Essays on the Liquidity of Financial Markets

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Business Administration)
in The University of Michigan
2016

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This dissertation is dedicated to my mother, Foteini Zafeiridou, without whose unending help, guidance, love, and support these pages and a lot more would not have been possible. Her strength, perseverance, talents, and mind continue to inspire me.

ACKNOWLEDGEMENTS

This dissertation is the result of my interaction with people and ideas at the University of Michigan. It is imperative that I thank my adviser and co–author of one of the chapters of this dissertation, Professor Paolo Pasquariello, to whom, along with Professor Stefan Nagel, fell the unenviable burden of supervising my work. His help, critique, advice, and encouragement have made these pages possible. He personifies scholarly excellence and as such has been great inspiration for me. It goes without saying that I am heavily indebted to and greatly benefited from the help and guidance of Professor Stefan Nagel, whose continual strive for academic and technical rigor have given impetus to this dissertation's quality. I am also particularly grateful to Professor Martin Schmalz, whose advice and support have acted as a catalyst in the completion of this dissertation. I would also like to thank Professors Christopher House and Kyle Handley, who dedicated long hours to this dissertation. I would also like to express my deep gratitude to Professor Lutz Kilian for his enthusiastic encouragement and useful critiques of the main chapter of this dissertation; without his support the completion of this would not have been possible.

I would also like to express my great appreciation to friends, colleagues, and the faculty members and PhD students of the Finance area at the University of Michigan, Ross School of Business, who have read and commented on various iterations of the chapters that make up this dissertation. I have benefited from discussions with Taylor Begley, Sugato Bhattacharyya, Indrajit Mitra, Spiros Papageorgiou, Isacco Piccioni, Amiyatosh Purnanandam, Uday Rajan, Nejat Seyhun, Tyler Shumway, Denis Sosyura, Santhosh Suresh, Yifei Wang, Toni Whited, and Stefan Zeume. My research was made possible by the financial support provided by the Ross Business School, Rodkey Fellowship, Rackham Graduate Student Research Grant, and Ross School of Business Doctoral Research Grant.

Finally, I would like to express my deep gratitude to my husband, Ismail Fajrie Alatas, whose mind and character are a never ending source of light.

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ABSTRACT

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This dissertation examines the effects of political uncertainty surrounding the outcome of U.S. presidential elections on financial market quality – i.e., the ability of a market to price assets correctly – as well as the liquidity spillovers across four asset classes traded in U.S. futures markets.

In the first chapter of the dissertation, entitled "Political Uncertainty, Liquidity, and Information Asymmetry"and co–authored with Paolo Pasquariello, we examine the effects of political uncertainty, as captured by the U.S. Presidential elections, on financial market liquidity, returns, and volatility. We find that liquidity deteriorates (trading volume decreases, fraction of zero returns increase) in the months leading up to the presidential elections (when political uncertainty is higher), but it improves (trading volume increases, price impact and fraction of zero returns decrease) in the months following the elections. We also find that average stock returns are higher

both before and after the elections. The effects are more pronounced for more uncertain elections and more politically sensitive firms. We postulate that the effects of political uncertainty on financial markets depend on a positive relation between political uncertainty and information asymmetry among investors, ambiguity about the quality of their information, or dispersion of their beliefs. To test these hypotheses, we use direct proxies for market wide information asymmetry and disagreement, and find that the proxies only for the former are significantly affected by political uncertainty. These findings provide the strongest support for the predictions of the ambiguity hypothesis.

In the second chapter of the dissertation, entitled “Liquidity Spillovers Across Asset Classes”, I argue that liquidity spillovers – i.e., the transmissions of liquidity shocks from one asset to another – are an important yet not fully understood feature of price formation in financial markets. Using a reduced–form VAR, I measure the liquidity spillovers across four assets in the U.S. futures market and find significant evidence of liquidity spillovers across these assets, especially during periods of financial and macroeconomic turmoil. My findings also suggest that these spillovers are driven by liquidity supply channels (as opposed to information channels): when liquidity providers face higher funding constraints, liquidity spillovers across assets increase.

CHAPTER I

Political Uncertainty, Liquidity and Information Asymmetry

Long before the appointed day [of a Presidential election] arrives, the election becomes the greatest, and one might say the only, affair occupying men's minds...
– *Alexis de Tocqueville,* Democracy in America, 1848

1.1 Introduction

Political uncertainty matters. Many recent studies conjecture that uncertainty about political outcomes has important effects on asset returns and corporate decisions.[1] We study the uncertainty regarding the outcome of the U.S. Presidential elections and conjecture that political uncertainty is greater in the months prior to those elections (relative to non-election periods) but is resolved once the outcome

[1]e.g., see *Pantzalis et al.* (2000), *Bernhard and Leblang* (2006), *Bialkowski et al.* (2008), *Durnev* (2011), *Bond and Goldstein* (2015), *Pástor and Veronesi* (2012), *Julio and Yook* (2012), *Goodell and Vahamaa* (2013), *Belo et al.* (2013), *Pástor and Veronesi* (2013), and *Boutchkova et al.* (2012).

of the elections is determined. Our conjecture is based on the idea that in most developed economies, political uncertainty pertains primarily to possible changes in government policy or national leadership. Having defined a measure of political uncertainty, we then study liquidity and returns in the presence of political uncertainty. We find that (1) prior to U.S. Presidential elections, as compared to non–election periods, liquidity in the financial markets deteriorates, returns are on average higher, and volatility decreases, and (2) in the months following the elections, liquidity improves, returns continue to be higher, and volatility increases. We also show that these results are due to a positive relationship between political uncertainty and information asymmetry, i.e., the quantity of information available to investors.

Liquidity plays a central role in the functioning of financial markets and many pages have been rightfully devoted to measuring it and identifying its determinants. What has received less attention empirically however, is how liquidity changes in the presence of uncertainty and why. The effects of uncertainty are especially relevant in light of the recent liquidity dry–ups and subsequent, financial and liquidity crises.[2] A priori, uncertainty has an unclear effect on liquidity. To measure liquidity we concentrate on trading volume, the fraction of zero returns, and the *Amihud* (2002) illiquidity measure because of both their widespread use and their strong link with the theoretical microstructure literature on the process of price formation in financial markets in the presence of uncertainty (e.g., see *Vives* (2008) and *Goyenko et al.* (2009)). To examine why uncertainty may affect liquidity, we first rely on the theoretical literature to identify the possible channels and we then test the empirical

[2]see, for instance, *Gromb and Vayanos* (2012) and *Cespa and Foucault* (2014)

predictions of each channel.

We conjecture that political uncertainty may affect liquidity and the price formation process via three channels related to *information asymmetry, ambiguity*, and *disagreement*. *Miller* (1977) notes that uncertainty implies dispersion of beliefs among market participants, which according to *Varian* (1985) can arise either because of differences in information or differences in opinion (i.e., disagreement). Subsequent literature (e.g., *Epstein and Schneider* (2008)) suggests that differences in information are either due to differences in information quantity or information quality. Information asymmetry refers to the dispersion in the quantity of information that investors possess, whereas ambiguity to the dispersion in the quality of information. The information asymmetry channel conjectures that information asymmetry and uncertainty are positively correlated. As a result, during periods of high political uncertainty, adverse selection risk is higher and therefore, liquidity lower. The ambiguity channel assumes that during high uncertainty periods, the quality of investors' information is higher, which in turn leads to lower trading volume and deteriorating liquidity. Finally, the disagreement channel conjectures that greater uncertainty increases differences in opinion among market participants, leading to higher trading volume and, under certain conditions, improved liquidity.

These three hypotheses make distinct predictions (summarized in Table 1.1) regarding the impact of uncertainty on liquidity, returns, and volatility. As noted earlier, we test these predictions by using all U.S. presidential elections between 1926 and 2012 as a proxy of political uncertainty over our sample period and investigate its effects on trading volume, the fraction of zero returns, and the *Amihud*

(2002) illiquidity measure. We find that trading volume decreases in the months preceding presidential elections and increases in the months immediately following the elections. Popular measures of illiquidity continuously available over our long sample period (*Amihud* (2002) illiquidity measure (1927) and the fraction of zero returns (1927) significantly increase in the months before and decline in the months after the elections. The effects of political uncertainty on liquidity are larger during more uncertain elections (i.e., with smaller popular vote margin and final Gallup survey results), consistent with the notion that political uncertainty is higher prior to the elections and dissipates once their outcome is determined. These effects are in addition more pronounced for politically sensitive industries and firms.

Recent works have also shown that firm performance under different ruling parties varies, presumably due to the differential effects of government policies. *Santa-Clara and Valkanov* (2003), for instance, show that stock returns are on average higher under the Democratic party. In line with the current literature, we also show that the Democratic party, whether it is the incumbent party or the winning party, has a more positive effect on market liquidity and market returns, both prior and after the presidential elections. These results further reinforce our hypothesis that our findings are driven by political uncertainty.

These results are consistent with the predictions of the information asymmetry and ambiguity hypotheses, but not the disagreement hypothesis. To further test the former hypotheses, we examine the impact of political uncertainty on working capital accruals – a common measure of information asymmetry – and the analysts' forecasts dispersion – a common measure of differences of opinion. We show that working capital accruals increase prior to U.S. presidential elections and decrease following the elections. We find no effect on analysts' forecast dispersion. These results provide evidence in favor of the information asymmetry hypothesis.

Cross-sectional analysis provides further insights about the determinants of the effects of political uncertainty on liquidity. If the ambiguity hypothesis is true, we expect these effects to be most pronounced for more "speculative" and difficult-to-value stocks (e.g., *Baker and Wurgler* (2007); *Brunnermeier and Pedersen* (2009)). Using size and market beta portfolios, we find no varying effect of political uncertainty on the process of price formation for smaller stocks and stocks with lower market beta. Again, these dynamics are consistent with the predictions of the *information asymmetry* hypothesis and suggest that political uncertainty does not decrease the quality of information available to speculators but rather the quantity. That is, when political uncertainty is high, investors are less informed.

These findings provide the strongest — albeit only *indirect* — support for the predictions of the *information asymmetry* hypothesis. Time-varying ambiguity is elusive and difficult to measure and we thus cannot test it directly.

Our paper is related to recent empirical and theoretical studies on presidential elections around the world and their effects on firm-level investment, stock returns, and return volatility (e.g., *Pantzalis et al.* (2000), *Bernhard and Leblang* (2006), *Durnev* (2011), *Bialkowski et al.* (2008), *Goodell and Vahamaa* (2013), *Julio and Yook* (2012), *Pástor and Veronesi* (2012), *Pástor and Veronesi* (2013), *Boutchkova et al.* (2012)). For instance, *Julio and Yook* (2012) document cycles in corporate investment in correspondence with the timing of national elections in 48 countries between 1980 and 2005. *Goodell and Vahamaa* (2013) show that political uncertainty around U.S. presidential elections affects option-implied stock market volatility insofar as the winner of the presidential elections becomes more uncertain. *Boutchkova et al.* (2012) show that this effect is stronger for firms operating in politically sensitive industries. *Pástor and Veronesi* (2012) and *Pástor and Veronesi* (2013) develop a general equilibrium model to show that government policy uncertainty and political uncertainty, respectively, may have ambiguous effects on stock prices because of their effects on both future cash flows and discount rates (e.g., by exposing stocks to an additional source of non-diversifiable risk). Relative to these studies, our focus is on the determinants and implications of investors' behavior for financial market quality when political uncertainty is high.

In the rest of the paper, we proceed as follows. In Section 1.2 we further discuss our notion of political uncertainty relative to the existing literature. In Section 1.3 we discuss in detail the three hypotheses. We describe our data and empirical design in Section 1.4 and present our results. Section 2.6 concludes.

1.2 Political Uncertainty

Within the political science literature, political uncertainty typically refers to the lack of sureness or absence of strict determination in political life. As *Dahl et al.* (1963) note, uncertainty appears to be an important characteristic of all political life. Elections, wars, governmental processes, threats, and other political phenomena are all inherently uncertain political occurrences (Cioffi (2008)). In this study, we define political uncertainty as the uncertainty regarding the outcome of U.S. Presidential elections. We concentrate on presidential elections because in developed countries with stable political regimes, such as the United States, regularly scheduled Presidential elections are (exogenous) political events that define who holds office. Therefore, the timing of Presidential elections does not depend on economic conditions or business cycles.

One may argue that political uncertainty is merely a reflection of policy uncertainty. These two forms of uncertainty, while related, use distinct features. Policy uncertainty is the uncertainty regarding any government policies (monetary and fiscal policies) and their impact on economic activity or financial markets (e.g., *Pástor and Veronesi* (2012), *Pástor and Veronesi* (2013), *Pasquariello* (2014)). A popular index of economic policy uncertainty is developed by *Baker et al.* (2015) and is comprised of news coverage about policy related economic uncertainty, tax code expiration, and analysts' disagreement. Insofar as there may be uncertainty about the government policies proposed by competing candidates for office, political uncertainty may also stem from policy uncertainty. Political uncertainty however is broader in scope for it entails greater uncertainty regarding the possible states of nature that can occur. In particular, political uncertainty encompasses both uncertainty about the election outcome and uncertainty about the policies that may ensue from that outcome.

Another important distinction is the one between political uncertainty and economic uncertainty. Economic uncertainty is the uncertainty regarding the economic conditions or the business cycles. Economic uncertainty may affect political uncertainty since during periods of high economic uncertainty the uncertainty regarding who wins the Presidential elections may increase. This raises the possibility that any investigation of the impact of political uncertainty on market quality may be plagued by endogeneity concerns. For instance, both market quality and political uncertainty may be amplified by economic uncertainty surrounding downturns in economic activity or outright recessions. However, as noted in the Introduction, in our study we make the important identification assumption that, although being possibly state-dependent, political uncertainty is always higher in the months leading to U.S. presidential elections and lower once their outcome is determined. Of course, economic conditions may (and often do) affect political outcomes as well. Nonetheless, given the above assumption, endogeneity concerns are mitigated by our prior observation that the timing of U.S. presidential elections is *exogenous* to current and expected economic uncertainty.

If, however, our identification assumption is not supported, then our results may be driven by political business cycles ("election year economics") rather than political uncertainty. As *Alesina* (1988) notes, "social planners" and "representative consumers" do not exist. Politicians are driven by their incentive to be re-elected ("office-motivated" politicians; e.g., see *Nordhaus* (1975), *Rogoff* (1987)). Office-motivated politicians can manipulate monetary and fiscal policy instruments to influence the level of economic activity and increase their chances of being re-elected. Under this scenario, our results may merely reflect the peaks and troughs of the political business cycle. However, according to *Drazen* (2001), there is much less hard evidence about the prevalence of "election-year economics" in developed countries (and especially in the United States) than suggested by both the aforementioned theoretical models and conventional wisdom. For instance, *Drazen* (2001) (p. 76) observes that "although there is wide — but not universal — agreement that aggregate economic conditions affect election outcomes in the United States, there is significant disagreement about whether there is opportunistic manipulation that can be observed in the macro data." Thus, we argue that U.S. presidential elections may provide a clean setting to examine the effects of political uncertainty on financial market quality.

1.3 Hypotheses

Motivated by the theoretical literature on market microstructure and uncertainty, we conjecture that political uncertainty may affect market quality via three channels related to *information asymmetry, ambiguity*, and *disagreement*. With the *information asymmetry* hypothesis we assume that political uncertainty, as a source of fundamental uncertainty, may affect the information asymmetry between informed and uninformed investors, or investors and firms. Numerous rational expectations equilibrium (REE) models since *Grossman and Stiglitz* (1980) illustrate this linkage. Intuitively, greater fundamental uncertainty — e.g., before Presidential elections, when political uncertainty is likely higher — makes private fundamental information more valuable, thus increasing adverse selection risk. The opposite would then occur after those elections. The effects of information asymmetry on market quality in REE models are less clear. According to *Wang* (1994), greater information asymmetry leads to lower trading volume as it decreases the informativeness of asset prices. However, informed trading volume may also increase with political uncertainty if liquidity trading is exogenous and inelastic, as in *Kyle* (1985). In addition, greater adverse selection risk may increase market-makers' inventory cost, leading to lower market liquidity — e.g., higher bid-ask spreads (*Ho and Stoll* (1981), *Amihud and Mendelson* (1986)) or lower depth (*Kyle* (1985)) — and consequently higher fraction of zero returns and Roll's price impact.

With the *ambiguity* hypothesis we postulate that greater political uncertainty may lead to greater ambiguity about the *quality* of information available to market participants. Standard REE models (e.g., *Vives* (1995a); *Vives* (1995b)) assume investors' information to be of known quality. Recent studies (e.g., *Epstein and Schneider* (2008); *Ozsoylev and Werner* (2011)) extend these models to incorporate ambiguity by allowing investors to have a distribution of beliefs about the mean and/or variance of the fundamentals of the traded asset. For instance, in the model of *Ozsoylev and Werner* (2011), greater fundamental uncertainty distorts the quality (rather than the quantity) of investors' information by worsening the ambiguity of their prior beliefs about asset fundamentals. Faced with greater such uncertainty, ambiguity-averse investors and arbitrageurs may choose to trade less or not trade at all. Thus, in this setting trading volume and liquidity would decline prior to U.S. elections — when both political uncertainty and ambiguity of information quality are high — and improve afterwards, once the election outcome is determined.

Finally, with the *disagreement* hypothesis we conjecture that greater political uncertainty may increase differences in opinion among market participants. In heterogeneous beliefs models (e.g., *Banerjee and Kremer* (2010), *Hong and Stein* (2007)), greater fundamental uncertainty increases disagreement among investors about the fundamental value of the traded asset, leading them to trade more with one another, i.e., increasing equilibrium trading volume. Thus, trading volume may first increase in the months preceding presidential elections — when both political uncertainty and accompanying information heterogeneity among market participants are likely high — and then decrease afterwards, when political uncertainty is resolved. However, according to *Pasquariello and Vega* (2007) and *Pasquariello and Vega* (2009) more heterogeneously informed speculators may instead trade more cautiously (i.e., less, rather than more) with their private information, leading to deteriorating trading volume and market liquidity.

These three hypotheses make distinct predictions (summarized in Table 1.1) regarding the impact of uncertainty on market quality.

Table 1.1: Hypotheses

This Table reports a brief description of the hypotheses and a summary of their main predictions regarding trading volume and liquidity (the fraction of zero returns and Roll's impact) in the months preceding and following the presidential elections. The plus (minus) sign (+) indicates an increase (decrease), the question mark (?) the fact that no predictions have been developed, and the plus-minus sign (+/−) that there are theories that predict both an increase and a decrease in the corresponding variable.

Hypothesis	Description	Trading Volume		Liquidity	
		Before	After	Before	After
Information Asymmetry	Higher political uncertainty increases information asymmetry between informed and uninformed investors.	+/−	+/−	−	+
Ambiguity	Higher political uncertainty increases the ambiguity about the information quality.	−	+	+	−
Disagreement	Higher political uncertainty increases divergence in opinions.	+/−	+/−	+/?	−/?

1.4 Data

1.4.1 Election Data

Our analysis focuses on U.S. presidential elections from 1926 to 2012. The U.S presidential elections are held every four years, the Tuesday between November 2nd and 8th. Traditionally, there have been two major political parties participating, Democratic and Republican.[3] The candidates are nominated through a series of primary elections and caucuses. This process however, is not part of the U.S. Constitution and as a result, the exact time that the nominees are selected is not pre-specified and in fact, has varied a lot across elections.[4] We thus choose to study the effects of the presidential elections over a fixed window of six months around the actual election day (from August pre–election to April post–election).

We consider 21 U.S. presidential elections from 1926 until 2012.[5] Table 1.2 shows summary characteristics of the presidential elections; incumbent president and party, winning candidate and party, popular vote margin and the margin of the final Gallup survey prior to the elections. The data on the U.S. presidential elections have been collected from CQPress and Gallup.[6]

[3] During the elections of 1968, 1980, 1992, 1996 and 2000, however, there were three candidates.

[4] For instance, in the 1976 elections, the Republican's party nominee was not selected until the party's national convention when the incumbent President, Gerald Ford, narrowly defeated Ronald Reagan.

[5] There are 22 elections between 1926 and 2012, we however, exclude the presidential elections of 2000 between George W. Bush (R) and Al Gore (D) because of its unusual progression.

[6] http://www.cqpress.com

Table 1.2: Election Characteristics

This table reports summary characteristics of U.S. presidential elections from 1926 to 2012. The characteristics we report are the year of elections, whether there was an incumbent President, the incumbent party and the winner party, the popular vote margin, and the Final Gallup Survey. We use two different specifications of uncertain elections; by the popular vote margins and the results of the final Gallup survey. The highlighted popular vote and survey margins are the top 7 we use in order to define uncertain elections. They overlap in most cases with the exception of 1952 and 1992 elections. We exclude the presidential elections of 2000 (George W. Bush vs. Al Gore) from all of our tests because the final winner in those elections was determined in December 12th, 2000.

Year	Incumbent	Incumbent Party	Winner	Party	Margin	Gallup
1928		Republican	H. Hoover	Republican	17.41%	
1932	H. Hoover	Republican	F. Roosevelt	Democratic	17.76%	
1936	F. Roosevelt	Democratic	F. Roosevelt	Democratic	24.26%	11.4%
1940	F. Roosevelt	Democratic	F. Roosevelt	Democratic	9.96%	4%
1944	F. Roosevelt	Democratic	F. Roosevelt	Democratic	7.50%	3%
1948		Democratic	H. Truman	Democratic	4.48%	5%
1952		Democratic	D. Eisenhower	Republican	10.85%	**2%**
1956	D. Eisenhower	Republican	D. Eisenhower	Republican	15.40%	19%
1960		Republican	J. Kennedy	Democratic	**0.17%**	**0.5%**
1964		Democratic	L. Johnson	Democratic	22.58%	28%
1968		Democratic	R. Nixon	Republican	**0.6%**	**1%**
1972	R. Nixon	Republican	R. Nixon	Republican	23.16%	24%
1976		Republican	J. Carter	Democratic	**2.7%**	**1%**
1980	J. Carter	Democratic	R. Reagan	Republican	9.74%	3%
1984	R. Reagan	Republican	R. Reagan	Republican	14.21%	18%
1988		Republican	G.H. Bush	Republican	7.72%	12%
1992	G.H.Bush	Republican	B. Clinton	Democratic	**5.56%**	12%
1996	B. Clinton	Democratic	B. Clinton	Democratic	8.52%	3%
2000		Democratic	G.W. Bush	Republican	**0.51%**	**2%**
2004	G.W. Bush	Republican	G. W. Bush	Republican	**2.46%**	**0%**
2008		Republican	B. Obama	Democratic	7.21%	11%
2012	B. Obama	Democratic	B. Obama	Democratic	**3.86%**	**1%**

1.4.2 Financial Market Data

We measure monthly equity returns and liquidity using daily data from CRSP for all stocks listed on the NYSE, NASDAQ, and AMEX from 1926 to 2013. NYSE and AMEX stocks span the whole period from 1926 to 2013, but NASDAQ stocks enter the sample in 1973 when it was first introduced. We include only common stocks (CRSP share code 10 and 11) and as conventional, omit ADRs, SBIs, REITs, and closed-end funds. We implement additional filters to exclude any outliers that may drive or distort our results. Hence, we exclude stocks with zero trading or whose price is missing (or is below $0.5). We also winsorize the data at the top and bottom 5% trading volume and 1% returns. Additionally, we only include stocks that have been listed and actively traded in either of the exchanges for at least 3 years.

Table 1.3 shows the number of firms in our sample. Overall, there are 17,102 unique stocks for the period 1926-2013 that meet our criteria. After the recent financial crisis however, there has been a significant drop in the number of firms that are listed on the exchanges.

On the account of the well known double counting issue related to NASDAQ volume (*Atkins and Dyl* (1997)) and the fact that the structure and capitalization differences between NASDAQ and NYSE may have important implications for the measurement and behavior of volume, most of the empirical literature analyzes the two exchanges separately. Particularly, the double counting issue arises because NASDAQ is primarily a dealer market, whereas the NYSE is an auction market. For instance, when an investor sells 100 shares of a firm x to a dealer, the dealer reports a 100-share transaction; when another investor buys these 100 shares of firm x from the dealer, the dealer reports another 100-share transaction. The reported trading volume for firm x is 200 shares, when only 100 shares have been exchanged between the two investors. Thus, the reported trading volume on the NASDAQ is overstated (*Atkins and Dyl* (1997)). For our purposes however these differences do not play a major role. Thus, in the main regression specification we do not separate between the exchanges.

1.4.3 Cumulative Excess Returns and Measures of Liquidity

Our analysis focuses on equity returns and liquidity around the U.S. presidential elections, starting from pre–election August, to post–election January, until post–inauguration April. We measure three month cumulative excess returns and liquidity for the specified period with a special emphasis on the pre–election (from August to October) and post–election (from November to January). The cumulative excess returns are in excess of the value–weighted market portfolio. Table 1.3, panel A, reports the average monthly returns from 1926 to 2013 and subperiods.

We proxy liquidity through trading volume, the *Amihud* (2002) illiquidity measure, and the fraction of zero returns. Although the empirical microstructure literature has developed many proxies for liquidity, we concentrate on these three measures because they can be easily interpreted and computed using daily data.

Trading volume is a natural measure of trading activity, although, it does not always comove with liquidity; during several low liquidity periods trading volume has been shown to increase. Nonetheless, it is a measure of the quantity traded and as such, it plays an important role in the determination of equilibrium prices. As a measure of volume we use the log share turnover.[7] For each individual stock i, we define 3–month share turnover in period t as:

$$\tau_{i,t} = \frac{V_{i,t}}{N_{i,t}} \ , \tag{1.1}$$

where V_{it} is the total 3–month share volume of stock i, and N_i are the number of shares outstanding of stock i. Table 1.3, panel B, reports the summary statistics for the 3–month turnover from 1926 to 2013 and subperiods. Turnover exhibits positive skewness – it cannot be negative – and has a very fat tail (1210 kurtosis in 1926-2013)[8]. To correct for these characteristics we apply the logarithmic function:

$$log(\tau_{i,t}) = log(\frac{V_{i,t}}{N_{i,t}}) \ . \tag{1.2}$$

Table 1.3, panel C, shows the transformed skewness and kurtosis, -0.251 and 3.552 respectively, which match closely the skewness and kurtosis of a normal distribution, allowing us to perform OLS regressions.[9]

[7]Extended discussion and theoretical justification of the measure can be found in *Lo and Wang* (2001).

