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 find that franchise-value contagion dominates, accounting for 95% of all contagion. Furthermore, unlike liquidity contagion which disappears after the Federal Reserve and Treasury market interventions in the Fall of 2008, 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 compare the relative importance of different contagion channels.

To understand 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.

The liquidity channel of contagion is based on Brunnermeier (2009) and Brunnermeier and Pedersen (2009). A single large dealer's failure directly causes a large, systematic negative liquidity shock. 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. Therefore, according to the liquidity channel of contagion, distress at a single large dealer does not directly cause problems for other dealers; rather, distress spreads indirectly through the mediating effect of illiquidity.

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. In fact, in an extension of Allen and Gale (2000), Zawadowski (2013) develops a model in which investors do not rollover short-term funding to banks because investors do not trust banks with failing counterparties. 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. Indeed, with a mechanism similar to that in Leitner (2005), 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 fatal deterioration in franchise value if the financial sector is perceived to be weak.

We recognize that franchise-value contagion is a broad category, and one that encompasses several possible mechanisms. Otherwise healthy dealers might be vulnerable to the distress of other dealers because of credit or counterparty exposure, or distress at other dealers might cause market participants' to update unfavorably about the aggregate solvency of the financial system. Alternatively, otherwise healthy dealers' perceived probability of default might increase with the distress of other dealers because the latter can impact perceptions about the government's willingness to keep the system solvent. Our methods do not allow us to pin down the relative importance of these precise mechanisms driving franchise-value contagion. Nevertheless, there is 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. For instance, while stress tests address franchise value contagion, they do not directly address liquidity contagion. In contrast, interventions such as the Term Auction Facility are designed to cushion dealer banks against liquidity shocks. Hence, determining the relative economic importance of liquidity contagion and franchise-value contagion is important; otherwise we cannot possibly infer the usefulness of different interventions to arrest contagion.

We test for the presence and compare the relative economic importance of the two contagion channels by estimating a seemingly unrelated regression (SUR) and a structural vector autoregression model (SVAR) over the 2007-2009 crisis period. Our SUR allows us to 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. The SUR also allows us to control for each dealer's unique exposure to the securitized products at the root of the crisis. This method enables us to determine whether any apparent contagion effects are really just the result of common credit shocks in the mortgage markets that drove the crisis. Our SVAR allows us 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 relationships between contemporaneous and lagged variables. Therefore, the SVAR allows us to compare the relative economic importance of the two contagion channels taking into consideration the relationship between contemporaneous and lagged CDS spreads.

It is important to note that our methods do not establish the causal relationship that is the essence of the concept of economic contagion. Our methods, however, allows us to gauge the relative importance of the two mechanisms of contagion presuming they exist. Specifically, the liquidity channel of contagion implies that illiquidity is a mediating variable in the relationship between the CDS spreads of the riskiest and safest dealers.[3] The statistical methods we employ allow us to test the extent to which illiquidity mediates the relationship between the CDS spreads of the riskiest and safest dealers without establishing whether this is a causal relationship.

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, perhaps as a consequence of dealer spreads after the interventions reflecting perceptions about the government's willingness and ability to keep the system solvent.

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, before the major interventions that followed the Lehman Brothers bankruptcy, the liquidity channel accounted for a statistically significant but economically modest 5% of total contagion.[4]

Naturally, our conclusions regarding the economic significance of the liquidity channel depend on the quality of our liquidity proxy. 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 (LOOP) in recently-issued 10 year US Treasury notes and old 30 year bonds that mature in 10 years. It is similar to the funding liquidity factor of Fontaine and Garcia (2012) (which is based on LOOP violations across the term structure), but we cannot use the latter measure because it is only available in a monthly frequency. Both the theoretical and empirical literature provides

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

[4] Liquidity contagion in the pre-Lehman period might be modest because some earlier liquidity interventions were successful, consistent with Berger, Black, Bouwman, and Dlugosz (2014)'s evidence on the Federal Reserve's Term Auction Facility, initiated in 2007.

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.[5] 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. Moreover, we find that the importance of the liquidity channel of contagion decreases as a result of the strong liquidity interventions implemented after Lehman's bankruptcy. This finding serves as a certification that the Musto, Nini, and Schwarz (2011) liquidity measure captures the aspects of liquidity that are important for our analyses. Finally, in robustness checks we use other proxies of illiquidity (the Hu, Pan, and Wang (2013) yield curve model fit error statistic and the off-the-run spread). When we use these alternative proxies, we fail to find any evidence of liquidity contagion, though franchise value contagion remains just as strong. Therefore, the small economic significance of the liquidity channel that we find is not due to our liquidity measure failing to capture liquidity.

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.[6] 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 Duygan-Bump, Parkinson, Rosengren, Suarez, and Willen (2013) and Afonso, Kovner, and Schoar (2011), 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

[5] See Brunnermeier (2009), Brunnermeier and Pedersen (2009), Duffie (2010), Fontaine and Garcia (2012), Gromb and Dimitri (2010), Griffoli and Ranaldo (2011), Mitchell, Pedersen, and Pulvino (2007), Garleanu and Pedersen (2011), Musto, Nini, and Schwarz (2011), and Schwarz (2014).

[6] 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).

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 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. Duarte and Eisenbach (2014) apply the method developed by Greenwood, Landier, and Thesmar (2014) to infer that spillover effects of fire sale of assets could be potentially large. 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 that show evidence that the 2007-2009 crisis was a run on the securitized-banking system.[7] We extend this literature by showing that the run on the securitized-banking system mostly happened through a franchise-value channel 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.[8] Previous works on contagion across banks and nonfinancial firms utilize actual failures or defaults in their research designs.[9] Instead, we examine co-movements in credit default swaps since there are few actual dealer failures in our data period. Moreover, to the best of our knowledge, we are the first to examine channels of contagion using methods commonly used in the statistics literature to analyze mediating effects.

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.

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

[8]While many empirical contagion studies (e.g. Aharony and Swary (1983), Aharony and Swary (1996), Iyer and Peydro (2011), Swary (1986), and Jayanti and Whyte (1996)) look at commercial banks, 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 our paper fills an important gap in the literature. In addition, because we focus on contagion across institutions, our study differs from those examining contagion across countries (e.g. Kaminsky, Reinhart, and Vegh (2003) and Forbes (2012)), asset classes (e.g., Longstaff (2010)), or particular securities (e.g., Coval and Stafford (2007)).

[9]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.

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. Figure 1 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.[10]

Our main liquidity proxy is the Musto, Nini, and Schwarz (2011) yield-based measure, computed as the difference between the yield to maturity on the most recently the issued off-the-run 10-year note and the internal rate of return on a replicating portfolio consisting of STRIPS and an old 30-year bond. We label this variable "*Illiquidity*". 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

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

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 2 suggests that dealer failure can lead to large illiquidity discounts. The figure graphs the time series of the three different illiquidity proxies over the 2006–2009 period. Note how all measures increase dramatically following the distressed sale of Bear Sterns to JP Morgan (March 2008) as well following the failure of Lehman Brothers.

For our tests that require controlling for dealer exposure to the subprime market, we obtain Markit's CMBX.NA and ABX.HE indices for BBB-tranche commercial and subprime residential mortgage-backed securities, respectively. In both cases we use the vintage of the index from the second half of 2006 so that we capture the performance of securitized real estate-linked products issued just before the crisis hit, at the peak of the securitization boom. We then compute the daily returns for the two indices. To keep our SVAR analysis parsimonious, we take a simple average of these returns and denote this average as the variable *Credit*.[11] However, in the robustness tests in our SUR analysis, we also include the returns on the ABX.HE and CMBX.NA indices separately as control variables, and our results do not change.

In addition to our analysis with CDS spreads, we also consider daily dealer stock returns. We do so because we want to ensure that none of our results showing greater franchise value than liquidity contagion in CDS spreads are driven by a common factor unique to the CDS market. Collin-Dufresne, Goldstein, and Martin (2001) find that changes in credit spreads are driven by a common factor that is unrelated to macroeconomic conditions or to liquidity. Therefore it is possible that changes in CDS spreads that are common across different dealers are due to a common factor unrelated to the contagion assumptions that we examine. Thus we define two equal-weighted, daily-rebalanced stock portfolios: one for dealers who are in the riskiest quintiles based on CDS spread quotes for that day, as well as one for the dealers within the safest quintile based on CDS spreads for that day. We then compute daily equal-weighted total returns for each portfolio.[12] We

[11] *Credit* increases when the fundamentals of the real estate market improve. See Stanton and Wallace (2011) for a description of the ABX.HE index. See Todd and Iwai (2006) for a description of the CMBX.NA index.

