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Abstract

We introduce a novel method to aggregate the different dimensions of liquidity (tightness, depth and resilience) into a single 'unified' market-wide liquidity index. We rely on twenty-four measures of market liquidity divided into eight groups. Each group either represents direct trading costs, which refer to the spread estimates (tightness), or indirect trading costs, which span the price impact estimates (depth and resilience). The weights assigned to the different groups are time-varying and depend on three components: the correlation between groups, the liquidity pressure conveyed through the measures in the group, and their conditional variance. Our liquidity index succeeds in tracking the most important historic episodes of financial stress. Moreover, it shows the expected macroeconomic and financial relationships mentioned in the literature, and has some predictive power for future growth rates. Finally, our methodology can gauge the individual importance of each liquidity group over time. Our results show that price impact measures receive higher weights during tranquil periods, while spread estimates play a prominent role during periods of financial distress.

Keywords: market liquidity; trading volume; transaction costs; price impact; effective spread; financial crises; signal-to-noise ratio; macro-financial linkages

JEL Classification: G01, G12, G14, E44

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Non-Technical Summary

Market liquidity is an intuitive concept. It is widely used in the financial world, and refers to the ease of trading an asset. Preferably a trade happens quickly, without incurring excessive costs, and against a fair price. During good times, we tend to take market liquidity for granted. However, when it disappears, investors suddenly distrust each other, and stop trading. As a result, liquidity droughts are closely intertwined with moments of financial distress, and should therefore be carefully monitored by policymakers.

Despite its popularity, market liquidity is impalpable, ambiguous, and behaves differently depending on the state of the economy. Moreover, it is hard to define as it describes multiple properties of an asset. Broadly speaking, we can summarize three dimensions of liquidity: tightness, depth and resilience. The literature offers many definitions and ways to measures these. They are often categorized as spread estimates (tightness) and price impact estimates (depth and resilience). However, there is no consensus on how to deal with this high degree of dimensionality. Some authors use dimension reduction techniques, while others run horse races to appoint a single winner. Both approaches have their shortcomings. We contribute to the literature by introducing a new method to aggregate market liquidity measures into an index that incorporates the different dimensions and their strengths.

We first calculate twenty-four liquidity measures for every stock in the S&P 500, and aggregate these into market liquidity indices. These twenty-four indices are then divided into eight groups based on their construction method. Every market liquidity group contains two types of information. On the one hand, there is a common element across groups, as they reflect closely related concepts, at least in equilibrium. When multiple dimensions simultaneously pick up the same signal, this gives us valuable information. We reflect this in our aggregation by incorporating the correlations between the groups. On the other hand, there is a group-specific element, as some dimensions might diverge at times. Especially during financial distress, some groups might succeed better at capturing the volatility in the markets. While seemingly dissonant, this information may still be systemically important, as it reflects the market as a whole. We therefore also want to incorporate signals that only some dimensions can pick up, and that others might neglect. We do so by adding weights to our aggregation scheme. As a result, we reunite the individual strengths of the different dimensions, emulating the investor's general feeling of liquidity. Some groups provide more meaningful information in turbulent markets, while others may be more helpful for tranquil periods.

Our unified market liquidity index is able to identify important historic episodes of financial stress. It performs well as an early warning mechanism, allowing policymakers to detect true distress signals, while producing very few false warnings. Moreover, our index shows the expected relationship with macroeconomic and financial variables, especially with volatility and spread measures. It also significantly affects asset prices, most prominently the Federal Funds rate and the US dollar-Euro exchange rate. The latter relates to the flight-to-safety mechanism during highly illiquid episodes. Our index is useful when forecasting real variables, and liquidity shocks seem to have spillovers to the real economy. Moreover, within our framework we can inspect the individual importance of each liquidity group over time. Our results reveal that price impact measures receive higher weights during tranquil periods, while spread estimates play a prominent role during periods of financial distress. Bringing together these qualities of each liquidity group leads to a measure which is better equipped at handling the different states of the economy.

Our index is easy to compute, and can be applied to many countries and time periods. Our methodology can be extended to accommodate the asset-specific or high frequency aggregation of liquidity dimensions. Moreover, it would be useful to study the interactions between monetary policy shocks and liquidity over prolonged periods of time. Finally, a theoretical model, which would allow for liquidity to behave differently in equilibrium than during financial stress, could be a nice complement to our empirical setup.

"*Everything falls into place, irrelevancies relate, dissonance becomes harmony, and nonsense wears a crown of meaning. But the clarifying leap springs from the rich soil of confusion, and the leaper is not unfamiliar with pain.*"

— John Steinbeck, Sweet Thursday

1 Introduction

Market liquidity refers to the ease of trading a security. Its absence is associated with important episodes of financial stress. The concept has a strong intuitive appeal.[1] As a result, it has been incorporated into different strands of the literature, ranging from empirical finance to monetary economics.[2] It has taken up a prominent role in studies on asset pricing. For example, Acharya and Pedersen (2005, p. 405) caution investors about the performance and tradability of their securities "both in market downturns and when liquidity dries up".

However, despite its ubiquitous use, measuring liquidity remains a challenging task since no single measure within the literature can capture the different dimensions of liquidity simultaneously (Amihud et al., 2005). Moreover, the relative importance of these dimensions may fluctuate over time (Sarr and Lybek, 2002). Liquidity measures that generally perform well may no longer be useful during stressful times, given that financial markets tend to behave differently under turbulent conditions than they do in normal times (Upper, 2001).

The aim of this paper is to construct a comprehensive market liquidity index that brings together the multiple dimensions of liquidity by allowing their weights to vary endogenously over time. On the one hand, we use the correlation between the dimensions. When several dimensions simultaneously pick up the same signal, this gives us valuable information. On the other hand, we also want to incorporate signals that only some dimensions can pick up, and that others might neglect, especially during times of extreme, or volatile, illiquidity pressure. As a result, we reunite the individual strengths of the different dimensions, emulating the investor's general feeling of liquidity.

Our unified market liquidity index succeeds in identifying episodes of financial stress and recessions over a long time period from 1962 to 2013. It is closely

[1] Keynes (1936, p. 160) refers to the soothing quality of liquidity: "For the fact that each individual investor flatters himself that his commitment is 'liquid' (though this cannot be true for all investors collectively) calms his nerves and makes him much more willing to run a risk".

[2] e.g. Mitchell et al. (2007); Chordia et al. (2008); Avramov et al. (2015) in the finance literature. Adrian and Shin (2009); Bruno and Shin (2014); Lagos and Zhang (2018) in the realm of monetary policy.

linked with several well-established crisis indicators, and produces comparatively high signal-to-noise ratios. Moreover, the novel measure exhibits a significant relationship with various macro-financial variables. We uncover real spillovers from liquidity droughts, and can attribute some forward looking power to our liquidity index, above and beyond other commonly used forecasting variables. These results are markedly more robust for our novel index than for the underlying measures, thus reinforcing the importance of taking separate dimensions together. Importantly, our index is easily applicable, and can be computed for long samples as well as for many countries.[3]

When constructing and evaluating our market liquidity index, we have to be mindful of its latent, multidimensional and endogenous nature.[4] Firstly, liquidity is a latent characteristic (Pástor and Stambaugh, 2003). Agreeing on a unique definition has therefore been challenging. The literature is scattered with numerous descriptions of liquidity (Baker, 1996). Moreover, due to this impalpable nature, liquidity can only be approximated through the measurement of liquidity-related quantities or proxies (Kim and Lee, 2014). However, Mahanti et al. (2008) highlight that these empirical measures can be markedly disparate from each other. Due to the elusive nature of liquidity, a formal appraisal of liquidity measures is not straightforward. We can, however, gauge their adequacy indirectly given our understanding of variables that co-move with liquidity, or phenomena that are linked with its disappearance.

Secondly, liquidity is a broad concept covering multiple dimensions. Most famously, Kyle (1985) refers to the depth, resilience and tightness of an asset, which add up to a general feeling of liquidity. They describe the ability of trading a substantial amount of assets quickly, at low cost, and at a reasonable price (Harris, 2003). However, underlying the ease of converting an asset into cash are many different cost components and market frictions.[5] Table 1 offers an overview. In trying to account for all the aspects affecting liquidity, there has been a proliferation of liquidity measures, making it impossible for one single measure to capture all these layers (Hallin et al. 2011). As a result, low correlations between different

[3]Our measure does not require any specialized or high frequency data series, and solely relies on ten basic financial series. In the US, these are provided at the stock level by the Center for Research in Security Prices (CRSP).

[4]There are three broad strands of liquidity: market liquidity, funding liquidity, and central bank liquidity. Our focus will be on the former. However, all three strands are closely related (Brunnermeier and Pedersen, 2009), and we will examine these relations when we evaluate our liquidity measure.

[5]Gorton (2012, p. 48) argues that "markets are liquid when all parties to a transaction know that there are probably not any secrets to be known: no one knows anything about the collateral value and everyone knows that no one knows anything. In that situation it is very easy to transact."

individual measures do not necessarily imply that one is inferior to the other. Instead, the measures could be gauging different dimensions (Liang and Wei, 2012). Similarly, there is evidence that different frequencies capture different phenomena (Vayanos and Wang, 2012). Unsurprisingly, there is little consensus on which proxy to use. Many authors rely on a whole spectrum of liquidity measures in their analysis, as each proxy is considered to have its strengths and weaknesses (Asparouhova et al., 2010). We follow Lesmond (2005), and divide the measures up in direct trading costs which refer to the spread estimates (tightness), and indirect trading costs which span the price impact estimates (depth and resilience). In our analysis, we incorporate eight groups of liquidity, five of these are spread proxies (bid-ask, etick, Roll, Fong, zero-returns), while the other three are price impact proxies (Amihud, volume, order flow). Within every dimension, the groups embody different ways of measuring that specific dimension, and can thus be interpreted as closely related subdimensions. These measures are explained in detail in Section 3.

Thirdly, adding to the complexity, liquidity is an endogenous concept. It is closely entwined with its macro-financial surroundings through multiple channels, including its interaction with sentiment (Baker and Wurgler, 2006), real economic activity (Næs et al., 2011), monetary policy (Goyenko and Ukhov, 2009), and the level of uncertainty in the economy (Watanabe and Watanabe, 2008). It depends on trading patterns in financial markets (Chordia et al., 2011), and therefore also on the total volatility of the financial system.[6] Moreover, it has leading and lagging relations with credit ratings (Odders-White and Ready, 2005), and strong interlinkages with the interbank market (Nyborg and Östberg, 2014). Hence, in line with the Lucas critique (1976), different economic environments, with disparate shocks hitting the economy, can influence the importance and even the proficiency of the liquidity measures over time.

Our method for combining the liquidity groups builds on recent developments in the field of financial stress indicators (Oet et al., 2011; Holló et al., 2012). We provide some useful extensions to tackle the specific latent, multidimensional and endogenous nature of liquidity. We start off at the micro-level, by constructing measures of liquidity for each stock that is present in the S&P 500 index that month, tracking additions and deletions. As a result, we end up with twenty-four monthly liquidity time series for each of the 500 stocks in the index during that month. Each liquidity proxy is then transformed into a S&P-500 wide, market liquidity index by taking weighted averages of the individual stocks. We assign these twenty-four

[6] Pagano (1989, p. 269) warns that "thinness and the related price volatility may become joint self-perpetuating features of an equity market, irrespective of the volatility of asset fundamentals".

market liquidity indices to eight separate groups, according to the dimension of liquidity they characterize. Next, we apply the portfolio approach (Illing and Liu, 2006) in order to aggregate these eight groups into one single market liquidity index. We use time-varying correlations to determine which dimensions of liquidity are simultaneously picking up the same signal. This offers a first indication about the relative importance of each liquidity group.

Up to this point, our framework simply provides an alternative aggregation method to the common factor or principal component analysis (Korajczyk and Sadka, 2008; Hallin et al., 2011). However, we do not solely want to rely on the commonality across liquidity groups, and therefore introduce the following two extensions. Firstly, we add a time-varying weighting scheme that additionally incorporates important idiosyncratic signals whenever a specific group hints at extreme pressure relative to its peers. Given the discordant backgrounds of each liquidity group, there will be times when a single or several specific groups pick up a signal that the others ignore. Although these signals may seem dissonant, they are still systemic as they reflect the liquidity of the whole S&P 500 market. In these cases, simply weighting the different classes by their correlations would imply that we neglect such signals. Some measures of liquidity may provide more meaningful information in turbulent markets, while others may be more helpful for tranquil periods. Secondly, we further refine our time-varying weights, by making the assumption that volatile liquidity groups attract more investor attention than tranquil groups, thus meriting a higher weight.

While our primary focus is the aggregation of liquidity, our methodology allows us to inspect the importance of the constituent liquidity groups over time. During turbulent periods, our aggregation scheme attributes the highest weights to the spread estimates. In contrast, during more tranquil times, the price impact estimates play a more prominent role in the movements of liquidity. Hence, unifying these distinct properties of each liquidity group allows for the construction of a proxy which is better equipped at handling the different states of the economy.

The paper is organized as follows. Section 2 explores several strands of closely related literature, while Section 3 describes the construction method of our unified liquidity measure. Next, in Section 4, we examine how our liquidity measure behaves over the financial cycle, and specifically during episodes of financial stress. For that purpose, we assess its performance in terms of signal-to-noise and its interlinkages with macroeconomic and financial variables. Section 5 provides a more introspective view on our liquidity measure, as we gauge the importance of the separate liquidity groups. Finally, we offer some concluding remarks in Section 6.

2 Related Literature

Many liquidity proxies have been proposed in the literature covering various dimensions. Several approaches in dealing with this multiplicity have been put forward. Some authors rely on data-reduction techniques in order to manage this high dimensional dataset. Others run horse races to find the most optimal measure from a wide array. We discuss how these existing techniques relate to our approach, and point to some of their drawbacks. Our contribution is a novel aggregation method that allows for a intuitive way to deal with these multiple dimensions, using the commonality across groups but also allowing for group-specific signals.

2.1 Data Reduction

Several authors rely on data reduction techniques in order to achieve a sparse representation of liquidity. Lesmond (2005) examines whether a common liquidity factor is being captured by four traditional liquidity estimators, as he is doubtful whether any individual measure can capture all of the liquidity dimensions. Korajczyk and Sadka (2008) use principal component methods to construct an estimate of the overall market liquidity based on several liquidity measures. Their study focuses on combining information from various sources into a single measure of liquidity. Similarly, Hallin et al. (2011) apply a generalized dynamic factor model to produce a data-driven proxy of unobservable market liquidity. They succeed in identifying the commonality over several liquidity measures. Our approach is close in spirit to these data-reduction techniques but offers a more intuitive aggregation of the different dimensions. We adjust our approach as a response to some of the drawbacks these techniques exhibit when applied to liquidity. We will discuss these issues more in depth, as they provide the motivation for our new methodology.

Firstly, most of these methodologies yield an unobservable "systematic" liquidity measure, leaving no room for any measure-specific, idiosyncratic contribution to the final liquidity metric. They rely heavily on the commonality across the liquidity measures as the sole feature which concerns the investor. This would be warranted if every liquidity measure is considered to be a proxy for the same dimension of liquidity, or at least highly correlated classes of liquidity. However, if one believes that alternate measures are a proxy for different dimensions of liquidity, then merely looking at their commonality can be restrictive, and does not necessarily tell the full story. The return of a specific stock could potentially also be influenced by a purely idiosyncratic liquidity signal, and should therefore not be de facto dismissed.[7] Investors might therefore care about multiple dimensions, and these might have a time-varying importance, especially if we believe that some dimensions are more useful during crisis periods and others are better at monitoring tranquil times, as a result of changes in the underlying fundamentals.[8]

Secondly, most data reduction techniques routinely start by standardizing the raw liquidity measures using their full sample mean.[9] However, there have been important changes during the sample period causing considerable shifts in the mean of many of the liquidity measures, and making it problematic to use their full sample mean to perform the standardization. As a result, some of these measures have become less widespread in the literature, even though they might still contain useful information when examined more locally.[10] It would therefore be more suitable to apply a time-varying mean in this case, thus performing the standardization over a smaller window.[11] Moreover, Holló et al. (2012) warn that the standardized variables might be sensitive to irregular observations, especially since many conventional liquidity measures violate the assumption of being normally distributed.