[8]The extreme skewness (111) and kurtosis (33297) in the subperiod 1957-1986 are driven by the October 1987 crash. The anomalous properties for both returns and volume in the 1986-1987 period have been well documented in the empirical literature.

[9]Several studies have documented that trading volume exhibits characteristics of non–stationarity and a time-trend. To address the issue of the time trend we use year fixed effects and refrain from using any de-trending techniques. *Lo and Wang* (2001) apply several such techniques on the turnover time series and show that the characteristics of the de-trended series vary across the de-trending methods. Thus, they conclude that it is optimum to use the raw turnover. Non–stationarity is addressed with changes.

Amihud (2002) defines the illiquidity of stock i in the 3–month period t as:

$$ILLIQ_{i,t} = \frac{1}{n_{i,t}} \sum_{d=1}^{n_{i,t}} \frac{|r_{i,t,d}|}{DV_{i,t,d}}, \tag{1.3}$$

where $n_{i,t}$ are the number of trading days in period t for stock i and $DV_{i,t,d}$ is dollar trading volume ($Price \times Volume$) on day d in period t for stock i. To adjust the size of the measure, the *Amihud* (2002) is typically multiplied by 10^6. The monthly *Amihud* (2002) measure is a proxy for price impact, i.e., the monthly price response associated with a given dollar trading volume. It is thus a measure of *illiquidity*; the higher the change in price for a given trading volume, the more illiquid the asset. The *Amihud* (2002) measure is intuitive and simple to compute and is widely accepted as a good measure of illiquidity. *Hasbrouck* (2002) shows that "among the [liquidity] proxies . . . , the illiquidity measure appears to be the best" at capturing Kyle's λ. Panel D in table 1.3 shows the summary statistics for the Amihud illiquidity measure. As one would have probably expected, U.S. stocks are on average less liquid during the recent financial crisis, post–2007. Also, given that the measure can only have positive values, it is naturally skewed.

Finally, following *Lesmond et al.* (1999) we calculate the fraction of zero returns for stock i in period t as following:

$$Zeros_{i,t} = \frac{(\#\text{of days with zero returns})_{i,t}}{n_{i,t}} \tag{1.4}$$

where $n_{i,t}$ is the number of trading days in 3–month period t for stock i. This measure is again a measure of illiquidity; the higher is the fraction of days with zero returns the more illiquid is the asset. Although not a widely used measure of liquidity, we nonetheless choose to use it because *Goyenko et al.* (2009) show that zeros outperform other measures of liquidity both when using high frequency data and daily/monthly data. Table 1.3, panel E, shows the first four moments of the measure. On average 20% of the days exhibit zero returns, with a relatively low variance.

1.5 Empirical Results

In this section we present the empirical findings of the paper. We first document the positive excess return and decrease in liquidity in the August–November period prior to the U.S. presidential elections and reversal in the October–January post–election period. We then look at

1.5.1 Returns and Liquidity around the U.S. Presidential Elections

To quantify the impact of the U.S. presidential elections on returns and liquidity during the pre– and post–election periods we run the following dummy variable regression model:

$$y_{it} = \mu_i + \lambda_t + q_t + \beta_1 \mathbf{1}_t(Election) + \beta_x X_{it} + \varepsilon_{it} \ , \tag{1.5}$$

where $y \in \{Ret_{it}, log(\tau_{it}), ILLIQ_{it}, Zeros_{it}, VOL_{it}\}$ and $Election$ is either a pre–Election, post–Election, or post–Inauguration dummy. The pre–Election period is from August to October, the post–Election from November to January, and the

Table 1.3: Liquidity and Return Summary Statistics

This table reports summary statistics of the 3–month log excess percentage returns, percentage turnover, log turnover, *Amihud* (2002) illiquidity measure, fraction of zero returns, as defined in section 1.4.3. The data contain both NYSE and NASDAQ stocks, from 1926 to 2012. We include stocks with at least 3 years of consecutive observations. The summary statistics are the mean, standard deviation (SD), skewness, kurtosis and the number of firms traded at each period.

Period	Mean	SD	Skewness	Kurtosis	No. of Firms
		Panel A: 3–Month Log Excess Return (%)			
1926-2013	-0.011	0.228	-0.543	12.51	17,102
1926-1950	0.004	0.188	0.174	11.23	1,218
1951-1986	0.0008	0.192	-0.038	8.067	9,139
1987-1998	-0.031	0.256	-0.814	12.35	10,388
1999-2006	-0.007	0.265	-0.181	11.35	7,721
2007-2013	-0.022	0.257	-0.974	13.78	4,593
		Panel B: 3–Month Turnover (%)			
1926-2013	232.8	422.5	18.18	1211	
1926-1950	120.1	342.4	21.90	852.1	
1951-1986	101.6	164.8	111.3	33297	
1987-1998	238.5	323.2	8.045	223.5	
1999-2006	404.4	679.9	19.22	899.0	
2007-2013	545.3	636.4	5.615	87.16	
		Panel C: 3–Month Log Turnover (%)			
1926-2013	4.667	1.303	-0.251	3.552	
1926-1950	3.851	1.376	-0.390	4.992	
1951-1986	4.106	1.045	-0.311	4.028	
1987-1998	4.889	1.158	-0.543	4.139	
1999-2006	5.367	1.200	-0.421	3.350	
2007-2013	5.731	1.219	-0.803	3.818	
		Panel D: 3–Month Amihud Measure			
1926-2013	4.034	2288	110.8	21365	
1926-1950	16.42	133.7	44.28	3194	
1951-1986	2.499	13.03	54.06	8542	
1987-1996	3.832	1358	89.50	14467	
1997-2006	1.335	7.706	28.16	1440	
2007-2013	4.480	63.72	94.77	14394	
		Panel E: 3–Month Fraction of Zero Returns			
1926-2013	0.237	0.212	1.397	4.780	
1926-1950	0.220	0.135	1.509	6.377	
1951-1986	0.326	0.236	1.278	3.261	
1987-1996	0.282	0.169	1.555	6.484	
1997-2006	0.065	0.083	2.241	9.614	
2007-2013	0.030	0.042	2.805	16.60	

post–Inauguration from February to April. Ret_{it} are the cumulative excess log returns, over the value–weighted market portfolio, for the specified periods, and VOL_{it} is defined as the 3–month standard deviation of daily returns. The liquidity measures are specified as in equations 1.2, 1.3, and 1.4. In this baseline specification, the explanatory variables are dummy variables that are equal to one prior to elections ($\mathbf{1}_t$(pre–Election)), after the elections ($\mathbf{1}_t$(post–Election)), after the inauguration ($\mathbf{1}_t$(post–Inauguration)) and zero otherwise. λ_t are year fixed effects and q_t are pre– and post–Election and post–Inauguration period fixed effects – similar to quarter effects. Firm, year, and quarter fixed effects are included to account for all the time–invariant differences between the stocks and across time. In addition the inclusion of year and quarter fixed effects alters the interpretation of the β_1 coefficient. If $Election = Pre - Election$, then β_1 captures the y differential compared to the non–election August–October period. In other words, the comparison is between the August–October period (December–January, or February–April) of an election year and the same period for all non election years. In the regressions excluding the vector of other control variables, X_{it}, the coefficient β_1 is the mean excess y variable differential on pre– pr post–election periods versus the same periods in non election years. Including the controls, the β_1 coefficient captures the conditional changes of the mean excess y variable differential. Standard errors are clustered by time throughout the paper.[10] In alternative specifications, we also include additional control variables denoted by the vector X_{it}.

[10]We do not cluster by firm because it is unlikely that there is error autocorrelation that extends beyond 4 months. Recall, that the comparison is between Novembers of election and non election years, which would require a 12 month autocorrelation of the errors. In non tabulated regressions, we use two–way clustering and the results remain qualitatively the same.

Table 1.4 reports estimates for β_1, pre– and post–Election and post–Inauguration, excluding the vector of controls. As seen in the pre–Election result columns, during the 3–month period prior to elections, from August to October, returns are higher than non–election Aug–Oct periods, trading volume is lower and liquidity is worse (both the *Amihud* (2002) illiquidity measure and the fraction of zero returns increase), and volatility decreases. Post–election, from November to January, however liquidity improves (both the *Amihud* (2002) illiquidity measure and the fraction of zero returns decrease) and trading volume increases. Returns and volatility on the other hand increase. We also include the post–Inauguration period (from February to April), since this is the period that the new government takes office. During the post–Inauguration period, returns and trading volume decrease, liquidity deteriorates significantly (the *Amihud* (2002) illiquidity measure increases sharply and the fraction of zero returns increases), and volatility increases.

The results from the baseline specification are consistent with the hypothesis that the uncertainty associated with presidential elections is high prior to elections, leading to higher cost of trading (higher returns, lower liquidity) prior to the elections. Post–Election, political uncertainty decreases, leading to improved liquidity conditions. Post–Inauguration however, policy uncertainty is high leading to worse liquidity conditions, lower returns, and higher volatility.

Table 1.4: Baseline Return and Liquidity Regressions

This table reports the results of the following regression:

$$y_{it} = \mu_i + \lambda_t + q_t + \beta_1 \mathbf{1}_t(Election) + \varepsilon_{it} \ ,$$

where $y \in \{Ret_{it}, log(\tau_{it}), ILLIQ_{it}, Zeros_{it}\}$ and $Election$ is either a pre–Election, post–Election, or post–Inauguration dummy. Ret_{it} are the cumulative excess log returns, over the value–weighted market portfolio, for the September–November pre–election period and December–January post election period. $log(\tau_{it}), log(ILLIQ_{it})$, and $Zeros_{it}$ are the log turnover, the log *Amihud* (2002) illiquidity measure, and the fraction of zero returns, as defined in eq. 1.2, 1.3, and 1.4 respectively. In this specification, the explanatory variables are dummy variables that are equal to one prior to elections ($\mathbf{1}_t$(pre–Election)) and after the elections ($\mathbf{1}_t$(post–Election)), and zero otherwise. Firm, year and quarter fixed effects are included to account for all the time–invariant differences within the firms and across time. Standard errors are clustered by time throughout the paper.

	Ret	Ret	Ret	$log(\tau)$	$log(\tau)$	$log(\tau)$			
Pre–Election	0.011**			-0.079***					
Dummy	[0.004]			[0.022]					
Post–Election		0.017***			0.047***				
Dummy		[0.004]			[0.005]				
Post–Inaugur.			-0.025***			-0.056***			
Dummy			[0.006]			[0.005]			
	$ILLIQ$	$ILLIQ$	$ILLIQ$	Zeros	Zeros	Zeros	Vol	Vol	Vol
Pre–Election	0.030			0.006***			-0.002***		
Dummy	[0.179]			[0.0003]			[0.0006]		
Post–Election		-0.285			-0.004***			0.001**	
Dummy		[0.208]			[0.0004]			[0.0004]	
Post–Inaugur.			1.746***			0.005***			0.003**
Dummy			[0.287]			[0.0005]			[0.001]
Obs	933,248	933,248	933,248	851,669	851,669	851,669			
Obs	933,248	933,248	933,248	933,248	933,248	933,248	933,248	933,248	933,248
R^2	0.05	0.04	0.05	0.26	0.23	0.23			
R^2	0.006	0.004	0.004	0.35	0.33	0.35	0.14	0.10	0.10

standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.5.2 Subsample Analysis – Uncertain elections

Having shown that market liquidity deteriorates in the months preceding the presidential elections and improves in the months following the elections, we now deepen our analysis by introducing variation in the degree of uncertainty across the elections. If our main identification assumption holds, i.e., that political uncertainty is higher on average in the months leading up to presidential elections and is resolved when the outcome of the elections is declared, then the impact of political uncertainty on market quality should be more profound during more uncertain elections.

To incorporate the degree of election uncertainty, we split the election sample into two sub-samples; uncertain and non-uncertain elections. We define uncertain elections based on the results of the final Gallup survey prior to each election. The uncertain elections are the following six elections: 1952, 1960, 1968, 1976, 2004, and 2012. Table 1.2, column 6 and 7, show the popular vote margin across the U.S. presidential elections and the final Gallup survey results. Both the methods identify the same elections as uncertain elections, with the exception of the 1952 and 1992 elections.

Table 1.5 reports the results of the following regression:

$$\begin{aligned} y_{it} = \mu_i + \lambda_t + q_t + \beta_1 \mathbf{1}_t(Election) + \beta_2 \mathbf{1}_t(Election) \times \mathbf{1}_t(UncertainElection) \\ + \beta_3 \mathbf{1}_t(UncertainElection) + \varepsilon_{it}\ , \end{aligned} \tag{1.6}$$

where $\mathbf{1}_t(UncertainElection)$ is equal to one when the election is uncertain and zero otherwise. The interaction term (β_2) picks up the differential effect of uncertain election on the level of y. The results, reported in table 1.5, are confirming our main conjecture, i.e., that our baseline results are driven by political uncertainty. During uncertain elections, the effects on liquidity, return, and volatility are more pronounced both during the pre–election and the post–election period. In particular, in the pre–election period during uncertain elections turnover decreases and price impact and the fraction of zero returns increase more as compared to all other elections. Similarly, in the post–election period during uncertain elections, liquidity improves and returns increase.

Table 1.5: Election and Liquidity: Uncertain Elections

This table reports the results of the following regression:

$$y_{it} = \mu_i + \lambda_t + q_t + \beta_1 \mathbf{1}_t(Election) + \beta_2 \mathbf{1}_t(Election) \times \mathbf{1}_t(UncertainElection) + \beta_3 \mathbf{1}_t(UncertainElection) + \varepsilon_{it} \ ,$$

where $y \in \{Ret_{it}, log(\tau_{it}), Zeros_{it}, Vol_{it}\}$ and $Election$ is either a pre–Election or post–Election dummy.Ret_{it} are the cumulative excess log returns, over the value–weighted market portfolio, for the September–November pre–election period and December–January post election period. $log(\tau_{it}), log(ILLIQ_{it})$, and $Zeros_{it}$ are the log turnover, the log *Amihud* (2002) illiquidity measure, and the fraction of zero returns, as defined in eq. 1.2, 1.3, and 1.4 respectively. In this specification, the explanatory variables are dummy variables that are equal to one prior to elections ($\mathbf{1}_t$(pre–Election)) and after the elections ($\mathbf{1}_t$(post–Election)), and zero otherwise. In other words, the comparison is between the September–October period (November–January or February–April) of an election year and the same period for all non election years. Uncertain Election is a dummy variable that is equal to one if the presidential election is uncertain according to the results of the final Gallup survey, i.e., when the difference is less than 2%. Firm, year, and quarter fixed effects are included to account for all the time–invariant differences within the firms and across time. Standard errors are clustered by time.

	Ret	*Ret*	$log(\tau)$	$log(\tau)$	Zeros	Zeros	Vol	Vol
Pre–Election	0.016**		-0.054***		0.003***		-0.001**	
Dummy	[0.006]		[0.011]		[0.0004]		[0.0004]	
Uncertain Election ×	0.012***		-0.106***		0.012***		-0.003***	
Pre–Election Dummy	[0.002]		[0.009]		[0.0007]		[0.0007]	
Uncertain Election	-0.036***		0.017***		-0.001***		0.0002***	
Dummy	[0.004]		[0.003]		[0.0004]		[0.00005]	
Post–Election		0.001		0.038**		-0.005***		0.002***
Dummy		[0.001]		[0.014]		[0.0004]		[0.0001]
Uncertain Election ×		0.061***		0.046***		0.001*		-0.003***
Post–Election Dummy		[0.013]		[0.005]		[0.0006]		[0.0002]
Uncertain Election		-0.021**		-0.029***		0.005***		-0.001***
Dummy		[0.008]		[0.008]		[0.0004]		[0.0001]
Obs	933,248	933,248	851,669	851,669	933,248	933,248	933,248	933,248

standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.5.3 Subsample Analysis – Variation across Industries

Prior to U.S. presidential elections, when political uncertainty is high, liquidity deteriorates, volatility decreases, and returns increase. These effects are more pronounced during more uncertain elections and they revert in the following the elections. Since political uncertainty matters, its impact should depend on the degree of a firm's or industry's sensitivity to changes in government policies. Accordingly, we except to observe variation in the magnitude of liquidity, return, and volatility changes across firms and industries.

We first exploit the variation across industries. We use the 12 industry portfolio classification proposed by Kenneth French. For each n, where n denotes industry, we run the baseline specification,

$$y_{it} = \mu_i + \lambda_t + q_t + \beta_1 \mathbf{1}_t(Election) + \varepsilon_{it} \ , \forall n \in \{1, \ldots, 12\} \ . \tag{1.7}$$

Table A.1 in the appendix shows the results. Pre–election, almost all industries experience a deterioration in liquidity, higher returns, and lower volatility. There also seems to be an interesting correlation between returns and the *Amihud* (2002) illiquidity measure. The industries, whose returns do no react prior to the elections, are the only ones that have significantly higher price impact. Post–election, the results are not as homogeneous. Industries that are considered more politically sensitive (Energy, health, and money) react the most post–election. They are the only ones that experience higher returns and improved liquidity. These results indicate that industries that are more sensitive to government policy changes are affected the most

Table 1.6: Politically Sensitive Industries: SIC Codes

This table reports the politically sensitive industries, their SIC codes, and the Fama-French 48 Industry codes.

Industry	SIC Codes		Fama-French	
Tobacco	2100-2199		5	
Guns and Defense	3760-3769	3795	26	26
	3480-3489		26	
Natural Resources	0800-0899			
Mining	1000-1119			
Utilities	4900	4910-4911	31	31
	4920-4925	4930-4932	31	31
	4939-4942		31	
Alcohol	2080	2082-2085	4	4

both pre– and post–election.

To dig deeper, we refine our definition of political sensitivity and following *Hong and Kostovetsky* (2012), we define as politically sensitive industries the following industries: tobacco, alcohol, guns, defense, utilities, and natural resources (mining and forestry). Table 1.6 shows the SIC codes for the industries and the Fama–French 48 industry code. The results are somewhat surprising. The politically sensitive industries in the U.S have higher returns and fraction of zero returns both prior and after the elections. They are also more liquid (lower *Amihud* (2002) illiquidity) both prior and after the elections, suggesting that the higher returns may not be due to illiquidity premium. A conclusion further reinforced by the fact that their trading volume is not affected by elections.

Table 1.7: Election and Liquidity: Politically Sensitive Industries

This table reports the results of the following regression:

$$y_{it} = \mu_i + \lambda_t + q_t + \beta_1 \mathbf{1}_t(Election) + \beta_2 \mathbf{1}_t(Election) \times \mathbf{1}_t(PSI) + \beta_3 \mathbf{1}_t(PSI) + \varepsilon_{it} \ ,$$

where $y \in \{Ret_{it}, log(\tau_{it}), ILLIQ_{it}, Zeros_{it}\}$ and $Election$ is either a pre–Election or post–Election dummy.Ret_{it} are the cumulative excess log returns, over the value–weighted market portfolio, for the September–November pre–election period and December–January post election period. $log(\tau_{it}), log(ILLIQ_{it})$, and $Zeros_{it}$ are the log turnover, the log *Amihud* (2002) illiquidity measure, and the fraction of zero returns, as defined in eq. 1.2, 1.3, and 1.4 respectively. In this specification, the explanatory variables are dummy variables that are equal to one prior to elections ($\mathbf{1}_t$(pre–Election)) and after the elections ($\mathbf{1}_t$(post–Election)), and zero otherwise. In other words, the comparison is between the September–October period (November–January or February–April) of an election year and the same period for all non election years. we define as politically sensitive industries the following industries: tobacco, alcohol, guns, defense, utilities, and natural resources (mining and forestry). Table 1.6 shows the SIC codes for the industries and the Fama–French 48 industry code. Firm, year, and quarter fixed effects are included to account for all the time–invariant differences within the firms and across time. Standard errors are clustered by time.

	Ret	Ret	$log(\tau)$	$log(\tau)$	$ILLIQ$	$ILLIQ$	Zeros	Zeros
Pre–Election	0.01***		-0.080***		0.073		0.0056***	
Dummy	[0.004]		[0.015]		[0.187]		[0.0004]	
PSI ×	0.012***		0.016		-0.716***		0.007***	
Pre–Election Dummy	[0.002]		[0.008]		[0.265]		[0.001]	
PSI	0.003		0.015		1.094		-0.035**	
Dummy	[0.003]		[0.065]		[0.752]		[0.012]	
Post–Election		0.018***		0.047***		-0.235		-0.004***
Dummy		[0.004]		[0.011]		[0.215]		[0.0004]
PSI ×		0.061***		-0.002		-0.821***		0.003**
Post–Election Dummy		[0.013]		[0.008]		[0.262]		[0.0012]
PSI		0.005		0.017		1.099		-0.035**
Dummy		[0.003]		[0.065]		[0.752]		[0.012]
Obs	933,248	933,248	851,669	851,669	933,248	933,248	933,248	933,248

standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.5.4 Subsample Analysis – Variation across Parties

In the previous section we examined the effect of political uncertainty across different industries and, in line with previous literature, we concluded that politically sensitive industries are more exposed to political uncertainty around the U.S. presidential elections, i.e., the effects on returns, liquidity, and volatility are more profound. In this section we exploit the variation across parties. An extended empirical literature documents that firms and the overall economy perform substantially differently under different ruling parties. In the macroeconomic literature, *Chappell and Keech* (1986) show that under Democratic administrations, inflation rates are on average higher by 2.5% than under Republican administrations. *Alberto Alesina* (1988), on the other hand, document that, from 1948 to 1984, the first two years of a Democratic administration are associated with higher annual rates of gross national product (GNP) growth (5% vs. 1.2%) than the first two years of a Republican administration. In the finance literature, *Santa-Clara and Valkanov* (2003) find that returns are on average higher during Democratic administrations.

To exploit the variation across parties, we first create a dummy variable for the incumbent party, $\mathbf{1}_t(Incumbent)$, which is equal to one if the incumbent party is the Democratic party and zero if it is the Republican party. Column 3 in table 1.2 shows the incumbent party for each election. We then estimate the following regression,

$$\begin{aligned} y_{it} = \mu_i + \lambda_t + q_t + \beta_1 \mathbf{1}_t(Election) + \beta_2 \mathbf{1}_t(Election) \times \mathbf{1}_t(Incumbent) \\ + \beta_3 \mathbf{1}_t(Incumbent) + \varepsilon_{it} \ . \end{aligned} \tag{1.8}$$

Table 1.8 shows that results. First, it seems that the higher average returns prior to elections are due to Democratic incumbent, an effect that dissipates after the election. If the incumbent party is the Democratic party then liquidity, measured as the *Amihud* (2002) illiquidity and the fraction of zero returns, is higher both prior to elections and after the elections. Trading volume is also lower in both periods. Overall these results show that, if the incumbent party is the Democratic party, the financial markets are more liquid both pre– and post–election.

To further exploit the variation across parties, we create a dummy variable for the winning party, $\mathbf{1}_t(Winning)$, which is equal to one if the incumbent party is the Democratic party and zero if it is the Republican party. Column 5 in table 1.2 shows the winning party for each election. Based on the previous results, if the winning party is the Democratic party one would expect the liquidity to be further improved compared to the Republican party. In addition, based on the results in the existing literature, one would also expect the liquidity and returns to be higher during the post–Inauguration period, since under the Democratic party policy uncertainty is lower. To test these hypotheses, we estimate the following regression,

$$\begin{aligned} y_{it} = \mu_i + \lambda_t + q_t + \beta_1 \mathbf{1}_t(Election) + \beta_2 \mathbf{1}_t(Election) \times \mathbf{1}_t(Winning) \\ + \beta_3 \mathbf{1}_t(Winning) + \varepsilon_{it} \ , \end{aligned} \tag{1.9}$$

where *Election* is either a post–Election or post–Inauguration dummy. The post–Election from November to January, and the post–Inauguration from February to April. Table 1.9 shows the estimates. In line with our previous results, when the winning party is the Democratic party, returns are higher and liquidity is further improved in the post–election period. In fact, we find that returns are higher in the post–election period only if the winning party is the Democratic party. During the post–inauguration period however, we do not find a positive Democratic effect as the results are mixed. That is, during the period that the winning Democratic party takes office, returns are lower and the fraction of zero returns higher, but the trading volume is also higher. In addition, returns are lower in the post–Inauguration period only if the winning party is the Democratic party.

Our results in the previous section indicated that during the post–Inauguration period, returns and trading volume decrease and liquidity deteriorates significantly and we conjectured that this must be due to the increase in policy uncertainty. In this section, we also found that this is the case only when the winning party is the Democratic party. Nonetheless, if our policy uncertainty hypothesis is true then, if the incumbent president wins the election, these results should be less significant, regardless of the party. To test this hypothesis, we create a dummy variable that is equal to one if the incumbent President wins the election and zero otherwise. Table 1.2 shows the winning and incumbent Presidents. Table 1.10 shows the results that confirm our hypothesis. Indeed, if the incumbent President wins the election, liquidity improves significantly. In fact, liquidity deteriorates only when a non–incumbent President wins the election. This results supports our hypothesis that liquidity deteriorates due to policy uncertainty, which is lower if the incumbent President wins. Returns are also significantly lower,which again may be due to decreasing policy uncertainty.

