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Essays on Liquidity in Financial Markets

Christoph Koser

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PhD in Economics

Essays on Liquidity in Financial Markets

Christoph Koser

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PhD student:

Christoph Koser

Advisors:

Helena Chuliá
Jorge M. Uribe

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Contents

List of Tables

List of Figures

1 Introduction

Liquidity - Fundamental Concept

Constant reappearances of crisis periods, unanticipated asset bubbles and market crashes remind us on how important the financial sector is for the real economy. Liquidity, herein, is at its heart, if present, with its distinctive relevance for markets to operate smoothly. Black (1971) defines a market for a stock to be liquid when the following conditions are satisfied: «(1) there are always bid and ask prices for the investor who want to buy or sell small amounts of stock immediately, (2) the difference between the bid and asked prices (the spread) is always small, (3) an investor who is buying or selling a large amount of stock, in the absence of special information, can expect to do so over a long period of time at a price not very different, on average, from the current market price and (4) an investor can buy or sell a large block of stock immediately, but at a premium or discount that depends on the size of the block. The larger the block, the larger the premium or discount », (p.30). While the financial literature and practitioners widely agree on the above definition of liquidity, the actual concept of liquidity is much more complex and resembles a variety of dimensions that simply cannot be expressed in one single measure. For instance, Sarr and Lybek (2002) refer to five liquidity dimensions: (1) Tightness - low transaction costs; (2) Immediacy - speed of trade settlement; (3) Depth - large amount of buy and sell orders at any given price (generally, above and below current market price); (4) Breadth - large volumes with minimal impact on price movements and (5) Resiliency - new order-flow corrected trade imbalances. Together, these two expositions jointly convey a comprehensive view on the concept of liquidity that paves the way for a better understanding of the research object of this thesis.

Today's Relevance of Liquidity

Today, both, liquidity and trading have steadily increased due to a more electronic-based infrastructure of trade execution, enabling investors and market makers to buy and sell financial assets in seconds, with algorithms and smaller spreads between bid and ask prices. Nevertheless, these improvements and the concomitant increase in market efficiency over the years have not kept liquidity from co-moving among similar asset classes and across time. Indeed, several studies identified two fundamental sources of commonality in liquidity: A demand-driven explanation which relates commonality to correlated trading behavior, i.e. index trading, and its pressure on market maker's inventories, simultaneously across many asset classes, (see Chordia et al. (2000), Hasbrouck and Seppi (2001), Huberman and Halka (2001); A supply-driven explanation which links commonality with funding tightness induced through a shortage in the supply of funding capital to investors, (see Brunnermeier and Pedersen (2009), Coughenour and Saad (2004), Hameed et al. (2010)). Confronted with the finding of commonality in liquidity, the academic literature has then moved towards a more market-wide concept of liquidity. According to this branch of the literature, market-wide liquidity has been found to be a priced risk factor when explaining asset prices, with theoretical considerations and empirical findings that indicate not only statistical significance but also economic relevance, (see Pástor and Stambaugh (2003), Acharya and Pedersen (2005), Martınez et al. (2005) among others). However, on an aggregate view, as long as financial markets are in a period of stability, market participants are not concerned about the actual level of liquidity in the market. This story changes in times of financial distress when liquidity becomes of systemic nature. Historical events such as the LTCM (Long-Term Capital Management) crisis in 1999 and the global financial crisis in 2008 have reminded financial market participants of their own preference for liquidity. In these periods of extreme turmoil, liquidity alters its characteristics with respect to tightness, immediacy, depth, breadth and resiliency. During market liquidity dry-ups, risk averse investors offload investment positions across many asset classes and rebalance portfolios towards more liquid and less risky assets, known as flights-to-liquidity and flights-to-quality, Baele et al. (2020) and Beber et al. (2009). Large trade volumes on short positions, often induced by institutional investors, i.e. mutual funds, amplify this shift and cause market liquidity to worsen even further, (demand-driven commonality in liquidity), (see Kamara et al. (2008) and Koch et al. (2016)). Parallel on the supply side, an initial liquidity shock causes prices to be more volatile. As a result, financial intermediaries expect higher future price volatility, which subsequently increases margin requirements. In turn, higher margins require investors to sell off existing positions, hence market liquidity continues to fall. Consequently, losses on existing positions and higher margin requirements reduce further funding capital, leading to preventions in entering the market again, (see Brunnermeier and Pedersen (2009)). Thus, this downward trended liquidity spiral in conjunction with correlated trading among institutional investors can explain a falling level of aggregate liquidity and sudden liquidity dry-ups.

If markets are illiquid, investors are prone to avoid trading, hence liquidity declines. Affected either directly through the market microstructure channel or indirectly through external determinants such as general market movements, macro-financial indicators and ultimately by investor sentiment, liquidity affects the market clearing mechanism in financial markets and hereby reinforces its directional trend.[1]

Measurement of Liquidity and Challenges

The inaccessibility of liquidity data, foremost TAQ (trades and automated quotes) data, for U.S. financial markets and fewer documentation on non-U.S. financial markets has urged academics to model liquidity with data that is available to them, mostly with price and volume data. Thus, today the financial literature acknowledges many of these liquidity measures as proxies. In their article "The Best in Town", Johann and Theissen (2017) conduct estimations and compare the performance of recent liquidity measures. Some of these measures have been frequently used in the recent literature. From a methodological approach, many of these measures either cover the aspect of (i) transaction costs as a friction when engaged in trading or (ii) of volume-related price changes in its definition of a liquid market.[2] For instance, Amihud (2002) relates daily absolute returns to trade volume in the denominator. Similarly, Pástor and Stambaugh (2003) construct a portfolio-like market liquidity factor based on order-flow induced price-reversals. Both measures target the relative depth in the market to absorb high volume trades without substantial price movements. The more recent study by Corwin and Schultz (2012) relates liquidity to the aspect of transaction costs and constructs a bid-ask spread estimator from daily high and low prices of stocks. This spread can then be used as per-stock or per-market version, depending on the desired purpose. In this thesis, I mostly make use of a recently proposed bid-ask spread measure by Abdi and Ranaldo (2017) to proxy for market liquidity (Chapter 2 & 3). This spread utilizes a wider range of information (i.e. close, high and low prices) compared to other low-frequency estimates and provides the highest cross-sectional and average time-series correlation with TAQ effective spread. Belated access to the Wharton Data Research Service (WRDS) makes it possible to use TAQ data and hence examine even more liquidity dimensions in Chapter 4.

[1] Sarr and Lybek (2002) show a summary of factors that affect asset and market liquidity.

[2] See Sarr and Lybek (2002) for a more comprehensive description.

Contribution of this Thesis

The objective of this thesis is to provide a better understanding of liquidity in global equity markets. Following this purpose includes the usage of existing tools and methods to measure and analyze market liquidity from different perspectives and in the interaction with other variables in the market.

Specifically, my research contributes to a more comprehensive understanding on: (i) how market-wide liquidity is measured; the dynamic nature of commonality in liquidity; how commonality in liquidity relates to volatility on a global scale and dynamically; (ii) how market liquidity becomes a priced systemic risk factor in asset pricing in extreme scenarios, i.e. down and up-market states and finally (iii) the properties and determinants of daily sectoral liquidity and trading. My research has implications for risk management, portfolio diversification and policy-design.

Chapter 2

Chapter 2 of this thesis is entitled «Uncovering the Time-Varying Relationship between Commonality in Liquidity and Volatility ». In this chapter, I study the relationship between commonality in liquidity and volatility among nine stock markets, representing 67.3% of the world's total market capitalization. My first contribution is the construction of a dynamic measure for commonality in liquidity. Although recent studies have provided evidence for commonality in liquidity neither of them have analyzed its dynamic nature nor covered major international stock market linkages in this regard. I show that inter-market liquidity innovations predominately induce the variation in market liquidity in each country, indicating the relative strength of the propagation of liquidity shocks from foreign markets. Compared to the previous literature that has used a similar methodology, I find that liquidity propagates more strongly than volatility or price shocks. These linkages provide evidence for both, the demand- and supply-driven explanation for commonality in liquidity. I document that commonality increases after down-market periods, peaks during crisis episodes and exhibits a high degree of persistence in the aftermath of the global financial crisis. My second contribution in this chapter relates the dynamic commonality in liquidity measure to global market volatility for nine international stock markets, on an aggregate view. I document that market volatility always Granger-causes commonality in liquidity. Reversely, I find that commonality in liquidity Granger-causes market volatility only in crisis periods and the subsequent aftermath period. These findings provide important insights from a regulatory standpoint, in the context that market liquidity and its commonality across assets is a relevant factor that underlies returns and volatility dynamics and hence can be regarded as one of the fundamental sources of malfunctioning financial markets in the case of dry-ups and downward trended market performance.

Chapter 3

In Chapter 3, which is entitled «Analyzing the Nonlinear Pricing of Liquidity Risk according to the Market State », I examine the asymmetric pricing of market liquidity as a risk factor on asset pricing across different market scenarios and show that aggregate liquidity becomes a relevant factor for the explanation of stock market returns when markets are in a particular good or bad state. Recent contribution have provided evidence on the relationship between market-wide liquidity and asset pricing but solely focused on the linear and cross-sectional setting, Pástor and Stambaugh (2003), Martınez et al. (2005), Acharya and Pedersen (2005). In this chapter, I show that the relationship is in fact nonlinear. My contribution can be summarized as follows: I exploit the possibility of quantile regressions to examine a liquidity-augmented but otherwise traditional factor model on different parts of the stock return distribution over time, directly associated to the definition of good and bad market states. Hereby, lower quantiles relate to bad market states, higher quantiles are linked with good market states and the median represents regular market states. Hereby, I challenge the linear relationship as suggested by the previous literature, as I find that systemic liquidity risk is not always a priced factor in the explanation of asset prices. I document, on the one hand, that when returns are already negative and large, an increase in investor's willingness to short their positions as a response to expected future illiquidity in the market, depresses contemporary returns even further. On the other hand, if the market exhibits large gains (right tail of the distribution), I report a positive relation between systemic liquidity risk and returns. Finally, I show that systemic liquidity and stock returns do not have a significant relationship during regular times, supporting the initial claim that during normal times, market participants are not particularly interested in the level of liquidity in the market.

I show that the nonlinear relationship between market-wide liquidity, as a relevant risk factor, and asset prices holds for a variety of different settings, i.e. value-weighted portfolio returns; different sample periods, industry levels and regions, i.e. U.S. versus European portfolios. In all cases, stability tests show that the corresponding coefficients for systemic liquidity risk in the regression design are instable, which translates into the above-mentioned nonlinear relationship.

Chapter 4

Chapter 4 is entitled «Liquidity and Trading Activity of Energy Stocks ». In this chapter, I study daily liquidity and trading characteristics for energy stocks traded at U.S. stock exchanges, categorized into five energy segments, that is, *oil and gas*, *coal mining*, *renewables*, *electric- and multi-utilities*. Precisely, I examine *average effective spreads*, *price impact of trades*, *number of trade executions* and *share volume*. I chose to analyze daily liquidity and trading characteristics of energy stocks because of the following reasons: (1) The energy sector is a solid pillar of the U.S. economy and yet the literature on liquidity for energy stocks is still scarce. (2) The discussion on the future energy decomposition associated with the debate around climate change has moved investor's and policy maker's attention to the renewable sector and potential growth opportunities, but lacked knowledge about its corresponding market microstructure characteristics on capital markets in comparison to those stocks issued by traditional energy firms (i.e. oil and gas, coal or utilities). (3) Sectoral, cross-sectional differences in daily liquidity and trading have not been within the focus of the existing literature on liquidity. I document that daily sectoral liquidity and trading is volatile, trended and serial dependent for all energy stock segments. I report that average spreads for electric- and multi-utility stocks are nearly half of those of the oil and gas, coal and renewables. In contrast, I find that average trade volume of utility stocks is higher than the average volume of oil and gas stocks. These findings shed new light on the magnitude of cross-sectional differences among energy stocks. I also identify a number of debt- and stock market based factors that drive liquidity and trading of energy stocks, namely - concurrent market movements, five-day market momentum, default spreads and stock market volatility. Although there are differences in the explanatory power, I herein document a strong commonality effect in the exposure of liquidity and trading of energy stocks to these factors. These findings support a commonality in liquidity component, possibly induced by correlated trading behavior across many stock segments, here visible on a day-to-day perspective and suggest further exploration of liquidity differences across the industry level. The inclusion of oil price dynamics as an explanatory factor enriches our understanding of the importance of the crude oil price, first and foremost as global economic indicator and secondly with its significance for trading energy stocks. I find that liquidity increases (that means lower spreads) and trading decreases for renewable and utility stocks in times of a rising oil price. Reversely, I document that the market for oil and gas stocks is slightly less liquid (higher spreads) with higher crude oil prices. I also report that higher oil price variability leads to a reduction in liquidity for most energy segments, which translates into higher average spreads. In conjunction with a decrease in trading across most sectors, this result shows that uncertainty about the oil price is a relevant factor for liquidity and trading patterns of energy stocks, despite controlling for stock market volatility.

The various chapters in this thesis can be found in:

- Chuliá, H., Koser, C., Uribe, J. M. (2020). Uncovering the time-varying relationship between commonality in liquidity and volatility. *International Review of Financial Analysis*, 69, 101466.
- Chuliá, H., Koser, C., Uribe, J. M. (2020). Analyzing the nonlinear pricing of liquidity risk according to the market state. *Finance Research Letters*, Accepted.
  (This dissertation includes an extended version of this paper. The extension covers a broader range of data and additional methods and computations.)

I have also contributed to the following publication during the PhD program:

- Klaus, J., Koser, C. (2020). Measuring Trump: The Volfefe Index and its impact on European financial markets. *Finance Research Letters*, 101447.

2 Uncovering the Time-Varying Relationship between Commonality in Liquidity and Volatility

[1]

This study examines the dynamic linkages between commonality in liquidity in international stock markets and market volatility. Using a recently proposed liquidity measure as input in a variance decomposition exercise, we show that innovations to liquidity in most markets are induced predominately by inter-market innovations. We also find that commonality in liquidity peaks immediately after large market downturns, coinciding with periods of crisis. The results from a dynamic Granger causality test indicate that the relationship between commonality in liquidity and market volatility is bi-directional and time-varying. We show that while volatility Granger-causes commonality in liquidity throughout the entire sample period, market volatility is enhanced by commonality in liquidity only in sub-periods. Our results are helpful for practitioners and policy makers.

[1] This paper is co-authored with Helena Chuliá and Jorge M. Uribe.

2.1 Introduction

Liquidity and commonality among financial assets are a first-order consideration in the decision-making process of investors and market makers, and in the designing of optimal policy frameworks by regulators. Market liquidity is the ability to trade large quantities of an asset without changing its equilibrium price and, as such, it constitutes a crucial feature of any financial asset. It is of great importance for an investor's portfolio choices and policy considerations. In recent decades, empirical studies have shown that stock returns carry a premium for liquidity, (see Amihud et al. (1986); Eleswarapu and Reinganum (1993); Brennan and Subrahmanyam (1996); Datar et al. (1998); Amihud (2002)).[2] Studies by Chordia et al. (2000), Amihud (2002), Hasbrouck and Seppi (2001) and Huberman and Halka (2001) find that the level of liquidity co-moves among similar stocks and across time, while studies by Acharya and Pedersen (2005), Holmström and Tirole (2001) and Pástor and Stambaugh (2003) show that stocks are exposed to a systemic (market-wide) level of liquidity.

Commonality in liquidity can be defined as the co-movement in liquidity among individual stocks (Karolyi et al. (2012)). From a theoretical perspective, Acharya and Pedersen (2005) develop an asset pricing model in which investors are willing to pay a higher premium for stocks that allow them to curtail positions at a relatively lower cost during systemic market declines or liquidity dry-ups. As in any asset pricing model, liquidity becomes a systemic factor of common variation among stocks and therefore merits research efforts. The literature has pointed out two fundamental sources of common variation, demand or supply-side driven. Demand-generated commonality can be attributed to correlated trading behavior (Chordia et al. (2000); Hasbrouck and Seppi (2001); Huberman and Halka (2001)). According to this branch of the literature, large trading orders across a wide range of markets put significant pressure on the inventory of dealers, inducing variation in inventory levels and leading to co-movements in the level of liquidity. Studies by Kamara et al. (2008) and Koch et al. (2016) stress the increasing importance of institutional investors and their index-related trading as a source of

[2] Amihud et al. (1986) were the pioneers in bridging market microstructure and asset pricing. Eleswarapu and Reinganum (1993) examined the seasonality effects of this same measure, while Brennan and Subrahmanyam (1996) incorporated it into a Fama-French factors framework. Using the turnover rate, research by Datar et al. (1998) and Brennan and Subrahmanyam (1996) further examined the role of liquidity for stock returns.

demand-oriented co-movements in liquidity. The latter authors find that stocks held by mutual funds, traded in similar time-patterns, experience large trade imbalances and, hence, give rise to commonality in liquidity. Supply-generated commonality in liquidity, on the other hand, can be related to funding constraints in the provision of liquidity by financial intermediaries. Studies by Coughenour and Saad (2004) and Hameed et al. (2010) report a rise in liquidity commonality within industries, when returns in other industries are large and negative. Furthermore, they argue that this phenomenon of spillovers in the level of illiquidity in industries is partial proof of commonality as the dry-up in funding liquidity affects all stocks.

Empirical evidence of commonality in liquidity focuses primarily on U.S. financial markets. To the best of our knowledge, the only relevant exception are the studies by Brockman et al. (2009) and Karolyi et al. (2012). Brockman et al. (2009) investigate the extent to which commonality is a global vs. local phenomenon and identify the sources of commonality both within and across countries. Karolyi et al. (2012) examine commonality in liquidity in 40 countries and link global commonality to a variety of capital market conditions. Their study provides a comprehensive view of liquidity commonality and its intra-market determinants across time and countries. Yet, the literature to date has not provided reliable empirics that can shed light on the dynamic nature of the relationship between commonality in liquidity and market volatility.

Here, we offer solid, novel empirical evidence of the causal relationship between global commonality in liquidity in international stock markets and global market volatility and we show that this relationship is time-varying and that it displays feedback effects during episodes of crisis. Unlike the scarce extant literature studying commonality in liquidity around the world (i.e. Brockman et al. (2009) and Karolyi et al. (2012)), we propose measuring commonality in liquidity *dynamically*. To do so, we construct systemic liquidity measures, based on individual stocks for every market in a sample of nine mature markets,[3] following a recently proposed market liquidity indicator developed by Abdi and Ranaldo (2017). We

[3]We consider the market capitalization of NASDAQ, NYSE, EURONEXT, Deutsche Boerse AG, Six Swiss Exchange, LSE, BME, TMX Group and Japan Exchange Group Inc., which represents 67.3% of total world stock market capitalization, as reported by the World Federation of Exchanges in December 2018.

then use these country-specific liquidity measures as inputs in a variance decomposition exercise, which allows us to break down the total variation in liquidity for each market into its own liquidity shocks and foreign-market liquidity shocks. We estimate a global commonality index that reflects liquidity spillovers across these nine major stock markets and which, in line with Diebold and Yilmaz (2012), is constructed as the sum of cross-variance shares in liquidity for all markets in our sample. This allows us to clearly decompose intra- and inter-market spillover effects and their relative strengths. Next, we relate our commonality index to a measure of aggregate global market volatility using data for the same markets. To carry out this step, we use a dynamic Granger causality test, as proposed by Shi et al. (2018), which allows us to detect directional causality in a time-varying fashion between commonality and market volatility.

Several novel, significant insights can be drawn from our main results. First, we show that the relationship between commonality in liquidity and market volatility is complex and time-varying. That is, we document that volatility Granger-causes commonality in liquidity throughout the entire sample period. This is consistent with theoretical models, including, for example, that developed by Brunnermeier and Pedersen (2009). In this framework, high market volatility leads to an increase in commonality as a consequence of a reduction in the provision of liquidity available for all financial intermediaries. Second, for the first time, we are able to document that commonality in liquidity also Granger-causes volatility, and that this occurred in the aftermath of the Global Financial Crisis, coinciding with high levels of uncertainty in European bond markets. This finding might be interpreted as evidence of the existence of adverse loop effects in which shocks to market liquidity endogenously cause stock market volatility and vice versa. Such a feedback effect sheds new light on the endogenous nature of financial shocks arising during crisis episodes, which we show are intensified by liquidity considerations.

In addition to the main finding outlined above, we also show (as expected) that global commonality in liquidity peaks during episodes of market turmoil and that it remains at very high levels even after peaks in market liquidity have fallen. Indeed, we document high levels of commonality in liquidity from the beginning to the end of the subprime crisis. Global commonality remains high even when market specific liquidity measures have returned to their pre-crisis levels. We also find that three-quarters of the variation in market liquidity depends on foreign market liquidity shocks, which provides a more cross-market oriented explanation of commonality. Finally, we show that the measure, proposed by Abdi and Ranaldo (2017), performs well when measuring liquidity in several international stock markets, in the sense that it provides sensible results which are consistent with our knowledge of these markets and their dynamics between July 2000 and December 2016.

The rest of this paper is organized as follows: Section 2.2 lays out the methodology used in our analysis. Section 2.3 describes the data. Section 2.4 discusses the empirical results and, finally, Section 2.5 concludes.

2.2 Methodology

We divide our empirical investigation into three sections. First, we calculate commonality in liquidity for each of the nine stock markets in our sample (Canada, Germany, France, Italy, Japan, Spain, Switzerland, the U.K., and the U.S.), using the bid-ask spread proposed by Abdi and Ranaldo (2017). This sample includes seven of the world's advanced economies (G7) and represent 67.3%[4] of the total world stock market capitalization. We then estimate global commonality in liquidity, following Diebold and Yilmaz (2012). Finally, we use the new time-varying Granger causality test, as developed by Shi et al. (2018), to investigate the dynamic causality between commonality in liquidity and market volatility.

2.2.1 Systemic Liquidity

To measure systemic liquidity risk, we follow a recently proposed estimator for market liquidity, as developed by Abdi and Ranaldo (2017). Their method is based on close, high and low prices and bridges the well-established bid-ask spread formulated by Roll (1984) and the more recent High-Low (HL) spread developed by Corwin and Schultz (2012). This measure has several advantages over competing alternatives. For example, compared to other low-frequency estimates, this method uses wider information (i.e. close, high and low prices), it provides the highest cross-sectional and average time-series correlations with the TAQ effective spread, and it delivers the most accurate estimates for less liquid stocks.

[4] World Federation of Exchanges, (n.d.). Retrieved from `https://www.world-exchanges.org`

Abdi and Ranaldo (2017)'s measure is based on the same theoretical assumptions as those made for the spread modelled by Roll (1984). The effective spread s is estimated as

$$s = 2\sqrt{E(c_t - \eta_t)(c_t - \eta_{t+1})}, \tag{2.1}$$

where c_t represents the daily observed close log-price, and η_t refers to the mid-range, defined as the mean of daily high and low log-prices. Although this closed-form solution of the bid-ask spread measure is similar to the autocovariance measure by Roll (1984), it builds on the covariance of consecutive close-to-midrange prices rather than on close-to-close prices.

Owing to errors in the estimation procedure, some estimates of equation 2.1 are negative. Following Corwin and Schultz (2012), Abdi and Ranaldo (2017) propose two versions of the spread. In the first - known as the *two-day corrected* version - negative two-day estimates are set to zero and then the average of the two-day calculated spreads is taken. In the second - known as the *monthly corrected* version - negative monthly estimates are set to zero. Equations 2.2 and 2.3 show how the spreads are calculated.

$$\widehat{s}_{twodayscorrected} = \frac{1}{N}\sum_{t=1}^{N}\widehat{s}_t, \widehat{s}_t = \sqrt{max(4(c_t - \eta_t)(c_t - \eta_{t+1}), 0)} \tag{2.2}$$

$$\widehat{s}_{monthlycorrected} = \sqrt{max(4\frac{1}{N}\sum_{t=1}^{N}(c_t - \eta_t)(c_t - \eta_{t+1}), 0)} \tag{2.3}$$

where N is the number of trading days in a month. Finally, we calculate a monthly country-specific systemic liquidity measure as the equally-weighted average of the monthly spread of individual stocks.

2.2.2 Global Commonality in Liquidity

Our approach to estimate commonality in liquidity is based on the methodology introduced by Diebold and Yilmaz (2012), which builds on the seminal work on VAR models by Sims (1980) and the notion of variance decomposition. The starting point for the analysis is the following VAR(p):

$$x_t = \sum_{i=1}^{p}\Phi_i x_{t-i} + \varepsilon_t, \tag{2.4}$$

where $x_t = (x_{1t}, x_{2t}......, x_{Kt})$ is a vector of K endogenous variables. Φ_i is a KxK matrix of parameters to be estimated, and ε_t is a vector of disturbances that has the property of being independently and identically distributed (i.i.d) over time, $t = 1, ...T$, with zero mean and Σ is a covariance matrix. If the VAR model is covariance stationary, we can derive the moving average representation of model (2.5), which is given by

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}, \tag{2.5}$$

where $A_i = (\Phi_1 A_{i-1} + \Phi_2 A_{i-2}, ...\Phi_p A_{i-p})$, A_0 is the KxK identity matrix and $A_i = 0$ for $i < 0$. Variance decomposition allows us to break down the h-step ahead forecast error variance into *own variance shares*, the fraction of the forecast error variance in forecasting y_i due to shocks to y_i, for $i = 1, 2, ...N$, and cross variance shares, or spillovers, the fraction of the forecast error variance in forecasting y_i due to shocks to y_j for $j = 1, 2, ...N$ and $j \neq i$. Diebold and Yilmaz (2009) proposed using Cholesky decomposition to break down the variance. However, Cholesky decomposition are sensitive to ordering. Diebold and Yilmaz (2012) resolve this ordering problem by exploiting the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), in which variance decomposition is invariant to the ordering of the variables. Variable $j's$ contribution to $i's$ h-step ahead generalized forecast error variance decomposition is given by:

$$\vartheta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i{'} A_h e_j)^2}{\sum_{h=0}^{H-1} (e_i{'} A_h \Sigma A_h{'} e_i)} \tag{2.6}$$

where Σ is defined as the covariance matrix of the error vector ε, σ_{jj} is the (estimated) standard deviation of the error term for the variable j, and e_i is a selection vector with a value of one on the *ith* element and zero otherwise. The sum of contributions to the variance of the forecast error of each market do not necessarily add up to one; thus, we normalize each entry of the variance decomposition matrix as:

$$\tilde{\vartheta}_{ij}(H) = \frac{\vartheta_{ij}(H)}{\sum_{j=1}^{N} \vartheta_{ij}(H)} \tag{2.7}$$

where $\sum_{j=1}^{N} \tilde{\vartheta}_{ij}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}(H) = N$.

This normalization enables us to construct the following spillover measures:

- The *total spillover index* which measures the contribution of spillovers of shocks across all markets to the total forecast error variance:

$$TS(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\vartheta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}(H)} \cdot 100 \tag{2.8}$$

- The *directional spillovers* received by market i from all other markets j:

$$DS_{i\longleftarrow j}(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\vartheta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}(H)} \cdot 100 \tag{2.9}$$

- The *directional spillovers* transmitted by market i from all other markets j:

$$DS_{i\longrightarrow j}(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\vartheta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}(H)} \cdot 100 \tag{2.10}$$

- The *net spillover*, namely the difference between the gross shocks transmitted to and the gross shocks received from all other markets, which identifies whether a market is a receiver/transmitter of shocks from/to the rest of the markets being examined. The net spillover index from market i to all other markets j is obtained by subtracting Eq.(2.9) from Eq.(2.10):

$$NS_i(H) = DS_{i\longrightarrow j}(H) - DS_{i\longleftarrow j}(H) \tag{2.11}$$

2.2.3 Global Market Volatility

Our measure of volatility is based on the traditional realized volatility (RV) estimator, as explained, for example, in Andersen and Todorov (2010). This has been shown to be an useful methodology for estimating and forecasting conditional variances for risk management and asset pricing.[5] The RV estimator can be expressed as:

$$RV_{monthly} = \sqrt{\sum_{t=1}^{N} r_t^2}, \tag{2.12}$$

where r_t are the ln returns and N is the number of trading days per month. In order to examine the time-varying relationship between commonality in liquidity in international stock markets and market volatility, we need to aggregate individual volatilities and, to do so, we employ a principal component analysis, taking the first component as our measure of global market volatility.

2.2.4 Dynamic Granger Causality

To analyze the dynamic relationship between commonality in liquidity in international stock markets and global market volatility, we follow the methodology proposed by Shi et al. (2018). While emphasizing that the Granger causality test is highly sensitive to the time horizon of its estimation, they propose considering time dynamic to detect periods of instability in the causal relationship. The method proposed is based on an intensive recursive calculation of Wald test statistics for all sub-samples in a backward-looking manner in which the final observation of all samples is the (current) observation of interest.

The traditional testing for Granger Causality within a VAR system (as for the instance described in Eq.(2.4)) involves the following null hypotheses:

$$H_0 : y_{it} \nrightarrow y_{jt}, \tag{2.13}$$

$\phi_{l,ij} = 0$, for $i \neq j$ and $l = 1, ..., p$, where the causality runs from variable i to variable j, and the reverse causality between the two variables is given by

$$H_0 : y_{jt} \nrightarrow y_{it}, \tag{2.14}$$

$\phi_{l,ij} = 0$, for $i \neq j$ and $l = 1, ..., p$, where the symbol $\nrightarrow$ means "does not Granger

[5] See Liu et al. (2015) and references therein.

cause”. This hypothesis can be contrasted with the data by constructing a traditional Wald statistic (W) to test it against the alternative of at least one significant coefficient. Shi et al. (2018) and Shi et al. (2020) compare different statistics for the data-driven discovery of change points in causal relationships and they conclude in favor of a rolling window estimation of the traditional Wald statistics. Namely for each observation of interest $f \in [f_0, 1]$, where f_0 is the minimum window size that is required to estimate the model, the Wald statistics are computed using subsamples of the original data set. The starting and end points of the regression are defined as f_1 and f_2, respectively, and the Wald statistic for the subsample starting at f_1 and ending at f_2 is denoted W_{f_1,f_2}. The ending point of the regression f_2 is fixed on the observation of interest (the date on which we want to test for causality). Therefore, as the observation of interest moves forward from f_0 to 1, the starting point of the regression follows and keeps a constant distance from f_2, i.e. $f_1 = f_2 - f_w$, where f_w is the fraction that represents the window size that is used for the regression. Shi et al. (2018) show that within a stationary VAR system under the assumptions of homoscedasticity, conditional heteroscedasticity of an unknown form, or unconditional heteroscedasticity, W_{f_1,f_2} has a limiting distribution that is given by the following:

$$W_{f_1,f_2} \Rightarrow [\frac{W_d(f_2) - W_d(f_1)}{(f_2 - f_1)^{\frac{1}{2}}}]'[\frac{W_d(f_2) - W_d(f_1)}{(f_2 - f_1)^{\frac{1}{2}}}], \tag{2.15}$$

where W_d is a vector Brownian motion with covariance matrix I_d and d is the number of restrictions under the null (as in Eq.(2.4) and Eq.(2.5)). Hence, if causality is detected, its sign (positive or negative) is identified, as well as its intensity. Finally, the testing framework considers the potential heteroscedasticity (conditional and unconditional) of the data, thereby reducing the potential for incorrect inferences.

Inferences regarding the presence of Granger causality for this observation rely on the supremum taken over the values of all the test statistics in the entire recursion. As the sample period moves forward, all subsamples more forward and the calculation rolls ahead in a changing rolling window framework - hence its name, ”recursive rolling algorithm”. The estimation procedure is based on a VAR model framework in which the selection of the lag order is obtained using the Bayesian Information Criterion (BIC). As in Shi et al. (2018), the 5% critical value sequences over time are obtained through bootstrapping with 500 replications.

2.3 Data

We collect daily close, high and low prices, for the period July 2000 through to December 2016, for the following markets (Canada, Germany, France, Italy, Japan, Spain, Switzerland, the U.K. and the U.S.). We confine our sample of stocks to those listed in the country's specific major stock market index. To obtain a measure for market-wide liquidity in each stock market, we first calculate the daily spreads of our restricted set of stocks defined above and aggregate them on a monthly basis. Then, we sum the monthly stock-specific spreads and weight them equally by the number of stocks in each market so as to obtain a monthly market-wide aggregate spread for each market.

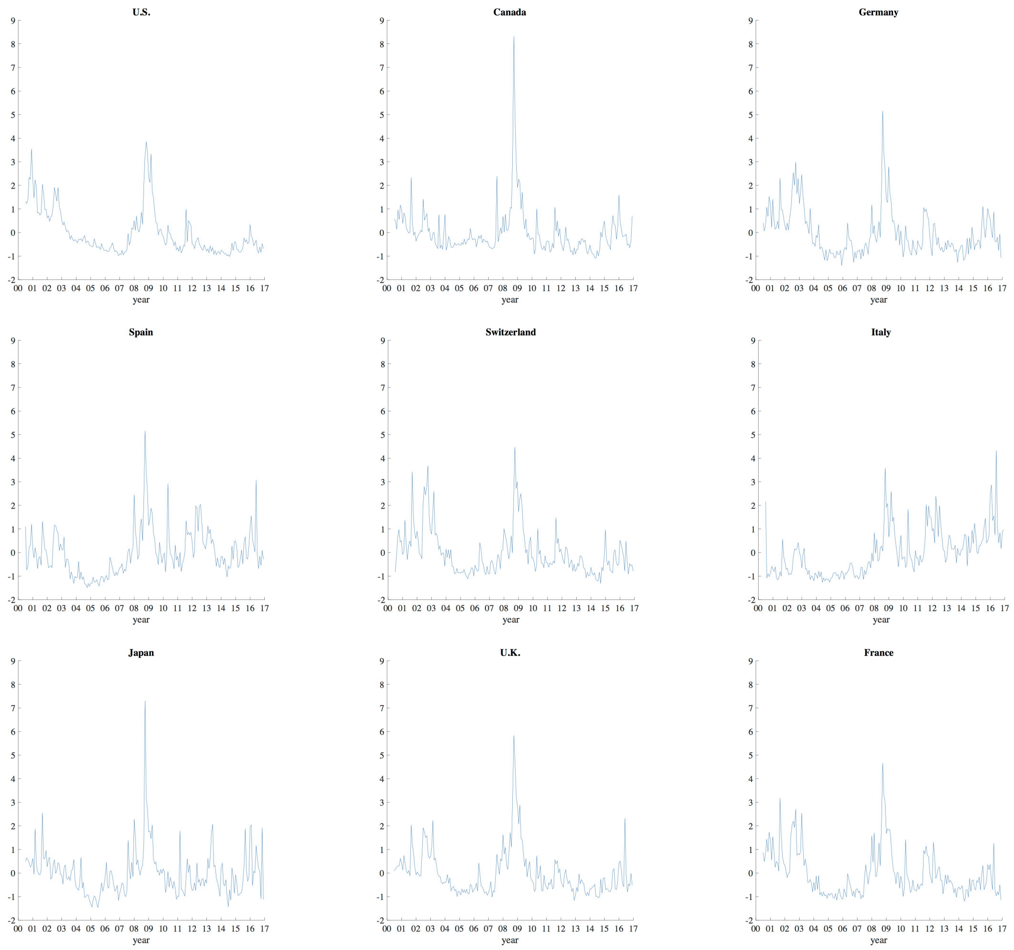
The number of stocks in each index is subject to fluctuations over the entire sample period. This reflects the fact that some firms have gone public after the sample start date while others have recently delisted for reasons of financial restructuring or the merging of business activities. We control for these possibilities by adjusting the weighting over time. In compliance with the screening principles proposed by Karolyi et al. (2012), we aim to obtain a broad range of stocks within each country while avoiding any differences in trading behavior or conventions. In keeping with this objective, we also exclude depositary receipts (DRs), real estate investment trusts (REITs), investment funds and preferred stocks from our sampling. Moreover, we exclude stocks with price data for less than 24 months, although this is rarely applicable. The monthly spread estimates for U.S. stocks are taken from Angelo Ranaldo's website.[6]. All other daily price data for stocks are extracted from Datastream. Our final sample of stocks outside of the U.S. consists of 505 stocks from eight different countries.

2.4 Results

In this section we report our empirical results. We first provide the reader with insights into the dynamics of market liquidity for selected countries. Then, we present our measure of global commonality in liquidity. Finally, we describe the time-varying relationship between global commonality in liquidity and aggregate market volatility.

[6]Research Material - Angelo Ranaldo. (n.d.). Retrieved from: `https://sbf.unisg.ch/en/lehrstuehle/lehrstuhl_ranaldo/homepage_ranaldo/research-material`

Figure 2.1: Dynamics of Market-wide Liquidity



Note: Time-series variation in market liquidity for selected countries. Monthly country-specific liquidity measures are calculated as the equally-weighted average of the monthly spread of individual stocks. The sample runs from July 2000 to December 2016. For illustrative purposes, the liquidity measures in the plots are standardized.

2.4.1 Liquidity Measure

Figure 2.1 shows the estimated market liquidity measures for each country in our sample. An increase in the spread is associated with a higher level of illiquidity in the respective stock market. We observe that market liquidity is substantially higher in some periods than in others and tend to decrease during financial crises. For example, market illiquidity was high in the U.S., Switzerland, Germany and France during the dot-com bubble. Likewise, for all countries, illiquidity dramatically increased during the financial crisis of 2008-2009. It is also noteworthy that Italy exhibited higher illiquidity than the rest of the countries between 2011-2017. Table A2 shows the descriptive statistics of market liquidity for each country. Our results show that market illiquidity was higher and more volatile during the financial crisis (2008-2009) than before or after it. The U.S., Canada, Germany and Japan are the countries with the lowest levels of market liquidity during this subperiod. Interestingly, the mean and the standard deviation during the post-crisis period are lower than during the pre-crisis period (except for Japan and the peripheral countries, Italy and Spain, due to the European Sovereign debt crisis).

