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Two Essays on Liquidity Endogeneity and Effects of Political Connections

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TWO ESSAYS ON LIQUIDITY ENDOGENEITY AND EFFECTS OF POLITICAL CONNECTIONS

by

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ABSTRACT

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The two essays in my dissertation explore separately the issues related to stock market liquidity and corporate financial distress. My first essay examines the effects of widespread liquidity demand on the stock liquidity. My second essay explores the effect of political connections on the corporate financial distress.

In the first essay, I explore several questions related to the effect of liquidity demand on the individual stock liquidity level. I find that domestic actively managed equity funds in general hold less liquidity than their corresponding benchmarks. This leads them to rely more on the small fraction of liquid assets for immediacy when faced with financial distress and significant outflows. I further find that mutual funds sell more of liquid stocks when they are faced with negative fund flows. Consistent with prior literature that funds have to meet redemptions and reduce price impact, their engagement in liquid stock sale is more severe when the market volatility is high and when the aggregate market flow is low. Consequently, a widespread liquidity shock would be more likely to exert pressure on the liquidity of the stocks they sell. Using the mutual fund involuntary sale to proxy for the exogenous widespread liquidity demand, I find that a stock with a greater level of mutual fund forced sale tends to be less liquid in the

next period. This liquidity erosion exists mostly among liquid stocks. I further find that the liquidity demand deteriorates liquid stocks' liquidity even more during volatile periods, when more funds face outflows and are forced to sell. The liquidity deterioration is also followed by return reversals in the subsequent quarter as the compensation for investors to provide liquidity, especially for liquid stocks and during bad market times. My overall evidence provides empirical evidence of the endogenous effect of liquidity demand on the stock liquidity and helps to at least partially explain the market liquidity spiral during turmoil periods by showing that liquid assets worsen in liquidity due to the market wide liquidity demand. One lesson to learn is that the market is far from resilient to absorb the liquidity demand.

In the second essay, I propose and test several hypotheses to examine the impact of politically connected debtors on the resolution of distress. The results suggest that firms with politically connected debtors are more likely to exit the Chapter 11 process as a going-concern rather than through acquisition or liquidation. Additionally, I find that firms with politically connected debtors are less likely to undergo a subsequent distressed restructuring following emergence from Chapter 11. The findings suggest that the effects of debtors' political connections on bankruptcy outcomes are most likely due to the economic benefits associated with political connections rather than the potential for debtors to use political capital to coerce creditors into approving suboptimal continuations of unprofitable firms. Further, my findings indicate that firms with politically connected debtors are able to effectively reduce their financial leverage to the industry level after getting out of bankruptcy, while leverage ratios in firms without politically connected debtors remain above industry levels. Further evidence shows that creditors of firms with politically connected debtors are more willing to take equity in exchange for their debt claims. This result is indicative of investors' greater confidence in the firm's viability due to

implicit guarantees linked to debtors' political connections. Overall, the study provides evidence that politically connected debtors may improve the debtors' bargaining power, thereby resulting in a higher incidence of out-of-court restructurings.

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Chapter 1

Liquidity Dry-ups in Equity Markets

1.1 Introduction

Liquidity has become important considerations for mutual fund investment decisions. Several recent studies, such as Ben-Rephael (2014), Huang (2015) and Rzeznik (2016), show that fund managers are actively involved in liquidity management in their overall portfolio management decisions. Specifically, they show that fund managers adjust their portfolio to more liquid stocks during volatile periods, when funds are more likely to experience outflows. Presumably, the highly liquid stocks can better serve the purpose of liquidity provision for fund managers – these stocks can be sold more quickly and with less adverse price impacts than other stocks when mutual funds face liquidity demand.

However, the common preference for liquid stocks and the liquidity-driven sales of the liquid stocks by mutual funds can result in a "crowding" effect. When mutual funds experience fund outflows, fund managers typically sell part of their holdings to cover redemptions. If funds with similar liquid assets simultaneously experience outflows and choose to sell the liquid stocks at the same time, the concentrated selling of these stocks can have significant effects on their liquidity and price. During market turmoil when fund outflows are both systemic and massive, the common liquidity demand of the mutual funds could result in lower liquidity of the highly liquid stocks or liquidity dry-up in the equity market.

The purpose of this paper is to empirically study how investor demand for liquidity endogenously affects stock liquidity in the equity market. Using mutual fund holdings and transactions, we show that mutual funds exhibit strong preference for liquid stocks as means of liquidity provision in portfolio decisions. We study the effects of the liquidity-driven trades based on mutual fund trading activities in association with fund flows.[1] Mutual funds tend to sell the more liquid stocks in their holdings when experiencing outflows. The concentrated selling of liquid stocks, however, significantly reduces the liquidity of these stocks, resulting in liquidity deterioration or dry-up among the highly liquid stocks in periods of high market-wide liquidity demand. We find that the effects of asset fire sale on stock prices as documented in Coval and Stafford (2007) are most prominent among the highly liquid stocks and are largely driven by common liquidity demands.

We start our analysis by looking at how US actively managed equity funds hold liquid assets. Essentially, if it holds more liquid assets, a fund's large selling needs would be shared by a variety of liquid assets. The fund would be able to avoid the selling crowds, and the selling pressure on specific stocks is less likely to happen. We compare the funds' value-weighted portfolio liquidity and that of their corresponding benchmark index funds. Following Berk and Binsbergen (2015), a fund's benchmark is determined among eight Vanguard index funds. The evidence shows that funds in our sample generally tend to maintain a portfolio that is less liquid than their respective benchmarks. The lower benchmark-adjusted holding liquidity indicates that funds would be likely to rely more on the smaller fraction of their liquid assets when it comes to liquidity needs, and increases the likelihood of creating pressure on the liquidity of these assets.

In order to explore how funds utilize their liquidity, we first look at how funds' trading activities change with the increase of liquidity needs. Specifically, we regress the fund sale of each quarter on a dummy variable that indicates the time when the fund experiences extremely low flows. The fund sale is defined as the dollar value of the stocks sold by the fund during a quarter over the dollar value of its holdings in the prior quarter. We find that funds tend to sell more of their holdings when facing outflows. This indicates that the

[1]Koch, Ruenzi and Starks (2015) indicate that mutual funds are a typical group of investors who have time-varying liquidity demands resulting from the fund net flows. Thus, the observable fund flows is an important indicator of the fund liquidity demand.

liquidity demand from funds would increase for stocks that they hold. We further interact the fund net flows with market state indicators, namely the aggregate market flow or the VIX index of implied volatility of S&P 500 index options. The test shows that funds are forced to sell even more during bad market states.

If funds treat liquid stocks and illiquid stocks equally when they need to sell, the selling pressure on specific liquid stocks is also less likely to happen because the selling pressure would be shared by wide categories of stocks. We thus examine whether funds have any stock preferences when they have to sell. We calculate the fund sell liquidity as the value-weighted liquidity of a fund's sell trades over the value-weighted liquidity of the fund holdings minus one. The variable captures whether the proportion of liquid stocks among the fund's sell trades is greater than that among the fund holdings. We find that the fund sell portfolio tend to be more liquid stocks facing negative flows. This indicates that funds tilt towards selling more liquid stocks when they need more liquidity. We further find that the stock liquid sale is more during high VIX periods, when the market is more volatile and more funds are likely to demand liquidity. The evidence is generally consistent with studies such as Brown, Carlin and Lobo (2010) and Manconi Massa and Yasuda (2010) and Jotikasthira, Lundblad and Ramadorai (2009). Thus, while funds hold less liquidity than their benchmarks, they tend to utilize more liquidity when necessary. The way in which funds hold and trade liquid assets places significant selling pressure on a small number of stocks because the trades are concentrated in these stocks.

We next investigate how stock liquidity is endogenously affected by liquidity demand for a stock. To proxy for the liquidity demand for a stock, we use actual sales of the stocks by actively managed mutual funds. However, mutual funds also sell stocks for information reasons, which have little to do with liquidity needs. Hence, it is necessary to differentiate the selling actions due to liquidity needs from those due to information purposes. Alexander, Cici and Gibson (2006) and Coval and Stafford (2007) both stress the importance of fund flows in determining the motivations of trades. Specifically, when mutual funds sell with concurrent heavy outflows, the trades are more likely to be due to liquidity needs. Therefore, each quarter we construct a stock's liquidity demand, forced sale (FS), by aggregating the shares of the stock that are sold by mutual funds which experience extreme negative fund flows.[2] We examine the effect of liquidity demand on stock liquidity by regressing change in stock liquidity on its FS measure. Consistent with the model of Eisfeldt (2004), we find that a stock experiencing higher liquidity demand becomes less liquid during the concurrent quarter. The evidence indicates that widespread liquidity demand generally deteriorates the stock liquidity.

The sensitivity of liquidity to the liquidity demands may be different in liquid and illiquid stocks, since funds are more likely to sell liquid stocks than illiquid stocks when liquidity is required. We next interact our FS measure with an indicator that represents stocks falling into the most liquid tertile. This cross-section test shows that the liquidity deterioration exists mostly among liquid stocks. The evidence is consistent with our earlier findings that funds sell more liquid stocks to fulfill their liquidity needs, which in turn make these stocks suffer more from the forced sale.

The influence of liquidity demand on stock liquidity could be intensified by market conditions, as a number of studies suggest (Vayanos, 2004; Brunnermeier and Pedersen, 2009; Ben-Rephael, 2014, Bigio, 2015). When the market is more volatile, more funds experience outflows and, therefore, the market-wide demand for liquidity increases. We further explore how the effect of liquidity demand varies across market states. Specifically, we split the sample period into low and high market flow periods, based on the median aggregate market flow across the sample period. Subsample analysis is conducted for the two different periods. We find that the reduction in liquidity for liquid stocks from forced sale is greater in more volatile market times. The liquidity of illiquid stocks, on the other hand, does not appear to be affected as severely by the forced sale. Nor is the liquidity of illiquid stocks decreased during volatile market states.

[2] The aggregated shares are scaled by the stock's total shares outstanding as of last quarter end.

The liquidity demand from funds can create temporary price effects on the stocks, as shown in Coval and Stafford (2007), in the form of asset fire sales. Hence, we expect to find more price pressures for stocks with greater liquidity demand. The price of stocks with large liquidity demand would decrease due to the selling pressure, but it will recover in the latter period since the price drop is not because of information reasons. Therefore, we examine the price effect on a stock from liquidity erosion by looking at the stock's return reversal in the subsequent quarter. Specifically, when sorting stocks based on its FS measure, we find that stocks in the top FS decile display positive return reversals in the subsequent quarter. We do not find significant return reversals for stocks in the bottom FS decile. The difference in the return reversal of the two extreme deciles is significantly different. This indicates that funds who get stuck in the crowd selling have to pay higher liquidity premium. In our further extended tests, we find that such price effects are different both cross sectionally and across varying market states. In particular, stocks in the most liquid quintile experience significant positive return reversals in the subsequent period when they are sold more for immediacy. Furthermore, the return reversals of these stocks are more pronounced during periods of low aggregate market flows. In contrast, illiquid stocks do not experience similar price pressures. In general, the evidence indicates that the erosion of liquidity in liquid stocks makes the sales of these stocks more costly.

Our work contributes to the literature in several aspects. First, our work intends to provide an explanation of individual stock liquidity from the demand side. Chordia, Roll and Subrahmanyam (2002) show that liquidity levels are affected by trading activities, in the form of trade imbalance. Næs, Skjeltorp and Ødegaard (2011) document a correlation between change in investors portfolio composition and stock market liquidity. Following the strand, previous studies have attempted to explain the change in stock liquidity from the perspective of the supply side (Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009; Nagel, 2012; Hameed, Kang and Viswanathan, 2010), where the market has time-varying funding constraints. However, the empirical evidence of Brockman and Chung (2002) and Bauer (2004) indicates that the supply side explanation cannot fully account for the whole liquidity story. [3] On the liquidity demand side, studies focus on decoding liquidity commonality (Kamara, Lou and Sadka, 2008; Karolyi, Lee and Dijk, 2012; Aymo and Gil-Bazo, 2013; Koch, Ruenzi and Starks, 2016). That is, different stocks tend to co-move in liquidity when they are traded by funds at the same time. However, there is little, if any, empirical evidence on how liquidity demand for a specific stock affects the stock as well as investors who have to trade it. Our work adds to the literature by filling in this gap.

Second, our paper provides empirical evidence of the endogenous effect of liquidity demand on the stock liquidity level. A strand of literature documents the fund managers' tilt toward more liquid stocks during market downturns (Vayanos, 2004; Huang, 2015; Rzeznik, 2016; Ben-Rephael, 2014). They assume that the stock liquidity is exogenous regardless of the liquidity-driven trading actions. We argue that the large demand of liquid stocks for immediacy would create a pressure on these stocks as funds are forced to sell them facing outflows. We find that, instead of remaining highly liquid, liquid stocks that are heavily sold by mutual funds tend to become less liquid.

Our work also sheds lights on the stock market fragility and fund liquidity management efficiency. Greenwood and Thesmar (2001) show that a stock can become more fragile due to correlated liquidity shocks faced by its owners. Kamara, Lou and Sadka (2008) show that the sensitivity to market liquidity has increased for large-cap firms, which are more likely to be liquid, due to increased institutional ownership. Their results indicate that the equity market is more fragile to liquidity shocks as the ability of large stocks to diversify liquidity shocks has declined. We show that one source of this stock fragility is the liquidity erosion due to forced sale, which makes liquidity decrease among liquid stocks that are heavily sold. Consequently, these liquid stocks are less efficient to act as liquidity cushions. A more recent

[3] In particular, these studies find that liquidity commonality can be observed from order-driven markets, where individual investors post their bid and ask offers. Compared to a quote-driven market where market makers post the bid and ask prices, an order-driven market reflects the public's liquidity demand and is hence less subject to the liquidity supply.

study from Nanda and Wei (2018) show that mutual funds that intentionally reduce their overlapping in holdings with their peers tend to outperform. We add to the literature arguing that funds' such overlap management should concentrate on liquid stocks.

The paper is organized as follows. The next section discusses the liquidity measures and the data. Section 1.3 documents the mutual fund portfolio liquidity and their trades associated with fund flows. Section 1.4 describes the relation between the liquidity demand and the change in stock liquidity. Section 1.5 discusses robustness tests. The final section concludes.

1.2 Data

1.2.1 Mutual Fund Data

We obtain mutual fund data from Thompson Reuters CDA/Spectrum Mutual Fund Holdings Database. Other fund variables are matched to the holdings from CRSP Survivorship-bias Free Mutual Fund Database using MFLinks. The funds with multiple classes are matched and aggregated on the WFICN level. We limit our analysis to US actively managed equity funds from 1993 to 2015.[4] A fund must have at least $10 million total net asset (TNA) as of the prior quarter end to be included. The calendar quarter ends (*i.e.,* March, June, September and December) are used as the quarter end dates. To derive the trades of the actively managed funds each quarter, we follow Frazzini and Lamont (2008) and Koch, Ruenzi and Starks (2015) by filling the missing quarter with the holdings of the funds from last most recent quarter. However, this is only done for a maximum of a 6-month gap. [5] The holdings of each fund are also adjusted for split events. Consequently, this leads to 3,805

[4]As shall be described in the next subsection, the DTAQ data with which we construct liquidity measures starts from 1993.

[5]We also try dropping these observations with gaps. This does not alter our findings.

funds across the sample period and 161,475 fund-quarter observations.

To be consistent with the quarterly frequency of fund holdings, we construct other variables on the quarterly basis. We measure fund size as the TNA of the fund at the end of each quarter. Fund return is the fund's cumulative monthly return within each qurater. Fund cash is the fraction of a fund's assets held as cash as of the end of each quarter. We also construct the quarterly fund flow as the percentage monthly flow aggregated over the quarter. Specifically, for fund i during month t,

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})}{TNA_{i,t-1}} \tag{1}$$

where $TNA_{i,t}$ is the TNA of fund i at the end of month t, and $R_{i,t}$ is the fund's return for month t. If there is a fund merger involved during month t, the corresponding flow is then dropped. We also summarize the fund selling activities. Specifically, each period we calculate the fund sale of a fund as the dollar value of stocks sold by the fund over the dollar value of the fund stock holdings as of last quarter end. For the purpose of later analysis, we also construct the fund sell liquidity (*SellLiquidity*), defined as the value-weighted liquidity of a fund's sell trades during a certain quarter over the value-weighted fund portfolio liquidity in the prior quarter. Specifically, for each fund in quarter q,

$$SellLiquidity_{i,t} = \frac{\sum \tilde{w}_{j,q} LM_{j,q-1}}{\sum w_{i,q-1} LM_{i,q-1}} - 1 \tag{2}$$

where $\tilde{w}_{j,q}$ is the dollar-value weight of stock j, which is sold by the fund during quarter q, among all the stocks that are sold by the fund during the same quarter. $w_{i,q-1}$ is the dollar-value weight of stock i held by the fund in quarter $q-1$. $LM_{j,q-1}$ and $LM_{i,q-1}$ represent the stock's liquidity in quarter $q-1$. We employ four liquidity measures, namely, $NormAmihud$, *QSpread*, *RSpread* and $ESpread$ to represent the stock liquidity. [6] *SellLiquidity* intends

[6] The construction of the four liquidity measures will be discussed in the next subsection.

to capture a fund's trading preferences to liquid stocks. The numerator of the first term in Eq.(2) captures the value-weighted liquidity of the fund's sell trades, while the denominator captures the value-weighted liquidity of the fund's portfolio. The ratio is then compared with 1. Therefore, a more negative level of *SellLiquidity* in Eq.(2) indicates that the fund sells more liquid stocks than illiquid stocks. [7]

We winsorize all the variables at 5% and 95% level to reduce the influence of outliers. The full-sample summary statistics of fund-level characteristics is reported in Panel A, Table 1.1. Funds in our sample display an average quarterly return of 2.2% and an average cash ratio of 3.0%, with the median 2.8% and 1.4%, respectively. The fund flow has a mean of 1.7% and a median of -0.8%. The fund sale has a mean of 0.201. The mean of *SellLiquidity* as measured in Eq.(2) ranges from -0.264 to 0.731. *SellLiquidity* as measured with $NormAmihud$ and *ESpread* shows a sell portfolio that is more liquid than the fund portfolio, with a negative mean of -0.018 and -0.265, respectively. *SellLiquidity* as measured in *QSpread* and *Rspread*, on the other hand, displays a positive mean of 0.066 and 0.731, respectively. Panel B and Panel C report the fund characteristics during the period of 1993-2003 and 2004-2015, respectively. Funds in the later period display a lower average fund net flow, with a mean of 0.4% during 2004-2015 compared to 3.7% during 1993-2003. Similarly, fund appear to hold less cash during the period of 2004-2015 compared to earlier times, with a mean of 5.3% in Panel B versus 2.8% in Panel C. The lower net fund flows and less cash holding in the later subperiod may be due to the shocks from the 2008-2009 financial crisis.

1.2.2 Liquidity Measures and Stock Characteristics

We employ four measures in the analysis for stock liquidity. The first measure is derived from the Amihud's (2002) illiquidity ratio. The data is obtained from CRSP daily stock files dataset. Specifically, the Amihud (2002) illiquidity ratio (*Amihud*) for stock i in month m

[7] As shall be described in the next subsection, the four liquidity measures actually measure the "illiquidity" of the stock. Thus, a liquidity measure is smaller if the stock is more liquid.

is defined as follows,

$$Amihud_{i,m} = \frac{1}{D_{i,m}} \sum_{t=1}^{D_{i,m}} \frac{|r_{i,t}|}{|dvol_{i,t}|} \tag{3}$$

where $D_{i,m}$ is the number of days with available data in month m, $r_{i,t}$ is the return of stock i on day t , and $dvol_{i,t}$ is the dollar trading volume for stock i on day t. To reduce the influence of outliers, we follow Acharya and Petersen (2005) to normalize the Amihud's (2002) illiquidity ratio. The normalized Amihud is defined as follows,

$$NormAmihud_{i,m} = min(0.25 + 0.30 * Amihud_{i,m} * C_{t-1}, 30) \tag{4}$$

where C_{t-1} is the factor ratio, which is defined as the ratio of the market portfolio capitalization as of the end of month t to that of the end of July 1962. As the mutual fund holding data is on a quarterly basis, we construct the quarterly Amihud's ratio by averaging the monthly Amihud illiquidity over each quarter.

The Amihud (2002) ratio captures the price impact and is considered most efficient among daily illiquidity measures in paralleling high-frequency measures , as argued by Hasbrouck (2009). In their comparisons of a group of liquidity measures, Goyenko, Holden and Trzcinka (2009) also show that the Amihud (2002) measure does a good job in measuring liquidity. However, a more recent study from Lou and Shu (2017) find that, instead of measuring the compensation for illiquidity, the Amihud (2002) captures the mispricing from the trading volume. Therefore, to ensure the robustness of the test, we construct the other three illiquidity measures, namely percent quoted spread (*QSpread*), percent realized spread (*RSpread*) and percent effective spread (*ESpread*), from intraday tradings to represent the stock liquidity level.[8] The trade and quote data are obtained from the NYSE Daily Trade And

[8]In the study of Goyenko, Holden and Trzcinka (2009), *RSpread* and *ESpread* win the majority of the horseraces.

Quote (DTAQ) database, which has the frequency of *millisecond*. [9] Following Holden and Jacobsen (2014), for stock i at time t,

$$QSpread_{i,t} = (Ask_{i,t} - Bid_{i,t})/M_{i,t} \tag{5}$$

$$RSpread_{i,t} = 2D_{i,t}(P_{i,t} - M_{i,t+5})/M_{i,t} \tag{6}$$

and

$$ESpread_{i,t} = 2D_{i,t}(P_{i,t} - M_{i,t})/M_{i,t} \tag{7}$$

where $Ask_{i,t}$ is the highest ask price of stock i at time t, $Bid_{i,t}$ is the lowest bid price of stock i at time t, $M_{i,t}$ is midpoint of $Ask_{i,t}$ and $Bid_{i,t}$ of stock i at time t, $M_{i,t+5}$ is midpoint of stock i at time $t+5$, $P_{i,t}$ is the transaction price of stock i at time t, and $D_{i,t}$ is an indicator with the value 1 for buy orders and -1 for sell orders. $D_{i,t}$ is determined according to the algorithm of Lee and Ready (1991).