Table 1.8: Election and Liquidity: Incumbent Party

This table reports the results of the following regression:

$$y_{it} = \mu_i + \lambda_t + q_t + \beta_1 \mathbf{1}_t(Election) + \beta_2 \mathbf{1}_t(Election) \times \mathbf{1}_t(Incumbent) + \beta_3 \mathbf{1}_t(Incumbent) + \varepsilon_{it} \ ,$$

where $y \in \{Ret_{it}, log(\tau_{it}), ILLIQ_{it}, Zeros_{it}, Vol_{it}\}$ and $Election$ is either a pre–Election or post–Election dummy. Ret_{it} are the cumulative excess log returns, over the value–weighted market portfolio, for the September–November pre–election period and December–January post election period. $log(\tau_{it}), log(ILLIQ_{it})$, and $Zeros_{it}$ are the log turnover, the log *Amihud* (2002) illiquidity measure, and the fraction of zero returns, as defined in eq. 1.2, 1.3, and 1.4 respectively. In this specification, the explanatory variables are dummy variables that are equal to one prior to elections ($\mathbf{1}_t$(pre–Election)) and after the elections ($\mathbf{1}_t$(post–Election)), and zero otherwise. In other words, the comparison is between the September–October period (November–January or February–April) of an election year and the same period for all non election years. The dummy variable $\mathbf{1}_t(Incumbent)$ is equal to one if the incumbent party is the Democratic party and zero if it is the Republican party. Column 3 in table 1.2 shows the incumbent parties for each election. Firm, year, and quarter fixed effects are included to account for all the time–invariant differences within the firms and across time. Standard errors are clustered by time.

	Ret	*Ret*	$log(\tau)$	$log(\tau)$	*ILLIQ*	*ILLIQ*	Zeros	Zeros
Pre–Election	-0.002		-0.067***		0.262		0.0111***	
Dummy	[0.002]		[0.014]		[0.246]		[0.0004]	
Incumbent ×	0.038***		-0.028***		-0.628*		-0.013***	
Pre–Election Dummy	[0.007]		[0.005]		[0.320]		[0.0007]	
Incumbent	-0.016***		-0.009***		0.111		0.001***	
Dummy	[0.004]		[0.003]		[0.194]		[0.0004]	
Post–Election		0.037***		0.072***		0.074		-0.004***
Dummy		[0.012]		[0.017]		[0.254]		[0.0004]
Incumbent ×		-0.049***		-0.049***		-0.986**		-0.002**
Post–Election Dummy		[0.015]		[0.013]		[0.328]		[0.0006]
Incumbent		-0.007***		-0.029***		0.207		0.002***
Dummy		[0.002]		[0.008]		[0.170]		[0.0004]
Obs	933,248	933,248	851,669	851,669	933,248	933,248	933,248	933,248

standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.9: Election and Liquidity: Winning Party

This table reports the results of the following regression:

$$y_{it} = \mu_i + \lambda_t + q_t + \beta_1 \mathbf{1}_t(Election) + \beta_2 \mathbf{1}_t(Election) \times \mathbf{1}_t(Winning) + \beta_3 \mathbf{1}_t(Winning) + \varepsilon_{it} \ ,$$

where $y \in \{Ret_{it}, log(\tau_{it}), ILLIQ_{it}, Zeros_{it}\}$ and $Election$ is either a post–Election or post–Inauguration dummy.Ret_{it} are the cumulative excess log returns, over the value–weighted market portfolio, for the September–November pre–election period and December–January post election period. $log(\tau_{it}), log(ILLIQ_{it})$, and $Zeros_{it}$ are the log turnover, the log *Amihud* (2002) illiquidity measure, and the fraction of zero returns, as defined in eq. 1.2, 1.3, and 1.4 respectively. In this specification, the explanatory variables are dummy variables that are equal to one after the elections ($\mathbf{1}_t$(post–Election)) and after the inauguration of the new government,($\mathbf{1}_t$(post–Inaugur.)), and zero otherwise. In other words, the comparison is between the November–Januart period (or February–April) of an election year and the same period for all non election years. The dummy variable $\mathbf{1}_t(Winning)$ is equal to one if the winning party is the Democratic party and zero if it is the Republican party. Column 5 in table 1.2 shows the winning party for each election. Firm, year, and quarter fixed effects are included to account for all the time–invariant differences within the firms and across time. Standard errors are clustered by time.

	Ret	Ret	$log(\tau)$	$log(\tau)$	$ILLIQ$	$ILLIQ$	Zeros	Zeros
Post–Election	0.000		0.040**		-0.026		-0.004***	
Dummy	[0.002]		[0.010]		[0.246]		[0.0005]	
Winning ×	0.043***		0.045***		-1.102***		0.003***	
Post–Election Dummy	[0.010]		[0.013]		[0.342]		[0.0006]	
Winning	-0.028***		-0.070***		1.329***		0.085***	
Dummy	[0.006]		[0.011]		[0.196]		[0.0004]	
Post–Inauguration		-0.004		-0.032***		1.587***		-0.0003
Dummy		[0.002]		[0.004]		[0.469]		[0.0004]
Winning ×		-0.050***		0.019***		-0.450		0.004***
Post–Inaugur. Dummy		[0.011]		[0.006]		[0.637]		[0.0008]
Winning		0.006*		-0.049***		0.580		0.004***
Dummy		[0.003]		[0.005]		[0.305]		[0.0005]
Obs	933,248	933,248	851,669	851,669	933,248	933,248	933,248	933,248

standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.6 Empirical Tests of the hypotheses

So far we have shown that prior to U.S. presidential elections, financial market liquidity worsens, returns increase, and volatility decreases. Once the uncertainty regarding the outcome of the election has been resolved, liquidity improves, returns continue to increase and volatility decreases. Confirming our hypothesis that these effects are due to political uncertainty, which is higher in the months prior to the elections and is resolved after the elections, we find that during uncertain elections they are more pronounced. They are also more pronounced for industries that politically more sensitive. Next, we examine where does political uncertainty stem from. As discussed in section 1.3, we conjecture that there are three potential channels, namely, the asymmetric information, ambiguity, and disagreement.

One of the primary empirical implications of the disagreement hypothesis is that trading volume and disagreement are positively correlated. In our setting that would imply that trading volume increases prior to elections and decreases afterwards, a result that we do not observe. In fact, we show that trading volume decreases prior to elections and increases afterwards. Although this results is strong evidence against the disagreement hypothesis, we conduct further tests of the hypothesis. To directly test the disagreement hypothesis we proxy disagreement with the dispersion in the analysts' forecasts. Subsection 1.6.1.1 shows the results.

Testing directly the information asymmetry and ambiguity channels is quite challenging. First, our baseline empirical results are in line with both hypotheses. A differentiating point is that information asymmetry predicts lower liquidity prior to elections, whereas the ambiguity hypothesis predicts a decrease in liquidity. Our di-

Table 1.10: Election and Liquidity: Incumbent Winning

This table reports the results of the following regression:

$$y_{it} = \mu_i + \lambda_t + q_t + \beta_1 \mathbf{1}_t(Post\text{–}Inaug.) + \beta_2 \mathbf{1}_t(Election) \times \mathbf{1}_t(Win.Incum.) + \beta_3 \mathbf{1}_t(Win.Incum.) + \varepsilon_{it} \ ,$$

where $y \in \{Ret_{it}, log(\tau_{it}), ILLIQ_{it}, Zeros_{it}\}.Ret_{it}$ are the cumulative excess log returns, over the value–weighted market portfolio, for the September–November pre–election period and December–January post election period. $log(\tau_{it}), log(ILLIQ_{it})$, and $Zeros_{it}$ are the log turnover, the log *Amihud* (2002) illiquidity measure, and the fraction of zero returns, as defined in eq. 1.2, 1.3, and 1.4 respectively. In this specification, the explanatory variables are dummy variables that are equal to one after the inauguration of the new government,($\mathbf{1}_t$(post–Inaugur.)), and zero otherwise. In other words, the comparison is between the February–April of an election year and the same period for all non election years. The dummy variable $\mathbf{1}_t(Win.Incumb.)$ is equal to one if the incumbent President wins the election and zero otherwise. Table 1.2 shows the winning party for each election and whether there was an incumbent president. Firm, year, and quarter fixed effects are included to account for all the time–invariant differences within the firms and across time. Standard errors are clustered by time.

	Ret	$log(\tau)$	*ILLIQ*	Zeros	Vol
Post–Inauguration	0.0004	-0.022***	3.121***	-0.0002	0.005***
Dummy	[0.002]	[0.003]	[0.474]	[0.0005]	[0.001]
Winning Incumb. ×	-0.056***	0.026***	-3.216***	0.002**	-0.002***
Post–Inaugur. Dummy	[0.012]	[0.006]	[0.571]	[0.0008]	[0.0005]
Winning	-0.006	-0.075***	0.039	0.007***	-0.002**
Dummy	[0.002]	[0.018]	[0.248]	[0.0005]	[0.0003]
Obs	933,248	851,669	933,248	933,248	933,248

standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

rect measure of liquidity, the *Amihud* (2002) illiquidity measure, unfortunately is not significant in the baseline specification. When we however, exploit the political sensitivity of different industries and in particular, we explicitly define these industries as in *Hong and Kostovetsky* (2012), the Amihud illiquidity measure decreases, indicating that liquidity improves pre– and post–election for politically sensitive firms. This results provides some evidence in favor of the ambiguity hypothesis.

1.6.1 Information Asymmetry and Disagreement Hypotheses Test

To shed more light on the *asymmetric information* and *disagreement* hypotheses, and since *ambiguity* is elusive and difficult to measure, we next test indirectly these two hypotheses. To proxy for information asymmetry we use two different types of variables, i.e., analysts' forecast error and working capital accruals.

The empirical literature on political uncertainty provides evidence of information asymmetry. Lower investments and higher cash flows (*Julio and Yook* (2012)), higher accounting conservatism (*Dai and Ngo* (2012)), and lower investment to price sensitivity *Durnev* (2011) indicate that in the months prior to national elections the adverse selection and moral hazard problems worsen thus, leading to higher information asymmetry. In order to directly test the *information asymmetry* hypothesis we employ working capital accruals (*Calomiris and Himmelberg* (1997), *Levy* (2010)) as a proxy for information asymmetry.

We motivate this approach through existing literature that relates the working capital accruals to information asymmetry. Working capital accruals are associated with earnings management (*Burgstahler and Dichev* (1997)). The theoretical models of *Dye* (1988), and *Trueman and Titman* (1988) predict a positive relationship between earnings management and information asymmetry. The literature finds empirical evidence for this relationship as well (*Richardson* (2000)). Thus, we hypothesize that higher working capital accruals indicate potential earnings management which in turn implies higher information asymmetry.

We recognize a potential endogeneity issue with this approach. During periods of high political uncertainty, managers may be managing earnings in order to provide more conservative estimates rather than hide information from the market and investors. If that is the case, increases in working capital accruals would indicate an effort to better estimate future earnings rather than manipulation, i.e., adverse selection and moral hazard. If managers increase working capital accruals in order to be 'on the safe' side, they still provide less accurate information to the market and investors, leading possibly to worsening liquidity.

To test this hypothesis, we estimate the following regression,

$$y_{it} = \mu_i + \lambda_t + q_t + \beta_1 \mathbf{1}_t(Q) + \varepsilon_{it} \ , \tag{1.10}$$

where y_{it} is either $\Delta(WC)_{it}$, the change in working capital, or the change in cash, $\Delta(Cash)_{it}$, another proxy for measuring earnings management. We measure accruals as the change in non–cash current assets (COMPUSTAT data item ACT less COMPUSTAT data item CHE) less the change in current operating liabilities (COMPUSTAT data item LCT less COMPUSTAT data item DLC less COMPUSTAT data item TXP). We obtain the quarterly data from Standard Standard and Poor's Compustat North America files; they extend from 1966 to 2012. The dummy variable

$\mathbf{1}_t(Q$ is equal to one during the 3rd quarter, the 4th quarter, or the 1st quarter of an election year. The 3rd quarter is from July to September and in this specification is considered the pre–election period. The 4th quarter, from October to December, of an election year is considered the post election period. An important drawback in the above specification is that the first quarter following an election begins in October, i.e., during a month that the uncertainty has not yet been resolved. Finally, the 1st quarter refers to January–March post–election and it would the equivalent of the post inauguration period.

Table 1.11 shows the results. We find that working capital accruals do change significantly prior to the elections and after the elections. In particular, during the 3rd quarter, which is from July to September, accruals increase, implying that indeed information asymmetry increases. During the 4th quarter, from October to December, they however do not change. This result is expected given that the 4th quarter contains months both pre– and post–election. Finally, in the first quarter after the elections accruals decrease, a result that confirms our hypothesis that information asymmetry increases in the months prior to the elections and decrease after the elections.

Table 1.11: Information Asymmetry and Working Capital Accruals

This table reports the results of the following regression:

$$y_{it} = \mu_i + \lambda_t + q_t + \beta_1 \mathbf{1}_t(Q) + \varepsilon_{it} \ ,$$

where $y \in \{\Delta(WC)_{it}, \Delta(Cash)_{it}\}$. $\Delta(WC)_{it}$ is the change in working capital and measured as the change in non–cash current assets less the change in current operating liabilities. The data begin in 1966 and extend to 2012. We thus, lose a significant portion of elections. The dummy variable $\mathbf{1}_t(Q$ is equal to one during the 3rd quarter, the 4th quarter, or the 1st quarter of an election year. The 3rd quarter is from July to September and in this specification is considered the pre–election period. The 4th quarter, from October to December, of an election year is considered the post election period. An important drawback in the above specification is that the first quarter following an election begins in October, i.e., during a month that the uncertainty has not yet been resolved. Finally, the 1st quarter refers to January–March post–election and it would the equivalent of the post inauguration period. Firm, year, and quarter fixed effects are included to account for all the time–invariant differences within the firms and across time. Standard errors are clustered by time.

	$\Delta(WC)$	$\Delta(WC)$	$\Delta(WC)$	$\Delta(Cash)$	$\Delta(Cash)$	$\Delta(Cash)$
Pre–Election, Q_3	13.896*			-27.289		
Dummy	[6.222]			[32.625]		
Post–Election, Q_4		-7.162			11.590	
Dummy		[7.953]			[46.33]	
Post–Inaugur., Q_1			-30.617***			-72.49
Dummy			[8.178]			[67.74]
Obs	90,643	90,552	90,164	136,003	135,609	134,977

standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.6.1.1 Analysts' Forecast Error

The literature on analysts' forecasts has identified the analysts' absolute forecast error as proxies for information asymmetry (*Lang and Lundholm* (1996) and *Levy* (2010)) and information heterogeneity (*Pasquariello and Vega* (2007) and *Pasquariello and Vega* (2009)).[11] In particular, *Barron et al.* (1998) develop a model that relates the properties of the analysts' forecasts to their information environment. They show that forecast error has two components; the idiosyncratic and common component. The idiosyncratic component is driven by the private information that analysts rely on, whereas the common error arises from the errors in the public information. They find that the forecast dispersion reflects only the idiosyncratic error while the absolute forecast error reflects primarily the common error. We thus use the forecast dispersion as a proxy for differences in opinion and the absolute forecast error as a proxy for information asymmetry.

Following the theoretical findings of *Barron et al.* (1998), we define the dispersion in earnings forecasts as:

$$\text{Dispersion}_{it} = \frac{\sigma(\text{Earnings Forecasts})_{it}}{\text{Price}_{it}} \,, \tag{1.11}$$

and the absolute forecast error as:

$$|\text{Forecast Error}_{it}| = \frac{|\text{Actual} - \text{Median Earnings Forecasts}|_{it}}{\text{Price}_{it}} \,, \tag{1.12}$$

[11] See also the work of *Diether et al.* (2002) and *Scherbina* (2004) who use the dispersion in the analysts' forecasts as a proxy for differences in opinion.

where σ(Earnings Forecasts) is the standard deviation of the quarterly earnings forecasts, and Price is the quarter closing price. We obtain the data on earnings forecasts and the dispersion of analysts' beliefs from Thomson and Reuters I/B/E/S files, which extend from 1975 to 2012; thus, we miss two elections: 1968 and 1972.

We investigate the following regression specification:

$$y_{it} = \mu_i + \lambda_t + q_t + \beta_1 \mathbf{1}_t(Q) + \varepsilon_{it} \ ,\epsilon_{it} \ , \tag{1.13}$$

where y_{it} is either the dispersion of the analysts' forecasts or the absolute forecast error (definitions are in eq. 7 and 8), and $\mathbf{1}_t(Q)$ is a dummy variable for the quarters preceding and following the presidential elections, as in eq. 1.10. Table 1.12 shows the results of this regression specification. We find no statistically significant results. In fact, we notice that both the measures experience a decrease rather than an increase in the quarters preceding and an increase following the elections. Of course, we cannot draw any conclusions from these effects as the coefficients are not significant; that is, they are not estimated precisely.

These results lead us to reject the disagreement hypothesis.

Table 1.12: Disagreement and Information Asymmetry: Analysts' Forecasts

This table reports the results of the following regression:

$$y_{it} = \mu_i + \lambda_t + q_t + \beta_1 \mathbf{1}_t(Q) + \varepsilon_{it} \ ,$$

where $y \in \{Dispersion_{it}, |\text{Forecast Error}_{it}|\}$. $Dispersion_{it}$ is the the dispersion in earnings forecasts as defined in eq. 1.11 and $|\text{Forecast Error}_{it}|$ is the absolute forecast error as defined in eq.1.12. We obtain the data on earnings forecasts and the dispersion of analysts' beliefs from Thomson and Reuters I/B/E/S files, which extend from 1975 to 2012. The dummy variable $\mathbf{1}_t(Q$ is equal to one during the 3rd quarter, the 4th quarter, or the 1st quarter of an election year. The 3rd quarter is from July to September and in this specification is considered the pre–election period. The 4th quarter, from October to December, of an election year is considered the post election period. An important drawback in the above specification is that the first quarter following an election begins in October, i.e., during a month that the uncertainty has not yet been resolved. Finally, the 1st quarter refers to January–March post–election and it would the equivalent of the post inauguration period. Firm, year, and quarter fixed effects are included to account for all the time–invariant differences within the firms and across time. Standard errors are clustered by time.

	Dispersion	*Dispersion*	*Dispersion*	|Forecast Error|	|Forecast Error|	|Forecast Error|
Pre–Election, Q_3	0.000			-0.003		
Dummy	[0.011]			[0.003]		
Post–Election, Q_4		-0.006			-0.034	
Dummy		[0.005]			[0.052]	
Post–Inaugur., Q_1			0.008***			0.789
Dummy			[0.0009]			[0.733]
Obs	59,370	73,295	60,584	74,251	55,237	69,006

standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.6.1.2 Subsample Analysis – Variation across Firm Characteristics

Our results so far indicate that the disagreement hypothesis is the weakest to support. Between the information asymmetry and ambiguity hypothesis, we find mixed support, although, in direct tests of the information asymmetry we indeed find that information asymmetry increases prior to elections and decreases in the months following the elections. In this section, as the last test of these two hypotheses, we exploit the variation in firm characteristics. In particular we examine whether the impact of political uncertainty varies across size and market beta portfolios.

We conjecture that if the ambiguity hypothesis is true, more 'speculative ', opaque and harder–to–value firms will be affected more both pre– and post–election. That is, these stocks will be the ones facing the highest uncertainty regarding the quality of information available to investors. The characteristics do not necessarily affect the quantity of information available.

We begin first by examining the effect of political uncertainty on firms of different size. We separate the sample into deciles and estimate the baseline regression for each size portfolio, i.e.,

$$y_{it}^{p} = \mu_{i}^{p} + \lambda_{t}^{p} + q_{t} + \beta_{1}^{p}\mathbf{1}_{t}(Election) + \varepsilon_{it}^{p} \; \forall p \in \{1, 2, \ldots, 10\} \; , \tag{1.14}$$

where $p = 1$ contains the smallest firms and $p = 20$ the largest firms. Table B.1 of the appendix shows the results. We observe that there is almost no variation across different size portfolios. The sole difference is regarding the level of the turnover change, which is higher for small firms. Both large and small firms are affected in exactly similar fashion by political uncertainty. The size variation results therefore, fail to accept the ambiguity hypothesis.

The results in this section provide evidence in favor of the information asymmetry hypothesis.

1.7 Conclusion

Our empirical analysis shows that political uncertainty has a significant impact on financial market quality, i.e., returns, liquidity and volatility. In the months leading up to presidential elections, liquidity deteriorates, returns increase, and volatility decreases; we find that trading volume (measured by log turnover) decreases during the months prior to the elections and increases in the months following the elections. The fraction of zero returns increases and *Amihud* (2002) illiquidity decreases during the period preceding the elections and reverse after the elections are over. We also find that these results are more pronounced for politically sensitive firms and under Republican administrations.

Such results can be explained by the increased information asymmetry, that is the information quantity available to investors in the months preceding the elections (*information asymmetry* hypothesis). Under the *information asymmetry* hypothesis, we expect the asymmetry of the quantity of information available to investors to increase with higher political uncertainty, i.e., prior to the presidential elections. After the elections, once political uncertainty is resolved, the asymmetry decreases leading to higher trading volume and liquidity. The information asymmetry hypothesis is confirmed by our tests on working capital accruals, that increase prior to elections and decrease afterwards. The information asymmetry hypothesis is reinforced by our cross-sectional results; the impact of political uncertainty does not vary across size and market beta.

CHAPTER II

Liquidity Spillovers Across Asset Classes

[. . .] the question isn't whether there will be spillovers –
it's how big they will be,
and where they will hit the hardest.
– *Bloomberg, February 2015*

2.1 Introduction

In recent financial crises the financial press and market participants have often referred to liquidity spillovers, i.e., the transmissions of liquidity shocks from one asset to another. A growing theoretical literature has also addressed the potential channels and frictions that could generate liquidity spillovers. Yet despite the recurring reference to liquidity spillovers, they remain poorly understood with very little evidence of their existence. Do liquidity spillovers actually exist? What are their properties? Are they more significant during periods of crisis? What are the transmission channels that generate them? These are among the pertinent questions that remain unanswered. This paper addresses these questions by providing novel evidence of liquidity spillovers across four different asset classes (Crude Oil, S&P500, Eurodollar, and Ten–year Treasury Note) within the U.S. futures market. It also investigates the empirical relevance of the transmission channels proposed by the theoretical literature.[1] The results of this paper indicate that (1) the liquidity and price dynamics of one asset are significantly related to the liquidity of other assets, in particular, during periods of financial turmoil, and (2) such dynamic relationships are at least partly due to the funding ability of liquidity providers.

Understanding how liquidity spillovers develop has important asset pricing and policy implications. First, a growing empirical literature provides evidence of priced liquidity risk; therefore, disentangling the relevant transmission channels of liquidity spillovers can shed light on how asset prices are affected by liquidity risk and commonality in liquidity.[2] Second, central banks and financial institutions have come to rely more on asset prices as a guide for policy and risk management, in particular during periods of financial turmoil. Consequently, determining the empirically relevant price formation and liquidity processes has acquired an increasingly central role for financial stability. For instance, knowing why liquidity dries up in many otherwise unrelated markets – as was the case during the great recession – provides an important policy tool on how to prevent or mitigate their impact.[3]

A number of transmission channels have been proposed to explain how liquidity

[1] e.g., *Brunnermeier and Pedersen* (2009), *Gromb and Vayanos* (2012).

[2] *Amihud* (2002), *Pastor and Stambaugh* (2003), and *Acharya and Pedersen* (2005), among others, show that liquidity and commonality in liquidity are priced.

[3] *Gromb and Vayanos* (2012) mention that "the large losses banks incurred in the subprime market has led them to cut their lending across the board, notably their financing of other intermediaries, causing liquidity to dry up in many otherwise unrelated markets."

spillovers transpire. These channels can be broadly categorized into information–based and liquidity supply–based channels. Information–based channels conjecture that, in the presence of correlated or common fundamentals, shocks to one asset may have price and liquidity implications for other assets via the cross–market rebalancing activity of informed traders, who can be homogeneously or heterogeneously informed. In particular, these traders respond to shocks in one market by optimally re–adjusting their portfolios in other markets, effectively transmitting the shocks and generating spillovers (*Kodres and Pritsker* (2002), *Pasquariello* (2007)). Liquidity supply–based channels postulate that, in the presence of agents providing liquidity in multiple assets, shocks to their funding needs or risk aversion may propagate across assets (*Kyle and Xiong* (2001), *Brunnermeier and Pedersen* (2009)). Both information and liquidity supply–based theories predict higher liquidity spillovers during periods of financial turmoil either because of higher adverse selection risk from order flow or tighter traders' financial constraints.

Measuring liquidity spillovers across assets and testing the proposed channels posit a number of empirical challenges. First, spillovers are difficult to define.[4] In line with the aforementioned theoretical literature, this paper defines liquidity spillovers from asset i to asset j as the lagged responses of asset j's liquidity to changes in asset i's liquidity. It is important to note that models of price formation in multi–asset markets generate contemporaneous, rather than lagged, responses to liquidity shocks. Yet market frictions often omitted by these models (such as the slow incorporation of information, slow moving capital, and slow resolution of uncertainty) make lagged

[4] An interesting but short discussion can be found in *Bekaert and Harvey* (2003).

responses more plausible. Additionally, this definition and the subsequent empirical specification exclude liquidity responses that are more likely to be due to common shocks.

Secondly, any attempt to assess the intensity of liquidity spillovers requires measuring market liquidity, a fundamental, albeit elusive, concept. Liquidity is most often described as the ability to buy or sell any quantity of an asset quickly and with minimal or no price impact. Motivated by the aforementioned theoretical literature on liquidity transmission channels, this paper concentrates on the price impact, or market depth, dimension of liquidity, which is estimated with a modified *Amihud* (2002) measure – a standard proxy for market depth in the literature.

Thirdly, when comparing liquidity across different assets, one has to account for their intrinsic characteristics (asset size, payoff schedule, etc.), different regulatory and market environments (over the counter, exchange traded, trading rules and platforms), and barriers to entry (funds and knowledge). Accordingly, any comparison of liquidity across assets must allow for the possibility of heterogeneous market microstructure across markets. To overcome these challenges, I use data from the U.S. futures market. Contracts in the U.S. futures market are exchanged in the same trading environment and under the same market microstructure. The U.S. futures market is also among the most liquid markets and often, more liquid that the respective cash market. In addition, data are reported accurately and systematically, akin to the U.S. stock market data.