[12] We use CRSP returns if the dealer has its stock or an ADR listed on a US exchange. For some periods, BNP Paribas stock does not have ADR data in CRSP, so we use total return data from Datastream to compute its total

label these returns *HighCDS_Ret* and *LowCDS_Ret.*

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. As a result we analyze the importance of each of these contagion channels during different sample periods. We provide a timeline of the government 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 1). 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.

HighCDS, *LowCDS* and *Illiquidity* are very persistent. The Dickey-Fuller and Kwiatkowski-Phillips-Schmidt-Shin tests both reveal these variables are non-stationary in levels.[13] As a result, we conduct all of our analysis in the first differences of these variables, rather than levels. The variable *Credit* is not as persistent as *HighCDS*, *LowCDS* and *Illiquidity*, and both tests confirm it is level stationary. This is expected since *Credit* is an average of returns. Consequently we conduct

daily return in US dollars.

[13]The KPSS test rejects the null hypothesis that each variable is trend stationary, as well as level stationary, at the 1% level or lower. P-values for the augmented Dickey-Fuller test of the null hypothsis that *HighCDS*, *LowCDS*, and *Illiquidity* follow a unit root process are, respectively, 0.022, 0.209, and 0.7.

our analysis on the level of $Credit$ and not in its first difference. Table 1 presents descriptive statistics for first differences in $HighCDS$, $LowCDS$ and *Illiquidity* along with the descriptive statistics for *HighCDS_Ret*, *LowCDS_Ret*, and $Credit$. Table 1 also presents the mean of the returns and of first differences in the individual CDS spreads of dealers whose spread is never in the top quintile.[14] We include statistics for the entire sample and for the Pre-Lehman, transition and Post-TARP periods. A salient feature of the statistics in Table 1 is the large standard deviation of all the variables during the transition period. For example, during the month between September 15 and Oct 14, 2008 the standard deviation of $\Delta HighCDS$ is about nine times the standard deviation of $\Delta HighCDS$ during the Pre-Lehman and Post-TARP periods. This finding highlights the importance of isolating the transition period from the rest of the sample in empirical studies to avoid conclusions that are driven by the data outliers of the transition period.

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 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 related to 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 feedback and lagged effects. Our SVAR analysis in Section 2.2 allows us to measure the extent to which contagion is related to the franchise or to the liquidity channel taking into account feedback and lagged relationships between the variables.

[14] 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.

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 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 $Illiquidity_t$ since these variables are very persistent. Recall that $Credit_t$ is the average of returns of ABX.HE and CMBX.NA indexes, so there is no need to first-difference it.

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:

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

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

Where $Transition_t$ and $PostTarp_t$ are dummy variables indicating that the observation belongs to the Transition and Post-TARP periods, as defined in Section 1.

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 $\Delta HighCDS_t$. 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 3 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. All specifications assume the residuals are contemporaneously correlated across dealers, have degree one within-dealer autocorrelation, and have a different standard deviation for each dealer.

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 3, 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 to 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.

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 $\Delta Illiquidity_t$ 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 $\Delta CDS_{i,t}$ is that the coefficient on $\Delta HighCDS_t$ must decrease when $\Delta Illiquidity_t$ is added to the specification. That is, the coefficient on $\Delta HighCDS_t$ must be greater in equation (2) than in equation (1). In fact, as can be seen in Table 3, 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.

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 3) 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 $\Delta CDS_{i,t}$.

The results from Equation (4) in Table 3 indicate that the 2008 interventions altered the patterns 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 [1.19×0.461=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 the 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 the SUR does not model the effect of $\Delta Illiquidity_t$ on $\Delta HighCDS_t$ and $Credit_t$, as well as other possible feedback and lagged 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. 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 [$6.56 = 34.8 \times 0.1885$], which is close to the full sample standard deviation in $\Delta CDS_{i,t}$ of 7.32.

Hence franchise-value contagion becomes stronger after the interventions. This may be due to the fact that changes in CDS spreads in the Post-TARP period are strongly related to the perceptions about the government's willingness to keep the system solvent.

The validity of our inferences about the relative importance of franchise value and illiquidity contagion channels depend on the accuracy of our illiquidity measure. While, for reasons stated in the previous section, we believe the Musto, Nini, and Schwarz (2011) illiquidity measure is appropriate for our study, we also re-run all the above specifications with alternative measures. Namely, we use the Hu, Pan, and Wang (2013) measure, as well as the 10-year Treasury off-the-run spread, as described in the previous section. The results, presented in Table 4, are qualitatively similar, with an even smaller illiquidity effect when using the Hu, Pan, and Wang (2013) measure. We also fail to find any mediating effect of illiquidity with these proxies, either for the full sample period or for any of the subsample periods.

Our inference on the importance of the illiquidity channel also depends on the assumption that our credit variable measures fundamentals in the mortgage-backed securities markets rather than illiquidity effects. However, the findings of Stanton and Wallace (2011) give reason to doubt this assumption. They show that the AAA tranches of the ABX.HE index did not reflect fundamental mortgage credit risk during the crisis, but rather implied impossibly high expected mortgage loan loss rates. They attribute this mispricing to liquidity problems combined with a clientele effect. Large numbers of institutions, with limited ability to take risk, were forced to sell their AAA tranches as the latter were being downgraded during the crisis. At the same time, the market for these securities had insufficient liquidity to absorb the unexpectedly large sales, resulting in underpricing. Thus it is possible that $Credit_t$ does include some liquidity component, thereby invaliding our inferences. We mitigate this problem by constructing our credit variable with the BBB tranches of the ABX.HE and CMBX.NA indices, which were already known to be speculative prior to the crisis, and hence not prone to the same clientele effect. Nevertheless, if a significant amount of variation in $Credit_t$ is due to variation in illiquidity, then the coefficient on $\Delta Illiquidity_t$ in our specifications above will tend to understate the extent to which individual dealer CDS spreads are impacted by illiquidity. It will also cause us to underestimate the extent to which $\Delta Illiquidity_t$

mediates the effect of $\Delta HighCDS_t$. This is because the coefficient on $\Delta Illiquidity_t$ above reflects the impact on dealer CDS of just the changes in illiquidity that are orthogonal to $Credit_t$; it does not reflect the impact of changes in illiquidity that also impact $Credit_t$. To test whether the effect on dealer CDS of this component of $\Delta Illiquidity_t$ is large, we examine how the coefficients on $Credit_t$ change as we remove $\Delta Illiquidity_t$ from the specification. If the portion of $\Delta Illiquidity_t$ that is correlated with $Credit_t$ has a significant impact on dealer CDS spreads, we would expect the coefficients on $Credit_t$ to be significantly more negative in Equation (1) than they are in Equation (2). In fact, as can be seen in Table 3, the absolute difference in the mean of the $Credit_t$ coefficients between specifications is just 0.009, an economically negligible amount. In addition, when we examine the differences between specifications in the individual dealer coefficients on $Credit_t$ (not reported), we find that the largest difference is 0.011, also negligible. We thus conclude that our coefficient estimates on $\Delta Illiquidity_t$ captures a substantial part of the impact of changes in liquidity on dealer CDS spreads, and so, by extension, we are not underestimating the importance of the liquidity channel. We further note that our SVAR analysis below is immune from this problem, since it explicitly models the impact of $\Delta Illiquidity_t$ on $Credit_t$.

One possible explanation for the above results is that there is some unknown common factor unique to the CDS market (e.g. Collin-Dufresne, Goldstein, and Martin (2001)) that causes individual less-risky dealer CDS spreads to be more sensitive to the spreads of the riskiest dealers than they are to our Treasury-based proxy for $\Delta Illiquidity_t$. We thus run regressions identical to those discussed above, except we use the individual dealer's stock return in place $\Delta CDS_{i,t}$ as the dependent variable, and we use equal weighted return of the portfolio of riskiest dealers' stocks (*HighCDS_Ret*) in place of $\Delta HighCDS_t$. The results, in Table 5, are qualitatively similar the results above, in that individual dealer stock returns are highly sensitive to the riskiest dealers but register a low sensitivity to our measure of illiquidity. Furthermore, as before, the coefficient on *HighCDS_Ret* remains largely unchanged when our proxy for illiquidity is added to the model in the full sample. When we use our period dummies and interactions, the coefficient on illiquidity becomes marginally significant as before, but economically small. Furthermore, the coefficients on *HighCDS_Ret* in the pre-intervention period remains largely unchanged. Hence our model specification that uses stock returns confirms that liquidity does little, if anything, to mediate the relation between individual dealer stock prices and *HighCDS_Ret*, though there was some economically small effect of illiquidity during the Pre-Lehman period.