Thirdly, while these methodologies provide a valuable statistical method to reduce the dimension of the data, they do not offer a clear economic intuition. Moreover, the selection of the included variables in the literature seems to be done on an ad hoc basis, only including a limited number of liquidity proxies, which precludes a complete account of all the potential liquidity dimensions, in addition to the difficulty of reaching an agreement on which measures to incorporate.

2.2 Horse Races

An alternative strand within the recent literature runs horse races against a high frequency benchmark in order to single out the best performing liquidity measure, thus dealing with the large array of liquidity proxies in a different manner. Interestingly, these studies have shown that several low frequency proxies are relatively

[7] A individual liquidity measure is considered to be idiosyncratic if it diverges from the common trend laid out by the other liquidity measures, but still contains valuable information.

[8] To a certain degree, our methodology (applying the time-varying correlations) provides an alternative aggregation method to these more traditional data reduction techniques, and similarly focuses on the systematic components. However, we extend this procedure, and allow for idiosyncratic forces within the constituent liquidity groups to have an impact. We further refine this application by weighting this idiosyncratic information set by the volatility.

[9] This is motivated by the fact that the different measures of liquidity are expressed in a different unit of measurement (Fong et al., 2017).

[10] For example, measures based on the number of zero returns in a particular month are much less cited, as their occurrence has dropped markedly.

[11] In our approach, we use a similar local evaluation method when constructing the order statistic, which allows us to aggregate the differently measured liquidity units in a comprehensive manner.

successful in capturing the features of intraday data, thus legitimizing their use. However, there are similarly some drawbacks to this methodology when applied as a dimension reduction technique to single out one liquidity measure.

Firstly, the high frequency data is available for a limited period of time in the US,[12] and is only scarcely available for most other countries, thus restricting the time-frame available for these horse races (Hasbrouck, 2009).[13] In contrast, their low frequency counterparts can be formulated dating back many decades, and are available across many countries around the world (Holden, 2009). More importantly, the limited availability of the high frequency data potentially affects the stability of these horse races. When comparing short time spans, the results can be driven by the underlying shocks in the economy, and these can change over time (Lucas Jr, 1976). Hence, different periods might reward alternating winners, as other dimensions become more important or fade away over time.

Secondly, high frequency measures only capture one specific dimension of liquidity, similar to their low frequency counterparts. They are either estimates for the spread (percent-cost proxies), or for the price impact (cost-per-dollar volume proxies). Hence, these horse races only allow for comparison within every dimension, yielding a within-dimension winner.[14] Our aggregation method could therefore be extended to the high frequency domain, in order to allow for a more broad-based comparison.

3 Liquidity Groups

For our analysis, we incorporate twenty-four measures of liquidity, belonging to eight groups. We focus on low frequency measures that have been reported to perform well in the literature (Fong et al., 2017; Schestag et al., 2016).[15] The groups are formed by taking together measures that have a comparable construction method. Following Lesmond (2005), we distinguish two broad categories. On the one hand,

[12]In the US market, transaction data provided by the Institute for Study of Securities Markets (ISSM) and the Trade and Quote (TAQ) database are only available since 1983 (Chordia et al., 2009).

[13]Given that researchers, both in asset pricing and macroeconomic analysis, require long time series to ameliorate the power of their tests (Amihud et al., 2005), their application is still limited.

[14]For example, Holden (2009) employs the percent effective spread and the percent quoted spread as a high frequency benchmark. Goyenko et al. (2009) relies on two spread benchmarks and three price impact benchmarks. Fong et al. (2017) suggests four high frequency percent-cost benchmarks and one high frequency cost per volume benchmark. Corwin and Schultz (2012) incorporates TAQ effective spreads. Hasbrouck (2004) simply refers to estimates derived from detailed trade and quote data.

[15]Naturally, we want to include as many measures as possible, while facing limitations regarding both the availability and the frequency of some data series.

we observe direct trading costs, which can be measured by spread proxies. On the other hand, there are indirect trading costs, which we gauge using price impact measures.[16] The first five liquidity groups consist of spread measures; the last three groups consist of price impact measures. Our results show that price impact measures do better at explaining the level of liquidity, while spread estimates are especially useful in capturing the volatility in liquidity. An extensive survey on the construction of every individual liquidity measure can be found in Table 2.

3.1 The Bid-ask Group: Spread Estimates based on Bid-Ask Prices

The bid-ask spread is an intuitive measure of illiquidity. It relates to order processing costs, adverse selection, inventory components and monopoly power (Glosten, 1987). There are several versions of this measure. We use the quoted spread measure, which is the ratio of the *quoted bid-ask spread* and the bid-ask midpoint. However, many trades are executed within the spread, at more favorable prices (Vayanos and Wang, 2012). Following Korajczyk and Sadka (2008), we therefore incorporate the *effective spread*. This measures the difference between the transaction price and the mid-point of the quoted spreads.

Given that bid/ask prices are not consistently available,[17] we also compute *both spread measures using high and low prices*. The latter are more widely available in the CRSP database. Corwin and Schultz (2012) argue that daily high prices mostly correspond with buy orders, and low prices with sell orders. As a result, the ratio of daily high-to-low prices conveys both the bid-ask spread as well as the fundamental volatility of the stock.[18] This insight is further used to construct *alternative high-low spread estimates*. Price ranges over a two day period can be used to distinguish between the two, since the volatility component increases with the trading duration, while the spread component does not.[19]

Finally, we add the *measure by De Nicolò and Ivaschenko (2009)*. Although their approach may seem markedly different, their measure is highly correlated with the spread measures. The proxy is constructed as a variance-ratio measure, and is intended to track the dynamics of transaction and asymmetric information costs.

[16] Fong et al. (2017) similarly distinguish between percent-cost proxies and cost-per-dollar volume proxies.

[17] Pre-1982, the CRSP database does not allow us to retrieve bid and ask prices consistently for all the S&P 500 stocks that we are tracking in our analysis. Chung and Zhang (2014) give an overview of the availability of these series for the different exchanges.

[18] Holden (2009) similarly uses high/ask and low/bid values to compute the quoted spread on no-trade days.

[19] Corwin and Schultz (2012) report correlation values between their high-low spread estimates and the true spreads to be 0.9. For our estimates, we retrieve values in the same range.

This may explain the close relation with the above mentioned spread measures.

3.2 The Etick group: Spread Estimates Derived from Transaction Price Tick-Size

Holden (2009) and Goyenko et al. (2009) develop their proxy for the spread based on the observation that wider spreads coincide with larger *effective tick sizes*, which allows them to use price clustering to infer their estimate. This idea goes back to Christie and Schultz (1994) who report a close link between the effective tick size and bid-ask spreads for NASDAQ stocks in the early 1990s. Similarly, Harris (1994) detected that the minimum price variation limits the minimum bid-ask spread that can be quoted, and this restriction can be economically significant. We should therefore gauge how much bid ask spreads would change if the tick were a different size, and how the minimum price variation could impact market depth and trading volumes. Bessembinder (2000) supports the idea that changes in the tick size can affect equilibrium spreads on a dealer market, and advocates that this relations is more complex than the imposition of a constraint on minimum spread widths.

3.3 The Roll group: Spread Estimates Derived from Return Covariances

Roll (1984) provides estimates for the spread using observed price data alone, and does not require bid-ask price quotes or order flow information (Chen et al., 2019).[20] He assumes that the true value of a stock resembles a random walk process, that buy and sell order can occur with equal probability, and that the value process is serially uncorrelated (Harris, 1990). As a result, the expected autocorrelation of returns should yield a negative value. In reality, however, the covariance of price changes is regularly positive, so that the square root in the formula is not properly defined, yielding imaginary numbers for the spread estimate. Following Corwin and Schultz (2012), we incorporate two adjustments to deal with these cases. Firstly, we transform the *covariance into a positive number*, which allow us to calculate the covariance. We then reinsert the negative value, in order to get a negative spread estimate. Alternatively, we set the Roll *estimate to zero* when the covariance is positive (Hasbrouck, 2009).[21]

[20] Glosten (1987) highlights that Roll's spread estimator approximates the total spread only when there is no adverse-selection spread

[21] Harris (1990) finds that such positive values are usually linked with smaller spreads.

Additionally, we calculate the extensions to the Roll measure proposed by Holden (2009). We account for no-trade days as well as for splits and dividends. We also incorporate the idiosyncratic adjusted price changes in order to filter out the bid/ask/midpoint bounce. For this *extended Roll measure*, we similarly rely on the adjustments above to transform positive covariance values. Hence, we end up with four alternatives for the Roll measure.

3.4 The FHT Group: Spread Estimates based on a Simplified LOT model

Fong et al. (2017) explore the potential causes of zero returns. The true return lies between an upper and lower bound, given respectively by the transaction cost for buying and selling. When the volatility of the true return distribution is kept fixed, a higher proportion of zero returns leads to wider bounds and therefore also to wider spreads. Similarly, an increase in the volatility of the true return distribution leads to larger transaction bounds and higher spreads, when the share of zero returns remains constant.

The *FHT measure* builds on this relation between spreads and zero returns. The measure only requires return data, and is quick to compute. It has been used in many different settings, ranging from commodity markets (Karnaukh et al., 2015) and foreign exchange markets (Marshall et al., 2012), to stock markets in emerging economies (Bedowska-Sojka and Echaust, 2020).

3.5 The Zero-Returns Group: Spread Estimates based on the Number of Zero Returns

Lesmond et al. (1999) derive a proxy for liquidity based on the proportion of days with zero returns. Stocks with higher transaction costs will attract less private information collection. Therefore, it takes on average longer before an informed trade affects the price. As long as the value of the information signal is not large enough compared to the trading costs, the stock will not be traded, and will exhibit a zero return (Bekaert et al., 2007). Even on positive volume days, these stocks are more likely to reveal no information, and therefore will lead to an observed zero return (Goyenko et al., 2009).

We therefore incorporate two versions of this measure. One is based on the *zero returns* for all the days of the month. The other focuses on *zero returns which occur on positive volume days*. Lesmond (2005) highlights that this reasoning implies a direct relation between zero returns and the level of informed trade, and builds on various assumption about the type of traders, the information flows, and the sensitivity of prices to this type of trading. Given that this measure only relies on daily equity returns, it can be easily computed across a wide variety of markets (Lang et al., 2012).

3.6 The Amihud Group: Price Impact Estimates based on Amihud-type Measures

Firstly, Amihud (2002) inspects the absolute price change per dollar of daily volume. His measure describes the daily price response associated with one dollar of trading volume.[22] This proxy is more closely linked to Kyle's price impact definition of liquidity (Lesmond, 2005). As the data is widely available, it can be easily adapted to markets around the world. Moreover, it can be computed for days with no price change, although zero volume days still yield an undefined estimator. Next to *Amihud's original measure*, we also include the *extended Amihud measure* by Goyenko et al. (2009). They examine the ratio of the average daily spread to the average daily dollar volume. Their measure can therefore be interpreted as the liquidity cost attributed to one dollar of trading volume.

Secondly, we incorporate the *Hui and Heubel (1984) ratio*. We follow Sarr and Lybek (2002) for the construction method. The ratio compares the volume of trades with their price impact, and therefore touches on market breadth and resilience.[23] The numerator is given by the percentage change in the price, but alternatively bid-ask prices can be used. The denominator features the ratio of the traded volume to the outstanding volume. When gauging the price impact the measure therefore takes into account whether the volume traded represents a large proportion of the available volume in the market.

Thirdly, *Breen et al. (2002)* quantify the price impact as the change in a firm's stock price as a result of the observed trading volume. They interpret their measure as an extension of the linear pricing rule of Kyle (1985). The authors apply scaled measures, and rely on turnover and returns, instead of volume and prices (Korajczyk and Sadka, 2004).

Finally, *Liu (2006)* introduces a measure that simultaneously captures trading speed, trading quantity and trading cost. The measure is given by the standardized

[22] Similar to Acharya and Pedersen (2005), we scale our measure using a ratio of market capitalization of the CRSP S&P500 market index in t-1 and a reference date, which coincides with the start of our sample in 1962.

[23] The ratio can be calculated over a five day period to smooth the volatility.

turnover-adjusted number of zero daily trading volumes over the prior x-month period.

3.7 The Volume Group: Price Impact Estimates based on Volume and Turnover

In this group, we incorporate *(dollar) volume* based measures. Dufour and Engle (2000) highlight that volume affects asset prices, potentially even in a persistent manner, and therefore contains useful information. As a result, this measure is widely used in the literature. Rehse et al. (2019) study the effect of uncertainty on liquidity, and rely on the dollar volume of a stock, defined as the product of the number of shares times the closing price, as a measure of the trading volume. Similarly, Christoffersen et al. (2018) incorporate dollar volume when examining liquidity premia in equity option markets.

Moreover, we rely on the *turnover rate* as a proxy for liquidity (Datar et al., 1998). This measure is defined as the number of shares traded divided by the number of shares outstanding. Sarr and Lybek (2002) argue that it makes more sense to examine the trading volume by relating it to the outstanding volume of the stock. Turnover is relatively widely available, features in many applications, and has both an intuitive and theoretical appeal. However, the turnover measure sometimes moves counterintuitively as a result of its specific focus on trading liquidity. Especially during a liquidity crunch turnover will likely shoot up instead of underscoring the drop in market liquidity (Lesmond, 2005).

3.8 The Order Flow Group: Price Impact Estimates based on the Pastor-Stambough Measure

Pástor and Stambaugh (2003) introduce a novel measure of liquidity based on how returns respond to volume related fluctuations. Stronger volume related return reversals are associated with lower liquidity (Vayanos and Wang, 2012).[24] The *price reversal*, gamma, is measured through a regression using daily firm returns and signed volume as a proxy for order flow (Bekaert et al., 2007). Alternatively, we use turnover to calculate this liquidity measure. In practice, gamma is expected to have a negative sign. The price impact is interpreted to be stronger when the absolute value of gamma is higher (Goyenko et al., 2009).

[24] Campbell et al. (1993) similarly report that returns that reverse more strongly are linked with higher volume.

4 Statistical Design

While many authors refer to the multiple dimensions of liquidity, there have been few attempts at constructing an all-encompassing measure. To address this issue, we introduce a novel market liquidity index which summarizes the disparate liquidity groups into one single time-series, by allowing their weights to vary over time, thus approximating the investor's general feeling about liquidity in the US stock market.[25] We build on recent advances made in the measurement of financial crisis indicators (Oet et al., 2011; Holló et al., 2012), and provide useful extensions to the underlying portfolio approach (Illing and Liu, 2006) when we perform our aggregation, in order to accommodate the characteristics of the contributing liquidity groups.[26]

4.1 General Framework

We build up our market liquidity index through several steps. We start by constructing every liquidity measure at the stock level, tracking the S&P 500 over time. This allows us to transform each liquidity measure into its market equivalent by aggregating over all the stocks. We standardize these market liquidity indices by converting them into order statistics using their empirical cumulative distribution function (CDF), and group them according to their dimension. This results in eight separate market liquidity groups. Finally, we reach our unified market liquidity index by incorporating time-varying correlations between the different groups, and simultaneously allowing for volatility-adjusted, time-varying weights across groups.

In this last step, we implement two extensions to the traditional portfolio approach which better fit the needs of our liquidity index. Firstly, we introduce time-varying weights based on the relative liquidity pressures for each dimension of liquidity. This allows us to incorporate idiosyncratic signals of specific liquidity groups when they are systemic. Secondly, we adjust our time-varying weights to account for the volatility of each particular group. The underlying idea is that highly volatile

[25] We perform our aggregation method on the stock market as a whole, because of the increasing importance of commonality in liquidity across stocks (Chordia et al., 2000; Kamara et al., 2008; Rösch and Kaserer, 2013). However, our approach can be applied to the aggregation of different liquidity measures on a stock-specific level, which could be useful in an asset pricing framework.