I measure liquidity spillovers across the futures market over time by estimating a reduced–form vector autoregression (VAR), using daily data from the Chicago

Mercantile Exchange (CME) on the Crude Oil, S&P500, Eurodollar, and Ten–year Treasury Note contracts between 1986 and 2015. The VAR system uses daily return, volatility, and liquidity series and is estimated over 1–year rolling windows of daily data. This reduced-form VAR allows one to capture the dynamic interactions of liquidity, return, and volatility across the four contracts without any structural restrictions. Within this framework, I measure the intensity of liquidity spillovers from asset i to asset j as the improvement of fit from allowing for lagged liquidity shocks in asset i to affect liquidity in asset j.

I find significant liquidity spillovers across the four assets that increase substantially during periods of financial and macroeconomic turmoil. Liquidity spillovers to Crude Oil and Eurodollar, for instance, increased by three standard deviations during the 2007–2008 financial crisis. During the Asian crisis of 1997, liquidity spillovers to S&P500 increased by 2.5 standard deviations. To delve further into the time–series properties of spillovers, I use a Markov switching model to show that the spillover series are governed by higher mean and variance during major financial and macroeconomic events. These results contribute to an existing empirical literature that finds little direct evidence of liquidity spillovers across assets.[5]

What are the empirically relevant transmission channels that generate liquidity spillovers? To test these channels I use monthly data on theoretically motivated state variables for each channel and estimate time–series regressions using the monthly

[5] *Chordia et al.* (2005) use intra–day data on US equity and 10yr. Treasury bonds to explore cross–market liquidity dynamics, but find "no evidence of a causal" (in the Granger–causality sense) "relationship between stock and bond spreads [...]". *Goyenko and Ukhov* (2009) extend the Chordia et. al (2005a) sample by adding bonds of different maturities, and find evidence of "illiquidity integration between stock and bond markets".

average liquidity spillovers across assets. For the information based channels, I use monthly changes in unemployment, personal consumption expenditures, and the Chicago Fed's monthly index of U.S. real activity (CFNAI) as possible macroeconomic fundamentals. I choose these macroeconomic series because they are closely monitored by market participants. To measure information heterogeneity, I create a monthly forecast dispersion index using the commonality between Michigan's consumer confidence index and the dispersion of forecasts from the Survey of Professional Forecasters on a number of macroeconomic variables. For the liquidity supply–based channels, I proxy for risk aversion with the difference between implied volatility and realized volatility, as in *Bollerslev et al.* (2009). Finally, I measure traders' funding constraints via the monthly returns of the leverage factor mimicking portfolio of the *Adrian et al.* (2014) leverage factor.

The time–series regressions provide strong evidence in support of the liquidity supply based transmission channels. In particular, I find that lower returns on the leverage factor mimicking portfolio predict higher average liquidity spillovers. This result is in line with the *Brunnermeier and Pedersen* (2009) liquidity transmission channel which predicts that decreasing leverage (i.e., lower returns on the mimicking portfolio) predicts tightening funding constraints and thus, higher liquidity spillovers across assets. These results are robust to alternative definitions of liquidity spillover intensity and estimation windows.

The paper is organized as follows.Section 2.2 describes the data and discusses the VAR specification. Section 2.3 shows the main results on the time series of liquidity spillovers and the Markov switching model. Section 2.4 discusses the theoretical motivation of this investigation. Section 2.5 presents the state variables relevant to the theoretical transmission channels and the results of the time–series regressions. Section 2.6 concludes.

2.2 Data, Liquidity Measures, and VAR specification

2.2.1 Data

This study uses end–of–day (EOD) Futures Data from the Chicago Mercantile Exchange (CME) on the Crude Oil, S&P 500, Eurodollar, and the 10 year T–Note contracts. The EOD data contain all of the official closing information for CME Group contracts, including open and close price, high and low price, open interest, total volume, volume breakdown by venue, and settlement price. Because the contracts have different starting dates, I use July, 1986, as the earliest common one. Table 2.1 shows the contract specifications for each of the four contracts. The contracts share many similarities on contract cycles, minimum tick size, and trading hours. They however, have different termination dates and notional amounts.

To account for those differences I use the following methodology. For each contract, I only keep the March quarterly cycle contracts (Mar–Jun–Sep–Dec). This allows to construct four different time–series (for any measure) by starting with a contract having $x \in \{3, 6, 9, 12\}$ months to maturity and rolling over at the termination day of March, June, September, and December into successive contracts with the same original time to maturity. The S&P 500 contract, for instance, typically terminates eight days prior to last trade date for open outcry (3:15p.m. on Thurs-

Table 2.1: Contract Specifications

This table presents the futures contracts specifications for Crude Oil, S&P500, Eurodollar, and the 10yr. Treasury Note.

Unit	Contract Size	Price	Minimum Tick	Tick Value
Crude Oil	1,000 barrels	USD	\$0.01/barrel	\$10
S&P 500	\$250×S&P 500 Index	Index Points	0.05 index points	\$12.50
Eurodollar	\$1 million 3–month LIBOR	IMM points[b]	0.0025 price points	\$6.25[c]
10 yr T–Note	\$100,000 FV	Points (\$1000) and 1/2 of 1/32[e]	1/2 of 1/32	\$15.625[f]

Unit	Termination of Trading	Listed Contracts	Normal Trading Hours (CST)
Crude Oil	*(1)*	Monthly	5:00 p.m. – 4:15 p.m. (Sun-Fri)
S&P 500	*(2)*	March Cycle[a]	5:00 p.m. – 4:15 p.m. (Mon-Fri)
Eurodollar	*(3)*	March Cycle[d]	5:00 p.m. – 4:00 p.m. (Sun-Fri)
10 yr T–Note	*(4)*	March Cycle	5:00 p.m. – 4:00 p.m. (Sun-Fri)

(1) Trading in the current delivery month shall cease on the 3rd business day prior to the 25th calendar day of the month preceding the delivery month

(2) On the rollover date; typically 8 days prior to last trade date for open outcry (3:15p.m. on Thursday prior to 3rd Friday of the contract month).

(3) 2nd London bank business day before 3rd Wednesday of the contract month.

(4) 7th business day preceding the last business day of the delivery month.

[a] March Cycle is March–June–September–December.

[b] 100 points – the 3-month LIBOR for spot settlement on the 3rd Wednesday of contract month. E.g., a price quote of 97.45 signifies a deposit rate of 2.55% p.a.

[c] For the nearest expiring contract month. All other contract months: 0.005 price points = \$12.50/ contract.

[d] Plus the nearest 4 "serial" months not in the March Quarter Cycle.

[e] For example, 126-16 represents 126 16/32 and 126-165 represents 126 16.5/32. Par is on the basis of 100 points.

[f] Except for inter–month spreads, where the minimum price fluctuation shall be one-quarter of one thirty-second of one point (\$7.8125 per contract).

day prior to 3rd Friday of the contract month). That is, the March, 2014 S&P 500 terminated on Wednesday, March 12th, since the 3rd Friday of March, 2014 was on March 21st. On Wednesday, March 12th 2014, I rollover to the June contract for the 3–months to maturity, to the September contract for the 6–months to maturity, and to the December contract for the 9–months to maturity. I focus only on the 3–month, 6–month, and 9–month maturities because the 12–month maturity is not actively traded. To preserve space, I present results from the tests on three month contracts.

I delete all observations with settlement price zero or missing and total trading volume (from all venues) missing. I also, standardize all settlement prices to a 100 basis.

2.2.2 Liquidity Measures

Liquidity is a multifaceted concept that is difficult to define and measure as desired. Motivated by the theories discussed in section (2.4), this paper concentrates on the price impact (Kyle's λ) dimension of liquidity which, unless one observes transaction initiated data, is unobservable and thus must be estimated.

I proxy for price impact using a modified daily *Amihud* (2002) measure. It can be interpreted as the daily price response associated with one contract of trading volume, thus serving as a rough measure of price impact. According to this measure, an asset is illiquid if its price moves a lot in response to little volume. The *Amihud* (2002) measure is intuitive and simple to compute. *Hasbrouck* (2002) shows that "among the [liquidity] proxies . . . , the illiquidity measure appears to be the best" at capturing Kyle's λ.

Amihud (2002) defines the illiquidity of asset j in day t as following,

$$ILLIQ_{j,t} = \frac{|r_{j,t}|}{DV_{j,t}}, \tag{2.1}$$

where $r_{j,t}$ and $DV_{j,t}$ are, respectively, the return and dollar volume of asset j on day t. I modify the *Amihud* (2002) measure by substituting the dollar volume with volume, i.e.,

$$AM_{j,t} = \frac{|r_{j,t}|}{V_{j,t}}, \tag{2.2}$$

where $V_{j,t}$ is the trading volume of asset j on day t. To correct the *Amihud* (2002) measure scale, it is customary to multiply it by 10^4. I use the modified *Amihud* (2002) measure for two reasons. First, dollar volume is not meaningful for futures because there is no dollar investment required. I.e., in contrast to the cash market where each trade is accompanied by a cash transaction, in the futures market there is no cash transfer when a trader buys or sells a contract. Additionally, the modified *Amihud* (2002) measure is not affected by price levels.

To calculate daily volatility, I utilize high and low daily prices as following,

$$Vol_{j,t} = \sqrt{\frac{(\log H_{j,t} - \log L_{j,t})^2}{4\log 2}}, \tag{2.3}$$

where $H_{j,t}$ is the high settlement price of asset j on day t and $L_{j,t}$ the low price. *Parkinson* (1980) first suggested this measure as a more efficient and, under certain conditions, unbiased estimator of daily realized variance. *Martens and Van Dijk*

(2007) have a more detailed discussion.

Finally, daily returns are daily percentage changes of settlement prices. I.e.,

$$Ret_{j,t} = (P_{j,t} - P_{j,t-1})/P_{j,t-1}. \tag{2.4}$$

To correct for outliers, I winsorize the data at the bottom and top 1% for each variable.

Figure 2.1 shows the raw Amihud series for the 3–month maturity contract of each asset (monthly averages to improve the readability of the plot). According to the Amihud measure, the Eurodollar is the most liquid asset among the four considered. The liquidity of both the S&P500 and T–Note decreased significantly during the great recession. Only for the latter however, has liquidity returned to the pre–crisis levels of 2009. The liquidity of Crude Oil has been improving steadily and seems to have been unaffected by the great recession.

Figure 2.1 suggests that Amihud's liquidity measure is persistent and trending, and displays seasonal patterns. The autocorrelation of the modified *Amihud* (2002) measure, for instance, ranges from 0.62 to 0.85 at the daily frequency for the different contracts. The seasonality stems from the fact that as a contract nears its expiration date, trading volume increases (as traders often close their positions before contracts expire) and the settlement prices converge rapidly towards the price of the underlying asset. To account for these regularities, I first assume a first–order deterministic trend, i.e.,

$$AM_{j,t} = \delta t + u_{j,t}, \ \forall \ j, \tag{2.5}$$

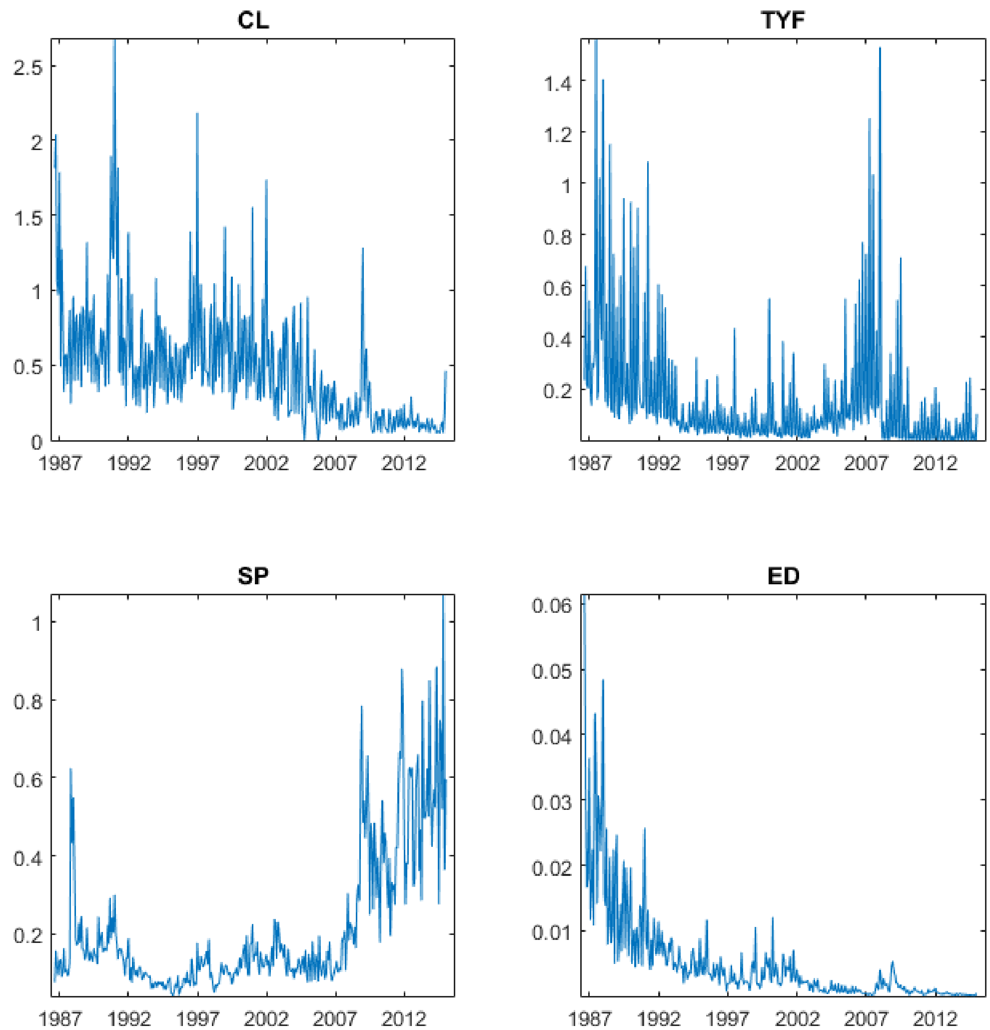

Figure 2.1: The raw modified *Amihud* (2002) measure is computed as shown in equation 2.2. To improve the readability of the plot, the raw Amihud measure is averaged to the monthly frequency.

and henceforth use the residuals, $\hat{u}_{j,t}$, as the detrended liquidity measures. I correct for the linear trend in order to account for technological changes and other advances that may have affected the futures contracts in different times and ways. To account for the seasonality and persistence, I then control for the number of days until the expiration of the contract and focus on innovations from the following ARMA(1,1) model, i.e.,

$$u_{j,t} = \alpha_0 + \alpha_1 u_{j,t-1} + \theta_1 \varepsilon_{j,t-1} + \alpha_2 RD_{j,t} + \varepsilon_{j,t}, \tag{2.6}$$

where $RD_{j,t}$ are the remaining days in the contract before it expires. I define the residuals, $\varepsilon_{j,t}$, as the adjusted Amihud illiquidity, which, for ease of exposition, I will denote by $LIQ_{j,t}$. The adjusted modified Amihud measure is an illiquidity measure; an increase in LIQ implies a higher price impact and thus, lower liquidity.

Volatility is also highly persistent (ranging between 0.75 and 0.90), I thus use its AR(1) innovations as modified volatility series.

Figure 2.2 plots the adjusted Amihud series (again, monthly averages to improve the readability of the plot). The figures suggest that the trend and persistency are, in part, corrected.

2.2.3 Reduced–form VAR

I propose a reduced–form 12–dimensional VAR(4) model based on daily data for $y_t = (Vol_{j,t}, Ret_{j,t}, LIQ_{j,t})'$. The reduced–form 12–dimensional VAR(4) is

$$y_t = \alpha + \sum_{i=1}^{4} \Phi_i y_{t-i} + e_t, \tag{2.7}$$

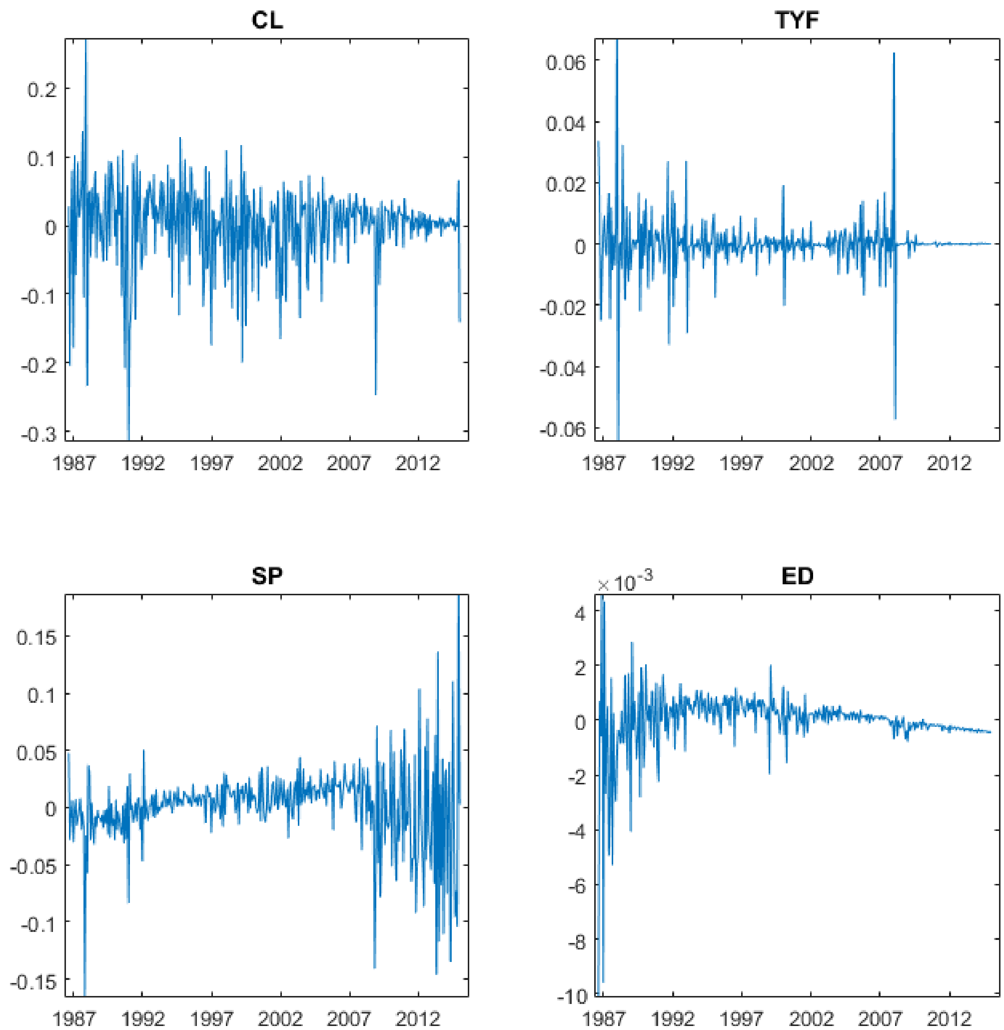

Figure 2.2: The adjusted Amihud series are the innovations of the ARMA(1,1) model of eq. (2.6). To improve the readability of the plot, the adjusted Amihud measure is averaged to the monthly frequency.

where y_t, α, and e_t are (12×1) vectors and Φ_i (12×12) matrices.

I include returns and price volatility because earlier literature has identified returns and volatility as the main drivers of liquidity measures.[6] *Chordia et al.* (2001), in particular, have clarified the significant role of volatility and returns in causing dynamic shifts in liquidity. The lag order of 4 days is chosen based on the Akaike Information Criterion (AIC).

The reduced–form VAR is consistently estimated by least squares. To investigate liquidity linkages across asset classes, I first perform pairwise Granger–causality tests between the endogenous variables of the VAR. Table 2.2 shows the baseline Granger Causality results, on the whole sample starting from July, 1986 to April 2015. To test the null hypothesis that (column) variable i does not Granger cause (row) variable j, I test whether the lag coefficients of i are jointly zero when j is the independent variable in the VAR, i.e., Wald test. The coefficients in Table 2.2 are the summed lag coefficients of variable i. Test statistics are in parentheses and critical values are from asymptotic χ^2–distribution with $p = 4$ degrees of freedom. The liquidity dynamics are shown in bold, in the lower right corner.

[6] e.g., *Amihud and Mendelson* (1986), *Hasbrouck and Seppi* (2001), *Chordia et al.* (2011)

Table 2.2: Baseline VAR – Granger Causality Tests

The table presents the baseline VAR results with endogenous variables (3 time–series for each variable) the Amihud measure (LIQ), returns (RET), and volatility (VOL). The number of lags is $p = 4$. The coefficients are the sum of the respective lag coefficients. The columns are the time t variables, so, column LIQ_{CL} shows the cumulative effect of changes on the Crude Oil liquidity to the other endogenous variables. I conduct a Wald test to test the null hypothesis of Granger–non causality, test statistics are in parentheses. The asymptotic χ^2 with $p = 4$ DF, critical values for the 1% level is 13.277, 5% level is 9.488, and 10% is 7.779.

	RET_{CL}	RET_{TYF}	RET_{SP}	RET_{ED}	VOL_{CL}	VOL_{TYF}	VOL_{SP}	VOL_{ED}	LIQ_{CL}	LIQ_{TYF}	LIQ_{SP}	LIQ_{ED}
RET_{CL}		0.021	0.057	-1.604	-6.09^c	5.367	-28.03	129.3	0.118^c	0.091	-0.329	-8.423
		(3.47)	(4.71)	(3.95)	(17.8)	(2.60)	(7.80)	(4.55)	(13.5)	(4.86)	(6.12)	(4.24)
RET_{TYF}	0.008		-0.005	1.040	-2.109	1.264	-1.10^c	-34.77	0.018	-0.052	0.048	0.468
	(2.24)		(10.7)	(0.99)	(1.86)	(10.5)	(20.9)	(5.76)	(0.85)	(7.15)	(3.67)	(0.69)
RET_{SP}	$-.002^c$	0.054		$-.047^a$	-1.15^c	3.762	10.64^c	-141^c	0.018^b	-0.010	0.137^c	1.938
	(13.8)	(1.26)		(7.87)	(27.5)	(1.70)	(308)	(22.0)	(10.9)	(7.17)	(57.1)	(3.87)
RET_{ED}	0.00	0.003^c	$-.002^a$		0.076	-0.243	0.787	12.97^b	0.003^a	0.00^c	-0.002	0.192
	(6.86)	(57.9)	(9.19)		(2.18)	(1.61)	(0.79)	(12.5)	(9.05)	(15.8)	(5.68)	(1.79)
VOL_{CL}	0.00	0.00	0.00	0.003		0.204^c	0.621^c	-2.24^c	0.00^c	0.00	-0.002	0.193
	(3.70)	(3.31)	(1.05)	(1.01)		(26.2)	(71.3)	(14.2)	(21.7)	(7.47)	(4.80)	(4.19)
VOL_{TYF}	0.00	0.00	0.00	0.00	0.037^c		0.118	0.600^b	0.00	0.00^b	$-.002^a$	0.004
	(3.00)	(5.60)	(0.61)	(0.99)	(14.3)		(9.27)	(38.6)	(6.59)	(11.5)	(9.33)	(0.92)
VOL_{SP}	0.00	0.00	0.00	-0.001	0.108^c	0.061^c		1.344^c	0.00^c	0.00^c	0.00^c	0.018
	(4.84)	(4.52)	(4.49)	(6.65)	(118)	(44.2)		(24.8)	(15.0)	(10.4)	(19.0)	(3.46)
VOL_{ED}	0.00	0.00	0.00	0.00^a	0.00^c	$-.009^a$	0.009^b		0.00^a	0.00	0.00^c	0.001^c
	(1.38)	(5.56)	(1.87)	(8.51)	(21.8)	(7.89)	(12.6)		(9.35)	(6.12)	(19.6)	(27.1)
LIQ_{CL}	-0.020	-0.011	0.003	0.521	4.104^c	7.410	3.267	-161^b		**$-.083^c$**	**0.054**	**1.913^a**
	(6.29)	(1.9)	(4.57)	(5.41)	(19.6)	(5.34)	(4.09)	(12.5)		**(22.1)**	**(3.34)**	**(8.37)**
LIQ_{TYF}	-0.002	0.011^a	0.005	$-.570^c$	-1.910	-15.12	7.360	21.85^b	**$-.056^c$**		**-.064**	**8.984^c**
	(1.25)	(8.97)	(6.81)	(31.6)	(0.99)	(7.50)	(2.56)	(10.1)	**(13.9)**		**(3.13)**	**(50.2)**
LIQ_{SP}	-0.005	0.021	-0.029	0.018	1.420^a	-0.358	-4.02^a	99.57^b	**$-.003^b$**	**-.003**		**3.104^c**
	(6.38)	(5.22)	(5.94)	(3.97)	(8.40)	(0.77)	(8.49)	(10.2)	**(9.47)**	**(3.77)**		**(49.1)**
LIQ_{ED}	0.00	0.00	0.00	0.002^b	-0.034	0.081	0.054	-2.78^c	**0.00^c**	**0.00^c**	**0.006^c**	
	(4.47)	(2.30)	(2.97)	(11.4)	(2.17)	(3.39)	(6.30)	(38.4)	**(15.1)**	**(98.1)**	**(31.0)**	

^{a} $p < 0.05$, ^{b} $p < 0.01$, ^{c} $p < 0.001$

Negative liquidity shocks to the ED (LIQ_{ED}) contract predict subsequent decrease in liquidity in all three contracts. This result may be justified by the fact that the ED contract is by far the most liquid market. The liquidity of ED is also affected by the liquidity shocks to all three contracts. Liquidity shocks of SP spillover only to ED. In other words, SP generates the fewer spillovers to and from other contracts. Finally, there is a strong bi–directional liquidity spillover link between the CL and the TYF contracts; negative liquidity shocks to TYF predict improved liquidity conditions in CL, and vice versa.