Each of the three liquidity measure is first averaged within a day during market hours to form a daily measure. While the daily *QSpread* is a time-weighted average, daily *ESpread* and daily *RSpread* are both share-weighted averages. The daily measure is then averaged over the month. To build a quarterly measure for our tests, the monthly measure is further averaged within each quarter. As the DTAQ data is only available from 1993, our analysis spans from 1993 to 2015.

A wide range of literatures considers certain firm characteristics, such as firm size and return volatility, as determinants of stock liquidity. Following previous literature, we obtain stock level characteristics as control variables from CRSP monthly database, as reported in

[9] Holden and Jacobsen (2014) argue that liquidity measures constructed from the Monthly Trade And Quote (MTAQ) databese turn out to largely differ from those constructed from DTAQ due to withdrawn quotes, relatively low frequency (*seconds* in MTAQ versus *milliseconds* in DTAQ) and other reasons. They argue that the DTAQ database has less potential measuring errors.

Table 1.2. Specifically, we measure firm size as the market capitalization as of the end of each quarter. Ret(-12,-1) is defined as cumulative stock monthly return over the past 12 months to capture potential information-motivated trades. We also define the return volatility as the standard deviation of a stock's monthly return over the past 12 months. Koch, Ruenzi and Starks (2015) show a demand-side source of liquidity commonality through mutual fund ownership. Thus, we obtain another two control variables from the mutual fund holdings to capture the liquidity commonality component. The first variable is mutual fund ownership (MF ownership), defined as the number of shares of a stock held by mutual funds scaled by total shares outstanding of the stock at each quarter. The other variable is mutual fund holding concentration (MF concentration), which is defined as the number of shares of a stock held by the top five mutual funds that hold the most shares of the stock. The full sample summary is reported in Panel A, Table 1.2. The sample consists of 231,505 firm-quarter observations, with both stock level characteristics, MF ownership and MF concentration data available. Ret(-12,-1) and return volatility have fewer observations because they need to be constructed with available data from the past 12 months. Firms included in the sample display an average positive perior-year performance of 22.6% and a median of 10.9%. The return volatility on average is 12.6%. In addition, stocks in our sample have an average MF ownership of 15.9% and MF concentration of 0.8%. The median firm has 14.9% of its shares owned by mutual funds and 0.4% of its shares owned among the top five mutual funds that hold the stock. Panel B and Panel C report the summary statistics for the period of 1993-2003 and 1994-2015, respectively. The stocks held by the funds during 2004-2015 seem to be relatively liquid stocks, with three out of four liquid measures displaying lower means and all of the four displaying lower medians compared to those of 1993-2003. Moreover, stocks held by funds in the second half tend to have lower prior-year return, lower return volatility, higher MF ownership and MF concentration.

To present a clearer picture of stocks' cross-sectional characteristics, in Table 1.3 we report the stock level characteristics using the one-way sort on one of the stock liquidity measure, *QSpread*.[10] In particular, each quarter we sort stocks held by funds in the sample into quintiles based on its *QSpread* as of last quarter end. Panel A of Table 1.3 shows that stocks at the most liquid quintile (Q1) tend to be larger firms with better past-year performance and lower return volatility. More importantly, these stocks are also more widely held by mutual funds, with a higher level of MF ownership but a lower level of MF concentration. The widespread ownership for liquid stocks indicates that these stocks are more likely to be used when it comes to liquidity needs, and that the "crowd" of selling these stocks are more likely to form. The subperiod statistics in Panel B and Panel C show similar patterns to those in Panel A across the *QSpread* quintiles.

1.2.3 Measure for Liquidity Demand

In order to proxy for the liquidity demand for a stock, we use actual sale of the stock by the actively managed mutual funds in our sample. However, funds also sell stocks for information reasons, which have little to do with liquidity needs. Studies such as Cao, Simin and Wang (2013) also show that mutual funds may trade for timing the market liquidity. Consequently, it is hard to document the relation of liquidity demand and liquidity change as causal. Hence, it is necessary to differentiate the selling actions due to liquidity needs from those due to information purposes. Besides, an ideal environment should be where a high liquidity demand can be detected and trades for liquidity reasons can be easily identified.

Alexander, Cici and Gibson (2006) and Coval and Stafford (2007) both stress the importance of fund flows in determining the motivations of trades. Specifically, when mutual funds sell with concurrent heavy outflows, the trades are more likely to be due to liquidity needs. The situation is also relatively exogenous because funds are "forced" to do so. Each quarter we construct a fund's trades on a stock by calculating the difference in the mutual fund holding of the stock between adjacent quarters. Hence, a positive difference in the stock

[10] The patterns of the stock level characteristics similar when stocks are sorted on the other three liquidity measures.

holdings identifies the fund's buy trade (Buy) for the stock, while a negative difference in the stock holdings identifies the fund's sell trade ($Sell$) of the stock. If a stock does not appear in the last quarter, we assume that the stock is initially bought for the current quarter and make the traded shares equal to the stock's holding; If a stock fails to show up in the next quarter end, we assume that this stock is completely sold during the next quarter and make the traded shares of the stock in the next quarter as the negative of the current quarter's stock holding.

Each quarter we require that a stock be held by at least ten mutual funds to be included in the sample. We identify the liquidity demand for stock i at quarter q, forced sale (FS) , as the shares of the stock i sold by funds whose flow is at the bottom flow quintile at quarter q, scaled by the total shares outstanding of the stock as of last quarter end, adjusted by split events. Specifically,

$$FS_{i,q} = \frac{\sum_j (\max(0, -Sell_{i,j,q}) | flow_{j,q} < 20^{th} Percentile_q)}{SharesOutstanding_{i,q-1}} \tag{8}$$

where $Sell_{i,j,q}$ is the sell trade of fund j on stock i in quarter q. For stock i at quarter q, a high forced sale stands for a high liquidity demand from actively managed funds. The summary statistics of the stock forced sale is reported in Table 1.2. Stocks held by these funds have an average FS ratio of 0.466% . Stocks seem to have a higher average FS level during the period of 2004-2015 (0.482%) than that during the earlier half (0.447%). Looking at the FS ratio of stocks with different liquidity levels in Panel A of Table 1.3, most liquid stocks (Q1) tend to have the highest average FS ratio at 0.558%, while illiquid stocks (Q5) have an average FS ratio of 0.121%.

1.3 Mutual Fund Holding Liquidity and Liquid Stock Sale

1.3.1 Mutual Fund Holding Liquidity

Like all the other investors, mutual funds face the risk-return tradeoff (Ippolitp,1989). On one hand, funds hold a fraction of their assets as the most liquid ones in order to withstand the market crash and liquidity shocks. If funds widely hold liquid stocks, the large forced sale of one certain stock is less likely to happen, because the pressure would be shared by a variety of stocks. On the other hand, however, mutual funds' goals of outperforming the benchmark may lead them to bet on more stocks that are riskier and less liquid. Consequently, their liquid holdings may be limited to only a small fraction of the funds' total assets and thus cause the selling pressure on these stocks upon liquidity shocks.

In this subsection, we explore mutual funds' portfolio liquidity by comparing their holding liquidity with their respective benchmarks. Essentially, if it holds more liquid assets, a fund's large selling needs would be shared by a variety of liquid assets. The fund would be able to avoid the selling crowds, and the selling pressure on specific stocks is less likely to happen. We follow Berk and Binsbergen (2015) to use the eight Vanguard's index funds as the benchmarks.[11] To determine the benchmark for a fund, we run a time-series regression of the fund's quarterly returns on those of each of the eight Vanguard index funds. The benchmark for the fund is the index fund which yields the greatest R-square in the regression. Since the eight index funds appear at different time periods, for each quarter, we only compare the

[11] In their paper, Berk and Binsbergen (2015) use eleven indexes funds, but three of them are international funds and are excluded here. Thus, the eight Vanguard's index funds used in our paper are: Vanguard S&P 500 Index Fund (VFINX), Vanguard Extended Market Index Fund (VEXMX), Vanguard Small-Cap Index Fund (NAESX), Vanguard Value Index Fund (VVIAX), Vanguard Balanced Index Fund (VBINX), Vanguard Mid-Cap Index Fund (VIMSX), Vanguard Small-Cap Growth Index Fund (VISGX), Vanguard Small-Cap Value Index Fund (VISVX).

R-squares of the index funds that already exist during the quarter.

Table 1.4 reports the benchmark-adjusted liquidity, which is calculated as the average difference in fund liquidity from that of their respective benchmarks. The difference is first averaged across the funds during the same quarter and then averaged across all quarters. As can be seen in Panel A, the actively managed funds in the sample tend to be less liquid than the benchmark, with the full-sample benchmark-adjusted liquidity positive in all of the four measures. We next sort the funds based on the fund TNA each quarter. We find that small funds are inclined to be less liquid than large funds compared to the benchmark. This evidence is consistent with Massa and Phalippou (2004), who show that mutual fund's portfolio liquidity is negatively related to the fund size. The evidence is also consistent with Chen et al. (2004) in that larger funds need more stock ideas and thus expand their holdings to liquid assets. Studies such as Golec (1996) and Daniel et. al (1997) indicate that funds with different investment objectives tend to hold stocks with different characteristics and thus have different return implications. In Panel B, we look at the benchmark-adjusted liquidity by sorting the funds in our sample on the CRSP investment objective code. We focus on only funds with the objective code as Micro funds (CI), Small-cap funds (CS), Medium-cap funds (CM), Balanced funds (YB), Income funds (YI), Growth funds (YB) and Style funds (S).[12] The cap-based funds have similar patterns as in Panel A, with funds greater in size more liquid then their respective benchmark. In particular, CM funds tend to be more liquid than the benchmark while both CI funds and CS funds hold less liquidity than their benchmarks. Moving to yield-based funds, it shows that funds with more aggressive investment goals hold less benchmark-adjusted liquidity. In particular, YG funds tend to hold less benchmark-adjusted liquidity than YI funds. YI funds display less-than-benchmark liquidity measured with $NormAmihud$ and $QSpread$. The benchmark-adjusted liquidity of YI funds tend to be indifferent with the $RSpread$ measure and marginally positive with

[12] The CRSP investment objective code also identifies S&P 500 index funds as Large-cap funds (CL), which are excluded from our sample.

ESpread. While benchmark-adjusted liquidity of YI funds is hard to define, it is smaller than that of YG funds across all of the four liquidity measures. The evidence is consistent with Da, Gao and Jagannathan (2010), who show that liquidity provision is more important for income-oriented funds. Overall, while CM funds and YI funds show some evidence to be more liquid than the benchmark, most of the funds in the sample tend to be less liquid than their respective benchmark. If liquid stocks are what these funds turn to when it comes to liquidity needs, the lower-than-benchmark liquidity indicates that funds have to rely more on the smaller fraction of liquidity stocks, which would aggravate selling pressure on these stocks.

1.3.2 Mutual Fund Liquid Stock Sale

The subsection above shows that actively managed funds tend to hold less liquidity than the benchmark. The lower-than-benchmark holding liquidity implies that funds would likely rely more on their liquid assets when facing liquidity needs, and increase the likelihood of creating pressure on the liquidity of these assets. However, another possibility can be that funds treat the stocks that they hold indiscriminately when they need to sell facing liquidity needs. In this case, the selling pressure on specific liquid stocks is less likely to happen because funds are able to diversify the pressure by selling wide categories of stocks.

In this subsection, we explore how funds utilize their liquidity. we first look at how funds' trading activities change with the increase in liquidity needs. Table 1.5 reports the regressions of fund sale on the fund flow. We define the fund sale as the fraction of fund portfolio dollar value sold during a certain quarter. As we focus on the situation where funds experience negative flows and thus need to sell, we use a dummy variable, $NegFlow$, to account for the effect of negative fund flows. $NegFlow$ is a dummy indicator which is equal to one if the flow of a fund is falling into the bottom flow quintile during a certain quarter. Fund fixed effects are included in each regression and coefficients are clustered on both the fund level and the time level. As shown in Column (1) of Table 1.5, a fund has greater fund sale when its flow is more negative. Intuitively, when it experiences heavy outflows, a fund has to sell more in order to cover the customer redemptions. In Column (2), $NegFlow$ remains significant after adding fund-level control variables, including the logarithm of fund TNA, quarterly fund return and fund cash ratio.

To explore how the effect of negative fund flows on the fund sale varies across market states, we also interact $NegFlow$ with market conditions. We use two measures to reflect market conditions. The first measure is logarithm of the S&P 500 Volatility Index price ($log(VIX)$) obtained from the Chicago Board Options Exchange (CBOE) following the literature (e.g. Longstaff, Pan, Pedersen and Singleton, 2010; Bao, Pan, and Wang, 2011; Nagel, 2012; Bollerslev, Chou and Kroner, 1992; Poon and Granger, 2003; Chung and Chuwonganant (2014)). For quarter q, the VIX price used is the price as of the last trading day of quarter $q-1$. For the second measure of market conditions, each quarter we calculate the aggregate market flow as of the prior quarter end and then rank them across the sample period. We denote $Mktflow$ as a dummy indicator, which is equal to one if the aggregate market flow as of last quarter end is below the median level, and zero otherwise. The regressions with the interaction item are reported in Columns (3) and (4) of Table 1.5. In both regressions, the interaction item is positive and significant. The result indicates that funds, facing negative flows, sell more during bad market states.

We next explore the fund trading preference. Essentially, funds is likely to sell liquid stocks first when they have to sell in order to reduce the price impact. We regress a fund's sell liquidity on the negative fund flow indicator, $NegFlow$, and the market condition indicators. The dependent variable is the fund sell liquidity, *SellLiquidity*, as defined in Eq.(2). As discussed in Section 1.2.1, *SellLiquidity* intends to capture a fund's trading preferences to liquid stocks. $NegFlow$ is constructed with the four liquidity measures. $NegFlow$ and the market condition indicators are defined as in Table 1.5. The results are reported in Table 1.6. Columns (1), (4), (7) and (10) of Table 1.6 report the regression on only the fund flow and other control variables. The results show that when it experiences negative flows, the fund value-weighted sell liquidity is higher than that of the fund portfolio. This indicates that the fund sells more of its liquid stocks than illiquid stocks. In Columns (2), (5), (8) and (11), we add the interaction of $NegFlow$ with the logarithm of VIX, $Log(VIX)$. The coefficients are negative and significant across the four measures. This shows that during high VIX periods, funds tilt towards selling even greater portion of liquid stocks facing outflows. Note that the dependent variable captures the ratio instead of the trading quantity. In other words, when the dependent variable, $SellLiquidity$, becomes more negative, it indicates that quantity of liquid stocks sold proportionally increases more than that of illiquid stocks sold. Hence, the regressions with $log(VIX)$ as the market state indicator show that funds increase the sale of liquid stocks more than that of illiquid stocks. Moving to the regressions with $Mktflow$ interacting with $NegFlow$, the interaction items do not appear to be significant in Columns (3), (6), (9) and (12). The proportion of liquid stock sale does not seem to increase during low market flow periods. However, with the coefficients of $NegFlow$ negative and significant, funds still tend to sell more liquid stocks.

In summary, Table 1.6 shows that when facing negative flows, funds prefer to selling more liquid stocks than illiquid stocks, especially during market turmoil. Our overall evidence is aligned with Manconi Massa and Yasuda (2010), Ben-David, Franzoni and Moussawi (2012), and Jotikasthira, Lundblad and Ramadorai (2009), who document that funds tend to liquidate liquid assets first during market downturns to reduce the price impacts.

1.4 Liquidity Demand and Change in Liquidity

Section 1.3 shows that, while they generally hold less liquidity than their benchmarks, actively managed funds count more on liquid stocks when faced with large outflows and when the market is turbulent. It indicates that the liquidity demand from funds are likely to exert pressure on the liquidity of stocks that are heavily traded by these funds if the large liquidity need is widespread. Eisfeldt (2004) develops a theoretical model with adverse selection, indicating that stock liquidity is lower due to adverse selection, which is determined by the amount of trades for reasons other than private information. Hence, trades due to non-information reasons, such as liquidity needs, would affect the asset liquidity. This indicates that even liquid stocks can become highly illiquid when stocks are coordinately sold by institutions without any news but liquidity needs. In this section, we empirically explore how a stock's liquidity is affected by the liquidity demand for the stock.

1.4.1 Forced Sale and Change in Liquidity

To test the effect of liquidity demand for a stock from mutual funds at the same time, the quarterly change in each stock's liquidity is regressed on the forced sale of the stock and other variables. Specifically,

$$\Delta LM_{i,q} = \alpha_i + aFS_{i,q} + b\mathbf{X}_{i,q-1} + c\mathbf{M}_{q-1} + \varepsilon_{i,q} \tag{9}$$

where $\Delta LM_{i,q}$ is the change of one of our four liquidity measures for stock i over quarter q, $FS_{i,q}$ is the forced sale of stock i as defined in Eq.(8), $\mathbf{X}_{i,q-1}$ is a vector of firm level characteristics at the end of quarter $q-1$ as control variables, and $\mathbf{M}_{q-1}$ is a vector of market wide variables, including the market excess return and market liquidity at the end of quarter $q-1$. $\mathbf{X}_{i,q-1}$ includes the firm-level characteristics as defined above in Table 1.2. In addition, we also add the mean of the liquidity measure over the prior four quarters, Prior LM, and the lag of the dependent variable, $\Delta LM_{i,q-1}$, to take into account the possible liquidity level reversal from the last period. We include firm fixed effects to account for the time-invariant firm variation that could also likely affect the stock liquidity level. The coefficients are all clustered on both the firm and the time level.

The effect of forced sale is reported in Table 1.7. In particular, the coefficients of the main variable, FS, are significant and positive in the regressions with all of our four liquidity measures. This indicates that, as it faces a higher level of forced sale, the stock's liquidity tends to decrease. Therefore, when a stock is traded more due to the liquidity demand from funds, the stock becomes less liquid. This evidence is consistent with the model of Elsfeldt (2004), in that the liquidity of an asset could be determined endogenously by the amount of trade for non-information reasons such as liquidity needs. Moving to controlling variables, the results show that the stock liquidity level decreases more among stocks that are greater in firm size, more widely held by mutual funds and that perform worse for the past 12 months. These stocks are more likely to be ones that are originally liquid. Therefore, the effect of FS seems to influence liquid stocks more. Hameed, Kang and Viswanthan (2010) show that the stock liquidity is affected more among high-volatility stocks, as these stocks suffer more from the funding constraints. Thus, we also include the stock return volatility to control for the funding constraints from the liquidity supply side. FS is still significant after taking into account the stock's liquidity supply. Moreover, the market excess return is negatively related to stock liquidity. Specifically, the result shows that the change in stock liquidity is more positive when the market excess return is negative. This indicates that the change in stock liquidity may differ across market states. Overall, the liquidity demand for a stock reduces the stock liquidity.

1.4.2 Liquidity Demand and Cross-sectional Change in Liquidity

In Section 1.3, we show that when facing negative flows, actively managed funds tend to sell relative liquid stocks. A strand of literature has shown similar evidence. For example, Brown, Carlin and Lobo (2010) show that investors could have a myopic insight to liquidate liquid assets when there is an immediate need for cash. Manconi Massa and Yasuda (2010) document the sell-offs among liquid securities of mutual funds during the 2007-2009 financial crisis. Jotikasthira, Lundblad and Ramadorai (2009) show that when funds are faced with outflows, they are likely to sell the most liquid stocks in the portfolio to reduce the price impact. Thus, for liquid stocks that are widely held by funds, a "crowd" of selling these stocks is more likely to form and in turn affect the stocks' liquidity, in comparison with illiquid stocks.

In this subsection, we explore the cross-section difference in the effect of liquidity demand. Specifically, we introduce an interaction item of FS and a dummy variable, *Liquid*, which is equal to one if the stock is at the most liquidity tertile as of last quarter end[13], and zero otherwise. In particular,

$$\Delta LM_{i,q} = \alpha_i + aFS_{i,q} + bFS_{i,q} * Liquid + c\mathbf{X}_{i,q-1} + d\mathbf{M}_{q-1} + \varepsilon_{i,q} \tag{10}$$

$\mathbf{X}_{i,q-1}$ and $\mathbf{M}_{q-1}$ are the same as defined in Eq.(9). We also put a middle tertile dummy, which is one if the stock is in the middle liquidity tertile and zero otherwise, in the analysis to account for the difference between the middle tertile and the extreme tertiles. The regressions are reported in Table 1.7. Again, firm fixed effects are included and the coefficients are clustered on both the firm and the time level. The coefficients of FS becomes significantly negative, as it represents the relation between the forced sale and the liquidity change among least liquid stocks. Interestingly, this result indicates that the forced selling actions seem to improve the liquidity of illiquid stocks. This may attribute to the fact that these stocks are not frequently traded. Consequently, any trade would help mitigate the mispricing and narrow the spread. However, the interaction item is positive and significant in all of the four regressions, indicating that the effect of forced sale is quite different for liquid stocks compared to illiquid stocks. In particular, the forced sale tend to deteriorate the stock liquidity of liquid stocks. In terms of the magnitude, the interaction item is greater than forced sale in most cases, indicating that liquid stocks are more likely to be less liquid in the next period. Besides, the middle tertile variables display similar coefficients to the liquid

[13] Quintile breakpoints are also used, the results are similar.

tertile but not as greater in magnitude. The overall results are consistent with those in Table 1.7, in that the forced sale actions create more pressure on the liquidity of liquid stocks.

1.4.3 Liquidity Demand and Market States

A lot of studies link market liquidity with market volatilities. For example, Vayanos (2004) develops a model to show that liquid stocks are more valuable due to performance-induced withdrawals. In the model of Brunnermeier and Pedersen (2009), they show that the high market volatilities would lead to liquidity spiral. When the overall market liquidity is low, mutual funds are more likely to experience heavy outflows (Huang, 2015). The forced sale is then greater. Besides, since liquid stocks are among the first to be sold during volatile periods, the forced sale that liquid stocks experience should be greater. It implies that the effect of forced sale on liquid stocks would be higher during turbulent market times. In this section, we explore the effect of liquidity demand on stock level liquidity under varying market conditions.