[26] Our paper is close in spirit to Chatterjee et al. (2017), as they similarly adjust the weighting scheme underlying the aggregation. Their goal is to construct an optimal financial stress index. Interestingly, they set their weights based on the relevance of certain subindices for the identification of past crises periods. However, given the underlying fundamentals can change, this weighting scheme might not be ideal for the detection of future periods of distress.

liquidity dimensions grab more attention, and hence impact investors more. Practically, we apply two variations which yield comparable results. On the one hand, we apply a 'shrinkage factor' to dampen the tranquil episodes, as applied in the Bayesian literature. On the other hand, we incorporate an 'augmentation factor' reinforcing volatile outbursts. Figure 1 and 2 show the changes induced to our market liquidity index by introducing the time-varying weights and the volatility adjustments respectively. By adding moments of financial stress, Figure 3 highlights how our index behaves over time. The next subsections explain each step in detail.

Admittedly, our analysis lacks a broader theoretical framework.[27] Such a framework could provide valuable insights to better comprehend the concept of liquidity, and its interlinkages with the macroeconomic world (Borio, 2014). However, in this particular setting, our focus is to create an empirical measure which takes into account all of the dimensions of liquidity, and which allows for time-variation in their weights. This allows us to incorporate the idea that different aspects of liquidity can be important during different times, depending on the macro-financial surrounding. Intuitively, the underlying dimensions of liquidity behave and interact differently over the course of the financial cycle. During financial stress episodes some dimensions will react more strongly than others, and might therefore need to be weighted more heavily, given their ability to capture this volatility. While in contrast, some less volatile dimensions might be more important during tranquil periods, as they perform better at signaling the general level of liquidity. However, as we will see in the next chapter, we can make this breakdown even more granular, since every different typology of financial stress, will trigger different movements in the underlying liquidity dimensions.

4.2 Construction of Liquidity Groups

As described in Section 3, we rely on twenty-four liquidity proxies belonging to eight different groups. Each group either represents direct trading costs or indirect trading costs. Starting from individual liquidity measures at the stock level, measures are successively aggregated to the market level, standardized and eventually summed up in eight liquidity groups.

[27] We share this feature with most of the empirical work on liquidity, and with most widely used financial stress indicators as these rely on similar methodologies (Vayanos and Wang, 2012; Chordia et al., 2009).

4.2.1 Data

We retrieve daily data from the CRSP database, ranging from 1957 to 2013.[28] All measures are expressed as such to denote illiquidity, and feature at a monthly frequency.[29] For each stock, we rely on a limited number of time series, as we only require data on prices, shares traded and outstanding, returns and volume.[30] Hence, our measure can be easily reproduced for different countries, and for lengthy time–periods.

4.2.2 From Stock to Market

Starting at the stock level, we construct time-series for each liquidity measure, while tracking the stocks that are included in the S&P500 during that particular month. At this point we have approximately 8 million observations in our data set.[31] Subsequently, we create market aggregates for each liquidity measure by constructing weighted averages of the stock-specific liquidity measures.[32] This approach offers an intuitive way of managing the different components of market liquidity, and does not simultaneously lump together commonalities across stocks and across measures, but carefully disentangles every step.

4.2.3 Standardizing Liquidity

We standardize the rudimentary market liquidity indices by converting them into order statistics using their empirical cumulative distribution function (CDF) (Holló et al., 2012). This process is particularly important for our liquidity proxies because of the differences in the unit of measurement as well as in their scale (Vayanos and Wang, 2012; Fong et al., 2017). We consider several alternative ordering techniques.

The most basic approach would be to perform the ordering based on the full sample. However, many liquidity measures show a dramatic drop in their mean over the long sample period. These shifts are caused by multiple factors. On the

[28]The initial date is chosen accordingly, as the required series for all S&P500 firms are only available from that point onwards.

[29]We work with monthly values because several of the liquidity proxies, e.g. volume and return based measures, are constructed by evaluating a certain metric over a month. The measures that can be computed on a daily frequency are therefore transformed to monthly values.

[30]For the prices we distinguish between high, low, bid and ask prices. Regarding the returns, we also seperately use dividend returns, and further add market returns to the data set.

[31]As we have twenty-four liquidity measures for each of the five hundred stocks over our sample of fifty-six year (or 672 monthly observations).

[32]For our main results, we rely on market-capital based weights. We perform robustness checks with equally weighted alternatives, but this does not change our results in a meaningful manner.

one hand, the US stock market experienced substantial institutional changes.[33] On the other hand, there has also been an overall increase in the activity on the stock market in recent decades. As a result, recent illiquidity pressures that are associated with important episodes of financial stress seem negligible in comparison to historic ones when using the full sample to order the variables. The same problem occurs when standardizing the liquidity variables using the full sample mean. As a result, many liquidity measures have fallen into disuse.

This issue can be mitigated by evaluating the liquidity indices more locally. Firstly, we create subsamples based on the changes in the underlying minimal tick size of the US stock exchange.[34] These moments signify important exogenous breaks in the series, as they led to a marked increase in liquidity as measured by many of our proxies. When we order the variables accordingly within each subsample, this already leads to a marked improvement, and we achieve a more sensible representation of liquidity over time. However, there might still be substantial shifts within each subsample that affect liquidity. A second, more flexible way to perform the local evaluation, which also takes into account these more gradual changes, is through a rolling window method. In this case, the ordering for each observation is done based on the last five years preceding that value. The rolling window approach has the added advantage that we do not have to exogenously administer the breakpoint dates, which can provide difficulties as new data is added to the time-series.[35] Moreover, having a five year window accommodates the idea that investors have a relatively short memory.[36] When gauging the particular gravity of a liquidity event, it seems reasonable to assume that they would be evaluated

[33]Most famously, there were adjustments in the minimal tick size. But there were also other institutional changes over the sample period that impacted liquidity. For example, there were sizable shifts in the factors that influence the information asymmetry on the stock market (Holmstrom, 2010)

[34]This yields three subsamples: the first spans from the start of the sample up to June 1997, when the tick size was adjusted from one sixteenth to one eight. This was the first time in history that an exchange had modified the minimum tick size. The second sample runs from July 1997 until February 2001, when the exchange witnessed a change in the tick size from one sixteenth to one cent on the NYSE. This change was applied more broadly for all stocks in April 2001, but the choice between these two dates does not change the results. The final subsample starts in March 2001 and lasts until the end of the sample (Bessembinder, 2003; Goldstein and Kavajecz, 2000). Corwin and Schultz (2012) apply a comparable division in their analysis of the correlation between liquidity measures. Holden (2009) similarly does so in the construction of his effective tick measure.

[35]Moreover, as breakpoints differ across countries, their inclusion would not allow for a uniform cross-country approach.

[36]Admittedly, the time frame of five years is somewhat arbitrary. However, our analysis is also robust for a time frame of ten years, which leads to similar time series properties for our liquidity measures. The only difference is that the liquidity groups exhibit less volatility, and thus feature comparatively less idiosyncratic pressure with this ten year alternative. Moreover, we refrain from using a symmetric window around the observation, or a five year forward looking window, as the investor does not possess this ex ante information in real time.

based on experiences of the last five years. This procedure slightly shortens the sample, as we lose the first five years of observations. Our analysis thus covers the 1962-2013 period.

Finally, in addition to producing liquidity variables that are more consistent with financial stress events over time, this method of ordering our variables locally also yields stationary variables. Table 3 highlights that standard unit root tests based on the full sample ordering technique cannot reject the hypothesis that several liquidity groups contain unit roots. More specifically, the returns, Fong, etick, Amihud and volume groups appear to be non-stationary.[37] In contrast, these groups all exhibit stationary time series when we apply the more local method of ordering, through breakpoints or with the five year rolling window. For the remainder of the paper we rely on the rolling window ordering method.

4.2.4 Grouping Liquidity

The groups are formed by taking together measures that are conceptually similar. We construct eight separate liquidity groups, denoted by $l_{i,t}$, by taking the arithmetic mean of the individual measures $z_{i,k,t}$ belonging to each group i:

$$l_{i,t} = \frac{1}{n}\sum_{k=1}^{n} z_{i,k,t}$$

where n represents the number of individual measures belonging to each group. Index k refers to an individual measure within a specific liquidity group. The formation of the groups is based on the underlying dimension. Section 3 highlights the measure within every group.

4.3 Construction of Market Liquidity Index

4.3.1 Time-Varying Correlations (Portfolio Approach)

We reach our market liquidity index L_t, which unifies the different dimensions of liquidity, by applying the portfolio approach (Illing and Liu, 2006) to the eight groups, i.e.

$$L_t = (w \circ l_t)C_t(w \circ l_t)'$$

[37] With the Perron test this is limited to the etick, Amihud and volume group.

where l_t symbolizes the vector of liquidity groups $l_t = (l_{1,t}, \ldots, l_{8,t})$, and w the vector of weights attached to the liquidity groups $w = (w_1, \ldots, w_8)$.[38] For now, the weights are set to unity, implying that the different liquidity groups all receive the same weight. This allows us to show the marginal impact of the first step within our aggregation method. C_t denotes the matrix of time-varying cross-correlations $\rho_{i,j}$ between liquidity groups i and j, i.e.

$$C_t = \begin{pmatrix} 1 & \rho_{12,t} & \cdots & \rho_{18,t} \\ \rho_{12,t} & 1 & \cdots & \rho_{28,t} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{18,t} & \rho_{28,t} & \cdots & 1 \end{pmatrix}.$$

Following Holló et al. (2012), we measure these cross-correlations recursively as the exponentially weighted moving averages of the covariances $\sigma_{ij,t}$ and volatilities $\sigma^2_{i,t}$, using a decay factor which is kept fixed to 0.94. By incorporating matrix C_t, a specific liquidity group affects our unified liquidity index to the extent that it is correlated with the other liquidity groups.

The rationale behind this approach is that every market liquidity measure can theoretically be broken down into a systematic component and its idiosyncratic counterpart (Amihud et al., 2005). On the one hand, the different liquidity groups might represent imperfect proxies of the same true underlying concept of liquidity. The cross-correlations offer a intuitive way to put higher weight on signals that are correlated across the different liquidity dimensions.[39] On the other hand, they might gauge different aspects of liquidity that are interconnected with each other, thus measuring closely related concepts.[40] As a result, diverging signals can still be valuable, and should not by neglected by solely focusing on the cross-correlations. We will built on this in the next subsection when we introduce the time-varying weights. So far, our aggregation solely relies on the systematic liquidity elements, thus providing an alternative to the more traditional principal component (Korajczyk and Sadka, 2008) and common factor analysis (Hallin et al., 2011).

Table 4 provides summary statistics for the time-varying correlations of every specific liquidity group with the seven other groups. Panel A highlights the values

[38] We use the Hadamard-product $w_t \circ l_t$, given that we need an element-by-element multiplication of the vector of weights and the vector of liquidity group measures.

[39] When several groups simultaneously indicate a dry spell in liquidity, we want them to receive relatively more weight, as multiple dimensions are picking up the same signal.

[40] Amihud et al. (1990, pp. 65-66) already highlighted this idea: "components of illiquidity cost are highly correlated, as stocks that have high bid-ask spreads also have high transaction fees and high search and market-impact costs, and are thinly traded. When the bid-ask spread widens, it signals that immediacy of execution is more costly, that is, asset liquidity is lower."

for the mean, the standard deviation and the interquartile ranges (IQ). Panel B repeats the mean for the full sample period ($n = 624$), but also differentiates between crisis periods[41] ($n = 111$) and tranquil times ($n = 513$). The interquartile values in Panel A highlight that the correlations considerably differ over the sample period. This finding justifies the use of time-varying cross-correlations in our methodology.

However, the breakdown in Panel B reveals that the timing does not exactly correspond with the crisis periods. Hence, the variation in the pooled correlations over time does not seem to be substantially affected by crisis periods. Possibly the pooled correlation values mask more detailed, group-specific changes, as the values are pooled over all the groups. Moreover, there could be significant lags in this process. However, it is reasonable that the commonalities across dimensions remains relatively stable over time. In contrast, as shown in the next section, this differentiation between periods of distress and tranquil periods leads to more substantial differences for the idiosyncratic pressure generated by each liquidity group.

4.3.2 Time-Varying Weights

Up to this point, we simply applied the portfolio approach to our setting, leaving no room for any idiosyncratic contribution, not even when this could be systemic. However, we refine our approach to better fit the needs of our market liquidity index. During periods of stress, and significantly changing fundamentals, financial markets can behave differently. As a result, the relative importance of the groups that make up market liquidity can change (Sarr and Lybek, 2002). Measures that capture liquidity well during tranquil times may no longer be meaningful during turbulent markets (Upper, 2001). Given the divergent backgrounds of each liquidity group, there will be times when a single or several specific groups pick up a signal that the others disregard (Vayanos and Wang, 2012). While this information may be idiosyncratic, it is still market-wide, as it reflects the liquidity of the S&P 500 as a whole. Merely weighting the different groups by their correlations would imply that we interpret these signals as noise, thus attributing less weight to them. Nonetheless, if these illiquidity pressures are sufficiently strong, they could be hinting at a systemic liquidity event, and should be accounted for in our weighting scheme.

For this purpose, we extend our framework to incorporate time-varying weights based on the relative illiquidity pressures in every group.[42] We model the weighting

[41] Crisis periods are defined as historic financial stress events, as explained in Section 5.1, and recessionary periods during the sample from January 1962 up to December 2013.

[42] In contrast, the CISS methodology only incorporates fixed weights for the full sample, based

function $w_{i,t}$ of group i at time t as an exponential function of the deviation of the group-specific liquidity value $l_{i,t}$ at time t from the threshold T[43]:

$$w_{i,t} = \frac{exp(l_{i,t} - T)}{\sum_{i=1}^{8} exp(l_{i,t} - T)}$$

This function ensures that larger deviations, which point towards stronger illiquidity pressure, get higher weights. We force the weights to sum to one over the different groups, as we are solely interested in the relative pressures present in the underlying liquidity groups. When all the groups similarly exceed their threshold, they simply receive equal weights. The equation for our liquidity measure now becomes:

$$L_t = (w_t \circ l_t)C_t(w_t \circ l_t)',$$

where $w_t = (w_{1,t}, \ldots, w_{8,t})$ depicts the vector of weights attached to the liquidity groups, which is now time-varying and group-dependent. Figure 1 shows the impact of introducing the time-varying weights to the basic weighting scheme. Allowing for idiosyncratic pressures, next to the systematic liquidity component, has a clear impact on our final measure. Logically, the new weighting scheme accentuates the peaks of our liquidity series. Moreover, during periods of financial distress and recessionary periods, the new series stays relatively more elevated, and exhibits less volatility than its counterpart with the fixed weighting scheme. When evaluating our liquidity measure more formally, we show that this adjustment leads to both a marked improvement in the signal-to-noise ratio, as well as closer relations with other macro-financial variables. In Section 6, we disentangle which changes in the underlying groups cause these improvements. Some groups are better at depicting liquidity during crisis periods, while others are more helpful during tranquil times. Allowing for time-variation in the weights helps to account for these group-specific qualities.

4.3.3 Volatility Adjustment for the Time-varying Weights

A second adjustment to our weighting scheme is based on the concept of limited attention (Kahneman, 1973), and the use of heuristics (Gigerenzer, 2008). Our aim is to build a liquidity measure that relates to the actual experience of investors, and

on the impact of each group on the economy.