Overall, these preliminary results suggest that short–maturity interest rate markets' liquidity conditions are significant leading indicators of general liquidity conditions. The flight–to–liquidity effect between the equity market and the Treasury bond is not evident in my sample. There is however, flight–to–liquidity effect between the 10yr T–Note and Crude Oil.

Using a non–structural approach and eliminating microstructure concerns, I find direct and significant liquidity spillovers across the four assets. These results add to the existing empirical literature that finds little direct evidence of spillovers. *Chordia et al.* (2005), for instance, use intra–day data on US equity and 10yr. Treasury bonds to explore cross–market liquidity dynamics, but find no evidence of cross-market causations. As they mention, "there is no evidence of a causal" (in the Granger–causality sense) "relationship between stock and bond spreads or between spreads in one market and volatility in the other." *Goyenko and Ukhov* (2009) extend the *Chordia et al.* (2005) sample by adding bonds of different maturities, and find that "illiquidity of one market has a predictive power for illiquidity of the other market".

Their results however pertain to short–maturity bonds.

2.3 Dynamic Liquidity Spillovers

The baseline results provide preliminary evidence of direct liquidity spillovers across assets. To gain further insight on the time dynamics of such spillovers, I propose a 1–year rolling over reduced–form VAR. The choice of 1 years allows for a large enough sample to consistently estimate the model and concurrently, capture spillovers on as high a possible frequency.

I define liquidity spillovers for each pair of assets as the mean squared error (MSE) ratio of a restricted VAR over an unrestricted VAR. The unrestricted VAR is the one on eq. (2.7), 12–dimensional VAR(4) on $y_t = (Vol_{j,t}, Ret_{j,t}, LIQ_{j,t})'$. For each liquidity spillover pair, the restricted VAR is the 12–dimensional VAR(4) with Granger non–causality type exclusion restrictions.

More specifically, to measure liquidity spillovers from asset i to asset j, I restrict in asset j's liquidity equation, the lagged coefficients of asset i's liquidity, return, and volatility to zero. The mean squared error of the restricted VAR(4) is then the variance (from the variance–covariance matrix) that corresponds to asset j's liquidity equation. Similarly, the unrestricted VAR(4) mean squared error is the variance that corresponds to the asset j's liquidity equation from the variance–covariance matrix of the unrestricted 12–dimensional reduced form VAR(4). I restrict the coefficients in return and volatility equations to control for indirect spillovers because results in the baseline VAR, table 2.2, show that there are indirect liquidity spillovers through shocks to returns and volatility.

Because the lag order is $p = 4$, there are $(4 \times 3 = 12)$ linear restrictions and the restricted VAR can be estimated by estimated GLS (see Appendix (**??**) for proofs and details). Pairwise liquidity spillovers are defined as the ratio of the MSE (for the liquidity of interest) of the unrestricted VAR and the restricted VAR. I.e., the liquidity spillover from asset i to asset j at time t is

$$LSPILL_{ij,t} = \frac{MSE^{r}_{j,t}}{MSE^{unr}_{j,i,t}}, \tag{2.8}$$

where $MSE^{unr}_{j,t}$ is the jth (liquidity) diagonal element of the innovation covariance matrix from the unrestricted VAR and $MSE^{r}_{j,i,t}$ is the jth (liquidity) diagonal element of the innovation covariance matrix from the restricted VAR, with the lag coefficients of the liquidity of the i asset set to zero. High [low] values of the MSE reduction mean higher [lower] absolute liquidity spillovers. In particular, an increase in the value of $LSPILL_{ij,t}$ means that when restricting the VAR, i.e., when shutting down the liquidity spillover, the increase in $MSE^{r}_{j,t}$ is greater than the increase in $MSE^{unr}_{j,i,t}$, and thus the restriction is blocking a meaningful liquidity channel. This measure, since it is a variance ratio, excludes responses to common shocks from being identified as liquidity spillovers. That is, in the case of common shocks, both the $MSE^{r}_{j,t}$ and the $MSE^{unr}_{j,i,t}$ are affected in the same way and thus, the total common shock effect drops out. Finally, defining liquidity spillovers as a ratio allows to control for heteroscedasticity, i.e., changes in the variance over time.

This measure of liquidity spillover, is in line with the theories discussed in section (2.4) and captures the absolute magnitudes of liquidity spillovers and not the signs. In addition, by concentrating on the MSE one uses the errors which are stationary and hence the measure of liquidity spillovers is stationary. If one were to use the coefficients then the measure of liquidity spillovers would not have been stationary. The rolling over VAR is estimated using 1-year period. In each iteration, I add one day and subtract the oldest day in the sample.[7]

2.3.1 Summary of Results

Figure 2.3 plots the average liquidity spillovers to each asset. To improve the readability of the plot, the daily spillovers have been averaged to the monthly frequency and standardized to have zero mean and unit variance for convenience. That is, "liquidity spillovers to CL" plots the (equally weighted) average liquidity spillovers from TYF, SP, and ED to CL. Quite interestingly, liquidity spillovers to CL do not exhibit significant time variation pre–2007, after which point they spike and are significant. During the great recession and the European sovereign crisis, spillovers to CL have increased by almost 3 standard deviations. These results support the idea of financialization of commodity markets, i.e., the large inflow of investment capital to commodity futures markets, that has turned commodities into popular asset class for portfolio investors, just like stocks and bonds.[8] This financialization has affected the liquidity of Crude Oil in a manner potentially consistent with my results. A similar pattern of liquidity spillovers is observed for the Eurodollar contract. What is also interesting is that liquidity spillovers to the S&P500 contract have decreased substantially post–2007 (by one standard deviation), although they were very significant

[7] Despite the decrease in the sub–samples length the estimated process remains stable, as determined by the roots of the polynomial $det(I_{12} - \hat{\Phi}_1 y - \hat{\Phi}_2 y^2 - \hat{\Phi}_3 y^3 - \hat{\Phi}_4 y^4)$.

[8] An interesting and more thorough discussion on the financialization of commodities can be found in *Cheng and Xiong* (2013).

in the prior years. During the Asian crisis, for instance, spillovers to SP increased by 2.5 standard deviations. Finally, the 10yr. T–Note, contrary to the other contracts, seems to serve as a flight–to–quality asset during some financial crises (Russian default, LTCM, Great Recession) during which liquidity spillovers drop significantly, as opposed to other major crises.

Figure 2.4 plots the time evolution of the (equally–weighted) average liquidity spillovers (again the daily spillovers have been averaged to the monthly frequency and standardized to have zero mean and unit variance for convenience). The measure increases during major events (1997 Asian crisis and 1998 Russian default and LTCM collapse, 2003 Iraq War, 2007 great recession, European sovereign crisis).

These results conform to the intuition of the theories discussed in section (2.4). Liquidity spillovers are expected to spike during periods of higher fundamental uncertainty, information heterogeneity, risk aversion, and financial constraints. These periods coincide with periods of financial turmoil, i.e., the periods during which the liquidity spillover measure spikes. I next use a Markov switching model to examine more thoroughly the time series properties of liquidity spillovers.

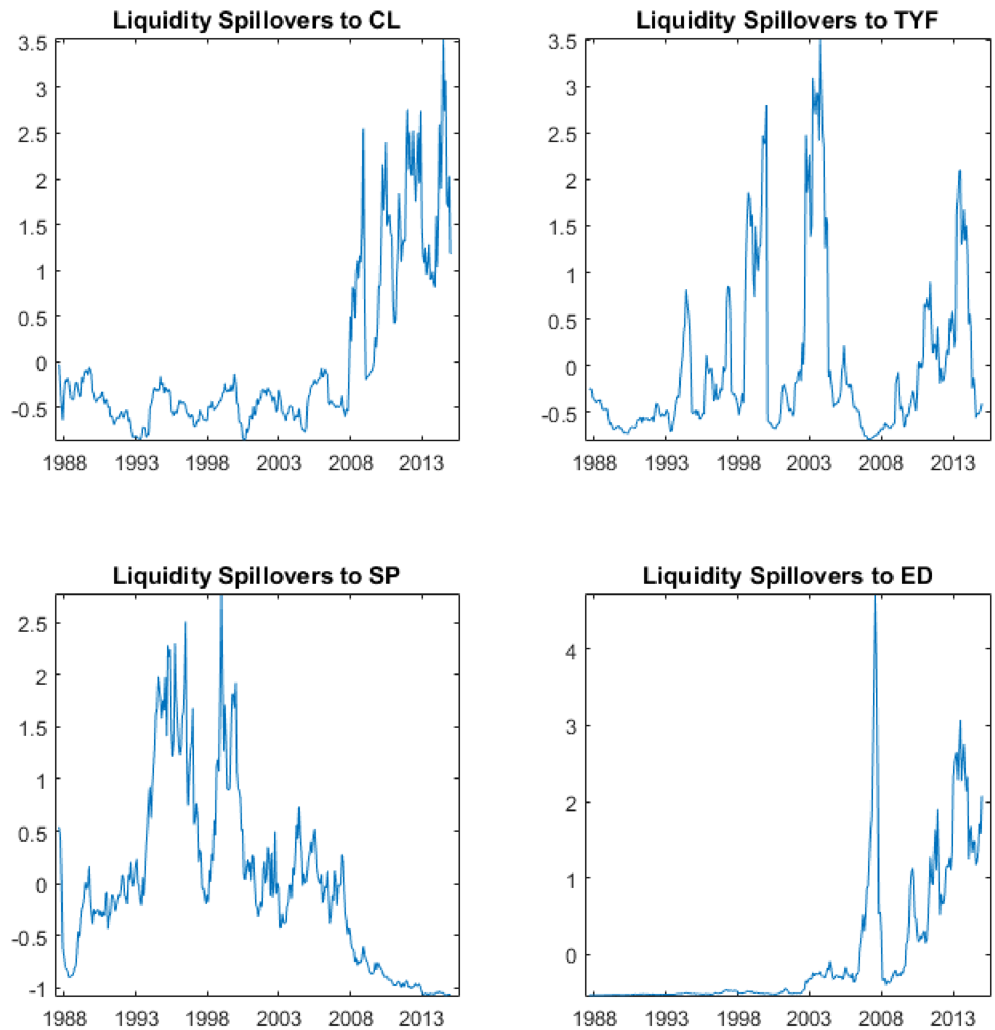

Figure 2.3: Each liquidity spillover pair is defined as in eq. (2.8). The figure plots the equally weighted average of liquidity spillovers across the three assets to one asset. That is, spillovers to CL show the average spillovers from TYF, SP, and ED to CL. To improve the readability of the plot, the daily spillovers have been averaged to the monthly frequency. I standardize each series to have zero mean and unit variance for convenience.

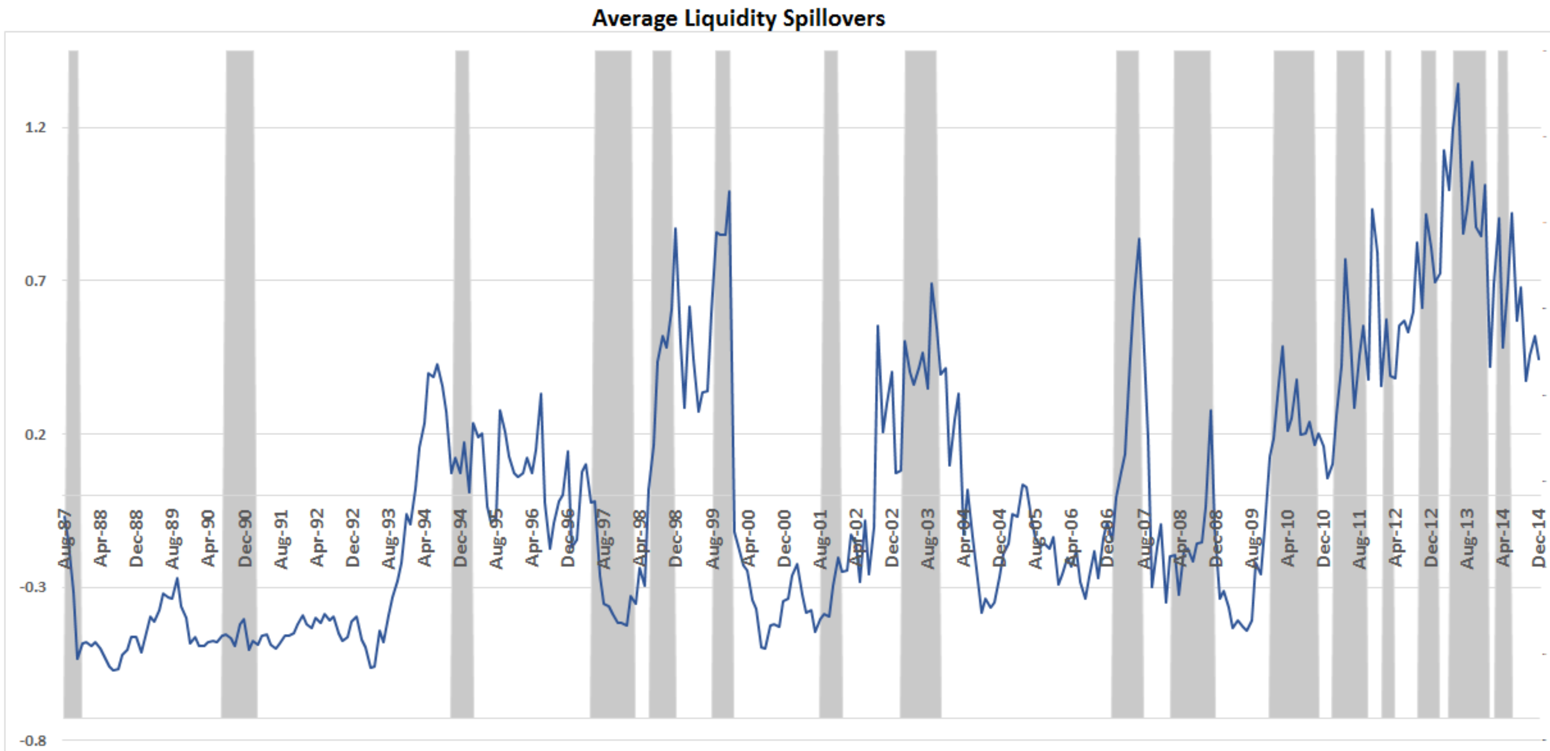

Figure 2.4: Each liquidity spillover pair is defined as in eq. (2.8). The figure plots the equally weighted average of liquidity spillovers across the 12 spillover pairs. The average is computed after each spillover pair is standardized to zero mean and unit variance. Daily spillovers have been averaged to the monthly frequency. The shaded areas represent periods of major financial and macroeconomics events.

2.3.2 Markov Switching Model

The pairwise liquidity spillovers seem to exhibit breaks in their behavior. One way to assess this behavior is to study the time–series properties of the conditional moments (mean, variance) of the liquidity spillovers via a regime switching model. That is, if indeed the liquidity spillover series follow a different process during periods that are characterized by major financial and macroeconomic events (regime 1) than during non–turmoil periods (regime 2), then the conditional moments of such spillovers must also be different in the two regimes. A convenient way to model this type of regime-switching behavior is in terms of an unobserved discrete state variable (regime 1 and regime 2) that is driven by a Markov chain.

I postulate that the average liquidity spillover is driven by the following process:

$$LSPILL_{i,t} = \mu_{i,s_t} + \varepsilon_{i,s_t}, \tag{2.9}$$

where $LSPILL_{i,t}$ is the (monthly) average liquidity spillover to asset i from the other three assets at time t, $s_t \in \{1, 2\}$, and $\varepsilon_t \sim N(0, \sigma^2_{s_t})$. In other words, in each regime, the average liquidity spillover has the following representation,

$$LSPILL_{i,t} = \begin{cases} \mu_{i,1} + u_{1t}, & \text{if } s_t = 1 \\ \mu_{i,1} + u_{2t}, & \text{if } s_t = 2, \end{cases} \tag{2.10}$$

where $u_{it} \sim N(0, \sigma_i^2)$. The state variable s_t determines whether it is regime 1 or regime 2 and the Markov switching probability for state transition is specified as

$$P\{s_t = k|s_{t-1} = l, s_{t-2} = n, \ldots, \mathcal{F}_{t-1}\} = P\{s_t = k|s_{t-1} = l\} = p_{lk}, \tag{2.11}$$

where p_{lk} denotes the probability of state k following state l. The transition matrix therefore, is

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}.$$

The estimation uses the *Hamilton* (1989) filter and the Expectation Maximization (EM) algorithm. Since the filter is fairly common, I will not provide the proofs; a lengthy discussion can be found in *Dempster et al.* (1977), *Hamilton* (1989), and *Krolzig* (2013).[9]

The Markov switching model of eq. (2.9) confirms there are indeed two states, one characterized by low conditional mean and variance (regime 1) and one by high conditional mean and variance (regime 2), with the exception of liquidity spillovers to the SP contract, that are more volatile in the low mean state. Table 2.3 shows the Markov switching model results. Regime 1 lasts longer than regime 2, as theories suggest (panel A). The transition matrix provides information regarding the non–linear persistence outside the usual autoregressive parameters. In particular, both regimes are very persistent. p_{11}, the probability that if the process is in regime 1 it will remain in regime 1, is 98% and p_{22} is 95%. Figure 2.5 plots the monthly equally weighted average liquidity spillovers, the conditional variance ($\sigma^2_{s_t}$), the conditional mean (μ_{s_t}), and the probabilities of each state occurring at each time. Similar to the

[9]The model is estimated using MATLAB® and minor changes on Perlin's code.

Table 2.3: Two–state Markov Switching Model

The table presents the parameters estimated by the Markov Switching model,

$$LSPILL_{i,t} = \mu_{i,s_t} + \epsilon_{i,s_t},$$

where $LSPILL_{i,t}$ is the (monthly) average liquidity spillover to asset i from the other three assets at time t, $s_t \in \{1, 2\}$, and $\epsilon_t \sim N(0, \sigma^2_{s_t})$.

Panel A					
Transition	Matrix		Expected	Duration of Periods	
0.98^{***}	0.05^{***}			Regime 1	439.31 days
0.02^{***}	0.95^{***}			Regime 2	110.61 days
Panel B –	Switching	Parameters			
	ED	CL	TYF	SP	
μ_1	$1.3 \times 10^{4***}$	1.644^{***}	3.782^{***}	4.923^{***}	
μ_2	$4.5 \times 10^{4***}$	2.519^{***}	68.437^{***}	7.710^{***}	
σ_1	6.3×10^{6}	0.607^{***}	2.510^{***}	77.964^{***}	
σ_2	$5.8 \times 10^{7***}$	5.381^{***}	3.621^{***}	64.050^{***}	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

results of section (2.3.1), liquidity spillovers increase significantly and become more volatile during periods of major financial and political events.

Although these results are in line with the theories discussed in section (2.4), they are different in spirit from the results in a sizeable international finance literature. *Bekaert and Harvey* (1995) and *Bekaert and Harvey* (2003) provide evidence of time–varying market integration in international markets. In particular, they show that during periods of financial turmoil, the degree of integration in international markets decreases and thus, there is lower contagion. These results, although different from the results of this paper, can be explained by a number of regularities that exist in international markets. International markets, for instance, are controlled by the respective countries which, during periods of financial turmoil, can take actions to protect their domestic markets, decreasing effectively contagion. Such interventions are not possible (or are less likely) within a country.

2.3.3 Robustness Checks

In untabulated results, I check a number of other possible explanations for the results. First, I examine the sensitivity of the results to the choice of rollover periods. I vary the period from 3 years to an increasing number of years (adding one day in each iteration). The results remain unchanged.

This paper estimates a reduced–form VAR and as such, it does not capture, by construction, the contemporaneous effects. In other words, it may be that during periods of low (lagged) liquidity spillovers, liquidity spillovers happen contemporaneously, and vice versa. If that is the case, then one would conclude that liquidity

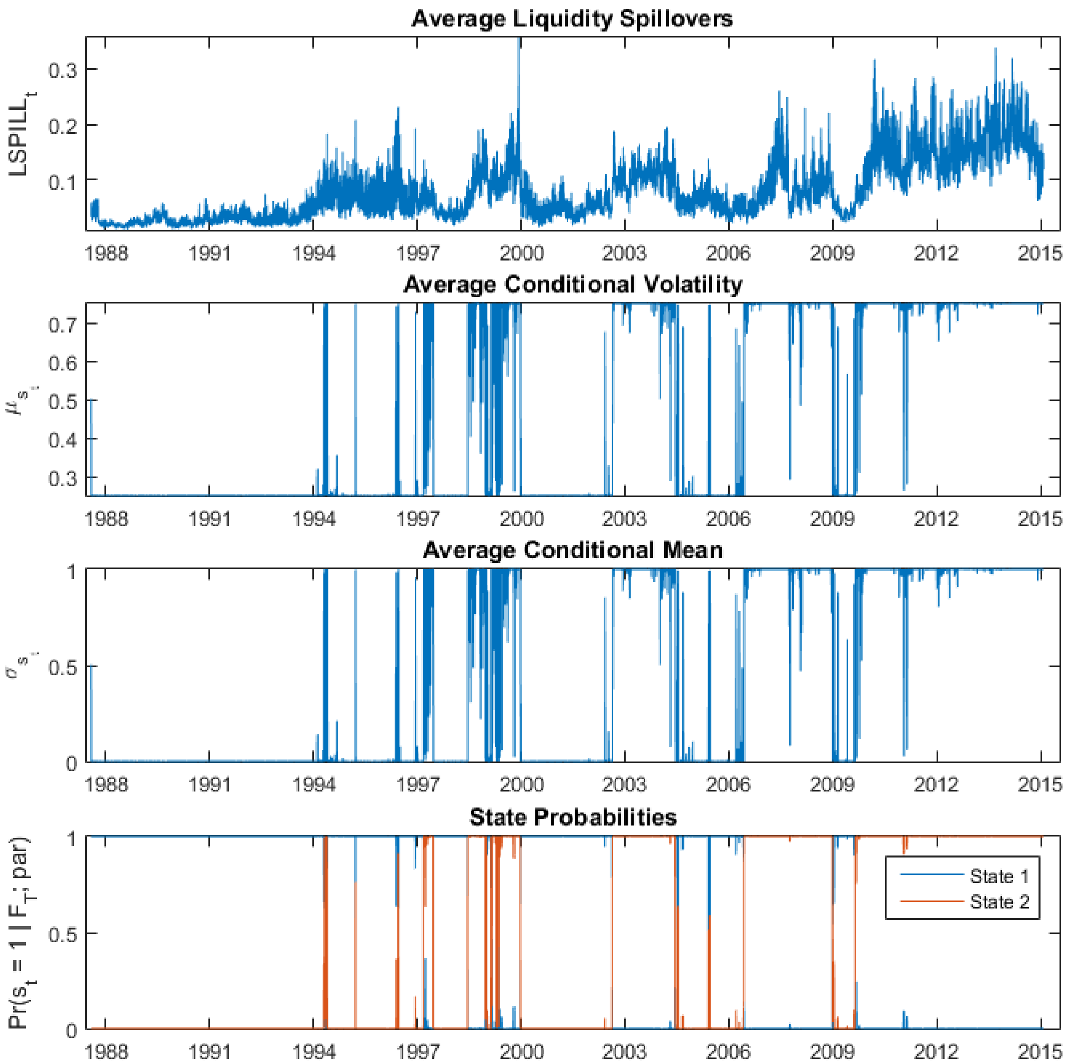

Figure 2.5: The Markov switching model is defined as in eq. (2.9). The figure plots the average liquidity spillovers on a monthly frequency (panel a), the conditional volatility (panel b), the conditional mean (panel c), and the state probabilities (panel d). State 1 [2] corresponds to the state with low [high] conditional mean and variance.

spillovers are not changing over time, but what changes over time is the timing (contemporaneous vs. lagged) of said spillovers. To avoid imposing structural assumptions, I address this concern by directly examining the time series properties of the covariances and indirectly through the alternative specification. The alternative specification takes into account both the variances and covariances, and thus indirectly addresses the concern of time varying contemporaneous effects. Both the alternative and main specification find similar results, which implies that covariances are not the driving variables. In untabulated results, I also find that covariances do not change significantly between periods of high and low liquidity spillovers. These results suggest that contemporaneous effects do not change between the two states and thus, it is not the contemporaneous effects that drive the main results of this papers.

In the main specification, I detrend the modified *Amihud* (2002) measure and remove the persistent component using an ARMA(1,1) process. Although this filtering process addresses concerns regarding the time series properties that may affect the conclusions of further analysis, it nevertheless comes with a tradeoff, i.e., the difficulty to clearly interpret the results of the subsequent analysis. As a robustness check, l also use the raw modified *Amihud* (2002) measure (as in eq. 2.2 and figure 2.1) in the VAR(4) and generate liquidity spillovers. Figure 2.6 shows the liquidity spillovers to each asset without the trend and ARMA(1,1) corrections. One immediately notices that the main difference between figure 2.3 and 2.6 is the magnitude of spikes and not their positions. That is, both the methods predict high and low liquidity spillovers at the same time periods, the magnitudes however for the high liquidity periods differ but not significantly. Figure 2.6 (green line) plots the (equally–weighted) average liquidity spillovers using the raw *Amihud* (2002) measure as liquidity. The blue line plots the original liquidity spillovers. The main difference between the two series is for the 1992 and post–1994 periods, during which the non–corrected series predict higher liquidity spillovers.

