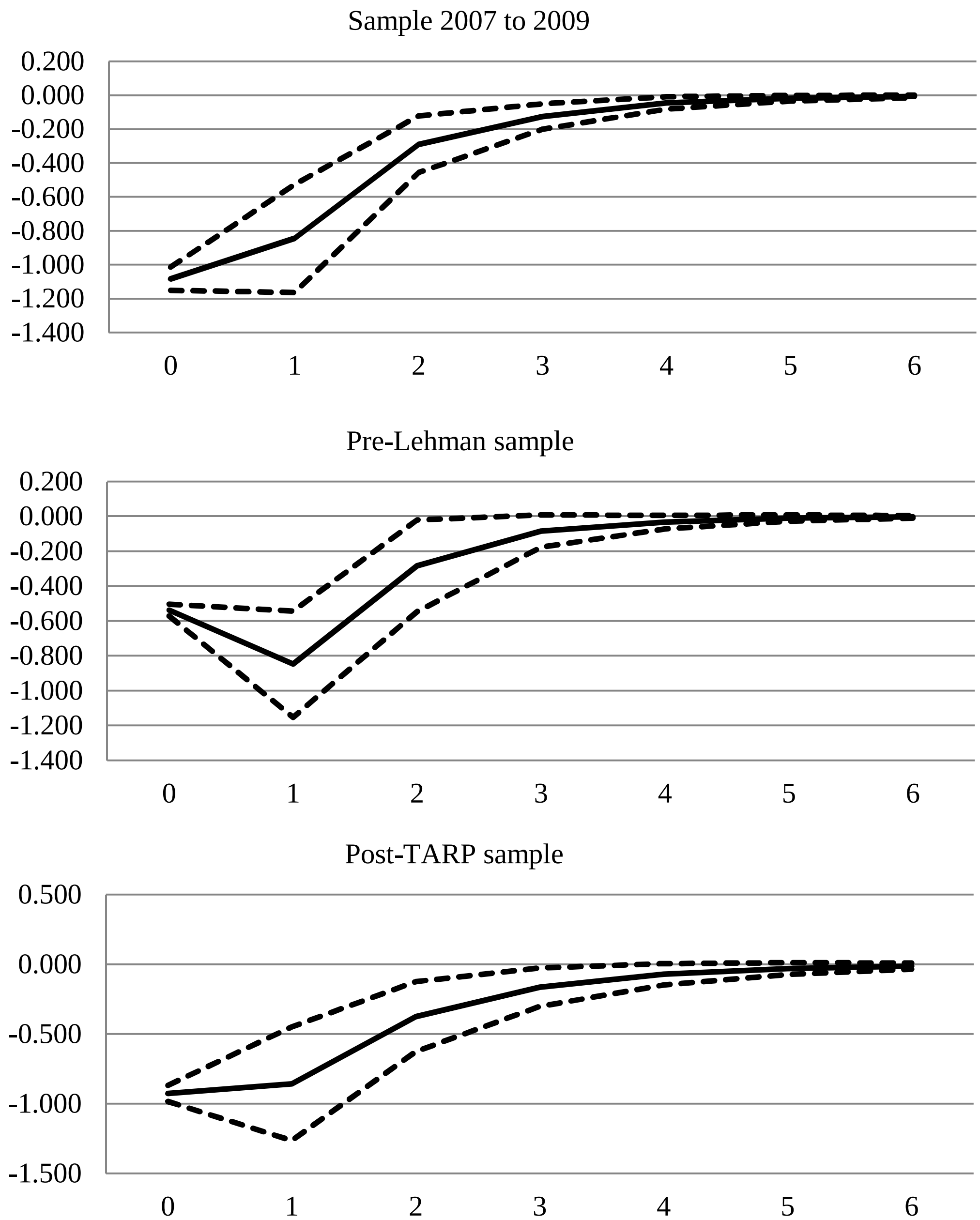


Figure 6 - The effect of the illiquidity channel of contagion

This figure presents the cumulative response on ΔLowCDS to a one standard deviation shock on ΔHighCDS. These functions are calculated with the parameters estimated for the structural VAR. The top panel considers the effect of ΔHighCDS onto ΔLowCDS through all the contagion mechanisms implied by the estimated structural VAR. The bottom panel shows the impulse response through the illiquidity channel only. That is, the bottom panel shows the results of the impulse response under the assumption that that the coefficients of ΔHighCDS and its lags in the ΔLowCDS and Credit -VAR equations are equal to zero. The curves labeled "Entire sample" include are based on the sample period that includes all trading days over 2007-2009. The curves labeled "Before Sep 15, 2008" uses the sample period that ends before Lehman Brothers bankruptcy (Sep 15, 2008). The curves labeled "After Oct 14, 2008" is related to the sample period that starts on Oct 15, 2008. The dotted lines are two standard errors under the null that the data conforms to the parameter estimates of the entire sample.