[43] As our liquidity proxies are between zero and one, imagine an arbitrary threshold of 0.75, where values above the threshold are weighted more strongly (see formula). However, as we force the respective weights over all the groups to sum to one, we simply examine relative values, and the outcome becomes independent of the chosen threshold.

not an abstract theoretical construct. Goyenko et al. (2009) argues that this seems to be missing in the literature. With the full spectrum of information, individual investors cannot be expected to pick up all the relevant signals that affect liquidity. Consequently, we suspect that signals that are more volatile will also attract more attention. Persaud (2003) similarly remarks that for most practitioners the variability and uncertainty of liquidity is more important than its average level. We therefore adjust the relative weights for the idiosyncratic pressure in a specific group, depending on whether this pressure reveals itself in a more volatile manner.[44] For example, if the illiquidity pressure in a certain group is comparatively high, this would yield a high time-varying weight due to the adjustment in the previous subsection. However, if this pressure has been persistently strong for the past months, investors would have grown more accustomed to this new environment.[45] In contrast, the same amount of pressure, brought about more virulently, could evoke a more pronounced impact. Attention grabbing liquidity groups may have a similar impact as attention grabbing stocks, when there are many dimensions to choose from (Barber and Odean, 2008). We therefore adjust our weighting function to incorporate the volatility of the particular group.[46] Using volatility as a weighting factor when aggregating subgroups is not uncommon. For example, Gerdesmeier et al. (2011) apply weights based on the volatility of different asset classes for their early warning indicator. Practically, we apply two variations on this theme which have a comparable impact. Firstly, we use a 'shrinkage factor' to dampen the less volatile signals, thus lowering their time-varying weights:[47]

$$w_{i,t}^{s} = \frac{exp(l_{i,t} - T) * \sigma_{i,t}^{2}}{\sum_{i=1}^{8} exp(l_{i,t} - T)}$$

where $\sigma_{i,t}^2$ is the volatility of liquidity measure $l_{i,t}$ of group i at time t.[48] Alternatively, we let the volatility term interact with the liquidity measure itself, leading to a 'volatility augmented' approach. In this case, volatile outbursts of liquidity

[44] Including a threshold and integrating a volatility metric is reminiscent of option pricing models, something already noticed by Copeland and Galai (1983).

[45] Additionally, they would have had time to take precautionary steps in order to safeguard against this new reality.

[46] As a consequence, the weights of the groups no longer sum up to one, due to the shrinkage, so we lose comparability with the previous weighting schemes. However, this approach is intuitively appealing, and yields the most powerful results.

[47] The idea of shrinking variables in the context of model selection is often used in Bayesian estimation (Carriero et al., 2015), but also in many other applications which are aimed at getting a more sparse representation, as is the case with penalized regression methodologies (e.g. ridge, lasso).

[48] Similarly, this is measured as an exponentially weighted moving average with a decay factor of .94.

are reinforced, and augment the time-varying weights of the respective liquidity dimension:[49]

$$w^a_{i,t} = \frac{exp(l_{i,t} - T) + (\sigma^2_{i,t} * l_i)}{\sum_{i=1}^{8} \left[exp(l_{i,t} - T) + (\sigma^2_{i,t} * l_i)\right]}$$

Both volatility-adjusted weighting functions w^s_t and w^a_t allow us to account for the heuristic approach many investors rely on. Figure 2 demonstrates the impact of incorporating a volatility metric into the weighting function. We use the time-varying weighting scheme from the previous subsection as a benchmark. As can be expected, the two volatility adjustments have a seemingly opposite effect on the liquidity values. When we incorporate the volatility augmentation this leads to values that are slightly tilted upwards compared to the benchmark, while the volatility shrinkage substantially compresses the liquidity series. However, in relative terms, they both reach the same outcome of accentuating more volatile liquidity groups. An additional advantage for the shrinkage method is that the series seems much less volatile during tranquil times than its two counterparts, only spiking upwards during more pronounced moments of distress. This is particularly noticeable in the run up to the financial crisis of 2007, when illiquidity values are remarkable low for a long time period using this weighting scheme. When evaluating the alternative weighting schemes in the next sections, the volatility shrinkage method with the time-varying weighting scheme also emerges as the superior option. Hence, this will be our preferred liquidity series throughout the paper.

4.3.4 Descriptive Statistics

To get a better understanding of each component within our aggregation method, we break down the dynamics of our market liquidity index, and compare the impact of the underlying weights. Table 5 reports the mean for our index based on the four different weighting schemes, namely the fixed weights w, the basic time-varying weights w_t, the volatility shrinkage time-varying weights w^s_t and the volatility augmented time-varying weights w^a_t. In addition to the values for the full sample period, we also differentiate between crisis periods and tranquil times, as explained in Section 4.3.1. Given that the underlying measures are constructed to denote illiquidity, higher average values represent higher degrees of illiquidity.

The different weighting methods do not allow a clear-cut comparison of the absolute values across methodology. More instructive are the relative changes in the values between the different periods. In Table 5, these are expressed as a percentage. As we step away from the full sample to the more tranquil times, or similarly

[49] With the additional advantage that this methodology allows the weights to sum to one again.

to the more turbulent episodes, we want this to be reflected through our weighting scheme. Focusing on the transition to the tranquil subperiod, the illiquidity values based on w, w_t, and w_t^a exhibit comparable fluctuations, whereas the drop using w_t^s is substantially larger. This difference is even more pronounced when we move to the turbulent subperiod. While the increase in the average value of liquidity is above fifty percent for the w_t^s methodology, it only amounts to thirty-three percent with the other options. The weighting method using the volatility shrinkage therefore performs best at capturing the expected pattern of higher relative illiquidity values during crisis times, and conversely of lower values during tranquil times. For the remainder of the paper, we focus on this specific weighting scheme of our unified liquidity measure, unless we mention otherwise.

Next to these general trends in the weighting schemes for our market liquidity index, the dynamics in the weights for each underlying liquidity group offer a more granular insight, and illustrate how the importance of the groups fluctuates across the different subsamples. Table 6 shows three diverging trends among the weights of the constituent groups. Firstly, for some groups these weights increase markedly during the crisis phase, and decrease (slightly) during the tranquil period. This pattern is most pronounced for the bid-ask, etick and Amihud group, and holds to a lesser extent for the Roll group. Secondly, the opposite trend, where the weights decrease noticeably during crisis and increase (moderately) in tranquil times, is present for the returns group, and to a lesser extent for the Fong and volume group. Finally, the order flow group remains mostly unaffected over the different subsamples.

These descriptive statistics indicate that the constituent liquidity groups behave considerably different over time, thus confirming the importance to incorporate them together in our unified measure. Section 6 explores this finding further by providing a detailed analysis on how each group contributes during well-known historic episodes of financial stress. Interestingly, the groups that exhibit a high degree of time-variation in their weights, are also the groups that perform well at crisis detection, and exhibit the closest link with the macro-financial variables.

5 Evaluation

5.1 Identifying Financial Stress

5.1.1 Financial Stress Events

Historically, researchers and policymakers have been interested in understanding the dynamics of liquidity, especially given the close link between financial market crises and liquidity droughts (Liang and Wei, 2012). Figure 3 portrays our unified market liquidity measure together with the NBER recession dates and a number of well-documented episodes of financial distress.[50] As expected, many of the upswings in illiquidity systematically coincide with market downturns, consistent with the existing literature (Næs et al., 2011).

Chronologically, we observe the following major events in the figure.[51] First, we discern a brief episode of domestic political unrest in 1970, matched with a spike in illiquidity. The second major collapse in market liquidity corresponds with the oil embargo of November 1973. Moreover, illiquidity remained relatively high throughout the seventies, as documented by Chordia et al. (2001) and Jones (2002). Third, the early eighties witnessed a double dip recession. During the aftermath of the second oil crisis, a recession was triggered due to Paul Volcker's shift in monetary policy (Rotemberg, 2013), and was followed in rapid succession by the debt crisis in Latin American.[52] Fourth, we highlight the stock market collapse in October 1987, during which the financial markets were highly illiquid (Grossman and Miller, 1988). As highlighted by Amihud et al. (1990), the crash was partly attributable to a decline in investors' awareness of the general market liquidity. Fifth, after witnessing spurts of illiquidity both during the Iraq invasion and the ensuing recession, as well as during the Mexican Peso crisis, we observe the impact of the Asian crisis in 1997, which was quickly succeeded by the collapse of Long Term Capital Management (LTCM) combined with the Russian debt crises (Lesmond, 2005). Both of these events are separately captured by our liquidity

[50] Our list is based on Hubrich and Tetlow (2015), who document financial events affecting the US economy from 1986 till 2012. However, we further refine and extend this list using similar tables provided in Brave and Butters (2010) and Bordo and Haubrich (2016). Hence, our analysis builds on their classification and interpretation of these events. A table summarizing these financial stress events, and how they are classified, can be obtained from the authors.

[51] We merely highlight some events, and this initial anecdotal evidence is not exhaustive.

[52] Latin American borrowing from banks in the US had intensified significantly during the 1970s, but became problematic when the Federal Reserve tightened their policy, and higher interest rates were being charged for the loans. While the crisis was triggered by Mexico's announcement that it would not be able to service its debt, ultimately sixteen Latin American countries rescheduled their debts. The resulting spillovers severely impacted the US banking sector, which had to set up significant loss provisions (Aggarwal, 2000).

proxy. Sixth, the relationship between liquidity and the tech bubble burst in 2000 is remarkable, given that the illiquidity levels already skyrocketed before the recession actually commenced. Interestingly, Adrian et al. (2017) report a similar dynamic in some of their funding liquidity measures, most prominently in the on-the-run/off-the-run spread.

Finally, the recent financial crisis, started off in August 2007 with the evaporation of market liquidity, as market participants were increasingly confronted with the inability to value and trade complex structured products (Borio, 2009). Money markets suddenly became highly-information sensitive due to the troubles in and the subsequent collapse of several important financial institutions, most prominently Lehman and the Reserve Primary Fund (Holmstrom, 2010). Financial distress soon became widespread, moving through the interbank market into the whole financial sector.[53] Caballero and Kurlat (2009) report stock market losses up to $9 trillion between the peak in October 2007 and March 2009, almost six time as much as the losses incurred in the bank sector alone. Our market liquidity index spikes up during these events, and stays elevated until early 2009. Interestingly, in the period leading up to these events, between 2002 and mid-2007, the mean of our liquidity series is extremely low, showing the availability of ample liquidity in the pre-crisis period, and potentially feeding into the discussion on policy rates being low-for-long. In order to counter the economic downturn, the Fed announced their quantitative easing program in November 2009, which commenced a month later, and was further intensified in March 2009. The first part of this program, known as QE1, mainly consisted of purchasing agency mortgage backed securities, together with a smaller amount of treasuries and agency debt (Kuttner, 2018). Looking at Figure 3, QE1 had a positive effect on our broader stock market liquidity measure, thus exhibiting spillover effects beyond the targeted securities.[54] From the second quarter of 2009 onward illiquidity values markedly decline. Having the presence of the Fed as a large committed buyer calmed the markets, especially at a time when the market for these instruments had frozen up due to information asymmetry and adverse selection problems (Christensen and Gillan, 2018). In contrast, during the second QE program,[55] market illiquidity spikes up again towards

[53]We witnessed a twenty percent drop in stock markets around the world in the second week of October 2008 due to the scarceness in liquidity (Brennan et al., 2012). Moreover, concerns about liquidity kept global equity markets tumbling until March 2009.

[54]Naturally, there are many simultaneous effects in play, and this visual inspection does not give any indication about the causality. But timing wise liquidity channels have been expected to have an effect early on in the program, while portfolio rebalancing can take more time to have an impact (Gagnon et al., 2011).

[55]The program was announced in August 2010, while actually commencing in November.

the end of 2010 and early 2011. Potentially, this part of the program, which focused on longer-dated securities had a detrimental effect on liquidity, as outlined in Bonner et al. (2018), partly due to a scarcity of safe assets. Moreover, there is another spike toward the end of 2011 which coincides with a deterioration in the macroeconomic situation for the euro area. For the final part of the program (QE3), market liquidity remains relatively stable, but this presumably also reflects the general recovery of the economic environment. Around the end of 2013, market illiquidity jumps up again, partly due to the taper tantrum in the US, but also caused by global factors.[56]

During this fifty year history, the shortage and abundance of liquidity deeply affected stock markets, and strongly interacted with the wider economy (Liang and Wei, 2012). Hameed et al. (2010) remind us that market liquidity evaporates when it is most necessary. In this setting, the concepts of market risk and liquidity risk seem to be closely intertwined, with investors often being simultaneously exposed to both factors (Rösch and Kaserer, 2013). Our market liquidity index manages to capture these rich dynamics, and succeeds in identifying the important historical episodes of financial stress.

5.1.2 Signal Extraction

In this subsection, we test whether our market liquidity measure can pick up signals of financial distress. Given the close link between financial stress and the disappearance of market liquidity, we expect our measure to produce reasonable signal-to-noise ratios. Such a metric allows us to objectively evaluate our liquidity index relative to several other widely used financial stress indices, and to compare the different weighting schemes within our own metric.

Evidently, our measure is not primarily designed as a financial stress indicator, but is constructed with the specific goal of unifying the various dimensions of liquidity, and hence it. As a result, we solely focus on one specific aspect of the financial markets, and rely on a limited number of data series. In comparison, the financial stress indices in our analysis encompass numerous data series from various markets.[57]

Furthermore, the occurrence of illiquidity does not necessarily coincide with moments of distress, and could have a leading or lagging pattern depending on the type of event and the underlying cause. For example, Borio (2009) argues

[56] This coincides with the start of the QQE program in Japan and continued weak macroeconomic environment in the euro area.

[57] For example, the Chicago Fed National Conditions Index integrates 105 series from money, debt and equity markets in a dynamic factor model.

that the financial crisis of 2007 saw market liquidity evaporate first, while turmoil during the LTCM crisis in 1998 initially disrupted funding liquidity. Hence, despite its association with financial stress, market liquidity might not always be able to provide us with a signal for crises.

In order to retrieve the historical stress dates, required for the calculation of our noise-to-signal ratio, we follow Christensen and Li (2014) and define a financial stress event as the moment when a financial stress index (FSI) exceeds a specific threshold:

$$fin\ stress_t = \begin{cases} 1 & if\ FSI_t > \mu_{FSI} + k\sigma_{FSI} \\ 0 & otherwise \end{cases}$$

where μ_{FSI} is usually set to be the sample mean of the FSI, and σ_{FSI} the sample standard deviation. However, given that the occurrence of extreme events during the sample period can heavily affect this threshold value, we prefer to evaluate financial stress events more locally, and therefore calculate both the mean and the standard deviation over a ten year moving average, instead of over the full sample.[58] Taking into consideration the volatility of the stress indices, the analysis is performed on a quarterly basis. In our framework, we set $k = 1.5$.[59]

Practically, we rely on fourteen separate indices in order not to be dependent on the choice of a specific stress index. Table 7 gives an overview of the full information set we incorporate. We categorize an observation as a financial stress event when at least two thirds of the available indices for that observation hint at stress.[60] This allows us to identify seventeen quarters of financial stress, which in our adjusted sample amounts to ten percent of the available quarterly observations.[61] We use this framework to examine how well different stress indices identify moments of financial stress in comparison to our liquidity measure.

[58]Applying the moving average, slightly shortens the sample size, which now starts in the first quarter of 1972, and ends in the fourth quarter of 2013, thus leading to 168 observations for this analysis.

[59]This is similar to Cardarelli et al. (2009). Alternatively, Illing and Liu (2006) set $k = 2$, and Christensen and Li (2014) apply $k = 1.5$. However, these adjustments do not change the identification of the crisis moments profoundly. They just mechanically alter the number of financial stress events, also allowing for less powerful signals from the FSI to be interpreted as moments of distress.

[60]We want to include as many indices as possible, but face the constraint that these stress indices have different availability in terms of their sample sizes. Hence, the number of included indices increases gradually over time, starting with four indices in 1972, growing to seven in the 90s, and reaching the full potential of fourteen indices in 2000.

[61]Although this ratio (for which we require two thirds of the FSIs to identify moments of financial stress) might seem restrictive, we belief that the resulting number of identified distress episodes is credible. Moreover, lowering this ratio to only half of the FSIs, leads to thirty-three quarters of financial stress, which already amounts to twenty percent of the available quarters in the sample. This seems to be considerably inflated, thus justifying our relatively stern condition. However, the resulting signal-to-noise analysis is robust to these changes.

Alternatively, we can add a forward looking aspect to this analysis, and examine whether our indices can signal financial stress ahead of time. More specifically, we gauge a time-span four quarters ahead. Practically, we can denote this as

$$fin\ stress_t = \begin{cases} 1 & if\ FSI_{t+k} > \mu_{FSI} + k\sigma_{FSI} with\ k = 1, ..., 4 \\ 0 & otherwise \end{cases}$$

Finally, we also assess whether our results remain robust when the financial stress events are chosen according to the narrative description within the literature. For this purpose, we apply the dates used in Section 5.1.1.