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. An increase in the illiquidity discount should, in turn, cause an increase in funding illiquidity and make 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. Indeed, 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 $LowCDS$. In this section, we analyze the extent to which *Illiquidity* mediates the relation between $HighCDS$ and $LowCDS$ in a structural VAR that allows for contemporaneous effects of *Illiquidity* on dealer CDS spreads and vice-versa.

Before estimating our structural VAR, we estimate a reduced-form VAR that 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 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 (Pre-Lehman period), 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 (Post-TARP period). 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 Post-TARP period. Moreover, increases in both $HighCDS$ and $LowCDS$ are normally followed by a reversal in the Post-TARP while they are not in the Pre-Lehman period. These may be 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 indicate that there was a regime shift in relationship between $\Delta LowCDS_t$ and lagged values of $\Delta HighCDS_{t-1}$, $\Delta Illiquidity_{t-1}$ during the transition period.

The above reduced-form VAR analysis is incomplete because the effect of $\Delta HighCDS$, $\Delta Illiquidity$, $\Delta LowCDS$ and $Credit$ on one another is in all likelihood instantaneous and 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 economic 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 and $E[u_t u_t^{'}] = D$ 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 mortgage 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.[15] Panel A presents the results based on the entire

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

sample period, Panel B presents the results based on the Pre-Lehman bankruptcy period, while Panel C presents the results based on the Post-TARP sample period. 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 Δ*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 $\Delta HighCDS$, Δ*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 $\Delta HighCDS$, Δ*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 Δ*Illiquidity* has a null effect on $\Delta LowCDS$. Overall, we interpret these findings as evidence that the interventions initiated during the Fall of 2008 insulated the safest dealers from shocks to Δ*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 Δ*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 Δ*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:

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

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 $\beta^*_{3,2}$ equal to zero, we eliminate any direct effect that a shock to $\Delta HighCDS_t$ has on the contemporaneous $\Delta LowCDS_t$ that is not mediated by illiquidity. Moreover by setting $\beta_{2,2}$, $\beta_{2,3}$, and $\beta_{2,4}$ equal to zero, we eliminate any direct effect that a shock to $\Delta HighCDS_t$ has on the future $\Delta LowCDS_{t+s}$ through the matrix β^s in Equation 7.

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. Moreover, 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, $\Delta HighCDS$ captures both contagion channels. We see three ways by which $\Delta HighCDS$ could capture both contagion channels in our SVAR. We now discuss them in turn.

First, 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. Theory suggests that adverse liquidity shocks should impact dealers closer to default more than those further from default. Perhaps this restriction makes $\Delta HighCDS$ capture both contagion channels. 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 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.[16] That is, the restriction that $\beta^*_{2,1} = \beta^*_{3,1}$ does not drive our conclusion that the economic importance of the liquidity channel is small.

Second, our proxy for liquidity may be noisy and hence may not reflect the liquidity channel.

[16] 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.

As a robustness check 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, the evidence of a liquidity channel is even weaker than the one with the Musto, Nini, and Schwarz (2011) measure of illiquidity. To better understand why neither of these two illiquidity measures result in a liquidity channel, we regress changes in the spreads of the safest dealers on these illiquidity measures. The results of these regressions are in Table 8. They clarify that the reason why we fail to find a liquidity contagion channel with the Hu, Pan, and Wang (2013) illiquidity measure or with the off-the-run spread is that the first differences in these measures are negatively correlated with changes in safest dealer CDS spreads ($\Delta LowCDS$) during the Pre-Lehman period. For instance, the point estimate of the coefficient of the off-the-run spread on the third column of Table 8 (-0.11) is negative. That is, according to these measures of illiquidity, increases in illiquidity are associated with decreases in the CDS spreads of the safest dealers. Hence, neither of these two illiquidity measures can possibly mediate any contagion effect between the riskiest and safest dealers.

Third, it is possible that a common factor that is specific to the CDS market and is unrelated to contagion drives the correlation between $\Delta LowCDS$ and $\Delta HighCDS$. To check for this possibility we replace $\Delta LowCDS$ and $\Delta HighCDS$ by $LowCDS\_Ret$ and $LowCDS\_Ret$ in the Equations 5 and 6. The results of this new reduced form VAR are in Table 9 and the results of this new structural VAR are in Table 10.

The results of the VARs in Tables 9 and 10 are qualitatively similar to those of the VARs estimated with CDS spreads. One difference though is that in the reduced form VAR with returns neither $HighCDS\_Ret$ nor $\Delta Illiquidity$ Granger causes $LowCDS\_Ret$ in both the Post-TARP and the Pre-Lehman periods. As in the SVAR with CDS spreads, there is evidence of liquidity contagion channel in the Pre-Lehman period while there is no evidence of liquidity channel in the Post-TARP period. Indeed, the results in Panel B of Table 10 indicate that a shock to $HighCDS\_Ret$ leads to a shock to $Illiquidity$, which in turn leads to a shock to $LowCDS\_Ret$, while the results in Panel C of Table 10 indicate that the same chain of contagion is not present in the Post-TARP period.

Figure 7 displays the impulse response decomposition based on the VAR with returns. The results in Figure 7 are qualitatively similar to those in Figure 6. The first panel of Figure 7 indicates that liquidity contagion was stronger in the Pre-Lehman period. The economic significance of liquidity contagion in the VAR with stock returns is about the same as that in the VAR with CDS spreads. Indeed, one standard deviation shock in $HighCDS\_Ret$ $\left(\sqrt{0.00149} = 3.86\%\right)$leads to a shock of about one percent in the $LowCDS\_Ret$ in the Pre-Lehman period. Panel A of Figure 7 indicates that about four percent of this one percent is related to illiquidity.

The results of the VAR with stock returns indicate that we cannot explain our finding through a factor that is specific to the CDS market. Therefore, to explain our findings, we 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. However, the proposition that all our measures of liquidity fail to capture illiquidity is inconsistent with the fact that our estimate of the relative importance of illiquidity channel, when estimated using the Musto, Nini, and Schwarz (2011) measure of illiquidity, is statistically significant in the Pre-Lehman period, while it is not significant in the Post-TARP period. Therefore, all of our results, taken together, indicate that if illiquidity is indeed a contagion channel, then 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, 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 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 get the same results when we use dealer equity returns in place of CDS spreads.We infer that while the interventions succeeded in arresting liquidity contagion, franchise-value contagion remained.

Naturally our results are specific to the 2007-2008 financial crisis. It is possible and perhaps likely that liquidity spirals as described in Brunnermeier and Pedersen (2009) are quite important in other contexts. However, our results indicate that the liquidity channel was only a small part of the 2007-2008 financial crisis. In fact, our results are more in line with the models of Goldstein and Leitner (2013) and Zawadowski (2013) in which illiquidity does not mediate the contagion across dealers. Overall, our results suggest that 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 aimed to provide liquidity to the financial system are in place.

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Table 1: Descriptive statistics

This table presents the number of observations (N), the mean, standard deviation and the percentiles of each of our main variables. Summary statistics on the first differences of the highly persistent variables are presented. *HighCDS is* the average CDS spread for dealers with CDS spreads in top quintile in a given day, and *HighCDS_Ret* is the daily return on the equal weighted stock portfolio made of up these dealers. *LowCDS is the* average CDS spread for dealers with CDS spreads in the bottom quintile in a given day, and *LowCDS_Ret* is the return on the equal weighted stock portfolio made up of these dealers. *Illiquidity* is the Musto-Nini-Schwarz illiquidity measure. *Credit* is the average of the returns on the ABX.HE and CMBX.NA indices. CDS (Ret) is the average CDS spread (daily stock return) of the dealers that never have their CDS spread in the top quintile during the entire sample period.