2.4.2 Global Commonality in Liquidity

Table 2.1 shows the estimation results for the full-sample spillover analysis based on a 6-month-ahead forecast error variance decomposition. Element ij^{th} of the matrix represents the contribution to the forecast error variance of market i from shocks to market j. The diagonal elements display the intra-market spillovers, where $(i = j)$. The off-diagonal elements of the matrix show the cross-market spillovers. The row sums (labeled "From others") represent the total spillovers received by the respective market as denoted in this particular row, whereas the column sums (labelled "To others") represent the sum of spillovers transmitted by market i in the respective column. The difference between the column and the row sum represents the net spillover. It describes whether the respective market has transmitted (received) more shocks to (from) all of its counterparts. Finally, the total spillover statistic, shown in the bottom-right corner, indicates the degree of interconnection between the system of variables, i.e. our measures of systemic market liquidity.

As can be observed, the inter-market spillovers are higher than the intra-market spillovers, since both, the column *from others* and the row *to others* display higher figures than those on the diagonal. This means that variation in market-wide liquidity depends mainly on global sources of liquidity innovations. This result contrasts with findings reported by Brockman et al. (2009) who show that local sources of commonality represent roughly 39% of the firm's total commonality in liquidity, while global sources contribute around 19%.[7] We also observe that the "contribution from others" figures are quite similar across countries, with Switzerland being the largest receiver of liquidity spillovers. However, the "contribution to

[7] This contrasting result could be due to the different methodologies followed by each study. To analyze the relative impact of the local and global components of commonality on the liquidity of individual firms, Brockman et al. (2009) perform univariate time-series regressions. Here, our methodology is based on a VAR model, the main advantages of which are that all the variables in the system are treated as endogenous variable, which provides a systemic way to capture rich dynamics in multiple time-series by way of the lag structure.

others" figures show interesting differences across countries. The largest transmitters are Germany, the U.K., France and Canada and, in fact, the "net contribution" row also shows them to be the largest transmitter countries.

Table 2.1: Global Commonality in Liquidity

	US	CA	GER	SP	SWI	IT	JP	UK	FR	From others
US	18.82	15.53	13.02	8.47	9.40	5.61	4.58	11.73	12.79	81.17
CA	10.40	25.06	11.48	8.27	7.51	7.18	7.38	13.26	9.43	74.92
GER	10.32	10.77	18.86	8.95	11.92	7.90	5.45	12.31	13.48	81.13
SP	8.34	9.92	11.30	16.96	9.27	12.94	5.60	12.37	13.25	83.03
SWI	9.58	9.99	15.15	9.67	16.14	7.50	4.24	13.53	14.17	83.85
IT	7.19	10.23	11.43	14.03	8.16	20.20	5.52	11.98	11.22	79.79
JP	7.19	13.16	12.81	9.46	7.69	7.41	21.42	11.77	9.04	78.57
UK	8.60	12.88	13.06	10.95	10.16	9.03	5.37	17.39	12.51	82.60
FR	10.35	9.99	14.57	11.39	11.71	8.27	4.34	12.90	16.43	83.56
To Others	90.82	117.58	121.71	98.19	92.00	86.09	63.94	117.28	112.37	Total Spillover = 80.96
Net contrib. (to-from)	9.65	42.64	40.57	15.15	8.15	6.30	-14.63	34.67	28.80	

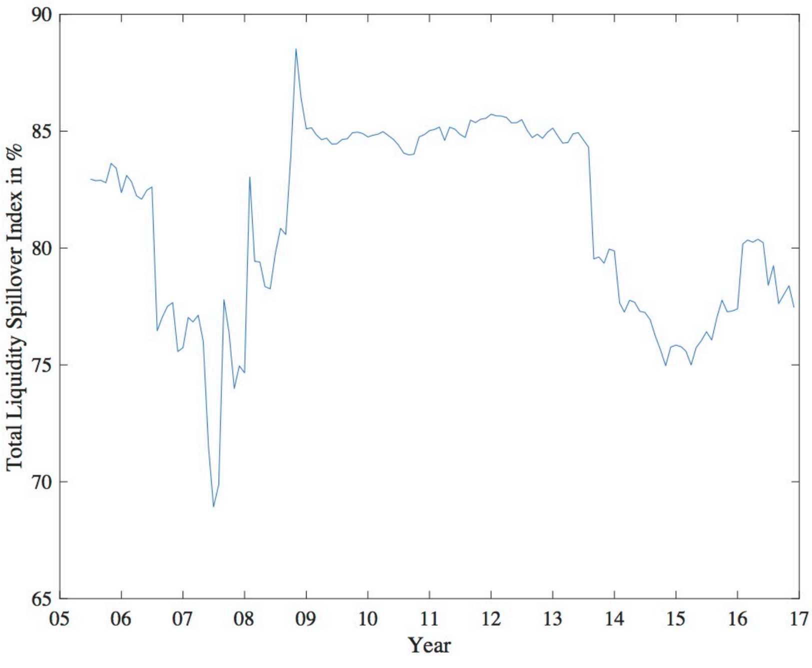
Note: Columns show the market producing the shock and rows the market receiving the shock. The diagonal elements represent intra-market spillovers while the off-diagonal elements represent the pairwise liquidity directional spillovers. The table shows the 6-month ahead forecast error variance decomposition, based on a VAR model with a lag length of 2, following the Akaike information criterion (AIC).

The above results point to a more cross-market oriented explanation of commonality in liquidity. From the demand-side perspective, this favors the hypothesis that large institutional investors, holding large-cap stocks from a variety of markets in their portfolio, can influence the systemic level of liquidity across markets by inducing high volume-related buy-sell trade imbalances (see Koch et al. (2016)). From a supply-side perspective, a liquidity contagion effect from one market to another provides evidence that tightness of funding liquidity affects all securities across different markets (see Hameed et al. (2010)). Finally, the total liquidity spillover (displayed in the bottom right-hand corner of Table 2.1) indicates that on average, across our entire sample, 80.96% of the total variance forecast error come from cross-market liquidity spillovers, which gives an idea of the degree of cross-market connectedness. This result contrasts with the results reported by Diebold and Yilmaz (2009) in terms of volatility and return spillovers across different global equity markets. These authors conclude that, on average, around 40%

of the forecast error variances comes from cross-spillovers, as regards both returns and volatilities. Our results suggest that liquidity connectedness across national markets is much higher than that of returns and volatilities.

The static analysis provides a good characterization of the spillovers over the full sample period. However, as this study investigates commonality in liquidity over a period affected by extreme economic events, including the global financial crisis, it seems fairly unlikely that liquidity spillovers will not change over time. To assess the time-varying nature of commonality, we estimate the VAR for the underlying variance decomposition, using a 60-month rolling window and a 6-month forecasting predictive horizon. From this, we obtain the total dynamic spillover index, which serves as our proxy for commonality in liquidity.

Figure 2.2: Global Commonality in Liquidity



Note: Monthly total cross-spillover index. Window length equals 60 months. The results are robust to the use of a 60-month rolling window and a 10-month forecasting horizon.

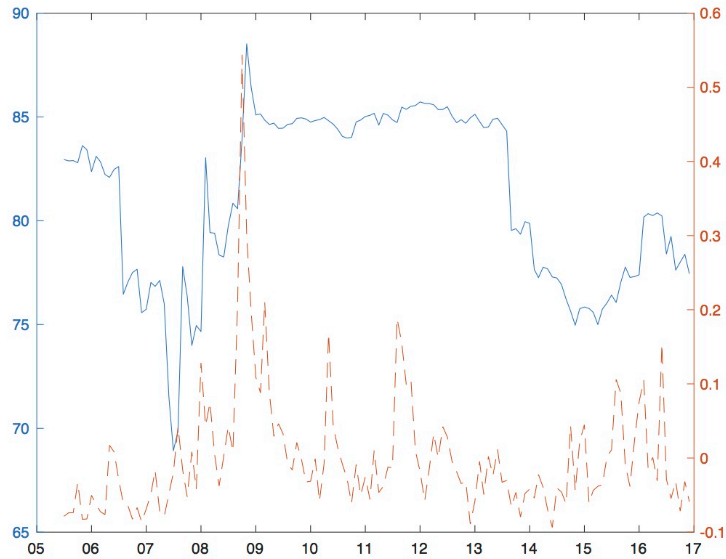
Figure 2.2 shows the total liquidity spillover index obtained from the rolling window estimation. It clearly highlights the changing dynamics over the sample period, with the level of commonality in liquidity mostly oscillating between 70 and 87%. The low peak at the beginning of 2008 can be associated with the liquidity constraints faced by Bear Stearns while the collapse of Lehman Brothers in September 2008 is associated with an even steeper increase in commonality in illiquidity. This increment is consistent with the findings of Hameed et al. (2010), indicating that peaks in commonality in liquidity often result from large negative market returns and coincide with liquidity crises. Thus, the dynamics show that commonality in liquidity increases during episodes of market turmoil. Our findings are coherent with the theoretical discussion in Brunnermeier and Pedersen (2009), where funding and market liquidity interact with each other, leading to higher margins and less capital-intensive trading positions in periods of crisis, which in turn leads to tight funding constraints and to changing levels in market-wide liquidity as funding liquidity diminishes.

Interestingly, we also observe that commonality is very persistent and that it remains at high levels even after market turmoil and funding tightness has passed. In fact, it remains at high levels event though the level of market-wide illiquidity in each country declined substantially after the effects of the Lehman Brother collapse, to moderate levels (see Figure 2.2). Commonality continues being high during the European sovereign debt crisis. Investors seem to chase liquidity by rushing from periods of flight-to-quality to periods of flight-to-liquidity, running from Eurozone bond markets back to equities which, in turn, keeps commonality high. Goyenko and Ukhov (2009), who analyze the dynamics between stock and bond market liquidity in the U.S. market, show that positive shocks to the level of illiquidity in the stock market reduce illiquidity in the bond market. Following a period of persistence in commonality in liquidity, a downward shift is observed at the end of 2013, suggesting the normalization of conditions in both bond and equity markets. The level of market commonality in the last few months of the sample is similar to that recorded in the months leading up to the global financial crisis.

2.4.3 Dynamics between Global Commonality in Liquidity and Global Market Volatility

Figure 2.3 shows the joint dynamics of global commonality in liquidity and global market volatility. We observe an increase in both trends during the financial crisis, although the upward trend starts earlier in the case of commonality in liquidity. Remarkably, we find that while volatility returns to lower levels, albeit with sudden peaks, levels of commonality in liquidity remain persistent. To analyze the time-varying relationship between the two, we use the dynamic Granger Causality test proposed by Shi et al. (2018).

Figure 2.3: Global Commonality in Liquidity and Global Market Volatility



Note: This figure shows the index for global commonality in liquidity (solid line) and the proxy for global market volatility (dashed line).

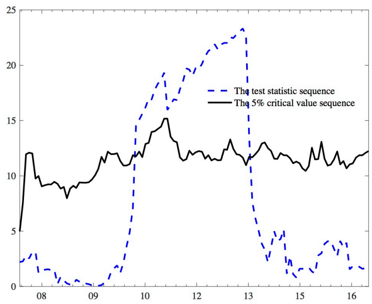
Our proxy for global market volatility is the first principal component factor of realized market volatilities in the nine stock markets.[8] Figure 2.4a and 2.4b displays the dynamic Wald test statistics proposed by Shi et al. (2018) for the detection of instability in the causal relationship between two time-series, namely commonality in liquidity and market volatility. The sequence of t-statistics starts in May 2008, as the first 22 months are used as the minimum window size.[9] We observe that global market volatility Granger-causes commonality in liquidity throughout

[8]As a robustness check, we have also calculated an equally-weighted average volatility index for the same sampling countries, and the results (available on request) were found to hold.

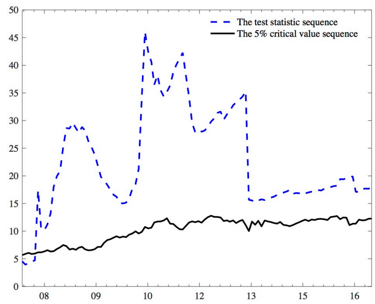
[9]Our initial sample starts in July 2000. We use 60 months in our rolling window estimation to obtain the total dynamic liquidity spillover. Using this index as input into the dynamic Granger test, we then take an additional 22 months as the minimum window size to perform the dynamic causality test.

the entire sample period. This is in line with the theoretical model developed by Brunnermeier and Pedersen (2009), in which higher market volatility leads to an increase in commonality as a consequence of a reduction in the provision of liquidity available for all financial intermediaries.

Figure 2.4: Test Statistic Sequences of the Time-Varying Granger Causality Test - Commonality in Liquidity and Volatility



(a) Commonality in Liquidity to Volatility



(b) Volatility to Commonality in Liquidity

Note: The lag selection is determined using the BIC. The sequences are calculated using a recursive rolling procedure from May 2007 to December 2016.

Conversely, and for the first time, we find that commonality in liquidity Granger-causes volatility only from late 2009 to 2013, that is, in the aftermaths of the global financial crisis and during the European sovereign debt crisis. These feedback effects between commonality in liquidity and volatility coincide with periods of high commonality in liquidity in global markets. This finding might be interpreted as evidence of the existence of adverse loop effects in which shocks to stock market liquidity endogenously cause stock market volatility and vice versa. Such feedback effects sheds new light on the endogenous nature of financial shocks arising during episodes of crisis, which we show are aggravated by liquidity considerations.

2.5 Conclusion

We document a dynamic relationship between global commonality in liquidity and global market volatility in a sample of nine stock markets, representing most of the world's stock market capitalization. Our results show that global commonality in liquidity and market volatility share a dynamic bi-directional relationship. Market volatility Granger-causes commonality in liquidity as a general rule (i.e. throughout the whole sample period), while commonality Granger-causes market volatility only during sub-periods of crises and their aftermaths. This latter relationship raises a warning about the presence of endogenously enhanced adverse loop effects between commonality in liquidity during crises, which are documented and measured here for the first time.

We also find that variation in market-wide liquidity depends predominately on inter-market liquidity innovations, which reveals the relative strength of the propagation of liquidity shocks originating from foreign stock markets. Illiquidity shocks are indeed shown to propagate more strongly than volatility and return shocks extensively analyzed by the previous literature. These strong liquidity linkages provide support for both a demand-side explanation of commonality (i.e. correlated trading behavior and the increasing importance of institutional investors in the market) and a supply-side explanation (i.e. funding constraints and liquidity spirals). The dynamics show that commonality in liquidity increases after large market downturns and peaks during episodes of market turmoil and funding tightness. We also observe that commonality is highly persistent and that it remains at high levels even after market turmoil has passed.

Our results should prove helpful for practitioners, as the relationship identified herein can usefully be taken into account in portfolio risk management. They might also be useful for policy makers as they highlight the high level of commonality across markets, which stresses the importance of designing an integrated policy framework to prevent common sources of liquidity shortage in global financial markets. Indeed, from a regulatory point of view, our results call for a closer monitoring of market-wide liquidity from an integrated and coordinated perspective. Commonality means that liquidity dry-outs are likely to be correlated and therefore the provision of liquidity during crisis episodes, frequently fostered by domestic monetary policy authorities as to preserve the normal functioning of national financial markets, should be certainly addressed in a coordinated way across different markets and countries. The relatively high transmission of liquidity shocks (compared to price shocks) invites regulators and market participants to think of (i) liquidity as a prominent feature of financial markets that impact different assets and markets simultaneously, and therefore, this makes it harder to diversify risk.

Our results in this regard also emphasize the possibility of market contagion, and shock transmission, explained by the market liquidity channel. That is, market liquidity and systemic commonality appear to be crucial factors underlying market return and volatility co-movements frequently reported by the literature. In other words, our main findings provide support for liquidity as a theoretical factor explaining returns co-movements in stock markets.

Here we study commonality in liquidity of stocks, however, analyzing commonality across different asset classes can complement our results. In this way, international investors would be able to reach diversification benefits unexplored here, by diversifying liquidity risk across asset classes (bonds, commodities, etc.) instead of across countries (in which case we document relatively low room for diversification).

2.6 Appendix

Table A1: Unit Root Test - Time-Series Liquidity Measures

	ADF-Test(2)	PP-Test(2)
Country	Levels	Levels
US	-2.71*	-2.96**
CA	-4.19***	-5.55***
GER	-3.44**	-4.46***
SP	-3.74***	-5.49***
SWI	-3.58***	-4.71***
IT	-3.17**	-5.51***
JP	-4.74***	-7.32***
UK	-3.28**	-4.21***
FR	-3.39**	-4.74***

Note: This table reports the results of the unit root tests, that is the Augmented Dickey Fuller (ADF) and the Phillips-Perron (PP-Test) for the time-series market liquidity measure proposed by Abdi and Ranaldo (2017). Lags used in these tests are indicated in brackets. The sample period spans from July 2000 to December 2016. *** indicates statistical significance at the 1% critical value, ** at the 5% critical value and * at the 10% critical value. This table is supplementary material to Chuliá et al. (2020).

Table A2: Summary Statistics of Commonality in Liquidity

Stock Market in	Mean	Median	St.D.	Min	Max	Skew	Kurt	$AC(1)$	$AC(2)$
Pre-Financial Crisis (2000 - 2007)									
US	1.736	1.431	0.666	0.906	3.865	0.894	2.998		
CA	1.144	1.056	0.280	0.794	2.326	1.520	5.943		
GER	1.830	1.793	0.632	0.893	3.521	0.674	2.673		
SP	0.793	0.737	0.274	0.433	1.462	0.830	2.714		
SWI	1.104	1.003	0.491	0.535	2.683	1.311	4.351		
IT	0.613	0.551	0.215	0.396	1.800	2.749	13.63		
JP	1.256	1.262	0.322	0.668	2.463	0.650	4.497		
UK	1.175	1.130	0.366	0.714	2.246	1.032	3.551		
FR	1.288	1.173	0.523	0.682	2.822	0.886	3.016		
Financial Crisis (2007 - 2009)									
US	1.943	1.659	0.876	0.925	4.069	1.001	3.041		
CA	1.594	1.253	0.902	0.824	5.313	2.322	9.390		
GER	1.978	1.719	0.827	1.057	4.820	1.556	5.380		
SP	1.204	1.042	0.485	0.656	2.870	1.448	5.210		
SWI	1.291	1.081	0.568	0.620	3.034	1.210	3.914		
IT	1.030	0.919	0.443	0.447	2.383	1.110	3.920		
JP	1.633	1.448	0.686	0.878	4.582	2.368	10.575		
UK	1.647	1.474	0.730	0.704	3.956	1.291	4.564		
FR	1.537	1.302	0.660	0.708	3.557	1.100	3.892		
Post-Financial Crisis (2010 - 2016)									
US	1.202	1.169	0.239	0.883	2.192	1.628	6.239		
CA	1.004	0.965	0.257	0.627	1.958	1.194	4.629		
GER	1.531	1.436	0.341	0.970	2.394	0.948	3.171		
SP	1.055	0.977	0.299	0.600	2.102	1.325	4.929		
SWI	0.857	0.824	0.226	0.447	1.692	1.120	4.837		
IT	1.141	1.080	0.361	0.578	2.689	1.375	6.028		
JP	1.255	1.167	0.357	0.686	2.246	1.258	4.269		
UK	1.001	0.952	0.244	0.635	2.288	2.102	10.886		
FR	1.093	1.031	0.285	0.660	1.951	1.257	4.231		
Full Sample (2000 - 2016)									
US	1.547	1.295	0.654	0.883	4.069	1.655	5.450	0.9032***	0.8425***
CA	1.166	1.033	0.498	0.627	5.313	4.076	28.90	0.7093***	0.5454***
GER	1.730	1.545	0.599	0.893	4.820	1.604	6.649	0.7843***	0.6811***
SP	0.979	0.915	0.366	0.433	2.870	1.442	6.643	0.7138***	0.5561***
SWI	1.033	0.900	0.448	0.447	3.034	1.771	6.444	0.7757***	0.6446***
IT	0.914	0.840	0.410	0.396	2.689	1.206	4.770	0.7142***	0.6480***
JP	1.324	1.256	0.446	0.668	4.582	2.585	16.713	0.5484***	0.4209***
UK	1.187	1.060	0.474	0.635	3.956	2.344	10.877	0.8117***	0.6925***
FR	1.251	1.100	0.495	0.660	3.557	1.504	5.613	0.7574***	0.6558***

Note: This table reports the summary statistics for the liquidity measure proposed by Abdi and Ranaldo (2017). Our dataset spans a time range from July 2000 to December 2016. $AC(1)$ and $AC(2)$ show the autocorrelation coefficients (AC) for the first and second lag, which denotes supplementary material to Chuliá et al. (2020). *** indicate statistical significance at the 1% level.

3 Analyzing the Nonlinear Pricing of Liquidity Risk according to the Market State

[1]

This study examines the asymmetric impact of systemic liquidity on asset prices across market states. We use time-series conditional quantile regressions to estimate an otherwise traditional liquidity-augmented three factor model for asset prices. We find the exposure of equity returns to aggregate liquidity risk to be dependent on the market state. On the one hand, we document a positive effect of systemic liquidity risk on contemporaneous asset returns in a good market state (i.e. when market returns are large and positive, that is, in the right tail of the probability distribution) and, on the other hand, a negative effect when the market state is bad (that is, in the left tail of the distribution). During regular times, market-wide liquidity risk is rarely priced. Contrary to general assumptions, our results show that liquidity is not always a relevant factor for explaining stock market returns and that it only becomes relevant when the market state is particularly good or bad. Search-for-yield and flight-to-liquidity considerations help to explain our findings.

[1] This paper is co-authored with Helena Chuliá and Jorge M. Uribe. This chapter represents an extended version of the paper by Chulia et al. (2020).

3.1 Introduction

Long-Term Capital Management's related events at the end of the 90's reminded us that investors have a marked preference for liquidity (Amihud et al. (2005)). In episodes of extreme turmoil, when liquidity appears to vanish from financial markets, investors engage in fire sales and financial intermediaries seem to renounce their function as purveyors of liquidity for the rest of the economic and financial system (Hameed et al. (2010)).[2] During these periods of market liquidity dry-ups, risk aversion leads investors to rebalance their portfolios toward less risky and more liquid assets, episodes referred to, respectively, as flights-to-quality and flights-to-liquidity (Baele et al. (2020), Beber et al. (2009). In contrast, when the market scenario and associated economic conditions are stable and optimistic, investors generally experience excess liquidity, leading them to rebalance their portfolios towards riskier and less liquid assets, with search-to-yield considerations in mind (Kiendrebeogo (2016), Fratzscher et al. (2018)).[3] Both, flight-to-liquidity and search-for-yield are naturally associated with extreme market conditions, that is, bad and good, respectively.

For these reasons, the role played by liquidity as a factor-explaining asset prices should ideally be examined from a general perspective that allows for a changing (and non-linear) association between liquidity and prices. Indeed, we might naturally expect the price of liquidity risk to differ, depending on the market state. Yet, the study of the effect of market-wide liquidity on asset prices has traditionally been confined to the linear, cross-sectional world (Martınez et al. (2005), Pástor and Stambaugh (2003), Acharya and Pedersen (2005)). In this paper, we seek to fill this gap by testing the economically motivated hypothesis of nonlinearity in the relationship between systemic liquidity risk and asset prices (returns). We show how stock market returns are exposed to systemic liquidity risk during tail events and compare these outcomes with median market scenarios. Our main results show a significant asymmetric liquidity risk-return relationship, depending on the market state.

To test our hypothesis we build upon Fama and French (1993)'s traditional three-factor model augmented with the bid-ask spread liquidity factor recently

[2]The literature refers to these two phenomena as demand and supply effects, respectively.

[3]These two papers study this phenomenon in relation to the excess liquidity produced by the quantitative easing policies implemented by the Federal Reserve after the Global Financial Crisis.

proposed by Abdi and Ranaldo (2017).[4] We conduct our estimations using quantile regressions, but rather than focusing on the cross-sectional effect (i.e. the cross-sectional liquidity premia associated with different portfolios at a given time insofar as they are illiquid or sensitive to a market-wide liquidity factor), we fit quantile regression returns to time-series returns.

By adopting this strategy, we are able to isolate the effect of liquidity on different parts of the stock return distribution over time, which in turn, are naturally related to different market states. Notice, however, that the definition of "market state" can be elusive. Cooper et al. (2004), for instance, define a good (bad) market state based on the average market return over the preceding three years. Thus, depending on whether this average is positive or not, the market state is considered good or bad. Pagan and Sossounov (2003) and Edwards et al. (2003) define market states by locating turning points and the duration of peaks and troughs. According to these authors, a bad market state starts with a peak, i.e. a local maximum within an 8-month wide window, and ends with a trough, i.e. a local minimum. However, these definitions are unnecessarily arbitrary given that the window widths are unjustified and selecting them may involve the cherry picking of results. Worse, they may also be misleading. What is deemed a bad market state, for example, might simply be a sequence of bad market results observed over a short number of days within an otherwise perfectly functioning and regular market presenting an average performance. Such misinterpretations can arise because markets are extremely volatile. For this reason, identifying a market state as an ex-post general trend in the data seems inappropriate in our context. Indeed, such trends might revert very quickly - within a matter of days, even - as the literature on momentum pricing and trading has documented extensively (Daniel and Moskowitz (2016)), and, therefore, it is necessary to seek alternative definitions of the market state.

In contrast, using the market return quantiles of the probability distribution to define a market state is much less arbitrary. Quantiles-in-time can be considered as constituting a collection of market states, ranging from very good in the case of the highest quantiles (i.e. large positive returns) to very bad states in the case of the lowest quantiles (large negative returns).[5] These states can occur either as a correlated sequence of bad market performance over a number of weeks, months or years, or as unexpected outliers within a sequence of otherwise positive results.

[4] Angelo Ranaldo (n.d.) - Research Material. Retrieved from `https://sbf.unisg.ch/en/lehrstuehle/lehrstuhl_ranaldo/homepage_ranaldo/research-material`

[5] see Aslanidis et al. (2016), Jareño et al. (2016), Zhu et al. (2017), Balcilar et al. (2018), Galvao et al. (2018), Shahzad et al. (2018) and Mensi et al. (2019), among others.

Being an order statistic that is robust to outliers, the independent estimation of different quantiles of the return distribution (conditional on relevant explanatory factors) has the advantage of allowing us to explore the full spectrum of the relationship between liquidity and stock returns, which is also preferable to simply focusing on two unrealistic ”good” and ”bad” states. In this way, our estimations allow us to observe the transition of liquidity betas from lower to higher quantiles - corresponding to very bad and very good market states, respectively - and naturally evaluate untroubled states around the median of the observed market realizations.

Our results show that systemic liquidity risk is a price factor dependent on the market state. However, it is a price factor only in certain states (good or bad, but not regular ones). First and foremost, we show that when the market is in a bad state, systemic liquidity risk exhibits a negative relation with *contemporaneous* stock returns that exceed the risk-free rate. That is, when returns are negative and large, market-wide liquidity risk depresses prices even further. Lower contemporaneous prices are naturally associated with higher future expected returns (under constant market fundamentals), which is consistent with the previous literature that assigns a positive premia to liquidity risk. Indeed, Amihud (2002) shows that unexpected market liquidity risk lowers contemporaneous stock prices, because a higher realized liquidity risk raises trader’s expectations about future illiquidity in the market and motivates them to request a higher return for their positions. Driven by uncertainty about future variability and the timing of illiquidity events, market participants prefer to sell their positions rather than face margin calls, which leads to lower contemporaneous returns.

Second, we show that excess stock returns are positively related to systemic liquidity risk during good market states. This is at odds with the traditional understanding of the literature, because it means that conditional on a good market state a generalized increase in systemic illiquidity is associated with higher contemporaneous market returns (and hence lower *expected* returns under constant market fundamentals). This is a consequence of investors rebalancing their portfolios towards more illiquid assets when market performance is good, as it occurs, for instance, when investors use excess gains to buy riskier and illiquid assets with search-for-yield considerations in mind.

Finally, we observe that during regular times (i.e. with quantiles close to the median), there is no significant relationship between systemic liquidity and market returns. This also challenges the traditional mean-to-mean effects reported in the literature that measures the importance of liquidity as an asset-pricing factor and restricts this importance to episodes of extreme realizations of market returns.

We contribute to the aforementioned literature that assesses the impact of liquidity risk in a linear fashion (Martınez et al. (2005), Pástor and Stambaugh (2003), Acharya and Pedersen (2005)) by extending the analysis with the consideration of different market states. We show liquidity to be an important concern for asset prices and market dynamics, as indeed the extensive literature on the topic has previously documented (Amihud et al. (1986); Eleswarapu and Reinganum (1993); Brennan and Subrahmanyam (1996); Datar et al. (1998); Chordia et al. (2000); Hasbrouck and Seppi (2001); Huberman and Halka (2001); Amihud (2002); among many others), but unlike these studies we show that this is not always the case. Basically, liquidity does not influence contemporaneous returns when they are not particularly high or low.

Interestingly, unlike in the empirical literature, there are significant precedents in a series of theoretical studies that point to a nonlinear relationship between market liquidity and asset prices. For instance, Vayanos (2004) provides a model in which liquidity premia are time-varying according to market uncertainty. In this model, investment managers are more likely to withdraw their positions during volatile times, becoming less willing to hold illiquid assets and, so, raising their liquidity premia. These actions usually result in flight-to-quality episodes, the subject of analysis of Morris and Shin (2004). From a different but related perspective, Brunnermeier and Pedersen (2009) study the interaction between funding liquidity and aggregate market liquidity, showing how shocks to the former might lead to lower market liquidity and higher margins on existing positions and, ultimately, to negative illiquidity-volatility-price spirals. These spirals, resulting from the complex interaction between liquidity, volatility and prices, also motivate the nonlinear approach that we adopt to the subject of this study.

An important precedent of the present study, and one that merits attention, is the contribution of Watanabe and Watanabe (2008). These authors analyze the time-varying role of liquidity as a factor explaining asset prices. They find that cross-sectional liquidity betas vary over time, resulting in two distinct liquidity states: one of high liquidity betas, characterized by high volatility and a large liquidity risk premium (which is extremely short-lived), and another of low liquidity betas, which is more stable and houses a lower risk price for liquidity. They attribute the changing role of liquidity as a factor in the cross-section of the returns to changing levels of traders uncertainty about their trading counterparties (i.e. preference uncertainty), and proxy this in their estimations with trading value (the greater the uncertainty, the higher the trading value). Related studies include Longstaff (2002) and Gibson and Mougeot (2004), who also highlight a changing relationship between market-wide liquidity and asset prices conditioning on market sentiment and the probability of future recessions, respectively. Unlike this closely related line in the literature, our emphasis is placed on the market price itself. Hence, our definition of a market state is broader and more general: a good market state is related to a good return realization and a bad market state to a bad realization (in the same spirit as Cooper et al. (2004)). Because it depends on the return quantile, instead on a specific variable (which might be correlated with other variables outside the model and subject, therefore, to criticisms of omitted confounding variables), we consider our approach more appropriate to tackle the problem that we seek to analyze here. We also analyze a continuum of states, which allows us to identify when and how liquidity is priced by the market, which is novel for the literature.

The rest of the paper is organized as follows. In Section 3.2, we describe the methods employed to test our hypothesis. In Section 3.3, we describe the data. In Section 3.4, the empirical results are discussed and robustness checks are provided. Finally, Section 3.5 concludes.

3.2 Methodology

We augmented a Fama and French (1993) standard three-factor model with the systemic liquidity risk factor proposed by Abdi and Ranaldo (2017), and used conditional quantile regression to identify nonlinearities in the liquidity-risk-return relationship.

3.2.1 Systemic Liquidity

To measure systemic liquidity risk, we employ the estimator recently proposed by Abdi and Ranaldo (2017). This measure is based on close, high and low prices and bridges the well-known bid-ask spread (Roll (1984)) and the more recent high-low spread (Corwin and Schultz (2012)). In comparison with other possible measures, this method makes use of wider information (i.e. close, high and low prices). Moreover, it presents the highest cross-sectional and average time-series correlation with Trade and Quote's (TAQ) effective spread and provides the most accurate estimate for less liquid stocks.

The effective spread shares the same theoretical assumptions as Roll (1984) and can be written as:

$$s = 2\sqrt{E(c_t - \eta_t)(c_t - \eta_{t+1})}. \tag{3.1}$$

where c_t is the daily observed close log-price and η_t represents the mid-range between daily high and low log-prices. This closed-form bid-ask spread estimate resembles Roll (1984) autocovariance measure, the only difference being the covariance of consecutive prices is close-to-midrange rather than close-to-close.

In estimating the effective spread, some estimates are found to be negative. Following Corwin and Schultz (2012), Abdi and Ranaldo (2017) estimate the squared spread s^2 in (1) over two-day periods. If a two-day estimate is negative, they set it to zero. Second, they take the square root and then take the monthly average.

$$\hat{s}_{monthlycorrected} = \sqrt{max(4\frac{1}{N}\sum_{t=1}^{N}(c_t - \eta_t)(c_t - \eta_{t+1}), 0)}, \tag{3.2}$$

where N displays the number of trading days in a month.

Finally, the monthly systemic liquidity risk indicator can be calculated as the gross return-weighted average of the monthly spread of individual stocks. We use the measure that is available on the website of Angelo Ranaldo.[6] The measure is constructed on the basis of NYSE, AMEX and NASDAQ stocks. In the context of an European version of this analysis, we also construct an European systemic liquidity risk estimate in the same fashion with an equally-weighted aggregation of the spreads of the underlying constituents of the EuroStoxx50 stock market index, (see Appendix A12).

3.2.2 Liquidity-Adjusted Three-Factor Model

Following the Fama and French (1993) three-factor model approach, the liquidity-augmented three factor model can be written as follows:

$$r_{it} - r_{ft} = \beta_1^L Liq_t + \beta_2(r_{mt} - r_{ft}) + \beta_3(SMB)_t + \beta_4(HML)_t + \varepsilon_{it}, \tag{3.3}$$

where $(r_{it} - r_{ft})$ gives the monthly excess returns on 25 U.S. portfolios, sorted according to size and book-to-market value (BE/ME) quintiles; the excess return on

[6] Angelo Ranaldo - Research Material. (n.d). Retrieved from `https://sbf.unisg.ch/en/lehrstuehle/lehrstuhl_ranaldo/homepage_ranaldo/research-material`

a broad market portfolio is denoted as $(r_{mt} - r_{ft})$, (hereafter RMKT); r_{ft} is the risk-free rate, proxied by the one-month treasury bill rate; ε_{it} is the error term, assumed to be independent with zero mean and variance σ^2. The factors (SMB) and (HML) are portfolios, mimicking the risk factor in returns related to size and book-to-market equity, respectively. The (SMB) factor is constructed as the difference between the average returns on small- and big-stock portfolios (small minus big) with the same weighted-average book-to-market ratio. The (HML) factor is referred to as a value premium between the average returns on portfolios with high book-to-market and low book-to-market stocks (high minus low) with the same weighted average size[7], Liq_t denotes the systemic liquidity risk measure, which is not an asset nor a portfolio, rather it is the gross return-weighted average of the monthly spread of individual stocks. The coefficient β_1^L captures the sensitivity of excess returns on systemic liquidity in the market. The inclusion of a systemic liquidity risk factor would appear to be appealing to the asset-pricing literature, especially after recent liquidity dry-ups in financial markets. Using factor models, Pástor and Stambaugh (2003), Martınez et al. (2005) and Acharya and Pedersen (2005) have previously provided evidence that the level of aggregate liquidity is a priced risk factor, when explaining expected stock returns.[8]

3.2.3 Quantile Regression

Here, we adopt Koenker and Bassett Jr (1978)'s quantile regression technique (see also Koenker and Hallock (2001)). Quantile regression provide insights into the impact of explanatory variables on the entire conditional distribution of the response variable. In this setting, conditional quantile regressions are linear in parameters for each selected quantile. We explore how systemic liquidity risk affects the different quantiles of excess returns. Moreover, we interpret these return quantiles as different market states, i.e. positive vs. negative abnormal returns, as extreme scenarios, which leads directly to a comprehensive analysis of systemic liquidity risk scenarios.

Ando and Tsay (2011) and Allen and Powell (2011), among others, undertake studies of the emerging field of quantile regression and factor models, but do not

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[7] See Fama and French (1992), Fama and French (1993), Fama and French (1996) for details about factor construction and description.

[8] Pástor and Stambaugh (2003) construct an aggregate liquidity measure based on volume-related price reversals which then is incorporated into a Fama and French (1993) three-factor model. Acharya and Pedersen (2005) adjust a CAPM with the illiquidity measure proposed by Amihud (2002).

explore the effect of systemic liquidity as a priced and nonlinear risk factor. Applying a quantile regression method to factor models is similar to using a risk assessment tool, such as VaR (value-at-risk) or the ES (expected shortfall), except that we are not solely concerned of tail losses of the return distribution but with how systemic liquidity risk relates to returns in normal times and periods when the market is in a good (bad) state, coinciding with extreme tail events. Eq.(3.3) relates to the conditional mean scenario of excess returns and exposure to aggregate liquidity risk. To investigate excess returns across its conditional distribution, the time-series quantile liquidity-adjusted factor model for quantile τ can be written as follows:

$$(r_{it} - r_{ft}) = \beta(\tau)x + \varepsilon_{it}(\tau), \tag{3.4}$$

where all quantile parameters are displayed in a vector $\beta(\tau) = \{\beta_1(\tau)^L, \beta_2(\tau), ..\ \beta_3(\tau), \beta_4(\tau)\}$ and all factors in a $Nx4$ matrix, denoted as $x = \{Liq_t, RMKT_t, SMB_t, HML_t\}$. We further assume that the vector of error terms conditional on the parameter matrix is zero, $Q_\tau(\varepsilon_{it|x} = 0)$. We can then specify the τ *th* conditional quantile function as follows:

$$Q_{(r_{it}-r_{ft})}((\tau)|x) = \beta(\tau)x. \tag{3.5}$$

To obtain an estimate $\widehat{\beta}(\tau)$ for the unknown coefficient(s) for the τ *th* quantile, the following function is minimized:

$$\widehat{\beta}(\tau) = argmin \sum_{i}^{n} \varrho_\tau((r_{it} - r_{ft}) - \beta x) \tag{3.6}$$

where $\varrho_\tau(\mu) = \mu(\tau - I(\mu < 0))$ with $0 < \tau < 1$ is a check function with asymmetric weights, which depend on the quantile selected. While we collect all quantile estimates in a set $\Phi = (\beta_1(\tau)^L, \beta_2(\tau), \beta_3(\tau), \beta_4(\tau))$, we only report the liquidity betas, $\beta_1(\tau)^L$, in the result section below for every quantile.[9] The liquidity-adjusted three-factor model is estimated as a conditional quantile function at a range of quantiles, $\tau = (0.1 - 0.95)$, in 0.05 intervals. By doing so, we observe a transition between market states, from the negative tail of the return distribution, $(\tau = 0.1)$, to the extreme positive market scenarios, $(\tau = 0.9)$.