When evaluating the signal extraction, we are interested in the ability of our indices to detect both the occurrence and non-occurrence of financial stress events correctly. As a result, the following four situations, depicted in Panel A of Table 8, can be discerned: a true positive, when a financial stress event is signaled by the measure under investigation (A); a true negative, referring to a tranquil period correctly interpreted (D); a false positive, implying that a tranquil period is wrongly classified as a stress event (B); and a false negative, when a financial stress event is not captured (C). The noise-to-signal ratio can then be summarized as [B/(B+D)]/[A/(A+C)]. We additionally report both the percentage of financial stress events signaled correctly, [A/(A+C)], as well as the percentage of tranquil periods signaled correctly, [D/(D+B)].

Panel B of Table 8 compares the performance of our unified market liquidity measure, as a potential warning mechanism for financial stress, with those of the Aruoba-Diebold-Scotti business conditions index (ADSBCI), the National Financial Conditions Index (NFCI), the excess bond premium (EBP), the house price gap (HP), and the credit gap (Cred).[62] Our results indicate that our liquidity measure performs comparatively well at signaling financial stress episodes. It consistently outperforms the other stress measures across the three different types of signal extraction.

Starting with the basic analysis, where we focus on real-time crisis detection, the liquidity metric has the lowest noise-to-signal ratio. This result is achieved by its ability to detect a relative proportion of financial stress episodes correctly, while restricting the amount of false positives, and thus also identifying a high proportion of non-stress events correctly. In comparison, the ADSBCI, the NFCI and the EBP

[62]We limit our analysis to these measures as they have the longest data series, which allows for a more meaningful comparison. We added two single measure metrics that were not included in our exercise of finding financial stress events, but are often cited in the literature as useful early warning mechanisms (Aldasoro et al., 2018).

signal a higher percentage of financial stress events correctly, but do so by marking many events as distress periods. As a result, they accumulate a comparatively higher amount of false positives, and thus identify a lower percentage of non-stress events correctly. The latter increases their noise-to-signal ratio significantly. The highest noise-to-signal ratio in this setting can be found with the house price gap and the credit gap. Both do not succeed well in retrieving financial stress events in real time.

Moving to the forward looking analysis, we examine the ability of our variables to signal stress events four quarters ahead. The results seem mostly consistent with our earlier findings, with the lowest noise-to-signal ratio being awarded to the same variables. Given that the number of stress signals increases now (through the forward looking component), the percentage of correctly indicated stress events drops for all the variables, with the exception of the NFCI. Overall, the liquidity variable again reaches the lowest noise-to-signal ratio due the fact that the number of false positives are kept very low.

Moreover, when we use the narrative dates, our earlier conclusions are again confirmed, showing that our results are robust for the different methodologies. Similarly, the liquidity measure has the lowest noise-to-signal value, followed by the ADSBCI and the EBP. In comparison, the NFCI, the credit gap, and the house price gap have comparatively higher noise-to-signal ratios, despite the fact that the former two are able to detect more than half of the stress episodes correctly.

Finally, we compare the different weighting methods for our liquidity measure. Panel C of Table 8 reveals that the biggest gain in terms of signal detection occurs when we incorporate time-varying weights, and comes in the form of an increase in the share of correctly specified financial stress events. A visual inspection of Figure 1 highlights how the values for the liquidity measure significantly spike up during stress episodes when we incorporated the time-varying weights. We can thus better understand why the time-varying schemes are successful at identifying a much higher incidence of financial stress events. This increase is highest for the volatility adjusted weighting schemes, which are depicted in Figure 2. While this improvement comes at the cost of incurring more false negatives for the volatility augmented method, this is not the case for the volatility shrinkage method. As a result, the latter emerges again as our preferred method.[63]

[63] We also perform the forward looking exercise and apply the narrative dates for the alternative weighting schemes of our liquidity index. The results are similar for the three methodologies. They are not reported due to space constraints, but can be obtained from the authors.

5.1.3 Market Liquidity and Financial Stress Indicators

Further investigating the relationship between liquidity and financial stress, we perform a number of univariate regressions where we relate our liquidity measure to every individual stress indicator separately.[64] Table 7 gives an overview of the different indicators that we include in our analysis. We apply heteroscedasticity and autocorrelation consistent (HAC) estimators of the variance-covariance matrix, as proposed by Newey and West (1987). Table 9 reports the intercept, the regression coefficient, both their p-values, and the adjusted R-squared value. The estimation is done at a monthly frequency, and the number of observations, which is reported between brackets, depends on the sample size of the variable in question. The first three columns report the results for the full sample. In the next three, we restrict the sample to the stress periods. Finally, we focus on the tranquil periods in the last three columns.

Starting with the full sample, we unravel that our liquidity measure can explain a considerable part of the variation in several well-known crisis indicators. However, this relation does not hold uniformly over all the incorporated crisis measures. Liquidity can explain a reasonable proportion of the variation in BL+, IMF M, IMF C, KCFSI, ANFCI, NFCI, ORF FSI, REC and STLFSI. For some of the these meaures, liquidity alone can explain one third or more of the variation, which is substantial given that these variables are often quite volatile and unpredictable at a monthly frequency. In contrast, our liquidity measure does not show a close connection with the ADS, BL, CFSI, CLN, EBP and GS and SAHM measure, mostly fluctuating around the five percent threshold, and for some even lower.

Interestingly, when we move from the full sample to the crisis period subsample (second part of Table 9), the explanatory power of our liquidity measure shoots up dramatically for all the measures in our analysis. The financial stress measures that exhibit the closest relation with liquidity in the full sample analysis remain mostly the same. In contrast, liquidity is now able to explain close to, and sometimes even more than, half of the variation of the stress variables. Even for the variables that exhibit a low adjusted R-squared value in the full sample estimation, the values increase substantially. Overall, the p-values of the slope coefficients are markedly lower when focusing on moments of distress. Hence, we can conclude that our liquidity measure comoves closely with a common element that is present in most of the stress indicators, and that flares up during crisis periods.

[64]We now also include both the recession indicators, as well as two of the FSIs that were left out from our earlier analysis due to their close association with another measure, namely BL+ and ANFCI.

Finally, we examine whether the opposite is true for the tranquil period, displayed at the bottom of Table 9. The adjusted R-squared values are now uniformly lower. Moreover, the p-values for the slope coefficients are higher, and the coefficient itself more often exhibits a counter-intuitive sign.

5.2 Market Liquidity and its Macro-Financial Context

In order to better understand how our liquidity index interacts with the broader economic context, we examine how well our measure can explain the variation in related macro-financial variables, as conducted by Baele et al. (2020).[65] We find a close link between our liquidity measure and relevant macro-financial variables.[66] The results are summarized in Tables 10 to 12. We perform univariate regressions, and report the intercept, the regression coefficient, their p-values, and the adjusted R-squared value. We apply heteroscedasticity and autocorrelation consistent (HAC) estimators of the variance-covariance matrix, as proposed by Newey and West (1987). The sample size for the univariate regressions depends on the availability of the variable under examination, and is denoted between brackets.

When examining the relationship between illiquidity and several confidence indicators (Table 10, Panel A), we retrieve the expected negative sign, as higher illiquidity coincides with lower levels of confidence (Baker and Stein, 2004). The adjusted R-squared values for the confidence measures are relatively low, as liquidity is only able to explain less than ten percent of the variation in these variables. Similarly, we expect illiquidity to coincide with higher values of uncertainty (Rehse et al., 2019). However, we cannot retrieve a significant relationship (Table 10, Panel B), at least not with respect to the measures that capture economic policy and equity market uncertainty provided by Baker et al. (2016).

Turning to volatility measures, Pagano, 1989, p. 269 argues "that thin speculative markets are ceteris paribus more volatile than deep ones". The same type of interdependence between liquidity and volatility is discussed more broadly by Chordia et al. (2009). Moreover, Brennan et al. (2012) highlight that their market wide illiquidity proxies are significantly positively correlated with the TED spread, and with the implied market volatility measure (VIX).[67] Finally, on a stock specific

[65] Brennan et al. (2012) perform a similar exercise for liquidity measures

[66] Moreover, we find similar interlinkages for the alternative weighting methods of our unified liquidity measure, albeit these relations are considerably less pronounced, uniformly exhibiting lower R^2 values for all of the subcategories. These additional results can be obtained from the authors.

[67] Both these values are typically associated with funding liquidity (Asness et al., 2013). Correspondingly, Adrian et al. (2017) show the link between their market liquidity index and several measures of funding liquidity. In a similar vein, Nyborg and Östberg (2014) report that the market share of volume for more liquid stocks expands with the Libor-OIS spread, above and beyond what

level, Han and Lesmond (2011) report a robust positive correlation between idiosyncratic volatility and liquidity. In our analysis, as presented in Panel A and B of Table 11, we detect a similar positive relation between illiquidity and various measures of implied market volatility, each associated with different financial markets. The same story holds both for the TED spread, as well as for the different versions of the option adjusted spread, ranging from AAA to higher yielding spreads. The adjusted R-squared values are relatively high overall for both the volatility as the spread measures.[68]

The relation between market liquidity and state variables of the economy, which is reported in Panel A of Table 12, yields a more mixed picture.[69] For example, we retrieve a significant coefficient for capital utilization, and (on a higher significance level) for labor market conditions. In contrast, there seems to be no clear-cut relationship between liquidity and the coincident index. We might, however, need richer dynamics to capture these relations more accurately.

In the final segment of this analysis we focus on asset prices, interest rates, and monetary variables. The results are shown in the remainder of Table 12. House prices often play an important role during financial crises (Case and Shiller, 2003; Mian and Sufi, 2011), and are helpful in identifying financial cycles (Borio, 2014). Hence, it is not surprising that higher illiquidity coincides with lower levels of house price inflation (Panel B).[70] Moving to the realm of monetary policy, we can discern that higher illiquidity is associated with higher short term interest rates (Panel C). Goyenko and Ukhov (2009) show an important link between monetary policy and market illiquidity. Moreover, higher illiquidity levels concur with a flattening of the yield curve (Panel D). When incorporating monetary aggregates in our analysis, we follow Calza et al. (2003) and rely on the concept of real money gap.[71] Illiquidity seems to be negatively related to the real money gap (Panel E). Finally, we examine the relationship with exchange rates, because financial crises usually coincide with flights to home and flights to safety. Both for the US-Euro as well as for the US-UK

can be explained by the VIX.

[68]Logically, we retrieve the highest adjusted R-squared value for the volatility measure related to the S&P500, given that this is the market we focus on. Interestingly, liquidity by itself is able to explain almost half of the variation in this volatility measure.

[69]Unsurprisingly, the adjusted R-squared values are relatively low, as the relation between liquidity and these state variables is less direct.

[70]Despite the coefficient being significant, the adjusted R-squared value is relatively low, as many other variables help to explain the variation in house price inflation, which are all omitted here in this analysis. This remark holds for most of these univariate regressions. However, the purpose is merely to establish whether we can retrieve the basic interlinkages with these macro-financial variables.

[71]Similar to Drescher (2011), we retrieve the real money gap proxy from a recursive long-run M3 demand function.

exchange rate, there seems to be a flight to home effect, where higher illiquidity levels concur with higher relative values for the US dollar.[72] The same effect is measurable through the real trade-weighted exchange rate, as measured towards a broad range of currencies (Panel F).[73]

5.3 Impact of Market Liquidity on Future Economic Growth

Many authors hint at the potential of illiquidity to affect future growth rates, e.g. De Nicolò and Ivaschenko (2009); Næs et al. (2011). To better understand this relationship for the US, we examine the forecasting ability of market liquidity in a multivariate setting, together with a number of control variables.[74] We start off with an in-sample forecasting analysis by gauging the effect of illiquidity both on industrial production (IP) growth one-quarter ahead, as well as on the industrial production gap one-quarter ahead.[75] These results are reported in Panel A and B of Table 13 respectively. Most importantly, including our liquidity measure helps explain a substantially larger share of the variance in future IP growth (or gap). Moreover, we detect that higher illiquidity levels lead to lower growth levels.[76]

We assess whether the impact on future growth rates is generated by illiquidity, and not vice versa, via Granger causality tests (Table 14). The p-values for these tests are reported between brackets. A value below .05 provides evidence of Granger causality. We uncover that our unified liquidity measure Granger causes output growth, while the reverse causality is not present. This causal relation is absent for our liquidity measure with the basic time-varying weighting function. The causality even reverses, with output growth Granger causing illiquidity, for the fixed weight alternative.[77] When looking at the control variables, the excess market returns and the term spread, on a higher significance level, Granger cause output growth, while output growth also Granger causes the latter, but not the former. No causality is found with the corporate bond spread measure.

[72] Especially for the exchange rate with respect to the euro area, our liquidity variable is able to explain more than a quarter of the variation in the exchange rate movement.

[73] The sign is different, as this measure is expressed conversely to the other exchange rate measures, i.e. the foreign exchange value of the U.S. dollar.

[74] We incorporate the term spread, excess market return and corporate bond yield as control variables.

[75] We use industrial production as a proxy for output, since we conduct our analysis on a monthly level. Moreover, we construct the gap measure using a Hodrick Prescott filter.

[76] Similarly, our unified market liquidity measure can explain a markedly higher proportion of variation of future growth values than its uni-dimensional counterparts, indicating that incorporating our novel methodology improves on capturing the existent macroeconomic relations. These results can be obtained from the authors.

[77] This further supports our preference for the more advanced time-varying weighting options.

Additionally, we perform a pseudo-out-of-sample forecasting exercise for future economic growth over different horizons, respectively 3, 6 and 9 months. We obtain our forecast estimates through a standard rolling window approach. The initial estimation is done over a forty-five year period (1962-2007), while the out of sample forecast covers the period 2008-2013. We compare a model which includes the term spread, excess market return, corporate bond yield and our unified liquidity measure to a benchmark model without liquidity. Table 15 reports the relative mean squared forecasting error and the relative out-of-sample R-squared value for our four different unified liquidity measures. The model which incorporates liquidity performs markedly better at forecasting out of sample than its counterpart which neglects liquidity. This improvement is most pronounced for our preferred weighting scheme. Moreover, the results are comparatively robust for the different forecasting horizons ($h = 3, 6, 9$).

We get a similar outcome when estimating a five variable Vector Autoregression (VAR) model, with five lags based on lag selection criteria. We use a Cholesky decomposition to identify liquidity shocks with the ordering consisting of our unified market liquidity measure, year-on-year money growth, federal funds rate, year-on-year CPI inflation, and year-on-year industrial production growth. We thus set the contemporaneous response of slower moving macro variables to zero to help us retrieve the impact of our liquidity shock. A positive, one standard deviation shock to illiquidity leads to a lower rate of growth in industrial production. This effect is persistent and leads to significantly lower growth rates for a year. Moreover, the impact is economically significant, as IP growth would be up to 2.5 percentage points lower. In contrast, the shock does not have a meaningful impact on consumer prices or the monetary aggregate. Further, we see a drop in the policy rate up to around 1.25 percentage point, which only becomes significant after 2 quarters, but this policy response is only short-lived. The impulse response functions of our VAR analysis are summarized in Figure 4.

6 Dynamics of the Liquidity Dimensions

6.1 Stylized Facts across Historical Financial Stress

Our methodology allows us to assess the importance of each liquidity dimension over time. We focus specifically on important episodes of financial stress, and categorize these events according to the liquidity groups that contribute most prominently to the overall level of liquidity.[78] This classification allows us to discern some general characteristics across crises with a similar liquidity typology. The resulting breakdown is reported in Figure 5.