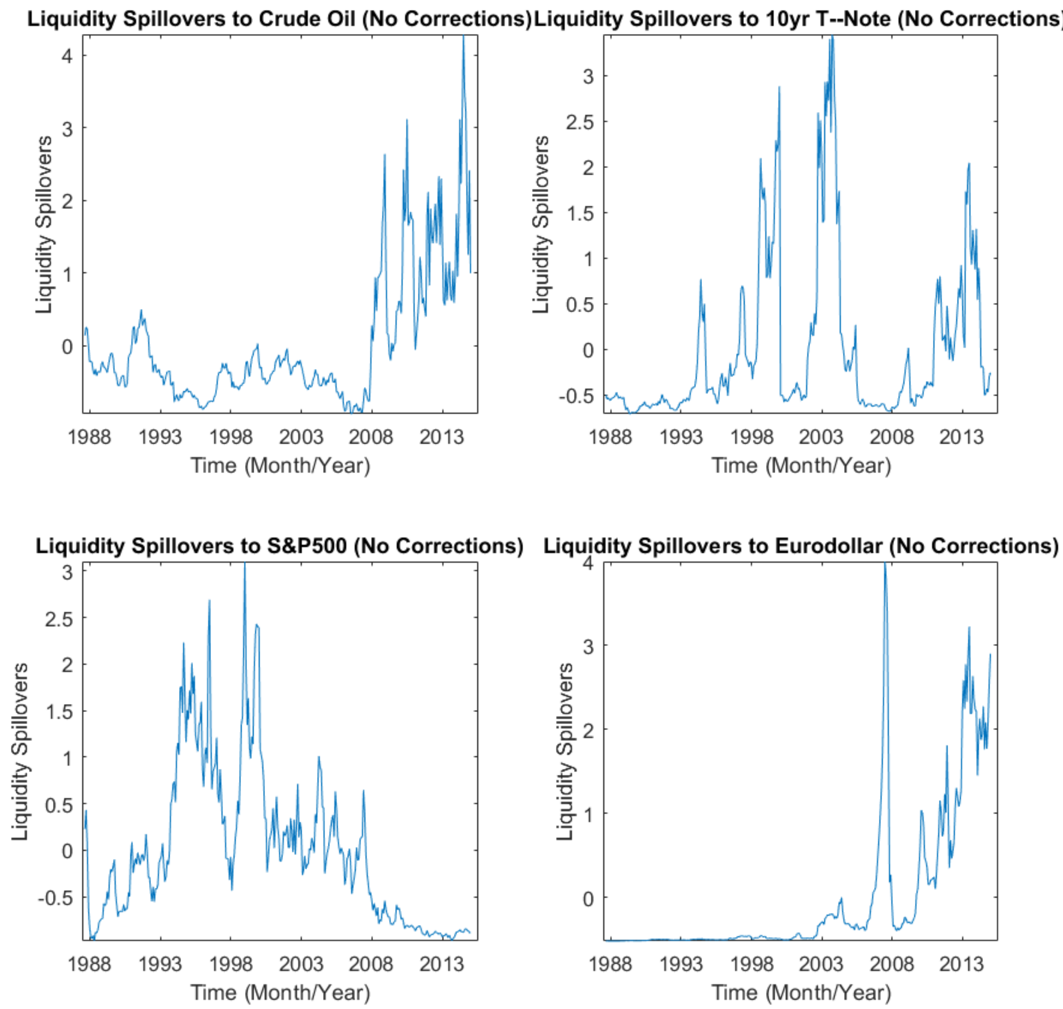

Figure 2.6: Each liquidity spillover pair is defined as in eq. (2.8) and liquidity is defined as the raw modified Amihud measure (eq. 2.2), i.e., without any trend or persistence corrections. The figure plots the equally weighted average of liquidity spillovers across the three assets to one asset. That is, spillovers to CL show the average spillovers from TYF, SP, and ED to CL. To improve the readability of the plot, the daily spillovers have been averaged to the monthly frequency. I standardize each series to have zero mean and unit variance for convenience.

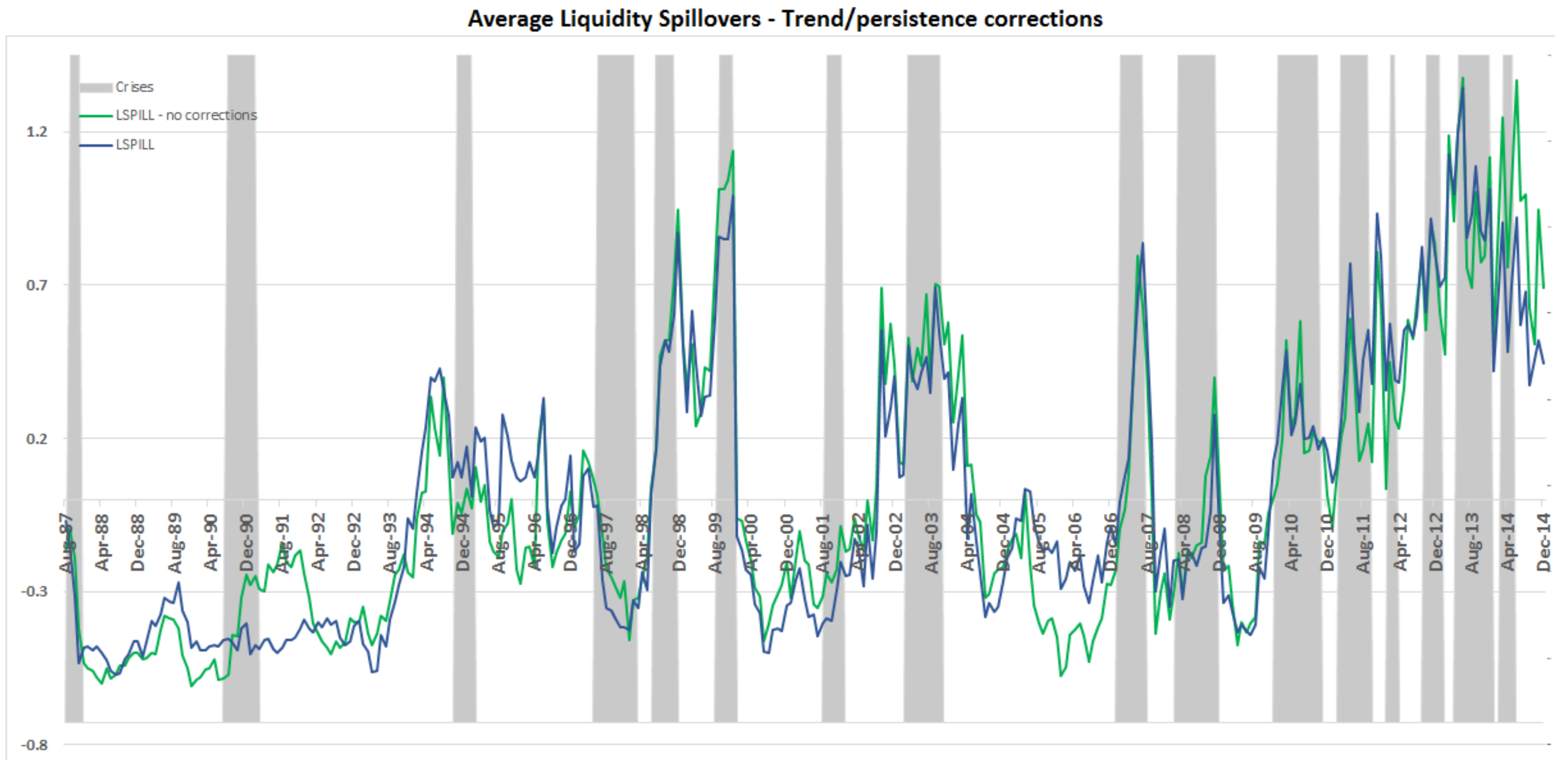

Figure 2.7: The figure plots the equally weighted average of liquidity spillovers across the 12 spillover pairs. The blue line plots the liquidity spillovers after liquidity has been corrected for trend and persistence. The green line plots the liquidity spillovers without any corrections for trend and persistence, i.e., liquidity is defined as the raw modified Amihud measure (eq. 2.2). The average is computed after each spillover pair is standardized to zero mean and unit variance. Daily spillovers have been averaged to the monthly frequency. The shaded areas represent periods of major financial and macroeconomics events.

2.4 Transmission Channels of Liquidity Across Assets

In the theoretical literature, liquidity spillovers are attributed to two sets of frictions and transmission channels, namely, information channels (cross–market rebalancing and information heterogeneity) and liquidity supply channels (funding constraints and traders' risk aversion). These models provide the theoretical underpinning of this empirical investigation of liquidity spillovers. In this section, to illustrate the intuition of these models, I briefly discuss the proposed transmission channels.

2.4.1 Cross–Market Rebalancing

Kodres and Pritsker (2002) use a multi–asset extension of the noisy rational expectation model of *Grossman and Stiglitz* (1980) to show that, in the presence of cross–market rebalancing, liquidity may spill across assets because of fundamental uncertainty about future asset values and information asymmetry. They describe an economy populated by informed (risk–averse) traders who receive homogeneous private signals and optimally choose their exposure to systematic risk factors across markets. Informed traders respond to shocks in one market by optimally re–adjusting their portfolios in other markets. If the portfolio rebalancing happens in markets with information asymmetry, liquidity spillovers can occur.

2.4.2 Heterogeneous Information

Pasquariello (2007), who uses a multi–asset, multi–trader extension of *Kyle* (1985), attributes liquidity spillovers to shocks in the degree of information heterogeneity among sophisticated market participants. He shows that, even in the absence of risk aversion, heterogeneously informed speculators may trade strategically across assets in order to reveal less of their informational advantage. Shocks to market wide information heterogeneity therefore, may affect the equilibrium liquidity of many markets by making the inference of market makers more difficult in all affected markets. In other words, such shocks make market makers more vulnerable to adverse selection from strategic trading.

2.4.3 Traders' Funding Constraints

Brunnermeier and Pedersen (2009), use a model similar in spirit to *Grossman and Stiglitz* (1980), to argue that liquidity spillovers across assets may stem from traders' funding constraints. They consider an economy where uninformed traders (speculators) provide liquidity across assets and finance their trades through collateralized borrowing, on a margin, from financiers. Speculators can face funding liquidity constraints either through higher margins, a decline in the value of the assets they hold, or both.

In such an economy, liquidity has commonality across assets because shocks to funding liquidity (capital constraints) affect all assets in which speculators are supplying liquidity. For spillovers to arise however, speculators must have high leverage, i.e., they must be close to their funding constraints or risk hitting their funding constraints, and markets must be illiquid.

2.4.4 Traders' Risk Aversion

Kyle and Xiong (2001) attribute liquidity spillovers across assets to shocks to traders' risk aversion. They model an economy with (convergence) traders who bet in multiple markets against short–lived deviations of prices from their fundamental values induced by noise trading. Trading losses in any one market, especially when large, reduce traders' willingness to bear risk, motivating them to liquidate positions in other markets. This wealth effect may result in reduced liquidity and increased price volatility across different markets. Liquidity thus, has commonality across assets because shocks to traders' risk aversion may lead them to manage their positions across all assets more conservatively, amplifying and transmitting the effects of a shock from one market to another.

2.4.5 Liquidity

The aforementioned models of information and liquidity supply use different but related notions of liquidity. In *Kodres and Pritsker* (2002) and *Pasquariello* (2007) liquidity is defined as market depth in face of adverse selection risk from the informativeness of order flow – which, in these models, depends on market wide fundamental uncertainty and information heterogeneity. In *Brunnermeier and Pedersen* (2009) liquidity is defined broadly as market quality, measured as the (absolute) distance between an asset's transaction price and its fundamental value.[10] The extent to which however, the former approaches the latter depends on fundamental volatility and noise trading and thus, adverse selection risk. The two notions of liquidity therefore, are expected to be empirically highly correlated.

Accordingly, in this paper, I focus on spillovers across proxies for observed market

[10] *Kyle and Xiong* (2001), although not explicitly, rely on the same notion of liquidity.

depth.

2.5 State Variables

The evidence presented in this paper confirms the notion postulated by all the theories discussed in section (2.4); liquidity spillovers are an intrinsic and important feature of price formation in financial markets. Each theory predicts a state variable that explains the cross–section and time–series of liquidity spillovers. In this and next section, I investigate the specific channels through which the spillovers may take place.

According to the cross–market rebalancing channel, fundamental uncertainty about future asset values and information asymmetry explain liquidity spillovers. Fundamental uncertainty arises from the uncertainty about the future macroeconomic state, which is measured by the realizations of macroeconomic factors. To test the cross–market portfolio rebalancing thus, I use monthly changes in unemployment, changes in personal consumption expenditures, and the Chicago Feds monthly index of U.S. real activity (CFNAI) as possible macroeconomic factors. Monthly data on these series are obtained from the Federal Reserve Bank of St. Louis. Figure 2.8 plots the monthly changes on PCE, the CFNAI, and the unemployment rate. All measures comove and increase during major financial crises.

Kodres and Pritsker (2002) predict that higher [lower] fundamental uncertainty predicts higher [lower] (absolute) liquidity spillovers (*Hypotheses 1*).

The information heterogeneity channel predicts that increased heterogeneity in private signals explains increased liquidity spillovers. To proxy for information het-

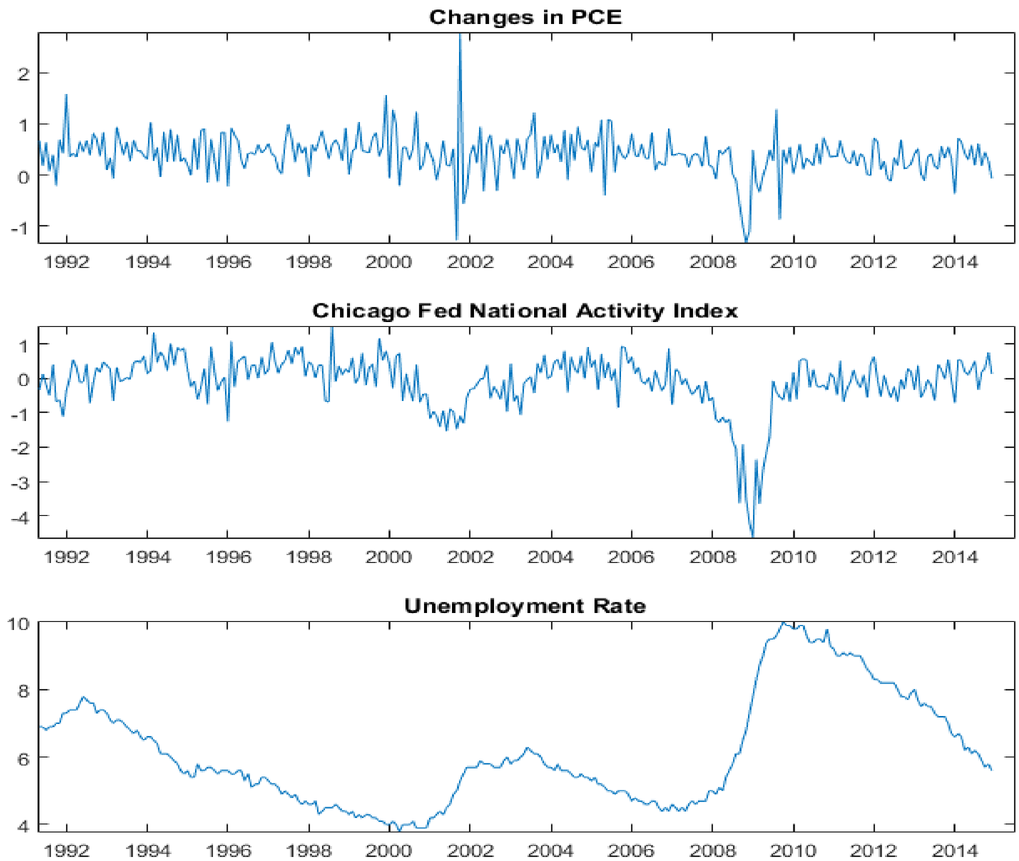

Figure 2.8: The figures plot monthly changes in the Personal Consumption Expenditures (PCE), the Chicago Fed National Activity Index (CFNAI), and the unemployment rate. The data on PCE and unemployment are obtained from the St. Louis Fed and data on CFNAI are from the Chicago Fed. The changes in PCE are monthly changes on the seasonally adjusted expenditures. The unemployment rate refers to civilian unemployment. CFNAI is designed to capture the current and future course of U.S. economic activity and inflation. It uses 85 economic indicators drawn from Production and Income, Employment, Unemployment, and Hours, Personal Consumption and Housing, and Sales, Orders, and Inventories.

erogeneity I use a measure of dispersion in beliefs. To calculate a proxy for the difference in beliefs about fundamentals, sampled at the monthly frequency, I use the Survey of Professional Forecasters, managed by the Federal Reserve Bank of Philadelphia, and Michigan's Consumer Confidence index. Given that I am interested in heterogeneity regarding macroeconomic fundamentals, it is most fitting to use dispersion of beliefs about macroeconomic fundamentals rather than firm–specific fundamentals. From the Survey of Professional Forecasters, I use the quarterly individual forecasts about the one quarter ahead Price Index of GDP, the level of Real GDP, the level of unemployment, and the index of industrial production. From the University of Michigan's survey, I use their monthly Consumer Confidence index. Each survey serves a different goal; the Survey of Professional Forecasters is based on the opinions of market professionals while the consumer confidence index is a barometer of household opinions. Additionally, the consumer confidence index is constructed at a monthly frequency, allowing me to create a monthly index of dispersion in beliefs. I compute the time series of the cross-sectional standard deviations of the forecasts from the Survey of Professional Forecasters and then aggregate the information from the two time series by computing the first principal component. This gives me a proxy sampled at a monthly frequency. Figure 2.9 plots the first principal component. As expected, the dispersion index spikes during periods of major financial and political events.

The information heterogeneity channel of *Pasquariello* (2007) predicts that higher [lower] information heterogeneity predicts higher [lower] absolute liquidity spillovers (*Hypotheses 2*).

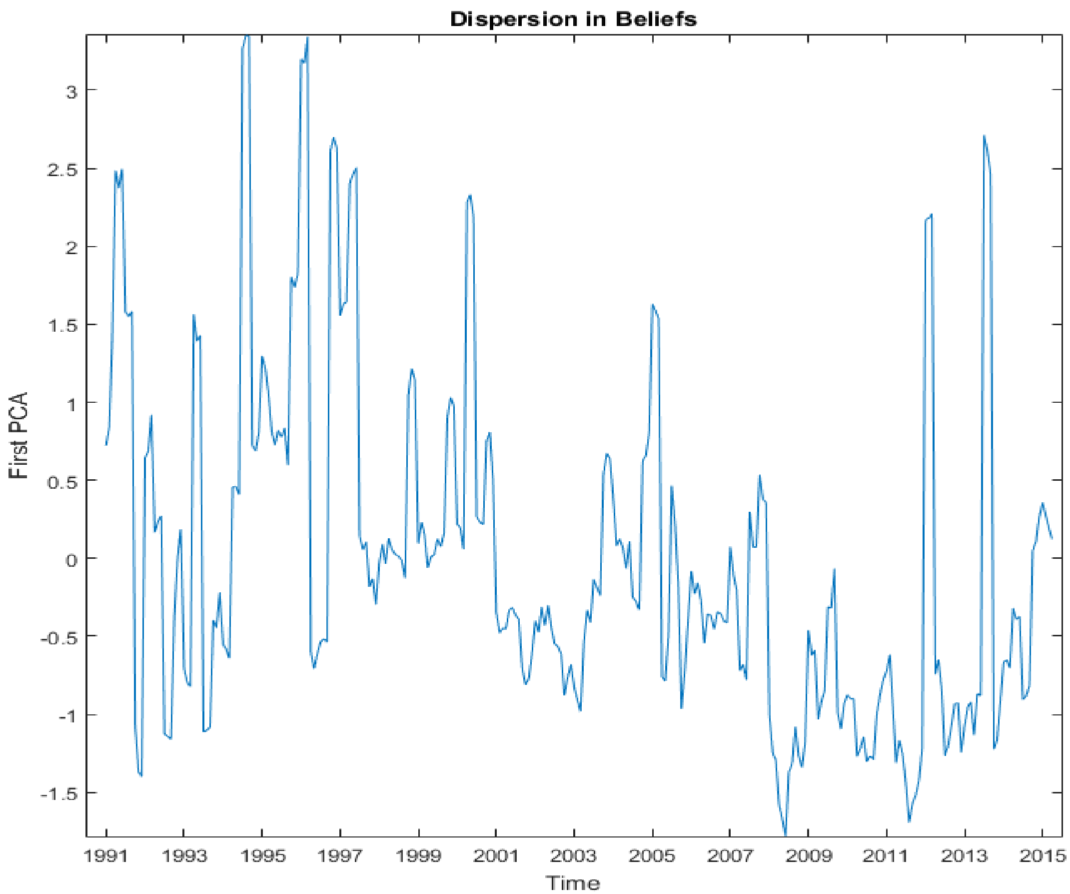

Figure 2.9: The figure plots the monthly dispersion in beliefs measure. I create the measure using the survey of Professional Forecasters and Michigan's Consumer Confidence Index. From the Survey of Professional Forecasters, I use the quarterly individual forecasts about the one quarter ahead Price Index of GDP, the level of Real GDP, the level of unemployment, and the index of industrial production. From the University of Michigan's survey, I use their monthly Consumer Confidence index. To generate a monthly series, I compute the time series of the cross-sectional standard deviations of the forecasts from the Survey of Professional Forecasters and then aggregate the information from the two time series by computing the first principal component.

According to *Kyle and Xiong* (2001), an increase in traders' risk aversion implies an increase in liquidity spillovers. I use the difference between the implied and expected volatilities as an indicator of the representative agent's risk aversion[11]. The data are publicly available on Hao Zhou's website.[12] The implied volatility is based on monhtly VIX (S&P500 options implied volatilities), as computed by the Chicago Board of Options Exchange (CBOE). The expected volatilities are computed from intraday data for the S&P500 composite index and are model–free. Figure 2.10 plots the risk aversion measure, which spikes during periods characterized by financial turmoil. The risk aversion measure is highly persistent and for the time–series regressions of the next section, I use the percentage difference.

Finally, based on the traders' funding constraints channel proposed by *Brunnermeier and Pedersen* (2009) and *Gromb and Vayanos* (2012), tightening funding conditions should explain increases in liquidity spillovers. I proxy for funding conditions using the leverage factor of *Adrian et al.* (2014). The factor is constructed as the seasonally adjusted log changes in the level of broker–dealer leverage, which are available on quarterly frequency. To bypass the frequency problem (inference on quarterly data would be very problematic in this setup), I use the monthly returns on their leverage factor mimicking portfolio, that uses the excess returns of the six Fama–French benchmark portfolios on size (Small and Big) and book–to–market (Low, Medium and High) in excess of the risk-free rate and the momentum factor. I obtain the monthly data from Kenneth French's website and the CRSP.

Tightening funding constraints imply decrease in the leverage of liquidity providers.

[11]see, again, *Rosenberg and Engle* (2002), *Bakshi and Madan* (2006), and *Bollerslev et al.* (2009)
[12]https://sites.google.com/site/haozhouspersonalhomepage/

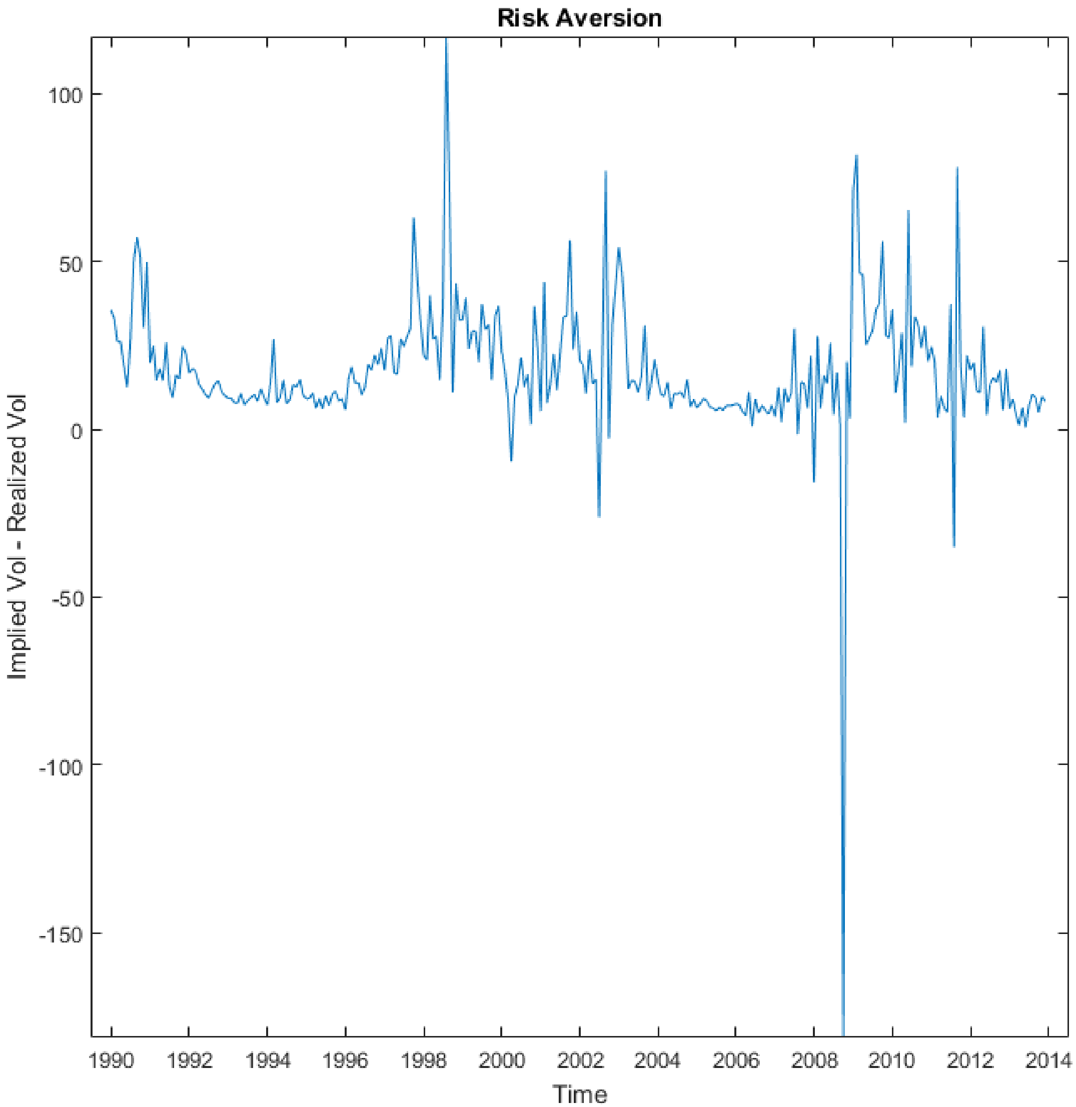

Figure 2.10: The figure plots the monthly risk aversion measure of *Bollerslev et al.* (2009), who define it as the difference between implied volatility (VIX) and expected volatility computed from intraday data on the S&P500 composite index. The data are at the monthly frequency.