We repeat the regression in Eq.(10) by partitioning the sample into two groups based on the market conditions. We use the overall market flow to represent the market conditions. In particular, we calculate the aggregate market flow of each quarter and rank them. The quarters in the sample are then split into two groups based on the time-series median market flow. A quarter is identified as the low-market-flow quarter if its aggregate market flow is below the median market flow level across our sample period. The analysis is reported in Table 1.9. The regressions during low market periods are reported in Columns (1), (3), (5) and (7), while higher market flow periods in Columns (2), (4), (6) and (8). In groups of all the four measures, the interaction of forced sale with the liquid tertile dummy, $FS * Liquid$, is greater when the aggregate market flow is lower. Thus, liquid stocks' liquidity hurts more by the forced sale actions when the market is overall bad. Several studies have documented market liquidity spiral during extremely bad market times (e.g. Brunnermeier and Pedersen, 2009; Nagel, 2012; NÆS, Skjeltorp and ØDegaard, 2011). Our evidence shows that the liquidity of liquid stocks decreases during these periods, which coincides with the market liquidity spiral. In unreported analysis, we also divide the market states using the VIX index from CBOE, the results are consistent. In a nutshell, liquid stocks that are frequently used by distressed funds for liquidation experience large pressure on the stock liquidity, especially during bad market times.

1.5 Price Effects

Previous sections show that the funds' widespread liquidity demand for a stock erode the stock liquidity, especially that of liquid ones. Essentially, it arises from the investors' sentiment for liquid stocks when it comes to liquidity needs and thus would exert impacts on the stock prices (Frazzini and Lamont, 2008). Coval and Stafford (2007) show that the liquidity demand from funds can create temporary price effects on the stocks, in the form of asset fire sales. The price of stocks with large liquidity demand would decrease due to the selling pressure, but it will recover in the latter period since the price drop is not because of information reasons. With stocks affected differently by the liquidity demand across ex ante liquidity levels and across market states, the pricing implications could also be different. In this section, we explore the stock price effects following the forced sale.

Inspired by the methodology of Mitchell, Pulvino, and Stafford (2004) and Coval and Stafford (2007), each quarter we rank the stocks on its FS into deciles. We then calculate the cumulative abnormal returns (CARs) and the average abnormal returns (ARs) over the subsequent quarter. Each month, abnormal returns are calculated by following Daniel et al. (1997) (DGTW). The DGTW-adjusted excess returns are constructed on both the equal-weighted and the value-weighted basis. ARs and CARs of each decile are first averaged across the stocks within the same quarter and then across the quarters. In our effort to replicate the evidence of Coval and Stafford (2007), we find consistent results and report it in Appendix Table. The results show a monotonic pattern across forced sale deciles. Stocks experiencing greater forced sale display stronger price effects and greater return reversals in the subsequent quarter.

The abnormal return represents the compensation for the liquidity deterioration of the stocks that suffer from the flow-induced liquidity selling. Therefore, funds that sell these stocks pay higher liquidity premium. During volatile market times, when the overall market funding is constrained and mutual fund are more likely for liquid selling, the stock liquidity should be affected more and the price effect thus greater. We thus examine how the price effects change across varying market times. We partition the sample into normal times and relative volatile periods based on the aggregate market flows. A quarter is defined as volatile periods when the aggregate market flow of this quarter is below the median aggregate market flow across our sample period. We then calculate CARs and ARs on both the value-weighted (VW) and equal-weighted (EW) basis for each group. The results are reported in Table 1.10. As can be seen in Panel A of Table 1.10, stocks at the top FS decile do not seem to have significant return reversals following the forced sale during normal market times. The difference in abnormal returns between the top and bottom decile is not significant. During volatile market times, however, stocks falling in the top FS decile display significant abnormal return reversals in the subsequent quarter, with VW (EW) CAR of 1.544% (1.518%) and VW (EW) AR of 0.498% (0.483%). The difference between the top and bottom FS decile significantly different. This is consistent with our prior evidence that stock liquidity is eroded more during volatile market times, when the market liquidity provision is limited and liquidity demand surges. Investors thus ask for higher compensations to provide liquidity.

We next examine the cross-sectional price effects. We show in Section 1.3 and 1.4 that mutual funds have greater sentiment for liquid stocks and that the liquidity of liquid stocks are decreased more. In Table 1.11, we report the ARs and CARs across different stock liquidity levels. Each quarter, we do a unconditional double way sort. Stocks are divided into five liquidity quintiles based on its ex ante liquidity level represented by four liquidity measures. Stocks are also categorized into five FS quintiles. As can be seen in Table 1.11, across all of the four liquidity measures, liquid stocks display significant differences in both ARs and CARs between the top and the bottom FS quintile. Liquid stocks tend to experience greater price impacts experiencing the forced sale, while illiquid stocks, again, do not display striking return differences across FS quintiles. One potential concern is that the significant difference in returns between extreme FS quintiles under $NormAmihud$ and $QSpread$ might be driven by the underperformance at the low FS quintile instead of the positive return reversal from top FS quintile. We attribute to the measure deficiency. Lou and Shu (2017) show that the Amihud ratio captures the price impact from the trading volume component instead of the return-to-volume ratio. Hence, the significant underperformance of Low FS quintile in Table 1.11 with $NormAmihud$ may capture the mispricing from trading volume instead of the liquidity premium. Moreover, Goyenko, Holden and Trzcinka (2009) show that $ESpread$ and $RSpread$ are more efficient as liquidity measures compared to $QSpread$. Thus, our evidence is reliable with $RSpread$ and $ESpread$ better capturing price effects.

To examine the price effects on both the liquidity and time dimension, we also repeat the test in Table 1.11 for different market times. Table 1.12 reports the cross-sectional price effects across varying market states. Consistent with Table 1.10, Panel A of Table 1.12 shows little evidence of the price effects during high market flow periods. Liquid stocks as measured by $NormAmihud$ show some evidence of having significant price impact differences between the bottom and top FS quintile. Again, this may capture the mispricing due to trading volume. The return reversal is more pronounced for liquid stocks with greater forced sale during low market period, as can be seen in Panel B of Table 1.12. Illiquid stocks do not seem to have great price impacts. Overall, the evidence in this section extends that of Coval and Stafford (2007), showing that the price effects of the widespread liquidity demand is different across the stock liquidity levels and across market states. Liquid stocks experience greater price impacts when experiencing greater forced sale, especially during market turmoil.

1.6 Robustness Tests

We further perform additional analysis to ensure the robustness of our analysis. First, Koch, Ruenzi and Starks (2015) argue that the stock liquidity can be affected by mutual fund common ownership. Specifically, if a stock is widely held by a large group of mutual funds, they are likely to trade the stock at the same time. Consequently, the pressure exerted on the stock might be greater. Following their spirit, we also look at how a stock is coordinately traded by a group of mutual funds using an alternative measure that accounts for the correlated trades among mutual funds. Specifically,

$$FS_{i,t} = \frac{(N\_Sell_{i,t}|flow_{j,t} < 20^{th}Percentile_t)}{N\_all_{i,t-1}} \tag{11}$$

where $N\_Sell_{i,t}$ is the number of funds selling stock i at time t, and $N\_all_{i,t-1}$ is the total counts of mutual fund owners for stock i at time $t-1$. The results with this alternative measure, not tabulated for the sake of brevity, are qualitatively consistent with the ones that are presented.

Second, the forced selling activities of liquid securities are well documented for extreme market downturns such as the 2007-2009 financial crisis (e.g. Manconi, Massa and Yasuda, 2010; Ben-David, Franzoni and Moussawi, 2012). During the financial crisis, the market liquidity dries up, so do the liquidity of liquid stocks. Hence, it is possible that the positive effect of selling pressure on liquid stocks illiquidity is mainly driven by the crisis periods. In unreported tests, we exclude the financial crisis periods (from 2007 Q3 to 2009 Q1) to eliminate the influence from extreme events. Our findings still stand.

Third, we show that our results are robust across varying benchmarks, cut-off points, and measures. Specifically, in comparing the fund holding liquidity with benchmarks, we also use the 19 indexes benchmark as suggested in Cremers and Petajisto (2009). Specifically, each quarter a fund's benchmark is the index that this fund is least deviated from in holdings.[14] The results are consistent.

In addition, to ensure that our results is not driven by any outliers. We also try constructing the four liquidity measures using the fractional rank. In particular, each quarter, each stock is ranked among the stock universe based on each of the four liquidity measures we construct. The stock will then be assigned a "rank", which is a decimal between 0 and 1, for each of the four measures. A lower rank means that the stocks is more liquid compared to its peers on the market. The rank is also representative of a stock's relative liquidity "hierarchy". Our results still stand.

1.7 Conclusion

We explore several questions related to the effect of liquidity demand on the individual stock liquidity level. We find that domestic actively managed equity funds in general hold less liquidity than their corresponding benchmarks. This leads them to rely more on the small fraction of liquid assets for immediacy when faced with financial distress and significant outflows. We further find that mutual funds tilt toward selling more of liquid stocks when they are faced with negative fund flows. Consistent with prior literature that funds have to meet redemptions and reduce price impact, their engagement in liquid stock sale is more severe during market turmoil. Consequently, a widespread liquidity shock would be more likely to exert pressure on the liquidity of the liquid stocks they sell.

Using the mutual fund involuntary sale to proxy for the exogenous widespread liquidity demand, we find that a stock with a greater level of mutual fund forced sale tends to be less liquid in the next period. This liquidity erosion exists mostly among liquid stocks. We

[14] The 19 indexes that Cremers and Petajisto (2009) are: S&P 500, S&P 400, S&P 600, S&P 500/Barra Value, S&P 500/Barra Growth, Russell 1000, Russell 2000, Russell 3000, Russell Midcap, and the value and growth components of the four, Wilshire 5000, and Wilshire 4000. Due to limited data availability for all the Russell and Wilshire indexes, we use instead the index funds that replicate these indexes.

further find that the liquidity demand deteriorates liquid stocks' liquidity even more during volatile periods, when more funds face outflows and are forced to sell. However, it does not appear to affect illiquid stocks similarly. The liquidity deterioration is also followed by positive return reversals in the subsequent quarter, especially for liquid stocks and during bad market times. Thus, funds who have to trade in the traffic will need to pay higher liquidity premium and are likely to sacrifice fund returns. Thus, it is critical for funds to avoid overlapping their portfolios with others, especially when it comes to liquid stocks holdings.

Table 1.1
Fund-level Summary Statistics

This table presents the summary statistics of the mutual funds in the sample across the firm-quarter observations. A fund has at least \$10 million total net asset to be included in the sample each quarter. $Log(TNA)$ is logarithm of the total net asset of the fund at the end of each quarter. Fund return is the fund's cumulative monthly return within each quarter. Fund cash is defined as the fraction of a funds asset held as cash at the end of each quarter. Fund flow is the fund's percentage monthly flow aggregated over the quarter, where a fund's monthly flow is calculated using Eq.(1). Fund sale is the dollar value of stocks sold by a fund during a certain quarter over the dollar value of the fund stock holdings as of last quarter end. *Sellliquidity* is the value-weighted liquidity of stocks sold by a fund during a certain quarter over the value-weighted fund portfolio liquidity, as defined in Eq.(2). Panel A reports the full-sample summary. Panel B reports the summary for the period of 1993-2003. Panel C reports the summary for the period of 2004-2015. All the variables are winsorized at 5% and 95% level.

Table 1.1
Fund-level Summary Statistics

	N	Mean	Median	Std	25%	75%
Panel A: 1993-2015						
$log(TNA)$	161475	5.508	5.452	1.818	4.179	6.749
Fund return	161475	0.022	0.028	0.094	-0.023	0.076
Fund cash	97415	0.030	0.014	0.055	0.003	0.035
Fund flow	161475	0.017	-0.008	0.144	-0.040	0.038
Fund sale	161475	0.201	0.161	0.157	0.079	0.282
$SellLiquidity$						
$NormAmihud$	161475	-0.018	0.000	0.157	-0.031	0.016
$QSpread$	161475	0.066	0.029	0.345	-0.171	0.251
$RSpread$	161475	0.731	0.505	0.988	0.041	1.187
$ESpread$	161475	-0.265	-0.363	0.382	-0.529	-0.093
Panel B: 1993-2003						
$log(TNA)$	63829	5.314	5.254	1.781	4.013	6.515
Fund return	63829	0.021	0.026	0.106	-0.035	0.080
Fund cash	14577	0.053	0.032	0.068	0.012	0.067
Fund flow	63829	0.037	0.002	0.162	-0.032	0.058
Fund sale	63829	0.212	0.165	0.175	0.070	0.313
$SellLiquidity$						
$NormAmihud$	63829	-0.030	-0.003	0.222	-0.076	0.025
$QSpread$	63829	0.070	0.031	0.381	-0.199	0.289
$RSpread$	63829	1.034	0.774	1.163	0.174	1.625
$ESpread$	63829	-0.023	-0.088	0.440	-0.358	0.245
Panel C: 2004-2015						
$log(TNA)$	97646	5.635	5.601	1.831	4.304	6.891
Fund return	97646	0.022	0.029	0.086	-0.015	0.074
Fund cash	82838	0.028	0.013	0.053	0.003	0.032
Fund flow	97646	0.004	-0.014	0.128	-0.045	0.025
Fund sale	97646	0.194	0.160	0.145	0.084	0.265
$SellLiquidity$						
$NormAmihud$	97646	-0.010	0.000	0.091	-0.016	0.012
$QSpread$	97646	0.063	0.028	0.320	-0.155	0.227
$RSpread$	97646	0.534	0.375	0.794	-0.015	0.925
$ESpread$	97646	-0.423	-0.455	0.227	-0.572	-0.304

Table 1.2
Stock-level Summary Statistics

This table presents summary statistics on the stock-level characteristics across the firm-quarter observations. *NormAmihud*, *QSpread*, *RSpread* and *ESpread* are the liquidity measures, namely normalized Amihud illiquidity ratio, percentage quoted spread, percentage realized spread and percentage effective spread, as defined in Eq.(4), Eq.(5) and Eq.(6) and Eq.(7), respectively. $Log(Size)$ is the logarithm of stock market capitalization as of the end of each quarter. Ret(-12,-1) is defined as the stock's cumulative return over the past 12 months. Return volatility is defined as the stocks monthly return standard deviation over the past 12 months. MF ownership is defined as the number of shares held by mutual funds scaled by total shares outstanding of the stock as of the end of each quarter. MF concentration is defined as the number of shares held by the top five mutual funds that hold the most shares of the stock, scaled by total shares outstanding of the stock, as of the end of each quarter. FS is stock's quarterly forced sale as defined in Eq.(8). Each quarter, we require that the stock be held by at least ten funds in order to be included. Panel A reports the full-sample summary. Panel B reports the summary for the period of 1993-2003. Panel C reports the summary for the period of 2004-2015. All the variables are winsorized at 5% and 95% level.

Table 1.2
Stock-level Summary Statistics

	N	Mean	Median	Std	25 %	75%
Panel A: 1993-2015						
$NormAmihud$	231505	1.038	0.314	3.064	0.263	0.565
$QSpread$ (%)	231505	0.698	0.379	0.931	0.150	0.876
$RSpread$ (%)	231505	0.382	0.154	0.600	0.055	0.461
$ESpread$ (%)	231505	0.649	0.416	0.720	0.202	0.839
$log(Size)$	231505	6.760	6.575	1.607	5.617	7.731
Ret(-12,-1)	224862	0.226	0.109	0.854	-0.141	0.394
Return volatility	224862	0.126	0.105	0.086	0.073	0.154
MF ownership	231505	0.159	0.149	0.095	0.083	0.223
MF concentration	231505	0.008	0.004	0.015	0.002	0.009
FS (%)	231505	0.466	0.165	0.769	0.013	0.572
Panel B: 1993-2003						
$NormAmihud$	102966	0.829	0.329	2.038	0.269	0.583
$QSpread$ (%)	102966	1.036	0.737	0.992	0.399	1.329
$RSpread$ (%)	102966	0.579	0.320	0.721	0.106	0.809
$ESpread$ (%)	102966	0.864	0.657	0.758	0.362	1.123
$log(Size)$	102966	6.683	6.486	1.514	5.606	7.575
Ret(-12,-1)	98763	0.250	0.107	0.933	-0.150	0.412
Return volatility	98763	0.137	0.113	0.092	0.078	0.168
MF ownership	102966	0.145	0.131	0.087	0.077	0.199
MF concentration	102966	0.006	0.004	0.010	0.002	0.007
FS (%)	102966	0.447	0.120	0.826	0.002	0.503
Panel C: 2004-2015						
$NormAmihud$	128539	1.206	0.303	3.677	0.260	0.548
$QSpread$ (%)	128539	0.428	0.191	0.781	0.090	0.435
$RSpread$ (%)	128539	0.224	0.095	0.419	0.038	0.239
$ESpread$ (%)	128539	0.476	0.275	0.638	0.139	0.548
$log(Size)$	128539	6.821	6.655	1.676	5.628	7.862
Ret(-12,-1)	126099	0.207	0.111	0.786	-0.133	0.380
Return volatility	126099	0.118	0.100	0.080	0.069	0.144
MF ownership	128539	0.170	0.165	0.099	0.091	0.239
MF concentration	128539	0.010	0.005	0.018	0.002	0.010
FS (%)	128539	0.482	0.203	0.719	0.027	0.621

Table 1.3
Summary Statistics Across Stock Liquidity Levels

This table reports the stock-level characteristics and the forced sale pressure measures using one-way sorts on the one of the stock liquidity measures, $QSpread$. $QSpread$ is the percent quoted spread as defined in Eq.(4). In particular, each quarter we sort stocks into quintiles based on $QSpread$ as of last quarter end. We then calculate the average stock characteristics across the firm-quarter observations within each quintile . N represents the number of firm-quarter observations. $Log(Size)$ is the logarithm of stock market capitalization as of the end of each quarter. Ret(-12,-1) is defined as the stock's cumulative return over the past 12 months. Return volatility is defined as the stocks monthly return standard deviation over the past 12 months. MF ownership is defined as the number of shares held by mutual funds scaled by total shares outstanding of the stock as of the end of each quarter. MF concentration is defined as the number of shares held by the top five mutual funds that hold the most shares of the stock, scaled by total shares outstanding of the stock, as of the end of each quarter. FS is stock's quarterly forced sale as defined in Eq.(8). All the variables are winsorized at 5% and 95% level.

Table 1.3
Summary Statistics Sorted on Stock Liquidity Level

	Liquid (Q1)	Q2	Q3	Q4	Illiquid (Q5)
Panel A: 1993-2015					
N	87049	64556	46079	26170	7641
$NormAmihud$	0.284	0.422	0.857	2.419	11.173
$QSpread$ (%)	0.280	0.576	0.990	1.295	2.686
$RSpread$ (%)	0.137	0.316	0.590	0.738	1.251
$ESpread$ (%)	0.295	0.549	0.893	1.207	2.129
$log(Size)$	8.186	6.505	5.712	5.166	4.447
Ret(-12,-1)	0.256	0.261	0.210	0.104	0.077
Return volatility	0.101	0.136	0.151	0.143	0.124
MF ownership	0.180	0.173	0.138	0.110	0.094
MF concentration	0.003	0.007	0.012	0.017	0.019
Forced sale (%)	0.558	0.517	0.425	0.244	0.121
Panel B: 1993-2003					
N	47743	30043	19284	5122	1364
$NormAmihud$	0.299	0.542	1.293	4.724	14.422
$QSpread$ (%)	0.455	1.023	1.852	3.107	5.825
$RSpread$ (%)	0.208	0.549	1.117	1.954	3.785
$ESpread$ (%)	0.433	0.864	1.456	2.391	4.438
$log(Size)$	7.796	6.113	5.383	4.779	4.175
Ret(-12,-1)	0.299	0.281	0.158	-0.065	-0.173
Return volatility	0.111	0.154	0.168	0.167	0.160
MF ownership	0.160	0.139	0.123	0.127	0.138
MF concentration	0.003	0.007	0.010	0.017	0.026
Forced sale (%)	0.480	0.454	0.399	0.355	0.449
Panel C: 2004-2015					
N	39306	34113	26795	21048	6277
$NormAmihud$	0.264	0.316	0.544	1.858	11.011
$QSpread$ (%)	0.068	0.178	0.370	0.855	5.825
$RSpread$ (%)	0.050	0.108	0.211	0.442	3.785
$ESpread$ (%)	0.128	0.267	0.487	0.919	4.438
$log(Size)$	8.659	6.855	5.949	5.260	4.460
Ret(-12,-1)	0.204	0.245	0.246	0.142	0.088
Return volatility	0.088	0.121	0.140	0.138	0.123
MF ownership	0.203	0.204	0.148	0.106	0.092
MF concentration	0.004	0.008	0.013	0.017	0.019
Forced sale (%)	0.627	0.594	0.444	0.217	0.105

Table 1.4
Fund Benchmark-adjusted Liquidity

This table reports the average difference in liquidity measures between the funds in the sample and their respective benchmark. For each mutual fund, a time-series regression of its quarterly return is run on the return of each of the eight Vanguard domestic index funds as in Berk and Binsberen (2015). The benchmark for the mutual fund for a quarter is the one which yields the greatest R-square and is available during the quarter. Panel A reports the average difference in liquidity measures sorted on the fund size as of last quarter end. Panel B reports the average difference in each of the four liquidity measures by the CRSP investment objective code. The funds objectives that are reported are Micro funds (CI), Small-cap funds (CS), Medium-cap funds (CM), Balanced funds (YB), Income funds (YI), Growth funds (YB) and Style funds (S). The difference is first averaged across the fund during the same quarter and then averaged across all quarters. t-stats are reported in parentheses.