Firstly, Panel A portrays the category of financial stress episodes that assigns the highest weight to the bid-ask, etick and Amihud dimensions. The following events can be described in this way: The 1966 credit crunch (10/1966), the peak of the first oil shock (10/1974) and the Iraq invasion (08/1990).[79] These periods were characterized by some degree of foreign contamination, namely an increase in spending due to the Vietnam war, the Yom Kippur war, and the Iraq Invasion. Similarly, they all witnessed a credit crunch,[80] and can be related to a stock market crash (only 1990 saw a mini crash). Moreover, these episodes of financial stress were preceded by a tightening in the Fed's fund rate. Finally, we can discern no (1966) or only a slight (1990) recession, except for 1974 when there was a severe recession.[81]

The second category (Panel B) centers around the bid-ask, etick, and Fong dimension. We retrieve this typology during the 1970s crisis (06/1970), the peak of the 1980s crisis (04/1980),[82] and the Tech Bubble burst (03/2000). We discern a credit crunch both in 1970 and 1980 (1982), but not in 2000. Additionally, there was a stock market crash in 1970 and 2000, while this was not the case in 1980. Each of these crisis periods again tends to occur after a tightening in the Fed's fund rate, and contains no banking crisis, nor a major recession.[83]

Interestingly, this specific class of events bears a close resemblance with the first cluster, and both can therefore be seen as subclasses of a more general category. These events have similar features, most importantly a credit crunch, a tightening by the Fed, and a stock market crash; only the foreign component disappears. Moreover, they most prominently feature the same dimensions of liquidity. The bid-ask and etick group now simply go together with the Fong group, instead of with the Amihud group.

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[78] Hubrich and Tetlow (2015) provide an extensive historical account of such financial stress events. We further refine and extend this list using similar tables provided in Brave and Butters (2010) and Bordo and Haubrich (2016). Hence, our analysis mainly builds on their classification and interpretation of these events.The full list can be requested from the authors.

[79] The peak during the Russian crisis (08/1998) could also be added to these events, but only has the bid-ask and Amihud group as its main protagonists.

[80] Albeit for 1998 this was not a full blown credit crunch, and might thus explain a slightly divergent pattern.

[81] Both the events in 1974 and in 1990 are also associated with a banking crisis, although this was minor for 1974.

[82] The peak of the 1982 crisis (08/1982) can be closely linked to this event, and has similar dynamics.

[83] Except 1982, which witnessed a banking crisis, and was characterized as a severe recession.

For the third category (Panel C), the lion's share of the contributions can be attributed to the bid-ask and Roll group, and contains the 1987 stock market crash (10/1987), the decline of LTCM (05/1998)[84] and the AIG-Lehman collapse (09/2008). We can observe a minor[85] or a more full-fledged (during the 2008 financial crisis) stock market crash. We cannot ascertain any underlying recession for the earlier crises (1987 and 1998). In contrast, the 2008 collapse featured a major recession, banking crisis and housing bust.

A closely related subcategory emerges when we examine the aftermath of the events described in Panel C. More specifically, we can group together the aftermath of the 1987 stock market crash (which experienced a peak in illiquidity in 01/1988), and the aftermath of the 2008 financial crisis (the TALF announcement of 11/2008; the stress test announcement on 02/2009). Logically, the composition (Panel D) is very similar to the above mentioned events, only with the addition of the etick group. Again, this cluster shows a close association with the first two categories described above, where the etick and bid-ask groups play a prominent role, but this time they are combined with the Roll group.

Finally, Panel E features a more dispersed category of events, during which the returns, Fong, etick, and order flow group have the highest weights.[86] We can associate this typology with the 1977 dollar crisis (10/1977), the second oil shock (01/1979) and the Mexican crisis (12/1994). All three events can broadly be described as an external crisis. In 1977 the dollar declined against major currencies, in 1979 there was the second oil shock, and in 1994 huge losses on the Mexican stock market led to the rebalancing of portfolios. However, none of these events caused a severe disruption of the US financial markets, or a domestic stock market crash, or witnessed a tightening in the Fed's policy rate.[87] Finally, there was no recession associated with these events. Hence, we could potentially describe these events as being the least severe, certainly in comparison to the previous episodes.

To summarize, the most prominent liquidity groups during moments of financial stress are the bid-ask group and the etick group. Both of these liquidity dimensions are essential to capture moments when liquidity dries up. Subsequently, they can be combined with the Roll, Fong and Amihud group to portray specific events with

[84] Similarly, the closely linked events of the Asian Crisis (07/1997), and the Hong Kong speculative attack (10/1997).

[85] In 1987 there was black Monday, as well as the savings and loans crisis; while in 1998 the US witnessed a mini crash due to the Asian financial crisis, together with the demise of LTCM, which brought the country almost on the verge of a liquidity crash.

[86] The only class of events where the return group or the order flow group come into play.

[87] At least not preceding the respective crisis events. For example there were interest rate hikes starting from 10/1979.

their own characteristics, thus allowing for a more intricate narrative. In contrast, the order flow, returns and volume group seem to be less important liquidity dimensions during moments of distress.[88] Although, this categorization mostly has an illustrative purpose,[89] it shows how some liquidity dimensions are more important than others during periods financial stress periods, and how some play a bigger role during tranquil periods.[90] The financial stress episodes that we group together have a similar narrative (Shiller, 2019), affect the expectations and beliefs of economic agents in a similar way, and could therefore trigger similar dimensions in liquidity, as well as similar macro-financial dynamics.[91]

This time-varying pattern in the weights of the liquidity groups over the financial cycle is reflected in the construction method of our unified liquidity measure. The liquidity groups that spike up during recessions and are more volatile, also receive a higher weight. Merely using the correlation structure between the measures would imply that we neglect this information. In our case, the groups that see the highest increase in their weights when moving from a tranquil period to a stress period, as portrayed in Table 6, are also the most prominent groups when we specifically focus on the financial stress events. Interestingly, for most of these groups the weights also go down spectacularly during the tranquil periods, which shows that other groups become relatively more important, and all the dimensions of liquidity together are important to get a sensible representation over time (Sarr and Lybek, 2002; Upper, 2001). This result is further confirmed by the univariate regressions for the eight liquidity groups discussed in the next Section.

6.2 Univariate Regressions for the Liquidity Dimensions

Similarly to our analysis in Section 5.2, we examine how liquidity relates to its macroeconomic and financial environment. This time we look at these relations from the perspective of the underlying liquidity groups. Our focus again is on the following four categories: confidence and uncertainty indices; corporate spread and volatility measures; crisis indicators; productivity and monetary/exchange rate

[88] We can discern a similar pattern when we perform the same analysis for the recession periods as a whole, instead of the mere crisis dates. Hence, our conclusions are more broadly applicable than for the historic snapshots analyzed above.

[89] Naturally, many characteristics of these financial stress episodes can be debated upon.

[90] However, we acknowledge that the groups can be formed differently. This would not fundamentally change the conclusion of this section. The same holds for different identification criteria, and for the definitions used to classify the financial stress events.

[91] The latter can involve the interaction between market, funding and monetary liquidity. It also involves the interaction of liquidity with uncertainty and volatility of financial markets, and the behavior of financial intermediairies, and the interbank market.

variables. The main results are summarized from Tables 16 to 19. We report the adjusted R-squared for the univariate regressions. Moreover, whenever the coefficients have a counter-intuitive sign, we add brackets to the R-squared value.

The univariate regressions seem to yield the highest number of significant relations for the bid-ask and the etick group, posting comparable and at times higher R-squared values than the unified measure.[92] However, in contrast to the unified measure, the regression results are not uniform across all categories, confirming that some dimensions of liquidity are more closely related to certain segments of their macro-financial surroundings than others. For example, the bid-ask group does not display the expected monetary interlinkages, while the etick group shows little or no connections with the option-adjusted spreads and productivity subcategories. In comparison, the performance of the Roll and Amihud group is even more mixed. Whereas the Roll group exhibits a close relation with some of the volatility, corporate spread and crisis indicators, the Amihud measure does so for the monetary, volatility and crisis variables. However, both perform relatively poorly in detecting relationships with many of the other categories. Finally, the Fong, volume and order flow groups exhibit many counter-intuitive signs and weak relationships with the investigated categories, which are expected to be closely linked to liquidity.

The dimensions that are most closely related to the macro-financial variables and crisis indicators strongly overlap with the prominent liquidity groups during the financial stress events of the previous Section. This result is most pronounced for the bid-ask and the etick group, but can also be found to a lesser extent with the Roll and the Amihud group.[93] We can therefore conclude that some groups are better equipped at capturing the more volatile episodes in liquidity, while others are more useful to model its relative tranquil counterparts.

Overall, our unified market liquidity measure succeeds at catching a much broader array of dynamics with its macro-financial surroundings than the underlying unidimensional groups. Whereas the interlinkages are more confined to certain subcat-

[92]For several of these categories, the bid-ask and etick group show an even higher R-squared value than for our market liquidity index. Hence, a hasty conclusion might be to dismiss the unified measure (and its more complex aggregation methodology) and simply use one of the (adequately performing) constituent groups as well. However, this cannot be seen as a surprising result, as the unified liquidity measure is merely the sum of the underlying groups. Its performance, de facto, has to be comparable with its building blocks. It cannot suddenly outperform them. In contrast, it may be outperformed by its constituent elements in specific domains, as it incorporates all of the different qualities. However, whereas the performance of the underlying groups is always flawed in one or several categories, the unified measure performs consistently.

[93]These groups also perform best in signaling financial stress moments, when looking at their signal-to-noise ratios or the amount of correct crisis events they signal.

egories for the individual dimensions of liquidity, our aggregation helps remediate this issue, and allows for a more comprehensive liquidity measure, that ticks all the expected boxes. Therefore, merely relying on one aspect of liquidity can be dangerous, as it only tells part of the story, and misses the complexity needed to capture the richer dynamics.

7 Conclusion

Liquidity is a latent, multidimensional and endogenous concept. Hence, it is impossible for one single measure to capture all of its layers. We contribute to the literature with a novel market liquidity index which unifies the strengths of the constituent liquidity groups, while addressing their specific characteristics. Although many authors refer to the multiple dimensions of liquidity, there have been few attempts at integrating this feature in an all-encompassing measure. The recent literature mostly relies on horse races to single out one preferred measure. In contrast, our novel index incorporates both spread and price impact estimates through a mechanism of time-varying correlations and time-varying weights. For this purpose, we build on the recent advances made in the field of financial crisis indicators, and apply several extensions to the portfolio approach.

Our unified liquidity measure succeeds in capturing episodes of financial stress. It is closely linked with several prominent crisis indicators, and produces reliable noise-to-signal ratios. Moreover, our measure exhibits the expected relationship with various macro-financial variables. We can detect spillovers to the real economy from liquidity droughts, and can attribute forward looking power to our liquidity index, above and beyond the variables commonly used to forecast. These features are comparatively more robust for our novel index than for the underlying liquidity groups, thus reinforcing the added value of incorporating multiple dimensions.

The weights of the underlying groups differ markedly over time. During turbulent periods, our aggregation scheme attributes the highest importance to the spread estimates, namely the bid-ask and etick group. Depending on the type of crisis, the Roll, Fong and Amihud groups each respectively take on increased prominence, thus creating a narrative for each historical event. Unsurprisingly, these groups also exhibit the strongest relationships with the macro-financial variables. In contrast, during tranquil times, the order flow, volume and return based groups aid more in understanding the movements of liquidity. Hence, unifying the distinct properties of the liquidity groups allows for the construction of an index which is better equipped at handling the different states of the economy.

Our index can be easily computed for long samples as well as for many countries. Future research could therefore potentially build on these methods, and expand our findings. One route would be to explore our approach in an asset pricing framework, by constructing the counterpart of our market liquidity measure on an asset-specific level. This would lead to a stock-specific liquidity index that incorporates all the information across the liquidity groups. The same adaptation could be done for high frequency data, allowing horse races to be conducted with a more broad based index.

Another route would be to examine the impact of monetary policy shocks on liquidity, by incorporating our measure in a macroeconomic analysis. Moreover, our extension to the portfolio approach could be useful for constructing more elaborate early warning indicators by including other markets as well. A final idea would be to break down the rich dynamics of liquidity with its macroeconomics surroundings, potentially building a general theoretical framework, thus giving a foundation to our empirical exercise. Ideally, such a model would depict that the behavior of liquidity in equilibrium is substantially different than during financial stress.

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Table 1: Overview of underlying costs and frictions reflecting the different dimensions of liquidity

This table reports the costs and frictions underlying the concept of liquidity, as described in the literature.

Year	Author	Background Measures	Measures/Explanation
1985	Kyle	Resiliency	Time dimension
		Tightness	Cost
		Depth	Volume
2005	Lesmond	Direct trading costs (tightness)	Bid–ask spread (quoted or effective)
		Indirect trading costs (depth,resiliency)	Costs based on price behavior (price impact)
			From firm-level data
			Occurrence of zero returns
2005	Amihud et al.	Exogenous transaction costs	
		Demand pressure, Inventory risk	
		Private info	
		Difficulty locating counterparty	
		Imperfect competition	
2006	Amihud;Mendelson	Price-impact costs	Bid-ask spread, Depth
		Search and delay costs	
		Direct trading costs	Exchange fees, Taxes, Brokerage commissions
2009	Holden	Proxy for effective spread	
		Proxies for price impact	
2012	Vayanos;Wang	Price impact	Coefficient of returns on signed volume
		Price reversal	(-) Autocovariance returns
		Participation costs	
		Transaction costs	
		Funding constraints	
		Asymmetric info	
		Imperfect competition	
		Search frictions	
2013	Fong et al.	Percent-cost	Price concession required to execute trade
		Cost-per-volume	Price concession per currency unit of volume

Table 2: Eight liquidity groups representing the multiple dimensions in our analysis

This table describes the different groups which are incorporated in our market liquidity index, and explains how the measures are constructed.

Reference	Proxy
1. bid-ask Group	
Korajczyk, Sadka (2008)	$Qspread_{i,t} = \frac{1}{n_{i,t}} \sum_{j=1}^{n_{i,t}} \frac{Ask_{i,j}-Bid_{i,j}}{m_{i,j}}$ $m_{i,j} = (Ask_{i,j} + Bid_{i,j})/2$ $Espread_{i,t} = \frac{1}{n_{i,t}} \sum_{j=1}^{n_{i,t}} \frac{\lvert pi,j-m_{i,j}\rvert}{m_{i,j}}$ (Both spreads also calculated with high and low prices)
Corwin, Schultz (2012)	$S = \frac{2(e^{\alpha}-1)}{1+e^{\alpha}}$ with $\alpha = \frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma}{3-2\sqrt{2}}}$ where is β sum (over 2 days) of squared daily log(high/low) γ is squared log(high/low) but where high (low) is over 2 days
De Nicolò, Ivaschenko (2009)	$L_t = \frac{2\left(\left\lvert\sum_{i,j\in K,i\neq j} cov_t(R_i,R_j)_{-}\right\rvert+\sum_{i,j\in K,i\neq j} cov_t(R_i,R_j)_{+}\right)}{\sum_{s\in K} var_{t(R_s)+2\left(\left\lvert\sum_{i,j\in K,i\neq j} cov_t\left(R_i,R_j\right)_{-}\right\rvert+\sum_{i,j\in K,i\neq j} cov_t\left(R_i,R_j\right)_{+}\right)}}$
2. Roll Group	
Roll (1984)	$S = 2\sqrt{-cov(\Delta P_t, \Delta P_{t-1})}$ $\frac{1}{n}\sum_{t=1}^{n} \Delta P_t \Delta P_{t-1} - \bar{\Delta P}^2$ (Harris, 1990)
Holden (2009)	$\begin{cases} \sqrt{\frac{-Cov\left(\Delta P_t^{**}, \Delta P_{t+1}^{**}\right)}{\hat{\mu}}} & when \lvert Cov(\Delta P_t^{**}, \Delta P_{t+1}^{**}) < 0 \\ 0 & when\, Cov(\Delta P_t^{**}, \Delta P_{t+1}^{**}) > 0 \end{cases}$ $\Delta P_t^{*} = ar_t.P_{t-1}$with ar_t : adjusted returns $\Delta P_t^{*} = z_t.P_{t-1}$ $ar_t - r_f = \alpha + \beta\,(r_{mt} - r_f) + z_t$ Corwin and schultz (2012) provide extensions on how to treat positive covariances (hence 2 versions of each Roll measure)
3. Zero Return Group	
Lesmond, Ogden, Trzcinka (1999)	$Zeros = \frac{Number\ of\ days\ with\ zero\ return}{Number\ of\ trading\ days\ in\ month}$ $Zeros\ PV = \frac{Number\ of\ positive\ volume\ days\ with\ zero\ return}{Number\ of\ trading\ days\ in\ month}$
4. Fong Group	
Fong, Holden, Trzcinka (2017)	$FHT \equiv S = 2\sigma N^{-1}\left(\frac{1+Z}{2}\right)$ σ : Std(returns),z : Zeroreturndays/totaldays N^{-1} : Inverse function of cumulative distribution function
5. Effective tick (etick) Group	
Holden (2009)	based on observed probabilities of special trade prices correspondent to the jth spread (N_j) dependent on fractional 1/8, 1/16 system or decimal which are then transformed to constrained probabilities $F_j = \frac{N_j}{\sum_{j=1}^{J} N_j}$