[9] We do not provide estimates of the factor-portfolios (three factors) as they have been widely documented in the respective literature, for example, Fama and French (2016).

3.3 Data

First, we analyze the effect of systemic liquidity risk on the distribution of stock market returns. Second, we examine systemic liquidity risk on 25 value-weighted portfolios sorted according to size and book-to-market value. The market and portfolio returns are constructed each month and include stocks from the NYSE, AMEX, and NASDAQ. Subtracting the risk-free rate from the returns, excess returns denote the dependent variable. Data on the portfolios and three factors were retrieved from the webpage of Kenneth French.[10] The measure for systemic liquidity risk was retrieved from the author's webpage.[11] We standardized the liquidity measure to obtain comparable estimates with respect to the coefficients of the three factors commonly used in the literature. The sample period spans from January 2000 to December 2016. We also include robustness exercises: we expand the sample to a period ranging from January 1960 to December 2016; we examine 30 U.S. industry portfolios, similarly retrieved from Kenneth French's webpage, employing the same procedure as for the 25 value-weighted U.S. portfolios. In Appendix 3.6, we also take on an European view on the matter of liquidity risk and stock market portfolio returns.

3.4 Results

3.4.1 Market Return and Systemic Liquidity Risk

Figure 3.1 summarizes the effect of liquidity, proxied by the market liquidity index of Abdi and Ranaldo (2017), on different quantiles of the excess stock return distribution from January 2000 to December 2016. As is evident, the effects are highly nonlinear, ranging from negative to positive as market returns increase.

The linear effect of liquidity on returns is also apparent in the figure (as indicated by the solid red line accompanied by two parallel dotted lines, representing the 95% confidence intervals of the regression). This effect is both negative and statistically significant, indicating that illiquidity reduces contemporaneous market returns. This outcome is consistent with findings in the literature that document

[10] Kenneth French - Data Library. (n.d.) Retrieved from `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

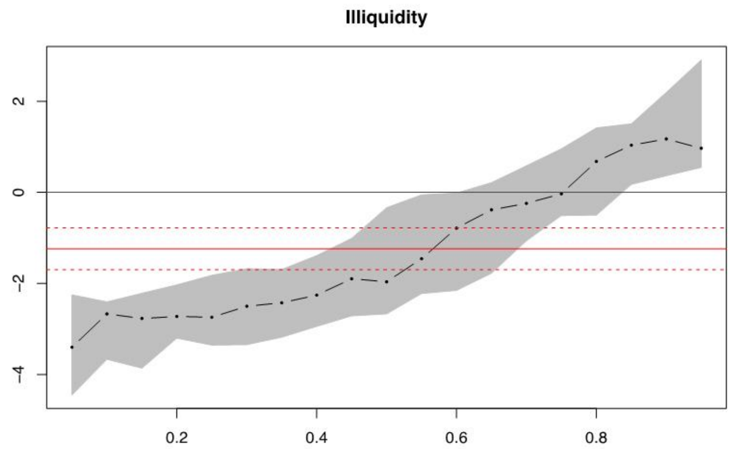
[11] Angelo Ranaldo - Research Material. (n.d.) Retrieved from `https://sbf.unisg.ch/en/lehrstuehle/lehrstuhl_ranaldo/homepage_ranaldo/research-material`

a positive premia in the cross-section of returns for assets that are more sensitive to market-wide liquidity risk (and for less liquid assets). In other words, a generalized increase in market liquidity risk forces investors to rebalance their portfolio towards *more liquid* and *less risky* assets (flight-to-quality and flight-to-liquidity), which, in turn, depresses the contemporaneous prices of less liquid and riskier assets. Under constant expectations about the future cash flows of such assets, a reduction in contemporaneous prices is associated with an increase in their future expected returns. In this way, a positive cross-sectional relationship emerges between systemic liquidity risk and *expected market returns*, which is consistent with a negative time-series relationship between *contemporaneous returns* and liquidity risk.

However, in Figure 3.1, it is evident that the aforementioned story does not always hold. Indeed, when we examine the effect of market-wide liquidity risk under different quantiles of the market return - as captured by the dash-dotted black line and the associated bootstrapping confidence intervals of the quantile regressions (grey-shaded area) - a contrasting landscape emerges. On the one hand, the negative and expected effect of illiquidity on market returns is higher under very bad market states (quantiles below the 20^{th} percentile). Not only is this effect higher, it is also statistically different from the linear effect, as witnessed by the fact that the shaded bootstrapped confidence intervals do not include the linear effect below the 30^{th} percentile of the market returns. This means that the liquidity risk effect on market returns (and, therefore, the liquidity premium) is underestimated by the cross-sectional and linear models traditionally employed when the market state is bad.

On the other hand, and more interestingly, this negative effect of market-wide illiquidity is reversed and even becomes positive and statistically different from zero for very high quantiles of the excess stock return distribution (above the 90^{th} percentile). This is at odds with the traditional line taken by the literature, because conditional on a good market state a generalized increase in systemic illiquidity is associated with higher market returns. Although this outcome might, at first glance, seem unexpected, it should be understood as a consequence of a general trend in portfolio rebalancing, observed in markets that experience a boom, towards more illiquid and risky assets. That is, in situations in which the market is experiencing considerable gains, investors usually use such newly generated excess funds to invest in riskier and less liquid assets with search-for-yield considerations

Figure 3.1: Systemic Liquidity Effects on Excess U.S. Stock Market Returns



Note: This figure shows the effect of systemic liquidity on monthly U.S. excess stock market returns from January 2000 to December 2016. The underlying model is: $r_{mt} - r_{ft} = \beta_1(\tau)^L Liq_t + \beta_2(\tau)(SMB)_t + \beta_3(\tau)(HML)_t + \varepsilon_t(\tau)$. The linear effect is indicated by the solid red line accompanied by two parallel dotted lines, representing the 95% confidence intervals of the regression. The effects of liquidity risk under different quantiles of the market return are captured by the dash-dotted black line accompanied by the associated bootstrapping confidence intervals of the quantile regression (gray-shaded area).

in mind. Investing in riskier and less liquid assets naturally increases contemporaneous market returns, because the returns generated by investing in less liquid assets exceed returns lost by disinvesting in liquid assets, which in turn leads to the emergence of a positive relationship between contemporaneous market returns and liquidity risk (conditional on a good market state). Finally, in the mid-range quantiles (between the 55^{th} and 90^{th} percentiles), the effect of market-wide liquidity risk on market returns is not statistically different from zero. Only between the 50^{th} and 60^{th} percentiles, it cannot be statistically distinguished from the traditional linear effect.

All in all, liquidity risk is not always a factor priced by the market, as a linear relationship usually indicates. Its impact on concurrent market returns is mostly negative (its impact on the excess market return distribution conditional of liquidity is asymmetric, with the effects of liquidity risk being higher on the negative tail of the returns), but sometimes these effects are positive, specifically at the end of the right tail of the distribution, when the market records unusually high gains. Hence, our main conclusion: liquidity only becomes a relevant factor for explaining asset returns under extreme market states (both good and bad), and the premia associated with liquidity-sensitive assets change from positive to negative as market conditions improve or, in other words, the concurrent correlation between returns and illiquidity is negative for bad market states and positive for very good ones.

In the following section, we support this nonlinear approach by analyzing different portfolio types, different industries and different sample periods. We include other more traditional factors that might explain market returns. All in the conclusions reached in this section are found to hold after controlling for such factors as size, value and momentum (Results not included here but available on request). We also seek to verify the nonlinear effect of liquidity risk on returns by means of various stability tests.

3.4.2 Value-growth Portfolios and Systemic Liquidity (2000-2016)

Our results for the 25 U.S. portfolios are reported in Figure 3.2. Panel A presents the liquidity betas of 25 portfolios, sorted according to size and book-to-market criteria, for different quantiles of the time-series distribution, $\tau = 0.10, ...0.90, 0.95$. The x-axis denotes the portfolio (from small-low to big-high portfolios) and the y-axis corresponds to the quantiles. Lower quantiles are associated with negative returns and, therefore, with bad market states (darker shades through to red), while higher quantiles are associated with positive returns and, therefore, with good market states (lighter shades through to yellow). Panel B presents a binary visualization of the associated t-statistics of the quantile regressions, where 1 - depicted in black - indicates whether the respective liquidity estimate made in the same coordinates of Panel A is statistically different from zero and 0 - depicted in white, indicates the contrary. The axes follow the same convention in both panels.

Figure 3.2 clearly shows the transition of the liquidity betas associated with the systemic liquidity factor across states (represented by different quantiles) and across portfolios and, at the same time, it indicates whether (and when) these effects are significant. We document a clear pattern across market states, but we are unable to extract a reliable pattern across portfolios. We find that systemic liquidity risk tends to produce an effect on portfolio returns, with estimates ranging from -1.3 to 2.6. The sign and significance of these effects clearly depend on the market state. On the one hand, the coefficients associated with the liquidity factor tend to be negative for bad market states and positive for good market states. This means that an increase in illiquidity when the market is experiencing losses hurts the portfolio performance and that an increase in illiquidity busts portfolio returns when the market is experiencing gains.

The effect of systemic liquidity risk on portfolio returns lying close to the median is, by general rule, statistically equal to zero. That is, around the median,

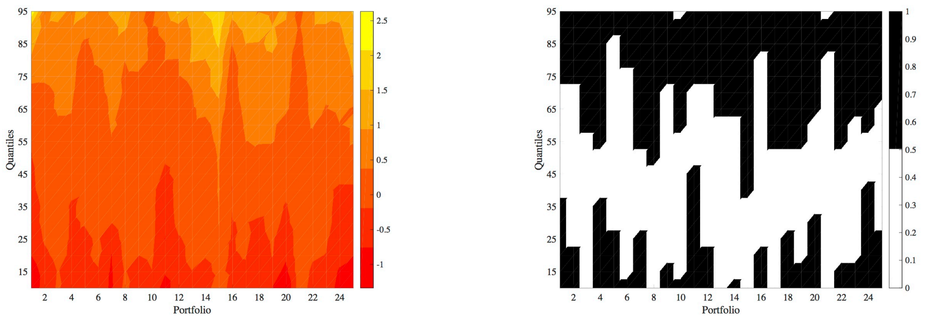
$\tau = (0.5)$, with the exception of two portfolios, we do not find significant liquidity betas, suggesting that the market does not price systemic liquidity risk in regular time, when neither extreme losses nor gains are experienced. This result is consistent, for instance, with the findings of Watanabe and Watanabe (2008), who show that during ordinary transaction months, the pricing of illiquidity in the market is quite flat across portfolios. This contrasts with what these authors document for high liquidity states, when liquidity risk premia are disproportionately large, amounting to more than twice the value premium.

In episodes of extreme market turmoil, when the markets are experiencing significant and recurring losses, market-wide liquidity falls dramatically. The negative spirals documented in the literature as emerging between funding liquidity and market-wide liquidity may lead traders to engage in fire sales or precautionary transactions, as they seek to avoid expected margin calls. This situation is, in turn, accompanied by an increase in preference uncertainty, market sentiment and, in general, a deterioration in future economic outlooks on the part of market participants. All these reasons are consistent with the previously literature and show an increasing appetite for safe and liquid assets (i.e. flights-to-quality and flight-to-liquidity). Moreover, they point to a contemporaneous reduction in market prices, following an increase in generalized market illiquidity. Such reductions are to be found in the left tail of the returns distribution, which correspond to its lowest quantiles. As can be observed in Figure 3.2, the lower the quantile, the higher is the negative impact of liquidity risk on the contemporaneous stock returns (regardless of the market portfolio analyzed).

The positive effects in the right tail of the return distribution implies that when the market state is good (in the sense that positive and large returns are recorded), traders perceived liquidity as a relevant factor to inform their decisions about portfolio composition. In other words, exposure to the market-wide liquidity of a certain asset is valuable information priced by the market, in accordance with expectations in the literature. This situation is expected in a search-for-yield scenario[12], in which investors start to rebalance their portfolios in a diametrically opposite way to the strategy they adopt during a bad market state. Thus, they rebalance towards riskier and less liquid assets, which can provide greater returns.

[12] Kiendrebeogo (2016) and Fratzscher et al. (2018) study this phenomenon in relation to excess liquidity produced by the quantitative easing policies after the Global Financial Crisis.

Figure 3.2: Systemic Liquidity Betas - 25 U.S. Portfolios (2000-2016)



(a) Panel A (b) Panel B

Note: Panel A shows the liquidity betas for $\tau = 0.1 - 0.95$, in 0.05 intervals, for all 25 value-weighted U.S. portfolios. Panel B presents the corresponding t-statistics of the liquidity betas. The black-shaded area is defined as being statistically significant at the 5% level whereas the white-shaded area corresponds to insignificant coefficients associated with the liquidity betas.

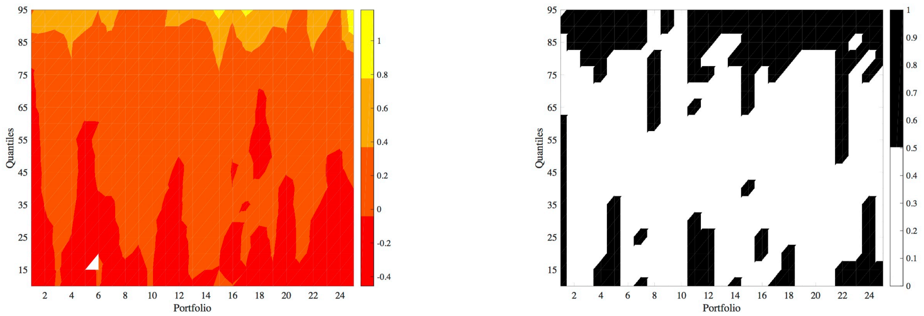
This is generally the case when market and funding liquidities are both perceived as sufficiently high and, therefore, traditional and safe assets yields unusually low gains, which traders aim to offset by resorting to less liquid and riskier assets. If market portfolios consist of these riskier and less liquid assets, returns naturally increase, as traditional compensation for risk demands, at the same time as market-wide liquidity falls. This explains the positive time-series pattern that we observed for the highest quantiles of the return distribution, which depicts a positive relationship between returns and systemic liquidity risk. (As for the European version of the 25 value-weighted portfolios, regressed on an European systemic liquidity risk estimate, we report similar results, but with a more pronounced positive effect, see Figure A7).

Our results show that for most of the quantiles - essentially between $\tau = (0.35)$ and $\tau = (0.75)$ - the effects of market-wide liquidity on excess returns are statistically equal to zero. Thus, we can conclude that market-wide liquidity is not priced by the market, above all when the market state is regular. This result challenges the traditional belief that commonality and market-wide liquidity risk are determinants of asset prices. On the contrary, it would seem that liquidity is not always relevant and it only matters when market realizations are abnormally high or low.

3.4.3 Value-growth Portfolios and Systemic Liquidity (1960-2016)

In this section, we enlarge the sample - January 1960 to December 2016 - to see whether the liquidity-augmented three-factor model is also able to explain systemic liquidity exposure of excess portfolio returns in the long run.[13]

Figure 3.3: Systemic Liquidity Betas - 25 U.S. Portfolios (1960-2016)



(a) Panel A (b) Panel B

Note: Panel A shows the liquidity betas for $\tau = 0.1 - 0.95$, in 0.05 intervals, for all 25 value-weighted U.S. portfolios for an enlarged sample period from January 1960 to December 2016. Panel B presents the corresponding t-statistics of the liquidity betas. The black-shaded area is defined as being statistically significant at the 5% level whereas the white-shaded area corresponds to insignificant coefficients associated with the liquidity betas.

Figure 3.3 shows the results of the enlarged analysis for 25 value-weighted U.S. portfolios for a comprehensive selection of quantiles. We find a similar pattern for the liquidity factor as in the previous section. Specially, in the lower quantile area, most portfolios are negatively exposed to systemic liquidity risk and statistically, however with fewer betas being statistically different from zero. We observe that this negative liquidity beta coefficient reaches almost the 55^{th} quantile for some portfolios. Reversely, we also find evidence for a positive systemic liquidity risk beta but with less statistical power than in the previous section. Thus, in light of the large time range that we consider in this section, it seems impressive that these results tend to be robust for a time horizon of 56 years.

[13] Although we have access to data on portfolio returns back to 1926 on the webpage of Kenneth French, we believe that major regime changes such as the global depression around 1930 or the introduction of Bretton Woods in 1944 can bias the pricing of our risk factor.

3.4.4 Industry Portfolios and Systemic Liquidity (2000-2016)

In this section, we examine the effect of systemic liquidity risk on industry-specific stock returns. We use the 30 U.S. industry portfolios, as commonly acknowledged by the literature, see Table 3.1. Figure 3.4 shows the liquidity betas and their corresponding t-statistics for each industry. The results show that some industries are more exposed to aggregate liquidity than others. For instance, with the exception of (3) Tobacco, (11) Construction, (13) Fabricated Products, (17) Mines and (27) Retail, all other industries display a negative sensitivity up to their 40^{th} quantile. Up to the 80^{th} quantile, the Steel Industry (12) shows an even more extreme negative sensitivity to market-wide liquidity risk.

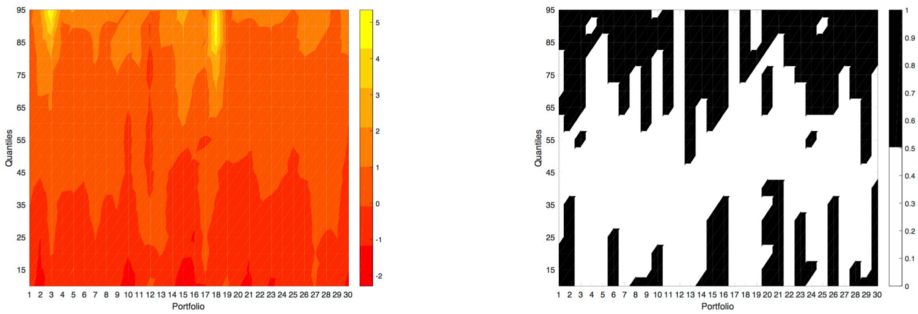
Table 3.1: Industry Portfolio Classification

Portfolio Nr.	Industry	Portfolio Nr.	Industry
1	Food	16	Aircraft, Ships
2	Beer	17	Mines
3	Tobacco	18	Coal
4	Games	19	Oil/Petroleum/Gas
5	Books	20	Utilities
6	Households	21	Telecommunication
7	Clothes	22	Personal/Business Services
8	Healthcare	23	Business Equipment
9	Chemicals	24	Paper/Business Supplies/Shipping Equip.
10	Textiles	25	Transportation
11	Construction	26	Wholesale
12	Steel	27	Retail
13	Fabricated Products	28	Gastronomy
14	Electrical Equipment	29	Finance
15	Automobiles	30	Other

Note: Stocks from NYSE, AMEX and NASDAQ are assigned to industry portfolios based on a four-digit SIC code. For a more detailed description of the industry definition, refer to Kenneth French - Data Library (n.d.). Link: `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

In contrast, the positive liquidity estimates show a similar magnitude as for the 25 portfolios, sorted by size and book-to-market value. Only (3) Tobacco and (18) the Coal Industry seem to fall outside of this range. However, for most industry portfolios, there is statistical significance only for the upper quantiles, i.e. $\tau = 0.65 - 0.95$, coinciding with a bullish market state. At the other end of the spectrum, the lower quantiles, corresponding to a bearish market state, excess portfolio returns of many industries do not seem to be statistically different from zero, i.e. (3) Tobacco, (4) Games, (5) Books, (7) Clothes, (11) Construction, (13) Fabricated Products, (17) Mines, (18) Coal and (25) Transportation. Similar to the 25 U.S. portfolios, sorted by size and book-to-market value, we observe that for the median case the aggregate liquidity risk betas seems to be non-significant across all industries.

Figure 3.4: Systemic Liquidity Betas - 30 U.S. Industry Portfolios



(a) Panel A (b) Panel B

Note: Panel A shows the liquidity betas for $\tau = 0.1 - 0.95$, in 0.05 intervals, for all 30 U.S. industry portfolios from January 2000 to December 2016. Panel B presents the corresponding t-statistics of the liquidity betas. The black-shaded area is defined as being statistically significant at the 5% level whereas the white-shaded area corresponds to insignificant coefficients associated with the liquidity betas.

3.4.5 Testing for Nonlinearity in the Relationship between Systemic Liquidity and Asset Pricing

In this section, we conduct an explanatory analysis of the stability of the parameters in Fama and French (1993)'s three-factor model augmented with a liquidity factor. The results are reported in Table 3.2. We estimate ten stability tests for each of the 25 U.S. portfolios from 2000 to 2016, its enlarged version with a sample running from 1960 to 2016 and finally for 30 U.S. industry portfolios, giving us 800 statistics and their respective critical values.

To facilitate the reporting of these results, Table 3.2 only records the mean, maximum, minimum and standard deviation values across all portfolios, for each set of statistics. More importantly, the table records the number of rejections of the null hypothesis, which in all cases correspond to the stability of the parameters. The

Table 3.2: Structural Change Test Statistics

25 U.S. Portfolios (2000-2016)					
Test	*Rec-Cusum*	*Ols-Cusum*	*Score-Cusum*	*Chow*	*Nyblom-Han.*
Mean	0.955	0.951	1.977	6.417	2.773
Std.Dev.	0.367	0.293	0.350	6.422	0.701
Min	0.366	0.471	1.188	0.707	1.232
Max	1.775	1.748	2.666	30.811	4.010
Null Rejections	11	2	23	19	23
	SupF	*AveF*	*ExpF*	*RE*	*ME*
Mean	60.344	29.114	26.742	2.060	1.624
Std.Dev.	39.361	20.523	19.484	0.636	0.288
Min	14.517	7.205	4.487	0.945	1.189
Max	171.30	92.122	82.24	3.350	2.486
Null Rejections	23	24	24	19	21
25 U.S. Portfolios (1960-2016)					
Test	*Rec-Cusum*	*Ols-Cusum*	*Score-Cusum*	*Chow*	*Nyblom-Han.*
Mean	0.743	1.578	1.934	6.296	2.669
Std.Dev.	0.185	0.407	0.312	3.110	0.847
Min	0.426	0.822	1.327	1.249	1.455
Max	1.119	2.248	2.708	14.21	4.715
Null Rejections	4	16	20	22	24
	SupF	*AveF*	*ExpF*	*RE*	*ME*
Mean	52.87	24.404	22.412	2.696	2.373
Std.Dev.	20.233	8.673	9.970	0.599	0.697
Min	25.658	11.088	9.107	1.892	1.442
Max	10.475	45.806	48.243	4.050	3.684
Null Rejections	25	25	25	24	25
30 U.S. Industry Portfolios (2000-2016)					
Test	*Rec-Cusum*	*Ols-Cusum*	*Score-Cusum*	*Chow*	*Nyblom-Han.*
Mean	0.667	0.846	1.763	4.033	2.454
Std.Dev.	0.245	0.325	0.369	1.790	0.693
Min	0.284	0.415	1.113	1.037	1.322
Max	1.214	1.819	2.697	7.032	4.122
Null Rejections	7	3	16	25	25
	SupF	*AveF*	*ExpF*	*RE*	*ME*
Mean	31.161	17.127	12.724	1.669	1.449
Std.Dev.	11.888	6.173	5.663	0.394	0.188
Min	11.649	5.801	3.497	0.782	1.069
Max	60.204	29.210	26.64	2.600	1.796
Null Rejections	27	28	28	16	22

Note: We use ten tests of structural change in order to identify any possible instabilities in the three-factor models. We use 25 value-weighted U.S. portfolios sorted by size and book-to-market value from (i) January 2000 to December 2016; (ii) January 1960 to December 2016 and (iii) 30 U.S. industry portfolios from January 2000 to December 2016. Rec-Cusum, Ols-Cusum and Score-Cusum are based on cumulative residuals of recursive, OLS and score estimates, respectively. RE and ME are based on recursive OLS estimates of the regression coefficients and moving OLS estimates, respectively, Chow and Nyblom-Hansen correspond to the statistics proposed by those authors. SupF, AveF and ExpF are tests of structural change based on F-statistics.

ten statistics employed included three based on the cumulative sum of the regression, the recursive regression residuals, and the scores of each regression parameter - that is, OLS-Cusum, Rec-Cusum, and Score-Cusum, respectively, and two constructed using recursive OLS estimates of the regression coefficients and moving OLS estimates - that is, RE and ME, respectively. The remaining five included tests developed by Nyblom (1989) and Hansen (1992); Hanson (2002), the recursive Chow (Chow (1960); Andrews and Ploberger (1994)) and three tests based on F-statistics: namely, SupF, AveF and ExpF. Procedures of this kind are well documented, for instance, in Zeileis (2005) or in the accompanying documentation of the 'strucchange' package in the statistical software R used to conduct the estimations (Zeileis (2006)).

As is evident, with the exception of two out of the three cusum-tests, in most instances the tests indicate the presence of unstable coefficients, with the number of null rejections, most of the time, above 20 (out of 25 portfolios). We find very similar results for the enlarged sample period of the 25 value-weighted U.S. portfolios, the 30 U.S. industry portfolios and the 25 value-weighted European portfolios (see Appendix A15). Summarizing, we conclude from this section that a non-linear behavior continues to characterize the parameters in the three-factor model, which justifies the use of quantile regressions.

3.5 Conclusion

We have reported the asymmetric effects in the pricing of systemic liquidity risk after controlling for a number of well-documented risk factors, including market beta, size and book-to-market value. Using a conditional quantile regression approach, we match tail events in the return distribution directly to the definition and the assessment of up and down market states.

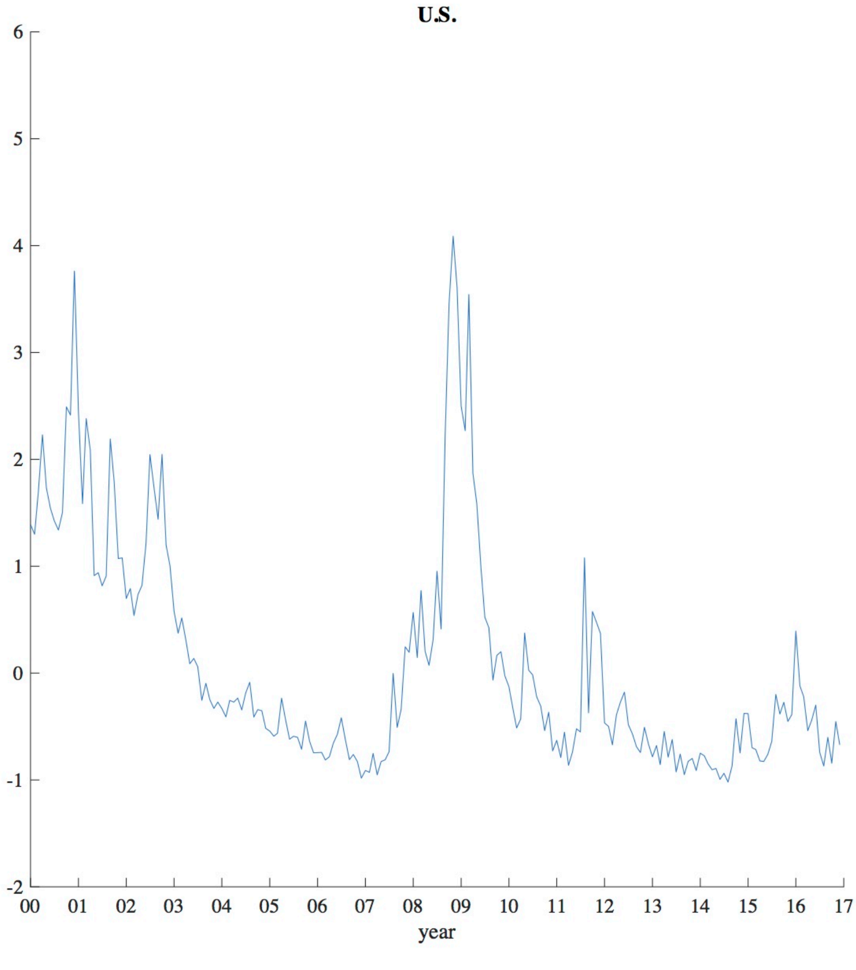
For most portfolios, we find that the effects of liquidity risk on excess returns exhibits a nonlinear pattern. In markets experiencing gains, we show that contemporaneous returns are positively associated with systemic liquidity risk. That is, market participants care about appropriate compensations for any illiquid position in the market that they are willing to buy. In contrast, we observe that in bearish markets systemic liquidity risk is negatively associated with returns, which, in line with the previous literature, translates into higher expected returns for illiquid assets. This can be explained by investor's shifting risk preferences and uncertainty about the variability and timing of illiquidity events, resulting in downward effects on asset prices.

During regular times, the market rarely prices liquidity risk. This shows that investors are less concerned about illiquidity in untroubled market states, corresponding to returns around the median. We also find that none of the portfolios, sorted by size and book-to-market value, exhibit any size effect, neither during up, down or normal market swings. Our robustness checks provide similar evidence across an extended sample period (from 1960 to 2016), in a different portfolio formation (30 U.S. industries) and regional setting (European portfolios).

These results have clear implications for portfolio risk management, as extreme economic events can suddenly alter the sensitivity of asset prices to aggregate liquidity risk. Likewise, our findings should be of interest to policy makers and regulators that seek to evaluate market scenarios in which a shortage of market-wide liquidity can be seen as a starting point for financial distress.

3.6 Appendix

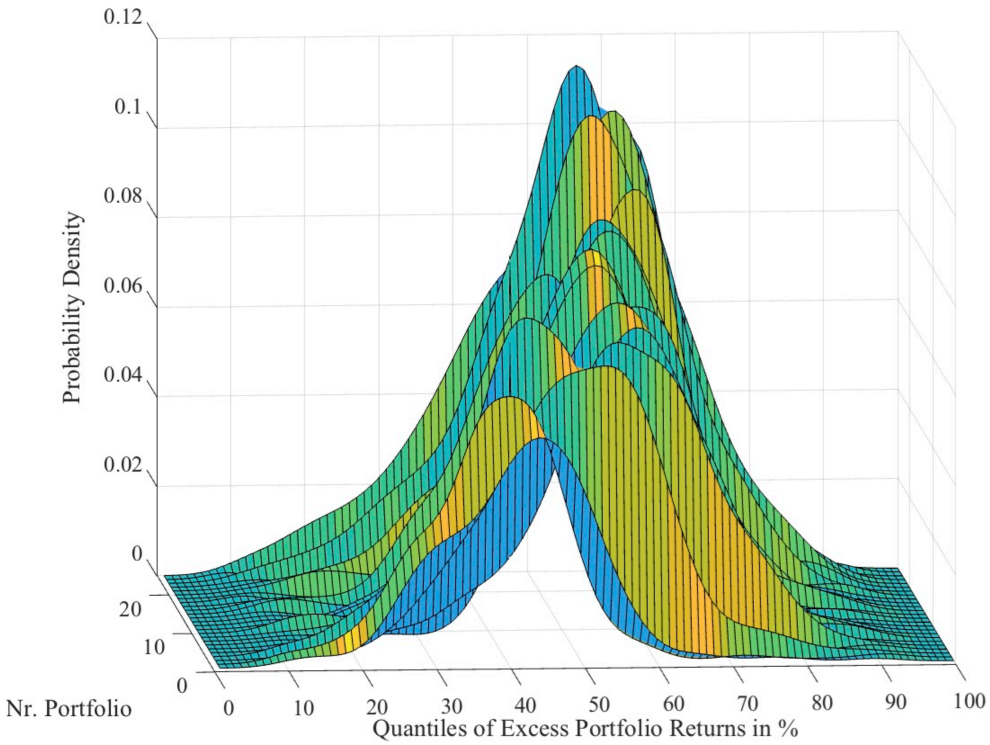
Figure A1: Systemic Liquidity Risk Estimate - U.S. Stock Market



Note: This plot represents the standardized systemic liquidity risk measure as proposed by Abdi and Ranaldo (2017). The raw measure can be found on Ranaldo's webpage - Link: `https://sbf.unisg.ch/en/lehrstuehle/lehrstuhl_ranaldo/homepage_ranaldo/research-material`

A U.S. Portfolios (Supplementary Analysis)

Figure A2: Density Function of 25 U.S. Excess Portfolio Returns



Note: This figure shows the density function of the 25 U.S. excess portfolio returns, sorted after size and book-to-market value, from January 2000 to December 2016. The x-axis denotes the number of each portfolio whereas the z-axis shows the quantile of excess returns (i.e. $15th$ quantile refers to tail losses whereas upper quantiles in the range between 80-90 (in %) match tail gains in the return distribution. Median returns coincide with the $50th$ quantile on this scale).

Table A3: Descriptive Statistics: Excess Returns on 25 U.S. Portfolios

Size Quintile	Book-to-Market (BE/ME) Quintiles									
	Low	2	3	4	High	Low	2	3	4	High
	Mean					Standard Deviation				
Small	0.07	0.79	0.78	1.09	1.10	8.60	7.49	6.00	5.89	6.14
2	0.44	0.87	0.96	0.91	0.92	7.24	5.91	5.50	5.54	6.68
3	0.37	0.87	0.89	0.99	1.14	6.67	5.31	5.18	5.30	6.17
4	0.57	0.83	0.74	0.93	0.70	6.06	4.98	5.31	5.15	6.36
Big	0.24	0.52	0.63	0.29	0.52	4.30	4.19	4.27	5.37	6.56
	Variance					Skewness				
Small	74.09	56.10	36.01	34.74	37.72	0.40	0.48	-0.004	0.07	-0.47
2	52.55	35.01	30.27	30.73	44.63	-0.14	-0.34	-0.29	-0.52	-0.61
3	44.61	28.27	26.88	28.11	38.16	-0.37	-0.22	-0.23	-0.27	-0.44
4	36.80	24.81	28.27	26.57	40.45	-0.18	-0.48	-0.68	-0.65	-0.55
Big	18.52	17.58	18.30	28.89	43.14	-0.45	-0.40	-0.41	-1.09	-0.20
	Kurtosis					Jarque Bera				
Small	5.21	6.88	3.68	4.35	3.80	47.12***	136.63***	4.03*	15.74***	13.08***
2	3.83	4.27	3.61	4.10	4.23	6.69**	17.93***	6.16**	19.85***	25.70***
3	4.16	3.98	3.62	4.23	4.16	16.22***	9.99**	5.12*	15.52***	18.29***
4	4.98	4.65	5.87	4.93	4.47	34.56***	31.29***	86.54***	46.33***	28.99***
Big	3.59	3.99	3.75	7.28	3.65	10.12***	13.80***	10.71***	196.91***	5.03*
	Min					Max				
Small	-24.06	-20.37	-18.97	-15.77	-21.78	38.51	40.62	21.43	24.97	17.43
2	-22.61	-23.58	-18.69	-19.65	-21.71	27.74	17.08	16.34	16.24	19.00
3	-23.62	-18.35	-17.55	-20.00	-20.57	24.17	18.17	17.16	16.23	17.38
4	-20.06	-20.48	-25.23	-22.48	-21.95	25.79	15.85	16.87	14.36	16.95
Big	-14.47	-15.58	-13.16	-27.09	-17.22	10.18	10.99	12.63	15.62	23.61

Note: This table reports the summary statistics of excess returns of 25 value-weighted U.S. portfolios, sorted after size and book-to-market value. The sample period ranges from January 2000 to December 2016. *** indicates statistical significance at the 1%, ** at the 5% and * at the 10% level.