Panel A: Sort on Fund Size							
	Full	Small	S2	S3	S4	Big	
$NormAmihud$	0.0072	0.0490	0.0111	-0.0027	-0.0240	-0.0258	
	(1.68)	(5.37)	(4.66)	(3.09)	(1.32)	(1.59)	
$Qspread$	0.0421	0.0575	0.0500	0.0322	0.0341	0.0302	
	(7.75)	(8.28)	(7.27)	(6.40)	(5.73)	(6.16)	
$Rspread$	0.0313	0.0487	0.0403	0.0316	0.0298	0.0256	
	(8.31)	(9.35)	(8.13)	(7.64)	(6.12)	(7.49)	
$Espread$	0.0363	0.0413	0.0336	0.0287	0.0278	0.0218	
	(8.72)	(8.31)	(7.57)	(7.73)	(6.80)	(7.51)	
Panel B: Sort on Fund Objectives							
	CI	CS	CM	YI	YB	YG	S
$NormAmihud$	1.0406	0.0872	-0.2915	-0.0875	0.0263	0.0429	0.0665
	(52.20)	(8.22)	(-13.88)	(-12.35)	(9.94)	(9.12)	(5.01)
$Qspread$	0.4874	0.1097	-0.0773	-0.0048	0.0292	0.0187	0.0566
	(14.90)	(7.49)	(-10.03)	(-1.82)	(8.36)	(6.06)	(5.83)
$Rspread$	0.4043	0.0984	-0.0496	0.002	0.0188	0.0084	0.0536
	(19.47)	(7.91)	(-9.96)	(0.87)	(8.01)	(4.02)	(7.19)
$Espread$	0.2603	0.0939	-0.0298	0.0021	0.0124	0.0072	0.0421
	(11.36)	(7.68)	(-6.38)	(1.97)	(7.00)	(3.56)	(6.96)

Table 1.5
Mutual Fund Sale, Fund Flows and Market States

This table reports the regressions of the fund sale on fund flows. The dependent variable is the fund sale, defined as the fraction of fund portfolio dollar value sold during a certain quarter. $NegFlow$ is a dummy variable that is equal to one if the fund's concurrent percentage quarterly flow falls into the bottom flow quintile compared to the rest of the funds in the sample. $log(VIX)$ is the logarithm of the VIX index of implied volatility of S&P 500 index options as of the end of prior quarter. $Mktflow$ is a dummy indicator, which is equal to one if the aggregate market flow of the concurrent quarter is below the median level, and zero otherwise. $Log(TNA)$ is logarithm of the total net asset of the fund at the end of each quarter. Fund return is the fund's quarterly return as of the end of each quarter. Fund cash is defined the fraction of a funds asset held as cash at the end of each quarter. Fund fixed effects are included and the coefficients are clustered on both the fund level and the time level. $t-$statistics are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
$NegFlow$	0.074***	0.077***	0.074***	0.076***
	(42.05)	(40.03)	(5.48)	(39.84)
$NegFlow$*$log(VIX)$			0.003**	
			(2.24)	
$NegFlow$*$Mktflow$				0.007**
				(2.12)
$log(VIX)$			0.002	
			(1.19)	
$Mktflow$				-0.003
				(-0.37)
$log(TNA)$		-0.010***	-0.010***	-0.010***
		(-5.58)	(-6.01)	(-5.56)
Fund return		0.024	0.028	0.023
		(0.79)	(0.96)	(0.76)
Cash		0.049***	0.055***	0.049***
		(2.87)	(3.24)	(2.84)
Constant	0.184***	0.232***	0.226***	0.233***
	(70.99)	(20.74)	(7.53)	(20.49)
Fund FE	Yes	Yes	Yes	Yes
Obs.	161475	97415	97415	97415
Adjusted R^2	0.036	0.062	0.062	0.062

Table 1.6
Mutual Fund Sell Liquidity, Fund Flows and Market States

This table reports the regressions of the fund sell liquidity on variables associated with fund flows , market volatility and other control variables. The dependent variable is the fund sell liquidity as defined in Eq.(2). $log(VIX)$ is the logarithm of the VIX index of implied volatility of S&P 500 index options as of the end of prior quarter. $Mktflow$ is a dummy indicator, which is equal to one if the aggregate market flow of the concurrent quarter is below the median level, and zero otherwise. $NegFlow$ is a dummy variable that is equal to one if the fund's concurrent percentage quarterly flow falls into the bottom flow quintile compared to the rest of the funds in the sample. $Log(TNA)$ is logarithm of the total net asset of the fund at the end of each quarter. Fund return is the fund's quarterly return as of the end of each quarter. Fund cash is defined the fraction of a funds asset held as cash at the end of each quarter. Columns (1), (4), (7) and (10) report the regression on only $NegFlow$ and other control variables. Columns (2), (5), (8) and (11) report regressions on $NegFlow$, the interaction of $NegFlow$ with $Log(VIX)$, and other control variables. Columns (3), (6), (9) and (12) report regressions on $NegFlow$, the interaction of fund flow with $Mktflow$, and other control variables. In Panel B, Columns (1), (4), (7) and (10) report the regression on only $NegFlow$ and other control variables. Columns (2), (5), (8) and (11) report regressions on $NegFlow$, the interaction of $NegFlow$ with $Log(VIX)$, and other control variables. Columns (3), (6), (9) and (12) report regressions on $NegFlow$, the interaction of fund flow with $Mktflow$, and other control variables. Fund fixed effects are included and the coefficients are clustered on both the fund level and the time level. $t-$statistics are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

Table 1.6
Mutual Fund Sell Liquidity, Fund Flows and Market States

Panel A: Regressions with *Flow*

	NormAmihud			*QSpread*			*RSpread*			*ESpread*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NegFlow	-0.005***	-0.003	-0.005***	-0.032***	-0.012**	-0.033***	-0.045***	-0.023	-0.046***	-0.015***	-0.009*	-0.015***
	(-3.69)	(-1.32)	(-3.39)	(-6.91)	(-2.31)	(-6.72)	(-2.62)	(-1.18)	(-2.92)	(-3.32)	(-1.67)	(-2.97)
*NegFlow***log*(*VIX*)		-0.003*			-0.015**			-0.022*			-0.002	
		(-1.83)			(-2.09)			(-1.77)			(-0.19)	
log(*VIX*)		0.010			-0.006			0.470**			0.036	
		(0.53)			(-0.07)			(2.02)			(0.57)	
*NegFlow***Mktflow*			-0.001			-0.001			-0.006			-0.003
			(-0.35)			(-0.09)			(-0.29)			(-0.38)
Mktflow			-0.008			0.013			0.500***			0.119**
			(-0.87)			(0.26)			(2.71)			(2.07)
log(*TNA*)	0.000	0.000	0.000	-0.006	-0.006	-0.006	-0.019	-0.015	-0.021	-0.015	-0.015	-0.015
	(0.03)	(0.04)	(0.03)	(-0.49)	(-0.53)	(-0.48)	(-0.59)	(-0.46)	(-0.63)	(-1.07)	(-1.00)	(-1.23)
Fund return	0.041	0.054	0.044	-0.321	-0.335	-0.326	-0.127	0.549	-0.304	-0.026	0.024	-0.068
	(0.78)	(1.32)	(0.78)	(-1.35)	(-1.57)	(-1.41)	(-0.17)	(0.82)	(-0.43)	(-0.14)	(0.15)	(-0.39)
Cash	0.135*	0.134*	0.133*	0.152	0.153	0.155	0.709*	0.768*	0.568	0.665***	0.670***	0.632***
	(1.85)	(1.91)	(1.88)	(1.29)	(1.32)	(1.29)	(1.70)	(1.88)	(1.45)	(3.35)	(3.39)	(3.56)
Constant	-0.010	-0.040	-0.008	0.115	0.134	0.112	0.698***	-0.713	0.569***	-0.312***	-0.419*	-0.343***
	(-0.31)	(-0.57)	(-0.26)	(1.51)	(0.53)	(1.36)	(3.86)	(-1.02)	(2.89)	(-3.70)	(-1.93)	(-4.69)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	97409	97409	97409	97415	97415	97415	97415	97415	97415	97415	97415	97415
Adjusted R^2	0.005	0.006	0.006	0.011	0.011	0.011	0.004	0.035	0.075	0.026	0.027	0.060

Table 1.7
Regressions of Change in Stock Liquidity on Forced Sale

This table reports the regressions of the following model,

$$\Delta LM_{i,q} = \alpha_i + FS_{i,q} + b\mathbf{X}_{i,q-1} + c\mathbf{M}_{q-1} + \varepsilon_{i,q}$$

where $\Delta LM_{i,q}$ is the change of one of the four liquidity measures for stock i at quarter q. $\mathbf{X}_{i,q-1}$ is a vector of firm level characteristics at the end of quarter $q-1$, including the firm size, Ret(-12,-1), stock return volatility, MF ownership and MF concentration. $\mathbf{M}_{q-1}$ is a vector of market wide variables, including the market excess return and market illiquidity at the end of quarter $q-1$. Prior LM is the average of the stock liquidity measure over the last four quarters. ΔLM_{t-1} is the lag of the dependent variable. Column (1) to Column (4) reports the regressions with *NormAmihud*, *QSpread*, *RSpread* and *ESpread*, respectively, as the liquidity measure. Firm fixed effects are included to account for the time invariant firm variation. The coefficients are all clustered on both the firm level and the time level. t-statistics are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	(1) $NormAmihud$	(2) $QSpread$	(3) $RSpread$	(4) $ESpread$
FS	0.464**	0.010***	0.007***	0.011***
	(2.34)	(2.63)	(2.69)	(3.13)
Prior LM	0.011***	0.052**	0.017	0.018
	(6.99)	(2.41)	(1.18)	(1.14)
ΔLM_{t-1}	-0.095***	-0.087**	-0.276**	-0.224*
	(-5.25)	(-1.97)	(-2.26)	(-1.88)
$log(Size)$	0.007*	0.002***	<0.001	<0.001
	(1.85)	(2.81)	(0.82)	(0.68)
MF ownership	0.101***	0.002***	0.001**	0.001***
	(4.29)	(3.35)	(2.33)	(3.10)
MF concentration	-1.178*	-0.015	-0.007	-0.015
	(-1.94)	(-1.36)	(-1.03)	(-1.56)
Ret(-12,-1)	-0.007**	<0.001	<0.001	<0.001
	(-2.33)	(0.13)	(1.01)	(0.85)
Return volatility	-0.028	-0.003***	-0.002***	-0.003***
	(-0.65)	(-3.61)	(-3.03)	(-3.83)
Market excess return	-0.324**	-0.005	-0.003*	-0.005**
	(-2.30)	(-1.64)	(-1.75)	(-2.12)
Market illiquidity	0.031	-0.113**	-0.152*	-0.098
	(0.63)	(-2.40)	(-1.88)	(-1.37)
Constant	-0.083**	-0.002***	-0.001	-0.001
	(-1.97)	(-2.64)	(-0.67)	(-0.49)
Obs.	205562	205541	205557	205557
Adjusted R^2	0.039	0.063	0.099	0.079
Firm FE	Yes	Yes	Yes	Yes

Table 1.8
Cross-sectional Effect of Forced Sale on Stock Liquidity

This table reports the following regression,

$$\Delta LM_{i,q} = \alpha_i + FS_{i,q} + FS_{i,q} * Liquid + b\mathbf{X}_{i,q-1} + c\mathbf{M}_{q-1} + \varepsilon_{i,q}$$

where $\Delta LM_{i,q}$ is the change of one of the four liquidity measures for stock i at quarter q. *Liquid* is a dummy variable equal to 1 if stock i is at the most liquid tertile as of last quarter end. $\mathbf{X}_{i,q-1}$ is a vector of firm level characteristics, including the firm size, Ret(-12,-1), stock return volatility, MF ownership and MF concentration, at the end of quarter $q-1$. $\mathbf{M}_{q-1}$ is a vector of market wide variables, including the market excess return and market liquidity at the end of quarter $q-1$. ΔLM_{t-1} is the liquidity change at quarter $q-1$. Columns (1), (2), (3) and (4) report the regressions with $NormAmihud$, *QSpread*, *RSpread* and *ESpread*, respectively. $Middle$ is a dummy variable which is equal to one if the stock is at the middle liquidity tertile. Firm fixed effects are included and the coefficients are clustered on both the firm and the time level. $t-$statistics are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	(1) $NormAmihud$	(2) *QSpread*	(3) *RSpread*	(4) *ESpread*
FS*$Liquid$	3.259***	0.042***	0.034***	0.065***
	(4.24)	(2.66)	(3.46)	(3.35)
FS	-3.029***	-0.033**	-0.026***	-0.054***
	(-3.62)	(-2.11)	(-2.96)	(-3.10)
Liquid	0.123***	0.001***	0.002***	0.002***
	(9.22)	(4.44)	(5.79)	(3.64)
FS*$Middle$	2.973***	0.039**	0.029***	0.061***
	(3.57)	(2.44)	(3.27)	(3.45)
$Middle$	0.064***	0.001***	0.001***	0.001***
	(6.01)	(3.76)	(5.60)	(3.29)
ΔLM_{t-1}	-0.078***	-0.070	-0.247**	-0.198*
	(-4.41)	(-1.63)	(-2.16)	(-1.84)
$log(Size)$	-0.012***	<0.001	<0.001	<0.001
	(-3.36)	(-1.28)	(-0.90)	(-1.02)
MF ownership	-0.003	<0.001	<0.001	<0.001
	(-0.12)	(0.65)	(-1.15)	(-0.68)
MF concentration	0.018	-0.005	0.003	<0.001
	(0.03)	(-0.43)	(0.51)	(0.01)
Ret(-12,-1)	-0.005*	<0.001	0.001*	<0.001
	(-1.91)	(0.50)	(1.78)	(1.52)
Return volatility	-0.120***	-0.003***	-0.002***	-0.003***
	(-2.93)	(-4.37)	(-3.62)	(-4.16)
Market excess return	-0.346**	-0.005*	-0.003*	-0.005**
	(-2.47)	(-1.66)	(-1.82)	(-2.21)
Market illiquidity	-0.120**	-0.087**	-0.213***	-0.159**
	(-2.53)	(-2.21)	(-3.11)	(-2.53)
Constant	0.043	<0.001	<0.001	<0.001
	(1.03)	(-0.70)	(-0.93)	(-0.34)
Obs.	207369	207350	207367	207367
Adjusted R^2	0.042	0.032	0.108	0.086
Firm FE	Yes	Yes	Yes	Yes

Table 1.9
Stock Liquidity, Forced Sale and Market States

This table reports the regressions of stock liquidity change on the mutual fund forced sale of the stock across varying market states. A quarter with the market aggregate flow as of the last quarter end lower than the median market flow level across the sample period is defined as low market flow periods. Otherwise, a quarter is defined as high market flow periods. Under both low flow periods and high flow periods, we run the following regression,

$$\Delta LM_{i,q} = \alpha_i + aFS_{i,q} + bFS_{i,q} * Liquid + c\mathbf{X}_{i,q-1} + d\mathbf{M}_{q-1} + \varepsilon_{i,q}$$

where $\Delta LM_{i,q}$ is the change of one of the four liquidity measures for stock i at quarter q. *Liquid* is a dummy variable equal to 1 if stock i is at the bottom illiquid tertile (most liquid) as of last quarter end. $\mathbf{X}_{i,q-1}$ is a vector of firm level characteristics, including the firm size, Ret(-12,-1), stock return volatility, MF ownership and MF concentration, at the end of quarter $q-1$. $\mathbf{M}_{q-1}$ is a vector of market wide variables, including the market excess return and market liquidity at the end of quarter $q-1$. ΔLM_{t-1} is the change in liquidity at quarter $q-1$. $Middle$ is a dummy variable which is equal to one if the stock is at the middle tertile. Firm fixed effects are included and the coefficients are clustered on both the firm and the time level. $t-$statistics are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

Table 1.9

Stock Liquidity, Forced Sale and Market States

	NormAmihud		*QSpread*		*RSpread*		*ESpread*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Market flow	Low	High	Low	High	Low	High	Low	High
FS*$Liquid$	3.292**	3.111***	0.047*	0.032*	0.043**	0.020**	0.093***	0.031**
	(2.21)	(3.86)	(1.79)	(1.93)	(2.39)	(2.36)	(3.08)	(2.42)
FS	-2.815*	-3.174***	-0.034	-0.027	-0.026	-0.019**	-0.073***	-0.027*
	(-1.78)	(-3.51)	(-1.06)	(-1.52)	(-1.62)	(-1.96)	(-2.63)	(-1.93)
$Liquid$	0.136***	0.115***	0.002***	0.001***	0.002***	0.001***	0.003***	0.001***
	(5.67)	(7.12)	(2.65)	(3.73)	(3.36)	(8.92)	(2.62)	(7.36)
FS*$Middle$	2.893*	3.056***	0.047	0.028	0.034**	0.019**	0.088***	0.029**
	(1.84)	(3.41)	(1.46)	(1.59)	(1.99)	(2.01)	(3.11)	(2.10)
$Middle$	0.068***	0.064***	0.001**	0.001***	0.002***	0.001***	0.002**	0.001***
	(3.83)	(4.49)	(2.06)	(3.18)	(3.11)	(8.03)	(2.14)	(7.06)
ΔLM_{t-1}	-0.114***	-0.039	-0.116**	-0.008	-0.339**	-0.110**	-0.311**	-0.042
	(-4.88)	(-1.53)	(-2.09)	(-0.13)	(-2.13)	(-2.40)	(-2.05)	(-1.49)
$log(Size)$	-0.014**	-0.010**	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	(-2.27)	(-2.49)	(-0.94)	(-0.65)	(-0.65)	(-1.24)	(-0.85)	(-1.21)
MF ownership	-0.0369	0.0184	<0.001	0.001	-0.001	<0.001	-0.001	<0.001
	(-0.99)	(0.60)	(-0.49)	(1.10)	(-1.26)	(-0.32)	(-1.44)	(0.46)
MF concentration	0.793	-0.387	0.016	-0.018	0.017	-0.004	0.020	-0.011
	(1.04)	(-0.42)	(1.36)	(-1.02)	(1.51)	(-0.64)	(1.27)	(-0.81)
Ret(-12,-1)	-0.004	-0.009**	0.001*	<0.001	<0.001**	<0.001	<0.001*	<0.001
	(-1.13)	(-2.49)	(1.76)	(-0.39)	(2.32)	(0.36)	(2.18)	(0.11)
Return volatility	-0.087	-0.100**	-0.004**	-0.002***	-0.002**	-0.001***	-0.003**	-0.002***
	(-1.45)	(-2.06)	(-2.55)	(-2.90)	(-2.09)	(-3.02)	(-2.10)	(-3.56)
Market excess return	-0.263	-0.421*	-0.006	-0.004	-0.002	-0.002	-0.004	-0.005*
	(-1.51)	(-1.93)	(-1.49)	(-0.93)	(-1.05)	(-1.57)	(-1.30)	(-1.71)
Market illiquidity	-0.115	-0.354***	-0.084	-0.214**	-0.257***	-0.277**	-0.187**	-0.246**
	(-1.60)	(-3.34)	(-1.50)	(-2.14)	(-3.48)	(-2.29)	(-2.35)	(-2.15)
Constant	0.0457	0.114**	<0.001	<0.001	-0.001	<0.001	-0.001	<0.001
	(0.66)	(2.09)	(-0.49)	(-0.35)	(-0.89)	(-0.58)	(-0.50)	(0.10)
Obs.	94378	112991	94357	112993	94374	112993	94374	112993
Adjusted R^2	0.048	0.048	0.044	0.033	0.142	0.075	0.133	0.055
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 1.10
Abnormal Stock Returns Following Forced Sale Across Market States

This table reports the cumulative abnormal returns (CARs) and monthly average abnormal returns (ARs) for stocks following the forced sale. Each quarter the stocks are ranked on its FS into deciles. We then calculate the ARs and the CARs over the subsequent quarter by averaging first within the deciles of the same period and then across the quarters. A quarter with the market aggregate flow as of the last quarter end lower than the median market flow level across the sample period is defined as low market flow periods. Otherwise, a quarter is defined as high market flow periods. Abnormal returns are calculated by following Daniel et al. (1997) (DGTW). Abnormal returns for each stock are measured in excess of both equal-weighted and value-weighted DGTW portfolios. All reported statistics are calculated from the time series of CARs and ARs. t-statistics are reported below each variable in parentheses. Statistical significance of (H-L) $t-stat$ is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

Panel A: High Market Flow Periods

	Low FS	2	3	4	5	6	7	8	9	High FS	H - L
CAR-VW (%)	0.043	-0.332	0.860	0.201	0.475	0.097	-0.003	0.123	0.184	0.136	0.093
$t-stat$	(0.16)	(-1.04)	(1.03)	(0.97)	(2.38)	(0.50)	(-0.01)	(0.61)	(0.71)	(0.36)	(0.19)
AR-VW (%)	-0.024	-0.151	0.201	0.047	0.136	0.034	0.001	0.027	0.047	0.026	0.050
$t-stat$	(-0.25)	(-1.52)	(0.93)	(0.66)	(2.03)	(0.52)	(0.01)	(0.40)	(0.52)	(0.20)	(0.31)
CAR-EW (%)	-0.217	-0.571	0.731	0.124	0.435	-0.046	-0.099	0.011	0.072	0.113	0.330
$t-stat$	(-0.58)	(-1.39)	(0.82)	(0.48)	(1.86)	(-0.23)	(-0.38)	(0.05)	(0.25)	(0.29)	(0.61)
AR-EW (%)	-0.117	-0.230	0.154	0.022	0.118	-0.012	-0.033	-0.011	0.007	0.016	0.133
$t-stat$	(-0.96)	(-1.75)	(0.66)	(0.25)	(1.50)	(-0.18)	(-0.37)	(-0.14)	(0.06)	(0.12)	(0.72)

Panel B: Low Market Flow Periods

	Low FS	2	3	4	5	6	7	8	9	High FS	H - L
CAR-VW (%)	0.031	-0.567	-0.742	-0.249	0.169	0.201	0.082	0.128	-0.094	1.544	1.513**
$t-stat$	(0.06)	(-1.34)	(-1.41)	(-0.87)	(0.68)	(0.82)	(0.20)	(0.40)	(-0.23)	(3.31)	(2.20)
AR-VW (%)	0.034	-0.161	-0.238	-0.114	0.037	0.083	0.038	0.041	-0.018	0.498	0.464**
$t-stat$	(0.21)	(-1.17	(-1.64)	(-1.26)	(0.49)	(1.17)	(0.31)	(0.43)	(-0.13)	(3.21)	(2.09)
CAR-EW (%)	-0.180	-0.461	-0.671	-0.239	0.190	0.166	0.052	0.082	-0.129	1.518	1.698**
$t-stat$	(-0.32)	(-0.99)	(-1.26)	(-0.76)	(0.73)	(0.63)	(0.12)	(0.25)	(-0.30)	(3.07)	(2.07)
AR-EW (%)	-0.039	-0.129	-0.214	-0.115	0.043	0.071	0.020	0.025	-0.033	0.483	0.522**
$t-stat$	(-0.23)	(-0.89)	(-1.49)	(-1.19)	(0.54)	(0.92)	(0.16)	(0.25)	(-0.24)	(2.95)	(2.21)