Decreasing returns on the leverage factor mimicking portfolio therefore, are associated with decreasing leverage, which in turn is associated with tightening funding conditions. Figure 2.11 plots the log–changes on the quarterly *Adrian et al.* (2014) leverage factor and the returns on the leverage factor mimicking portfolio used in this paper. The plots suggest that indeed large decreases in leverage are associated with times of macroeconomic and financial turmoil, in line with the idea that decreases in leverage happen when funding is tight and marginal value of intermediary wealth is high.

The liquidity supply channels are not symmetric channels, i.e., they predict higher liquidity spillovers when either risk aversion of traders' funding constraints are higher (*Hypothesis 3* and *Hypothesis 4*, respectively), but not lower liquidity spillovers if these state variables are lower.[13]

2.5.1 Time–series regressions

For each state variable, I run the following baseline time–series regression,

$$\Delta LSPILL_t = \alpha + \beta X_t + \epsilon_t, \tag{2.12}$$

where $\Delta LSPILL_t$ is the monthly (equally–weighted) average liquidity spillover, $X_t \in$ {Leverage, Risk Aversion, Change in Unemployment, Change in Consumption, Chicago Fed Real Activity Index, Dispersion Index }. I use changes in liquidity spillovers because $LSPILL_t$ is highly persistent. Table 2.4 shows the results. Newey–West HAC standard errors with 3 lags are reported.

[13] To correct for outliers, I winsorize the data at the bottom and top 1%.

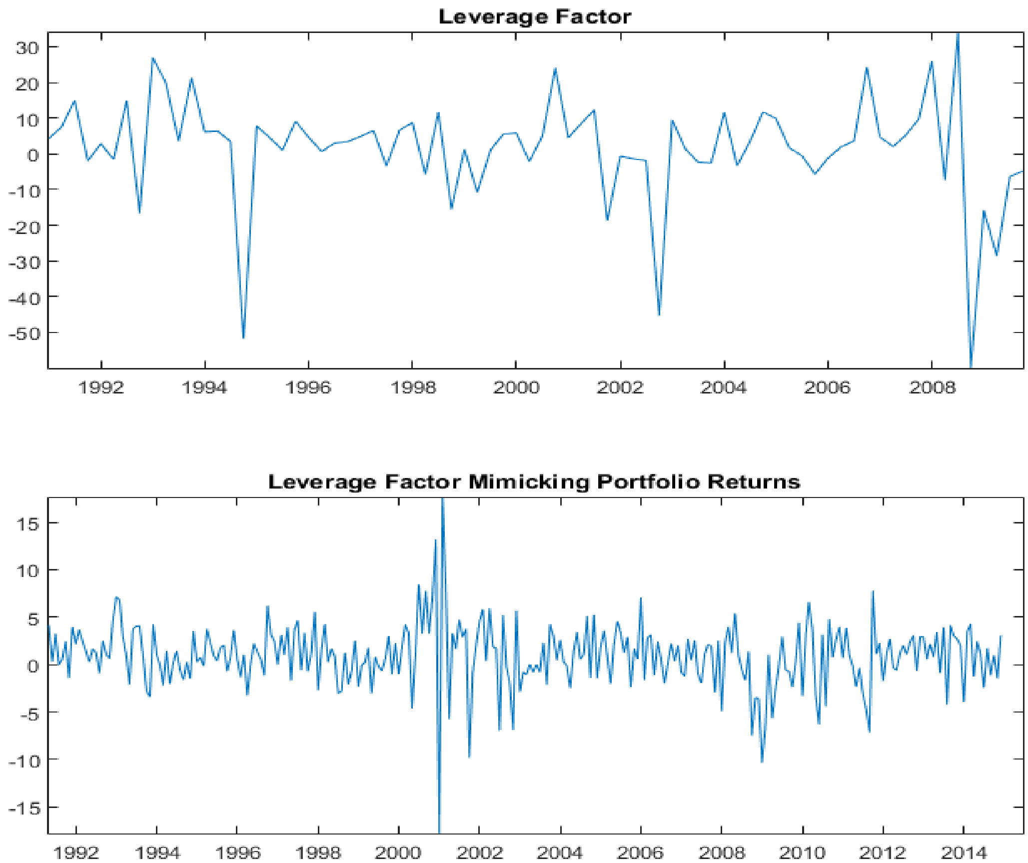

Figure 2.11: The figures plot the leverage factor (changes in log–leverage) and the returns of the leverage factor mimicking portfolio. The leverage factor is obtained from *Adrian et al.* (2014) who create the factor using quarterly Flow of Funds data. The leverage factor is computed as seasonally adjusted changes in log leverage of security broker–dealers on a quarterly frequency. The series has been standardized to have zero mean and unit variance. The leverage factor mimicking portfolio is created using the excess (of risk free rate) returns of the six Fama–French portfolios on size and book–to–market, and the momentum factor. The returns are on the monthly frequency.

Column (1) and (7) of Table 2.4 show the result of the state–variable regressions. The leverage coefficient is negative, -0.319, and significant at the 5% level. This finding of relationship between traders' funding constraints and liquidity spillovers is one of the main results in this paper. As mentioned in section 2.5, a decrease in the leverage of broker–dealers is associated with tightening funding conditions. Therefore, the lower are the returns of the mimicking portfolio, the more the liquidity providers delever (leverage decreases), i.e., the tighter the funding constraints, and thus, according to *Brunnermeier and Pedersen* (2009), the higher the liquidity spillovers.

Table 2.4: Time–Series State Variable Regression

This Table reports the results of the following regression:

$$\Delta LSPILL_t = \alpha + \beta X_t + \epsilon_t,$$

where $\Delta LSPILL_t$ is the monthly changes in liquidity spillover, $X_t \in \{$Leverage, Risk Aversion, Change in Unemployment, Change in Consumption, Chicago Fed Real Activity Index, Dispersion Index $\}$. Leverage are the monthly returns of the leverage factor mimicking portfolio of *Adrian et al.* (2014), Risk Aversion is the monthly changes in the difference between Implied and Estimated volatility as in *Bollerslev et al.* (2009), ΔUnemployment is the monthly changes in the [UNRATE] from Fred, ΔPCE is the monthly changes in the personal consumption expenditures from Fred, and CFNAI is the monthly changes in the Chicago Fed's U.S. real activity index, Dispersion is the monthly first principal component of the dispersion in beliefs measure. Newey– West HAC standard errors (with 3 lags; monthly data) are reported in brackets.

	ΔLSPILL	ΔLSPILL	ΔLSPILL	ΔLSPILL	ΔLSPILL	ΔLSPILL	ΔLSPILL
Leverage(Mimicking)	-0.347**						-0.319*
	[-3.52]						[-2.48]
Risk Aversion		-0.013					-0.011
		[-1.49]					[-1.16]
ΔUnemployment			-0.321				0.032
			[-0.26]				[0.02]
ΔPCE				8.942			8.649
				[1.07]			[0.82]
CFNAI					2.663		1.464
					[1.21]		[0.38]
Dispersion						-1.978	-3.145
						[-1.01]	[-1.35]
Obs.	223	223	223	223	223	223	223

t statistics in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The bootstrapped critical values for the respective levels are: 3.716, 4.7145, 5.8523

Due to the fact that I essentially test 6 different state variables, the statistical tests would be unreliable if this is not reflected in the choice of critical values. I adjust critical values for the t–statistics by block bootstrapping the six liquidity spillover models. The block bootstrap addresses serial correlation in the residuals, among others. I provide more details regarding the block bootstrap in the appendix. The adjusted critical values for the 5%, 1%, and 0.1% are 3.716, 4.7145, and 5.635 respectively. With the bootstrapped critical values the *leverage* measure remains significant under the 10% level.

Table 2.5 shows the results of the time–series regressions with the alternative definition of liquidity spillovers. The alternative definition is described and discussed in the appendix. The alternative liquidity spillovers are defined in eq. (E.2) and the average alternative liquidity spillover is defined as the equally weighted sum of the liquidity spillover pairs. Column (7) shows the main result and confirms the results of the main specification; liquidity spillovers are explained by the returns of the leverage factor mimicking portfolio.

Table 2.5: Time–Series State Variable Regression – Alternative Definition of Liquidity Spillovers

This Table reports the results of the following regression:

$$\Delta LSPILL_t = \alpha + \beta X_t + \epsilon_t,$$

where $\Delta LSPILL_t$ is the monthly changes in the average liquidity spillover as defined in equation E.2, $X_t \in$ {Leverage, Risk Aversion, Change in Unemployment, Change in Consumption, Chicago Fed Real Activity Index, Dispersion Index }. Leverage are the monthly returns of the leverage factor mimicking portfolio of *Adrian et al.* (2014), Risk Aversion is the monthly changes in the difference between Implied and Estimated volatility as in *Bollerslev et al.* (2009), ΔUnemployment is the monthly changes in the [UNRATE] from Fred, ΔPCE is the monthly changes in the personal consumption expenditures from Fred, and CFNAI is the monthly changes in the Chicago Fed's U.S. real activity index, Dispersion is the monthly first principal component of the dispersion in beliefs measure. Newey– West HAC standard errors (with 3 lags; monthly data) are reported in brackets.

	ΔLSPILL	ΔLSPILL	ΔLSPILL	ΔLSPILL	ΔLSPILL	ΔLSPILL	ΔLSPILL
Leverage(Mimicking)	-0.087*						-0.087*
	[-1.98]						[-2.08]
Risk Aversion		-0.001					0.004
		[-0.71]					[1.85]
ΔUnemployment			0.498***				-0.188
			[3.15]				[-0.66]
ΔPCE				-2.160**			8.068*
				[-2.69]			[1.99]
CFNAI					-2.304***		-1.360
					[-5.33]		[-1.07]
Dispersion						-1.122	-0.530
						[-1.80]	[-0.70]
Obs.	223	223	223	223	223	223	223

t statistics in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The bootstrapped critical values for the respective levels are: 3.716, 4.7145, 5.8523

2.6 Conclusion

This paper examines liquidity spillovers across four different asset classes traded in the U.S. futures market, namely, Crude Oil, 10–year T–Note, Eurodollar, and S&P500. Concentrating on the futures alleviates any microstructure concerns raised when comparing the liquidity of assets traded in different environments. Liquidity spillovers from asset i to asset j are estimated via a reduced–form VAR and defined as the improvement of fit stemming from allowing for lagged liquidity shocks in asset i to affect liquidity in asset j. This specification is free of any structural assumptions.

The results of this paper can be summarized as following. There are significant, time–varying liquidity spillovers across the four assets. The average liquidity spillover is governed by two states; a state (1) of low spillovers (low mean and variance) and a state (2) of high spillovers (high mean and variance). State (2) coincides with periods typically characterized as periods of financial and macroeconomic turmoil.

A number of theories predict liquidity spillovers. These theories can be characterized as information and liquidity supply based theories. Information based theories discussed in this paper are the cross–market rebalancing proposed by *Kodres and Pritsker* (2002) and information heterogeneity by *Pasquariello* (2007). Liquidity supply based channels are the traders' risk–aversion channel of *Kyle and Xiong* (2001) and the traders' funding constraints channel of *Brunnermeier and Pedersen* (2009). The findings of this paper provide the strongest support for the *Brunnermeier and Pedersen* (2009) liquidity transmission channel that predicts that spillovers arise during periods of crises and when speculators have high leverage, i.e., when they are close (or risk being close) to their funding constraints.

APPENDICES

APPENDIX A

Election and Liquidity: Variation across Industries

This table reports the results of the following regression:

$$y_{it} = \mu_i + \lambda_t + q_t + \beta_1 \mathbf{1}_t(Election) + \varepsilon_{it} \ ,\forall n \in \{1, \ldots, 12\}$$

where $y \in \{Ret_{it}, log(\tau_{it}), ILLIQ_{it}, Zeros_{it}\}$ and $Election$ is either a pre–Election or post–Election dummy.Ret_{it} are the cumulative excess log returns, over the value–weighted market portfolio, for the September–November pre–election period and December–January post election period. $log(\tau_{it}), log(ILLIQ_{it})$, and $Zeros_{it}$ are the log turnover, the log *Amihud* (2002) illiquidity measure, and the fraction of zero returns, as defined in eq. 1.2, 1.3, and 1.4 respectively. In this specification, the explanatory variables are dummy variables that are equal to one prior to elections ($\mathbf{1}_t$(pre–Election)) and after the elections ($\mathbf{1}_t$(post–Election)), and zero otherwise. In other words, the comparison is between the September–October period (November–January or February–April) of an election year and the same period for all non election years. We run this specification for each industry separately. Firm, year, and quarter fixed effects are included to account for all the time–invariant differences within the firms and across time. Standard errors are clustered by time.

Industry	No.	Ret	$log(\tau)$	$ILLIQ$	Zeros	Vol
				Pre–Election Dummy		

Continued on next page

Industry	No.	*Ret*	$log(\tau)$	$ILLIQ$	Zeros	Vol
Non–Durable	(1)	0.008*	−0.075***	-0.869	0.009***	−0.002***
		[0.003]	[0.008]	[0.554]	[0.001]	[0.0002]
Durable	(2)	0.014**	−0.049***	-0.157	0.006***	−0.002***
		[0.006]	[0.013]	[1.056]	[0.002]	[0.0003]
Manufacturing	(3)	0.014***	−0.064***	-0.391	0.005***	−0.002***
		[0.003]	[0.006]	[0.249]	[0.001]	[0.0002]
Energy	(4)	−0.020***	−0.043***	1.264	0.003	−0.001**
		[0.005]	[0.013]	[1.254]	[0.002]	[0.00003]
Chemicals	(5)	0.018***	−0.104***	-1.361	0.007***	−0.002***
		[0.005]	[0.013]	[0.784]	[0.002]	[0.0003]
Business Equip.	(6)	0.006	−0.104***	0.964**	0.007***	−0.002***
		[0.004]	[0.008]	[0.373]	[0.001]	[0.0002]
Telecommunicat.	(7)	-0.003	−0.106***	2.570*	0.007**	-0.000
		[0.010]	[0.020]	[1.257]	[0.002]	[0.0005]
Utilities	(8)	−0.009***	−0.054***	-0.171	0.010***	−0.001***
		[0.003]	[0.009]	[0.154]	[0.002]	[0.0002]
Shop.	(9)	0.021***	−0.071***	-0.355	0.008***	−0.002***
		[0.004]	[0.008]	[0.465]	[0.001]	[0.0002]
Health	(10)	−0.012*	−0.143***	0.428	0.010***	−0.002***
		[0.006]	[0.010]	[0.259]	[0.002]	[0.0003]
Money	(11)	0.022***	−0.071***	0.4263	0.007***	−0.001***
		[0.003]	[0.007]	[0.678]	[0.001]	[0.0002]
Other	(12)	0.017***	−0.082***	-0.371	0.002	−0.002***
		[0.003]	[0.008]	[0.540]	[0.001]	[0.0001]
				Pre–Election Dummy		
Non–Durable	(1)	0.012***	0.041***	-1.176	−0.003**	0.000
		[0.003]	[0.008]	[0.668]	[0.001]	[0.0002]
Durable	(2)	0.013*	-0.001	−0.902*	-0.001	0.000
		[0.006]	[0.013]	[0.450]	[0.002]	[0.0004]
Manufacturing	(3)	0.006*	0.041***	0.029	−0.004***	0.0000**
		[0.003]	[0.006]	[0.208]	[0.001]	[0.0001]
Energy	(4)	0.028***	−0.053***	-0.867	−0.006***	0.002***
		[0.006]	[0.013]	[0.824]	[0.002]	[0.0005]
Chemicals	(5)	0.0021	0.021	-0.538	-0.003	0.000
		[0.006]	[0.013]	[0.443]	[0.002]	[0.0003]

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Industry	No.	Ret	$log(\tau)$	$ILLIQ$	Zeros	Vol
Business Equip.	(6)	0.0105**	0.037***	-0.426	-0.001	0.001***
		[0.004]	[0.007]	[0.284]	[0.001]	[0.0002]
Telecommunicat.	(7)	0.016	0.060**	0.389	-0.004	0.005***
		[0.011]	[0.020]	[0.577]	[0.003]	[0.0007]
Utilities	(8)	−0.006**	0.026**	0.283**	-0.000	0.0008***
		[0.003]	[0.009]	[0.099]	[0.002]	[0.0002]
Shop.	(9)	0.015***	0.037***	1.235	-0.002	0.0003
		[0.004]	[0.008]	[1.053]	[0.001]	[0.0003]
Health	(10)	0.052***	0.054***	0.599	−0.004***	0.003***
		[0.006]	[0.011]	[0.370]	[0.001]	[0.0005]
Money	(11)	0.029***	0.097***	-0.009	−0.008***	0.001***
		[0.003]	[0.007]	[0.355]	[0.001]	[0.0001]
Other	(12)	0.016***	0.042***	-1.618	−0.005***	0.001***
		[0.003]	[0.008]	[0.986]	[0.001]	[0.0002]

standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX B

Election and Liquidity: Variation across Size Portfolios

This table reports the results of the following regression:

$$y_{it}^{p} = \mu_i^p + \lambda_t^p + q_t + \beta_1^p \mathbf{1}_t(Election) + \varepsilon_{it}^p \ \forall p \in \{1, 2, \ldots, 10\} ,$$

where $y \in \{Ret_{it}, log(\tau_{it}), ILLIQ_{it}, Zeros_{it}\}$ and $Election$ is either a pre–Election or post–Election dummy.Ret_{it} are the cumulative excess log returns, over the value–weighted market portfolio, for the September–November pre–election period and December–January post election period. $log(\tau_{it}), log(ILLIQ_{it})$, and $Zeros_{it}$ are the log turnover, the log *Amihud* (2002) illiquidity measure, and the fraction of zero returns, as defined in eq. 1.2, 1.3, and 1.4 respectively. In this specification, the explanatory variables are dummy variables that are equal to one prior to elections ($\mathbf{1}_t$(pre–Election)) and after the elections ($\mathbf{1}_t$(post–Election)), and zero otherwise. In other words, the comparison is between the September–October period (November–January or February–April) of an election year and the same period for all non election years. We run this specification for each size portfolio separately. Firm, year, and quarter fixed effects are included to account for all the time–invariant differences within the firms and across time. Standard errors are clustered by time.

Size	Portfolio	Ret	$log(\tau)$	$ILLIQ$	Zeros	Vol
				Pre–Election Dummy		
Small	(1)	−0.002	−0.098***	1.837	0.002	−0.0009**
		[0.005]	[0.022]	[1.703]	[0.002]	[0.0004]
	(2)	0.014*	−0.091***	-0.141	0.002	−0.0014***
		[0.004]	[0.023]	[0.423]	[0.002]	[0.0003]
	(3)	0.016***	−0.092***	-0.388	0.005***	−0.0018***
		[0.004]	[0.031]	[0.207]	[0.001]	[0.0003]
	(4)	0.018***	−0.098***	0.122	0.01***	−0.0019**
		[0.005]	[0.031]	[0.192]	[0.002]	[0.0003]
Medium	(5)	0.016***	−0.092***	-0.061	0.012***	−0.0019***
		[0.005]	[0.030]	[0.055]	[0.001]	[0.0003]
	(6)	0.014***	−0.081***	−0.088*	0.010***	−0.0022***
		[0.004]	[0.022]	[0.040]	[0.001]	[0.0003]
	(7)	0.010*	−0.072***	-0.037	0.011***	−0.0021***
		[0.004]	[0.020]	[0.032]	[0.001]	[0.0005]
	(8)	0.014***	−0.064***	-0.014	0.010***	−0.0017***
		[0.004]	[0.019]	[0.014]	[0.001]	[0.0003]
	(9)	0.007**	−0.057***	-0.031	0.011***	−0.0016***
		[0.003]	[0.017]	[0.018]	[0.001]	[0.0003]
Large	(10)	0.001	−0.067***	-0.003	0.009***	−0.0014***

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Size	Portfolio	Ret	$log(\tau)$	$ILLIQ$	Zeros	Vol
		[0.002]	[0.013]	[0.004]	[0.0007]	[0.0003]
				Post–Election Dummy		
Small	(1)	0.031***	0.044***	-1.129	-0.008^{***}	0.0021***
		[0.006]	[0.012]	[2.00]	[0.001]	[0.0005]
	(2)	0.013**	0.053***	-0.418	-0.002	0.0011***
		[0.005]	[0.012]	[0.383]	[0.002]	[0.0003]
	(3)	0.018***	0.048***	0.333	-0.002	0.0011***
		[0.004]	[0.012]	[0.373]	[0.002]	[0.0002]
	(4)	0.025***	0.062***	-0.274^{**}	-0.001	0.0008***
		[0.005]	[0.012]	[0.107]	[0.001]	[0.0003]
Medium	(5)	0.026***	0.051***	-0.061	-0.000	0.0009***
		[0.005]	[0.011]	[0.054]	[0.001]	[0.0002]
	(6)	0.022***	0.051***	-0.089	-0.001	0.0009***
		[0.004]	[0.010]	[0.054]	[0.001]	[0.0002]
	(7)	0.012**	0.036**	-0.027	-0.002	0.0005***
		[0.004]	[0.009]	[0.048]	[0.001]	[0.0002]
	(8)	0.012***	0.067**	-0.019	-0.0001	0.0007***
		[0.003]	[0.021]	[0.015]	[0.001]	[0.0002]
	(9)	0.007*	0.046***	-0.013	0.0002*	0.0005***
		[0.003]	[0.007]	[0.012]	[0.001]	[0.0002]
Large	(10)	0.000	0.035***	-0.002	0.001	0.001***
		[0.002]	[0.005]	[0.010]	[0.001]	[0.0003]

standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX C

Election and Liquidity: Variation across Beta Portfolios

This table reports the results of the following regression:

$$y^p_{it} = \mu^p_i + \lambda^p_t + q_t + \beta^p_1 \mathbf{1}_t(Election) + \varepsilon^p_{it} \ \forall p \in \{1, 2, \ldots, 10\} \ ,$$

where $y \in \{Ret_{it}, log(\tau_{it}), ILLIQ_{it}, Zeros_{it}\}$ and $Election$ is either a pre–Election or post–Election dummy.Ret_{it} are the cumulative excess log returns, over the value–weighted market portfolio, for the September–November pre–election period and December–January post election period. $log(\tau_{it}), log(ILLIQ_{it})$, and $Zeros_{it}$ are the log turnover, the log *Amihud* (2002) illiquidity measure, and the fraction of zero returns, as defined in eq. 1.2, 1.3, and 1.4 respectively. In this specification, the explanatory variables are dummy variables that are equal to one prior to elections ($\mathbf{1}_t$(pre–Election)) and after the elections ($\mathbf{1}_t$(post–Election)), and zero otherwise. In other words, the comparison is between the September–October period (November–January or February–April) of an election year and the same period for all non election years. We run this specification for each beta portfolio separately. Firm, year, and quarter fixed effects are included to account for all the time–invariant differences within the firms and across time. Standard errors are clustered by time.

β	Portfolio	Ret	$log(\tau)$	$ILLIQ$	Zeros	Vol
				Pre–Election Dummy		
-0.95	(1)	-0.054^{***}	-0.090^{***}	0.388	0.008^{***}	-0.002^{***}
		[0.014]	[0.023]	[0.419]	[0.002]	[0.0007]
-0.49	(2)	-0.023^{***}	-0.078^{***}	-0.2871	0.008^{***}	-0.0024^{***}
		[0.005]	[0.021]	[0.223]	[0.002]	[0.0006]
-0.28	(3)	-0.005	-0.076^{***}	0.058	0.008^{***}	-0.0025^{***}
		[0.003]	[0.023]	[0.104]	[0.001]	[0.0005]
-0.11	(4)	-0.012^{***}	-0.086^{***}	-0.126	0.01^{***}	-0.0029^{**}
		[0.003]	[0.015]	[0.111]	[0.002]	[0.0006]
0.32	(5)	0.006^{*}	-0.067^{***}	-0.240	0.010^{***}	-0.0032^{***}
		[0.003]	[0.017]	[0.537]	[0.001]	[0.0007]
0.19	(6)	0.017^{***}	-0.059^{***}	-0.873	0.010^{***}	-0.0033^{***}
		[0.003]	[0.010]	[0.550]	[0.001]	[0.0007]
0.36	(7)	0.025^{***}	-0.062^{***}	-0.466	0.009^{***}	-0.0036^{***}
		[0.004]	[0.020]	[0.299]	[0.001]	[0.001]
0.57	(8)	0.034^{***}	-0.078^{***}	-0.995	0.007^{***}	-0.0035^{***}
		[0.008]	[0.021]	[0.573]	[0.001]	[0.0008]
0.86	(9)	0.048^{**}	-0.069^{***}	0.208	0.008^{***}	-0.0036^{***}
		[0.015]	[0.020]	[0.716]	[0.001]	[0.0006]
1.54	(10)	0.069^{***}	-0.091^{***}	-1.008	0.006^{***}	-0.0037^{***}

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Size	Portfolio	Ret	$log(\tau)$	$ILLIQ$	Zeros	Vol
		[0.017]	[0.028]	[0.831]	[0.0015]	[0.0008]
				Post–Election Dummy		
-0.95	(1)	0.034***	0.042***	0.309	-0.008^{***}	-0.0000
		[0.006]	[0.011]	[0.414]	[0.002]	[0.0002]
-0.49	(2)	0.023***	0.035***	-0.533^{***}	-0.004^{**}	-0.0002
		[0.004]	[0.009]	[0.163]	[0.001]	[0.0003]
-0.28	(3)	0.120***	0.037***	-0.258	-0.003^{*}	-0.0003
		[0.003]	[0.009]	[0.145]	[0.001]	[0.0002]
-0.11	(4)	0.021***	0.037***	-0.061	-0.002	-0.0005^{**}
		[0.004]	[0.008]	[0.254]	[0.001]	[0.0002]
0.32	(5)	0.014*	0.044***	-0.049	-0.005^{***}	-0.0004^{*}
		[0.004]	[0.009]	[0.324]	[0.001]	[0.0002]
0.19	(6)	0.007	0.0501***	0.673	-0.004^{**}	-0.0005^{**}
		[0.004]	[0.008]	[0.718]	[0.001]	[0.0002]
0.36	(7)	0.003	0.034***	-0.733^{**}	-0.004^{**}	-0.0004
		[0.004]	[0.009]	[0.282]	[0.001]	[0.0002]
0.57	(8)	0.004	0.047***	-1.832	-0.001	-0.001^{***}
		[0.004]	[0.009]	[1.257]	[0.001]	[0.0002]
0.86	(9)	0.003	0.031***	1.08*	-0.004^{**}	-0.0014^{***}
		[0.004]	[0.009]	[0.514]	[0.001]	[0.0002]
1.54	(10)	0.006	0.032***	-3.039^{***}	-0.006^{***}	-0.0019^{***}
		[0.005]	[0.009]	[0.901]	[0.001]	[0.0003]

standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX D

Restricted VAR – EGLS

I consistently estimate the restricted VAR by feasible GLS (estimated – EGLS). I follow *Lütkepohl* (2005), where a more extended discussion can be found.