Table A4: Results - Excess Returns on 25 U.S. Portfolios - (2000-2016)

Size Quintile	Book-to-Market (BE/ME) Quintiles									
	Low	2	3	4	High	Low	2	3	4	High
10*th* Quantile			β^L					$t(\beta^L)$		
Small	-1.28***	-0.48***	-0.15	-0.38***	-0.66***	-5.46	-3.32	-1.02	-3.22	-4.76
2	-0.45***	-0.85***	-0.05	-0.48***	-0.37***	-3.23	-6.67	-0.45	-3.33	-2.70
3	-0.98***	-0.44**	-0.22	-0.48**	0.12	-7.03	-2.19	-1.41	-2.38	0.52
4	-0.40***	-0.32*	-0.62***	-0.76***	-1.33***	-2.96	-1.92	-2.79	-4.70	-9.97
Big	0.08	-0.37***	-0.64***	-0.83***	-1.13***	1.07	-2.93	-3.85	-5.65	-3.89
25*th* Quantile			β^L					$t(\beta^L)$		
Small	-0.66***	-0.14	0.08	-0.26**	-0.27**	-3.35	-0.96	0.67	-2.15	-2.29
2	-0.14	-0.50***	-0.003	-0.12	-0.02	-0.93	-3.77	-0.02	-0.89	-0.20
3	-0.77***	-0.26*	-0.03	-0.10	0.27	-5.75	-1.82	-0.22	-0.55	1.35
4	-0.23*	-0.10	-0.39**	-0.12	-0.57***	-1.91	-0.72	-2.09	-0.74	-3.38
Big	0.08	-0.04	-0.12	-0.57***	-0.58***	1.10	-0.41	-0.93	-3.90	-2.82
50*th* Quantile			β^L					$t(\beta^L)$		
Small	-0.22	-0.07	0.25*	0.11	-0.16	-0.97	0.41	1.86	0.86	-1.32
2	-0.13	0.22*	0.25**	0.07	0.10	-0.80	1.66	1.96	0.66	0.81
3	-0.13	-0.04	0.23	0.05	0.39**	-0.92	-0.33	1.50	0.34	2.09
4	-0.14	0.26*	0.17	0.09	0.06	-1.03	1.71	0.99	0.53	0.30
Big	0.10	0.08	0.03	0.18	0.16	1.32	0.75	0.22	1.16	0.66
75*th* Quantile			β^L					$t(\beta^L)$		
Small	0.46**	0.43**	0.51***	0.54***	0.02	2.02	2.49	4.25	4.06	0.19
2	0.17	0.63***	0.29***	0.30**	0.35**	1.02	5.03	2.59	2.53	2.53
3	0.34**	0.35**	0.47***	0.69***	1.29***	1.98	2.21	3.21	4.49	6.46
4	-0.01	0.84***	0.76***	0.66***	0.58***	-0.11	5.01	5.18	3.76	2.76
Big	0.03	0.58***	0.54***	0.42***	0.90***	0.47	5.87	4.39	3.35	3.77
90*th* Quantile			β^L					$t(\beta^L)$		
Small	1.33***	0.82***	0.86***	0.89***	0.70***	4.60	4.07	7.91	6.74	4.45
2	0.59***	0.81***	1.03***	0.47***	0.31***	3.49	6.20	6.37	3.41	2.18
3	0.41**	0.76***	0.96***	1.18***	1.72***	2.50	4.25	4.61	6.94	9.22
4	0.76***	1.09***	1.39***	0.95***	0.81***	3.95	7.03	7.45	6.13	3.01
Big	0.30***	0.82***	0.80***	0.85***	1.31***	3.67	7.21	6.59	6.41	5.15

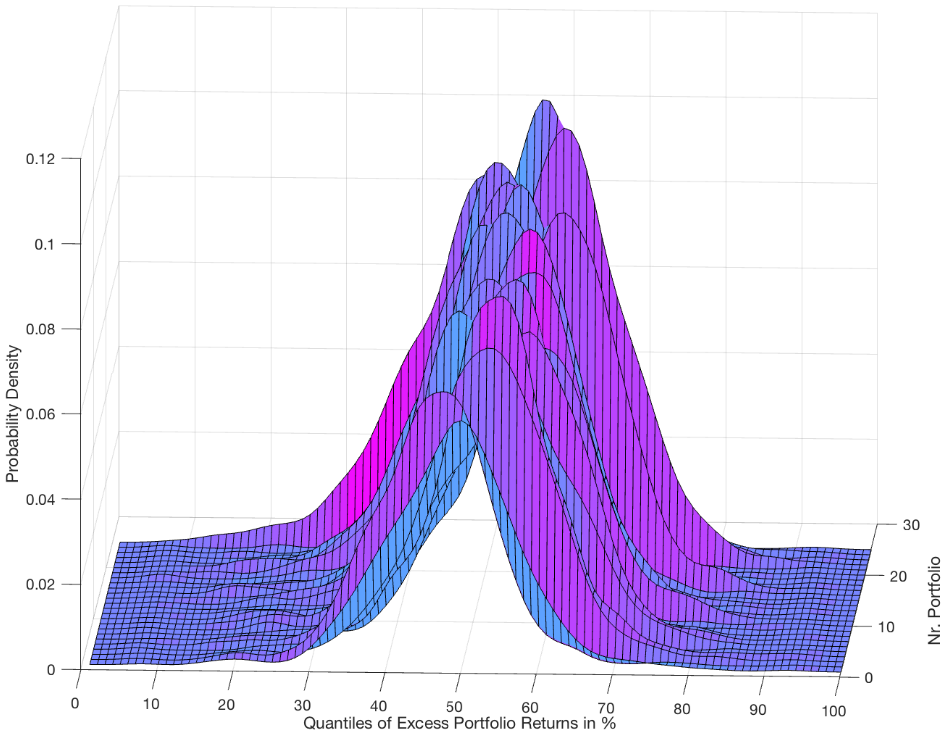
Note: The table shows the liquidity estimates for each of the 25 value-weighted U.S. portfolio returns, sorted according to size and book-to-market quintiles. The sample runs from January 2000 to December 2016. The first five columns show the respective liquidity betas for each portfolio in the size and book-to-market value quintile intersections. The last five columns show the associated t-statistics for each coefficient. Each section reports the estimates for a particular quantile of the excess portfolio returns in an ascending order. *** indicates statistical significance at the 1%, ** at the 5% and * at the 10% level.

Table A5: *PseudoR*^{2} - Excess Returns on 25 U.S. Portfolios - (2000-2016)

Size Quintile	Book-to-Market (BE/ME) Quintiles									
	Low	2	3	4	High	Low	2	3	4	High
25*th* Quantile	*PseudoR*^{2}					50*th* Quantile *PseudoR*^{2}				
Small	0.70	0.76	0.78	0.77	0.78	0.68	0.73	0.76	0.74	0.76
2	0.75	0.74	0.73	0.76	0.79	0.74	0.73	0.73	0.76	0.78
3	0.78	0.70	0.69	0.66	0.66	0.76	0.69	0.67	0.64	0.64
4	0.77	0.67	0.62	0.63	0.64	0.75	0.64	0.60	0.61	0.60
Big	0.84	0.71	0.65	0.67	0.60	0.81	0.69	0.61	0.63	0.57
75*th* Quantile	*PseudoR*^{2}					90*th* Quantile *PseudoR*^{2}				
Small	0.64	0.70	0.76	0.73	0.74	0.65	0.71	0.78	0.74	0.73
2	0.74	0.73	0.72	0.74	0.76	0.75	0.73	0.72	0.76	0.77
3	0.74	0.67	0.65	0.64	0.65	0.75	0.67	0.65	0.66	0.67
4	0.72	0.63	0.61	0.62	0.61	0.72	0.63	0.63	0.65	0.63
Big	0.81	0.70	0.60	0.64	0.58	0.79	0.71	0.63	0.65	0.62

Note: This table presents the pseudo R^2 estimates for the liquidity-augmented three-factor model for a selection of quantiles for each of the 25 value-weighted U.S. portfolios, sorted according to size and book-to-market quintiles. The sample period ranges from January 2000 to December 2016.

Figure A3: Density Function of 25 U.S. Excess Portfolio Returns (1960 - 2016)



Note: This figure shows the density function of the 25 U.S. excess portfolio returns, sorted after size and book-to-market value, from January 1960 to December 2016. The x-axis denotes the number of each portfolio whereas the z-axis shows the quantile of excess returns (i.e. $15th$ quantile refers to tail losses whereas upper quantiles in the range between 80-90 (in %) match tail gains in the return distribution. Median returns coincide with the $50th$ quantile on this scale).

Table A6: Descriptive Statistics: Excess Returns on 25 U.S. Portfolios (1960-2016)

Size Quintile	Book-to-Market (BE/ME) Quintiles									
	Low	2	3	4	High	Low	2	3	4	High
			Mean					Standard Deviation		
Small	0.25	0.74	0.75	0.99	1.08	7.91	6.86	5.93	5.64	5.96
2	0.42	0.73	0.84	0.93	0.98	7.12	5.95	5.38	5.21	6.00
3	0.47	0.77	0.71	0.87	0.98	6.56	5.38	4.96	4.91	5.60
4	0.57	0.59	0.69	0.84	0.81	5.85	5.05	4.92	4.78	5.65
Big	0.45	0.51	0.57	0.48	0.67	4.62	4.39	4.25	4.59	5.33
			Variance					Skewness		
Small	62.66	47.15	35.19	31.91	35.54	-0.01	0.04	-0.21	-0.11	-0.19
2	50.76	35.47	28.97	27.24	36.00	-0.33	-0.44	-0.46	-0.36	-0.38
3	43.08	28.97	24.69	24.11	31.36	-0.36	-0.52	-0.45	-0.28	-0.29
4	34.33	25.59	24.29	22.86	31.92	-0.25	-0.55	-0.50	-0.22	-0.30
Big	21.43	19.35	18.07	21.09	28.42	-0.25	-0.37	-0.28	-0.50	-0.20
			Kurtosis					Jarque Bera		
Small	5.09	6.16	5.29	5.93	6.20	124.66***	286.53***	155.43***	247.08***	297.34***
2	4.42	5.32	5.74	5.65	5.74	70.96***	176.74***	238.67***	216.26***	231.08***
3	4.42	5.72	5.05	5.20	5.80	73.51***	241.74***	143.50***	147.4***	234.55***
4	4.78	5.80	6.04	4.98	5.24	98.26***	258.44***	293.85***	118.79***	153.76***
Big	4.56	4.75	5.06	6.36	4.26	76.86***	103.47***	131.35***	351.13***	50.09***
			Min					Max		
Small	-34.81	-31.54	-29.36	-29.49	-29.46	38.51	40.62	27.58	27.26	33.29
2	-33.32	-32.25	-29.00	-25.63	-29.43	27.74	25.54	25.75	27.00	29.13
3	-30.32	-29.65	-24.93	-23.63	-26.71	24.17	24.38	21.35	22.82	28.62
4	-26.54	-29.42	-25.55	-22.48	-24.44	25.79	19.86	23.43	23.78	27.31
Big	-22.23	-23.02	-22.30	-27.09	-19.59	21.82	16.11	18.12	19.18	23.61

Note: This table reports the summary statistics of excess returns of 25 value-weighted U.S. portfolios, sorted after size and book-to-market value. The sample period ranges from January 1960 to December 2016. *** indicates statistical significance at the 1%, ** at the 5% and * at the 10% level.

Table A7: Results - Excess Returns on 25 U.S. Portfolios - (1960-2016)

Size Quintile	Book-to-Market (BE/ME) Quintiles Low	2	3	4	High	Low	2	3	4	High
$10th$ Quantile			β^L					$t(\beta^L)$		
Small	-0.40***	-0.18	-0.003	-0.21***	-0.30***	-2.79	-1.63	-0.04	-2.79	-3.98
2	-0.01	-0.24***	-0.15*	-0.10	-0.01	-0.12	-2.93	-1.76	-1.40	-0.19
3	-0.34***	-0.32***	-0.09	-0.17**	0.03	-3.80	-3.55	-1.17	-1.96	0.34
4	-0.03	-0.29***	-0.40***	-0.09	-0.07	-0.48	-3.03	-3.73	-0.94	-0.59
Big	-0.10*	-0.24***	-0.19**	-0.44***	-0.45***	-1.69	-2.71	-2.07	-4.51	-3.10
$25th$ Quantile			β^L					$t(\beta^L)$		
Small	-0.43***	-0.12	0.005	-0.04	-0.19***	-3.82	-1.49	0.08	-0.68	-2.94
2	-0.05	-0.13**	0.01	-0.02	0.03	-0.62	-2.03	0.23	-0.43	0.56
3	-0.22***	-0.15**	0.03	0.05	0.02	-2.76	-2.09	0.55	0.70	0.27
4	-0.13**	0.003	-0.13*	0.006	-0.18*	-1.98	0.04	-1.69	0.08	-1.81
Big	-0.001	-0.06	-0.08	-0.18**	-0.09	-0.02	-0.87	-1.02	-2.25	-0.82
$50th$ Quantile			β^L					$t(\beta^L)$		
Small	-0.33***	0.06	-0.01	0.02	-0.11*	-3.02	0.73	-0.18	0.35	-1.81
2	-0.02	0.03	0.04	0.01	-0.02	-0.31	0.59	0.75	0.19	-0.40
3	0.04	-0.04	0.03	0.005	0.14*	0.55	-0.59	0.43	0.07	1.78
4	-0.03	-0.02	-0.08	-0.04	0.04	-0.46	-0.28	-1.1	-0.55	0.45
Big	0.06	0.15**	-0.04	-0.07	0.08	1.14	2.40	-0.56	-1.04	0.76
$75th$ Quantile			β^L					$t(\beta^L)$		
Small	-0.09	0.16*	0.10	0.23***	0.08	-0.81	1.94	1.48	3.14	1.29
2	0.07	0.09	0.18***	0.08	0.04	0.86	1.27	2.76	1.29	0.60
3	0.19**	0.16**	0.04	0.11*	0.34***	2.30	1.99	0.63	1.75	3.82
4	0.12	0.25***	0.09	0.11	0.15	1.62	3.12	1.10	1.22	1.48
Big	0.06	0.21***	0.12	0.15**	0.22*	1.14	3.27	1.60	2.13	1.91
$90th$ Quantile			β^L					$t(\beta^L)$		
Small	0.45***	0.47***	0.41***	0.46***	0.48***	2.81	4.03	4.75	5.25	5.65
2	0.26**	0.43***	0.07	0.21***	0.12	2.57	4.15	0.81	2.67	1.40
3	0.36***	0.36***	0.26***	0.31***	0.65***	3.90	3.80	2.67	3.08	5.59
4	0.32***	0.64***	0.55***	0.37***	0.39***	3.32	5.68	4.94	3.29	3.17
Big	0.16**	0.52***	0.36***	0.23***	1.05***	2.30	6.44	3.49	2.71	7.37

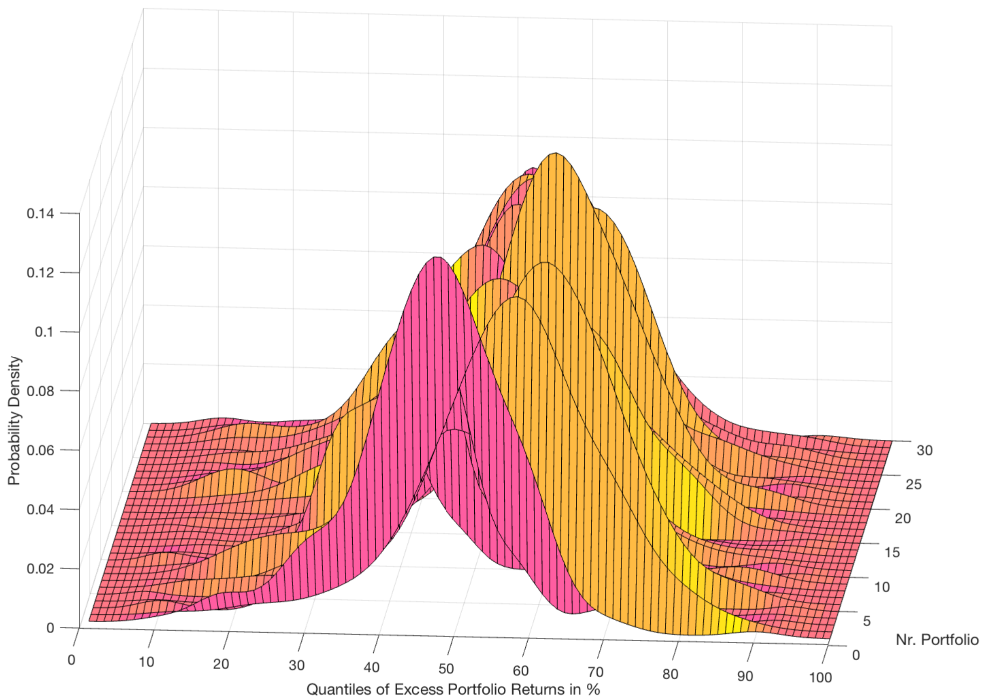
Note: The table shows the liquidity estimates for each of the 25 value-weighted U.S. portfolio returns, sorted according to size and book-to-market quintiles. The sample runs from January 1960 to December 2016. The first five columns show the respective liquidity betas for each portfolio in the size and book-to-market value quintile intersections. The last five columns show the associated t-statistics for each coefficient. Each section reports the estimates for a particular quantile of the excess portfolio returns in an ascending order. *** indicates statistical significance at the 1%, ** at the 5% and * at the 10% level.

Table A8: *PseudoR*^{2} - Excess Returns on 25 U.S. Portfolios - (1960-2016)

Size Quintile	Book-to-Market (BE/ME) Quintiles										
	Low	2	3	4	High		Low	2	3	4	High
25*th* Quantile	*PseudoR*^{2}					50*th* Quantile	*PseudoR*^{2}				
Small	0.70	0.75	0.77	0.77	0.78		0.69	0.74	0.76	0.75	0.76
2	0.77	0.77	0.75	0.77	0.78		0.76	0.76	0.74	0.76	0.77
3	0.77	0.71	0.70	0.70	0.69		0.77	0.71	0.69	0.69	0.67
4	0.76	0.69	0.67	0.66	0.64		0.75	0.67	0.66	0.65	0.62
Big	0.76	0.70	0.62	0.66	0.58		0.75	0.69	0.61	0.65	0.57
75*th* Quantile	*PseudoR*^{2}					90*th* Quantile	*PseudoR*^{2}				
Small	0.66	0.72	0.75	0.74	0.75		0.65	0.72	0.75	0.75	0.75
2	0.76	0.74	0.73	0.74	0.75		0.75	0.73	0.72	0.74	0.75
3	0.76	0.69	0.68	0.69	0.66		0.77	0.69	0.66	0.66	0.65
4	0.73	0.65	0.64	0.63	0.61		0.72	0.64	0.62	0.64	0.62
Big	0.75	0.68	0.60	0.65	0.56		0.74	0.68	0.60	0.66	0.56

Note: This table presents the pseudo R^2 estimates for the liquidity-augmented three-factor model for a selection of quantiles for each of the 25 value-weighted U.S. portfolios, sorted according to size and book-to-market quintiles. The sample period ranges from January 1960 to December 2016.

Figure A4: Density Function of 30 U.S. Industry Excess Portfolio Returns



Note: This figure shows the density function of the 30 U.S. industry excess portfolio returns, sorted after size and book-to-market value, from January 2000 to December 2016. The x-axis denotes the number of each portfolio whereas the z-axis shows the quantile of excess returns (i.e. $15th$ quantile refers to tail losses whereas upper quantiles in the range between 80-90 (in %) match tail gains in the return distribution. Median returns coincide with the $50th$ quantile on this scale).

Table A9: Descriptive Statistics: Excess Returns on 30 U.S. Industry Portfolios

Nr. Industry	Mean						Standard Deviation					
1-6	0.71	0.62	1.61	0.85	0.12	0.39	3.60	4.04	6.50	7.53	6.15	3.94
7-12	0.96	0.54	0.74	1.01	0.66	0.34	6.27	3.99	6.12	9.02	6.54	9.30
13-18	0.83	0.47	0.35	0.88	0.77	0.98	7.15	6.60	8.56	6.13	8.22	13.98
19-24	0.73	0.71	0.12	0.23	0.26	0.61	5.86	4.23	5.41	6.35	8.09	5.10
25-30	0.76	0.63	0.50	0.86	0.47	0.28	5.23	4.81	4.75	4.64	5.74	5.60
	Variance						Skewness					
1-6	13.02	16.35	42.37	56.72	37.88	15.53	-0.28	-0.50	0.12	-0.27	0.41	-0.77
7-12	39.35	15.95	37.54	81.52	42.79	86.60	0.08	-0.39	-0.12	1.04	-0.32	-0.34
13-18	51.24	43.67	73.44	37.67	67.70	195.67	-0.43	-0.30	0.54	-0.73	-0.49	-0.01
19-24	34.39	17.91	29.29	40.37	65.56	26.08	-0.10	-0.72	-0.22	-0.33	-0.47	-0.16
25-30	27.44	23.17	22.59	21.54	32.95	31.45	-0.22	-0.50	-0.22	-0.40	-0.49	-0.46
	Kurtosis						Jarque-Bera					
1-6	4.45	4.26	6.87	5.78	7.84	4.85	20.82***	22.14***	128.05***	68.53***	205.50***	49.85***
7-12	4.85	3.26	4.43	12.95	5.15	4.01	29.54***	6.03**	18.10***	878.71***	43.04***	12.82***
13-18	4.83	4.13	8.99	4.52	4.21	3.33	35.19***	14.11***	315.55***	37.97***	20.81***	0.98
19-24	3.35	3.95	4.30	3.91	4.83	4.71	1.40	25.83***	16.17***	10.98**	36.55***	25.82***
25-30	3.65	4.81	3.88	3.66	4.79	5.24	5.47**	36.65***	8.33**	9.41**	35.59***	50.15***
	Min						Max					
1-6	-11.08	-14.76	-22.18	-29.83	-26.56	-14.73	15.15	11.37	32.38	34.52	33.13	10.26
7-12	-21.68	-11.03	-21.03	-28.51	-28.30	-32.99	24.59	11.12	19.05	59.03	23.30	26.24
13-18	-30.02	-24.67	-36.49	-24.42	-34.55	-38.09	22.91	23.21	49.56	17.14	20.06	43.54
19-24	-16.95	-12.66	-16.44	-19.83	-32.07	-18.53	18.97	11.22	21.22	18.59	24.66	21.00
25-30	-16.09	-21.13	-14.94	-13.52	-20.90	-21.32	15.28	15.21	13.89	15.51	17.05	19.76

Note: This table reports the summary statistics of excess returns of 30 U.S. industry portfolios. The sample period ranges from January 2000 to December 2016. Industry classifications associated with these numbers can be found in Table 3.1. *** indicates statistical significance at the 1%, ** at the 5% and * at the 10% level.

Table A10: Results - Excess Returns on 30 U.S. Industry Portfolios

Nr. Industry	β^L						$t(\beta^L)$					
$10th$ Quantile												
1-6	-0.83***	-1.55***	-0.59	-0.17	-0.25	-0.74**	-2.79	-4.36	-0.83	-0.39	-0.80	2.19
7-12	-0.52	-0.85***	-0.68**	-2.28***	-0.54	0.05	-1.60	-3.01	-2.54	-3.59	-1.42	0.11
13-18	-0.44	-0.96***	-1.77***	-1.41***	-1.22	-0.42	-1.64	-2.90	-3.24	-3.54	-1.32	-0.30
19-24	0.09	-1.09**	-1.52***	-0.27	-1.54***	-0.36	0.20	-2.10	-5.69	-1.19	-6.01	-0.71
25-30	-0.24	-0.64**	-0.01	-1.01***	-0.34**	-1.47***	-0.84	-2.00	-0.05	-2.87	-2.34	-5.36
$25th$ Quantile												
1-6	-0.25	-1.18***	0.12	-0.53	-0.15	-0.72**	-0.95	-3.65	0.23	-1.47	-0.58	-2.48
7-12	-0.08	-0.46	-0.13	-0.77	-0.12	0.007	-0.22	-1.57	-0.47	-1.59	-0.35	0.01
13-18	0.06	-0.17	-0.84**	-1.27***	0.08	-0.99	0.20	-0.61	-2.13	-3.97	0.12	-0.85
19-24	-0.68*	-0.71**	-1.01***	-0.27	-0.66***	-0.25	-1.66	-2.01	-4.17	-1.32	-2.59	-1.12
25-30	-0.25	-0.67***	0.13	-0.23	-0.09	-0.96***	-0.79	-3.35	0.49	-0.77	-0.50	-3.64
$50th$ Quantile												
1-6	0.20	0.07	0.59	0.20	0.14	0.22	0.84	0.24	1.30	0.54	0.51	0.83
7-12	0.41	0.16	0.33	-0.27	0.21	-0.40	1.08	0.64	1.19	-0.54	0.66	-0.82
13-18	0.72**	0.19	-0.28	-0.05	0.08	0.52	2.30	0.67	-0.63	-0.17	0.12	0.45
19-24	0.03	0.23	-0.18	0.11	0.45	0.15	0.08	0.74	-0.73	0.57	1.53	0.68
25-30	-0.20	-0.03	0.04	0.12	0.41**	-0.24	-0.65	-0.16	0.17	0.47	2.11	-0.85
$75th$ Quantile												
1-6	0.39*	1.21***	1.07***	0.63	0.10	0.58***	1.85	4.54	2.69	1.36	0.32	2.97
7-12	0.84**	0.32	0.96***	0.21	0.76***	-0.45	2.09	1.18	3.28	0.39	2.60	-0.85
13-18	0.76**	0.57**	1.84***	1.10***	0.65	2.62**	2.44	2.10	4.56	3.77	0.98	2.36
19-24	0.65	0.58**	0.31	0.27	0.65**	0.81***	1.51	2.26	1.20	1.22	2.32	3.61
25-30	0.75**	0.74***	0.37	0.48**	0.51**	0.56*	2.57	3.80	1.52	2.03	2.33	1.83
$90th$ Quantile												
1-6	0.67**	1.52***	4.07***	0.73	1.05***	1.07***	2.45	6.06	11.52	1.56	2.66	5.68
7-12	1.32***	0.81***	0.90**	1.54***	1.23	-0.25	2.58	2.78	2.19	2.19	3.58	-0.45
13-18	1.23***	1.53***	2.10***	1.45***	1.12	4.83***	3.69	4.24	3.77	5.93	1.48	3.57
19-24	0.55	0.91***	0.81***	1.01***	1.02**	0.74***	1.17	3.12	2.95	3.48	2.51	2.97
25-30	0.51*	1.61***	1.67***	1.22***	0.43*	1.86***	1.83	6.66	6.31	3.46	1.98	6.21

Note: The table shows the liquidity estimates for each of the 30 U.S. industry excess portfolio returns. The sample runs from January 2000 to December 2016. The first five columns show the respective liquidity betas for each portfolio. The last five columns show the associated t-statistics for each coefficient. Each section reports the estimates for a particular quantile of the excess portfolio returns in an ascending order. Industry classifications associated with these numbers can be found in Table 3.1. *** indicates statistical significance at the 1%, ** at the 5% and * at the 10% level.

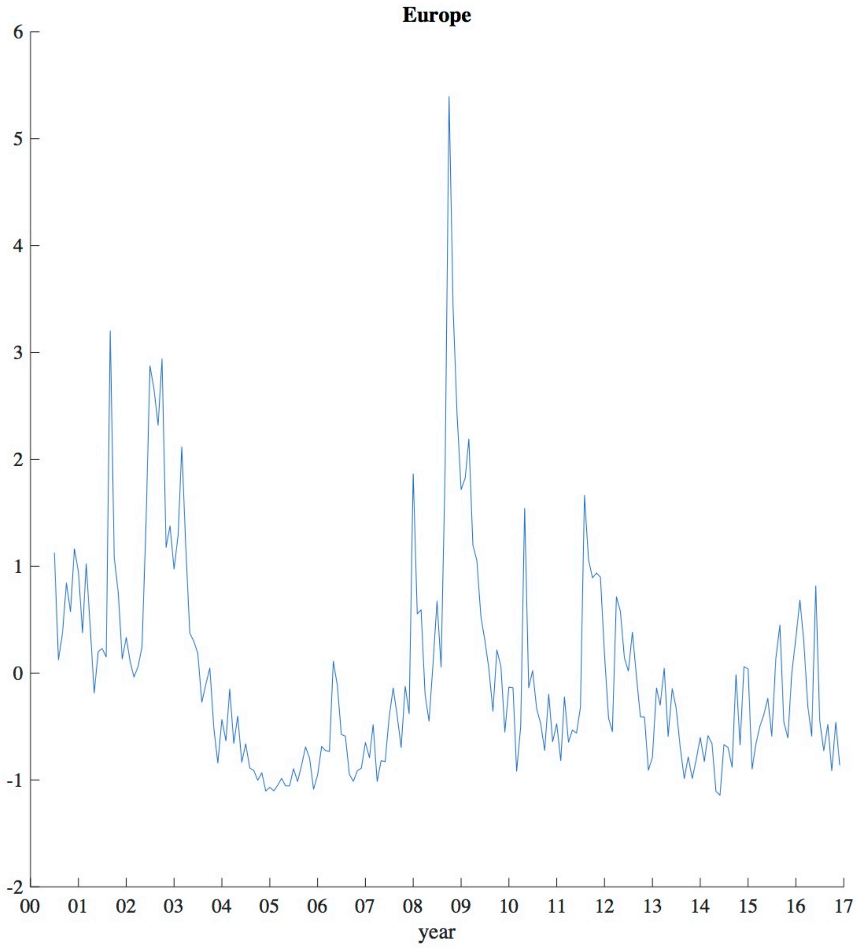
Table A11: *PseudoR*^{2} - Excess Returns on 30 U.S. Industry Portfolios

Nr. Industry													
25*th* Quantile			*PseudoR*^{2}				50*th* Quantile			*PseudoR*^{2}			
1-6	0.27	0.17	0.14	0.47	0.48	0.25		0.23	0.13	0.13	0.41	0.44	0.23
7-12	0.33	0.33	0.48	0.33	0.47	0.47		0.30	0.28	0.46	0.30	0.46	0.44
13-18	0.55	0.54	0.40	0.42	0.14	0.14		0.51	0.51	0.38	0.40	0.14	0.12
19-24	0.27	0.20	0.52	0.68	0.59	0.49		0.24	0.12	0.48	0.64	0.56	0.46
25-30	0.41	0.50	0.39	0.35	0.63	0.43		0.38	0.50	0.39	0.34	0.61	0.38
75*th* Quantile			*PseudoR*^{2}				90*th* Quantile			*PseudoR*^{2}			
1-6	0.23	0.15	0.09	0.38	0.43	0.24		0.21	0.18	0.16	0.40	0.43	0.26
7-12	0.31	0.23	0.45	0.30	0.49	0.44		0.39	0.21	0.49	0.37	0.53	0.47
13-18	0.51	0.51	0.38	0.39	0.17	0.12		0.54	0.52	0.43	0.40	0.19	0.16
19-24	0.23	0.12	0.46	0.60	0.55	0.45		0.24	0.13	0.46	0.62	0.57	0.48
25-30	0.40	0.48	0.38	0.34	0.60	0.37		0.47	0.48	0.39	0.32	0.63	0.42

Note: This table presents the pseudo R^2 estimates for the liquidity-augmented three-factor model for a selection of quantiles for each of the 30 U.S. industry portfolios. The sample period ranges from January 2000 to December 2016. Industry classifications associated with these numbers can be found in Table 3.1.

B European Portfolios (Supplementary Analysis)

Figure A5: Systemic Liquidity Risk Estimate - European Stock Market



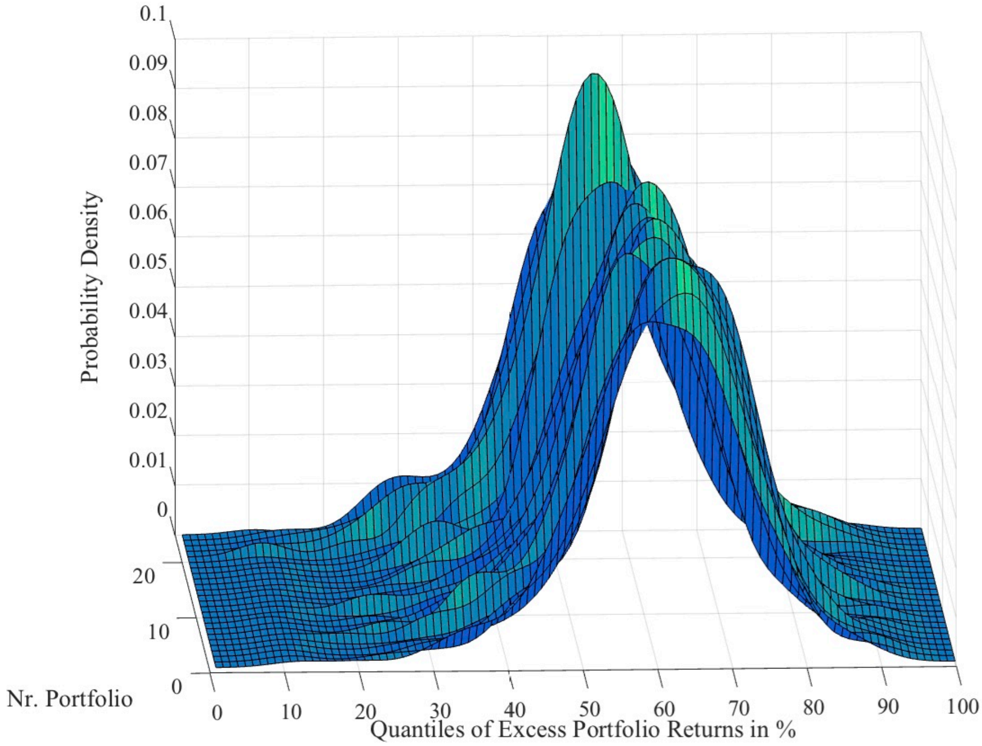
Note: This plot represents the European version of the systemic liquidity risk measure as proposed by Abdi and Ranaldo (2017). The estimate has been constructed on basis of the spreads of the constituents of the EuroStoxx50 stock market index. Instead of gross-return weighting, we equally-weight the spreads of all constituents. The estimate has been standardized for the comparison to the three factors in terms of magnitude.

Table A12: Systemic Liquidity Measure - European Stock Market

Stocks	Registered in	Stocks cont.	Registered in
Air Liquide SA	France	Nokia Oyj	Finland
Airbus Group SE	France	Orange SA	France
Allianz SE	Germany	Philips NV	Netherlands
Anheuser Busch in Bev SA	Belgium	Safran SA	France
ASML Holding NV	Netherlands	Saint Gobain SA	France
Assicurazioni Generali SpA	Italy	Sanofi SA	France
AXA SE	France	Santander SA	Spain
BASF SE	Germany	SAP SE	Germany
Bayer AG	Germany	Schneider Electrics SE	France
BBVA SA	Spain	Siemens AG	Germany
BMW AG	Germany	Societe¨ General Group SA	Spain
BNP Paribas SA	France	Telefonica SA	Spain
Carrefour SA	France	Unibail-Rodamco SE	France
Daimler AG	Germany	Unicredit SpA	Italy
Danone SA	France	Unilever NV	Netherlands
Deutsche Bank AG	Germany	Vinci SA	France
Deutsche Boerse AG	Germany	Vivendi SA	France
Deutsche Telekom AG	Germany	VW AG	Germany
Enel SpA	Italy		
Engie SA	France		
EON SE	Germany		
Essilor International SA	France		
Fresenius SE & Co.KGaA	France		
Iberdrola SA	Spain		
Inditex SA	Spain		
ING Groep NV	Netherlands		
Intesa Sanpaolo SpA	Italy		
L'Oreal SA	France		
LVMH SE	France		
Muenchner Rueck AG	Germany		

Note: We follow the methodology by Abdi and Ranaldo (2017) to construct a systemic liquidity risk measure for European stock markets, but with an equally-weighted aggregation of stock-specific spreads. We focus on the EuroStoxx50 stock market index as our representation of market liquidity in European stock markets. This index is comprised of the 50 largest and most liquid stocks in the European Monetary Union (EMU). This table represents the constituents of the index at the time of the creation our liquidity risk measure (2017).

Figure A6: Density function of 25 European Excess Portfolio Returns



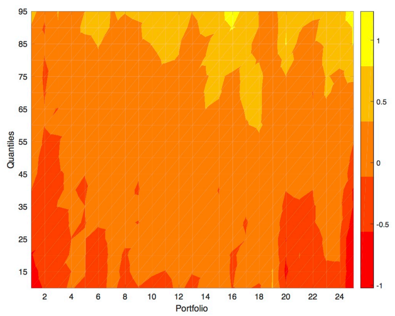
Note: This figure shows the probability density function of the 25 European excess portfolio returns, sorted by (i) and (ii) book-to-market value, from July 2000 to December 2016. The x-axis denotes the number of each portfolio (25 in total) whereas the z-axis shows the quantile of excess returns (i.e. 15^{th} quantile refers to tail losses whereas upper quantiles in the range between 80-90(%) match tail gains in the return distribution. Median returns coincide with the 50^{th} quantile on this scale).

Table A13: Descriptive Statistics: Excess Returns on 25 European Portfolios

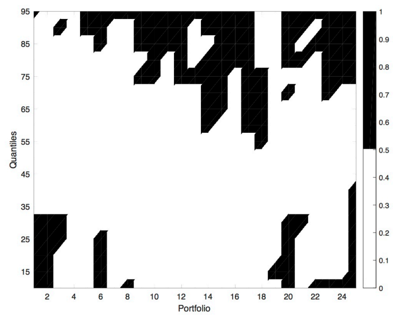
Size Quintile	Book-to-Market (BE/ME) Quintiles									
	Low	2	3	4	High	Low	2	3	4	High
			Mean					St.Dev		
Small	-0.51	0.05	0.28	0.48	0.69	5.97	5.76	5.49	5.43	5.34
2	0.05	0.40	0.53	0.72	0.80	6.24	5.98	5.67	5.72	5.95
3	0.10	0.44	0.59	0.62	0.74	6.48	5.92	5.74	5.85	6.22
4	0.32	0.47	0.57	0.60	0.51	6.01	5.55	5.60	5.92	6.54
Big	-0.05	0.27	0.19	0.33	0.24	5.25	5.11	5.72	6.09	7.14
			Variance					Skewness		
Small	35.70	33.23	30.15	29.57	28.58	-0.59	-0.80	-0.84	-0.91	-0.87
2	39.05	35.87	32.15	32.72	35.49	-0.84	-0.62	-0.72	-0.91	-0.62
3	42.01	35.06	33.00	34.25	38.75	-0.93	-0.82	-0.73	-0.71	-0.64
4	36.12	30.87	31.43	35.14	42.88	-0.67	-0.75	-0.45	-0.71	-0.47
Big	27.59	26.12	32.72	37.09	50.99	-0.55	-0.38	-0.35	-0.35	-0.34
			Kurtosis					Jarque Bera		
Small	4.45	5.27	6.05	5.92	5.99	29.21***	64.38***	100.46***	98.03***	98.79***
2	5.23	5.16	5.39	6.64	4.98	64.96***	51.61***	64.66***	137.00***	45.45***
3	5.12	5.61	5.62	5.46	4.59	66.23***	79.02***	74.61***	66.70***	34.85***
4	4.67	5.52	4.87	4.86	4.89	38.10***	71.01***	35.62***	45.19***	37.20***
Big	5.27	3.69	3.91	3.64	4.85	52.90***	8.94**	10.93**	7.64**	32.37***
			Min					Max		
Small	-25.00	-26.36	-26.71	-26.12	-26.29	14.18	14.85	15.04	14.73	14.33
2	-26.89	-25.80	-25.48	-27.75	-26.65	16.39	18.17	17.69	16.96	16.98
3	-27.39	-27.41	-26.55	-26.48	-26.64	16.78	14.87	17.78	16.10	17.73
4	-26.11	-25.60	-23.36	-25.41	-27.67	16.28	16.44	17.83	17.64	22.80
Big	-20.65	-17.56	-19.44	-19.65	-30.81	17.33	13.64	14.99	16.05	24.44

Note: This table reports the summary statistics of excess returns of 25 value-weighted European portfolios, sorted according to size and book-to-market value, over a time range from July 2000 to December 2016. *** indicates statistical significance at the 1%, ** at the 5% and * at the 10% level.