Panel A: Full Sample

	N	Mean	St. Dev.	1st percentile	25th percentile	median	75th percentile	99th percentile
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
HighCDS_Ret	750	-0.402	5.71	-13.3	-1.64	-0.175	1.33	13.6
LowCDS_Ret	750	0.0253	3.42	-10.8	-1.41	-0.00599	1.48	10.4
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
Ret	4506	0.0435	4.83	-14.0	-1.75	0.029	1.61	16.3

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

	N	Mean	St. Dev.	1st percentile	25th percentile	median	75th percentile	99th percentile
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
HighCDS_Ret	427	-0.592	5.40	-13.2	-2.14	-0.304	1.30	11.6
LowCDS_Ret	427	-0.0629	1.95	-4.49	-1.15	-0.0532	0.992	6.02
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
Ret	2556	-0.0482	2.48	-5.76	-1.31	-0.087	1.06	22.4

Panel C: Sept. 15 - Oct. 14, 2008 (Transition Period)

	N	Mean	St. Dev.	1st percentile	25th percentile	median	75th percentile	99th percentile
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
HighCDS_Ret	21	-1.83	19.8	-46.0	-9.24	-1.07	3.73	55.0
LowCDS_Ret	21	-0.797	7.77	-15.7	7.00	-1.30	2.98	14.9
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
Ret	126	-0.355	10.8	-22.0	-7.80	-0.368	6.27	27.1

Panel D: Oct. 15, 2008-Dec. 31, 2009 (Post-TARP Period)

	N	Mean	St. Dev.	1st percentile	25th percentile	median	75th percentile	99th percentile
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
HighCDS_Ret	303	-0.0368	3.66	-12.2	-1.05	-0.00810	1.33	12.7
LowCDS_Ret	303	0.20700	4.42	-12.1	-1.64	0.207	2.44	12.2
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
Ret	1818	0.200	6.40	-17.5	-2.54	0.111	2.74	21.1

Table 2: Timeline of selected major interventions directly impacting dealers

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

Date	Intervention
12/7/2007	Fed creates the Term Auction Facility (TAF), which makes available collateralized short-term loans, $20 billion in aggregate every two weeks, to depository institutions
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 securities
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 increased 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 reincorporate 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 from 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: 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. *PostTarp* is a dummy variable with value one in the Post-TARP period (after Oct 14, 2008), and *Transition* is a dummy variable with value one in all trading days between Sep 15 - Oct 14, 2008. *Credit* is constructed by taking the average daily return on the ABX.HE and CMBX.NA 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)	(3)	(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 Coefficients 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 4: SUR analysis with alternative Illiquidity measures

This Table presents results from a seemingly unrelated regression analysis that is identical to that of Table 3, except that the Hu, Pan and Wang measure or the off-the-run spread are used as measures of illiquidity instead of the Musto-Nini-Schwarz measure. Panel A presents the results with the Hu, Pan and Wang measure and Panel B presents the results with the off-the-run-spread. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% level. The sample period includes trading days over 2007-2009.

Panel A - SUR with Hu, Pan & Wang Illiquidity Measure

	(1)	(2)	(3)	(4)
ΔHighCDS	0.0713***	0.0714***	0.0963***	0.0941***
	(0.00381)	(0.00384)	(0.00783)	(0.00802)
ΔIlliquidity		0.757**		0.589
		(0.350)		(0.729)
ΔHighCDS*Transition			-0.0226***	-0.0192**
			(0.00867)	(0.00890)
ΔHighCDS*PostTarp			0.0903***	0.0918***
			(0.0121)	(0.0124)
ΔIlliquidity*Transition				0.424
				(1.003)
ΔIlliquidity*PostTarp				0.0293
				(0.841)
Mean of Coefficients on Credit	-0.644	-0.635	-0.446	-0.438
Joint χ^2 test statistic	112.90***	112.89***	105.15***	104.59***
N	4506	4506	4506	4506

Panel B - SUR with the Off-the-run spread as Illiquidity Measure

	(1)	(2)	(3)	(4)
ΔHighCDS	0.0713***	0.0718***	0.0963***	0.0964***
	(0.00381)	(0.00381)	(0.00783)	(0.00781)
ΔIlliquidity		0.0915		-0.0266
		(0.0672)		(0.0942)
ΔHighCDS*Transition			-0.0226***	-0.0199**
			(0.00867)	(0.00871)
ΔHighCDS*PostTarp			0.0903***	0.0914***
			(0.0121)	(0.0121)
ΔIlliquidity*Transition				0.495***
				(0.190)
ΔIlliquidity*PostTarp				0.118
				(0.127)
Mean of Coefficients on Credit	-0.644	-0.641	-0.446	-0.446
Joint χ^2 test statistic	112.90***	112.57***	105.15***	105.45***
N	4506	4506	4506	4506

Table 5: SUR results using dealer stock returns

This table presents results from a seemingly unrelated regression analysis of the dealer's own daily stock return (in percent) on the return of the equal-weighted equity portfolio of dealers whose CDS spread is in the of the riskiest quintile of dealers (*HighCDS_Ret)* for that day, as well as *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. *PostTarp* is a dummy variable with value one in the Post-TARP period (after Oct 14, 2008), and *Transition* is a dummy variable with value one in all trading days between Sep 15 - Oct 14, 2008. *Credit* is constructed by taking the average daily return on the ABX.HE and CMBX.NA indices. The coefficients on *HighCDS_Ret*, *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)	(3)	(4)
HighCDS_Ret	0.326***	0.326***	0.210***	0.204***
	(0.0184)	(0.0187)	(0.0223)	(0.0226)
ΔIlliquidity		-0.00770		-0.337*
		(0.0858)		(0.198)
HighCDS_Ret*Transition			0.119***	0.0969**
			(0.0388)	(0.0414)
HighCDS_Ret*PostTarp			0.702***	0.713***
			(0.0450)	(0.0452)
ΔIlliquidity*Transition				-0.0598
				(0.272)
ΔIlliquidity*PostTarp				0.433**
				(0.219)
Mean of Coefficients on Credit	0.346	0.346	0.246	0.235
Joint χ^2 test statistic	58.09***	57.98***	40.08***	37.099***
N	4506	4506	4506	4506

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.HE and CMBX.NA 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
$\Delta\text{Illiquidity}_{t-1}$	0.1123***	-2.3490**	-0.0893	0.0003
	(0.0368)	(1.0522)	(0.1445)	(0.0006)
$\Delta\text{HighCDS}_{t-1}$	0.0001	-0.1870***	0.0205***	0.00003
	(0.0014)	(0.0410)	(0.0056)	(0.00002)
$\Delta\text{LowCDS}_{t-1}$	-0.0002	1.0121***	-0.0132	-0.0002
	(0.0103)	(0.2958)	(0.0406)	(0.00017)
Credit_{t-1}	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
$\Delta\text{Illiquidity}_{t-1}$	-0.0477	-4.6113***	0.5325**	-0.0004
	(0.0503)	(1.5260)	(0.2587)	(0.0014)
$\Delta\text{HighCDS}_{t-1}$	0.0004	0.1462**	0.1213***	-0.0001**
	(0.0019)	(0.0584)	(0.0099)	(0.00005)
$\Delta\text{LowCDS}_{t-1}$	-0.0193**	-0.0583	-0.1789***	0.0002***
	(0.0084)	(0.2545)	(0.0431)	(0.00023)
Credit_{t-1}	-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
$\Delta Illiquidity_{t-1}$	0.2519***	-0.3099	-0.0583	-0.0001
	(0.0550)	(0.7111)	(0.1500)	(0.0009)
$\Delta HighCDS_{t-1}$	-0.0046*	-0.0872***	-0.0089	0.0001*
	(0.0026)	(0.0330)	(0.0070)	(0.00004)
$\Delta LowCDS_{t-1}$	0.0354	0.3088	0.0619	-0.0005
	(0.0235)	(0.3037)	(0.0640)	(0.00038)
$Credit_{t-1}$	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. Panels A to C presents the estimation of the contemporaneous relationships between the variables. 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***
	(0.1258)			(59.8255)
ΔLowCDS	0.2483**	0.0608***		-25.2274***
	(0.1258)	(0.0046)		(7.6646)
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		
		(0.0048)		
ΔHighCDS	0.1058			-264.8736***
	(0.1318)			(42.9044)
ΔLowCDS	0.1058	0.0918***		-15.3914*
	(0.1318)	(0.0109)		(8.6459)
Credit	0.00003			
	(0.0010)			

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)

Table 8: Safest dealer spreads and alternative liquidity measures

This table presents time series OLS regressions where changes in the average CDS spread of the safest quintile of dealers (ΔLowCDS) is the dependent variable. Independent variables include the first difference in three illiquidity proxies and the Credit variable, as indicated in the first column. Standard errors are reported in parentheses below each estimated coefficient. The symbols ***,**, and * indicate a significance level of one, five and the percent, respectively. Resulst are presented seperately for the pre-Lehman period (Jan 2, 2007 - Sep 14, 2008) and the Post-TARP period (Oct 15, 2008- Dec 31, 2009).