Table 1.11
Cross-Section Abnormal Stock Returns Following Forced Sale

This table reports the cumulative abnormal returns (CARs) for liquid stocks and illiquid stocks following the forced sale. Each quarter the stocks sorted on its liquidity (*NormAmihud*, *QSpread*, *ESpread*, and *RSpread*) as of last quarter end into quintiles. Independently, stocks are ranked on its FS into quintiles. We then calculate the CARs over the subsequent quarter by averaging first within the illiquidity quintiles of the same period and then across the quarters. This table reports CARs for stocks that are most liquid (G1) and least liquid (G5). Abnormal returns are calculated by following Daniel et al. (1997) (DGTW). Abnormal returns for each stock are measured in excess of both equal-weighted and value-weighted DGTW portfolios. t-statistics are reported below each variable in parentheses. Statistical significance of (H-L) $t-stat$ is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	NormAmihud				*Qspread*				*RSpread*				*ESpread*			
	CAR-VW (%)		CAR-EW (%)		CAR-VW (%)		CAR-EW (%)		CAR-VW (%)		CAR-EW (%)		CAR-VW (%)		CAR-EW (%)	
	G1	G5	G1	G5	G1	G5	G1	G5	G1	G5	G1	G5	G1	G5	G1	G5
Low FS	-1.592	0.394	-1.676	-0.102	-0.868	0.446	-0.961	0.379	-0.425	-0.241	-0.499	-0.579	-0.499	0.227	-0.549	-0.251
$t-stat$	(-2.77)	(0.46)	(-2.94)	(-0.11)	(-1.85)	(1.97)	(-2.05)	(1.75)	(-0.99)	(-0.23)	(-1.10)	(-0.52)	(-1.29)	(0.13)	(-1.44)	(-0.13)
2	-0.269	-0.844	-0.383	-1.038	-0.761	0.347	-0.795	0.356	-0.148	-0.675	-0.220	-0.487	0.009	-1.197	-0.101	-1.481
$t-stat$	(-1.12)	(-0.38)	(-1.56)	(-0.46)	(-2.06)	(1.09)	(-2.11)	(1.02)	(-0.51)	(-0.29)	(-0.76)	(-0.20)	(0.03)	(-0.50)	(-0.36)	(-0.59)
3	0.073	0.336	-0.057	-0.062	0.150	0.864	0.019	0.756	-0.005	1.202	-0.108	1.107	0.050	1.750	-0.072	2.281
$t-stat$	(0.52)	(0.15)	(-0.42)	(-0.03)	(0.46)	(1.57)	(0.05)	(1.16)	(-0.02)	(0.51)	(-0.45)	(0.46)	(0.22)	(0.57)	(-0.33)	(0.68)
4	0.032	0.392	-0.087	0.351	0.394	0.034	0.151	-0.203	-0.053	1.424	-0.155	1.454	0.097	-4.122	-0.018	-4.339
$t-stat$	(0.17)	(0.18)	(-0.49)	(0.15)	(0.99)	(0.04)	(0.31)	(-0.22)	(-0.19)	(0.44)	(-0.60)	(0.43)	(0.39)	(-1.31)	(-0.07)	(-1.38)
High FS	0.365	-1.554	0.306	-1.589	0.833	-0.618	0.559	-0.546	0.525	1.597	0.472	1.718	0.550	-0.259	0.488	-0.401
$t-stat$	(1.56)	(-0.70)	(1.36)	(-0.70)	(0.48)	(-0.20)	(0.31)	(-0.17)	(2.05)	(0.54)	(1.84)	(0.55)	(2.22)	(-0.10)	(1.96)	(-0.16)
H - L	1.957***	-1.948	1.982***	-1.487	1.701**	-1.064	1.520**	-0.925	0.950*	1.838	0.971*	2.297	1.049**	-0.486	1.037**	-0.652
$t-stat$	(3.15)	(-0.82)	(3.24)	(-0.61)	(2.52)	(-0.41)	(2.60)	(-0.32)	(1.90)	(0.58)	(1.87)	(0.69)	(2.29)	(-0.16)	(2.27)	(-0.05)

Table 1.12
Cross-Section Abnormal Stock Returns Following Forced Sale across Market States

This table reports the cumulative abnormal returns (CARs) for liquid stocks and illiquid stocks following the forced sale under varying market states. Each quarter the stocks sorted on its liquidity ($NormAmihud$, $QSpread$, $ESpread$, and $RSpread$) as of last quarter end into quintiles. Independently, stocks are ranked on its FS into quintiles. We then calculate the CARs over the subsequent quarter by averaging first within the illiquidity quintiles of the same period and then across the quarters. A quarter with the market aggregate flow as of the last quarter end lower than the median market flow level across the sample period is defined as low market flow periods. Otherwise, a quarter is defined as high market flow periods. Panel A reports CARs for stocks that are most liquid (G1) and least liquid (G5) under low market periods. Panel B reports CARs for stocks that are most liquid (G1) and least liquid (G5) under high market periods. Abnormal returns are calculated by following Daniel et al. (1997) (DGTW). Abnormal returns for each stock are measured in excess of both equal-weighted and value-weighted DGTW portfolios. t-statistics are reported below each variable in parentheses.

Table 1.12
Cross-Section Abnormal Stock Returns Following Forced Sale across Market States

Panel A: High Market Flow

	NormAmihud				*Qspread*				*RSpread*				*ESpread*			
	CAR-VW (%)		CAR-EW (%)		CAR-VW (%)		CAR-EW (%)		CAR-VW (%)		CAR-EW (%)		CAR-VW (%)		CAR-EW (%)	
	G1	G5	G1	G5	G1	G5	G1	G5	G1	G5	G1	G5	G1	G5	G1	G5
Low FS	-1.337	0.431	-1.350	-0.152	-0.707	0.952	-0.709	0.401	-0.043	0.280	-0.121	-0.213	-0.435	-0.022	-0.438	-0.616
$t-stat$	(-2.10)	(0.45)	(-2.27)	(-0.16)	(-1.11)	(0.89)	(-1.16)	(0.36)	(-0.08)	(0.33)	(-0.21)	(-0.23)	(-0.85)	(-0.02)	(-0.87)	(-0.50)
2	0.203	-1.024	0.055	-1.397	0.211	2.352	0.072	1.819	0.077	-2.883	-0.026	-3.246	0.355	-1.182	0.225	-2.003
$t-stat$	(0.78)	(-0.40)	(0.22)	(-0.53)	(0.72)	(0.96)	(0.25)	(0.74)	(0.22)	(-1.01)	(-0.07)	(-1.12)	(1.20)	(-0.37)	(0.76)	(-0.62)
3	0.215	0.663	0.067	-0.092	0.198	0.520	0.064	0.031	0.169	3.501	0.041	2.856	0.296	2.605	0.155	2.345
$t-stat$	(1.12)	(0.24)	(0.44)	(-0.03)	(1.07)	(0.17)	(0.41)	(0.01)	(0.62)	(1.15)	(0.16)	(0.98)	(1.22)	(0.79)	(0.70)	(0.72)
4	-0.050	-0.992	-0.174	-1.179	0.212	-0.955	0.090	-1.427	0.206	1.161	0.073	0.581	0.297	-5.310	0.174	-5.464
$t-stat$	(-0.22)	(-0.38)	(-0.82)	(-0.45)	(0.96)	(-0.39)	(0.43)	(-0.57)	(0.75)	(0.42)	(0.28)	(0.23)	(1.16)	(-1.60)	(0.72)	(-1.62)
High FS	-0.009	-0.584	-0.042	-0.518	0.177	-0.204	0.144	-0.363	0.578	-0.196	0.531	-0.788	0.501	-2.334	0.465	-2.614
$t-stat$	(-0.03)	(-0.19)	(-0.15)	(-0.17)	(0.62)	(-0.09)	(0.51)	(-0.16)	(1.90)	(-0.08)	(1.71)	(-0.33)	(1.63)	(-0.87)	(1.51)	(-0.98)
H - L	1.328*	-1.015	1.308**	-0.366	0.884	-1.156	0.853	-0.764	0.621	-0.476	0.652	-0.575	0.936	-2.312	0.903	-1.998
$t-stat$	(1.91)	(-0.32)	(1.99)	(-0.11)	(1.27)	(-0.46)	(1.36)	(-0.31)	(1.02)	(-0.19)	(1.00)	(-0.23)	(1.56)	(-0.79)	(1.53)	(-0.68)

Panel B: Low Market Flow

	NormAmihud				*Qspread*				*RSpread*				*ESpread*			
	CAR-VW (%)		CAR-EW (%)		CAR-VW (%)		CAR-EW (%)		CAR-VW (%)		CAR-EW (%)		CAR-VW (%)		CAR-EW (%)	
	G1	G5	G1	G5	G1	G5	G1	G5	G1	G5	G1	G5	G1	G5	G1	G5
Low FS	-1.866	0.352	-2.026	-0.045	-1.042	0.700	-1.232	0.738	-0.825	-0.815	-0.815	-0.980	-1.003	0.507	-1.032	0.160
$t-stat$	(-1.89)	(0.23)	(-2.03)	(-0.03)	(-1.49)	(0.20)	(-1.71)	(0.20)	(-1.78)	(-0.41)	(-1.67)	(-0.46)	(-1.85)	(0.14)	(-1.93)	(0.04)
2	-0.775	-0.527	-0.854	-0.406	-0.463	-4.969	-0.548	-4.436	0.159	2.770	0.164	3.818	0.024	-1.223	0.026	-0.619
$t-stat$	(-1.95)	(-0.12)	(-1.99)	(-0.10)	(-1.23)	(-1.70)	(-1.36)	(-1.48)	(0.34)	(0.72)	(0.35)	(0.86)	(0.06)	(-0.33)	(0.06)	(-0.15)
3	-0.079	-0.244	-0.190	-0.008	-0.137	-7.476	-0.235	-7.421	0.106	-2.093	0.060	-1.401	0.392	0.528	0.396	2.191
$t-stat$	(-0.39)	(-0.06)	(-0.84)	(0.00)	(-0.58)	(-1.87)	(-0.91)	(-1.80)	(0.26)	(-0.55)	(0.15)	(-0.34)	(1.00)	(0.09)	(1.01)	(0.32)
4	0.120	2.744	0.007	2.951	-0.105	-0.173	-0.214	-0.321	0.158	1.819	0.084	2.763	-0.084	-2.263	-0.092	-2.580
$t-stat$	(0.38)	(0.71)	(0.02)	(0.66)	(-0.32)	(-0.04)	(-0.71)	(-0.07)	(0.38)	(0.25)	(0.19)	(0.36)	(-0.18)	(-0.36)	(-0.19)	(-0.42)
High FS	0.767	-2.767	0.678	-2.929	1.023	-1.044	0.632	-0.735	1.274	3.639	1.228	4.572	0.901	2.131	0.874	2.147
$t-stat$	(2.07)	(-0.83)	(1.92)	(-0.85)	(2.07)	(-0.18)	(1.90)	(-0.12)	(2.09)	(0.63)	(1.99)	(0.75)	(1.65)	(0.49)	(1.58)	(0.50)
H - L	2.633**	-3.119	2.704**	-2.884	2.065**	-1.744	1.864**	-1.473	2.099***	4.454	2.043**	5.552	1.904**	1.624	1.906**	1.987
$t-stat$	(2.50)	(-0.85)	(2.55)	(-0.76)	(2.26)	(-0.26)	(2.35)	(-0.21)	(2.74)	(0.73)	(2.60)	(0.86)	(2.48)	(0.29)	(2.48)	(0.35)

Appendix
Abnormal Stock Returns Following Forced Sale

This table reports the cumulative abnormal returns (CARs) and monthly average abnormal returns (ARs) for stocks following the forced sale. Each quarter the stocks are ranked on its FS into deciles. We then calculate the ARs and the CARs over the subsequent quarter by averaging first across the deciles and then across the quarters. Abnormal returns are calculated by following Daniel et al. (1997) (DGTW). Abnormal returns for each stock are measured in excess of both equal-weighted and value-weighted DGTW portfolios. All reported statistics are calculated from the time series of CARs and ARs. t-statistics are reported below each variable in parentheses.

	Low FS	2	3	4	5	6	7	8	9	High FS	H - L
CAR-VW (%)	0.038	-0.445	0.192	-0.016	0.327	0.147	0.038	0.126	0.050	0.815	0.780**
$t-stat$	(0.16)	(-1.70)	(0.36)	(-0.09)	(2.07)	(0.95)	(0.16)	(0.67)	(0.21)	(2.68)	(1.98)
AR-VW (%)	-0.004	-0.156	0.018	-0.031	0.088	0.057	0.019	0.034	0.016	0.254	0.258*
$t-stat$	(-0.04)	(-1.86)	(0.13)	(-0.53)	(1.76)	(1.20)	(0.26)	(0.59)	(0.20)	(2.48)	(1.95)
CAR-EW (%)	-0.204	-0.518	0.147	-0.051	0.317	0.056	-0.026	0.045	-0.025	0.791	0.995**
$t-stat$	(-0.66)	(-1.69)	(0.26)	(-0.25)	(1.82)	(0.34)	(-0.11)	(0.23)	(-0.10)	(2.46)	(2.23)
AR-EW (%)	-0.090	-0.181	0.001	-0.044	0.082	0.028	-0.008	0.006	-0.012	0.241	0.331**
$t-stat$	(-0.91)	(-1.86)	(0.01)	(-0.67)	(1.47)	(0.54)	(-0.10)	(0.10)	(-0.15)	(2.25)	(2.28)

Chapter 2

Political Connections and the Resolution of Debt Restructuring

2.1 Introduction

The government's involvement in the bankruptcies of Chrysler and General Motors led to considerable debate among practitioners and academics on the potential conflicts of interest arising from politically connected claimholders.[15] In these cases, the claims of the politically powerful unions were elevated above other claimholders, resulting in higher recovery rates for unions compared to creditors with greater or equal priority. Building on these concerns, we examine how firms with and without politically connected debtors resolve distress. We use the term, debtor, throughout the paper to refer to shareholders' agents, such as the board of directors and top executives. To the best of our knowledge, our study is the first to empirically examine the effects of politically connected debtors on the resolution of distress.

Debtors have strong incentives to avoid liquidation (Gertner and Scharfstein, 1991) and therefore use their political capital to promote the suboptimal continuation of unprofitable firms. Furthermore, banks and hedge funds can be pressured into granting concessions to politically connected debtors in order to earn the good graces of regulators, which will lead to suboptimal outcomes and deviations from absolute priority. For example, some authors argue that banks did not fight the rulings in the Chrysler and General Motors cases because these same banks were also recipients of the Troubled Asset Relief Program (TARP) (Warburton,

[15]See Warburton (2010) for a concise summary of the ongoing debate.

2010).

Politically connected debtors can also pressure bankruptcy judges into approving certain provisions in the bankruptcy code that are costly to creditors or result in inefficient outcomes.[16] For example, politically connected debtors can tacitly compel bankruptcy judges to approve super-priority debtor-in-possession (DIP) financing that could result in the sub-optimal continuation of unprofitable firms; this would ultimately be harmful for existing creditors (White, 1989; Gertner and Scharfstein, 1991; Triantis, 1993; Ayotte and Gaon, 2011). Furthermore, bankruptcy judges can approve the sale of the firm's assets without the approval of creditors in what is known as a "363 sale."[17] This type of sale is one of the most controversial points in the Chrysler bankruptcy. In the Chrysler case, "Old Chrysler" sold all of its assets to "New Chrysler" which is owned by a subset of Old Chrysler's creditors, DIP lenders, and the unions. As part of the sale, the unions received equity in New Chrysler worth billions of dollars that amounted to a 55% recovery rate. Old Chrysler's secured lenders only recovered 29% of the value of their claims and other unsecured creditors received nothing (Warburton, 2010). These outcomes represent substantial deviations from priority and arguably preferential treatment to the politically powerful unions that are also unsecured claimholders. While we agree that Chrysler's bankruptcy contains unique circumstances, whether preferential treatment of politically connected claimholders is commonplace is an interesting empirical question to finance researchers, because the potential costs to claimholders associated with the resolution of distress is a prominent feature of many corporate finance theories.

We propose and test several hypotheses to examine the extent to which a debtor's political connections affect the resolution of distress. First, if debtors use their political connections

[16]Despite the considerable influence bankruptcy judges have on the bankruptcy process, they do not enjoy the tenure and salary protections enjoyed by other federal judges. The lack of these protections makes them more susceptible to political pressures than other federal judges (LoPucki, 2006; Gennaioli and Rossi, 2010).

[17]In a typical Chapter 11, claimholders vote on a plan of reorganization that dictates asset sales and the various distributions of the proceeds to creditors. However, a 363 sale only requires the approval of the bankruptcy judge. Several authors have suggested that 363 sales are used to by-pass the voting requirements in Chapter 11 (Warburton, 2010).

to obtain favorable treatment from bankruptcy judges at the expense of creditors and/or to pressure creditors to restructure their debts out of court, then politically connected firms will be more likely to reorganize their debts outside the bankruptcy court. This is a natural conclusion, all else equal, if the bankruptcy costs for creditors in firms with politically connected debtors are higher than in firms without politically connected debtors. Then, creditors of firms with politically connected debtors are more likely to agree to an out-of-court (i.e., private) restructuring or an exchange offer than creditors of firms without politically connected debtors.

Second, given that debtors typically have incentives to reorganize distressed firms rather than liquidate them (Gertner and Scharfstein, 1991), it is probable that debtors use their political capital to force creditors to agree to reorganizations of economically unviable firms. Thus, firms with politically connected debtors are more likely to reorganize under Chapter 11 compared to firms without politically connected debtors. Furthermore, if this higher incidence of reorganization is solely due to political pressures, we expect that firms with politically connected debtors are more likely to undergo additional rounds of distressed restructuring following emergence from bankruptcy compared to firms without politically connected debtors.

Finally, recent research has documented that politically connected firms enjoy greater access to credit (Johnson and Mitton, 2003; Chiu and Joh, 2004; Dinc, 2005; Cull and Xu, 2005; Khwaja and Mian, 2005; Claessens, Feijen, and Laeven, 2008; Faccio, 2010), and this evidence may be due to these firms receiving government bailouts (Faccio, Masulis, and McConnell, 2006). Such implicit guarantees will reduce creditors' concerns about the future prospects of distressed firms. Hence, firms with politically connected debtors are more likely to be reorganized than those without. However, unlike the case where debtors use their political capital to force reorganizations of economically unviable firms, we expect to observe that firms with implicit guarantees are less likely to undergo additional restructuring following emergence from bankruptcy.

Our study employs two different measures of political connections. Following Faccio, Masulis and McConnell (2006) and Faccio and Hsu (2016), we search the biographies of each firm's key personnel (top executives and board members) in the *Capital IQ* database for keywords that indicate a political connection.[18] We require the firm to have such connections at the time of filing for bankruptcy or undertaking an out-of-court debt restructuring. Our first measure of political connections is a dummy indicator that takes the value of one if the firm is politically connected. The other proxy is the total number of politically connected key personnel in *Capital IQ* for a given firm-year; this proxy measures the strength of a firm's political connections.

Our empirical findings are summarized as follows. Based on a sample of 514 Chapter 11 cases and 105 out-of-court debt restructurings occurring between 1991 and 2004, we provide evidence that politically connected firms are more likely to restructure their debts in an out-of-court restructuring versus in a Chapter 11 bankruptcy.[19] This finding is consistent with the prediction that political connections improve debtors' bargaining power vis-à-vis creditors.

Following the existing literature, we test the relationship between political connections and bankruptcy outcomes by separating distressed firms into three different groups of Chapter 11 outcomes, namely reorganization, acquisition, and liquidation (Hotchkiss, 1995). We find that politically connected firms are more likely to reorganize rather than liquidate under

[18]We employ the following 43 keywords: governor of the state; senator; congress; house of representatives; United States Department of Commerce; White House; congressman; democratic; republican; President Bush; President Obama; President Clinton; Department of the Treasury; National Economic Counsel; senate; Department of the State; Department of Defense; Department of the Interior; Department of Agriculture; Department of Labor; Department of Health and Human Services; Department of Housing and Urban Development; Department of Energy; Department of Education; Department of Veterans Affairs; Department of Homeland Security; Environmental Protection Agency; EPA; Office of Management and Budget; United States Trade Representative; United States Ambassador to the United Nations; Council of Economic Advisers; Small Business Administration; Congressional; legislature; legislative; Republican Party; GOP; Republican National Committee; Democratic Party; Democratic National Committee; President Reagan; President Carter.

[19] We limit the sample to cases filed before 2005 to maintain a constant regulatory environment due to the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 (BAPCPA). Further, we need several years of post restructuring data to avoid a truncation bias in our tests examining post-bankruptcy performance.

Chapter 11. This evidence is suggests that politically connected debtors use their political capital to force reorganizations of economically unviable firms and/or that political benefits such as implicit guarantees increase the going-concern values of firms with politically connected debtors. In order to investigate which of these two explanations is more consistent with the data, we examine the tendencies of firms with and without politically connected debtors to require additional restructuring following emergence from bankruptcy.[20] We find that firms with politically connected debtors are less likely to undergo a second distressed restructuring within five years of completing the initial debt restructuring compared to firms without politically connected debtors. The data suggest that politically connected debtors add to the going concern value of distressed firms rather than force the continuation of economically unviable firms.

One concern with our results is that economically viable firms (i.e., those that should be reorganized) may be more willing to bear the cost of becoming politically connected when they face financial distress as the expected long-term benefits of political connections may be greater for these firms. Hence, our results may be biased towards finding that politically connected firms are more likely to reorganize successfully. In order to mitigate this concern, we reconstruct our measure of political connections and only define firms as politically connected if the connection was in place prior to the onset of financial distress. Our results remain materially unchanged using this alternative measure of political connections.

Additionally, we find several other pieces of evidence that corroborate our main findings. First, we find that firms with politically connected debtors emerge from bankruptcy with capital structures that are closer to their industry peers compared to firms without politically connected debtors. Several authors have commented on the inability of distressed firms to reduce leverage to the level of industry peers upon emergence from Chapter 11 (see, for example, Hotchkiss, 1995; Gilson, 1997; Kahl, 2002). In particular, Kahl (2002) suggests

[20] Recidivism rates have been used as evidence of suboptimal reorganizations in several other papers (see, for example, Hotchkiss (1995) and Altman, Kant, and Rattanaruengyot (2009)).

that when creditors are uncertain about the firm's prospects they will keep the firm on a "short leash" by imposing high levels of leverage. Thus, evidence that firms with politically connected debtors are able to reduce leverage to industry levels suggests that creditors are more certain about the economic viability of these firms.