Figure A7: Systemic Liquidity Betas - 25 European Portfolios (2000-2016)



(a) Panel A



(b) Panel B

Note: Panel A shows the liquidity betas for $\tau = 0.1 - 0.95$ in 0.05 intervals, for all 25 value-weighted European portfolios. Panel B presents the corresponding t-statistics of the liquidity betas. The black-shaded area is defined as being statistically significant at the 5% level whereas the white-shaded area corresponds to insignificant coefficients associated of the liquidity factor.

Table A14: Results - Excess Returns on 25 European Portfolios

Size Quintile	Book-to-Market (BE/ME) Quintiles									
	Low	2	3	4	High	Low	2	3	4	High
$10th$ Quantile										
			β^L					$t(\beta^L)$		
Small	-0.66***	-0.55***	-0.16	-0.09	-0.17	-4.35	-3.77	-1.30	-0.76	-1.29
2	-0.36***	0.02	-0.31***	-0.12	-0.23	-2.90	0.20	-2.78	-0.85	-1.59
3	-0.28	-0.005	-0.24	0.05	0.19	-1.58	-0.03	-1.42	0.29	1.24
4	-0.13	-0.04	-0.19	0.34*	-0.48***	-0.77	-0.25	-1.30	-1.91	-2.60
Big	-0.19	-0.38***	-0.26**	-0.27**	-0.91***	-1.36	-2.64	-2.33	-2.08	-5.79
$25th$ Quantile										
			β^L					$t(\beta^L)$		
Small	-0.35**	-0.48***	-0.30**	-0.12	-0.09	-2.38	-3.19	-2.28	-1.22	-0.82
2	-0.32**	0.05	-0.06	-0.06	-0.04	-2.37	0.39	-0.66	-0.50	-0.33
3	0.08	0.23*	0.01	0.02	0.04	0.47	1.77	0.07	0.15	0.28
4	0.04	-0.09	0.01	0.21	-0.55***	0.35	-0.72	0.13	1.54	-3.66
Big	-0.21*	-0.27*	-0.06	-0.09	-1.02***	-1.94	-1.94	-0.57	-0.70	-5.94
$50th$ Quantile										
			β^L					$t(\beta^L)$		
Small	0.006	-0.20	-0.12	-0.05	-0.02	0.04	-1.47	-1.11	-0.48	-0.22
2	0.03	0.12	0.08	0.06	0.09	0.22	1.06	0.82	0.61	0.96
3	0.15	0.08	0.14	0.13	0.05	0.86	0.62	1.05	1.08	0.35
4	0.19	0.16	0.23	0.23*	-0.03	1.34	1.29	1.64	1.81	-0.19
Big	0.03	-0.08	0.12	0.09	-0.17	0.25	-0.67	1.09	0.70	-0.98
$75th$ Quantile										
			β^L					$t(\beta^L)$		
Small	0.16	-0.15	-0.01	-0.04	-0.03	0.97	-1.08	-0.12	-0.41	-0.31
2	0.20	0.08	0.05	0.17**	0.20**	1.29	0.69	0.55	2.12	2.10
3	0.17	0.32**	0.29**	0.30**	0.41***	1.02	2.30	1.97	2.50	2.81
4	0.24	0.39***	0.43***	0.11	0.32	1.59	3.00	2.81	0.83	1.88
Big	0.20*	0.08	0.34***	0.28**	0.41**	1.78	0.66	2.65	2.13	2.27
$90th$ Quantile										
			β^L					$t(\beta^L)$		
Small	0.30	-0.15	0.29**	0.002	0.48***	1.39	-1.03	2.06	0.02	3.78
2	0.55***	0.29*	0.16	0.24**	0.62***	3.12	1.88	1.11	2.12	4.31
3	0.64***	0.60***	0.20	0.45***	0.39**	3.38	3.87	1.51	3.28	2.24
4	0.81***	0.66***	0.32	0.01	0.73***	5.31	4.47	1.45	0.11	3.32
Big	0.41***	0.11	0.67***	0.52***	0.80***	2.92	0.74	4.43	2.82	3.82

Note: This table presents the coefficient estimates for the systemic liquidity factor for each of the 25 value-weighted European portfolios, sorted according to size and book-to-market quintiles. The sample period ranges from July 2000 to December 2016. The first five columns show the respective liquidity betas for each portfolio in the size and book-to-market value quintile intersections. The last five columns show the associated t-statistics for each coefficient. Each section reports the estimates for a particular quantile of the excess portfolio returns in an ascending order. *** indicates statistical significance at the 1%, ** at the 5% and * at the 10% level.

Table A15: Structural Change Test Statistics - 25 European Portfolios

25 European Portfolios (2000-2016)					
Test	*Rec-Cusum*	*Ols-Cusum*	*Score-Cusum*	*Chow*	*Nyblom-Han.*
Mean	0.698	0.916	1.709	4.269	2.280
Std.Dev.	0.275	0.308	0.316	2.453	0.807
Min	0.279	0.419	1.105	0.689	1.058
Max	1.496	1.496	2.282	12.217	4.178
Null Rejections	3	2	15	18	20
	SupF	*AveF*	*ExpF*	*RE*	*ME*
Mean	34.084	18.718	14.052	1.877	1.393
Std.Dev.	15.671	9.534	7.745	0.4540	0.228
Min	11.705	5.987	3.630	1.072	0.962
Max	76.386	46.708	34.70	2.960	1.814
Null Rejections	22	21	22	19	13

Note: We used ten tests of structural change in order to identify any possible instabilities in the three-factor models. We used 25 value-weighted European portfolios, sorted by size and book-to-market value. Our sample for these estimations runs from July 2000 to December 2016. Rec-Cusum, Ols-Cusum and Score-Cusum are based on cumulative residuals of recursive, OLS and score estimates, respectively. RE and ME are based on recursive OLS estimates of the regression coefficients and moving OLS estimates, respectively, Chow and Nyblom-Hansen correspond to the statistics proposed by those authors. SupF, AveF and ExpF are tests of structural change based on F-statistics.

Table A16: $PseudoR^2$ - Excess Returns on 25 European Portfolios

Size Quintile	Book-to-Market (BE/ME) Quintiles									
	Low	2	3	4	High	Low	2	3	4	High
$25th$ Quantile			$PseudoR^2$			$50th$ Quantile		$PseudoR^2$		
Small	0.74	0.76	0.79	0.82	0.82	0.72	0.76	0.79	0.80	0.81
2	0.79	0.82	0.83	0.82	0.83	0.76	0.81	0.82	0.81	0.83
3	0.77	0.79	0.79	0.78	0.79	0.74	0.77	0.76	0.78	0.77
4	0.79	0.80	0.77	0.79	0.79	0.76	0.77	0.75	0.78	0.76
Big	0.78	0.77	0.81	0.80	0.75	0.75	0.76	0.80	0.79	0.74
$75th$ Quantile			$PseudoR^2$			$90th$ Quantile		$PseudoR^2$		
Small	0.71	0.75	0.77	0.78	0.78	0.70	0.74	0.76	0.77	0.79
2	0.75	0.80	0.81	0.81	0.82	0.75	0.81	0.81	0.80	0.81
3	0.73	0.76	0.74	0.79	0.77	0.73	0.77	0.76	0.80	0.77
4	0.73	0.75	0.74	0.77	0.75	0.72	0.75	0.74	0.78	0.77
Big	0.74	0.76	0.79	0.78	0.75	0.72	0.76	0.80	0.77	0.75

Note: This table presents the pseudo R^2 estimates for the liquidity-augmented three-factor model for a selection of quantiles for each of the 25 value-weighted European portfolios, sorted according to size and book-to-market quintiles. The sample period ranges from July 2000 to December 2016.

4 Liquidity and Trading Activity of Energy Stocks

[1]

This study examines liquidity and trading activity for 154 energy stocks listed at U.S. stock exchanges, grouped into five energy segments, between January 2006 and December 2018. Using daily TAQ data, we study average *effective spreads*, *price impact of trades*, *number of trade executions* and *share volume*. We document that liquidity and trading is volatile, trended and serial dependent for each sectoral measure. Liquidity and trading activity display a strong commonality effect in the exposure to general market movements, including concurrent returns, momentum and stock market volatility. A widening term spread increases liquidity and trading across most energy segments, indicating potential clearance sales in times of financial distress. The oil price has a heterogenous effect on liquidity and trading, dependent on the energy segment, while oil price volatility predominately increases illiquidity in energy stocks. This study is useful for portfolio diversification strategies and regulatory interventions in energy markets.

[1] This paper is co-authored with Jorge M. Uribe.

4.1 Introduction

We study daily liquidity and trading characteristics of 154 energy stocks traded at U.S. stock exchanges, grouped into five energy segments. We show that liquidity and trading activity display trends and common spikes across all energy stock segments. We document that average spreads for stocks from firms operating in the primary energy exploration (oil and gas, coal mining and renewables) have higher average spreads than stocks of utility firms which generate electricity from oil and gas products. We also identify factors that drive liquidity and trading activity for energy stocks, that is concurrent market movements, recent market momentum, default spreads and stock market volatility. We herein document a strong commonality effect in the exposure to these factors. We find that negative concurrent market movements and negative market momentum trends increase liquidity (smaller spreads) and decrease trading across most energy stock segments. Similarly, and consistent with the previous literature, we find an increase in illiquidity across segments in times of higher stock market volatility. Crude oil prices have a heterogeneous effect on liquidity and trading but tend to decrease spreads and discourage trading for renewable and utility stocks. On the contrary, and higher in magnitude, spreads for oil and gas and coal mining stocks increase on average with higher oil prices. We also document higher illiquidity associated with oil price volatility, indicating that expectations related to the crude oil price matter for daily liquidity and trading of energy stocks. We find a strong day-of-the-week effect, that is, a decrease in liquidity and trading on Fridays. Finally, we show that trading of renewable and multi-utility stocks increases when climate-change related concerns get media attention.

Liquidity is a market microstructure element, important for all financial markets. It is commonly referred to how easy large volume positions on financial assets can be entered and exited without generating substantial price movements. Market liquidity has recently received more attention in the literature due to liquidity dry-ups, as during the global financial crisis or the recent COVID-19 outbreak. Yet, very little is known about liquidity and trading of energy stocks - The energy literature lacks a comprehensive analysis of the sources that drive daily variation in liquidity and trading for energy stocks. In-depth knowledge about market microstructure characteristics in energy market is important for several reasons: First, energy constitutes a core element of economic production and infrastructure and acts as significant contributor to the growth of the economy, (Stern (2010), Hamilton (2008)). Second, the discussion on the optimal future energy generation mix around the world, fundamental to current production economies and for financial markets in the light of the effects of climate change on such markets, NGFS (2019), is in great need of a more comprehensive analysis of market microstructure elements that help investors to compare between stocks, issued by firms in durable energy explorations (i.e. oil and gas and coal mining) or electricity generation; (electric- and multi-utilities), to finally provide a more accurate assessment of portfolio risks and potential prospects in those markets. Third, research has not questioned the importance of oil prices and its variability on the effect of liquidity and trading of energy stocks, other than on the oil and gas stock segment. Hence, a sectoral, cross-sectional study on liquidity and trading patterns for energy stocks beyond the oil and gas industry can benefit regulators and policy makers in energy-related fields or investors, who seek a better understanding of similarities and potential differences in liquidity and trading of the cross-section of energy stocks and its drivers in regards of (energy) portfolio diversification.

To explore liquidity and trading activity across stocks from various energy industries, we use aggregated TAQ (trades and automated quotes) data to construct daily time-series liquidity and trading activity averages for 154 energy stocks listed at U.S. stock exchanges, segmented into the following industries: *oil and gas*; *coal mining*; *renewables*; *electric-utilities* and *multi-utilities*. We examine a number of liquidity and trading activity characteristics such as *DollarEffectiveSpread*, *DollarPriceImpact*, *Number of Trades* and *Share Volume* on a day-to-day basis. To provide a profound reasoning on what causes daily movements in liquidity and trading pattern, we build upon the empirical framework provided by Chordia et al. (2001). Controlling for debt- and equity-market based factors, we are able to distinguish the effects of concurrent market swings, volatility, short-run momentum effects from financial stress indicators. Finally, the inclusion of daily dummy variables allows us to control for day-of-the-week effects, due to weekly cycles of liquidity and trading which is important to day traders and market makers when adopting in fast markets.

In comparison to the vast literature on liquidity, its commonality component across asset classes and its potential dry-ups during times of financial stress, research on liquidity and trading activity for energy stocks specifically has received very limited attention. The only recent study that discusses various market liquidity measures for energy stocks, namely bid-ask spreads, turnover, and price impact, is the study by Sklavos et al. (2013). Examining 130 oil and gas stocks listed at the NYSE, the authors find that stocks with higher trading intensity are less sensitive to liquidity changes. Further, they document that price impact of trades affect spreads with higher magnitude in illiquid than in normal periods, coinciding with the recent global financial crisis. Other studies focus more on the price formation and volatility of oil and gas stocks,(see Pindyck (2003) and Sadorsky (2001)), respectively. None of these studies include stocks from firms that operate in the coal mining, renewable energy or utility sectors which jointly account for approximately one-third of the energy consumption in the U.S.[2] Hence, comparisons between investments in renewable and nonrenewable energy sectors, as crucial as they are due to increasing climate-change concerns, and the consequent regulatory emphasis across U.S. markets in this aspect, are totally overlooked by the extant literature. We aim to fill this gap in the literature.

Suggested by a more general literature on the determinants of liquidity, focusing on the commonality aspect in a cross-sectional as well as time-series setting, co-movement in liquidity across stocks is induced by correlated trading behavior, which puts pressure on the market maker's inventories, see Chordia et al. (2000), Hasbrouck and Seppi (2001). This effect is then amplified with institutional ownership, i.e. mutual fund ownership and index trading, Kamara et al. (2008), Koch et al. (2016). The supply-side explanation of commonality in liquidity suggests that funding tightness restricts the supply of capital to traders who leverage their positions in the market and hence reduce their positions among many asset classes. This downward trending liquidity spiral between funding liquidity, provided by financial intermediaries, and the actual level of liquidity in the respective market(s) has been theoretically modelled by Brunnermeier and Pedersen (2009) and further empirical supported by Hameed et al. (2010).

The inclusion of the oil price as potential determinant for liquidity and trading activity of energy stock seems plausible as the oil price is regarded as a global economic indicator, signalling industrial production activity levels and demand for energy which subsequently affect energy stocks. Oil price dynamics and stock market returns have been examined by a number of studies (Sadorsky (1999); Kil-

[2] *EIA* - Monthly Energy Review (2019). Retrieved from `https://www.eia.gov/energyexplained/us-energy-facts/`

ian and Park (2009); Oberndorfer; Sadorsky (2009, 2012); Kumar et al. (2012); Cunado and de Gracia (2014); Diaz et al. (2016); Luo and Qin (2017); Ferrer et al. (2018); Dutta (2018) among many others). Yet, the literature on oil price dynamics and market liquidity is scarce. Sklavos et al. (2013) is the first to find that an increase in the WTI (West Texas Intermediate) crude oil price causes a reduction in volume traded and lower spreads for oil and gas stocks listed at the NYSE. They argue that higher oil prices discourage trading and favor energy firms, so indirectly reduce spreads. Zheng and Su (2017) examine the link between the oil price and stock market liquidity in China. They show that the relationship again depends on the source of the oil price shock. Besides these two studies, there is no further documentation on oil price dynamics and oil price volatility in conjunction with liquidity and trading activity.

This paper contributes to the existing literature in several ways: First, we conduct a systemic examination of liquidity and trading activity for energy stocks, which has not been done so far in sufficient depth. Second, we extent studies on oil prices and oil price volatility and the impact on energy stocks, not on returns, but for market microstructure characteristics such as liquidity and trading activity. Third, we add energy stocks to the observation space as we break down our sample into five different energy segments.

Moreover, this study makes a first attempt to model climate-change based investor sentiment and its impact on daily liquidity and trading activity for energy stocks. The importance of climate change has been communicated through global media over decades. However, there is no research that documents how investors react to the debate about climate change and how (energy) markets might move accordingly on a daily basis. From a theoretical perspective, the link between investor sentiment and market liquidity is worth addressing: De Long et al. (1990a,b) refer to investor sentiment as noise or irrational traders who force asset prices to deviate from its fundamental value, resulting in higher expected returns and redundant volatility. Baker and Stein (2004) argue that during short-sales constraints, unusually high liquidity is induced through the domination of those irrational investors who overvalue assets and hence supply an extra portion of liquidity to the market.

Finally, on a more general level, the study of daily-quoted liquidity and trading activity indicators needs re-assessment of its time-series properties (here for energy stocks) as the automation and speed of trade execution has dramatically increased post the 2000s, due to algorithmic and high frequency trading, (see Jovanovic and Menkveld (2016), Hendershott and Moulton (2011), Hendershott et al. (2011), Jain (2005)). The implication of the increase in frequency is particularly visible when looking at TAQ data which clearly indicates that bid-ask spreads and trading activity have steadily declined and increased, respectively, since the initial recording of TAQ data in 1993. For instance, average monthly share turnover for the NYSE has experienced an increase from 5% in 1993 to about 26% in 2008, while the daily number of trades increased by the ninety-fold on average, Chordia et al. (2011).

The remainder of this paper is organized as follows: In Section 4.2, we describe the selection of energy stocks and elaborate further on the use of TAQ data. Section 4.3 describes the summary statistics and dynamics of liquidity and trading activity. In Section 4.4, we present our time-series regression results for liquidity and trading activity measures on a set of explanatory variables. Finally, Section 4.5 concludes.

4.2 Data

4.2.1 Selection of Stocks

We construct daily sectoral time-series averages of liquidity and trading activity measures on basis of energy stocks listed at the NYSE, AMEX (now NYSEAmerican) and the NASDAQ stock exchanges.[3] We use 88 oil and gas stocks; 13 stocks issued by firms belonging to the coal mining industry; 15 stocks issued by renewable energy firms and 16 and 22 stocks from the electric-utility and multi-utility industry, respectively, to create sectoral averages of liquidity and trading activity. The industry segmentation of energy stocks is motivated by the S&P Global Platts Top 250 Global Energy Ranking which ranks publicly traded energy and utility firms based on asset worth, revenue, profit and returns on invested capital.[4] Using this ranking as a first benchmark, we filtered the CRSP (Center for Security Prices) database after stocks which match the SIC classification codes for the pre-defined energy industries and categorised them into the five sectors, as mentioned above.

[3] Although most stock classifications distinguish between energy and utility stocks, we use the term "energy stock" as an umbrella term for energy and utility stocks.

[4] S&P Global Platts - Top250 Global Energy Company Ranking (n.d.). Retrieved from `https://top250.platts.com`.

The selection and segmentation of energy stocks is an extremely difficult task to perform, due to the various interpretations of energy sources. The *EIA - U.S. Energy Information Administration*[5] distinguishes between nonrenewable energy and renewable energy sources. The first covers energy originating from coal mining, natural gas, nuclear or oil production while the latter defines energy use from biodiesel, biomass, ethanol, geothermic, hydropower, solar and wind. Now, as natural gas is often a side-product of the oil exploration process, it is difficult to disentangle the two, as many publicly listed firms operate in both fields. In addition, the *EIA* classifies electricity as secondary energy source which uses primary energy sources (i.e. coal or gas) as input to generate electricity as final energy product. Moreover, nuclear energy, categorised as nonrenewable energy source by the *EIA*, is used to provide electricity, which in turn is defined as secondary energy source. Hence, we combine these two sources into one energy segment of electric-utilities: SIC Code - 4911. This seems plausible as the SIC classification system does not provide a separate code for nuclear energy. Similarly, there are firms that use various sources for energy generation, i.e. multi-utilities. Hence, we consider firms of the following two SIC codes as multi-utilities: *4931 - Electric & Other Services Combined* and *4932 - Gas & Other Services Combined.* The construction of liquidity and trading averages for the renewable energy segment required a more comprehensive selection procedure. Following the decomposition of renewable energy sources by the *EIA*[6], we scanned the CRSP dataset based on SIC codes and matched single firms which specialize in the *EIA* pre-defined renewable energy sub-sectors. A detailed description on which SIC codes are used for which energy sector is provided in Appendix A18.

To be included in the sample, a firm's stock has to meet further criteria: (1) it has to be a common stock - due to different trading and liquidity characteristics, we exclude Real Estate Investment Trusts (REITs), Depositary Receipts (DRs), closed-end or mutual funds, preferred stock and over-the-counter (OTC) securities from our sample; (2) the stock must be listed at the Center for Research in Security Prices (CRSP) database. Our final sample consists of 154 stocks, categorised into five energy segments and spans from January 10, 2006 to December 31, 2018, resulting in 3263 daily observations.

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[5] EIA - Energy and the environment explained (n.d.). Retrieved from `https://www.eia.gov/energyexplained/energy-and-the-environment/`

[6] EIA - Energy Explained. (n.d.). Retrieved from `https://www.eia.gov/energyexplained/`

4.2.2 Liquidity and Trading Activity Measures

Our main data source is the WRDS Intraday Indicator Database (IID)[7] which contains intraday transaction data for securities listed at the NYSE, AMEX and the NASDAQ, obtained through the NYSE TAQ dataset. The WRDS aggregates trades and quotes from the TAQ dataset onto a daily average which fits perfectly to the construction of our daily time-series dataset. We select intraday indicators that only average trades and quotes during market hours.[8] Unlike suggested by Atkins and Dyl (1997), we include stocks from the NYSE, AMEX and NASDAQ exchanges, when constructing liquidity and trading averages for each energy segment. We are aware of a loss in accuracy for the volume measure, due to differences in trading protocols among U.S. stock exchanges. However, as our sample size is already negligible with the examination of energy and utility stocks, we follow this approach through. When aggregating liquidity and trading activity for each segment over time, we further account for the fact that some energy and utility firms have gone public later in the sample period while others have been delisted due to merging business activities. We do so by accounting for the weights dynamically throughout the sample. The classification of trades (e.g. into buyer- or seller-initiated trades) within the TAQ dataset is based on the algorithm by Lee and Ready (1991). We evaluate stock *i*'s specific measure of liquidity via the following indicators:

$$DollarEffectiveSpread_{(k)} = 2 \cdot D_k(P_k - M_k), \tag{4.1}$$

where P_k is the transaction price of the k^{th} trade and M_k the quoted midpoint of the consolidated national wide NBBO (National Best Bid & Offer) quote at the time of the k^{th} trade. D_k indicates the trade direction, i.e. (1) if trade k is a buyer- and (-1) if trade k is a seller-initiated transaction. Aggregated over time interval T, the $DollarEffectiveSpread_{TAQ}$ is the simple average of the $DollarEffectiveSpread_{(k)}$ of all trades during the interval T, in our study at a daily basis.

With the second liquidity measure we focus on the permanent component of

[7] WRDS. (n.d.). Retrieved from `https://wrds-web.wharton.upenn.edu/wrds/`

[8] The NYSE generally sells two TAQ databases, (i) the *Monthly Trade and Quote (MTAQ)* database where intraday trade and quote data is time-stamped on the *second* and (ii) the *Daily Trade and Quote (DTAQ)* database with data time-stamped onto the *millisecond* - that is the $1/1000^{th}$ of a second. The first is available on a daily basis from 1993 to 2014 and the latter start from 2003 and is recorded continuously up to today. Following Holden and Jacobsen (2014) who examine a comparative analysis between the two databases, we select the WRDS Intraday Indicators based on the DTAQ database as millisecond time-stamped trade and quote data is more accurate in fast markets and further allow us to use a longer and more recent time horizon than with the MTAQ.

the *DollarEffectiveSpread* - that is the *DollarPriceImpact* measure which is commonly known as a measure for order-related price changes. Goyenko et al. (2009) describes the price impact as the increase (decrease) in the quote midpoint after a signed trade within a certain time interval. Specifically, stock *i*'s TAQ five-minute price impact measure on the k^{th} trade is

$$DollarPriceImpact_{(k)} = 2 \cdot D_k(M_{k+5} - M_k), \tag{4.2}$$

where M_{k+5} is the midpoint of the consolidated NBBO quote, five minutes after the k^{th} trade and M_k the midpoint at the moment of the k^{th} trade. Similarly as for the effective spread, the $DollarPriceImpact_{TAQ}$ is the simple average of the $DollarPriceImpact_k$, computed over all trades during the interval T, again, here on a daily basis.[9]

Turning to trading activity measures, we examine each stock's trading characteristics as follows (both based on Lee and Ready (1991)):

- *Volume*: the total volume traded during the day (in shares)
- *Number of Trades*: the total number of transactions made during the trading day.

We apply filters to eliminate records that seem anomalous in the overall cross-section of quotes and trades data, e.g. negative quotations in the spread and price impact measures are deleted. Further, as a general rule, we delete quotations that satisfy the following condition: *DollarEffectiveSpread* > 1; *DollarPiceImpact* > 1. This seems plausible as with higher market quality, i.e. algorithmic and automated trading, spreads have generally continued to fall even further. Then, we create lower (upper) bounds for stock *i's* daily liquidity and trading measures by subtracting (adding) twice the *interquartile range* from (to) the 1st (3rd) quartile. Any record outside of these boundaries is deleted to prevent possible biases. In a final step, we calculate an equally-weighted industry-specific average of each liquidity and trading measure.

[9]See Goyenko et al. (2009) and Holden and Jacobsen (2014) for a more detailed description on these measures. The WRDS Intraday Indicator Formulate Note provides a more detailed explanation on these indicators. Besides the simple average aggregation of the TAQ liquidity measures, the WRDS provides two other forms of aggregating trades over a specific time interval T - (i) dollar value and (ii) share volume-weighted averages of spread and price impact measures.

4.3 Results

4.3.1 Summary Statistics

Table 4.1 provides the summary statistics on market liquidity and trading activity for all energy segments. The average effective spread is the highest for the oil and gas sector, followed by the coal and renewable sector. Reversely, we find that the average spreads in the utility sectors are the lowest, hence display more liquid markets. This can also be seen by looking at the relative difference of the trade volume and price impact measure. Utility stocks are more frequently traded and display the lowest price impact measures (both 0.013) among all sectors. That means, utility stocks are on average less sensitive to changes in trade volume, as measured by the price impact, which implies deeper markets. Supportive to this finding is that the price impact measure for utility stocks is also less volatile than for any other energy segment. Stocks from nonrenewable sectors, that is, oil and gas, coal mining, and the renewable sector, display almost similar characteristics for liquidity. In contrast to the utility segment, stocks from both primary energy sources have relative higher standard deviations for liquidity. All average spreads with exception of the renewable segment (2.91) exhibit an excess kurtosis.

Turning to trading activity, we regard that investors tend to execute four times more trades of oil and gas stocks on average than for renewables, followed by the electric-utility segment. Although, we average over four times more stocks in the oil and gas sector, the huge discrepancy of average trade volume between oil and gas stocks and the other segments still seems puzzling. Trade volume for oil and gas stocks is on average less than ten times the trade volume of renewables and over 30 times less the share volume of stocks from the electric-utility and coal segment. In other words, investors trade roughly 60,000 units of oil and gas stocks while there are almost two million units in trade execution for electric-utilities per day (similar amount for coal stocks). Another finding is that the maximum trade volume for oil and gas stocks occurred on the day where the Western Texas Intermediate (WTI) crude oil price reached its second lowest point in our sample period, January 20, 2016 with 26.68 \$ per barrel.[10] Finally, the statistics of the Jarque-Bera test display the non-normal properties of liquidity and trading.

[10] The lowest observation point in our sample period was on February 11, 2016 with 26.19 \$ per barrel.

Table 4.1: Summary Statistics - Liquidity and Trading Activity

	Mean	St.Dev.	Max	Min	Skewness	Kurtosis	Jarque-Bera
			$Eff.Spread				
Oil & Gas	0.032	0.007	0.070	0.016	0.67	3.81	340.34***
Coal	0.028	0.010	0.110	0.008	1.33	7.61	3,853.50***
Renewables	0.027	0.006	0.049	0.014	0.53	2.91	158.81***
Electric Utilities	0.016	0.003	0.042	0.010	1.01	6.20	1,950.50***
Multi-Utilities	0.016	0.003	0.044	0.011	1.80	12.38	13,741***
			$PriceImpact				
Oil & Gas	0.020	0.005	0.043	0.008	0.31	2.80	57.48***
Coal	0.017	0.006	0.069	0.004	1.56	8.90	6,068.60***
Renewables	0.018	0.005	0.042	0.005	0.57	3.20	184.72***
Electric Utilities	0.013	0.003	0.029	0.004	0.06	3.33	17.15***
Multi-Utilities	0.013	0.002	0.028	0.005	0.28	3.41	67.31***
			NumTrades				
Oil & Gas	13,161	4,632	27,148	1,611	0.12	2.92	9.23**
Coal	9,401	4,810	34,599	1,822	0.89	3.59	484.71***
Renewables	3,399	1,353	9,363	421	0.61	3.31	222.32***
Electric Utilities	11,323	4,348	27,693	1,036	-0.01	2.98	0.109
Multi-Utilities	9,147	3,624	24,615	801	0.16	3.19	19.50***
			Volume				
Oil & Gas	59,622	18,266	175,719	14,635	0.98	5.20	1,193.20***
Coal	1,995,899	908,085	6,257,108	369,181	0.55	3.11	167.23***
Renewables	722,238	283,189	2,047,419	103,297	0.88	3.94	542.86***
Electric Utilities	1,899,860	522,141	6,807,620	359,785	0.63	6.22	1,631.50***
Multi-Utilities	1,436,915	399,250	3,618,592	244,478	0.65	3.87	338.98***

Note: Descriptive Statistics for time-series market-wide liquidity and market-wide trading activity measures. The time-series measures are constructed by equally-weighting effective spreads, price impact of trades, number of trades and share volume of each stock on each trading day. The sample period runs from January 10, 2006 to December 31, 2018, resulting in a total of 3263 observations. *** indicates statistical significance at the 1%, ** at the 5% and * at the 10* level.

4.3.2 Dynamics of Liquidity and Trading Activity

Table 4.2 reports the time-series properties of the selection of liquidity and trading activity variables. We employ two unit root tests which are standard in time-series analysis, that is the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) test. The statistics of both tests support the non-existence of any unit root for all series. The optimal lag length is four, as suggested by the information criteria, (AIC, HQIC and BIC). We also estimate the autocorrelation coefficients (AC) for all measures up to 75 trading days but only report a selection of lags. As can be seen for both cases, in levels and ln changes, there is significant autocorrelation for all series up to a high number of lags. These findings are not surprising, as spreads are usually trended and seasonal. In fact, since its initial start in 1993, when the WRDS started recording intraday indicators, spreads have experienced a decline from just below 4% in 1993 to less than 1% in 2018 but still exhibit trended downward dynamics. Similar dynamics are true for the price impact of trades. Reversely, trading activity has increased, due to a more efficient market infrastructure. For daily ln changes, we find sufficient evidence for first- and second-order negative serial dependence. Unlike trended level series, daily changes of those variables oscillate around a constant mean with negative first- and second-order dependence.

Figures A8-A11 show the plots of the liquidity and trading activity measures, including a Savitzky-Golay smoothing, Savitzky and Golay (1964), between January 10, 2006 and December 31, 2018.[11] In general, the dynamics for liquidity and trading exhibit common characteristics across sectors, i.e. foremost around the financial crisis. We find a continuous upward trend for the number of trades for oil and gas and utility stocks. Trade numbers and volume for the coal segment decrease again close to the end of the sample. Liquidity dynamics of utility stocks are more tranquil and roughly half of the nonrenewable (oil and gas, coal) and renewable segment. Spreads for the coal segment drop significantly right after the global financial crisis and again in the interval of the years 2015-2016, indicating high liquidity periods (lower spreads).

[11] Due to the number of energy segments and liquidity and trading activity measures analyzed in this paper, we report the plots (20 in total) in the Appendix A8-A11.

Table 4.2: Time-Series Properties - Liquidity and Trading Activity

	ADF	PP	ADF(4)	PP(4)	AC(5)	AC(15)	AC(30)
Levels				$Eff.Spread			
Oil & Gas	-25.42***	-27.80***	-7.96***	-24.28***	0.6363***	0.5643***	0.5011***
Coal	-21.30***	-21.72***	-7.32***	-19.19***	0.7056***	0.6426***	0.5705***
Renewables	-23.33***	-24.75***	-8.22***	-21.86***	0.6460***	0.5866***	0.5208***
Electric Utilities	-18.27***	-17.38***	-6.85***	-15.68***	0.7409***	0.6686***	0.5919***
Multi-Utilities	-23.17***	-24.56***	-8.63***	-21.77***	0.6264***	0.5249***	0.4266***
				$PriceImpact			
Oil & Gas	-22.41***	-23.53***	-7.01***	-20.61***	0.6961***	0.6501***	0.6041***
Coal	-31.32***	-36.32***	-9.59***	-31.94***	0.5117***	0.4569***	0.4057***
Renewables	-33.20***	-38.59***	-10.95***	-34.24***	0.4537***	0.4252***	0.3730***
Electric Utilities	-23.64***	-25.30***	-8.22***	-22.29***	0.6389***	0.5667***	0.5126***
Multi-Utilities	-26.87***	-30.04***	-9.35***	-26.48***	0.5629***	0.4945***	0.4392***
				NumTrades			
Oil & Gas	-13.09***	-10.84***	-6.51***	-10.50***	0.8043***	0.7342***	0.6949***
Coal	-15.28***	-13.43***	-7.51***	-12.82***	0.7469***	0.6853***	0.6576***
Renewables	-25.06***	-27.02***	-10.24***	-24.24***	0.5401***	0.4782***	0.4476***
Electric Utilities	-14.34***	-12.34***	-7.28***	-11.86***	0.7679***	0.6825***	0.6383***
Multi-Utilities	-13.38***	-11.26***	-7.11***	-11.04***	0.7765***	0.6968***	0.6412***
				Volume			
Oil & Gas	-19.30***	-18.92***	-9.32***	-17.46***	0.6250***	0.5122***	0.4921***
Coal	-19.02***	-18.43***	-8.81***	-17.01***	0.6536***	0.5808***	0.5545***
Renewables	-28.45***	-31.29***	-12.18***	-28.38***	0.4271***	0.3656***	0.3047***
Electric Utilities	-23.06***	-23.92***	-11.59***	-22.02***	0.5030***	0.3380***	0.3240***
Multi-Utilities	-21.94***	-22.37***	-11.01***	-20.67***	0.5359***	0.3998***	0.3505***
ln changes				$Eff.Spread			
Oil & Gas	-94.80***	-152.84***	-40.69***	-129.42***	0.0363***	0.0046***	0.0109***
Coal	-92.52***	-147.02***	-40.71***	-122.88***	-0.0044***	-0.0234***	-0.0139***
Renewables	-90.12***	-140.53***	-41.93***	-116.94***	0.0024***	-0.0025***	-0.0315***
Electric Utilities	-89.36***	-129.03***	-38.48***	-110.07***	-0.0062***	0.0039***	0.0094***
Multi-Utilities	-90.47***	-131.43***	-38.40***	-113.48***	0.0283***	-0.0119***	-0.0187***
				$PriceImpact			
Oil & Gas	-94.39***	-156.46***	-41.62***	-128.13***	0.0241***	-0.0080***	-0.0170***
Coal	-96.47***	-164.84***	-41.13***	-134.82***	0.0427***	-0.0144***	0.0207***
Renewables	-97.03***	-163.23***	-41.94***	-131.93***	0.0268***	0.0004***	-0.0143***
Electric Utilities	-92.03***	-140.06***	-39.33***	-118.45***	-0.0078***	0.0129***	-0.0476***
Multi-Utilities	-94.82***	-147.49***	-40.06***	-123.65*	-0.0119***	-0.0115***	-0.0112***
				NumTrades			
Oil & Gas	-76.64***	-98.17***	-35.11***	-87.13***	-0.0013***	0.0122***	-0.0037***
Coal	-79.50***	-105.53***	-36.90***	-91.85***	-0.0397***	0.0047***	-0.0261***
Renewables	-85.25***	-126.15***	-39.29***	-103.67***	-0.0119***	-0.0002***	-0.0133***
Electric Utilities	-79.24***	-101.55***	-34.45***	-89.83***	-0.0161***	0.0162***	-0.0111***
Multi-Utilities	-76.23***	-95.52***	-34.34***	-84.72***	0.0006***	0.0329***	-0.0051***
				Volume			
Oil & Gas	-77.81***	-101.09***	-35.84***	-88.90***	0.0053***	-0.0038***	0.0004***
Coal	-82.14***	-112.92***	-37.03***	-96.36***	-0.0276***	-0.0007***	-0.0126***
Renewables	-85.11***	-127.80***	-39.41***	-104.62***	0.0040***	0.0140***	-0.0352***
Electric Utilities	-80.67***	-106.00***	-35.48***	-92.21***	-0.0055***	-0.0135***	-0.0094***
Multi-Utilities	-79.56***	-104.44***	-35.80***	-89.92***	-0.0084***	0.0033***	-0.0044***

Note: This table reports the time-series properties of daily liquidity and trading activity. The sample period is from January 10, 2006 to December 31, 2018. The criteria for the model selection (AIC, HQIC and BIC) jointly suggest that all time-series include a lag order of 4 for further estimation purposes. As for unit roots test, we report the statistics of the Augmented Dickey Fuller (ADF) and Phillips-Perron (PP). *** denotes statistically significant at the 1% critical value. A selection of autocorrelation coefficients of all time-series measures are also reported. Lags are indicated in brackets.