	Pre-Lehman Period			Post-TARP Period		
Musto, Nini & Schwarz	0.538*			0.0746		
	(0.296)			(0.148)		
Hu, Pan & Wang		-0.863			0.598	
		(0.877)			(0.506)	
10Y off-the-run spread			-0.110			0.142
			(0.114)			(0.105)
Credit	-0.562***	-0.612***	-0.603***	-0.507***	-0.507***	-0.503***
	(0.0961)	(0.0950)	(0.0942)	(0.0861)	(0.0859)	(0.0859)
Constant	-0.100	-0.0947	-0.0986	-0.0406	-0.0276	-0.0367
	(0.185)	(0.186)	(0.186)	(0.222)	(0.222)	(0.221)
N	427	427	427	303	303	303

Table 9: Reduced form VAR using stock returns

This table presents parameter estimates (and standard errors) for a reduced-form vector autoregression that includes a credit variable constructed from the ABX.HE and CMBX.NA indices (*Credit*), the first difference in the Musto-Nini-Schwartz illiquidity measure (Illiquidity), and the daily average of stock returns of dealers in the riskiest quintile in a given day (*HighCDS_Ret*), and of dealers in the safest quintile in a given day (*LowCDS_Ret*). 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	HighCDS_Ret	LowCDS_Ret	Credit
ΔIlliquidity$_{t-1}$	0.1203***	0.0024	0.0029***	0.0003
	(0.0368)	(0.0018)	(0.0010)	(0.0006)
HighCDS_Ret$_{t-1}$	-0.0571	-0.0118	-0.0273	0.00179
	(0.8905)	(0.0426)	(0.0253)	(0.01511)
LowCDS_Ret$_{t-1}$	2.6315*	-0.1137	-0.1148***	-0.0029
	(1.5186)	(0.0727)	(0.0431)	(0.02577)
Credit$_{t-1}$	-1.0039	0.2573**	0.0596	0.3726***
	(2.1005)	(0.1006)	(0.0596)	(0.03564)
Constant	-0.0027	-0.0035*	0.0003	-0.0015**
	(0.0437)	(0.0021)	(0.0012)	(0.00074)
N	750	750	750	750

Panel B - Pre-Lehman sample period.

	Dependent Variable			
	ΔIlliquidity	HighCDS_Ret	LowCDS_Ret	Credit
ΔIlliquidity$_{t-1}$	-0.0539	-0.0056	-0.0001	-0.0009
	(0.0505)	(0.0043)	(0.0016)	(0.0014)
HighCDS_Ret$_{t-1}$	-0.9045	0.1343**	0.0115	0.0158
	(0.6739)	(0.0578)	(0.0210)	(0.01824)
LowCDS_Ret$_{t-1}$	2.4778	-0.4226**	-0.1033*	-0.0274
	(1.9242)	(0.1652)	(0.0600)	(0.05208)
Credit$_{t-1}$	-0.6427	-0.0116	0.0851	0.2889***
	(1.8265)	(0.1568)	(0.0570)	(0.04944)
Constant	0.0275	-0.0053**	-0.0003	-0.0027***
	(0.0311)	(0.0027)	(0.0010)	(0.00084)
N	426	426	426	426

Table 9: Reduced form VAR using stock returns (contd.)

Panel C - Post-TARP sample period

	Dependent Variable			
	ΔIlliquidity	HighCDS_Ret	LowCDS_Ret	Credit
$\Delta Illiquidity_{t-1}$	0.2402***	0.0010	0.0019	0.0000
	(0.0552)	(0.0014)	(0.0017)	(0.0009)
$HighCDS\_Ret_{t-1}$	-2.0368	0.0197	-0.0383	-0.0267
	(2.1361)	(0.0530)	(0.0642)	(0.03461)
$LowCDS\_Ret_{t-1}$	3.7929	-0.0776	-0.1198*	-0.0078
	(2.3244)	(0.0576)	(0.0699)	(0.03766)
$Credit_{t-1}$	-1.1539	0.2763***	0.0220	0.4294***
	(3.3965)	(0.0842)	(0.1021)	(0.05503)
Constant	-0.0443	0.0000	0.0026	-0.0003
	(0.0834)	(0.0021)	(0.0025)	(0.00135)
N	303	303	303	303

Table 10: Results of structural VAR using stock returns

This table presents the results of the structural VAR estimation using the average stock returns of the riskiest (*HighCDS_Ret*) and safest dealers (*LowCDS_Ret*) instead of the changes in their CDS spreads (*ΔHighCDS and ΔLowCDS*). 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. Panels A to C presents the estimation of the contemporaneous relationships between the variables. 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	HighCDS_Ret	LowCDS_Ret	Credit
ΔIlliquidity		-3.1401*		
		(1.7464)		
HighCDS_Ret	-0.0011			0.5089***
	(0.0029)			(0.0993)
LowCDS_Ret	-0.0011	0.2698***		0.4133***
	(0.0029)	(0.0231)		(0.0510)
Credit	-0.0007			
	(0.0005)			

Panel B - Pre-Lehman sample period

	Independent Variable			
	ΔIlliquidity	HighCDS_Ret	LowCDS_Ret	Credit
ΔIlliquidity		-1.4244*		
		(0.7613)		
HighCDS_Ret	-0.0036*			0.5843***
	(0.0020)			(0.1508)
LowCDS_Ret	-0.0036*	0.1749***		0.2232***
	(0.0020)	(0.0146)		(0.0467)
Credit	-0.0052***			
	(0.0013)			

Panel C - Post-TARP sample period

	Independent Variable			
	ΔIlliquidity	HighCDS_Ret	LowCDS_Ret	Credit
ΔIlliquidity		-0.4705		
		(3.2763)		
HighCDS_Ret	-0.00004			0.3079***
	(0.0013)			(0.0847)
LowCDS_Ret	-0.00004	0.7014***		0.4031***
	(0.0013)	(0.0536)		(0.0807)
Credit	0.00034			
	(0.0010)			

Table 10: Results of structural VAR using stock returns (contd.)

Panel D - Variances of disturbances

	Sample period		
	2007-2009	Pre-Lehman	Post-TARP
ΔIlliquidity	1.20	0.35	2.20
	(0.07)	(0.03)	(0.17)
HighCDS_Ret	0.00334	0.00149	0.00114
	(0.00016)	(0.00018)	(0.00010)
LowCDS_Ret	0.00074	0.00020	0.00112
	(0.00504)	(0.00118)	(0.00008)
Credit	0.00038	0.00024	0.00049
	(0.00002)	(0.00002)	(0.00004)

Figure 1: Time series of CDS spreads

This figure presents the time series of the average 5 year CDS spread of the dealers that happen to be in the riskiest quintile (HighCDS), the least risky quintile (LowCDS), and the average CDS of all dealers over all trading days over the 2007-2009 period.