Second, creditors in firms with politically connected debtors are more likely to exchange their debt claims for equity than creditors in unconnected firms. Creditors typically do not want to exchange their claims for claims with lower priority in case the firm requires additional restructuring following emergence from bankruptcy.[21] Thus, finding that creditors in firms with politically connected debtors are more likely to accept equity in exchange for their debt claims indicates that creditors are more certain of the economic viability of firms with politically connected debtors than those without. Finally, the stock returns of firms with politically connected debtors outperform those of firms without politically connected debtors over the five years following the restructuring. This evidence is also consistent with political connections improving the going concern value of distressed firms that reorganize.

Overall, our results suggest that debtors use their political connections to avoid filing for bankruptcy in favor of an out-of-court restructuring. This interpretation makes sense as bankruptcy is often accompanied by the removal of top executives and a change in corporate control. Conditional on filing for bankruptcy, we find little evidence that politically connected debtors receive preferential treatment that leads to suboptimal continuation. In fact, the data suggest that firms with politically connected debtors are less likely to require additional restructuring following emergence from bankruptcy. Additionally, political connections appear to help resolve some of the uncertainty about distressed firms' prospects resulting in post-bankruptcy capital structures that are similar to industry peers.

Our study contributes to the literature on the resolution of distress and political connections in significant ways. First, our research contributes to the literature that focuses on

[21] Nearly 30% of firms in our sample that emerge from bankruptcy refile for bankruptcy within 5 years of emergence. This finding is consistent with the 32% recidivism rate reported in Hotchkiss (1995).

whether bankruptcy judges are influenced by debtors' political connections (for example, see Block-Lieb, 1998; Samahon, 2008; McKenzie, 2009). We find evidence that firms with politically connected debtors are more likely to resolve distress by undertaking an out-of-court restructuring instead of filing for Chapter 11. This finding indicates that Chapter 11 is a more costly venue to resolve distress for creditors in firms with politically connected debtors. While our analysis shows little evidence that politically connected debtors receive preferential treatment under Chapter 11, it does not necessarily rule out the fact that firms with the most powerfully connected debtors are likely to resolve distress out of court. Overall, our evidence suggests that political connections improve debtors' bargaining power vis-à-vis creditors'.

Second, our study addresses an outstanding question in the literature as to whether creditors in firms with politically connected debtors are pressured into taking economically questionable actions (Faccio, Masulis, and McConnell, 2006). We find that firms with politically connected debtors are more likely to resolve distress successfully, an evidence suggesting that creditors are not being coerced into taking any undesirable action. Hence, our evidence is more consistent with the hypothesis that political connections provide benefits, such as implicit guarantees or procurement of government contracts (Goldman, Rocholl, and So, 2013).

Finally, we acknowledge that our empirical strategy may not resolve all potential endogeneity issues related to firms' decisions to become politically connected or to choose different venues to resolve financial distress. However, this is the first paper to empirically examine the relation between politically connected debtors and the resolution of distress using a large sample of distressed firms, and therefore, our work serves as a basis for future research in this area.

The paper is organized as follows. The next section discusses the hypotheses. Section 2.3 describes the data. Section 2.4 examines the role of political connections in the bankruptcy outcomes and recidivism. Section 2.5 investigates the channel through which political connections help the firms with favorable outcomes. The final section concludes.

2.2 Hypothesis Development

We propose that political connections may improve the bargaining power of debtors vis-à-vis creditors. If debtors use their political capital to pressure lenders to provide concessions, this can result in inefficient reorganizations. However, if debtors use their political capital to provide creditors with implicit guarantees, then political connections are likely to lead to more successful resolutions of distress. We present a simple example based on White's (1989) model to illustrate these points.

Assume that debtors and creditors are risk neutral and that all information is known by both the debtors and creditors. The firm has debts outstanding with a face value of D and assets with a market value of A. The firm is insolvent, such that $A < D$, and therefore must restructure. Suppose that the reorganization process proceeds as follows. First, faced with insolvency, the debtors (the firm's management) approach the creditors with a plan to reorganize out of court (OOC). If the creditors do not accept the plan, the firm files for Chapter 11. Then, if the creditors do not ratify the plan of reorganization in bankruptcy, the firm is liquidated according to strict priority. The debtors have a first mover advantage in the sense that under Chapter 11, the firm has exclusive rights to propose a plan of reorganization.[22] While the creditors wait for the debtors to file a plan, the firm may be undertaking value destroying investments, losing key employees, losing customers, and accumulating legal fees among other additional costs. These costs, or the threat of these extra costs in bankruptcy, will allow the debtors to extract concessions from the creditors.

[22] During our sample period, the Bankruptcy Code §1121(d) allowed a debtor 120 days to exclusively file a plan or reorganization. However, it placed no expressed limitation on the number or duration of extensions. Following Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 (BAPCPA), the debtor exclusivity period was limited to 18 months.

We now examine how politically connected debtors affect a firm's choice of venue for resolving distress (i.e. Out-of-court (OOC), Chapter 11 (Ch11), or liquidation (Liq)), bankruptcy outcomes, and the efficiency of the bankruptcy process. Creditor coordination and hold out problems may be very costly in an out-of-court restructuring. However, in court-supervised procedures, all creditors are required to abide by the plan of reorganization; thus, we assume no hold out problems under Chapter 11 or liquidation. The cost associated with these issues is represented by $H \geq 0$. Let $P \geq 0$ represent the firm's political capital, which is the amount by which creditors may suffer by not providing concessions. Finally, the costs associated with restructuring in each venue are represented by $C_{OOC} \geq 0$, $C_{Ch11} \geq 0$, and $C_{Liq} \geq 0$, respectively. These costs represent the direct costs associated with each procedure, such as legal fees and court costs. They also include potential indirect costs of each procedure, such as the loss of customers or the loss of intangible assets due to a piecemeal liquidation. Thus, C_{Liq} is most likely greater than C_{Ch11}, given that the former includes losses from liquidating intangible assets, such as human capital. However, if the firm is not economically viable, then the cost associated with a suboptimal reorganization (C_{Ch11}) would be greater than that associated with a liquidation (C_{Liq}).

We first examine the condition under which the firm is reorganized out of court. In order for creditors and debtors to agree to an out-of-court reorganization, they must get at least what they would get in the other venues. Consider the case where $A - P - C_{Ch11} > A - C_{Liq}$. Note that this condition also implies that the firm is worth more if it is reorganized (i.e., the firm is economically viable) than if it is liquidated. Thus, if the restructuring process is efficient, the firm will be reorganized. Suppose the debtors offer the creditors an amount equal to $A - C_{Liq}$ in an out-of-court reorganization. As long as what the creditors receive in an out-of-court restructuring, $A - H - C_{OOC}$, is at least $A - C_{Liq}$, the creditors will be willing to take the deal. However, the creditors also know that if the firm is liquidated, the debtors will receive less than they would in Chapter 11. Thus, the debtors' threat of liquidation is not credible. The lowest amount that the debtors can credibly offer the creditors is then

$A - P - C_{Ch11}$.

Assuming that $H + C_{OOC} \leq P + C_{Ch11}$, the creditors will accept the offer. The creditors will receive an amount equal to $A - P - C_{Ch11}$, and the debtors will retain an amount equal to $P + (C_{Ch11} - C_{OOC})$. The debtors' first-mover advantage and political connections allow them to extract this value from the creditors. Furthermore, if the debtors' political capital makes a Chapter 11 reorganization more costly to creditors compared to an identical firm without politically connected debtors, then the firm with politically connected debtors is more likely to reorganize out of court. This leads to our first hypothesis.

Hypothesis 1: *Firms with politically connected debtors are more likely to reorganize out of court than firms without politically connected debtors.*

Now suppose

$$A - H - C_{OOC} < A - C_{Ch11} < A - C_{Liq}. \quad (12)$$

In this case, the debtors are left with nothing if the firm is liquidated and hence, have strong incentives to use their political connections to coerce creditors into agreeing to a reorganization (e.g., creditors may be willing to acquiesce to debtors' demands in order to gain the good graces of regulators, and/or politically connected debtors may influence bankruptcy judges to approve actions that are harmful to creditors). Incorporating the costs of these political threats into equation (12) may result in the following payout,

$$A - H - C_{OOC} < A - C_{Ch11} > A - P - C_{Liq}, \quad (13)$$

in which case the firm will be reorganized under Chapter 11. However, because $A - C_{Ch11} < A - C_{Liq}$, such a reorganization is inefficient (i.e., the firm is not economically viable). This example implies two empirical predictions. First, compared to an identical firm without politically connected debtors, those with politically connected debtors are more likely to reorganize under Chapter 11 as opposed to being liquidated. Second, firms with politically connected debtors that reorganize under Chapter 11 are less likely to be economically viable as going-concerns and therefore are more likely to undergo additional restructuring after emerging from bankruptcy. These two predictions are formally stated in the following hypotheses.

Hypothesis 2: *Firms with politically connected debtors that file for Chapter 11 are more likely to be reorganized than those without politically connected debtors.*

Hypothesis 3: *Firms with politically connected debtors that reorganize under Chapter 11 are more likely to undergo additional restructuring following emergence from bankruptcy than those without politically connected debtors.*

We now consider the case where debtors' political capital is used to improve the going-concern value of the firm by providing an implicit guarantee to creditors. Let A' represent this improved going-concern value. Further, suppose these benefits do not result in solvency such that $D > A' > A$. Note that this improvement is only valuable in the case when the firm remains a going-concern. In the case of liquidation, the intangible assets associated with political connections will be destroyed. This uniform increase in asset values of out-of-court and Chapter 11 payouts will not alter *Hypothesis 1.* However, suppose now that the increase in firm value results in

$$A' - H - C_{OOC} < A' - P - C_{Ch11} > A - C_{Liq}. \tag{14}$$

Under this scenario, the firm will be reorganized under Chapter 11. The firm's threat of liquidation is not credible, and the creditors will receive more in a reorganization than in a liquidation or in an out-of-court restructuring. Consistent with *Hypothesis 2*, firms with politically connected debtors that file for Chapter 11 are more likely to reorganize. Unlike the previous scenario, however, this reorganization is efficient. The value of the firm reorganized as a going-concern $(A' - C_{Ch11})$ is now larger than its value under liquidation $(A - C_{Liq})$. This leads to the empirical prediction that if firms with politically connected debtors provide creditors with an implicit guarantee, then firms with politically connected debtors are less likely to require additional restructuring after emerging from bankruptcy. This leads to our final hypothesis.

Hypothesis 4: *If firms with politically connected debtors provide creditors with implicit guarantees, then politically connected firms will be less likely to undergo a subsequent distressed restructuring after emerging from bankruptcy than firms without politically connected debtors.*

In summary, a combination of several factors determines the effect of political connections in the restructuring process of distressed firms. But it is an empirical question as to which of these factors (i.e., debtors using their political capital to threaten dissenting creditors, or the benefits of political connections to firm value) plays the dominant role in the resolution of distress. The remainder of the paper will focus on answering this question.

2.3 Data

2.3.1 Out-of-Court Restructuring

Our main sample is derived from the sample used in Lemmon, Ma, and Tashjian (2009). It consists of firms that file for the Chapter 11 bankruptcy or that reorganize out of court from 1991 to 2004. The out-of-court restructuring sample is based on *Facitva* news search. In order to be included in the sample, the firm's creditors must have made a concession in the restructuring. Additionally, there must be a clear indication of distress (such as default on debt payments), delisting, or mention of a possible bankruptcy in the news. We also require that the out-of-court restructuring firms have at least $50 million in total assets (in 1997 dollars) in the fiscal year-end prior to the restructuring. If a firm files for bankruptcy within 12 months following an out-of-court restructuring, it is only counted as a Chapter 11 case. If a firm has a second out-of-court restructuring within 12 months, it is considered as a continuation of the first restructuring event and is counted only once. We are able to identify 149 out-of-court restructurings. However, as we shall describe later, we only include those cases that have available data to define their political connection status, leaving us 105 out-of-court restructurings.

2.3.2 Chapter 11 Bankruptcies

The Chapter 11 sample is also based on the sample used in Lemmon, Ma, and Tashjian (2009). It is derived from *New Generation Research's Public Major Company Database*, which contains all major public firms that filed for bankruptcy. We restrict the sample to those firms that filed for Chapter 11 between 1991 and 2004 with at least $50 million pre-filing assets (in 1997 dollars). Bankruptcy characteristics, including the filing date, the confirmation date and the bankruptcy outcome (namely reorganized, acquired, or emerged) are determined from *BankrutpcyData.com, LexisNexis, Factiva* or *U.S. Securities and Exchange Commission (SEC)* filings. This approach yields 531 Chapter 11 filings. Again, we only use 514 cases, where the firm can be defined as either politically connected or unconnected.

2.3.3 Political Connections

We follow the definition of political connections in Faccio, Masulis, and McConnell (2006) and Faccio and Hsu (2016). Specifically, we search the biographies of each firm's key personnel (executives, board members, etc.) in the *Capital IQ* database for the earlier mentioned 43 key words that indicate a political connection. We require that the connection be in place when the firm files for bankruptcy or undertakes an out-of-court restructuring. As illustrated above, a firm should have a clear indication of its political connection status in order to be included in our sample. We use a dummy variable, *PC*, to denote firms with politically connected debtors. We also use an alternate proxy, defined as the total number of political-connected key personnel, *PC Strength*, in *Capital IQ* for a given firm-year as the measure of the strength of the debtors' political connections.

In most instances, the *Capital IQ* database does not contain the dates when the key person started and ended his/her relationship with the firm. To ensure that a firm is politically connected at the time of bankruptcy, we manually check the firms' 10-K files and proxy statements from the *SEC*'s website. If we fail to find the person in the financial statements of the corresponding firm, we search for the person-firm combination on *LexisNexis, Proquest, or Google.com*. We are able to identify 289 politically connected persons resulting in a total of 177 politically connected firms within our combined sample of Chapter 11s and out-of-court restructurings with complete data. Politically connected firms make up about 29% of our combined sample.

2.3.4 Firm Level Characteristics

The firm level data are collected from the *Compustat North America Fundamentals Annual File*. We use the following dating conventions throughout the paper. We define pre-filing as the most recent fiscal year end occurring within 12 months of the bankruptcy filing date or the out-of-court restructuring date. We also define post-restructuring as the most recent fiscal year end following the emergence from the bankruptcy procedure or the completion of the out-of-court restructuring.

2.3.5 Summary Statistics

We are able to identify 514 Chapter 11 bankruptcies and 105 out-of-court restructurings over the period 1991 to 2004 with pre-filing *Compustat* data and *Capital IQ* biographies. As reported in Table 2.1, the number of Chapter 11s peaks in 2001 following the burst of the internet bubble, while the majority of the out-of-court restructurings took place in the early 1990s as well as the period following the internet bubble. Table 2.2 reports key pre-filing firm characteristics for both the Chapter 11 and the out-of-court restructuring in our sample (detailed variable definitions are summarized in the Appendix). As reported in Table 2.2, political connections are fairly common among our sample of distressed firms, with about 27% of Chapter 11s and 38% of out-of-court restructurings having politically connected debtors, respectively. The two political connection proxies merit more discussion. Both the occurrence (*PC*) and magnitude (*PC Strength*) of political connections are higher in the out-of-court restructuring sample. The differences are significant at the 5% level, indicating that Chapter 11 firms are less likely to have politically connected debtors compared to those that restructure out of court. This is our first piece of evidence that political connected debtors may have an effect on the resolution of distress. The results suggest that debtors' political capital grants them greater negotiating power leading to higher incidence of out-of-court restructurings.

Firms that restructure out of court and that file for Chapter 11 appear to have similar pre-filing leverage, profitability, and secured debts claims. Firms that restructure out of court tend to have lower Altman's (1968) z-scores than those that filed for Chapter 11, indicating that the latter are more distressed. Additionally, firms that restructure out of court have more tangible assets, spend more on R&D, and are less likely to be in a distressed industry at the time of filing compared to their Chapter 11 counterparts. We follow Acharya, Bharath, and Srinivasan (2007) and define an industry as distressed if the firm's median industry stock return is less than 30% in the year prior to the firm filing for Chapter 11 or undertaking an out-of-court restructuring. The high likelihood of industry distress may indicate that firms in the Chapter 11 subsample are more susceptible to asset fire sales than those of the out-of-court subsample (Shleifer and Vishny, 1992). Additionally, firms that restructure out of court are less likely to do so during a recession period compared to those that file for Chapter 11.[23] Finally, the summary statistics are broadly consistent with those reported in Ma and Tashjian (2012), suggesting that our sample is representative of the larger sample of both Chapter 11 and out-of-court restructuring firms used in their analysis.

In order to provide a clearer picture of the political connections within our sample, we classify politically connected key personnel into three categories: (i) Executives, which include all top level executives in the firm such as Chief Executive Officers (CEOs), Chief Financial Officers (CFOs), Presidents, and other top executives; (ii) Board Members, which include any member of the board of directors except those classified as executives above; and (iii) Others, which include other employees such as divisional presidents and outside advisors. In Table 2.3, Panel A, we report the percentage of each type of politically connected key personnel within our sample. As discussed above, there are 289 politically connected people within our 177 politically connected firms. Among the 289 politically connected people involved at filing, 139 of them could be classified as politically connected and involved in the same firm at least five years prior to the restructuring event. This result indicates that firms tend to become politically connected as they become more distressed. This finding is also consistent with Adelino and Dinc's (2014) finding that firms with weaker financial health increased their lobbying efforts following the financial crisis of 2008.

The endogenous decision of distressed firms to become politically connected affects the

[23] A recession period is defined by the National Bureau of Economic Research.

ability to interpret our main results as causal. Specifically, distressed firms could choose to become politically connected for several reasons that are likely to be correlated with their ability to successfully reorganize. For example, it is likely that faced with distress, debtors are willing to pay the cost associated with becoming politically connected if they perceive that they are more likely to enjoy the long-term benefits of the connections. Thus, observing a positive relation between politically connected debtors and reorganization may be due to unobservable firm characteristics that are positively associated with reorganization rather than the debtors' political connections. In order to mitigate this possibility, we measure a debtor's political connection status five years prior to the onset of distress. We acknowledge that this may not exclude every possible source of endogeneity, especially if the selection is based on time invariant factors. However, the ability to predict distress or the need to restructure is noisy five years out. Thus, we expect the reasons for becoming politically connected five years prior to the bankruptcy filing or the out-of-court restructuring are less likely to be correlated with the firm's ability to successfully reorganize.

As reported in Table 2.3, Panel A, about 9% of the politically connected persons in the sample are executives, about 80% are board members, and the remaining 11% are other employees or advisors of the firm. Given that we measure political connections at the time of bankruptcy filing or at the beginning of an out-of-court restructuring, the high level of management turnover documented during bankruptcy (Gilson, 1989; Hotchkiss, 1995) may separate the firm from its political connection prior to the resolution of distress. However, the majority of our political connections are through non-executive board members who are more likely to have substantial economic interests in the firm (Hotchkiss and Mooradian, 1997; Gilson, 1990) and are less likely to be replaced during the bankruptcy or the out-of-court restructuring. This result gives us confidence that our political connections remain intact throughout the bankruptcy process. However, this also raises a concern that endogenous matching of politically connected board members who also possess other skills useful for distressed firms (i.e., vulture investors (Hotchkiss and Mooriadian, 1997), or turnaround experts (Gilson, 1990)) is driving our results. Again, classifying political connections that exist prior to the onset of distress should mitigate this concern.

In Table 2.3, Panel B, we report the sources of the political connections among our sample of key personnel. Note that an individual can have more than one keyword matched in his/her *Capital IQ* biography. Thus, the percentages reported in the table do not sum to 1. We consolidate the 43 keywords used to determine political connections into five categories: (i) Legislative Branch, which includes keywords indicating a connection to the U.S. Senate or House of Representatives; (ii) Government Agency, which includes keywords indicating a connection with a government agency such as the Department of Defense or the Department of the Treasury; (iii) White House, which includes keywords indicating a connection to a U.S. President or to the White House; (iv) Governor, which includes a connection to a Governor of one of the states; and (v) Political party, which includes a connection to either the Democrat or Republican political party. About 70% of the politically connected key personnel in our sample are connected to the legislative branch, 38% are connected to a government agency, 35% are connected to the White House, 3% are connected to a governor, and 3% are connected to a political party. Overall, Table 2.3 suggests that the political connections in our sample are likely to be of sufficient quality to contribute to the outcomes discussed in the Section 2.2.

2.3.6 Distressed Firms' Characteristics

We now examine the pre-filing characteristics of both politically connected and unconnected firms in the multivariate setting. Table 2.4 reports the results from logistic (tobit) regressions of *PC* (*PC Strength*) on the firm characteristics summarized in Table 2.2. The industry dummies are based on the Fama-French 12 industries, while the year dummies account for any time trend in the data. The tobit specification is used in the regressions with *PC Strength* as the dependent variable due to its truncation at zero. Table 2.4 presents the regression results from the Chapter 11 subsample, the out-of-court restructuring subsample, and the combined sample. For the Chapter 11 subsample, $Log(Total\ assets)$ is a significant determinant of a debtor's political connection status. The evidence is consistent with prior studies who also find that firm size is a significant predictor of political connections (Hill et al., 2013; Faccio, 2010). This result could be purely mechanical, in that larger firms have larger boards and more employees, and hence more chances for one of them to be politically connected. On the other hand, larger firms may be more likely to have the resources and economic incentives to pursue political objectives. Nevertheless, it is important that we control for firm size in all of our subsequent analyses. Additionally, within the Chapter 11 subsample we fail to find a significant relationship between a debtor's political connection status and several firm level variables that have been shown to be correlated with bankruptcy outcomes (i.e., reorganization vs. liquidation). This finding assuages concerns that our results in the upcoming sections that examine the effect of political connections on bankruptcy outcomes are primarily driven by a debtor's endogenous decision to become politically connected.

Turning to the out-of-court restructuring subsample, in addition to the positive relationship between politically connected debtors and firm size, there are several other differences between firms with and without politically connected debtors. Specifically, firms with politically connected debtors tend to be less profitable, are less likely to be in a distressed industry, and are less likely to restructure during a recession. Furthermore, politically connected firms have higher leverage than the unconnected firms, which is interesting as firms with more leverage are less likely to restructure out of court due to creditor coordination problems associated with out-of-court restructurings (Gilson, John, and Lang, 1990). Additionally, the politically connected firms appear to be less distressed with higher Altman's z-scores. Overall, among the firms that restructure out of court, the politically connected firms appear to more closely resemble those that file for Chapter 11. For example, the combination of greater size and leverage among politically connected firms in the out-of-court restructuring subsample may suggest that these firms are more likely to have greater creditor coordination problems (high H). As shown in Section 2.2.3, a firm with high H is less likely to reorganize out of court unless the debtors have substantial bargaining power (high P). The results in this section suggest that political connections may facilitate out-of-court restructuring by improving the debtors' negotiating power.