The K–dimensional ($K = 12$) covariance stationary VAR(4) process is:

$$y_t = \alpha + \sum_{i=1}^{4} \Phi_i y_{t-i} + e_t \iff y_t = \nu + A_1 y_{t-1} + A_2 t_{t-2} + A_3 y_{t-3} + A_4 y_{t-4} + y_t,$$

where A_i are the companion matrices. This can be re–written in a matrix form as:

$$Y = BX + U$$

where $\underset{K\times T}{Y} = (y_1, \ldots, t_T)$, $\underset{K\times(Kp+1)}{B} = (\nu \; A_1 \; \ldots A_4)$, $\underset{(Kp+1)\times T}{X} = (X_0, \ldots X_{T-1})$, and $\underset{K\times T}{U} = (u_1, \ldots, u_T)$. The multivariate least squares estimator is:

$$\hat{B} = Y X'(X'X)^{-1}$$

$$\hat{\Sigma_u} = \frac{(Y - \hat{B}X)(Y - \hat{B}X)'}{T - Kp - 1}$$

Suppose that the linear constraints (Granger type exclusion restrictions) for B are given in the following form:

$$\beta = vec(B) = R\gamma + r,$$

where γ is the vector of unrestricted parameters (4×1, given that $p = 4$), R is the $K(Kp+1) \times 4$ matrix of known weights, and r is the $K(Kp+1) \times 1$ vector of known constants. This is not the conventional way of representing linear constraints but it is adopted by *Lütkepohl* (2005) for convenience. Let us now derive the estimated GLS estimator, γ.

$$Y = BX+U \iff vec(Y) = (X' \otimes I_K)vec(B)+vec(U) \iff y = (X' \otimes I_K)\beta+u \iff$$

$$y = (X' \otimes I_K)(R\gamma + r) + u \iff \underbrace{y - (X' \otimes I_K)r}_{x} = (X' \otimes I_K)R\gamma + u$$

The estimator in a restricted VAR,$\hat{\gamma}$, is defined to minimize the following sum of squared errors, $S(\gamma)$, rather than then standard $u'u$

$$S(\gamma) = u'(I_T \otimes \Sigma_u^{-1})u$$

and from the previous equation, that is equal to:

$$S(\gamma) = [x - (X \otimes I_K)R\gamma]'(I_T \otimes \Sigma_u^{-1})[x - (X \otimes I_K)R\gamma].$$

Thus, $\hat{\gamma}$ is

$$\hat{\gamma} = [R'(XX' \otimes \Sigma_u^{-1})R]^{-1} R'(X \otimes \Sigma_u^{-1})x,$$

which requires the knowledge of Σ_u, which is unknown. Using a consistent estimator $\bar{\Sigma}_u$, one gets an estimated GLS estimator

$$\hat{\hat{\gamma}} = [R'(XX' \otimes \bar{\Sigma}_u^{-1})R]^{-1} R'(X \otimes \bar{\Sigma}_u^{-1})x.$$

As a consistent estimator of Σ_u, I use the restricted least square estimator based on minimizing $u'u$ with respect to γ. The minimizing γ–vector is:

$$\hat{\gamma} = [R'(XX' \otimes R]^{-1} R'(X \otimes)x.$$

Denote the corresponding β–vector as:

$$\beta^r = R\hat{\gamma}^r + r$$

and

$$\hat{\Sigma}_u^r = \frac{(Y - \hat{B}^r X)(Y - \hat{B}^r X)'}{T}.$$

Note that the adjustment for the degrees of freedom is not clear. For proofs on the consistency of the estimator see *Lütkepohl* (2005).

APPENDIX E

Alternative Specification of Liquidity

To perform robustness checks, I consider an alternative, yet conceptually equivalent, definition of liquidity spillovers that concentrates on the predictive ability of the reduced–form VAR. In this alternative specification, I define liquidity spillover from asset i to asset j as the (percentage) change in the one–step ahead forecast error (FE) of a restricted versus an unrestricted VAR, where the restricted and unrestricted VAR are defined as in section (2.3.1).

Consider the unrestricted VAR of eq. (2.7). I define the one–step ahead forecast error as,

$$FE_t = \log(det[\bar{\Sigma}_u]) + \frac{2}{T}(K^2 p - r), \tag{E.1}$$

where T is the length of the sample, p the lag order, K the dimension of the time–series, r the number of linear restrictions, and $\bar{\Sigma}_u$ the least–squares estimated variance–covariance matrix of errors. See appendix for derivation. The lower is the prediction error, the better is the model at forecasting. This prediction error is very similar to the Akaike information criterion and as such is a tradeoff between the parsimony of the model and the fit.

Liquidity spillovers from asset i to asset j are then defined as

$$Spill_{ij,t} = \frac{FE^{r}_{ij,t} - FE^{u}_{t}}{FE^{r}_{ij,t=1}}, \tag{E.2}$$

where $FE^{r}_{ij,t}$ is the one–step ahead forecast error when the asset's j liquidity, return, and volatility coefficients are restricted to zero in the asset's i liquidity equation. $FE^{r}_{ij,t=1}$ is the restricted forecast error at the beginning of the sample. An increase [decrease] in $Spill_{ij,t}$ implies higher [lower] liquidity spillovers from asset i to asset j.

Although forecasting is not among the goals of this project, this alternative definition of spillovers allows me to take advantage of the entire variance–covariance matrix and thus, consider both the covariance and variance. It is also a more direct measure of the one–step ahead liquidity spillover. The main drawback of this measure however is the fact that is non–stationary.

Figure E.1 plots the unrestricted FE_t. As one might have expected, the model is better (lower FE_t) at predicting during non–turmoil periods. FE_t spikes during periods that are characterized by financial crises. Figure E.2 plots the equally weighted average of each pair of alternative liquidity spillovers. To improve readability of the plots, the frequency is monthly. In summary, the average liquidity spillover follows a pattern similar to that of the unrestricted FE_t and the main liquidity spillover specification (eq. (2.8). That is, liquidity spillovers spike during periods of financial and macroeconomic turmoil. This measure is also more volatile than the MSE measure since it depends on the entire variance–covariance matrix.

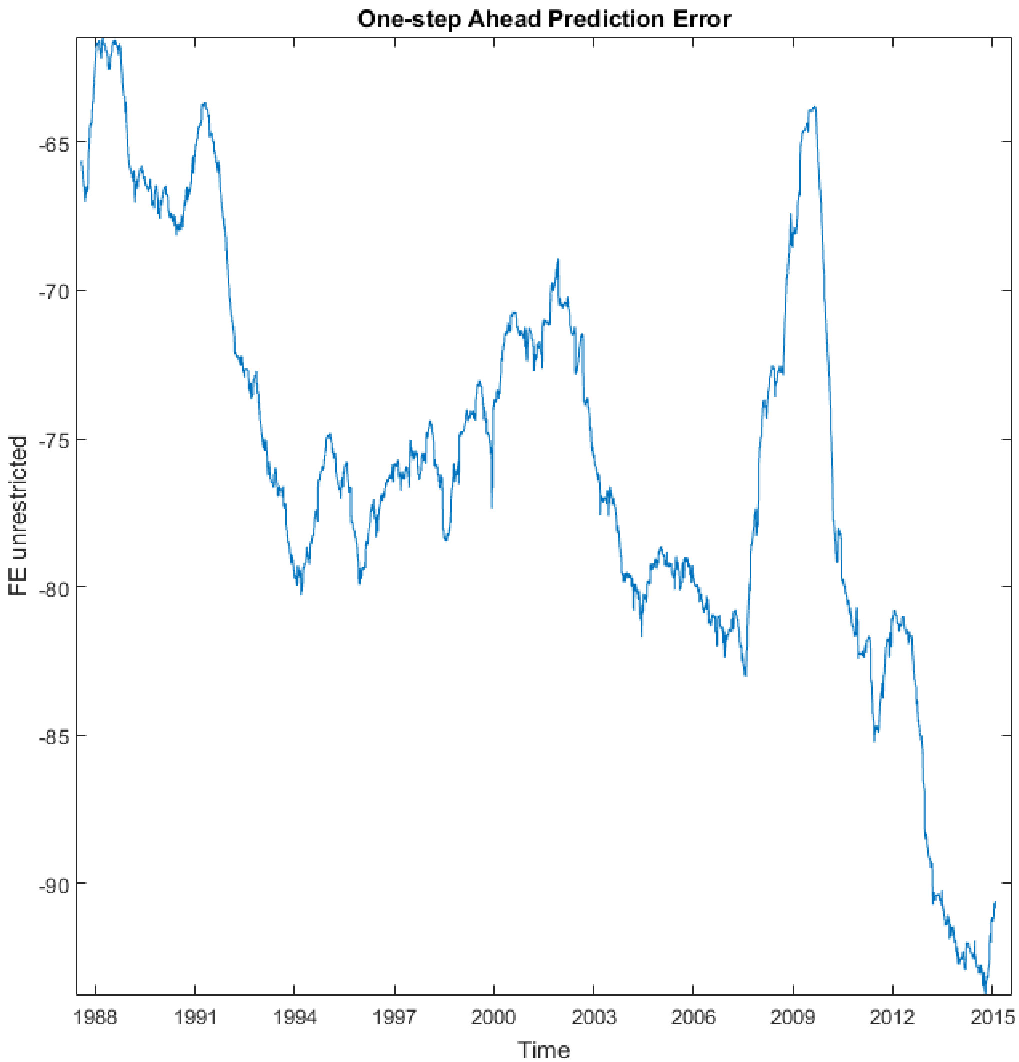

Figure E.1: The figure plots the unrestricted one–step ahead prediction error that is defined in eq. (E.8). The smaller the value of the prediction error the better is the model at forecasting.

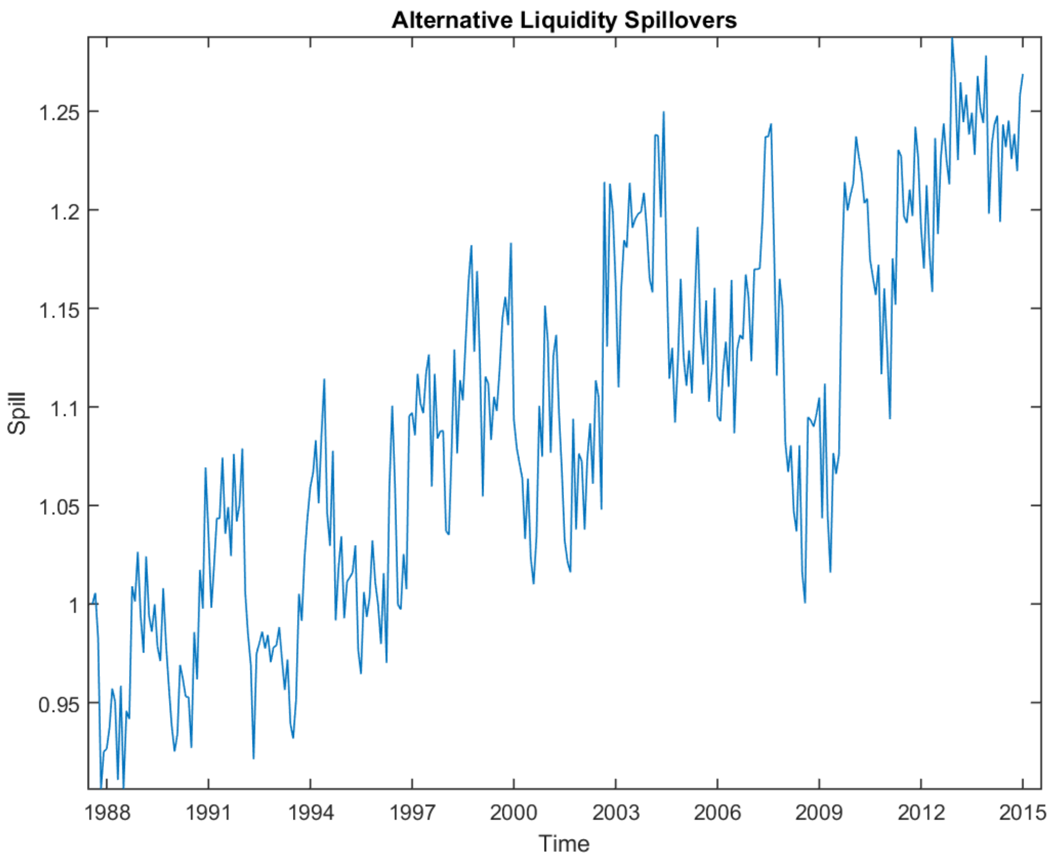

Figure E.2: The figure plots the average of the alternative definition of liquidity spillovers. Each alternative liquidity spillover pair is defined as in eq. (E.2) and the average is defined as the equally weighted sum. To improve readability of plot, the frequency is monthly.

The $MSE[\hat{y}_t(h)]$ of an h–step ahead forecast is,

$$MSE[\hat{y}_t(h)] = \mathbf{E}\{[y_{t+h} - \hat{y}_t(h)][y_{t+h} - \hat{y}_t(h)]'\}, \tag{E.3}$$

and the approximate one–step ahead forecast MSE is given by (see *Lütkepohl* (2005), p.94 for proof)

$$MSE(1) = \frac{T + Kp + 1}{T}\Sigma_u, \tag{E.4}$$

where T is the length of the sample, p the lag order, K the dimension of the time–series, and Σ_u the variance–covariance matrix of errors. To make the $MSE(1)$ operational, *Akaike* (1969) suggests replacing the unknown Σ_u by the least–square estimate, such that

$$MSE(1) = \frac{T + Kp + 1}{T - Kp - 1}\bar{\Sigma}_u, \tag{E.5}$$

where $\bar{\Sigma}_u$ is estimated. To obtain a scalar measure of forecast accuracy, *Akaike* (1969) focuses on the determinant of this measure

$$MSE(1) = det[\frac{T + Kp + 1}{T - Kp - 1}\bar{\Sigma}_u] = [\frac{T + Kp + 1}{T - Kp - 1}]^K det[\bar{\Sigma}_u]. \tag{E.6}$$

Given that both the restricted and the unrestricted prediction error have the same $[\frac{T+Kp+1}{T-Kp-1}]^K$, I disregard that term. To re–scale the measure, I take its log,

$$\log(MSE(1)) = \log(det[\bar{\Sigma}_u]). \tag{E.7}$$

As in the Akaike Information Criterion, the $\log(det[\bar{\Sigma}_u])$ is a measure of the fit of the model. To control for overfitting in small samples, Akaike adds a penalty term, $\frac{2(K^2p+K)}{T}$. I modify the model to account for the number of linear restrictions. I.e.,

$$FE_t = \log(det[\bar{\Sigma}_u]) + \frac{2}{T}(K^2p - r), \tag{E.8}$$

where r is the number of linear restrictions. The deduction of the number of linear restrictions decreases the penalty and benefits the restricted model in terms of its fit.

APPENDIX F

Alternative Exclusion Restrictions

In the main specification, for each pair of liquidity spillovers the restricted MSE imposes exclusion restrictions on the relevant liquidity. For instance, when measuring the liquidity spillovers from Crude Oil to S&P500, I set to zero the lagged coefficients of Crude Oil's liquidity in S&P500's liquidity equation. This specification takes into account only the direct liquidity spillovers and ignores the indirect channel of potential spillovers through returns and volatility. Prior research (see for instance, *Chordia et al.* (2005) and *Goyenko and Ukhov* (2009)) however shows that such indirect channels are significant and such findings are justified by the theoretical microstructure literature on the determinants of liquidity. In this paper, when performing Granger–causality tests, I do not find strong indirect channels (see Table 2.2, liquidity raws) of liquidity spillovers. Nonetheless, as a robustness check, in this section I compute each pair of liquidity spillovers by imposing exclusion restrictions on liquidity, return, and volatility. For example, when measuring the liquidity spillovers from Crude Oil to S&P500, I set to zero the lagged coefficients of Crude Oil's liquidity, return, and volatility in S&P500's liquidity equation.

Figure F.1 plots the average liquidity spillovers with the main specification and the alternative specification, i.e., the different exclusion restrictions. One immediately notices that the two measures are nearly identical with minor differences. These results confirm our findings in table 2.2., that the indirect liquidity links are not significant.

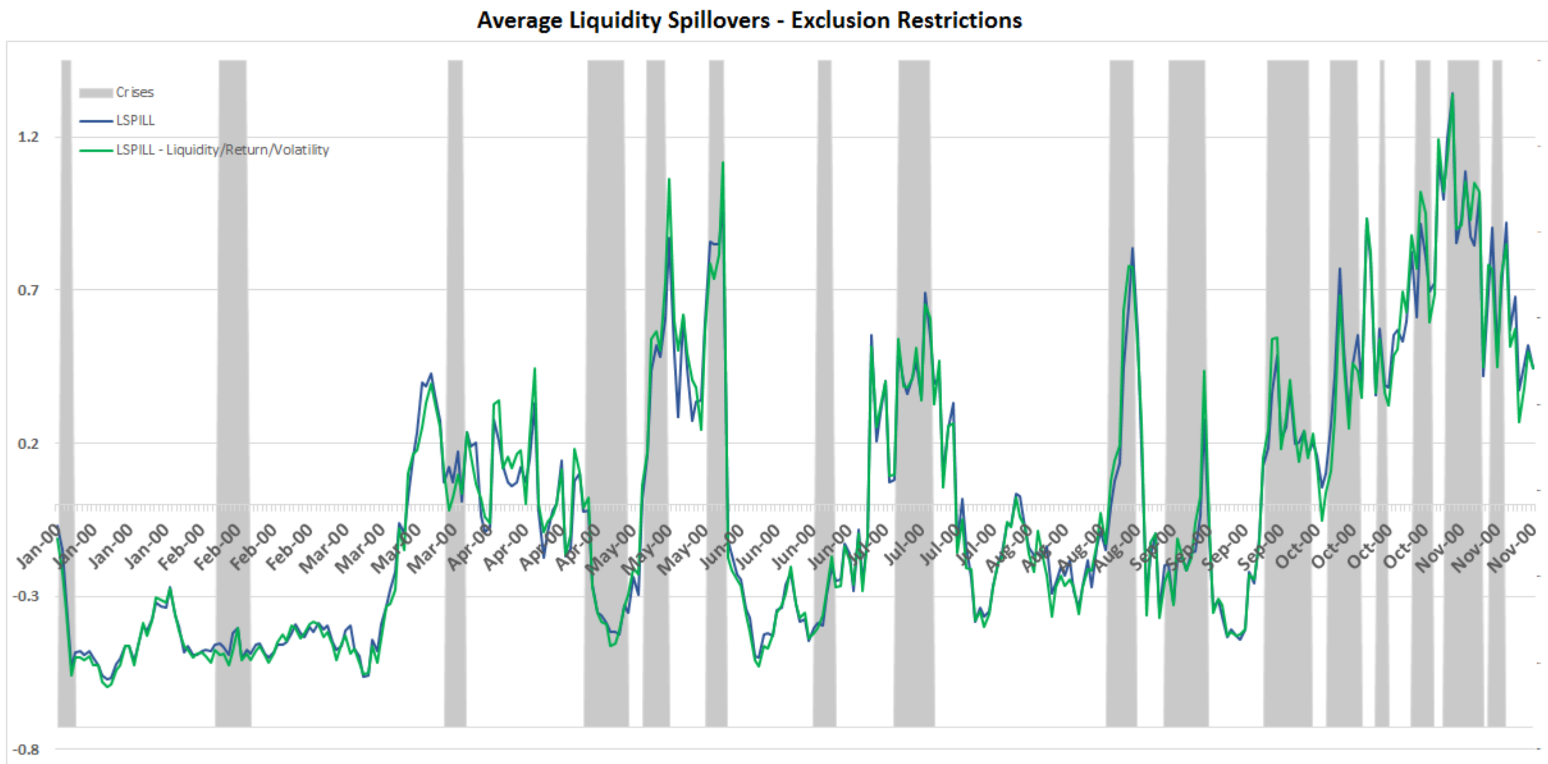

Figure F.1: The figure plots the equally weighted average of liquidity spillovers across the 12 spillover pairs. The blue line plots the liquidity spillovers with exclusion restrictions applied to liquidity only (main specification). The green line plots the liquidity spillovers with exclusion restrictions applied to liquidity, return, and volatility, i.e., taking into account indirect liquidity spillovers. The average is computed after each spillover pair is standardized to zero mean and unit variance. Daily spillovers have been averaged to the monthly frequency. The shaded areas represent periods of major financial and macroeconomics events.

APPENDIX G

Bootstrapped Critical Values

The estimation of each state–variable separately is essentially a set of six different equations. The statistical tests however, will be unreliable if they do not reflect the fact that six different models have been estimated. As Granger (1990) notes, for instance, "... with a limited amount of data available and a huge number of possible models ... specification search procedures ... make standard techniques of inference unreliable". To adjust therefore for possible data mining one must correct the critical values to reflect this fact. To adjust the critical values I bootstrap them as following.

My null hypothesis is that the liquidity spillovers are not explained by the state–variables, i.e.,

$$H_0: \ y_t = \alpha + u_t,$$

where $y_t = (y_t^1, \ldots, y_t^{12})$ since there are 12 different spillover pairs. The alternative specification in each of the six models is that spillovers are explained by the respective state variable, i.e,

$$H_1: \ y_t = \alpha_i + \beta_i x_{it} + u_{it}, \text{ for each } i$$

where $i \in \{1,2,3,4,5,6\}$ for each state variable.

1. I first estimate the alternative models for each state variable, i, to obtain the residuals, $\hat{u}_{it}$,

$$y_t = \alpha_i + \beta_i x_{it} + u_{it}, \text{ for each } i. \tag{G.1}$$

   That is I run 6 separate regressions, as in (G.1) and save the estimated residuals, $\hat{u}_{it}$. One could estimate the null model in order to obtain the estimated residuals, $\hat{u}_t$, but in either case they are consistently estimated.

2. I then bootstrap the null model with a block bootstrap to correct for serial correlation of residuals, $\hat{u}_{it}$. That is, first I estimate the null model,

$$y_t = \hat{\alpha}^R + \hat{u}_t^R, \tag{G.2}$$

   to obtain the restricted intercept $\hat{\alpha}^R$ and do the following block bootstrap for each alternative specification

$$y_t^* = \hat{\alpha}^R + \hat{u}_{it}^*, \tag{G.3}$$

   where the $\hat{u}_{it}^*$ are the estimated residuals from step 1, equation (G.1). Given that this specification requires the residuals, $\hat{u}_{it}$, to be mean zero, one has to demean the residuals. The length of the block is $l = 3$ and is chosen based on the autocorrelation function of the residuals.

The block–bootstrap proceeds in the following way. I begin by defining $b = T - l + 1 = 1269 - 3 + 1 = 1267$ set of overlapping blocks of length $l = 3$. The set of blocks I draw from, for each state variable i, is:

$$\hat{u}_{it}^{1*} = (\hat{u}_{it_1}, \hat{u}_{it_2}, \hat{u}_{it_3})$$

$$\vdots$$

$$\hat{u}_{it}^{1267*} = (\hat{u}_{it_1}, \hat{u}_{it_2}, \hat{u}_{it_3}),$$

where t_1, t_2, t_3 correspond to any random time t. I provide a subscript to point out that each block has distinct times that may be overlapping across blocks. Now, I can generate bootstrap data by sampling with replacement from the set $\{\hat{u}_{it}^{*}\}_{t=1}^{b}$. I concentrate the iid draws of $\hat{u}_{it}^{*}$ to form a bootstrap replication of the original time series of length T of the form (G.3), i.e.,

$$y_t^{*} = \hat{\alpha}^{R} + \hat{u}_{it}^{*}.$$

3. I repeat step (2) 5,000 times allowing me to build up the bootstrap distribution of the residuals and the dependent variable.

4. For each iteration and each state variable, I estimate

$$y_t^{*} = \alpha_i + \beta_i x_{it} + \hat{u}_{it}^{*} \tag{G.4}$$

I.e, using the bootstrap replication of the original time series y_t^*, I estimate (G.4) for each state variable (six times). I repeat step (2) 5,000 times and obtain six different t–statistics for each β_i. I then take the maximum t–statistic across the six β_i.

5. At the completion of step 4, I have 5,000 max t–statistics and I can now compute the critical values, at the percentile of interest.

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