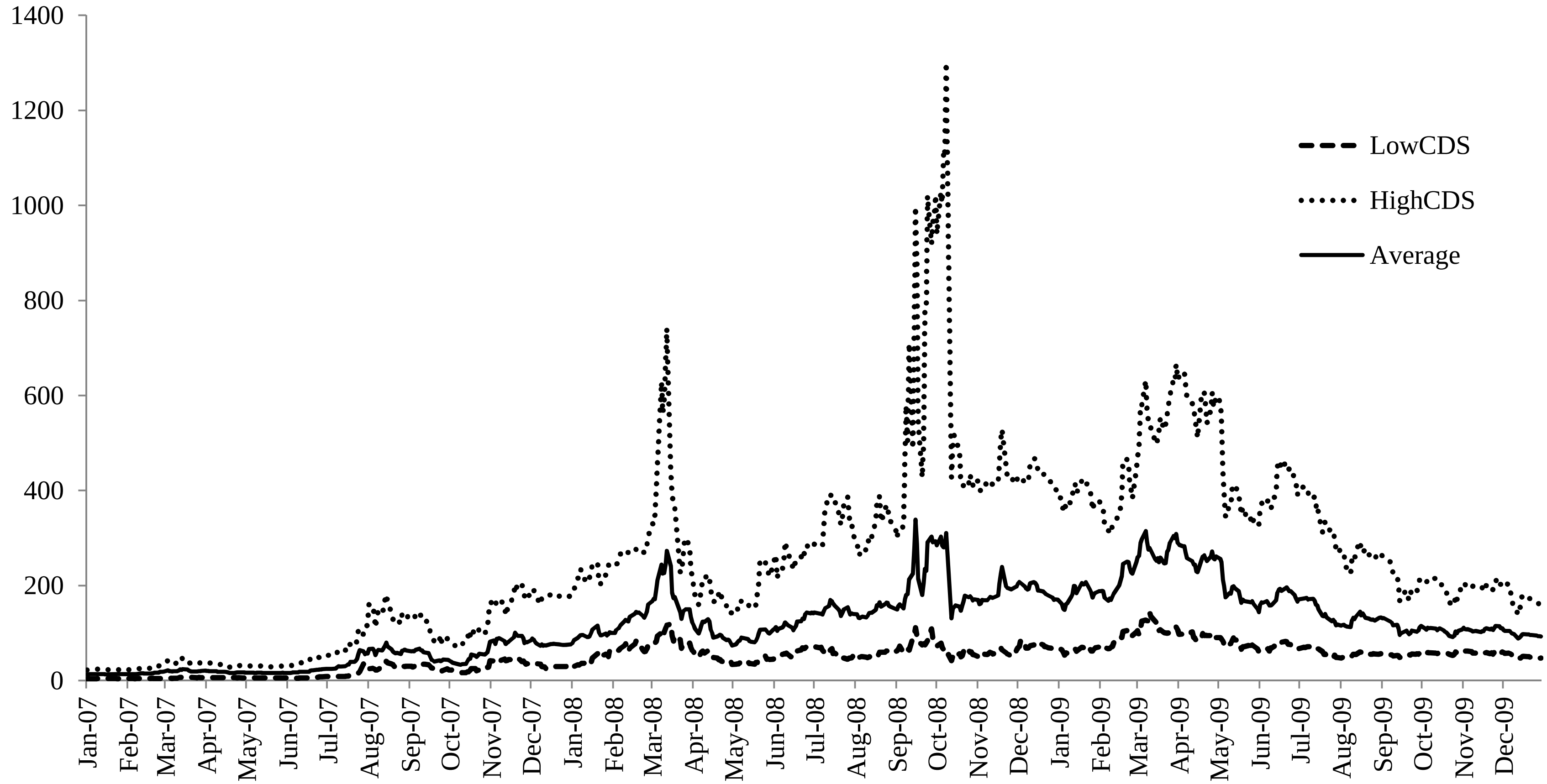


Figure 2: Comparison of Illiquidity Measures

This figure presents the time series of three alternative illquidity measures over all trading days during the 2007-2009 period: the Musto, Nini and Schwarz measure of mispricing in Treasury notes and bonds, the Hu , Pan and Wang Treasury yield curve fit error statistic, and the 10-year Treasury off-the-run spread (OTRSpread). OTRspread is computed as the yield to maturnity on the Merrill Lynch 9-11 year Treasury off-the-run index less the yield to maturity on the current on-the-run 10 -year Treasury note.

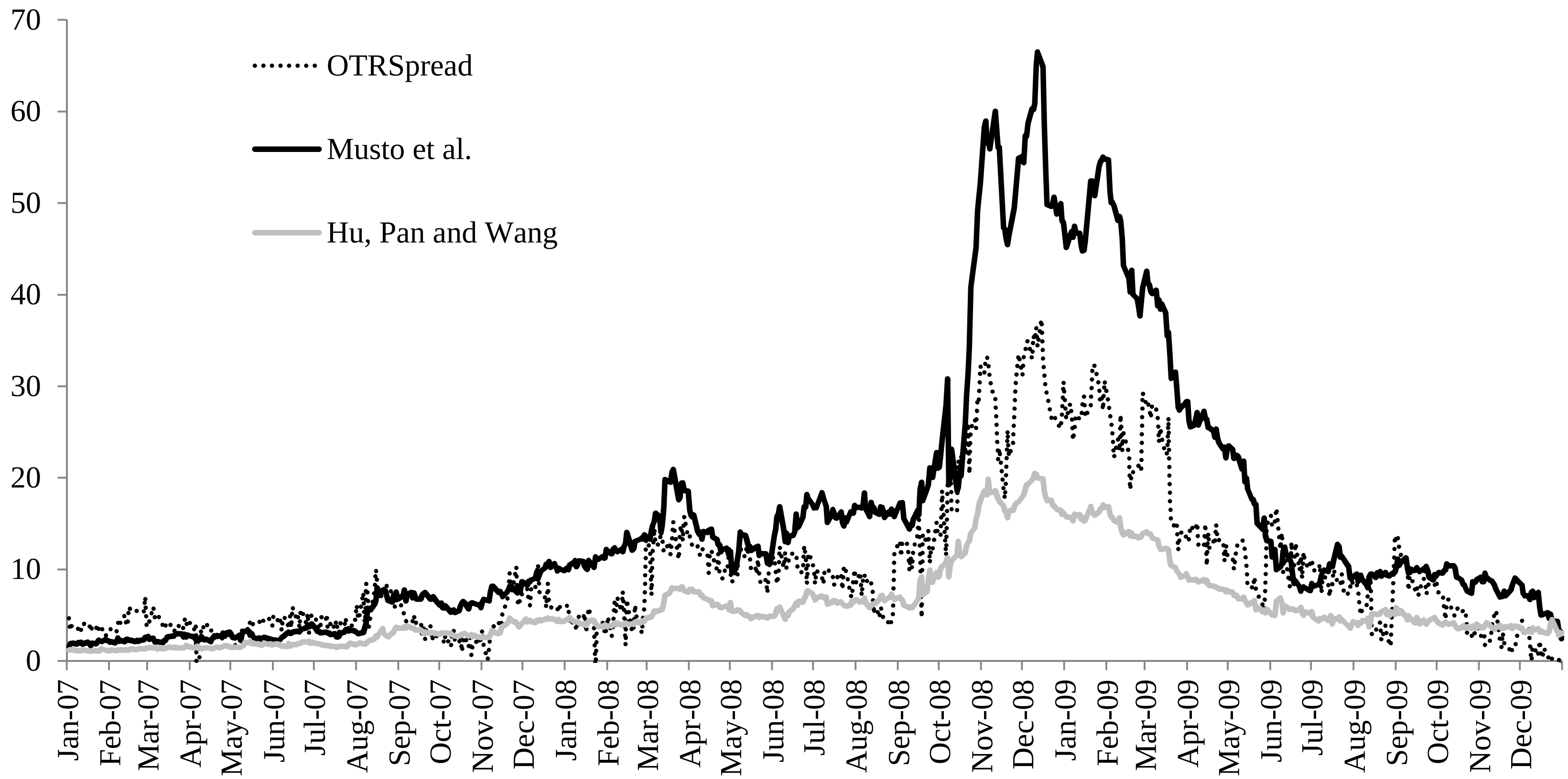


Figure 3 - Response of ΔLowCDS to a ΔHighCDS shock

This figure presents the daily response, in basis points, of ΔLowCDS to a shock of one standard deviation to ΔHighCDS. 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 standard errors are calculated with bootstrap. 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.