4.4 Determinants of Liquidity and Trading Activity

In this section, we present the time-series regression results of liquidity and trading activity variables on a set of determinants. Beforehand, we report a set of explanatory variables and provide some justification on its selection.

4.4.1 Explanatory Variables

We expect market liquidity and trading of energy stocks to response to the direction of contemporaneous stock market returns, that is, liquidity and trading increase with positive concurrent market swings and decrease with negative concurrent market movements. Chordia et al. (2001) refer to a widening spread in falling markets, due to challenges in the inventory adjustment of market makers.

We include a measure of volatility in our time-series regression model and expect to confirm the positive relationship between volatile markets and spreads, as well documented within the existing literature. Dating back to early theoretical models about inventory risk and asymmetric information cost paradigm, volatility is seen as an important factor that influences spreads, (see Demsetz (1968), Benston and Hagerman (1974), Stoll (1978)). Both paradigms serve as an example for market maker's precautionary motive to protect themselves against volatile asset and superior information-based trading in volatile times, i.e. adverse selection cost.

Moreover, we consider short-run momentum effects to be another determinant of spreads and trading activity. Avramov et al. (2016) find that up-market (down-market) momentum profits are large (low) when the overall stock market is liquid (illiquid). The rationale behind this finding could be based on how (new) information is processed by market participants. Irrational investors and market makers might react overconfident to information, inducing a direct effect on trade volume and liquidity. Ultimately, increased trading activity in a liquid (illiquid) market then results in a continuation of positive (negative) returns.[12]

To isolate extreme financial conditions from general market volatility and short-run momentum, we include measures that proxy financial distress via default spreads. Usually in these market states, investors rebalance their portfolios towards safer assets (flights-to-quality), resulting in a shift from stocks and corporate debt instruments to safer treasury bonds which depresses stock market activity, Beber

[12] Baker and Stein (2004) and Odean (1998) developed theoretical ideas on investor's overconfidence and its impact on trading volume, liquidity and serially correlated returns.

et al. (2009), Baele et al. (2020) and Vayanos (2004). Our first measure defines the spread between a corporate bond and its risk-free alternative, that is, a treasury bond. Second, we employ the *TermSpread*, known as difference in yields between a long- and a short-term treasury bond. When the *TermSpread* has inverted in recent history, meaning the yield on short-term bonds are higher than its long-term alternative, the overall economy has experienced a slowdown in output, i.e. early 2000s and shortly before the global financial crisis in 2008.

Similarly to Sklavos et al. (2013), we expect that an increase in the oil price decreases spreads and increases trading activity. As in Chordia et al. (2001), we also add the federal fund rate as benchmark for short rates. With the inclusion of the rate, we may infer how changes in the interest rate affects liquidity and trading activity from a standpoint of a reduction in inventory cost and ease of margin trading. Finally, we account for potential weekly patterns in liquidity and trading activity by including day dummies, (Monday to Thursday).

With the methodological approach, we closely follow the approach by Chordia et al. (2001) to capture daily variation in liquidity and trading activity. The time-series regression model for liquidity and trading activity measures can be written as follows:

$$Y_{k,t} = \alpha + \phi ShortRate_t + \sum_{d=1}^{2} \Phi_d Default_{d,t} + \sum_{m=1}^{5} \gamma_m Market_{m,t} + \sum_{j=1}^{4} \delta_j Days_{j,t} + \psi Oil_t + \beta_1 t_1 + \beta_2 t_2 + \beta_3 t_3 + \varepsilon_t, \quad (4.3)$$

where Y is *DollarEffectiveSpread*, *DollarPriceImpact*, *NumTrades* and *Volume*, ($k = 4$), for energy sector i; *ShortRate* is the federal funds rate[13]; *Default* represents two spread indicators: *TermSpread* is the spread between a 10-year treasury bond and the 3-month treasury bill rate; *QualitySpread* is defined as the spread between a Moody's BAA Corporate Bond Yield and 10-year constant maturity Treasury bond; *Market* sums the following variables based on the equally-weighted CRSP daily index[14]: *Concurrent Market Movements* as the contemporaneous CRSP daily index return if it is positive (negative) and zero otherwise; *Volatility* as the five-day average of daily absolute returns of the equally-weighted CRSP daily index and *Up- and (Down-market) Momentum* measured as average of the past five trading

[13] Chordia et al. (2001) also use the one-year treasury bill rate as a proxy for dealer's costs, however they find that the federal funds rate serves as a better determinant.

[14] The CRSP index consists of NYSE, AMEX and NASDAQ stocks.

days of the CRSP daily index, if it is positive (negative) and zero otherwise. *Days* are the dummy variables that take on the value of 1 if the trading day is a Monday, Tuesday, Wednesday or a Thursday and zero if otherwise, respectively. We employ the WTI crude oil price to proxy for oil price dynamics. Finally, we include three linear time trend sequences (t_1 for the full sample, t_2 until the start and t_3 until the end of the recent global financial crisis.) The dates that are associated with these time-trends mirror the dates of the recession indicator based on the business cycle dates of the National Bureau of Economic Research (NBER).[15] All interest rates, bond yields and the WTI oil price have been retrieved from the website of the Federal Reserve Bank of St. Louis, `https://fred.stlouisfed.org`. The CRSP stock market index return has been retrieved from the WRDS service, `https://wrds-web.wharton.upenn.edu/wrds/`.

4.4.2 Time-Series Regression Results

In this section, we report the time-series regression results for daily liquidity and trading activity measures, that is, *DollarEffectiveSpread*, *PriceImpact*, *NumTrades* and *Volume*. Liquidity and trading activity measures are constructed as equally-weighted, cross-sectional averages of all stocks that are considered in an energy segment. All measures display higher-order positive autocorrelation in levels and first- to second-order negative dependence in its logarithmic transformation. The stationarity tests confirm the non-existence of any unit root for all liquidity and trading measures, hence the proceeding in levels. We control for serial correlation with Newey and West (1987) corrected standard errors. The model specifications are jointly significant for most models. We split the sample into three subsections. First, we regress the proposed model in its initial setting, that is Eq.(4.3). Second, and instead of the oil price, we add an oil price volatility measure to the model and, finally, in the third model specification, we model climate change based investor sentiment and the effect on liquidity and trading of energy stocks.

Oil Price, Liquidity and Trading

Table 4.3 and 4.4 report the time-series results for liquidity and trading activity, respectively. We find that bearish markets are associated with larger liquidity in all sectors, (negatively contemporaneous returns associated to lower spreads). This

[15] Recession Indicator. (n.d.). Retrieved from `https://fred.stlouisfed.org`

effect is statistical significant with exception for the average spread of the renewables segment. While bullish markets are associated to heterogeneous effects on spreads and price impact, we find that there is less liquidity in the segment of coal and electric- utilities (the former has a significant increase in the spread and the latter in the price impact). The importance of concurrent market movements in general is particularly visible for the trading activity variables, see Table 4.4. The results reveal that trading (number of trades and share volume) decrease significantly with negative concurrent returns (statistically significant at the 1% level across all energy segments). In contrast, we observe that trading is encouraged with positive contemporaneous returns (except for trade numbers of renewables). Comparing relative magnitudes of the coefficients, we observe that changes in share volume for coal and utility stocks are significantly higher for an one-unit increase/decrease in contemporaneous returns.

Both, negative and positive market momentum trends are associated with smaller spreads, hence more liquid markets. This is in line with findings of Avramov et al. (2016). Although the effect of negative momentum is generally greater, we find a strong reduction in the spread for oil and gas stocks and the price impact of trades for utility stocks in the light of positive market trends. We also document that trading activity, both, in number of trades and share volume, decrease with negative momentum, statistically significant across all segments. Similarly, positive momentum tends to reduce trading but lacks statistical support.

High levels of stock market volatility reduces liquidity, (higher spreads and price impact of trades). This effect is statistically significant across all energy segments, except for the average spread of renewables. Similarly, trading activity increases with higher levels of volatility for most sectors. These findings provide reasoning for a collective exposure to overall stock market volatility. This is in line with studies by Stoll (1978), Benston and Hagerman (1974) and Vayanos (2004) more recently, which theoretically formulate the positive relationship of volatility and illiquidity. Precisely, these findings are attributed to the concerns of inventory risk on behalf of market makers to hold risky assets.

The federal fund rate as proxy for short-term interest rates is mostly negatively related to trading activity, (significant for the number of trades and volume of oil and gas and coal stocks). We attribute these findings to the extra cost of margin trading, and the fact, that it is more expensive to leverage investment positions,

Table 4.3: Regression Results - Equally-weighted (3,263 observations)

Energy Sector	Oil&Gas		Coal		Renewables		Electric-Utilities		Multi-Utilities	
Coefficients (in bps)	ES	PI	ES	PI	ES	PI	ES	PI	ES	PI
Concurrent Return (-)	-9.402***	-7.80***	-8.620***	-5.416***	-1.582	-2.178*	-4.944***	-4.877***	-5.430***	-4.680***
	(-4.47)	(-6.56)	(-3.65)	(-3.67)	(-1.20)	(-1.86)	(-4.68)	(-6.70)	(-4.68)	(-6.28)
Concurrent Return (+)	-1.450	0.36	4.410**	1.003	-2.076	-1.968	0.937	1.720**	1.010	1.039
	(-0.62)	(0.29)	(1.96)	(0.65)	(-1.47)	(-1.55)	(0.73)	(2.35)	(0.92)	(1.37)
Momentum (-)	-15.788**	-8.85**	-17.902*	-12.352**	-6.822	-3.657	-8.280**	-2.796	-7.795**	-3.989
	(-2.55)	(-2.30)	(-1.76)	(-2.47)	(-1.25)	(-0.84)	(-2.31)	(-0.96)	(-2.28)	(-1.48)
Momentum (+)	-14.466***	-4.873	5.047	-0.652	-2.906	-5.635	-5.930**	-9.492***	-6.678**	-8.284***
	(-2.90)	(-1.36)	(0.76)	(-0.17)	(-0.61)	(-1.51)	(-2.03)	(-3.27)	(-2.35)	(-3.38)
Volatility	26.589***	18.489***	35.233***	17.868***	7.536	10.839***	12.67***	14.13***	14.52***	14.264***
	(5.35)	(5.43)	(6.31)	(4.33)	(1.58)	(3.39)	(3.71)	(4.87)	(3.33)	(5.43)
ShortRate	-0.071	-0.150***	0.096	-0.036	0.140**	0.004	0.107***	-0.076**	0.039	-0.102***
	(-0.99)	(-2.99)	(1.10)	(-0.68)	(2.04)	(0.07)	(3.10)	(-2.17)	(1.05)	(-2.96)
TermSpread	-0.085	-0.109***	-0.492***	-0.241***	0.044	0.055	0.051**	-0.081***	-0.039	-0.105***
	(-1.55)	(-2.84)	(-7.07)	(-6.29)	(0.81)	(1.38)	(2.06)	(-3.17)	(-1.39)	(-4.00)
Quality Spread	-0.191*	-0.135**	-0.267**	-0.162***	-0.073	-0.282***	-0.068	-0.146***	-0.030	-0.103**
	(-1.94)	(-2.07)	(-2.47)	(-2.62)	(-0.73)	(-3.59)	(-1.51)	(-3.37)	(-0.64)	(-2.39)
Monday	-0.046*	-0.013	-0.095***	-0.002	0.057***	-0.0008	-0.050***	-0.037***	-0.044***	-0.051***
	(-1.90)	(-0.92)	(-3.10)	(-0.09)	(-2.70)	(-0.04)	(-6.02)	(-3.69)	(-4.50)	(-5.20)
Tuesday	-0.040	0.006	-0.100***	-0.016	-0.039*	0.015	-0.043***	-0.042***	-0.049***	-0.044***
	(-1.64)	(0.43)	(-3.31)	(-0.63)	(-1.86)	(0.71)	(-5.61)	(-4.22)	(-5.53)	(-4.49)
Wednesday	-0.021	0.053***	-0.071**	0.00008	-0.022	0.060***	-0.015*	-0.011	-0.024***	-0.014
	(-0.92)	(3.66)	(-2.43)	(0.00)	(-1.16)	(2.93)	(-1.81)	(-1.04)	(-2.62)	(-1.45)
Thursday	0.024	0.043***	-0.045	0.034	-0.04**	0.005	-0.022***	-0.016*	-0.019**	-0.015
	(0.99)	(2.90)	(-1.59)	(1.32)	(-2.23)	(0.26)	(-2.68)	(-1.67)	(-2.03)	(-1.51)
CrudeOil	0.008***	0.005***	0.017***	0.008***	-0.0001	-0.003***	-0.001**	-0.0009*	-0.0002	-0.00033
	(6.12)	(7.09)	(10.21)	(9.47)	(-0.08)	(-3.25)	(-2.39)	(-1.65)	(-0.39)	(-0.58)
t_1	-0.00032***	-0.00036***	-0.00027***	-0.0003***	0.00027***	0.0001***	0.0002***	0.00005**	0.00009***	-0.000008
	(-5.23)	(-10.07)	(-3.40)	(-7.33)	(4.10)	(3.06)	(9.13)	(2.33)	(2.79)	(-0.30)
t_2	0.0002	-0.009***	-0.003***	-0.002***	-0.0004	-0.0004*	-0.0003**	-0.0010***	-0.00006	0.0006***
	(0.78)	(-4.04)	(-4.80)	(-6.04)	(-0.99)	(-1.86)	(-2.05)	(-5.77)	(-0.41)	(-4.12)
t_3	0.0002	-0.00007	-0.00008	0.0001	0.0007***	0.0006***	0.0004***	0.0001	0.0001	0.0006
	(1.26)	(-0.43)	(-0.29)	(0.61)	(2.93)	(3.27)	(3.54)	(-1.21)	(1.23)	(0.53)
Constant	3.694***	2.770***	3.357***	2.415***	2.176***	2.358***	1.147***	1.840***	1.506***	1.883***
	(6.82)	(7.90)	(5.54)	(7.27)	(4.23)	(6.04)	(4.35)	(7.62)	(5.43)	(7.92)
F-Statistic	121.56	170.12	162.47	92.97	39.28	33.58	177.69	120.67	66.54	72.93
Adjusted R^2	0.37	0.45	0.44	0.31	0.15	0.13	0.46	0.36	0.24	0.26
DW Statistic	1.05	0.99	0.88	1.35	0.68	1.17	0.70	0.94	0.74	0.98

Note: Dependent variables are the liquidity measures as described in the data section. Due to limited space and a comprehensive amount of data to fit in this table, we have to shorten the description - ES stands for *DollarEffectiveSpread* and PI for *DollarPriceImpact*. T-statistics are reported in parentheses. Standard errors are correct for serial dependence and heteroscedasticity with the Newey and West (1987) method. *** indicate statistical significance at the 1%, ** at the 5% and * at the 10% level.

Table 4.4: Regression Results - Equally-weighted (3,263 observations)

Energy Sector	Oil&Gas		Coal		Renewables		Electric-Utilities		Multi-Utilities	
Coefficients	NumTr	Vol	NumTr	Vol	NumTr	Vol	NumTr	Vol	NumTr	Vol
Concurrent Return (-)	-85,977***	-439,740***	-99,331***	-17,748,000***	-15,326***	-2,581,300***	-100,580***	-15,016,000***	-77,272***	-11,541,000***
	(-6.68)	(-7.64)	(-7.07)	(-7.60)	(-4.41)	(-3.00)	(-8.02)	(-7.97)	(-7.77)	(-8.78)
Concurrent Return (+)	20,677**	171,420***	44,910***	9,191,600***	-898.90	440,970	40,866***	8,920,000***	25,081***	5,134,100***
	(2.20)	(3.14)	(4.33)	(3.76)	(-0.22)	(0.44)	(4.14)	(5.03)	(3.16)	(4.62)
Momentum (-)	-114,010**	-757,310***	-153,360***	-32,645,000***	-39,474***	-6,934,100***	-168,340***	-26,985,000***	-121,560***	-17,134,000***
	(-2.53)	(-4.65)	(-3.27)	(-4.66)	(-3.36)	(-2.76)	(-4.81)	(-3.60)	(-3.91)	(-3.31)
Momentum (+)	-55,368*	-83,407	9,357.10	2,075,000	-5,597.10	2,354,700	-38,266*	-4,422,500	-32,007	-3,644,300
	(-1.77)	(-0.63)	(0.24)	(0.28)	(-0.52)	(0.97)	(-1.77)	(-1.08)	(-1.46)	(-1.03)
Volatility	105,710***	400,340***	131,600***	15,427,000***	-5256.70	-2,150,900	152,640***	21,357,000***	159,140***	21,449,000***
	(3.18)	(3.13)	(4.96)	(2.66)	(-0.51)	(-0.96)	(6.93)	(6.20)	(7.89)	(6.46)
ShortRate	-945.77**	3,035.40*	-2,494.90***	-478,500***	-56.24	-24,241	-272.69	-72,960*	-199.17	-32,355
	(-2.31)	(1.87)	(-7.02)	(-7.44)	(-0.34)	(-0.80)	(-1.06)	(-1.74)	(-0.81)	(-0.93)
TermSpread	419.36	3,437.10***	-188.65	-153,010**	382.59***	78,986***	795.23***	91,805***	592.60***	88,467***
	(1.35)	(2.84)	(-0.56)	(-2.50)	(3.10)	(3.11)	(3.94)	(2.76)	(3.28)	(3.18)
Quality Spread	-873.58	-2,181.80	-1,410.00***	-304,830***	-541.21**	-130,170***	-671.24*	-104,990*	-628.03*	-31,451
	(-1.42)	(-0.85)	(-2.79)	(-3.27)	(-2.47)	(-3.38)	(-1.84)	(-1.71)	(-1.80)	(-0.66)
Monday	-270.62***	-2,307.50***	-47.60	-13,247	75.96*	23,619**	-316.93***	-102,120***	-253.14***	-88,053***
	(-2.73)	(-4.52)	(-0.45)	(-0.53)	(1.77)	(2.31)	(-3.34)	(-5.86)	(-3.27)	(-6.61)
Tuesday	272.70***	836.25*	239.67**	46,622*	190.11***	30,718***	294.65***	16,773	259.99***	7,412.50
	(2.85)	(1.68)	(2.11)	(1.87)	(4.05)	(2.80)	(3.06)	(0.91)	(3.28)	(0.53)
Wednesday	786.35***	3,113.10***	449.46***	82,912***	86.60*	33,605***	491.03***	36,264**	400.39***	18,048
	(8.31)	(6.04)	(3.88)	(3.27)	(1.77)	(2.97)	(5.31)	(2.20)	(5.33)	(1.42)
Thursday	636.64***	3,087.80***	491.86***	91,973***	115.44**	26,969**	395.90***	18,560	350.03***	7,667.90
	(6.86)	(6.01)	(4.55)	(3.76)	(2.57)	(2.57)	(4.40)	(1.14)	(4.66)	(0.60)
CrudeOil	-52.20***	-376.10***	30.92***	4572.60***	-6.95**	-1,143**	-17.335***	-1,523.30**	-13.66***	-166.88
	(-6.61)	(-11.12)	(4.29)	(3.25)	(-2.48)	(-2.12)	(-4.11)	(-2.25)	(-3.28)	(-0.26)
t_1	2.76***	5.40***	-2.72***	-731.37***	0.59***	-41.40	3.81***	213.42***	3.17***	70.58**
	(8.75)	(4.13)	(-8.97)	(-12.72)	(4.54)	(-1.63)	(19.75)	(6.87)	(16.32)	(2.42)
t_2	1.54	-36.07***	4.44**	588.31	-0.64	-355.47*	3.28**	724.49**	1.90*	614.63***
	(0.94)	(-4.48)	(2.26)	(1.24)	(-0.70)	(-1.73)	(2.13)	(2.08)	(1.87)	(2.65)
t_3	7.05***	16.00**	6.49***	696.73***	3.45***	660.14***	4.69***	388.95***	4.13***	250.68**
	(4.15)	(2.18)	(5.04)	(2.73)	(5.80)	(6.41)	(5.53)	(2.75)	(5.00)	(2.31)
Constant	12,880***	66,858***	15,847***	4,123,700***	3,234.60***	1,014,500***	4,393**	1,521,000***	3,444.10*	1,014,200***
	(4.26)	(5.74)	(6.08)	(8.56)	(2.75)	(4.63)	(2.47)	(5.20)	(1.94)	(4.08)
F-Statistic	338.49	164.44	352.31	213.28	68.61	49.02	545.30	147.33	513.23	142.25
Adjusted R^2	0.62	0.44	0.63	0.51	0.24	0.19	0.72	0.41	0.71	0.40
DW Statistic	0.48	0.70	0.70	0.80	0.86	0.97	0.83	0.91	0.71	0.83

Note: Dependent variables are the trading activity variables as described in the data section. Due to limited space and a comprehensive amount of data to fit in this table, we have to shorten the description - NumTr stands for *Number of Trades* and Vol for *Volume*. T-statistics are reported in parentheses. Standard errors are correct for serial dependence and heteroscedasticity with the Newey and West (1987) method. *** indicate statistical significance at the 1%, ** at the 5% and * at the 10% level.

which results in a depression of the demand side of the trade. Average spreads exhibit a mixed response in context with the short rate. For instance, spreads for renewables and electric-utility stocks increase with a rise in the short rate, (statistical significant at the 5% and 1% level, respectively).

With exception of trading of coal stocks, the *TermSpread*, mirroring potential economic stress, increases trading activity across all markets (statistically significant at the 1% level for the renewable and utility segments). Liquidity, in general, tends to increase with a higher *TermSpread*, as indicated by the negative coefficient, most likely, due to increased trading and its effect on price impact of trades (order-flow related price changes), except for renewables and the spreads of electric-utility stocks). This indicates that liquidity conditions seem still stable while there might be sufficient demanders and suppliers for energy stocks. For instance, we find a significant decrease in the price impact of trades for the oil and gas, coal and utility segment. Surprisingly, trading of coal stocks decreases while spreads and price impact of renewable stocks increase in the context of a widening *TermSpread*. We find similar effects of the *QualitySpread* on liquidity, however associated with a decrease in trading. More general, we may relate the link between the *TermSpread* and liquidity and trading to scenarios where market participants act precautionary while seeking safer investment opportunities which is consistent with the literature on flights-to-quality and flights-to-safety, (Beber et al. (2009), Baele et al. (2020)). However, this phenomenon is not attributed solely to energy stocks but provides an explanation on a broader scale. Investors seek safer options, i.e. government bonds instead of equities, or more traditional stocks, which benefits the market clearing process in times of higher trading activity, in this context, as a result of a widening *TermSpread*.

For a rising crude oil price, we find an increase in illiquidity (higher spreads) for oil and gas and coal stocks, on average. Less liquidity in these market segments is accompanied by significantly lower trading for oil and gas and higher trading for coal stocks (statistically significant at the 1% level). This finding is only partially consistent with Sklavos et al. (2013) who find that a rising oil price decreases spreads and discourages trading activity. However, their study only examines oil and gas stocks, listed at the NYSE. On the contrary, renewable and electric-utility stocks display lower spreads (although small in magnitude). We also find that a rising oil price discourages trading for renewables and utilities.

The day-of-the-week dummies are positive and statistically significant from Tuesday to Thursday for trading activity, but mostly negative for Monday, which indicates that trading activity is the lowest the first day of the week, except for renewables that are traded even less on Fridays. Especially, utility stocks are traded in fewer numbers and volume on Mondays than on average. By examining the spreads and price impact, we document that all markets tend to be less liquid (higher spreads and price impact of trades) on average on Fridays, which is consistent with Chordia et al. (2001), and suggest a day-of-the-week effect that goes beyond the sample of energy stocks.

Despite some heterogeneity, we perceive a strong commonality component in the exposure to concurrent stock market returns, downward momentum or volatility on liquidity and trading. These effects, common across sectors, provide evidence for correlated trading across many asset classes, see Chordia et al. (2000). High-volume shifts in trading are often induced through mutual fund ownership or index trading by institutional investors, Kamara et al. (2008) and Koch et al. (2016) and often take place parallel to general market swings or in the presence of higher volatility.

Oil Price Volatility, Liquidity and Trading Activity

In this section, we focus on the link between oil price volatility and liquidity and trading activity for energy stocks. We model oil price volatility with the *CBOE Crude Oil ETF Volatility Index*[16]. Table 4.5 and 4.6 illustrate the time-series regression results. The regression design is as follows:

$$Y_{k,t} = \alpha + \phi ShortRate_t + \sum_{d=1}^{2} \Phi_d Default_{d,t} + \sum_{m=1}^{5} \gamma_m Market_{m,t} + \sum_{j=1}^{4} \delta_j Days_{j,t} + \psi OilVola_t + \beta_1 t_1 + \beta_2 t_2 + \beta_3 t_3 + \varepsilon_t, \quad (4.4)$$

where Y is *DollarEffectiveSpread*, *DollarPriceImpact*, *NumTrades* and *Volume*, ($k = 4$), for energy sector i. The volatility measure is denoted as *OilVola*. Our results in Table 4.5 show that oil price volatility exhibits a positive relationship with illiquidity (higher spreads) across most energy segments (exception of the spread of

[16]The series is taken from the Federal Reserve Bank of St. Louis and is available since May 10, 2007, hence the shortening of the sample period. Retrieved from: `https://fred.stlouisfed.org/series/OVXCLS`

the coal mining segment). Spreads widen and price impact of trades rise in light of higher levels of oil price volatility. This effect is mostly statistically significant. It seems not surprising that liquidity for utility stocks is plummeting as oil price volatility increases. Oil and gas are important intermediary products for utility firms in the process of electricity generation. Thus, investors may precautionary trade utilities in times of higher oil price volatility. These findings are supported by a substantial decrease in share volume (statistically significant), indicating volume-related price changes related to significantly higher price impact of trades which subsequently marks less liquidity in the market for utilities than before, see Table 4.6. Average spreads and price impact of trades for oil and gas stocks response symmetrically to higher oil price volatility (the latter statistically significant at the 1% level). The results for coal stocks show a significant decline in the spread, an increase in price impact of trades and a decrease in trading and volume (all statistically significant at the 1% level). Trading of renewable stocks increases significantly but so does illiquidity for this segment (positive and significant coefficients for spreads and price impact). We could point the increase in spreads towards a motive of market makers to precautionary raise spreads in case of abnormal volume trades (higher demand for renewables).

Generally, these findings are not surprising, considering the extensive literature on the link between stock market volatility and liquidity. Overall, these results suggest that, despite of investor's and market maker's sensitivity to stock market volatility, fluctuations in the oil price volatility appear to play an important role when trading energy stocks. Investors tend to act precautionary when expectation indicators such as for the oil price are not in line with personal market perceptions which alters trading patterns accordingly. Further, these results are novel and indirectly confirm previous findings which find that oil price volatility depresses stock returns in general and more specific for energy stocks, (see Diaz et al. (2016), Luo and Qin (2017), Dutta (2018), Oberndorfer). We refer to *indirectly* because fundamental market microstructure characteristics (number of trade executions, trade volume, bid and ask prices among others) represent the essential dynamic mechanism which ultimately form the price and return figure of an individual stock.

Table 4.5: Regression Results - Equally-weighted (2,929 observations)

Energy Sector	Oil&Gas		Coal		Renewables		Electric - Utilities		Multi- Utilities	
Coefficients (in bps)	ES	PI	ES	PI	ES	PI	ES	PI	ES	PI
Concurrent Return (-)	-8.845***	-8.790***	-11.116***	-5.643***	-1.959	-2.856**	-4.00***	-4.964***	-5.111***	-4.906***
	(-3.98)	(-7.70)	(-4.33)	(-3.52)	(-1.44)	(-2.57)	(-3.98)	(-6.97)	(-4.29)	(-6.58)
Concurrent Return (+)	-2.433	0.894	4.867*	1.11	-2.541*	-1.084	0.645	1.944***	0.765	1.465**
	(-0.95)	(0.67)	(1.89)	(0.68)	(-1.78)	(-0.87)	(0.48)	(2.67)	(0.66)	(2.10)
Momentum (-)	-17.296**	-11.007***	-23.77**	-13.396***	-9.733*	-4.46	-8.547**	-4.180	-8.666**	-4.789**
	(-2.27)	(-2.79)	(-2.07)	(-2.62)	(-1.69)	(-1.03)	(-2.17)	(-1.60)	(-2.39)	(-2.11)
Momentum (+)	-18.944***	-1.950	-1.262	0.485	-4.343	-0.927	-5.725*	-7.850***	-7.339**	-6.346***
	(-3.33)	(-0.57)	(-0.16)	(0.12)	(-0.84)	(-0.27)	(-1.84)	(-2.94)	(-2.36)	(-3.02)
Volatility	25.347***	19.808***	43.153***	18.224***	7.136	10.446***	10.332***	13.435***	13.288***	14.149***
	(4.38)	(6.27)	(6.39)	(4.41)	(1.64)	(3.72)	(3.00)	(5.77)	(3.03)	(6.79)
ShortRate	-0.329***	-0.558***	-0.283***	-0.374***	0.004	-0.284***	0.046	0.238***	-0.038	-0.286***
	(-4.22)	(-12.27)	(-3.39)	(-7.39)	(0.05)	(-6.61)	(1.35)	(-8.13)	(-1.11)	(-9.80)
TermSpread	-0.119**	-0.085**	-0.616***	-0.336***	0.084*	0.152***	0.069***	-0.022	-0.017	-0.059***
	(-2.07)	(-2.43)	(-7.81)	(-8.00)	(1.77)	(4.53)	(2.79)	(-0.99)	(-0.63)	(-2.62)
Quality Spread	-0.549***	-0.360***	-0.616***	-0.498***	-0.038	-0.221***	-0.106**	-0.144***	-0.0712	-0.119***
	(-5.07)	(-7.89)	(-4.79)	(-8.43)	(-0.44)	(-4.08)	(-2.27)	(-4.75)	(-1.61)	(-4.01)
Monday	-0.062**	0.014	-0.106***	-0.002	-0.054**	-0.0006	-0.051***	-0.038***	-0.043***	-0.053***
	(-2.45)	(-0.93)	(-3.35)	(-0.08)	(-2.41)	(-0.028)	(-5.51)	(-3.55)	(-4.01)	(-5.16)
Tuesday	-0.052**	-0.001	-0.122***	-0.021	-0.040*	0.011	-0.049***	-0.045***	-0.048***	-0.049***
	(-2.07)	(-0.10)	(-3.86)	(-0.85)	(-1.76)	(0.53)	(-6.03)	(-4.19)	(-5.05)	(-4.68)
Wednesday	-0.042*	0.050***	-0.079***	-0.004	-0.025	0.063***	-0.017**	-0.011	-0.025**	-0.019*
	(-1.80)	(3.24)	(-2.59)	(-0.19)	(-1.26)	(2.85)	(-1.97)	(-1.03)	(-2.55)	(-1.83)
Thursday	0.015	0.040***	-0.046	0.031	-0.045**	0.001	-0.022***	-0.015	-0.018**	-0.015
	(0.61)	(2.60)	(-1.51)	(1.21)	(-2.19)	(0.05)	(-2.63)	(-1.49)	(-1.96)	(-1.43)
OilVola	0.0032	3.574***	-0.019***	1.470***	0.006**	3.619***	0.003**	1.511***	0.001	1.873***
	(0.96)	(8.90)	(-5.18)	(2.92)	(2.14)	(9.82)	(2.21)	(5.00)	(0.66)	(6.41)
t_1	-0.0004***	-0.0002***	-0.0005***	-0.0004***	0.0004***	0.0005***	0.0003***	0.0002***	0.0001***	0.0001***
	(-7.69)	(-7.35)	(-6.47)	(-9.51)	(8.45)	(12.59)	(12.67)	(11.06)	(5.54)	(7.43)
t_2	0.0011**	0.007***	-0.0022***	0.0012	0.0018***	0.0091***	0.0005**	0.0032***	0.00085***	0.0042***
	(2.36)	(9.20)	(-3.13)	(1.17)	(3.93)	(9.55)	(2.25)	(5.26)	(3.40)	(6.79)
t_3	0.0012***	-0.0039***	0.0013***	-0.0009	0.0013***	-0.0036***	0.0006***	-0.0014***	0.0004***	-0.0020***
	(4.44)	(-7.07)	(4.07)	(-1.31)	(4.96)	(-7.19)	(5.43)	(-3.47)	(3.60)	(-5.02)
Constant	5.623***	3.651***	7.224***	4.561***	1.889***	1.024***	0.861***	1.288***	1.399***	1.502***
	(13.48)	(16.23)	(12.81)	(15.78)	(5.27)	(4.07)	(4.56)	(8.17)	(7.35)	(9.60)
F-Statistic	91.51	188.02	71.58	53.80	59.60	66.55	200.75	157.72	75.57	107.20
Adjusted R^2	0.33	0.50	0.27	0.22	0.24	0.26	0.52	0.46	0.28	0.36
DW Statistic	0.95	1.04	0.88	1.37	0.75	1.38	0.74	1.13	0.75	1.16

Note: Dependent variables are the liquidity variables as described in the data section. Due to limited space and a comprehensive amount of data to fit in this table, we have to shorten the description - ES stands for *DollarEffectiveSpread* and PI for *DollarPriceImpact*. Coefficients are reported in bps in regards of its decimal value. T-statistics are reported in parentheses. Standard errors are corrected for serial dependence and heteroscedasticity with the Newey and West (1987) method. *** indicate statistical significance at the 1%, ** at the 5% and * at the 10% level.

Table 4.6: Regression Results - Equally-weighted (2,929 observations)

Energy Sector	Oil&Gas		Coal		Renewables		Electric - Utilities		Multi- Utilities	
Coefficients	NumTr	Vol	NumTr	Vol	NumTr	Vol	NumTr	Vol	NumTr	Vol
Concurrent Return (-)	-87,833***	-432,270***	-96,898***	-17,148,000***	-17,478***	-2,722,900***	-101,190***	-14,467,000***	-78,340***	-11,426,000***
	(-6.26)	(-6.56)	(-7.36)	(-7.49)	(-5.06)	(-3.13)	(-7.88)	(-7.86)	(-7.62)	(-8.90)
Concurrent Return (+)	28,376***	184,910***	42,462***	8,309,900***	3,900.20	1,042,300	44,278***	9,019,300***	27,934***	5,217,300***
	(2.78)	(3.15)	(3.99)	(3.41)	(0.96)	(0.99)	(4.38)	(5.08)	(3.34)	(4.73)
Momentum (-)	-103,930**	-735,770***	-145,130***	-33,801,000***	-39,632***	-7,223,600***	-162,980***	-25,645,000***	-117,270***	-15,818,000***
	(-2.11)	(-4.20)	(-3.17)	(-4.65)	(-4.03)	(-3.29)	(-4.56)	(-3.47)	(-3.55)	(-3.07)
Momentum (+)	-19,956	52,018	-15,119	-2,162,800	13,497	5,425,400**	-27,318	-4,066,100	-22,752	-3,686,100
	(-0.57)	(0.34)	(-0.41)	(-0.31)	(1.25)	(2.16)	(-1.16)	(-0.96)	(-0.96)	(-1.03)
Volatility	111,540***	368,490**	135,240***	14,424,000**	753.41	-1,379,900	157,180***	21,421,000***	165,100***	22,182,000***
	(3.01)	(2.46)	(5.19)	(2.39)	(0.08)	(-0.70)	(7.15)	(6.67)	(7.87)	(7.11)
ShortRate	-4.55	10,032***	-1,306.50***	-448,480***	-680.44***	-117,890***	516.48*	110,360***	333.36	103,730***
	(-0.01)	(4.58)	(-3.65)	(-6.52)	(-4.30)	(-3.64)	(1.95)	(2.66)	(1.36)	(3.21)
TermSpread	649.80*	6,451.90***	-893.82***	-192,430***	604.53***	117,260***	616.74***	18,368	484.94**	29,673
	(1.73)	(3.97)	(-2.79)	(-2.89)	(5.48)	(4.93)	(2.64)	(0.47)	(2.39)	(0.96)
Quality Spread	987.81*	10,179.00***	-2,190.70***	-457,470***	-231.74	-76,141**	-36.83	-48,910	-135.83	-9,877.90
	(1.65)	(3.51)	(-5.47)	(-5.37)	(-1.42)	(-2.43)	(-0.10)	(-0.86)	(-0.43)	(-0.24)
Monday	-313.04***	-2,469.40***	-81.62	14,848	67.79	16,813	-350.45***	-108,950***	-278.27***	-93,971***
	(-2.75)	(-4.33)	(-0.70)	(-0.57)	(1.46)	(1.55)	(-3.29)	(-5.65)	(-3.21)	(-6.43)
Tuesday	269.38**	663.70	264.85**	57,507**	165.93**	18,889	311.77***	14,413	276.51***	4,302.80
	(2.44)	(1.17)	(2.09)	(2.10)	(3.30)	(1.64)	(2.90)	(0.71)	(3.11)	(0.28)
Wednesday	784.18***	2,818.40***	441.33***	73,710***	53.83	22,631*	528.80***	37,231**	422.95***	13,851
	(7.24)	(4.90)	(3.44)	(2.73)	(1.01)	(1.89)	(5.11)	(2.05)	(5.00)	(0.99)
Thursday	627.49***	2,754.20***	458.54***	67,273***	103.80**	20,991*	432.51***	22,324	378.61***	5,862.60
	(5.85)	(4.80)	(3.85)	(2.63)	(2.11)	(1.89)	(4.27)	(1.24)	(4.46)	(0.42)
OilVola	7,083.10**	-5,492.40	-17,293.00***	-1,958,900***	13,984***	2,179,100***	-2,322.10	-1,651,900***	-578.97	-1,125,800***
	(2.07)	(-0.32)	(-5.62)	(-3.06)	(12.28)	(9.30)	(-0.99)	(-4.06)	(-0.30)	(-3.73)
t_1	4.05***	15.71***	-5.26***	-952.46***	1.53***	106.92***	3.66***	59.60	3.15***	-75.88**
	(9.23)	(7.74)	(-15.61)	(-12.34)	(14.92)	(4.83)	(13.78)	(1.32)	(13.77)	(-2.24)
t_2	14.50*	-27.01	-44.38***	-4,257.60***	29.92***	4,398.10***	-4.98	-3,573.40***	-1.64	-2,653.70***
	(1.80)	(-0.67)	(-6.91)	(-3.00)	(12.28)	(8.09)	(-1.02)	(-4.40)	(-0.38)	(-4.32)
t_3	-7.20	0.53	27.57***	3,518***	-15.26***	-2,266.60***	5.01	2,131.30***	2.84	1,383.60***
	(-1.49)	(0.02)	(6.54)	(3.92)	(-10.83)	(-7.16)	(1.46)	(3.63)	(1.04)	(3.26)
Constant	460.36	-24,056*	26,534***	5,418,800***	-310.19	431,050***	1,753.90	1,663,500***	1,128.80	1,318,900***
	(0.15)	(-1.74)	(13.41)	(12.52)	(-0.43)	(2.97)	(1.02)	(5.90)	(0.74)	(6.38)
F-Statistic	128.28	94.90	322.24	220.06	83.78	67.50	239.00	70.56	236.95	105.90
Adjusted R^2	0.41	0.33	0.63	0.54	0.31	0.26	0.56	0.27	0.56	0.36
DW Statistic	0.44	0.56	0.76	0.81	1.00	1.03	0.84	0.95	0.71	0.89

Note: Dependent variables are the trading activity variables as described in the data section. Due to limited space and a comprehensive amount of data to fit in this table, we have to shorten the description - NumTr stands for *Number of Trades* and Vol for *Volume*. T-statistics are reported in parentheses. Standard errors are correct for serial dependence and heteroscedasticity with the Newey and West (1987) method. *** indicate statistical significance at the 1%, ** at the 5% and * at the 10% level.