Reference	Proxy
6. Amihud Group	
Amihud (2002)	$\frac{1}{TradingDays} \sum Abs(DailyReturns)/DailyDollarvolume$
Goyenko, Holden, Trzcinka (2009)	$SpreadProxy/DailyDollarvolume$ in casu: $High - low\ Spread\ Measure/DailyDollarvolume$
Sarr Lybeck (2002)	Hui-Heubel ratio: $L_{HH} = [(P_{max} - P_{min})/P_{min}] / [V/S * \bar{P}]$ V: total dollar volume, S: number of instruments outstanding $\overline{P}$: Average closing price of instrument
Breen, Hodrick, Korajczyk (2000)	$r^{AR}_{i,t} = \theta_t + \phi_t r_{i,t} + BHK_t sign(r^e_{i,t}) * vol_t + \epsilon_t$ $r^{AR}_{i,t} = \theta_t + \phi_t r_{i,t} + BHK_t sign(r^e_{i,t}) * turn_t + \epsilon_t$
Liu (2006)	$(VolumezeroPreviousXmonths + \frac{1/PreviousXmonthsTurnover}{Deflator}) * \frac{21X}{NoTD}$ $\frac{21X}{NoTD}$: Standardizes amount of trading days in a month to 21
7. Volume Group	
	$Dollar\ Volume$
Datar et al. (1998)	$SharesTraded/SharesOutstanding$
8. Order Flow Measures	
Pastor, Stambaugh (2003)	$r^e_{i,t+1} = \theta_t + \phi_t r_{i,t} + \gamma_t sign(r^e_{i,t}) * vol_t$ $r^e_{i,t+1} = \theta_t + \phi_t r_{i,t} + \gamma_t sign(r^e_{i,t}) * turn_t$

Table 3: Augmented Dickey-Fuller test for the eight different liquidity groups

This table reports the test statistic and the accompanying p-value (between brackets) of the augmented Dickey-Fuller test, performed for our eight liquidity groups, according to the three ordering techniques (as explained in Section 4.2.3). ‘FS’ refers to the full sample ordering technique, ‘BP’ to the subsamples or breakpoint ordering technique, and ‘5y RW’ to the 5-year rolling window ordering method.

	Bid-ask	Roll	Returns	Fong	Etick	Amihud	Volume	Flow
FS	-4.64 (0.00)	-5.37 (0.00)	-2.15 (0.22)	-1.97 (0.30)	-1.48 (0.54)	-1.54 (0.51)	-1.47 (0.55)	-3.30 (0.02)
BP	-5.40 (0.00)	-6.89 (0.00)	-7.08 (0.00)	-3.49 (0.01)	-3.55 (0.01)	-3.69 (0.00)	-3.12 (0.03)	-5.65 (0.00)
5y RW	-5.05 (0.00)	-7.30 (0.00)	-5.27 (0.00)	-4.82 (0.00)	-5.14 (0.00)	-6.56 (0.00)	-5.63 (0.00)	-23.27 (0.00)

Table 4: Summary statistics for the time-varying correlations over the eight different liquidity dimensions

This table reports summary statistics for the time-varying correlations among the eight liquidity groups. Each column refers to the correlation of the specific group with the seven other groups. Panel A highlights values for the mean, standard deviation and the interquartile ranges (IQ). Panel B repeats the mean for the full sample ('fs'), while also providing a breakdown for two subperiods where we discern tranquil times ('tranq'), versus financial stress periods ('crisis'). Additionally, we report the changes of the subperiods relative to the full sample.

Panel A: Descriptive statistics

	Bid-ask	Roll	Return	Fong	Etick	Amihud	Volume	Flow
Mean	0.81	0.84	0.79	0.84	0.81	0.83	0.79	0.83
Stdev	0.07	0.05	0.09	0.08	0.11	0.06	0.09	0.06
IQ0 (min)	0.56	0.67	0.43	0.54	0.45	0.63	0.46	0.59
IQ1	0.77	0.80	0.74	0.80	0.73	0.79	0.73	0.80
IQ2 (med)	0.82	0.84	0.81	0.86	0.84	0.84	0.81	0.84
IQ3	0.87	0.88	0.86	0.89	0.90	0.88	0.85	0.88
IQ4 (max)	0.95	0.94	0.95	0.95	0.96	0.94	0.93	0.94

Panel B: Subsample analysis

	Bid-ask	Roll	Return	Fong	Etick	Amihud	Volume	Flow
fs	0.81	0.83	0.79	0.84	0.81	0.83	0.79	0.83
tranq	0.81	0.84	0.80	0.84	0.80	0.83	0.79	0.84
$\%\Delta$	-1%	0%	1%	1%	0%	0%	0%	1%
crisis	0.85	0.82	0.75	0.80	0.82	0.83	0.78	0.81
$\%\Delta$	4%	-1%	-6%	-4%	2%	0%	0%	-3%

Table 5: Descriptive statistics for unified liquidity measure over different weighting methods

This table summarizes descriptive statistics for our market liquidity index based on the four weighting schemes discussed in Section 4: the equal weights (w), the basic time-varying weights (w_t^s), and the two time-varying weighting schemes that include a volatility adjustment, respectively the shrinkage method (w_t^s) and the augmented method (w_t^a). We report the results for the full samples ('fs'), as well as for the two subperiods, namely tranquil times ('tranq') and financial stress periods ('crisis'). Additionally, we include the relative changes of the subperiods in comparison to the full sample.

	w	w_t	w_t^s	w_t^a
fs	0.21	0.28	0.12	0.35
tranq	0.19	0.26	0.11	0.33
$\%\Delta$	-7%	-7%	-11%	-7%
crisis	0.27	0.37	0.18	0.46
$\%\Delta$	33%	33%	52%	33%

Table 6: Descriptive statistics for the weights

This table summarizes the average value of the weights used in our unified liquidity measure, based on the three different weighting schemes as explained in Section 4. w_t denotes the basic time-varying weighting scheme, while the other two include a volatility adjustment, respectively the shrinkage method (w_t^s) and augmented method (w_t^a). We report the results for the full samples ('fs'), and for the two subperiods: tranquil times ('tranq') and financial stress periods ('crisis'). Additionally, we include the relative changes for the subperiods in comparison to the full sample.

Panel A: Spread and Roll

Bid-A	w_t	w_t^s	w_t^a
fs	0.13	0.08	0.14
tranq	0.13	0.07	0.13
$\%\Delta$	-4%	-11%	-8%
crisis	0.16	0.13	0.20
$\%\Delta$	20%	57%	40%

Roll	w_t	w_t^s	w_t^a
fs	0.13	0.07	0.13
tranq	0.13	0.07	0.13
$\%\Delta$	0%	-2%	0%
crisis	0.13	0.08	0.13
$\%\Delta$	1%	13%	4%

Panel B: Returns and Fong

Ret	w_t	w_t^s	w_t^a
fs	0.12	0.06	0.12
tranq	0.13	0.07	0.13
$\%\Delta$	5%	9%	8%
crisis	0.09	0.04	0.07
$\%\Delta$	-23%	-45%	-41%

Fong	w_t	w_t^s	w_t^a
fs	0.15	0.11	0.19
tranq	0.16	0.12	0.20
$\%\Delta$	3%	4%	5%
crisis	0.13	0.09	0.14
$\%\Delta$	-15%	-21%	-26%

Panel C: Etick and Amihud

Etick	w_t	w_t^s	w_t^a
fs	0.12	0.06	0.11
tranq	0.11	0.05	0.10
$\%\Delta$	-4%	-13%	-9%
crisis	0.14	0.10	0.16
$\%\Delta$	21%	61%	43%

Amih	w_t	w_t^s	w_t^a
fs	0.11	0.04	0.09
tranq	0.11	0.04	0.09
$\%\Delta$	-2%	-11%	-4%
crisis	0.12	0.07	0.11
$\%\Delta$	12%	54%	20%

Panel D: Volume and Order Flow

Vol	w_t	w_t^s	w_t^a
fs	0.10	0.04	0.09
tranq	0.11	0.04	0.09
$\%\Delta$	2%	3%	4%
crisis	0.09	0.03	0.07
$\%\Delta$	-9%	-18%	-19%

Flow	w_t	w_t^s	w_t^a
fs	0.13	0.08	0.13
tranq	0.13	0.08	0.13
$\%\Delta$	1%	0%	2%
crisis	0.13	0.08	0.12
$\%\Delta$	-4%	1%	-9%

Table 7: Indicators of Financial Stress

This table gives an overview of the financial stress, activity, and condition indicators that we use in our regression analysis, as well as in the calculation of the noise-to-signal ratios. We provide the data sources, and where possible also the reference, for each of the stress indicator. All variables are transformed to a quarterly frequency, and are expressed as such that higher values denote higher financial stress. All Federal Reserve based indices, together with the EBP, were retrieved from the FRED database, provided by the St Louis Federal Reserve Bank. The indices constructed by several financial institutions were acquired from Bloomberg. The remaining indices were made available to us by the respective authors.

	Financial Stress/condition/activity index	Abbreviation	Data Source	Reference
1	Aruoba-Diebold-Scotti business conditions index	ADSBCI	Philadelphia Fed	Aruoba et al. (2009)
2	Bloomberg financial conditions index	BFCI	Bloomberg	
	Bloomberg financial conditions index +	BFCI+	Bloomberg	
3	Cleveland financial stress index	CFSI	Cleveland Fed	Oet et al. (2011) (discont.)
4	Carlson-Lewis-Nelson financial stress index	CLN	Authors	Carlson et al. (2014)
5	Excess bond premium	EBP	Fed (authors)	Gilchrist and Zakrajsek (2012)
6	Goldman Sachs financial stress index	GS FSI	Bloomberg	
7	IMF US financial condition index (old)	IMF FCI M	Author	Matheson (2012)
8	IMF financial condition index (current, quarterly)	IMF FCI A	Authors	Antoshin et al. (2018)
9	IMF US financial stess index The	IMF FSI	Authors	Cardarelli et al. (2012)
10	Kansas City financial stress index	KCFSI	Kansas City Fed	Hakkio and Keeton (2009)
11	Chicago Fed national financial conditions index	NFCI	Chicago Fed	Brave and Butters (2011)
	Chicago Fed national financial conditions index, adj	ANFCI	Chicago Fed	Brave and Kelley (2017)
12	Office of financial research financial stress index	OFR FSI	Office of fin. research	Monin (2017)
13	St. Louis fed financial Stress Index	STLFSI	St. Louis Fed	Kliesen and Smith (2010)
14	Unified liquidity Measure	w_t^s	Own Calculations	

	Recession Probability	Abbreviation	Data Source	
	Smoothed U.S. Recession Probabilities	REC	Fed Reserve Database	
	Real-time Sahm Rule Recession Indicator	SAHM	Fed Reserve Database	

Table 8: Noise-to-signal Ratio

This table summarizes the results for the noise-to-signal analysis. Panel A describes the methodology by setting out the four possible outcomes. Panel B reports the noise-to-signal ratio, as well as the number of crisis respectively non-crisis events signaled correctly (in %), for our market liquidity index L_t, the Aruoba-Diebold-Scotti business conditions index (ADSBCI), the National Financial Conditions Index (NFCI), the excess bond premium (EBP), the house price gap (HP) and the credit gap (Cred). This section offers a real time analysis (*Basic*), a forward looking option four quarters ahead (*FL*), and alternatively using narrative dates (*Narr*). Panel C repeats the (basic) analysis using the different weighting schemes for the market liquidity index, as explained in Section 4. w refers to the constant weights; w_t denotes the basic time-varying weighting scheme; the other two include a volatility adjustment, respectively the shrinkage method (w_t^s) and augmented method (w_t^a).

Panel A: Four Possible Outcomes

	Stress event	No Stress event
Signal	A	B
No signal	C	D

Panel B: N/S for the market liquidity index and other stress indices

Basic	N/S	% stress correct	% No stress correct
L_t	0.10	70.6	92.7
ADSBCI	0.23	94.1	78.8
NFCI	0.51	82.3	57.6
EBP	0.19	94.1	82.1
HP	0.79	29.4	76.8
Cred	0.73	41.2	69.5

FL	N/S	% stress correct	% No stress correct
L_t	0.22	34.2	92.3
ADSBCI	0.37	55.6	79.2
NFCI	0.44	81.6	63.8
EBP	0.28	57.8	83.9
HP	1.17	21.1	75.3
Cred	0.90	34.2	69.2

Narrative	N/S	% stress correct	% No stress correct
L_t	0.19	44	91.6
ADSBCI	0.21	88	81.8
NFCI	0.68	64	56.6
EBP	0.30	64	81.1
HP	0.82	28	77
Cred	0.53	52	72

Panel C: N/S for the different weighting schemes of the market liquidity index

Basic	N/S	fin stress correct	No fin stress correct
w	0.18	58.8	89.4
w_t	0.12	64.7	92.1
w_t^s	0.10	70.6	92.7
w_t^a	0.14	76.4	89.4

Table 9: Univariate regressions for unified liquidity measure: Crisis indicators

This table reports the estimated intercept and slope coefficients from regressions of our market liquidity index (constructed with the volatility shrinkage weighting method, w_t^s) on a number of widespread crisis indicators. The variables we employ are listed and explained in Table 7. The sample size depends on the available data series (and is mentioned in the left column). P-values are denoted between brackets. The last column shows the adjusted R-squared.