2.4 Political Connections and Restructuring Venue

As proposed by our *Hypothesis 1*, firms with politically connected debtors may be more likely to restructure out of court rather than to reorganize under Chapter 11 because of the debtors' greater bargaining power. In this section, we examine the likelihood of firms with politically connected debtors to reorganize out of court compared to those without.

Table 2.5 reports the results from logistic regressions, where the dependent variable takes the value of one if the firm reorganized out of court and zero if the firm filed for Chapter 11. All regression models include the control variables in Table 2.4, as well as year and industry dummies, and $t-$statistics adjusted for heteroskedastic standard errors. The results suggest that consistent with our *Hypothesis 1*, the greater bargaining power of politically connected debtors under Chapter 11 results in a greater likelihood of politically connected firms restructuring out of court. The coefficients on all the proxies for political connections are significantly positive at the 5% level. Specifically, the presence of politically connected debtors increases the likelihood of an out-of-court restructuring rather than restructuring under Chapter 11 by approximately 8 percentage points in columns (1) and (3). The presence of one politically connected debtor increases the likelihood of an out-of-court restructuring rather than restructuring under Chapter 11 by approximately 3 percentage points in columns (2) and (4).[24] The evidence therefore suggests that the effect of politically connected debtors on a firm's choice of restructuring venue is economically significant.

[24]The marginal effects are evaluated at the sample means.

Furthermore, all four regressions in Table 2.5 show that firms with lower Altman's z-score, higher profitability and lower leverage tend to resolve distress via an out-of-court restructuring. These findings are broadly consistent with those of previous studies and corroborate our conjecture, based on the evidence in Table 2.4, that the politically connected firms within the out-of-court subsample are more likely to resemble firms that file for Chapter 11.

In summary, the findings suggest that politically connected debtors have greater bargaining power that offsets the potentially higher holdout costs of firms with politically connected debtors, thereby resulting in firms with politically connected debtors restructuring out of court more often than those without.

2.5 Political Connections and Chapter 11

In this section, we examine the role of politically connected debtors within Chapter 11 bankruptcies. Our *Hypothesis 2* proposes that when politically connected firms file for bankruptcy, they are more likely to emerge from the process as going concerns rather than to liquidate. As discussed, this may be due to the debtors' improved bargaining power or to the economic benefits associated with political connections. In order to be consistent with prior literature, we separate Chapter 11 outcomes into three categories: reorganization, acquisition, and liquidation (Hotchkiss, 1995). A firm is classified as reorganized if the firm emerges from the bankruptcy process as a stand-alone company. A firm that sells the majority of its assets to a single buyer is classified as an acquisition (M&A). A firm that sells the majority of its assets to multiple buyers is classified as liquidation. Among our sample of Chapter 11 cases, 40% of the cases resulted in a reorganization, 22% resulted in an acquisition, and 38% resulted in a liquidation. The distribution is broadly consistent with those reported in other studies (Lemmon, Ma, Tashjian, 2009).[25]

Table 2.6 presents the results of multinomial logistic regressions of bankruptcy outcomes on our measures of politically connected debtors and control variables. Firms with politically connected debtors are more likely to exit the Chapter 11 process via reorganization compared to firms without politically connected debtors. The results suggest that the presence of politically connected debtors increases the likelihood of reorganization versus the other outcomes (e.g., liquidation or acquisition), and this is more pronounced when one-year-prior-to-filing measures rather than when the five-year-prior-to-filing measures are employed. Additionally, the presence of politically connected debtors increases the likelihood of reorganization by approximately 10 percentage points in columns (1), (3), (5), and (7). The presence of one politically connected debtor also increases likelihood of reorganization by approximately 10 percentage points in columns (2), (4), (6), and (8).[26]

The evidence is consistent with *Hypothesis 2* that politically connected debtors use their bargaining power to force reorganization and/or that politically connected debtors improve the going-concern values of distressed firms. However, as discussed in Section 2.2, observing a positive relation between politically connected debtors and reorganization under Chapter 11 is not sufficient to distinguish whether or not politically connected debtors affect the efficiency of the Chapter 11 process. Therefore, we now turn to examining several post-bankruptcy outcomes that will indicate whether politically connected debtors are associated with suboptimal continuation decisions.

[25] Jiang, Li, and Wang (2012) report that 60% of their firms emerge while 30% are liquidated. However, their sample only contains large firms with assets greater than $100 million which are more likely to reorganize.

[26] We evaluate the marginal probabilities at the sample means.

2.5.1 Political Connections and Recidivism

As proposed by our *Hypothesis 3*, debtors exploiting political capital could lead to inefficient bankruptcy outcomes, and as a result, their firms may be more likely to undergo a subsequent restructuring event. However, our *Hypothesis 4* proposes that if debtors' political connections improve firms' going-concern values, we should observe that firms with politically connected debtors are less likely to undergo additional restructuring after emerging from bankruptcy. Recidivism following a Chapter 11 has been studied by several researchers. For example, Hotchkiss (1995) shows that over 40% of her sample of the firms that emerge from bankruptcy continue to have a negative operating income three years after the emergence. She further shows that 32% of her sample undergo a subsequent distressed restructuring within five years following the emergence from bankruptcy. In addition to high recidivism rates, Gilson (1997) also shows that firms that emerged from bankruptcy tend to have higher leverage than their counterparts from the same industry. Typically, researchers have cited this evidence as a failure of the Chapter 11 process to efficiently reorganize distressed firms. However, as Kahl (2002) points out, creditors in a distressed restructuring may want to keep distressed firms on a "short leash" when the uncertainty about the firms' viability is high, leading to higher than average leverage in restructured firms. In the context of our study, observing higher recidivism rates among firms with politically connected debtors that emerge from bankruptcy may indicate that debtors use their political capital to coerce creditors into approving suboptimal reorganizations.

Consistent with the prior literature, approximately 30% of our sample of firms undergo a subsequent distressed restructuring (an out-of-court restructuring or a court-supervised restructuring) within five years of emergence from Chapter 11. Table 2.7 reports the result from estimating a Cox-proportional hazard model that examines subsequent failure rates of firms following their emergence from Chapter 11. We re-measure each of our control variables using the most recent fiscal year end following the firm's emergence from bankruptcy. As shown in the table, the coefficient on each of our proxies for politically connected debtors is consistently negative, indicating that firms with politically connected debtors are less likely to require additional restructuring after emerging from bankruptcy. The effects of *PC* and *PC Strength* on the likelihood of a firm requiring additional restructuring following emergence from Chapter 11 relative to the baseline hazard function can be obtained by exponentiating the respective coefficients in Table 2.7. Firms with politically connected debtors are between 14 and 52 percent less likely to require additional distressed restructuring following emergence from bankruptcy. These results are consistent with *Hypothesis 4* that the economic benefits from debtors' political connections result in more successful resolutions of distress, compared to those of firms without politically connected debtors.

2.5.2 Political Connections and Post-Bankruptcy Capital Structure

The inability of firms to reduce leverage ratios to industry levels via Chapter 11 indicates the presence of transactions costs that prevent firms from attaining optimal capital structures (Gilson, 1997; Kahl, 2002). High post-bankruptcy leverage ratios may also contribute to the observed high recidivism rates among firms emerging from Chapter 11 (See Hotchkiss, 1995; Altman, Kant, and Rattanaruengyot, 2009). Thus, it is possible that the benefits provided to creditors of politically connected firms offset such transaction costs, leading to our finding of lower recidivism rates among firms with politically connected debtors. Therefore, in this section we examine whether politically connected firms have post-bankruptcy leverage ratios that are closer to their peers.

We focus on the 121 sample firms that emerged from the Chapter 11 procedure as going concerns. Among them, 41 firms have politically connected debtors, while the other 80 have none. In order to determine if our sample firms are able to reduce leverage to normal levels, we adopt the procedure employed in Faccio, Masulis and McConnell (2006) to construct a matched sample firms to use as a benchmark.[27] For each firm in our sample, we select a matching firm that (i) did not undergo a financial restructuring; (ii) is in the same industry as the sample firm according to the Fama and French 48 industry classifications; (iii) has the same political connection status; (iv) is of similar size, measured by the book value of total assets as of the last fiscal year end prior to the bankruptcy filing date; and (v) remains in the compustat sample for at least three years prior to the sample firm's bankruptcy filing date and at least three years after the effective date of the bankruptcy. This final screen ensures that our matching firm does not experience a major corporate event, such as delisting due to financial distress, because such firms are more likely to have suboptimal leverage ratios and are thus inappropriate benchmark firms.

Table 2.8 reports the mean and median financial leverage ratios of our samples of firms with and without politically connected debtors and those of their respective samples of matching firms. We calculate financial leverage as the sum of short-term and long-term debts, scaled by total assets times 100. In each of the three years prior to bankruptcy, both the mean and median financial leverage ratios of our samples of firms with and without politically connected debtors are significantly higher than those of their matching counterparts. Following emergence from bankruptcy, the mean and median leverage ratios of our sample of firms with politically connected debtors are not different from those of its sample of matching firms. However, this is not the case for our sample firms without politically connected debtors. Following emergence from bankruptcy, both the mean and median leverage ratios of our sample of firms without politically connected debtors are still significantly greater than those of its counterpart of matching firms. Furthermore, the difference in differential leverage ratios between firms with politically connected debtors and their matching counterparts and between firms without politically connected debtors and their matching peers also suggest that firms with politically connected debtors are more successful at reducing

[27]In unreported analysis, we find that a large number of politically connected firms are from the telecom sector, while unconnected firms are more likely to be in the retail industry.

leverage to optimal levels compared to firms without politically connected debtors.

There are several plausible reasons why firms with politically connected debtors are more successful at reducing leverage to optimal levels compared to firms without. For example, creditors may be more willing to grant concessions to firms with politically connected debtors in order to remain in the good graces of their "political friends." In this case, one might expect to observe that creditors of firms with politically connected debtors have lower recovery rates compared to the recovery rates of creditors in unconnected firms. It is also plausible that implicit government guarantees granted to firms with politically connected debtors reduce uncertainty about the firm's future viability (Kahl, 2002). Hence, we would expect that the creditors of firms with politically connected debtors are more likely to accept equity in exchange for their debt claims compared to firms without politically connected debtors. In order to test these hypotheses, we manually collect data on recovery rates and the amount of debt exchanged for equity in each of the cases.

In Table 2.9, we summarize what creditors receive during Chapter 11 for both firms with and without politically connected debtors. The data are hand-collected from the firms' plans of reorganization and disclosure statements that are confirmed by the bankruptcy court. These plans are available on *BankruptcyData.com*, *LexisNexis*, and in *SEC* filings. In Chapter 11, creditors are placed in creditor classes according to the type of creditors' claim on the firm. For each firm, we collect the total amount of its bank claims and non-bank debt claims. For each group of claims, we then record how it is restructured. For example, creditors in a certain class may receive a package of cash and new securities. We calculate the recovery rates of each creditor class by scaling the value of the package of cash and securities received by the total amount of allowed claims for the creditor class. In pricing the package of cash and securities received, we follow the procedures outlined in Kalay, Singhal, and Tashjian (2007). Additionally, we determine the proportion of debt claims exchanged for equity by scaling the market value of equity claims received by the creditor class by the total amount allowed claims for the creditor class.

As reported in Table 2.9, creditors in firms with politically connected debtors and creditors in firms without politically connected debtors have similar levels of recovery rates. The results suggest that the lower post-bankruptcy leverage ratios of firms with politically connected debtors do not appear to be due to creditors forgiving more debts in these firms compared to firms without politically connected debtors. However, an average of 34% of covered bank loans are exchanged for equity in firms with politically connected debtors, while only 9% of covered bank loans are exchanged for equity in firms without politically connected debtors. Similarly, on average, firms with politically connected debtors have 66% of covered non-bank debts converted to equity, while firms without politically connected debtors only have 48%. At the aggregate level, on average 45% and 32% of covered debts are converted to equity in the connected and unconnected groups, respectively. The differences are significant at least at the 10% level for five out of the six mean/median tests that examine differences in the proportion of equity received. These results suggest that the lower post-bankruptcy leverage ratios of politically connected firms are partially due to creditors' willingness to accept equity in exchange for debt. This evidence is consistent with political connections providing implicit government guarantees to firms with politically connected debtors that engender confidence in their future viability.

2.5.3 Political Connections and Post-Bankruptcy Stock Performance

Thus far, we have established that politically connected debtors assist firms in successfully restructuring their debts in Chapter 11. The majority of the above findings are consistent with our *Hypothesis 4* that political benefits received by creditors outweigh any political threats from debtors. If this is the case, we might also expect to observe that firms with politically connected debtors have better post-bankruptcy stock performance than firms without politically connected debtors.

To implement the test, we extract the CRSP daily returns of the 121 firms that emerge from bankruptcy for five years from their effective dates. For those that re-enter the bankruptcy within the first five years, we keep the returns until the last available date and adjust for the delisting return. We also drop the returns within the first 30 days from the effective date to avoid any mispricing due to the initial public offering process.

Table 2.10 reports the excess returns, computed using the calendar-time portfolio method developed by Fama (1998) for several event windows. The Fama-French 4-factor model is used as our measure of expected returns. The two groups have significantly different average excess returns, with the politically connected portfolio outperforming the unconnected portfolio, for the holding periods of more than one year. The difference is more evident for equal-weighted portfolios. One concern is that the difference between the two groups may be largely affected by firms that refile for bankruptcy. In two unreported analyses, we drop the refiling firms or set the refiling firms' returns to -100% when the firm refiles. These results are similar to those reported in Table 2.10. Consistent with the prior sections, the results in this section also suggest that politically connected debtors facilitate more successful resolutions of distress.

2.6 Conclusion

We propose and test several hypotheses to examine the impact of politically connected debtors on the resolution of distress. Overall, our study provides evidence that politically connected debtors may improve the debtors' bargaining power, thereby resulting in a higher incidence of out-of-court restructurings. The results suggest that firms with politically connected debtors are more likely to exit the Chapter 11 process as a going-concern rather than through acquisition or liquidation. Additionally, we find that firms with politically connected debtors are less likely to undergo a subsequent distressed restructuring following emergence from Chapter 11. The findings suggest that the effects of debtors' political connections on bankruptcy outcomes are most likely due to the economic benefits associated with political connections rather than the potential for debtors to use political capital to coerce creditors into approving suboptimal continuations of unprofitable firms.

Further, our findings indicate that firms with politically connected debtors are able to effectively reduce their financial leverage to the industry level after getting out of bankruptcy, while leverage ratios in firms without politically connected debtors remain above industry levels. Additionally, creditors of firms with politically connected debtors are more willing to take equity in exchange for their debt claims. This result is indicative of investors' greater confidence in the firm's viability due to implicit guarantees linked to debtors' political connections. Overall, our results indicate that firms' political connections facilitate successful debt restructurings.

Table 2.1
Number of Chapter 11 Filings and Out-of-Court Reorganizations by Year

This table summarizes the number of Chapter 11 and out-of-court cases by year. The sample period is from 1991 to 2004. N represents the number of cases during the certain year for the Chapter 11 or the out-of-court restructuring. What's also reported is the percentage of the number of cases for either Chapter 11 or the out-of-court sample on the total number of the sample throughout the sample period (%).

Chapter 11			Out-of-Court		
Year	N	%	Year	N	%
1991	12	2.33	1991	4	3.81
1992	6	1.17	1992	7	6.67
1993	12	2.33	1993	9	8.57
1994	11	2.14	1994	4	3.81
1995	14	2.72	1995	4	3.81
1996	23	4.47	1996	2	1.90
1997	24	4.67	1997	1	0.95
1998	29	5.64	1998	4	3.81
1999	48	9.34	1999	4	3.81
2000	71	13.81	2000	4	3.81
2001	107	20.82	2001	13	12.38
2002	77	14.98	2002	21	20.00
2003	50	9.73	2003	18	17.14
2004	30	5.84	2004	10	9.52
All	514	100.00		105	100.00

Table 2.2
Summary Statistics Across Chapter 11 and Out-of-Court Restructuring Samples

This table reports summary statistics on key variables. The political connection variables (*PC* and *PC Strength*) are defined based on the firm's political connection status one year prior to the time of filing. Other variables are pre-filing characteristics from the most recent fiscal year end occurring within 12 months of the Chapter 11 filing date or the out-of-court restructuring date. t represents the p-value of t-test of the two groups' means. If the variable is binary, the p-value of the mean difference is reported under χ^2. Ranksum reports the p-value of the Wilcoxon test of the two groups' medians. The definitions of all variables are described in Appendix Table A.

	Chapter 11			Out-of-court			*p-value*		
	N	Mean	Median	N	Mean	Median	t	Ranksum	χ^2
PC	514	0.27	0.00	105	0.38	0.00			0.02
PC Strength	514	0.43	0.00	105	0.67	0.00	0.02	0.02	
Industry distress	514	0.24	0.00	105	0.17	0.00			0.14
Recession	514	0.18	0.00	105	0.10	0.00			0.06
Log(Total assets)	514	2.75	2..36	105	2.74	2.37	0.88	0.37	
Profitability	514	-0.01	0.02	105	0.01	0.03	0.30	0.25	
Leverage	514	0.94	0.88	105	0.94	0.88	0.99	0.72	
Z-score	514	0.48	0.57	105	-0.22	-0.07	0.00	0.00	
Tangibility	514	0.35	0.32	105	0.39	0.37	0.05	0.12	
R&D	514	0.01	0.00	105	0.02	0.00	0.00	0.03	
Secured debt	514	0.35	0.23	105	0.34	0.15	0.75	0.48	
Prepack	514	0.15	0.00	n/a					

Table 2.3
Summary Statistics on Politically-Connected Positions

This table summarizes the positions of politically connected people and how these people are connected. We identify 289 people as politically connected at the bankruptcy filing; 139 of which are politically connected at least five years prior to the filing date. Panel A summarizes the positions of politically connected people across three groups. The executive group includes Chief Executive Officer, President, Chief Financial Officer, and other top executives. The board members group includes members of the board of directors who are non-executives. The other employees group includes other non-executive employees (such as divisional presidents or advisors). Panel B reports how these people are politically connected. The 47 keywords are divided into five groups: the legislative branch (*Senate*, *Senator*, etc.), affiliation with a political party (*Democrat*, *Republican*, etc.), White House (*White House*, *President Obama*, etc.), governmental agency (*House of Representative*, etc.) and governor of the state. The percentage of keywords is defined as the total frequency of a certain position group over the total number of people in the group. One person can be connected with more than one keywords.

Panel A: Positions of Politically Connected People

	At Filing		Five Years Prior	
Position	N	%	N	%
Executives	27	9.3	10	7.2
Board Members	229	79.2	115	82.7
Others	33	11.5	14	10.1
Total	289	100.0	139	100.0

Panel B: Political Connection Keywords

	Executives		Board		Other		Total	
Political Classification	Freq	%	Freq	%	Freq	%	Freq	%
Legislative Branch	6	22.22	174	75.98	25	75.76	205	70.93
Government Agency	14	51.85	82	35.81	13	39.36	109	37.71
White House	15	55.56	80	34.93	4	12.12	99	34.26
Governor	0	0.00	7	3.06	1	3.03	8	2.77
Political party	0	0.00	8	3.49	2	6.06	10	3.46
Total number of people	27		229		33		289	

Table 2.4
Determinants of Political Connections

This table presents logistic (Tobit) regressions of political connection proxies *PC* (*PC Strength*) on potential determinants. *PC* or *PC Strength* is measured a year prior to a Chapter 11 filing or an out-of-court restructuring. The other variables are pre-filing characteristics of a firm from the most recent fiscal year end occurring within 12 months of the bankruptcy filing date or the out-of-court restructuring date. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% level, respectively. t-statistics adjusted for robust standard errors are reported in parentheses. The definitions of all variables are described in Appendix.