Climate-based Sentiment, Liquidity and Trading

In this section, we analyze the effect of climate-change based investor sentiment on the variation of daily liquidity and trading patterns of energy stocks. Climate change has been a global concern for many decades and recently appeared to reach its peak in 2019 in terms of global media attention. News on climate change related topics and policies can easily be retrieved from the public press. To examine how investors have received global media attention related to climate change over the years and developed sentiment, we include a dummy variable that captures the annually held *United Nations Climate Conference* as part of the United Nations Framework Convention on Climate Change (UNFCC)[17], see Table 4.7.

Table 4.7: UNFCC - Conferences

Year	Symbol	Dates	City, Country
2006	COP 12/CMP 2	6-17 Nov.	Nairobi, Kenya
2007	COP 13/CMP 3	3-17 Dec.	Bali, Indonesia
2008	COP 14/CMP 4	1-12 Dec.	Poznan, Poland
2009	COP 15/CMP 5	7-18 Dec.	Copenhagen, Denmark
2010	COP 16/CMP 6	28 Nov. - 10 Dec.	Cancun, Mexico
2011	COP 17/CMP 7	28 Nov. - 9 Dec.	Durban, South Africa
2012	COP 18/CMP 8	26 Nov. - 7 Dec.	Doha, Qatar
2013	COP 19/CMP 9	11-23 Nov.	Warsaw, Poland
2014	COP 20/CMP 10	1-12 Dec.	Lima, Peru
2015	COP 21/CMP 11	30 Nov. - 12 Dec.	Paris, France
2016	COP 22/CMP 12	7-18 Nov.	Marrakech, Morocco
2017	COP 23/CMP 13	6-17 Nov.	Bonn, Germany
2018	COP 24/CMP 14	3-14 Dec.	Katowic, Poland

Note: The UNFCC - United Nations Framework Convention on Climate Change is a convention that unifies 197 countries to address the mutual concern of climate change. The COP, (Conference of the Parties), counts as a supreme decision-making body in the framework of the convention. The first meeting ever of this institutional body was in Berlin, 1995. Since then, member states meet once a year, see `https://unfccc.int`

[17] United Nations Framework Convention on Climate Change (UNFCCC) (n.d.). Link: `https://unfccc.int`

Regression coefficients are reported in Table 4.8 and 4.9. The amended form of the time-series regression can be written as follows:

$$Y_{k,t} = \alpha + \phi ShortRate_t + \sum_{d=1}^{2} \Phi_d Default_{d,t} + \sum_{m=1}^{5} \gamma_m Market_{m,t} + \sum_{j=1}^{4} \delta_j Days_{j,t} + \psi Climate_t + \beta_1 t_1 + \beta_2 t_2 + \beta_3 t_3 + \varepsilon_t, \quad (4.5)$$

where Y is *DollarEffectiveSpread*, *DollarPriceImpact*, *NumTrades* and *Volume*, ($k = 4$), for energy sector i and $Climate_t$ displays the dummy variable that takes on the value of 1 on the days on which the conference is held and 0 if otherwise. As we focus on variation and determinants of daily liquidity and trading patterns, the inclusion of a daily dummy variable seems the only plausible measure to proxy for climate change related sentiment in this setting. The remaining variables are identical to the regression in the previous sections.

We find that averages of effective spreads across all energy segments are not significantly higher during days on whose the conference is held. Moreover, we observe similar findings for the price impact measure across all energy segments, ruling out that price impact of trades, and hence order-flow related price changes, are higher during the conference days. Turning to the number of trade executions, (Table 4.9), we find that investors execute more trades for the renewable energy segment on days on whose the conferences take place (statistically significant at the 5% level). Similarly, we find trade volume of renewables to increase during the conference days (significant at the 10% level). This may indicate some degree of sentiment for renewable stocks, however without any significant impact on liquidity (i.e. order-related price impacts), as mentioned above. Similar findings with statistical significance can be regarded for trading activity (number of trades and volume) of stocks from the multi-utility sector.

In sum, we make a first attempt to initiate the consideration of climate change as source for investor sentiment in conjunction with its impact on liquidity and trading of energy stocks. Considering the difficulties in proxying for climate change based sentiment, our results may serve a purpose for other researchers to come up with new ways to model this concern within a financial model. Our findings can be attributed to higher noise trading during the annual conference for climate change, especially for stocks from the renewable and multi-utility sector.

Table 4.8: Regression Results - Equally-weighted (3,263 observations)

Energy Sector	Oil&Gas		Coal		Renewables		Electric-Utilities		Multi-Utilities	
Coefficients (in bps)	ES	PI	ES	PI	ES	PI	ES	PI	ES	PI
Concurrent Return (-)	-9.509***	-7.871***	-8.858***	-5.53***	-1.575	-2.114*	-4.913***	-4.854***	-5.427***	-4.666***
	(-4.41)	(-6.53)	(-3.63)	(-3.52)	(-1.20)	(-1.82)	(-4.62)	(-6.72)	(-4.68)	(-6.31)
Concurrent Return (+)	-1.938	0.001	3.359	0.500	-2.07	-1.788	1.018	1.772**	1.026	1.052
	(-0.79)	(0.0011)	(1.36)	(0.30)	(-1.46)	(-1.41)	(0.80)	(2.41)	(0.93)	(1.39)
Momentum (-)	-16.706**	-9.560**	19.857*	-13.261**	-6.834	-3.389	-8.168**	-2.733	-7.761**	-3.998
	(-2.36)	(-2.23)	(-1.69)	(-2.38)	(-1.25)	(-0.76)	(-2.36)	(-0.95)	(-2.28)	(-1.50)
Momentum (+)	-18.103***	-7.585*	-2.770	-4.369	-2.896	-4.352	-5.359*	-9.137***	-6.553**	-8.211***
	(-3.31)	(-1.89)	(-0.38)	(-1.05)	(-0.60)	(-1.18)	(-1.86)	(-3.19)	(-2.31)	(-3.40)
Volatility	26.858***	-18.633***	35.852***	18.212***	7.502	10.615***	12.554***	14.043***	14.524***	14.195***
	(4.84)	(5.02)	(5.09)	(4.09)	(1.58)	(3.23)	(3.74)	(4.87)	(3.34)	(5.47)
ShortRate	-0.218***	-0.257***	-0.221**	-0.189***	0.142**	0.061	0.133***	-0.059*	0.044	-0.096***
	(-3.53)	(-5.72)	(-2.34)	(-3.48)	(2.17)	(1.18)	(4.63)	(-1.91)	(1.39)	(-3.12)
TermSpread	-0.108*	-0.126***	-0.543***	-0.266***	0.044	0.064	0.056**	-0.079***	-0.038	-0.104***
	(-1.90)	(-3.10)	(-6.45)	(-5.82)	(0.82)	(1.55)	(2.26)	(-3.11)	(-1.40)	(-4.01)
Quality Spread	-0.447***	-0.322***	-0.820***	-0.428***	-0.070	-0.184***	-0.024	-0.118***	-0.022	0.094**
	(-5.25)	(-5.40)	(-6.65)	(-6.41)	(-0.78)	(-2.58)	(-0.69)	(-3.26)	(-0.58)	(-2.55)
Monday	-0.045*	-0.012	-0.092***	-0.0008	-0.057***	-0.001	-0.05***	-0.037***	-0.044***	-0.051***
	(-1.83)	(-0.84)	(-2.97)	(-0.03)	(-2.71)	(-0.07)	(-6.01)	(-3.70)	(-4.50)	(-5.20)
Tuesday	-0.041*	0.005	-0.103***	-0.017	-0.039*	0.015	-0.043***	-0.042***	-0.049***	-0.044***
	(-1.68)	(0.35)	(-3.39)	(-0.68)	(-1.86)	(0.73)	(-5.54)	(-4.19)	(-5.52)	(-4.46)
Wednesday	-0.022	0.052***	-0.074**	-0.001	-0.022	0.06***	-0.014*	-0.011	-0.024***	-0.014
	(-0.99)	(3.54)	(-2.52)	(-0.06)	(-1.16)	(2.95)	(-1.76)	(-1.01)	(-2.61)	(-1.43)
Thursday	0.025	0.044***	-0.043	0.035	-0.042**	0.004	-0.022***	-0.016*	-0.019**	-0.015
	(1.03)	(2.92)	(-1.49)	(1.35)	(-2.23)	(0.24)	(-2.70)	(-1.68)	(-2.03)	(-1.52)
ClimateChange	0.025	0.055	0.029	-0.018	0.021	0.074	0.043	0.036	-0.004	0.040
	(0.28)	(0.92)	(0.17)	(-0.24)	(0.24)	(0.89)	(0.96)	(1.12)	(-0.08)	(1.00)
t_1	-0.0005***	-0.0005***	-0.0007***	-0.0005***	0.0003***	0.0002***	0.0003***	0.000077***	0.0001***	-0.0000009
	(-11.08)	(-18.2)	(-8.69)	-12.86)	(4.88)	(5.06)	(13.24)	(4.04)	(3.76)	(-0.04)
t_2	0.0000	-0.0011***	-0.0041***	-0.0026***	-0.0004	-0.0003	-0.0003*	-0.0010***	-0.0001	-0.0006***
	(0.04)	(-4.52)	(-5.05)	(-6.07)	(-1.01)	(-1.57)	(-1.87)	(-5.50)	(-0.35)	(-4.02)
t_3	0.0008***	0.0003*	0.0011***	0.0006***	0.0007***	0.0004***	0.0003***	0.00008	0.0001	0.00004
	(3.71)	(1.73)	(3.12)	(3.02)	(3.14)	(2.58)	(3.69)	(0.79)	(1.38)	(0.42)
Constant	5.453***	4.052***	7.159***	4.250***	2.153***	1.669***	0.832***	1.637***	1.448***	1.814***
	(13.94)	(14.67)	(12.21)	(13.57)	(5.19)	(5.15)	(4.59)	(9.05)	(7.40)	(9.87)
F-Statistic	103.87	143.71	115.54	72.78	39.30	30.61	173.7	119.57	66.45	73.07
Adjusted R^2	0.33	0.41	0.35	0.26	0.15	0.12	0.45	0.36	0.24	0.26
DW Statistic	0.99	0.92	0.76	1.26	0.68	1.15	0.70	0.93	0.74	0.99

Note: Dependent variables are the liquidity variables described in the data section. Due to limited space and a comprehensive amount of data to fit in this table, we have to shorten the description - ES stands for *DollarEffectiveSpread* and PI for *DollarPriceImpact*. Coefficients are reported in bps in regards of its decimal value. T-statistics are reported in parentheses. Standard errors are corrected for serial dependence and heteroscedasticity with the Newey and West (1987) method. *** indicate statistical significance at the 1%, ** at the 5% and * at the 10% level.

Table 4.9: Regression Results - Equally-weighted (3,263 observations)

Energy Sector	Oil&Gas		Coal		Renewables		Electric-Utilities		Multi-Utilities	
Coefficients	NumTr	Vol	NumTr	Vol	NumTr	Vol	NumTr	Vol	NumTr	Vol
Concurrent Return (-)	-85,102***	-433,480***	-99,902***	-17,846,000***	-15,126***	-2,544,000***	-100,280***	-14,984,000***	-76,918***	-11,517,000***
	(-6.33)	(-6.86)	(-7.21)	(-7.75)	(-4.32)	(-2.92)	(-7.87)	(-7.86)	(-7.58)	(-8.73)
Concurrent Return (+)	23,692**	193,170***	43,157***	8,941,400***	-549.77	495,540	41,864***	9,003,800***	25,791***	5,130,600***
	(2.52)	(3.42)	(4.08)	(3.63)	(-0.14)	(0.50)	(4.23)	(5.03)	(3.23)	(4.62)
Momentum (-)	-108,970**	-720,780***	-156,110***	-32,987,000***	-39,176***	-6,905,500***	-166,690***	-26,867,000***	-120,800***	-17,212,000***
	(-2.37)	(-4.38)	(-3.33)	(-4.65)	(-3.43)	(-2.83)	(-4.67)	(-3.55)	(-3.80)	(-3.32)
Momentum (+)	-33,402	75,144	-3,262.20	314,550	-3,285.60	2,701,500	-31,020	-3,830,200	-27,180	-3,727,900
	(-1.02)	(0.51)	(-0.08)	(0.04)	(-0.30)	(1.10)	(-1.41)	(-0.93)	(-1.22)	(-1.05)
Volatility	102,930***	380,580**	133,550***	15,793,000***	-6,088.30	-2,312,700	151,680***	21,240,000***	157,720***	21,325,000***
	(2.89)	(2.57)	(5.06)	(2.71)	(-0.60)	(-1.04)	(6.71)	(6.05)	(7.52)	(6.39)
ShortRate	-5.16	9,812.70***	-3,051.10***	-560,460***	67.39	-3,999.30	39.52	-45,641	44.56	-29,754
	(-0.012)	(5.02)	(-8.67)	(-8.78)	(0.46)	(-0.14)	(0.15)	(-1.14)	(0.20)	(-0.94)
TermSpread	569.96*	4,522***	-278.04	-166,270***	402.91***	82,341***	845.26***	96,220***	632.41***	89,015***
	(1.67)	(2.93)	(-0.81)	(-2.66)	(3.23)	(3.22)	(4.07)	(2.89)	(3.45)	(3.23)
Quality Spread	744.67	9,481.90***	-2,361.70***	-443,700***	-336.49*	-97,092***	-134.73	-58,619	-220.69	-28,974
	(1.19)	(3.21)	(-5.03)	(-5.05)	(-1.73)	(-2.88)	(-0.38)	(-1.00)	(-0.69)	(-0.70)
Monday	-281.27***	-2,383.90***	-40.76	-12,096	73.73*	23,207**	-320.53***	-102,500***	-257.16***	-88,293***
	(-2.84)	(-4.64)	(-0.38)	(-0.48)	(1.72)	(2.26)	(-3.39)	(-5.90)	(-3.35)	(-6.67)
Tuesday	281.21***	897.66*	234.76**	45,928*	191.04***	30,861***	297.46***	17,006	261.93***	7,390.90
	(2.94)	(1.78)	(2.06)	(1.84)	(4.08)	(2.81)	(3.09)	(0.92)	(3.31)	(0.53)
Wednesday	797.35***	3,192.30***	442.80***	81,888***	88.30*	33,895***	494.71***	36,603**	403.61***	18,140
	(8.40)	(6.13)	(3.80)	(3.21)	(1.81)	(2.99)	(5.35)	(2.23)	(5.39)	(1.43)
Thursday	629.88***	3,039.40***	496.21***	92,710***	113.99**	26,702**	393.61***	18,320	347.44***	7,509.30
	(6.77)	(5.86)	(4.55)	(3.77)	(2.53)	(2.55)	(4.36)	(1.12)	(4.63)	(0.59)
ClimateChange	586.63	4,064.50	-560.26	-139,700	409.40**	85,262*	220.65	43,397	651.72***	84,938***
	(0.83)	(1.28)	(-1.33)	(-1.50)	(2.14)	(1.81)	(0.68)	(0.86)	(2.02)	(2.69)
t_1	3.90***	13.57***	-3.39***	-829.25***	0.75***	-17.66	4.19***	246.07***	3.46***	73.01***
	(12.67)	(8.83)	(-12.21)	(-15.77)	(6.76)	(-0.85)	(22.77)	(8.75)	(20.23)	(2.91)
t_2	3.07*	-25.09***	3.59*	476.36	-0.52	-339.50*	3.78**	762.54**	2.18**	599.65**
	(1.87)	(-2.75)	(1.93)	(1.10)	(-0.62)	(-1.81)	(2.40)	(2.15)	(2.17)	(2.57)
t_3	3.59**	-8.95	8.53***	991.33***	3.03***	591.44***	3.55***	290.50**	3.27***	247.77***
	(2.24)	(-1.18)	(6.64)	(4.02)	(5.91)	(6.52)	(4.19)	(2.03)	(4.51)	(2.61)
Constant	1,649.80	-14,066	22,482***	5,099,600***	1,768.40*	774,980***	666.08	1,195,600***	549.01	985,640***
	(0.57)	(-1.05)	(10.20)	(12.45)	(1.92)	(4.59)	(0.41)	(4.67)	(0.37)	(5.05)
F-Statistic	291.73	99.60	335.76	207.95	67.12	48.62	533.32	146.03	506.13	143.2
Adjusted R^2	0.58	0.32	0.62	0.50	0.24	0.18	0.72	0.41	0.71	0.41
DW Statistic	0.44	0.57	0.69	0.79	0.85	0.97	0.81	0.90	0.70	0.83

Note: Dependent variables are the Number of trade executions and the trade volume as described in the data section. Due to limited space and a comprehensive amount of data to fit in this table, we have to shorten the description - NumTr stands for *Number of Trades* and Vol for *Volume* T-statistics are reported in parentheses. Standard errors are corrected for serial dependence and heteroscedasticity with the Newey and West (1987) method. *** indicate statistical significance at the 1%, ** at the 5% and * at the 10% level.

4.5 Conclusion

We examine daily liquidity and trading activity of 154 energy stocks traded at U.S. stock exchanges. Grouping stocks into five energy sectors, namely, *oil and gas*, *coal mining*, *renewables*, *electric-utilities* and *multi-utilities*, we find that sectoral liquidity and trading activity is volatile and serial correlated (for levels and daily changes). Compared to previous studies, the dynamics of liquidity and trading activity, here for a subset of energy stocks, continue its downward and upward trends, respectively. This is mainly attributed to higher efficiency in faster equity markets. We find that trading activity for coal and utility stocks is on average higher than for oil and gas stocks. Spreads for utility stocks are roughly half of those from the renewable and nonrenewable sectors, indicating higher liquidity in comparison.

Our empirical analysis also shows a series of factors that help explain variation in the levels of daily liquidity and trading activity. In particular, we find that concurrent equity market returns significantly affect liquidity and trading pattern across most energy sectors. This effect is more pronounced for down-market movements, providing evidence for a higher degree of correlated trading behavior, i.e. offloading positions across many asset classes and stock segments. Recent market trends are associated with more liquid markets, (smaller spreads). Consistent with previous studies, we report a positive relationship between volatility and illiquidity and trading. Further, our results show that liquidity and trading increase for most sectors, in light of a higher term spread. We relate these findings to the historical importance of the term spread as recession indicator in the eyes of market participants.

Higher oil prices have a heterogenous effect on liquidity and trading, depending on the sector. Spreads and trading decrease for renewables and utilities in the light of a rising oil price. Spreads for oil and gas and coal mining stocks display the opposite, that is, increasing spreads (less liquidity). At the same time, oil price volatility tends to decrease liquidity for most sectors, despite controlling for stock market volatility. Moreover, oil price variability increases trade numbers of oil and gas stocks but decreases trade volume for utilities.

We document weekly regularities in liquidity and trading. Spreads tend to be higher, (less liquidity) on Fridays and trading is lower on Mondays or Fridays depending on the energy sector. Finally, we document higher trading (number of trade executions and trade volume) for renewable and multi-utility stocks on days on whose the annual *United Nation Climate Change* conference is held, suggesting a higher number of noise traders.

Our results are important for market participants (investors and market makers) who engage in daily transactions. The study on daily liquidity and trading seem crucial when entering and exiting positions on a daily basis. We do not deny that our findings, especially the influence of the selection of explanatory variables, i.e. financial stress indicators, volatility or down-market movements, are not exclusive to energy stocks and apply to a broader range of securities, but perhaps with differences in its explanatory power. As is known in the literature, liquidity and subsequently trading is to some degree a self-sustainable market microstructure element. Investors do not trade in illiquid periods and trade in liquid ones which decreases liquidity for the first and increase liquidity for the latter scenario even further, Admati and Pfleiderer (1988). Finally, given the data availability, future research is encouraged to explore day-to-day changes in liquidity and trading patterns for (energy) stocks on a more global scale and with a focus on sectoral heterogeneity.

4.6 Appendix

Additional Tables and Figures

Table A17: Summary Statistics - Explanatory Variables

Variables	Short Rate	TermSpread	QualitySpread	WTI (in $)	CRSP Index
			Levels		
Mean	1.22	1.83	2.69	74.45	0.03
Std.Dev.	1.74	1.05	0.84	22.55	1.11
Max	5.41	3.83	6.16	145.31	10.73
Min	0.04	-0.64	1.53	26.19	-7.83

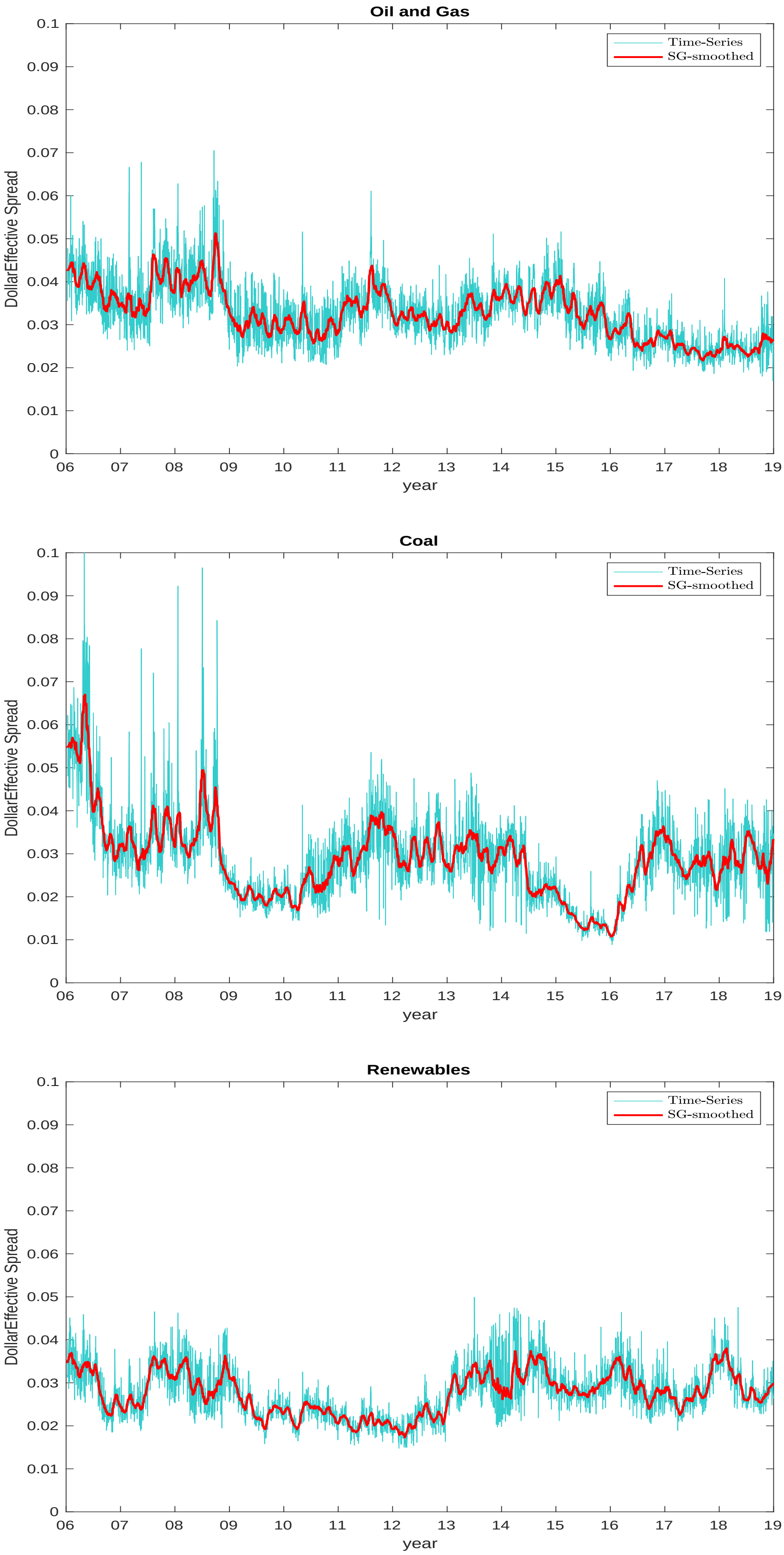
Note: The sample period spans from January 10, 2006 to December 31, 2018, resulting in 3,263 daily observations. Levels are reported in % and for the WTI in $. The explanatory variables are proxied as follows: *ShortRate*: Yield on the overnight Federal Fund Rate; *TermSpread*: Yield spread between the constant maturity 10-year U.S. treasury bond and the yield of the federal fund rate; *QualitySpread*: Yield spread between the Moody's BAA corporate bond and the yield on a 10-year constant maturity Treasury bond; *WTI*: Crude Oil Price - West Texas Intermediate; *CRSP index*: Returns on the equally-weighted CRSP equity index based on NYSE, AMEX and NASDAQ stocks.

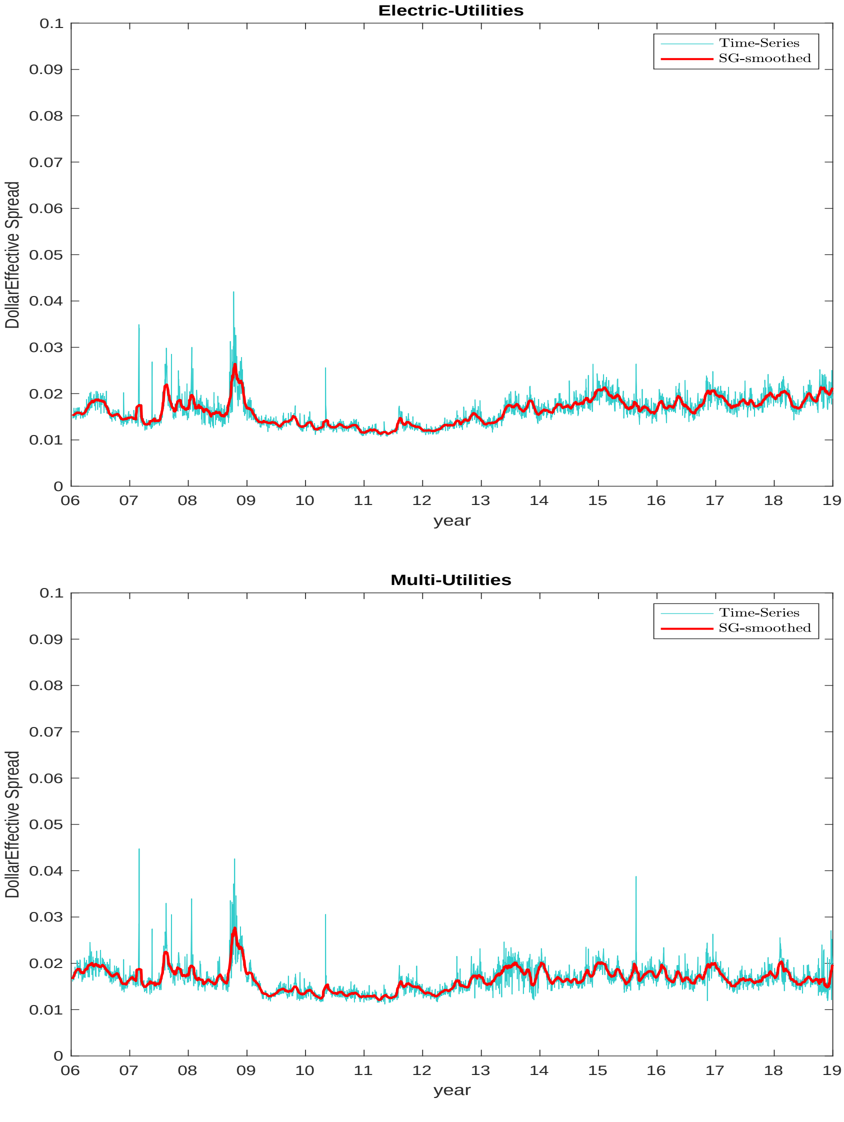
Table A18: Stock Decomposition - SIC Classification

Nr.	SIC-Code	SIC Industry	Sample Sector
1	1311	Crude Petroleum & Natural Gas	Oil&Gas
2	1381	Drilling Oil & Gas Wells	Oil&Gas
3	1382	Oil & Gas Field Exploration Services	Oil&Gas
4	1389	Oil & Gas Field Services	Oil&Gas
5	2911	Petroleum Refining	Oil&Gas
6	3533	Oil & Gas Field Machinery & Equipment	Oil&Gas
7	4922	Natural Gas Transmission	Oil&Gas
8	4923	Natural Gas Transmission & Distribution	Oil&Gas
9	4924	Natural Gas Distribution	Oil&Gas
10	1220	Bituminous Coal & Lignite Mining	Coal Mining
11	1221	Bituminous Coal & Lignite Surface Mining	Coal Mining
12	1090	Miscellaneous Metal Ores	Coal Mining
13	2860	Industrial Organic Chemicals	Renewables
14	3690	Miscellaneous Electrical Machinery, Equipment & Supplies	Renewables
15	3674	Semiconductors & Related Devices	Renewables
16	8731	Services-Commercial Physical & Biological Research	Renewables
17	4911	Electric Services	Electric-Utilities
18	4931	Electric & Other Services Combined	Multi-Utilities
19	4932	Gas & Other Services Combined	Multi-Utilities

Note: Stocks from the NYSE, AMEX and NASDAQ are assigned to industries based on the four-digit SIC code.

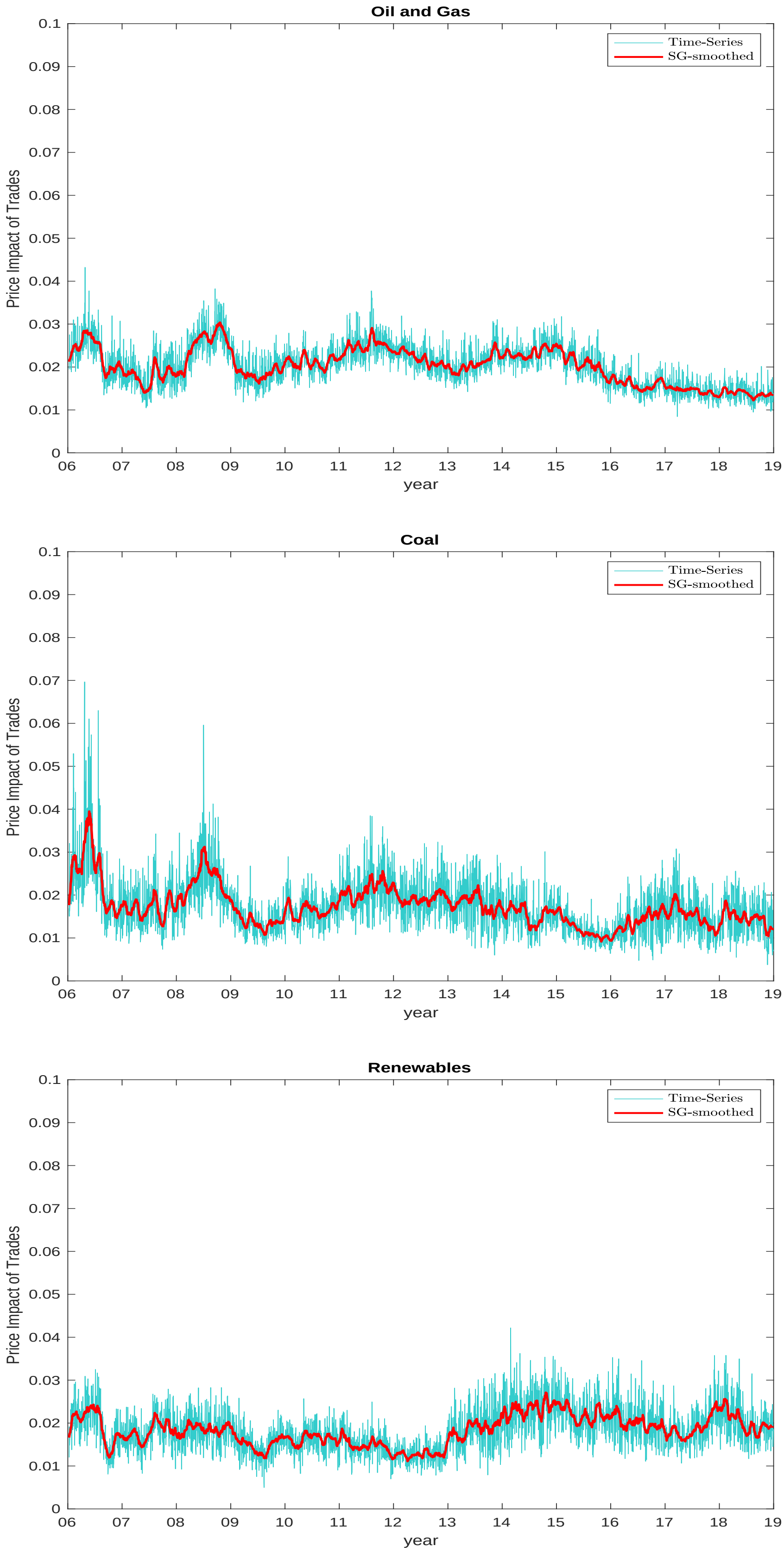
Figure A8: Daily *Effective Spread* per Energy Segment.

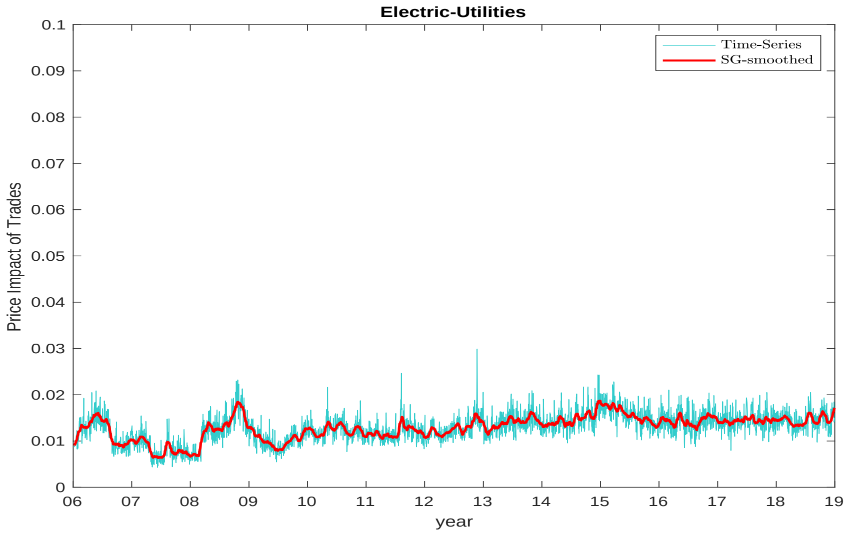


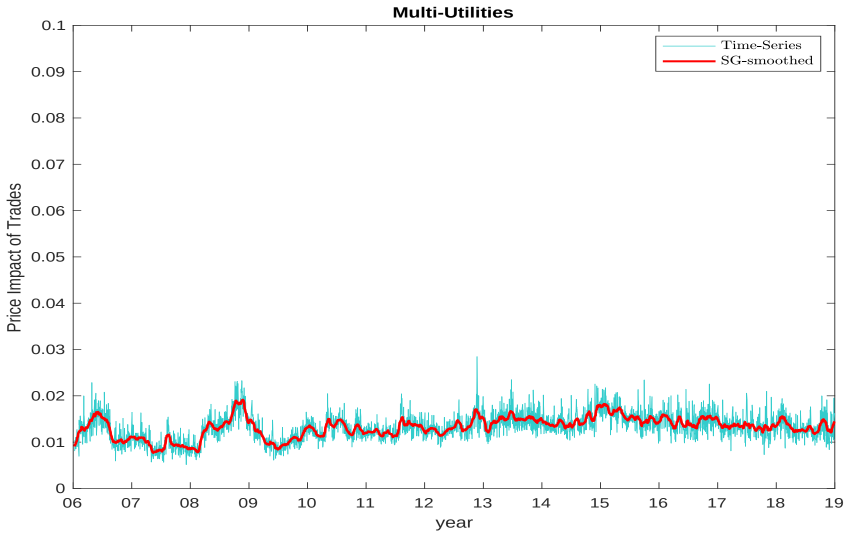


Note: Daily *effective Spread* between January 10, 2006 and December 31, 2018, n = 3263. The unfiltered time-series per energy segment is plotted in turquoise, Savitzky-Golay smoothing in red.