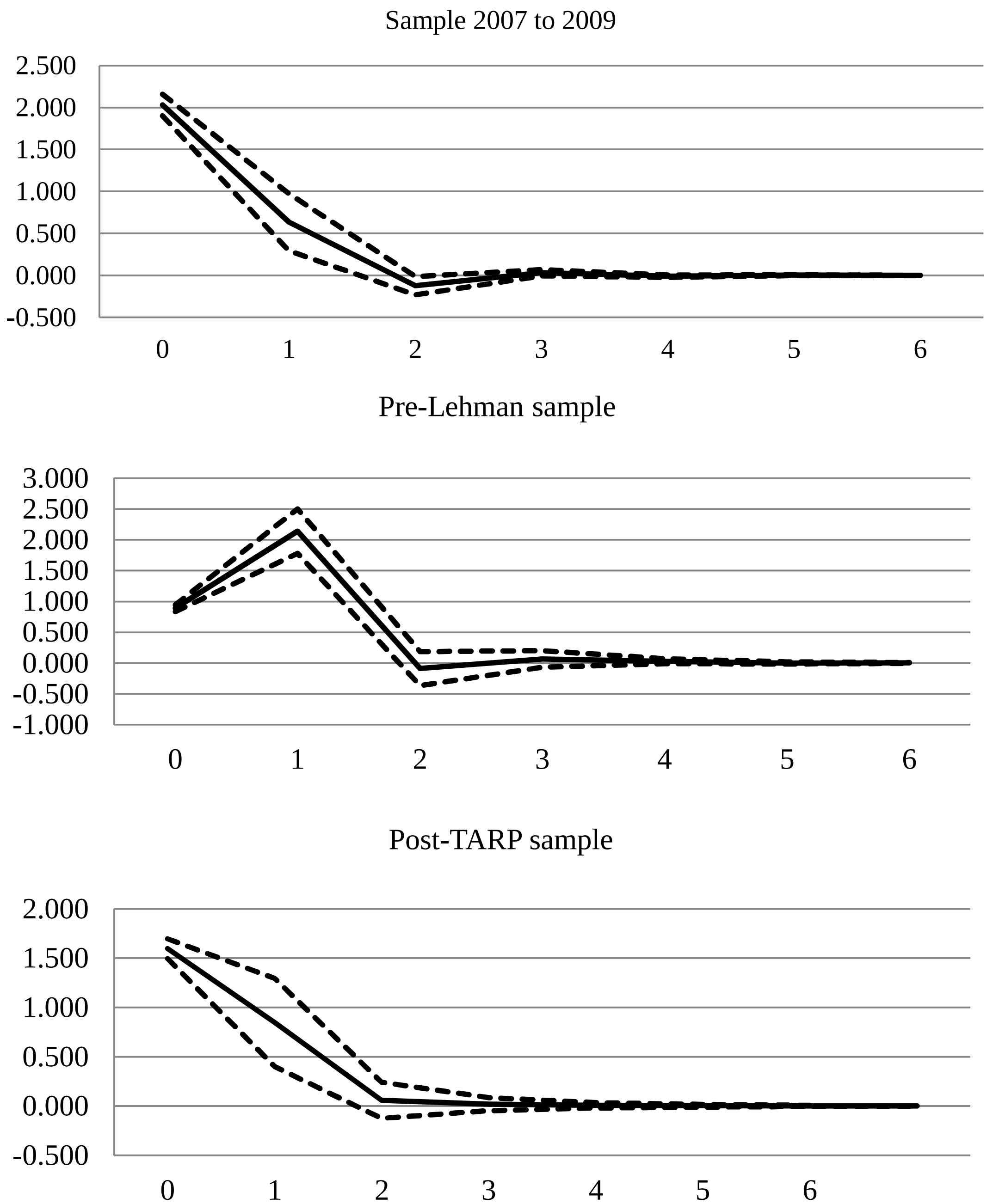


Figure 4 - Response of ΔLowCDS to an Illiquidity shock

This figure presents the daily response on ΔLowCDS, in basis points, to a shock of one standard deviation in ΔIlliquidity. 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 standard errors are calculated with bootstrap. 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.

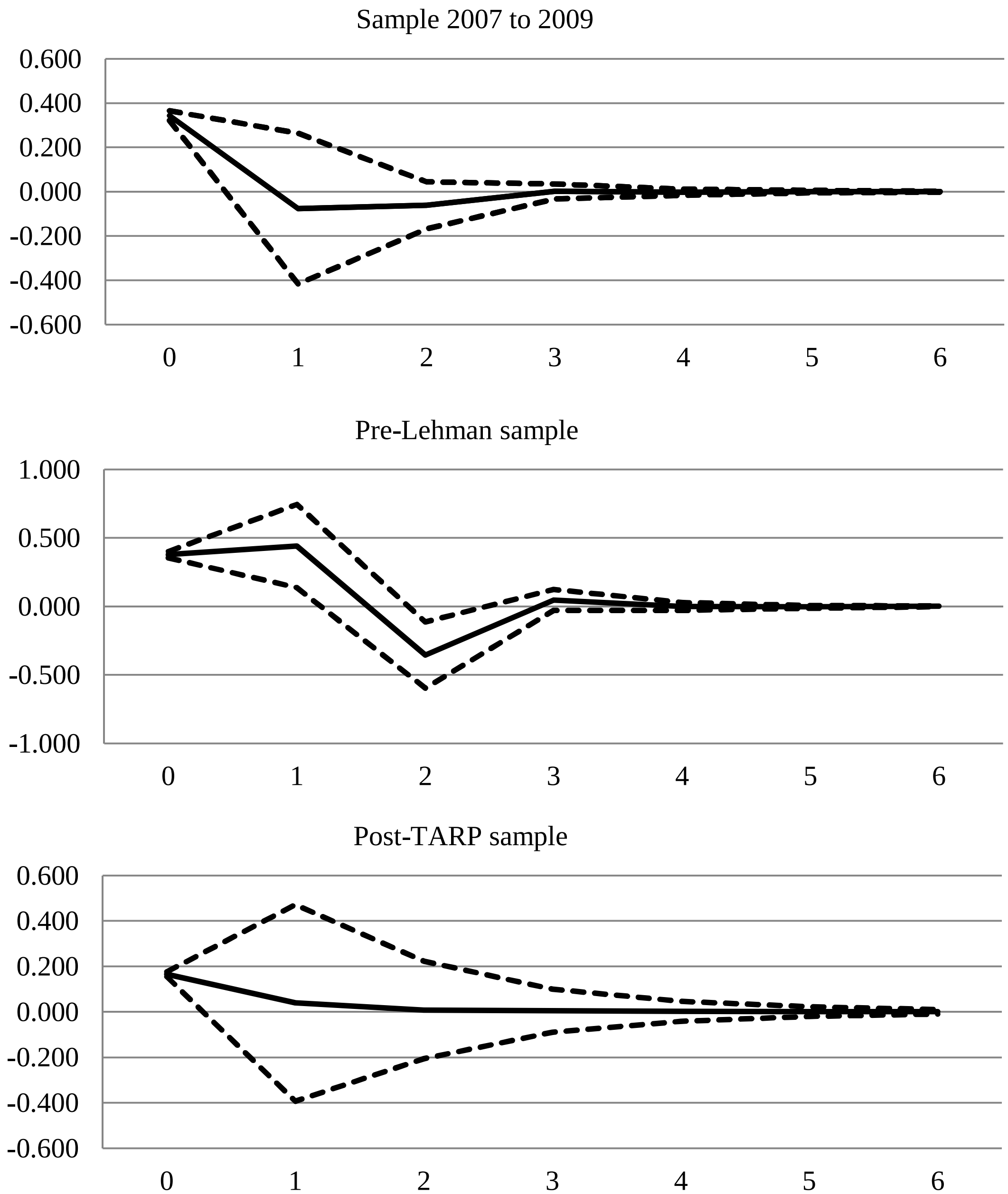


Figure 5 - Response of ΔLowCDS to a Credit shock

This figure presents the daily response on ΔLowCDS, in basis points, to a shock of one standard deviation to 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 standard errors are calculated with bootstrap. 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 Post-TARP sample.