	Chapter 11		Out-of-Court		Combined	
	PC	*PC Strength*	*PC*	*PC Strength*	*PC*	*PC Strength*
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Total assets)	0.545***	0.661***	0.211	0.455*	0.497***	0.636***
	(4.722)	(5.415)	(0.547)	(1.684)	(4.966)	(5.962)
Profitability	-1.065	-1.835	-9.807**	-1.858	-1.418	-1.624
	(-0.881)	(-1.392)	(-2.429)	(-0.519)	(-1.323)	(-1.328)
Leverage	0.093	0.391	3.693*	1.962*	0.339	0.445
	(0.219)	(0.780)	(1.901)	(1.827)	(0.897)	(0.965)
Z-score	-0.029	-0.006	1.756**	0.731*	0.014	0.007
	(-0.320)	(-0.067)	(2.527)	(1.879)	(0.177)	(0.078)
Tangibility	-0.766	-1.218	1.466	1.004	-0.423	-0.561
	(-1.174)	(-1.629)	(0.914)	(0.860)	(-0.744)	(-0.870)
R&D	-1.134	-0.767	8.672	3.600	2.834	2.808
	(-0.211)	(-0.132)	(0.579)	(0.399)	(0.659)	(0.604)
Secured debt	0.173	-0.017	-1.143	-0.589	0.071	-0.164
	(0.515)	(-0.047)	(-0.922)	(-0.709)	(0.234)	(-0.485)
Industry distress	0.176	0.189	-2.114**	-1.742**	0.002	-0.068
	(0.623)	(0.608)	(-2.071)	(-2.258)	(0.009)	(-0.238)
Recession	-0.291	-0.083	1.043	0.889	-0.325	-0.012
	(-0.517)	(-0.145)	(0.585)	(0.601)	(-0.657)	(-0.023)
N	514	514	105	105	619	619
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.5
Political Connections and Restructuring Venue

This table reports the results of logistic regressions of a firm's choice of Chapter 11 or out-of-court restructuring. The dependent variable is a binary variable that takes the value of one if the firm restructured out-of-court and zero if the firm filed Chapter 11. *PC* is a dummy variable that equals to one if the firm is politically connected and zero otherwise; *PC Strength* measures the strength of a firm's political connections, defined as the total number of politically-connected key personnel in Capital *IQ* for a given firm-year. *PC* (PC^*) and *PC Strength* (*PC Strength**) are measured one year (five years) prior to a Chapter 11 filing or an out-of-court restructuring date. All control variables are pre-filing characteristics of a firm from the most recent fiscal year end occurring within 12 months prior to the bankruptcy filing date or the out-of-court restructuring date, and are defined in Appendix. $t-$statistics, adjusted for robust standard errors, are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	One Year Prior to Filing		Five Years Prior to Filing	
	Binary Indicator (Out-of-Court=1, Chapter 11=0)			
	(1)	(2)	(3)	(4)
PC	0.769***			
	(2.702)			
PC Strength		0.242**		
		(2.233)		
PC^*			0.746**	
			(2.267)	
PC Strength*				0.312**
				(2.008)
Log(Total assets)	-0.188	-0.185	-0.175	-0.161
	(-1.512)	(-1.430)	(-1.370)	(-1.263)
Profitability	4.309***	4.195***	4.110***	4.112***
	(3.329)	(3.249)	(3.168)	(3.149)
Leverage	-1.194**	-1.170**	-1.166**	-1.181**
	(-2.384)	(-2.377)	(-2.383)	(-2.387)
Z-score	-0.301***	-0.295***	-0.295***	-0.294***
	(-2.969)	(-2.951)	(-2.909)	(-2.925)
Tangibility	0.250	0.258	0.287	0.269
	(0.394)	(0.404)	(0.449)	(0.421)
R&D	8.433*	9.116**	8.704**	9.156**
	(1.893)	(2.035)	(1.967)	(2.062)
Secured debt	-0.055	-0.015	-0.085	-0.013
	(-0.158)	(-0.043)	(-0.244)	(-0.036)
Industry distress	-0.421	-0.409	-0.430	-0.421
	(-1.305)	(-1.265)	(-1.328)	(-1.303)
Recession	-0.327	-0.432	-0.337	-0.396
	(-0.501)	(-0.672)	(-0.528)	(-0.619)
N	619	619	619	619
Pseudo R^2	0.182	0.176	0.178	0.176
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes

Table 2.6
Political Connections and Bankruptcy Outcomes

This table presents the multinomial logistic regressions of the Chapter 11 bankruptcy outcomes (reorganization, liquidation, or M&A) on a firm's political connection status. We employ two measures of the firm's political connections: (1) A dummy variable, *PC* , that takes the value of one if the firm is politically connected and zero otherwise; (2) The strength of a firm's political connections, *PC Strength*, defined as the total number of politically-connected key personnel in the Capital *IQ* database for a given firm-year. *PC* (PC^*) and *PC Strength* (*PC Strength**) are measured one year (five years) prior to a Chapter 11 filing or the out-of-court restructuring. All control variables are pre-filing characteristics of a firm from the most recent fiscal year end occurring within 12 months of the bankruptcy filing date or the out-of-court restructuring date, and are defined in Appendix. $t-$statistics, adjusted for robust standard errors, are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	One Year Prior to Filing				Five Years Prior to Filing			
	Reorg vs. Liq		Reorg vs. M&A		Reorg vs. Liq		Reorg vs. M&A	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PC	0.387		0.624*					
	(1.219)		(1.851)					
PC Strength		0.475***		0.441**				
		(2.801)		(2.537)				
PC^*					0.248		0.417	
					(0.661)		(1.021)	
PC Strength*						0.482**		0.338
						(2.259)		(1.380)
Log(Total assets)	0.524***	0.465***	0.476***	0.440***	0.541***	0.507***	0.500***	0.493***
	(4.269)	(3.760)	(3.103)	(2.859)	(4.436)	(4.243)	(3.275)	(3.505)
Profitability	4.511***	4.875***	0.399	0.747	4.453***	4.643***	0.340	0.484
	(3.211)	(3.454)	(0.260)	(0.483)	(3.152)	(3.251)	(0.223)	(0.328)
Leverage	1.180**	1.116**	0.657	0.585	1.170**	1.091**	0.622	0.563
	(2.307)	(2.214)	(1.113)	(0.985)	(2.283)	(2.153)	(1.042)	(1.008)
Z-score	-0.142	-0.150	0.085	0.072	-0.147	-0.155	0.074	0.067
	(-1.219)	(-1.291)	(0.651)	(0.548)	(-1.246)	(-1.315)	(0.557)	(0.544)
Tangibility	1.407**	1.517**	1.055	1.152	1.391**	1.469**	1.007	1.070
	(1.994)	(2.084)	(1.513)	(1.629)	(1.969)	(2.046)	(1.432)	(1.447)
R&D	-1.395	-1.812	-9.008	-9.070	-1.917	-2.543	-9.498	-9.904
	(-0.198)	(-0.258)	(-1.119)	(-1.115)	(-0.269)	(-0.354)	(-1.174)	(-1.439)
Secured debt	-0.378	-0.387	-0.940**	-0.931**	-0.364	-0.343	-0.923**	-0.900**
	(-0.970)	(-0.991)	(-2.356)	(-2.326)	(-0.937)	(-0.876)	(-2.318)	(-2.210)
Industry distress	-0.107	-0.129	0.362	0.343	-0.099	-0.118	0.371	0.350
	(-0.347)	(-0.414)	(1.052)	(0.984)	(-0.322)	(-0.381)	(1.082)	(0.959)
Recession	-1.155*	-1.244*	-1.331	-1.444*	-1.166*	-1.178*	-1.346	-1.361*
	(-1.731)	(-1.838)	(-1.622)	(-1.789)	(-1.738)	(-1.749)	(-1.628)	(-1.667)
Prepack	3.566***	3.515***	1.672***	1.653***	3.549***	3.536***	1.629***	1.627***
	(4.424)	(4.408)	(3.777)	(3.739)	(4.383)	(4.366)	(3.736)	(3.845)
N	514	514	514	514	514	514	514	514
Pseudo R^2	0.251	0.257	0.251	0.257	0.249	0.252	0.249	0.252
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.7
Political Connections and Recidivism

This table presents the Cox-Proportional Hazards models. *PC* and *PC Strength* are measured one year prior to a Chapter 11 filing or an out-of-court restructuring, whereas *PC** and *PC Strength** are measured five years prior to the Chapter 11 filing or the out-of-court restructuring. The other control variables are obtained from the first fiscal year end following the firm's emergence from the Chapter 11 procedure. The definitions of all variables are defined in Appendix. t-statistics adjusted for robust standard errors are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	One Year Prior to Filing		Five Years Prior to Filing	
	Log(Hazard Ratio)			
	(1)	(2)	(3)	(4)
PC	-0.740			
	(-1.130)			
PC Strength		-0.444**		
		(-2.126)		
*PC**			-0.146	
			(-0.181)	
*PC Strength**				-0.660**
				(-2.443)
Log(Total assets)	-0.161	-0.104	-0.176	-0.129
	(-0.495)	(-0.336)	(-0.570)	(-0.421)
Profitability	-9.781**	-11.030**	-10.028**	-10.028**
	(-2.060)	(-2.262)	(-1.963)	(-2.079)
Leverage	1.413	1.525	1.766	1.670
	(0.707)	(0.745)	(0.867)	(0.811)
Z-score	0.108	0.124	0.156	0.114
	(0.452)	(0.536)	(0.602)	(0.476)
Tangibility	0.223	0.021	0.564	0.127
	(0.227)	(0.023)	(0.606)	(0.135)
Secured debt	0.829	0.766	0.729	0.932
	(1.080)	(1.047)	(0.967)	(1.254)
R&D	44.789*	41.144*	45.785**	42.092
	(1.918)	(1.875)	(2.011)	(1.593)
AAA-BAA	-0.293	-0.325	-0.072	-0.186
	(-0.317)	(-0.348)	(-0.090)	(-0.224)
Prepack	0.396	0.309	0.412	0.401
	(0.355)	(0.295)	(0.369)	(0.375)
N	113	113	113	113
Pseudo R^2	0.259	0.267	0.255	0.266
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes

Table 2.8

Financial Leverage of Politically Connected and Unconnected Bankrupt Firms and Their Matching Peers

This table presents mean and median financial leverages for politically connected and unconnected bankrupt firms as well as their matching firms. The leverage is calculated as the sum of short-term debt, current portion of long-term debt, and long-term debt scaled by total assets times 100. Year -3, Year -2, and Year -1 are 3 years before, 2 years before, and 1 year before the firm's filing date, whereas Year +1, Year +2 and Year +3 are 1 year after, 2 years after, and 3 years after the firm's effective date, respectively. The number in the parentheses below the mean is the p-value of a matched pair *t*-test for the difference in means between our sample firms and their matching companies. The number in parentheses below the median is the *p*-value for the difference from zero, based on the Wilcoxon matched pairs test. The *p*-values for the mean (median) difference between the adjusted leverage difference of politically connected and unconnected firms are achieved by Mann-Whitney U tests.

	Mean Leverage						Median Leverage					
	Year -3	Year -2	Year -1	Year 1	Year 2	Year 3	Year -3	Year -2	Year -1	Year 1	Year 2	Year 3
Bankrupt connected firms (A)	53.1	68.6	119.0	36.1	31.8	30.1	49.5	57.2	91.3	36.5	30.4	26.5
Connected matching firms (B)	39.2	41.7	36.4	39.0	33.0	31.6	38.0	36.7	36.4	38.1	33.2	29.7
Difference (A)-(B)	13.9	26.9	82.6	-2.9	-1.2	-1.5	11.5	10.5	54.9	8.4	-3.2	-2.2
p-Value difference	(0.04)	(0.01)	(0.00)	(0.58)	(0.80)	(0.81)	(0.05)	(0.00)	(0.00)	(0.53)	(0.70)	(0.32)
No. of Pairs	41	41	41	41	39	33	41	41	41	41	39	33
Bankrupt unconnected firms (C)	54.3	66.1	105.0	48.8	45.6	53.7	52.7	59.7	83.1	47.6	43.6	41.7
Unconnected matching firms (D)	30.1	29.6	28.0	28.6	30.7	30.2	28.2	25.5	24.0	23.7	27.3	26.5
Difference (C)-(D)	24.2	36.5	77.0	20.2	14.9	23.5	24.5	34.2	59.1	23.9	16.3	15.2
p-Value difference	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
No. of Pairs	80	80	80	80	63	53	80	80	80	80	63	53
Difference [(A)-(B)]-[(C)-(D)]	-10.3	-9.6	5.6	-23.1	-16.1	-2.5	-13.0	-23.7	-4.2	-15.5	-19.5	-17.4
p-Value difference	(0.17)	(0.33)	(0.80)	(0.00)	(0.04)	(0.03)	(0.05)	(0.11)	(0.76)	(0.00)	(0.05)	(0.02)

Table 2.9

Debt Claims Recovery and Securities Taken under Chapter 11

This table reports the debts claims recovery rates and securities taken under Chapter 11 for both politically connected and unconnected firms. The data are manually collected from the firms' restructuring plan obtained from *Bankruptcy.Com*, *LexisNexis*, and SEC. Bank loans include the revolving credit facility, Term A loans, and Term B loans. Non-bank debts include public debts, institutional loans, private placement, etc. We define bank loans/non-bank debts recovery/total debts recovery by using the amount of what bank loan creditors/non-bank debtholders/all debt holders achieve scaled by total amount of bank loan/non-bank debts/total debts claims. We define equity recovery of bank creditors/non-bank debtholders/all debt holders by using the amount of equities taken scaled by total covered amount of bank loan/non-bank debts/total debts claims. The sample includes the 121 firms emerged from Chapter 11 in our sample, 41 of which are politically connected.

	Politically Connected Firms					Politically Unconnected Firms					Difference	
Variable	N	Mean	*p*-Value	Median	*p*-Value	N	Mean	*p*-Value	Median	p-value	MeanDiff *p*-Value	MedianDiff *p*-Value
Bank loans recovery	34	0.89	0.00	1.00	0.00	57	0.85	0.00	1.00	0.00	0.54	0.73
Non-bank debts recovery	37	0.42	0.00	0.35	0.00	69	0.67	0.00	0.50	0.00	0.19	0.06
Total debts recovery	39	0.59	0.00	0.57	0.00	72	0.73	0.00	0.63	0.00	0.39	0.62
Equity recovery by bank creditors	40	0.34	0.00	0.00	0.00	77	0.09	0.00	0.00	0.00	0.09	0.37
Equity recovery by non-bank debt holders	40	0.66	0.00	0.87	0.00	78	0.48	0.00	0.42	0.00	0.03	0.05
Total equity recovery by total debt holders	40	0.45	0.00	0.38	0.00	78	0.32	0.00	0.27	0.00	0.03	0.04

Table 2.10
Political Connections and Post-Bankruptcy Stock Performance

This table reports daily excess returns for portfolios of both politically connected and unconnected groups with the holding period of 3 months, 6 month, and one to five years. The daily stock returns are from CRSP, starting from the first available date after the firm's emergence for five years. For those that refile for bankruptcy within five years, returns are kept until the latest available date and adjust for the delist return. The first 30 days' returns are dropped to avoid the mispricing due to IPO. Returns are truncated at 1 and 99 percent. Returns of the two groups are adjusted for Fama-French 4 factors by running the time-series regressions simultaneously. p-Diff reports the p-value for the difference of the excess return between the connected and unconnected groups. 121 firms in our bankruptcy sample have post-bankruptcy stock returns available, among which 41 are politically connected.

Panel A: Value-weighted Portfolios

	Politically Connected Firms				Politically Nonconnected Firms				Difference	
Holding Periods	*alpha* (%)	*std*(%)	t-Stat	p-Value	*alpha* (%)	*std*(%)	t-Stat	p-Value	χ^2	p-Diff
3 Months	0.23	0.29	0.81	0.42	0.13	0.16	0.81	0.42	0.18	0.67
6 Months	0.32	0.14	2.33	0.02	0.12	0.09	1.28	0.20	1.42	0.23
1 Year	0.21	0.08	2.63	0.01	-0.01	0.06	-0.18	0.86	4.56	0.03
2 Years	0.09	0.06	1.54	0.12	-0.04	0.05	-0.95	0.34	3.20	0.07
3 Years	0.04	0.04	1.01	0.31	-0.05	0.04	-1.25	0.21	2.46	0.12
4 Years	0.03	0.04	0.91	0.36	-0.05	0.03	-1.64	0.10	3.08	0.08
5 Years	0.02	0.03	0.50	0.62	-0.07	0.03	-2.24	0.03	3.53	0.06

Panel B: Equal-weighted Portfolios

	Politically Connected Firms				Politically Nonconnected Firms				Difference	
Holding Periods	*alpha* (%)	*std*(%)	t-Stat	p-Value	*alpha* (%)	*std*(%)	t-Stat	p-Value	χ^2	p-Diff
3 Months	0.18	0.20	0.86	0.40	0.18	0.18	1.00	0.32	0.00	0.97
6 Months	0.22	0.14	1.61	0.11	-0.05	0.11	-0.50	0.62	2.57	0.11
1 Year	0.21	0.09	2.23	0.03	-0.08	0.07	-1.20	0.23	6.11	0.01
2 Years	0.10	0.06	1.61	0.11	-0.16	0.05	-3.47	0.00	11.06	0.00
3 Years	0.02	0.05	0.50	0.62	-0.17	0.04	-4.46	0.00	10.08	0.00
4 Years	0.01	0.04	0.40	0.69	-0.14	0.03	-4.17	0.00	10.01	0.00
5 Years	-0.01	0.03	-0.25	0.80	-0.13	0.03	4.22	0.00	7.78	0.01

Appendix

Variable Definition and Data Source

Variable	Definition	Data Source
PC	A dummy variable equals to one if the firm is politically connected, measured one year prior to a Chapter 11 filing or an out-of-court restructuring	*Capital IQ*
*PC**	A dummy variable equals to one if the firm is politically connected, measured five years prior to a Chapter 11 filing or an out-of-court restructuring	*Capital IQ*
PC Strength	The number of politically connected key personnel of a firm reported in *Capital IQ*, measured one year prior to a Chapter 11 filing or an out-of-court restructuring	*Capital IQ*
*PC Strength**	The number of politically connected key personnel of a firm reported in *Capital IQ*, measured five years prior to a Chapter 11 filing or an out-of-court restructuring	*Capital IQ*
Total assets	A firm's total assets (*Compustat* variable: AT)	*Compustat*
Profitability	The ratio of EBITDA to total assets (*Compustat* variables:EBITDA/ AT)	*Compustat*
Leverage	The ratio of total liabilities and total assets(*Compustat* Variable: LT/AT)	*Compustat*
Z-score	Altman's Z-score (Altman (1968))	*Compustat*
Tangibility	The ratio of net property plant and equipment and total assets (*Compustat* variable: PPENT/AT)	*Compustat*
Secured debt	The ratio of secured debt to total debt (*Compustat* variable: DRM/(DLC+DLTT)	*Compustat*
R&D	The ratio of R&D expense to total assets (*Compustat* variable: XRD/AT)	*Compustat*
Industry distress	A dummy variable that takes the value of one if the firm's industry median stock return over the 12 months prior to filing Chapter 11 or restructuring out-of-court is less than 30%	CRSP
Recession	A dummy variable that takes the value of one if the firm filed for bankruptcy or began an out-of-court restructuring in a NBER recession month.	NBER
Prepack	A dummy variable that takes the value of 1 if the firm filed a prepackaged or prenegotiated Chapter 11 bankruptcy	*EDGAR*, *Factiva*, *Lexis-Nexis*
AAA-BAA	The yield spread on AAA and BAA corporate bonds in the month of emergence from Chapter 11 bankruptcy.	*Federal Reserve*

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Education

Doctor of Philosophy in Finance (Minor: Econometrics), GPA 3.8/4, May 2018

Sheldon B Lubar School of Business, University of Wisconsin, Milwaukee, WI

Master of Financial Mathematics, GPA 3.6/4, May 2013

School of Mathematics, University of Minnesota Twin Cities, Minneapolis, MN

Bachelor of Economics, Finance Major, GPA 3.6/4, June 2011

School of Economics, Nankai University, China

Areas of Interest

Research: Mutual Funds, International Finance, Financial Institutions, Empirical Corporate Finance

Working Papers

"Liquidity Demand and the Cross-section of Stock Liquidity" Job Market Paper

"Political Connections and Debt Restructurings" with Joseph Halford, and Lilian Ng, 2016 FMA Conference Paper

Work in Progress

"Political Connections and Probability to Default"

"Complicated Firms and Post-Earning-Announcement-Drift"

"Liquidity Commonality and Locations"

Research Experience

Research Assistant, University of Wisconsin, Milwaukee, WI, Fall 2013-Summer 2014

"The Determinants of Firm Characteristics: An Explanation of Location" Research Project

"Geographic Effects Still Matter?" Research Project

"Corporate Bankruptcy and Recovery Rates" Research Project

Conference/Seminar Presentations

"Political Connections and Debt Restructurings"

- Midwest Finance Association (MFA) Annual Meeting, Chicago, IL, Spring 2015 (Presenter)
- Financial Management Association (FMA) Annual Meeting, Las Vegas, NV, Fall 2016 (Presenter)
- Brown Bag Seminar, University of Wisconsin Milwaukee, Milwaukee, WI, Fall 2016 (Presenter)

Professional Services

Discussant

- *"Learning from other firms' investments: corporate governance and firm"*, Konrad Raff and Patrick Verwijmeren, Midwest Finance Association Annual Meeting, Chicago, IL, Spring 2015
- *"The impact of managers' multiple team membership on fund performance", Jean Chen, Li Xie, and Si Zhou,* Financial Management Association Annual Meeting, Boston, MA, Fall 2017

Teaching Experience

Instructor, University of Wisconsin, Milwaukee, WI, 2015-Present

International Financial Management, Spring 2017: Two Sections (**Teaching Evaluation (TE): 4.7/5.0**)

International Financial Management, Fall 2016: Two Sections (**TE: 4.6/5.0**)

International Financial Management, Spring 2016: Two Sections (**TE: 4.4/5.0**)

International Financial Management, Fall 2015: Two Sections (**TE: 4.2/5.0**)

Principles of Finance, Summer 2015: One Section (**TE: 3.75/5.0**)

Teaching Assistant, University of Wisconsin, Milwaukee, WI, 2014-2015

Principles of Finance, Fall 2014-Spring 2015 (**TE: 4.1/5.0**)

Industry Experience

Muni Price Analyst Intern, DerivActiv, Minneapolis, MN, USA, 02/2012—05/2012

- Participated in project design, data acquisition and database construction
- Evaluated the relative efficiency of the dealer's distribution channel

Awards and Honors

Sheldon B. Lubar Doctoral Scholarship, University of Wisconsin, Milwaukee, WI, Spring 2014, 2015

Chancellor Award Scholarship, University of Wisconsin, Milwaukee, WI, 2013-2017

Merit Scholarship, Nankai University, Tianjin, Fall 2010

The Sumitomo Mitsui Banking Corporation (SMBC) Scholarship, Nankai University, Tianjin, Fall 2009

First Year Scholarship, Nankai University, Tianjin, Fall 2007

Skills, Membership and Personal

Programing: Visual Basic, SAS, Matlab, Minitab, GAUSS, Eviews, Latex, STATA

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Selected Abstracts

"Liquidity Demand and the Cross-section of Stock Liquidity", Job Market Paper

This paper examines the effect of liquidity demand on the individual stock liquidity. I find that funds tend to hold less liquidity than its respective benchmark and that they engage in more liquid stock sales during periods of market turmoil. The way that funds manage and utilize liquidity would aggravate the selling pressure of their liquid assets and erode their liquidity. Using a measure of forced sale, which accounts for funds' involuntary stock selling actions, my results show that stock liquidity decreases as the stock is sold more by distressed mutual funds with large negative fund flows. This liquidity deterioration exists mostly among liquid stocks. As a result, liquid stocks suffer more especially when the overall market is volatile. My evidence offers an important implication that the resulting stock liquidity from trading activities should be stressed in fund liquidity management

"Political Connections and Debt Restructurings", with Joseph Halford, and Lilian Ng

This paper examines the role of political connections in the debt restructurings of financially distressed firms. Based on a sample of 619 distressed firms over the period from 1991 to 2004, we find that politically connected firms are more likely to reorganize out of court than to undergo Chapter 11 bankruptcy. For corporations that file for Chapter 11 bankruptcy, those with political connections are more likely to reorganize than those without. We also show that politically connected firms are less likely to have a subsequent distressed restructuring following the first reorganization. In addition, politically connected firms are able to reduce their leverage to their industry level, while unconnected firms still remain at a higher-than-industry leverage after the Chapter 11 restructuring. Creditors from politically connected firms take more firm equity than those from unconnected firms. Overall, the evidence suggests that political connections facilitate successful debt restructurings.