Figure A9: Daily *Price Impact of Trades* per Energy Segment.

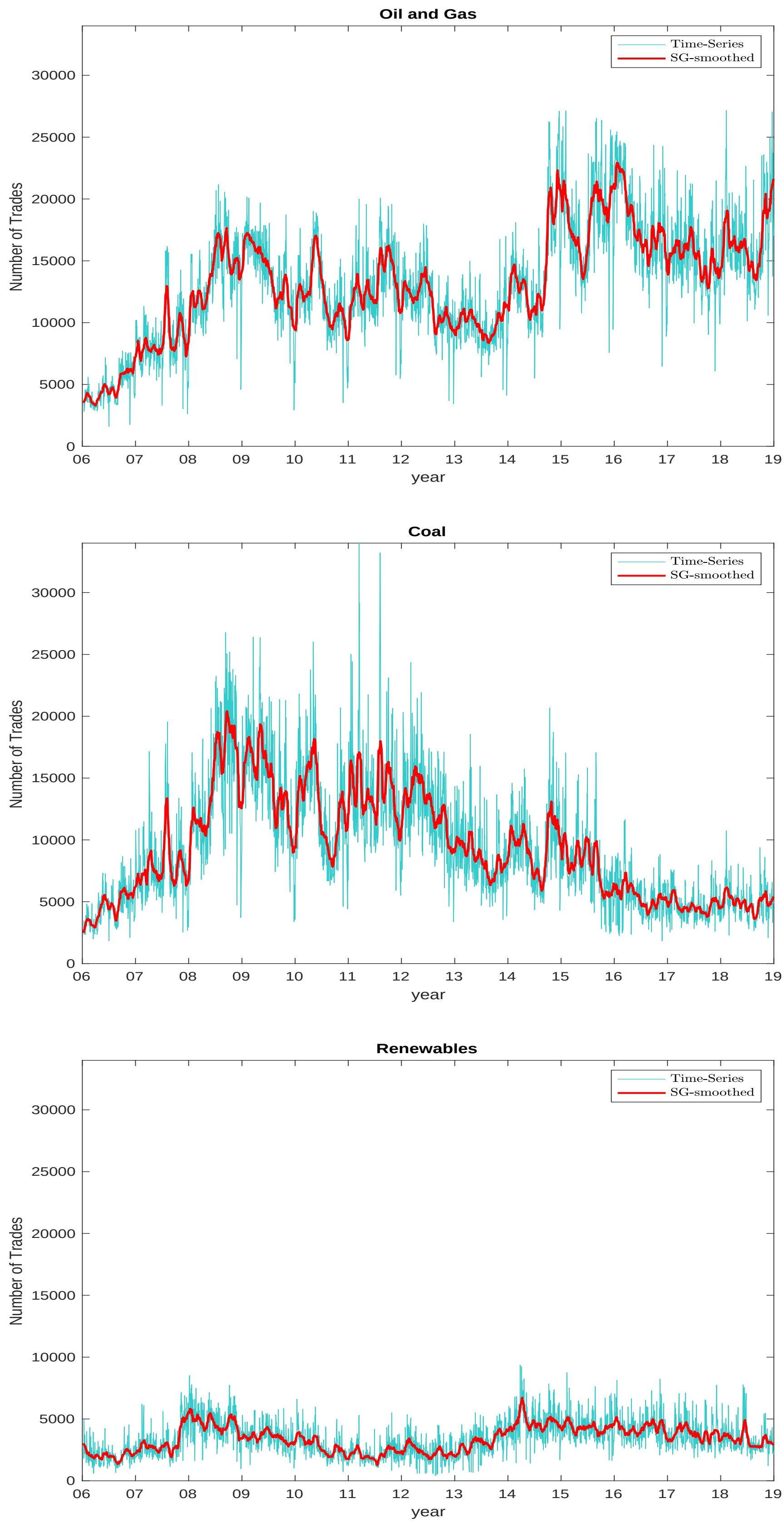


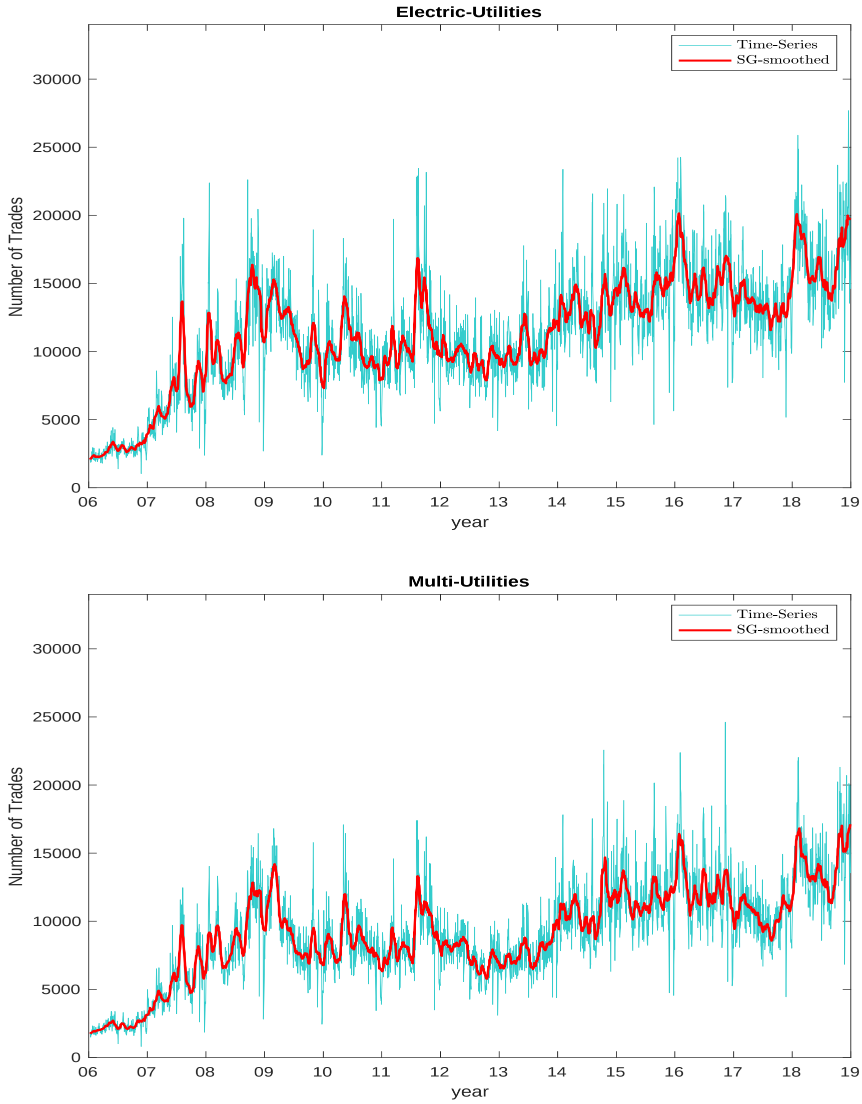




Note: Daily *price impact of trades* between January 10, 2006 and December 31, 2018, n = 3263. The unfiltered time-series per energy segment is plotted in turquoise, Savitzky-Golay smoothing in red.

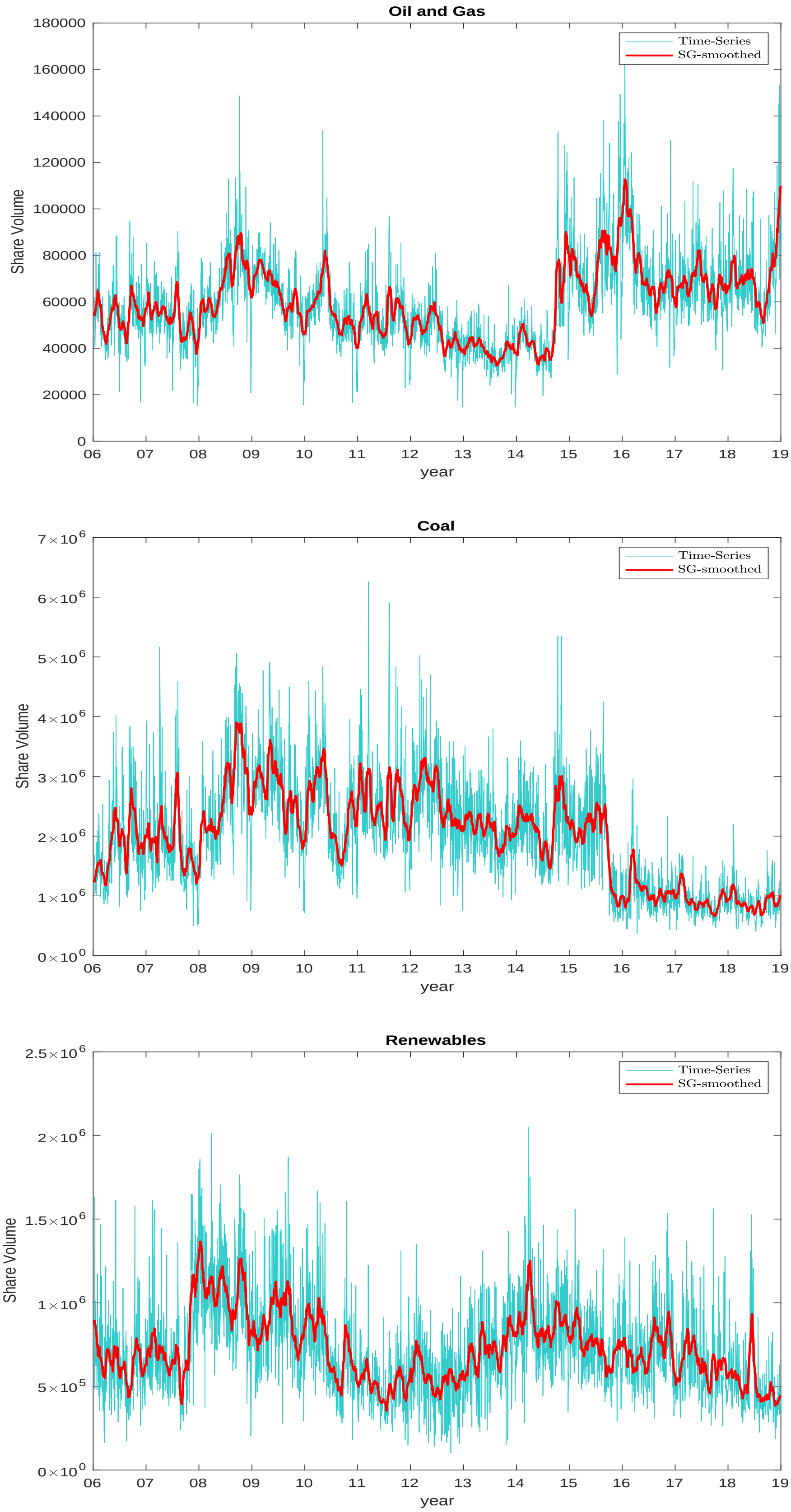
Figure A10: Daily *Number of Trades* per Energy Segment.

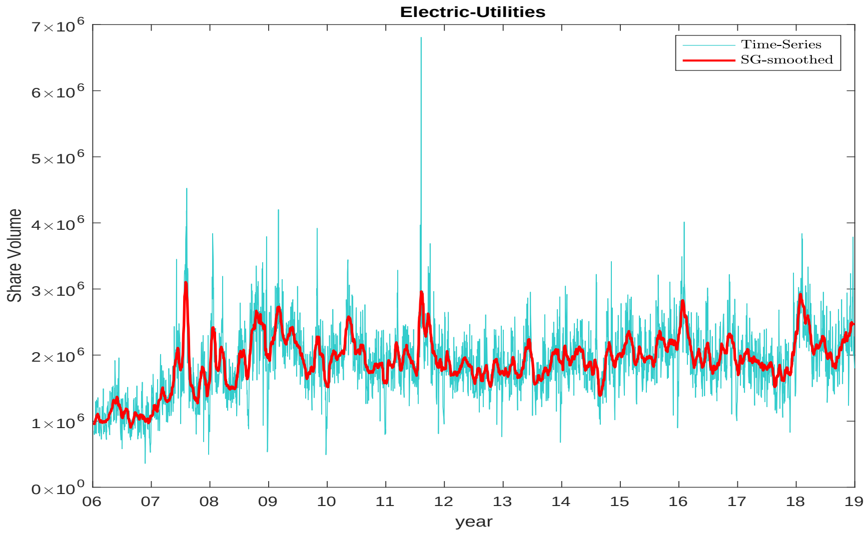


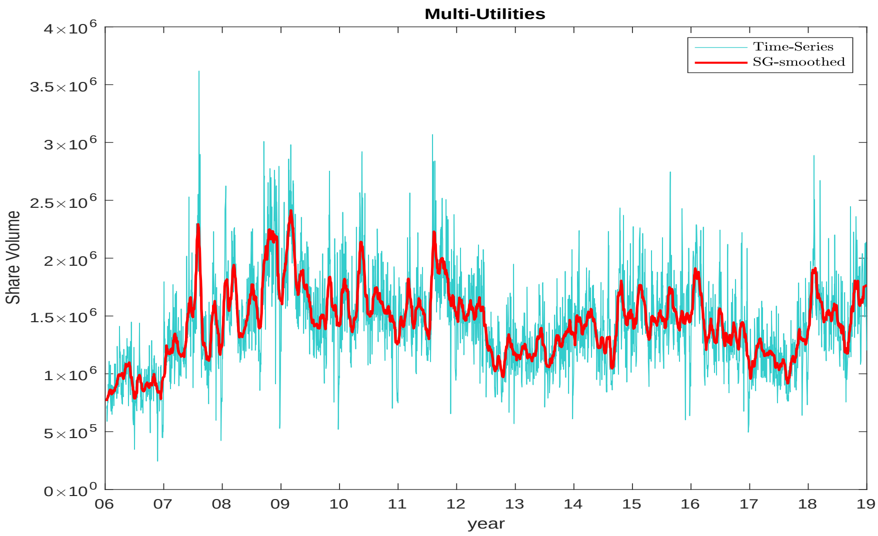


Note: Daily *number of trade executions* between January 10, 2006 and December 31, 2018, n = 3263. The unfiltered time-series per energy segment is plotted in turquoise, Savitzky-Golay smoothing in red.

Figure A11: Daily *Trade Volume (in Shares)* per Energy Segment.

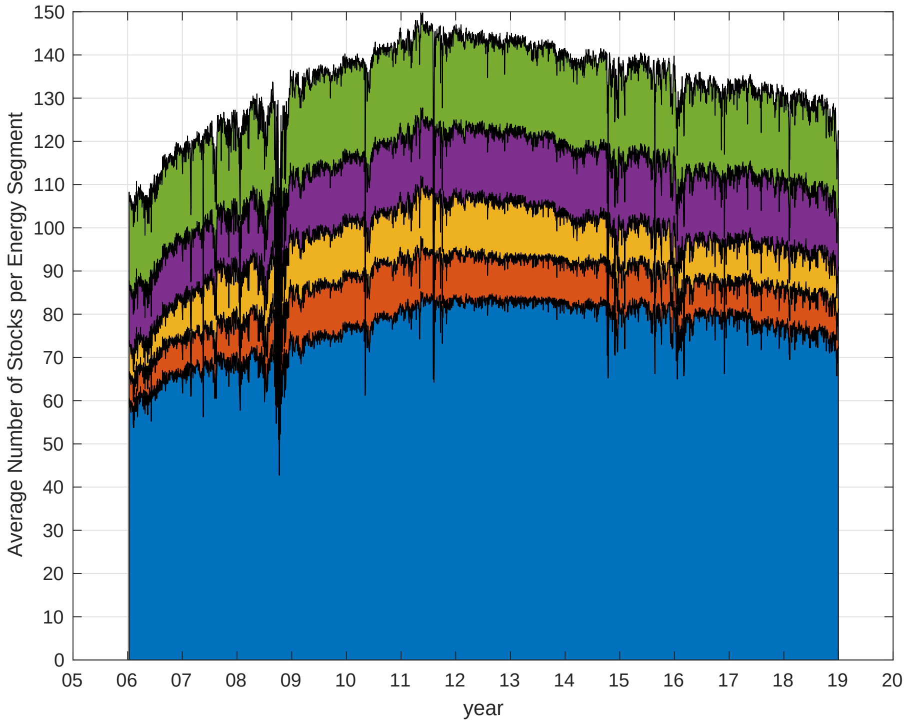






Note: Daily *trade volume* between January 10, 2006 and December 31, 2018, n = 3263. The unfiltered time-series per energy segment is plotted in turquoise, Savitzky-Golay smoothing in red.

Figure A12: Number of Stocks in Energy Segment



Note: This plot represents the average number of stocks in each energy sector. In our analysis, we aggregate stock-specific liquidity and trading activity characteristics and equally-weight them by the number of stocks in the sample for each segment. Due to the fact that some firms have gone public later in the sample period or others have merged business activities, we control for the weighting dynamically. In a second step, we use the interquartile method to delete outlier-like records for each measure that exceed twice the interquartile ranges. As result, we delete records and lose its counting as number of stocks on each trading day. As we may delete an outlier record of liquidity data for stock X but its corresponding trade volume on that particular day was well within the pre-defined interquartile range, we get different numbers in the counting of stocks for each measure. To finally get a compact average visualization of the number of stocks in each segment, we take the cross-sectional average of the count of stocks considered for each measure for each segment on each trading day.

Figure A13: Histogram - *Effective Spread* per Energy Segment.

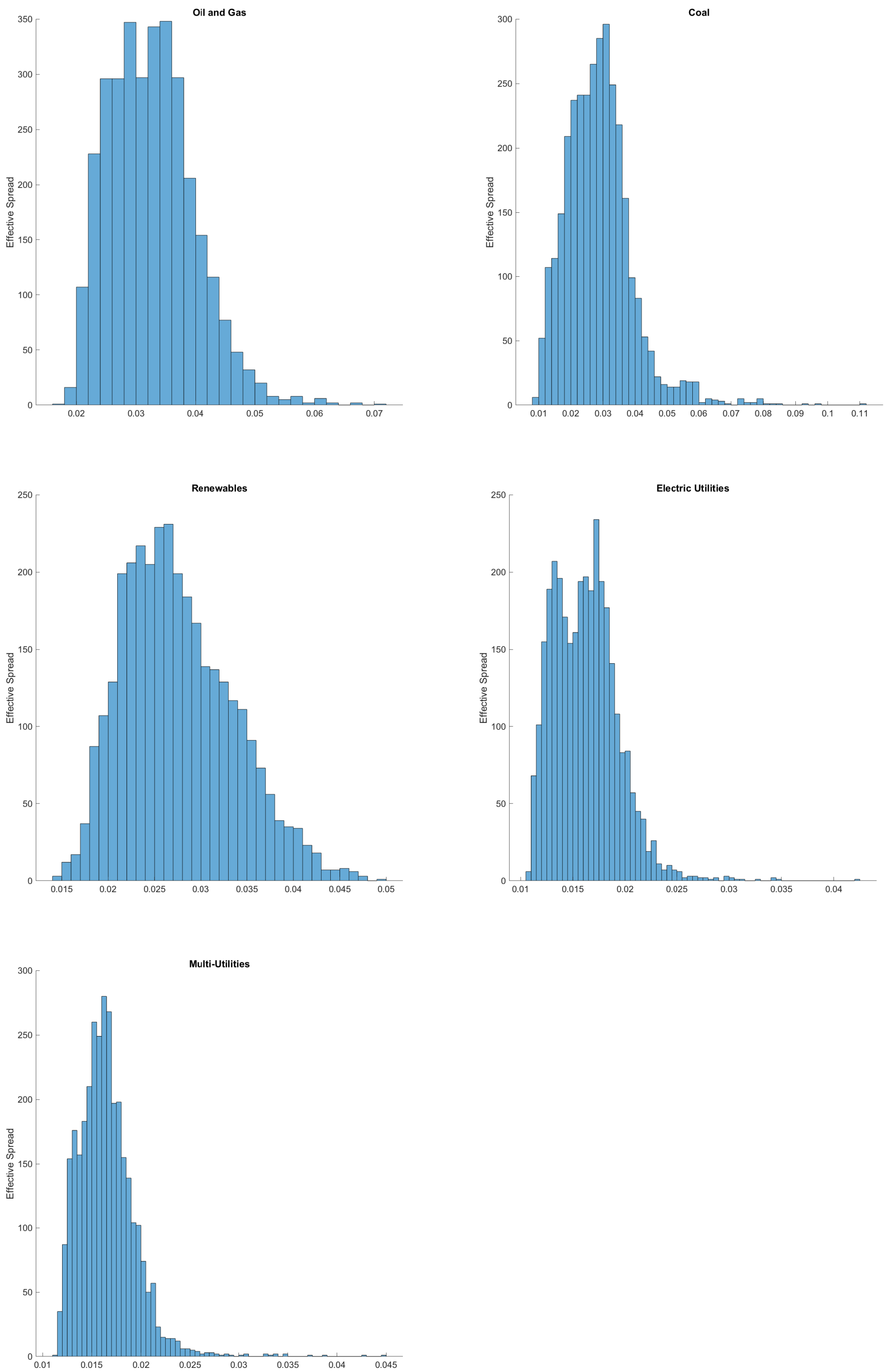


Figure A14: Histogram - *Price Impact* per Energy Segment.

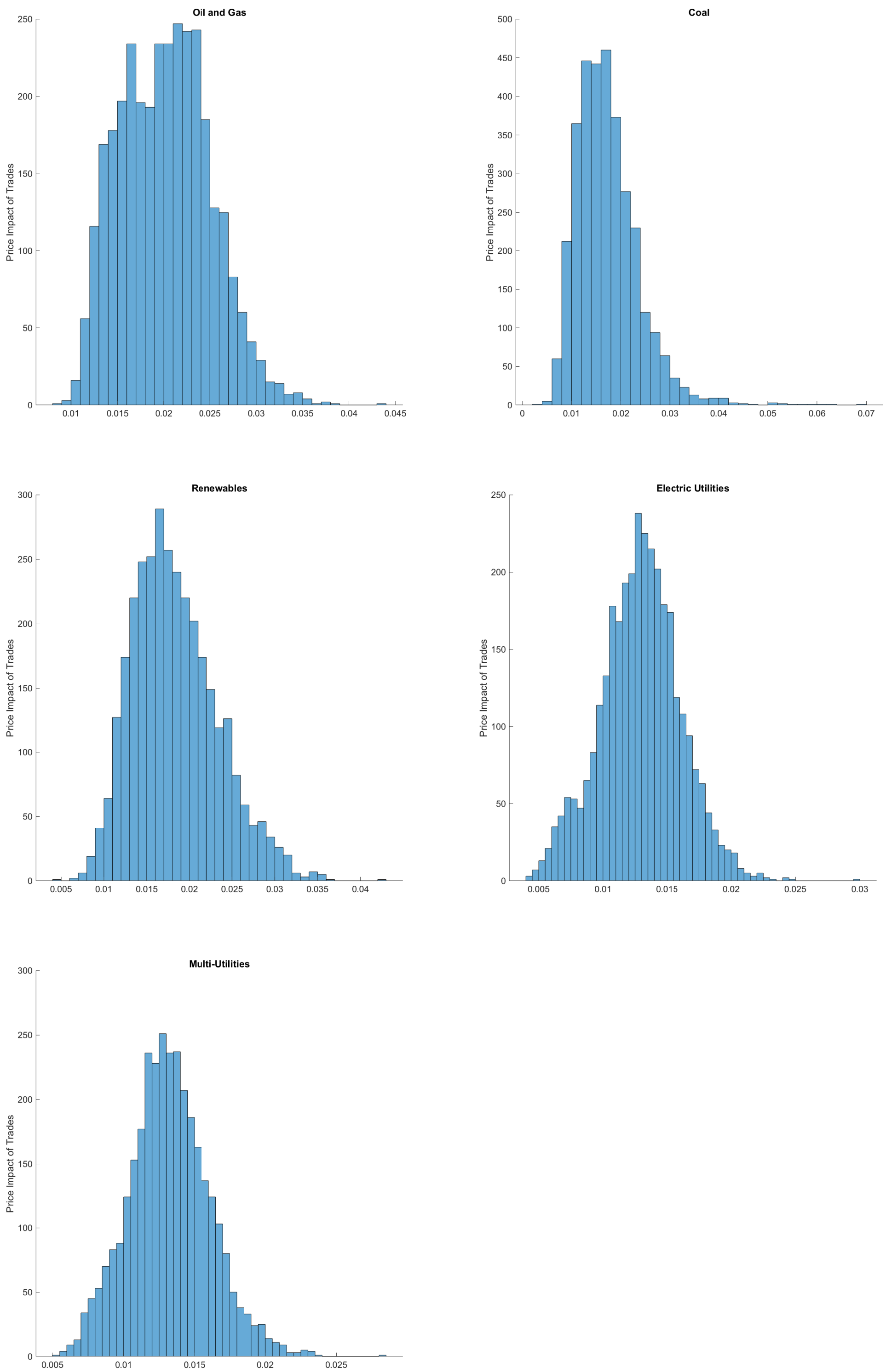


Figure A15: Histogram - *Number of Trades* per Energy Segment.

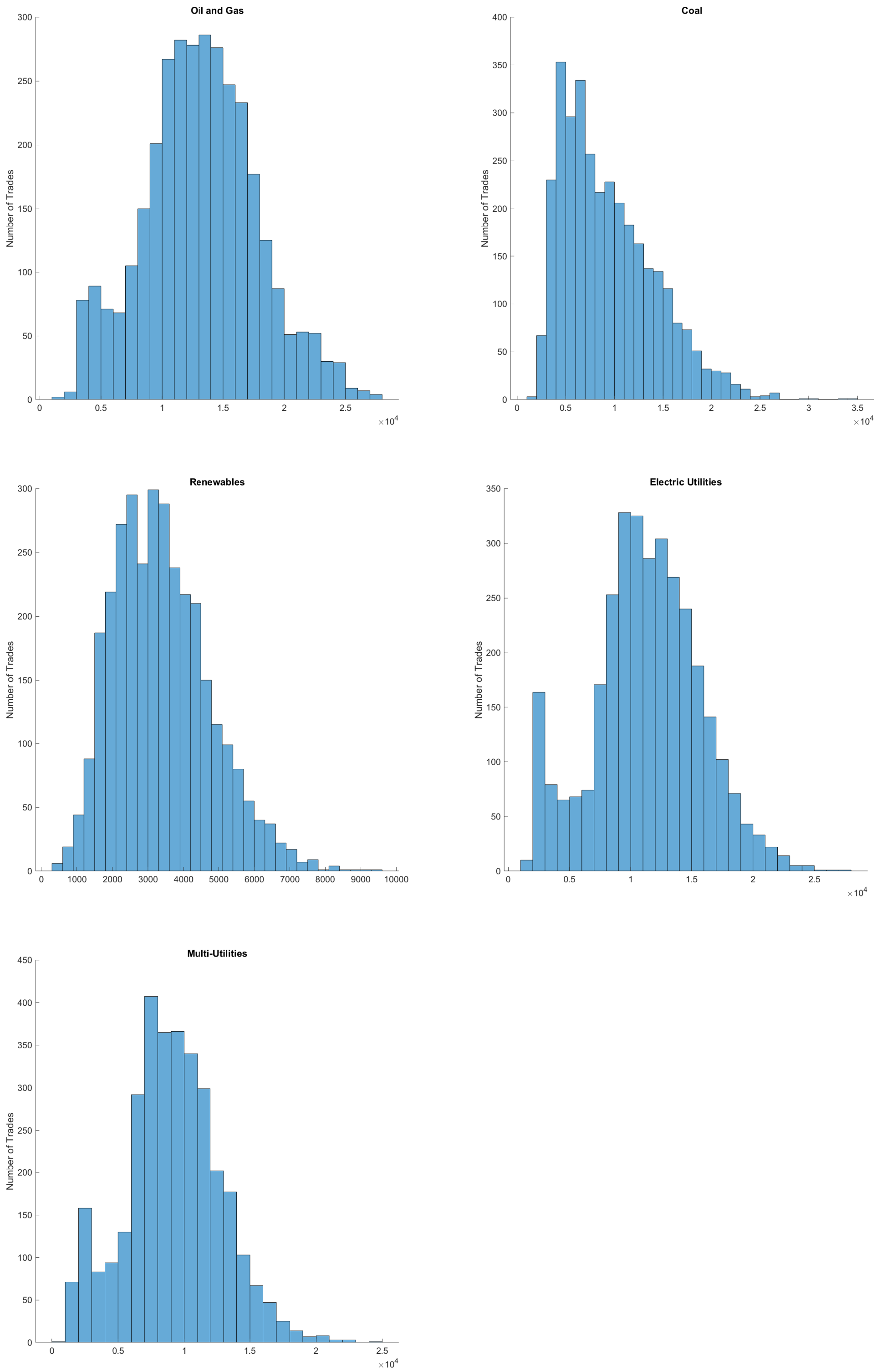
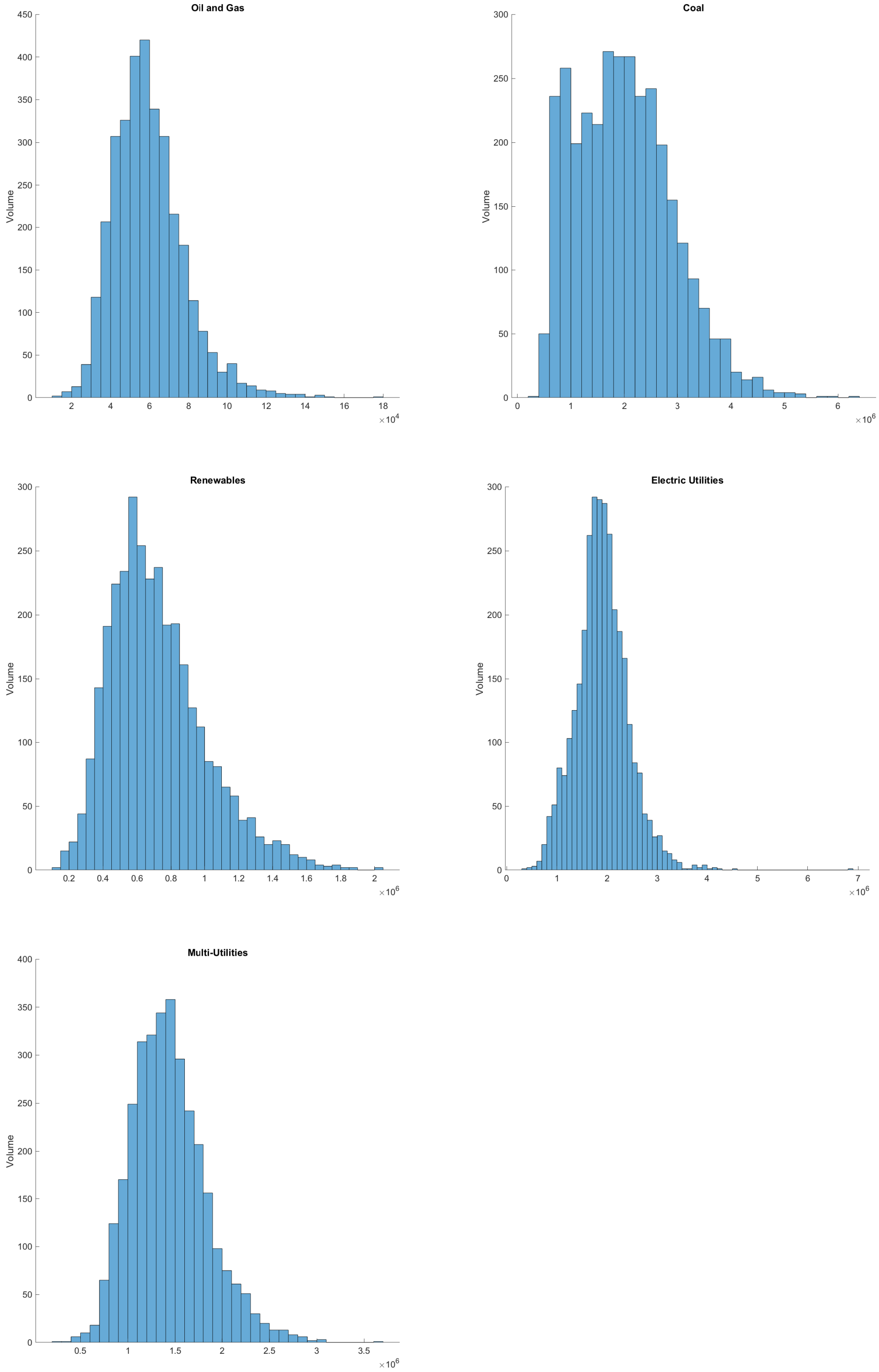


Figure A16: Histogram - *Trade Volume (in Shares)* per Energy Segment.



5 Conclusion

This dissertation contributes to a better understanding of liquidity in financial markets. Relying on the latest proxies for liquidity and TAQ (trades and quotes) benchmark data, this dissertation investigates liquidity in financial markets from different perspectives and gives answers to crucial challenges when assessing the importance of liquidity; its time-varying commonality across assets and stock markets; its impact on asset pricing in abnormal market states and finally its dynamics and determinants on a daily basis. This study has implications for investors and market makers as part of risk management and portfolio diversification and for policy makers in the context of designing optimal regulatory frameworks to predict and prevent common sources of liquidity tightness in global financial markets.

In the second chapter, I study commonality in liquidity and its association to market volatility. Taking on a global perspective on this matter and examining nine major stock markets, I first construct a novel and dynamic measure of commonality in liquidity. I show that liquidity commonality is present in global stock markets and increases parallel to crisis periods. This finding points towards abrupt changes in liquidity fundamentals and clearly provide evidence for demand- and supply-driven sources of commonality in liquidity (i.e. correlated trading behavior on institutional level paired with restrictions on funding capital) on a global scale. Driven by the well acknowledged findings of a positive relationship between volatility and illiquidity, I investigate a time-varying tie between common variation in liquidity and volatility. Using a dynamic granger-causality test, I find that global market volatility always causes commonality in liquidity while commonality in liquidity causes volatility only in sub-periods, spanning over the global financial crisis and its aftermath period.

In the third chapter, I examine the effect of systemic liquidity risk as a priced risk factor in asset pricing. Hereby, I challenge the previous literature in their finding of a linear relationship between systemic liquidity risk and asset prices. I show that systemic liquidity risk is not always a priced factor in the explanation of asset prices. I find that systemic liquidity risk and asset prices are negatively associated in bad market states. This finding can be explained by downward trended liquidity spirals, in other words, an interaction between demand- and supply-sided commonality in liquidity, which cause a depression in asset pricing during bad market states. I also show that liquidity risk has a positive link to asset pricing in good market states, which is mainly associated with search-for-yield considerations. Finally, I document that there is no significant relationship between systemic liquidity risk and asset pricing during normal market swings. This finding supports the initial claim that market participants do not worry too much about the state of market-wide liquidity during regular times.

In the fourth chapter, I investigate daily liquidity and trading activity of energy stocks traded at U.S. stock exchanges, categorized into five energy sectors, that is, *oil and gas*, *coal mining*, *renewables*, *electric- and multi-utilities*. Using TAQ data, I examine various dimensions of liquidity and trading - *effective spreads*, *price impact of trades*, *number of trades* and *volume* - on sectoral level. I document cross-sectional differences in the level of liquidity and trading across energy stock segments. Similar across sectors, I find that liquidity and trading exhibit trends and serial dependency up to several weeks. There is a weekly pattern for trading and liquidity, both decline on Fridays, on average. I also identify a number of factors that affect trading and liquidity of energy stocks, similarly across sectors, that is, general market movements, short-term momentum runs and overall stock market volatility, which points again towards the direction of correlated trading, amplified by institutional investors. Moreover, I show that trading and liquidity are sensitive to a widening Term Spread. I find a heterogeneous effect of the oil price on liquidity and trading activity, dependent on the energy segment. Despite controlling for stock market volatility, I observe that illiquidity and trading increase with higher levels of oil price volatility. Finally, I show that trading activity, both, in number of trade executions and share volume, increases for renewable and multi-utility stocks, when climate change receives global media attention.

Fast markets and increased trading make liquidity to be one of the top considerations in the smooth functioning of financial markets, especially in the light of financial distress and sudden, downward trended liquidity spirals, where liquidity adjusts to different equilibria levels. For future discussion, there is further need to address liquidity in its different dimensions and in the context of financial market quality, information efficiency and sentiment. This dissertation is yet another step for a more comprehensive knowledge on liquidity.

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