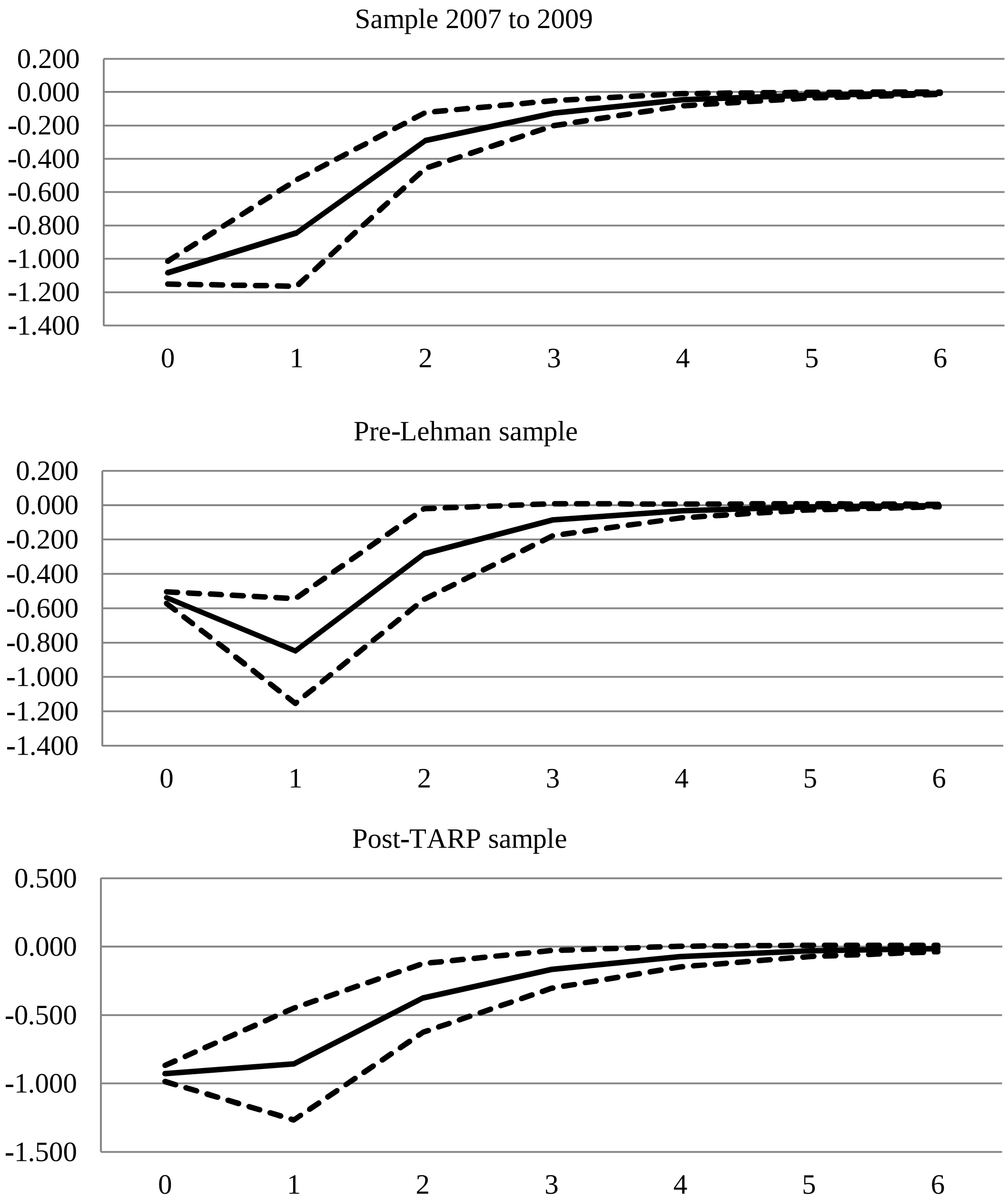
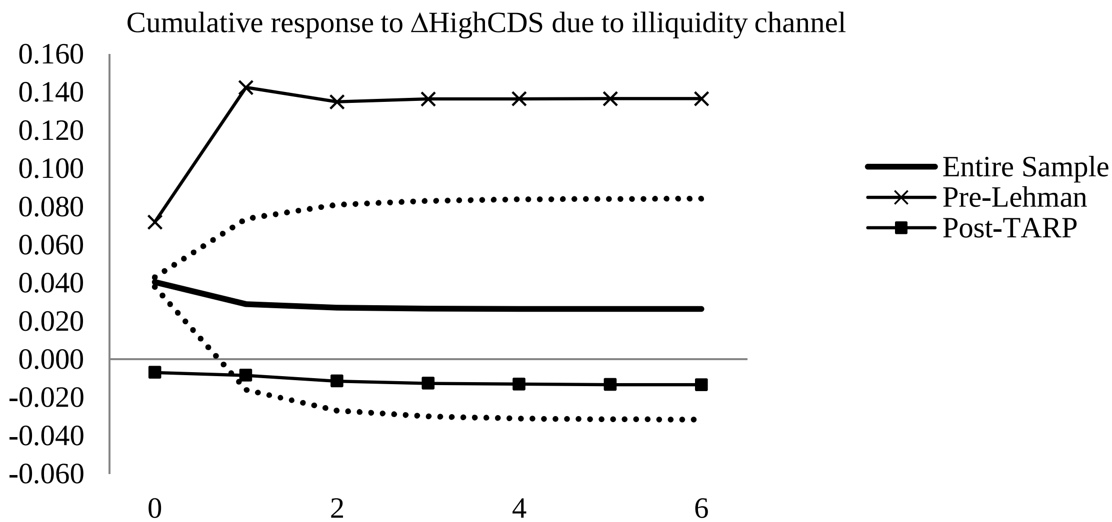


Figure 6 - The effect of the illiquidity channel of contagion

This figure presents the cumulative response of ΔLowCDS, in basis points, to a one standard deviation shock on ΔHighCDS. These functions are calculated with the parameters estimated for both the structural and reduced form VAR. The bottom panel considers the effect of ΔHighCDS onto ΔLowCDS through all the contagion mechanisms implied by the estimated structural VAR. The top panel shows the impulse response through the illiquidity channel only. That is, the top panel shows the results of the impulse response under the assumption 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 "Pre-Lehman" correspond to the sample period that ends before Lehman Brothers bankruptcy (Sep 15, 2008). The curves labeled "Post-Tarp" correspond to the sample period that starts on Oct 15, 2008. The dotted lines are two standard errors under the null hypothesis that the data conforms to the parameter estimates of the entire sample.



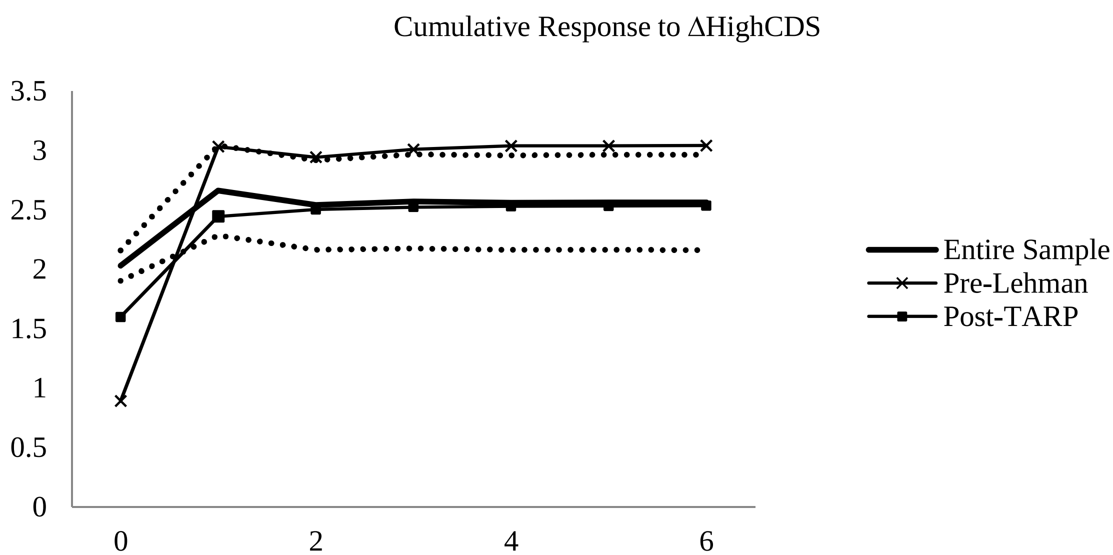


Figure 7 - The effect of the illiquidity channel of contagion (using returns)

This figure presents the cumulative response of *LowCDS_Ret* to a one standard deviation shock on *HighCDS_Ret*. These functions are calculated with the parameters estimated for both the structural and reduced form VAR. The bottom panel considers the effect of *HighCDS_Ret* onto *LowCDS_Ret* through all the contagion mechanisms implied by the estimated structural VAR. The top panel shows the impulse response through the illiquidity channel only. That is, the top panel shows the results of the impulse response under the assumption that the coefficients of *HighCDS_Ret* and its lags in the *LowCDS_Ret* 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 "Pre-Lehman" correspond to the sample period that ends before Lehman Brothers bankruptcy (Sep 15, 2008). The curves labeled "Post-Tarp" correspond to the sample period that starts on Oct 15, 2008. The dotted lines are two standard errors under the null hypothesis that the data conforms to the parameter estimates of the entire sample.