	Full Sample			Stress Periods			Tranquil Periods		
	$\hat{\alpha}$	$\hat{\beta}^{liq}$	R^2_{adj}	$\hat{\alpha}$	$\hat{\beta}^{liq}$	R^2_{adj}	$\hat{\alpha}$	$\hat{\beta}^{liq}$	R^2_{adj}
ADS_I	-0.468	3.800	0.067	0.419	5.528	0.149	0.116	1.411	0.015
(n=624)	(0.066)	(0.018)		(0.209)	(0.009)	n=99	(0.288)	(0.099)	n=525
BL	-0.409	6.367	0.058	-0.605	20.938	0.370	0.067	-2.181	0.014
(n=288)	(0.340)	(0.246)		(0.340)	(0.005)	n=46	(0.760)	(0.255)	n=242
BL+	-0.670	9.568	0.142	-0.375	20.848	0.452	-0.302	2.015	0.012
(n=288)	(0.107)	(0.059)		(0.542)	(0.002)	n=46	(0.174)	(0.186)	n=242
CFSI	-0.137	1.577	0.005	0.181	7.427	0.312	0.021	-1.943	0.012
(n=267)	(0.523)	(0.491)		(0.511)	(0.000)	n=37	(0.913)	(0.227)	n=230
CLN	-5.176	9.480	0.052	-3.123	11.896	0.195	-5.068	2.439	-0.002
(n=204)	(0.000)	(0.065)		(0.000)	(0.000)	n=35	(0.000)	(0.604)	n=169
EBP	-0.189	2.339	0.076	0.098	3.099	0.090	-0.089	0.563	0.004
(n=492)	(0.092)	(0.025)		(0.661)	(0.063)	n=88	(0.391)	(0.512)	n=404
GS	99.811	2.659	0.022	99.241	12.694	0.451	100.138	-2.318	0.020
(n=288)	(0.000)	(0.359)		(0.000)	(0.000)	n=46	(0.000)	(0.264)	n=242
IMF M	-0.593	7.452	0.203	0.171	11.311	0.482	-0.435	2.578	0.056
(n=204)	(0.018)	(0.016)		(0.581)	(0.000)	n=35	(0.005)	(0.071)	n=169
IMF C	-3.706	38.838	0.384	-3.472	62.475	0.673	-2.770	20.231	0.22
(n=204)	(0.000)	(0.000)		(0.000)	(0.000)	n=35	(0.000)	(0.000)	n=169
KCFSI	-0.575	7.246	0.151	-0.390	15.765	0.481	-0.292	1.606	0.014
(n=287)	(0.054)	(0.066)		(0.375)	(0.001)	n=45	(0.063)	(0.404)	n=242
ANFCI	-0.728	7.031	0.191	-0.555	11.550	0.457	-0.384	2.145	0.025
(n=516)	(0.000)	(0.000)		(0.041)	(0.000)	n=88	(0.001)	(0.032)	n=428
NFCI	-0.706	6.847	0.181	-0.676	12.060	0.470	-0.336	1.784	0.016
(n=516)	(0.000)	(0.000)		(0.011)	(0.000)	n=87	(0.000)	(0.030)	n=428
ORF	-2.191	44.006	0.288	0.396	59.851	0.55	-1.198	15.335	0.060
(n=168)	(0.059)	(0.004)		(0.767)	(0.001)	n=33	(0.000)	(0.001)	n=135
SAHM	0.027	3.104	0.062	0.214	5.237	0.189	0.2530	0.116	-0.002
(n=624)	(0.832)	(0.01)		(0.326)	(0.000)	n=99	(0.022)	(0.904)	n=525
REC	-11.354	176.65	0.217	14.889	228.600	0.284	-0.680	14.397	0.041
(n=559)	(0.002)	(0.000)		(0.122)	(0.000)	n=99	(0.198)	(0.036)	n=460
STLFSI	-0.447	8.119	0.317	0.036	10.686	0.505	-0398.	6.027	0.246
(n=240)	(0.020)	(0.000)		(0.912)	(0.001)	n=37	(0.006)	(0.000)	n=203

Table 10: Univariate regressions for unified liquidity measure: Confidence and uncertainty measures

This table reports the estimated intercept and slope coefficients from univariate regressions of our market liquidity index (constructed with the volatility shrinkage weighting method) on confidence measures (Panel A) and uncertainty measures (Panel B). The sample size depends on the available data series (and is mentioned in the left column). P-values are denoted between brackets. The last column features the adjusted R-squared.

Dependent Variable	$\hat{\alpha}$	$\hat{\beta}^{liq}$	$adjR^2$
Panel A: Confidence Measures			
Business Tendency Survey	100.653	-5.700	0.071
$(n = 624)$	(0.000)	(0.008)	
Consumer Opinion Survey	100.592	-5.228	0.051
$(n = 624)$	(0.000)	(0.010)	
Inventory Sentiment Index	61.426	11.165	0.045
$(n = 198)$	(0.000)	(0.014)	
Consumer Sentiment	88.030	-26.366	0.013
$(n = 430)$	(0.000)	(0.251)	
Panel B: Uncertainty Measures			
Economic Policy Uncertainty	101.737	24.454	0.000
$(n = 348)$	(0.000)	(0.772)	
Equity Market Uncertainty	69.894	256.980	0.029
$(n = 348)$	(0.000)	(0.136)	

Note that the sign for the inventory sentiment index is different from the other confidence measures, as an increase in this index leads to a greater degree of discomfort with current levels of inventory.

Table 11: Univariate regressions for unified liquidity measure: Volatility and spread Measures

This table reports the estimated intercept and slope coefficients from univariate regressions of our market liquidity index (constructed with the volatility shrinkage weighting method) on volatility measures (Panel A) and spread measures (Panel B). The sample size depends on the available data series (and is mentioned in the left column). P-values are denoted between brackets. The last column features the adjusted R-squared.

Dependent Variable	$\hat{\alpha}$	$\hat{\beta}^{liq}$	$adjR^2$
Panel A: Volatility Measures			
CBOE 10Y Treasury (n=132)	5.387 (0.000)	19.785 (0.001)	0.259
CBOE DJIA Vol Index (n=195)	15.333 (0.000)	60.974 (0.005)	0.206
CBOE Russel 2000 Vol Index (n=120)	16.521 (0.000)	119.575 (0.000)	0.400
CBOE SP500 (n=73)	14.769 (0.000)	101.461 (0.001)	0.428
Panel B: Spread Measures			
TED Spread (n=336)	0.291 (0.000)	3.320 (0.000)	0.204
ML AAA O-A Spread (n=204)	0.403 (0.015)	5.078 (0.044)	0.235
ML BBB O-A Spread (n=204)	1.359 (0.000)	8.592 (0.064)	0.177
ML CCC O-A Spread (n=204)	8.799 (0.000)	35.888 (0.060)	0.121
ML High Yield II O-A Spread (n=204)	4.236 (0.000)	18.981 (0.079)	0.141

Table 12: Univariate regressions for unified liquidity measure: Macroeconomic and monetary variables

This table reports the estimated intercept and slope coefficients from univariate regressions of our market liquidity index (constructed with the volatility shrinkage weighting method) on a series of macroeconomic and monetary variables.. The sample size depends on the available data series (and is mentioned in the left column). P-values are denoted between brackets. The last column features the adjusted R-squared. The values used for money are equilibrium values obtained through estimation of recursive money demand function.

Dependent Variable	$\hat{\alpha}$	$\hat{\beta}^{liq}$	$adj R^2$
Panel A: Output			
Coincident Index (n=408)	2.209 (0.000)	-0.183 (0.966)	0.000
Capacity Utilization (n=552)	1.955 (0.014)	-17.083 (0.014)	0.061
Labor Market Conditions (n=449)	4.184 (0.031)	-34.965 (0.070)	0.047
Panel B: Housing Prices			
CS HP Real ΔYOY (n=408)	3.111 (0.009)	-23.670 (0.013)	0.069
Panel C: Interest Rate			
Interest Rate FFR (n=624)	3.176 (0.000)	19.790 (0.000)	0.125
Panel D: Interest Rate Spread			
Term Spread 10Y-FFR (n=624)	1.655 (0.000)	-5.420 (0.014)	0.041
Term Spread 10Y-2Y (n=451)	1.419 (0.000)	-4.408 (0.001)	0.083
Panel E: Money (equilibrium values)			
M3 Real Mgap (n=598)	0.0225 (0.000)	-0.1185 (0.006)	0.0674
Panel F: Exchange Rate (flight to home effect)			
ER US Euro ΔYOY (n=168)	9.275 (0.000)	-87.839 (0.000)	0.264
ER Real TW Broad ΔYOY (n=408)	-3.739 (0.017)	37.634 (0.003)	0.088
ER US UK ΔYOY (n=408)	4.141 (0.038)	-42.205 (0.037)	0.057

Table 13: Multivariate regressions for unified liquidity measure: Future economic growth

This table reports the univariate regressions capturing the effect of of our market liquidity index on future industrial production growth (in the spirit of Næs et al., 2011). We test the specification for one-quarter-ahead industrial production growth (Panel A), as well as for a one-quarter-ahead industrial production gap measure (constructed with a HP filter) (Panel B). The sample size depends on the available data series (and is mentioned in the left column). P-values are denoted between brackets. The last column features the adjusted R-squared.

$\hat{\alpha}$	$\hat{\beta}^{liq}$	$\hat{\gamma}^{term\,spread}$	$\hat{\gamma}^{excess\,mkt\,ret}$	$\hat{\gamma}^{Moody's\,spread}$	$adjR^2$	$adjR^2$ (excl. liq)
Panel A: ΔIP 3m ahead						
9.066 (0.000)	-25.829 (0.000)	0.531 (0.090)	0.038 (0.429)	-4.020 (0.000)	0.264	0.144
Panel B: IPGap3m ahead						
2.611 (0.001)	-10.167 (0.003)	-0.343 (0.029)	-0.042 (0.043)	-0.899 (0.024)	0.199	0.085

Table 14: Granger causality test, accompanying in-sample forecast of ΔIP

This table reports the Granger causality tests which complement the in-sample forecasting exercise. Firstly, we perform a Granger causality test for our market liquidity index based on the equal weights (w) and based on the three alternative weighting schemes. w_t denotes the basic time-varying weighting scheme, while the other two include a volatility adjustment: w_t^s is based on the shrinkage method; w_t^a is based on the augmented method. Additionally, we apply a Granger causality test for the control variables which are incorporated in our in sample forecasting exercise. TS denotes the term spread between 10 year and 3 month rate; EMR represents the excess market return; SPR is the corporate bond yield versus 10 year rate. We test the null hypothesis that market illiquidity (or the control variable) does not Granger cause industrial production growth, and whether industrial production growth does not Granger cause market illiquidity (or the control variable). We report the F-value and p-value (in parentheses) for each test. We choose the optimal lag length for each test based on lag length selection criteria ."

	$LIQ \nrightarrow \Delta IP$	$\Delta IP \nrightarrow LIQ$		$CON \nrightarrow \Delta IP$	$\Delta IP \nrightarrow CON$
w	1.31 (0.26)	2.88 (0.01)	TS	2.32 (0.07)	4.49 (0.00)
w_t	1.81 (0.11)	1.80 (0.11)	EMR	7.83 (0.00)	1.86 (0.14)
w_t^s	2.96 (0.01)	1.61 (0.16)	SPR	1.64 (0.18)	1.88 (0.13)
w_t^a	2.07 (0.07)	1.52 (0.18)			

Table 15: Out-of-sample forecasting performance for future economic growth

This table presents the out-of-sample forecasting performance for future economic growth over different horizons, respectively 3, 6 and 9 months. The forecasting models are estimated through a rolling window technique (Naes et al, 2011). The initial estimation sample is set to 45 years (1962-2007). The out of sample estimation covers the period 2008-2013. Our forecasting model includes the term spread, the excess market return, the corporate bond yield and our market liquidity index, and is compared to a benchmark forecasting model without liquidity. RMSE is the mean squared forecasting error of our model including our market liquidity index, relative to the mean squared forecasting error of the benchmark model excluding the index. ΔR^2_{OS} is the out-of-sample R-squared value relative to the benchmark. We report the results for the unified liquidity measure based on the four different weighting schemes. w refers to the measure based on equal weights. w_t denotes the basic time-varying weighting scheme, while the other two include a volatility adjustment: w_t^s is based on the shrinkage method; w_t^a is based on the augmented method.

	RMSE ($h = 3$)	ΔR^2_{OS}	**RMSE** ($h = 6$)	ΔR^2_{OS}	**RMSE** ($h = 9$)	ΔR^2_{OS}
w	0,95	0,10	0,96	0,07	1,00	-0,01
w_t	0,93	0,14	0,93	0,13	0,98	0,04
w_t^s	0,83	0,30	0,85	0,29	0,92	0,15
w_t^a	0,91	0,18	0,88	0,22	0,92	0,16

Table 16: Univariate regressions for individual group measures: Confidence and uncertainty

This table reports the adjusted R-squared values from univariate regressions of the individual liquidity groups on confidence and uncertainty measures. When the sign of the slope coefficient is contrary to what is expected (first column) the adjusted R-squared value is featured between brackets. The sample size is dependent on the available data series (and mentioned in the left column).

	sign	L_t	**Spread**	**Roll**	**Return**	**Fong**	**Etick**	**Amihud**	**Volume**	**Flow**
Business Tend Sur (n=624)	-	0.07	0.11	0.02	(0.00)	0.01	0.03	(0.01)	(0.01)	0.02
Cons Opinion Sur (n=624)	-	0.05	0.03	(0.01)	(0.01)	0.00	0.05	(0.01)	(0.01)	0.02
Inventory Sent Ind (n=198)	+	0.05	0.09	0.05	0.00	(0.02)	0.13	0.11	0.08	0.07
Con Sent (n=430)	-	0.01	(0.01)	(0.02)	0.00	(0.03)	0.01	0.00	0.00	(0.00)
Econ Policy Uncert (n=348)	+	0.00	0.01	0.00	(0.01)	(0.02)	0.00	(0.00)	(0.01)	0.00
Equity Mkt Uncert (n=348)	+	0.03	0.09	0.00	0.02	(0.13)	0.18	0.19	0.12	(0.01)

Table 17: Univariate regressions for individual group measures: Volatility and spread measures

This table reports the adjusted R-squared values from univariate regressions of the individual liquidity groups on volatility and spread measures. When the sign of the slope coefficient is contrary to what is expected (first column) the adjusted R-squared value is featured between brackets. The sample size is dependent on the available data series (and mentioned in the left column).

	sign	L_t	**Spread**	**Roll**	**Return**	**Fong**	**Etick**	**Amihud**	**Volume**	**Flow**
CBOE 10Y Treasury (n=132)	+	0.26	0.46	0.24	(0.16)	(0.10)	0.24	0.06	-0.01	0.01
CBOE DJIA Vol Index (n=195)	+	0.21	0.54	0.28	(0.05)	(0.17)	0.20	0.12	0.04	0.01
CBOE R2000 Vol Index (n=120)	+	0.40	0.55	0.34	(0.30)	(0.07)	0.13	0.00	(0.06)	0.00
CBOE SP500 (n=73)	+	0.43	0.55	0.29	(0.20)	(0.09)	0.58	0.25	-0.01	0.04
TED Spread (n=336)	+	0.20	0.08	0.02	0.04	(0.04)	0.13	0.13	0.07	(0.03)
ML AAA O-A Spread (n=204)	+	0.24	0.14	0.11	(0.21)	(0.01)	(0.00)	(0.02)	(0.07)	0.00
ML BBB O-A Spread (n=204)	+	0.18	0.11	0.09	(0.31)	(0.00)	(0.01)	(0.06)	(0.15)	0.01
ML CCC O-A Spread (n=204)	+	0.12	0.35	0.14	(0.10)	(0.05)	0.10	0.02	0.00	0.04
ML HY II O-A Spread (n=204)	+	0.14	0.26	0.12	(0.24)	(0.03)	0.00	(0.00)	(0.04)	0.02

Table 18: Univariate regressions for individual group measures: Crisis indicators

This table reports the adjusted R-squared values from univariate regressions of the individual liquidity groups on a number of widespread crisis indicators. When the sign of the slope coefficient is contrary to what is expected (first column) the adjusted R-squared value is featured between brackets. The sample size is dependent on the available data series (and mentioned in the left column).

	sign	L_t	**Bid-A**	**Roll**	**Return**	**Fong**	**Etick**	**Amihud**	**Volume**	**Flow**
CFSI (n=268)	+	0.01	0.18	0.05	(0.26)	(0.00)	(0.15)	(0.09)	(0.19)	0.00
CFSI IB FUND (n=267)	+	0.26	0.13	0.08	0.06	(0.01)	0.12	0.17	0.11	0.00
CFSI IB LIQ (n=267)	+	0.33	0.12	0.10	0.12	(0.01)	0.16	0.28	0.17	0.00
CFSI LIQ (n=267)	+	0.07	(0.02)	(0.02)	(0.32)	0.01	(0.31)	(0.49)	(0.43)	0.00
NFCI (n=492)	+	0.21	0.04	(0.02)	0.05	(0.22)	0.20	0.24	0.20	0.01
FTS (n=386)	+	0.01	0.12	0.08	(0.10)	0.00	(0.05)	(0.04)	(0.06)	0.02
KCFSI (n=287)	+	0.15	0.38	0.14	(0.14)	(0.03)	(0.03)	(0.00)	(0.05)	0.00
REC P (n=559)	+	0.21	0.11	0.00	(0.00)	(0.03)	0.04	0.02	0.01	0.00
STLFSI (n=241)	+	0.27	0.47	0.24	(0.00)	(0.07)	0.05	0.07	0.01	0.01
ADSBCI (n=624)	+	0.07	0.13	0.03	(0.04)	0.01	0.00	(0.02)	(0.02)	0.02
IMF FSI (n=349)	+	0.19	0.18	0.02	(0.01	(0.04)	0.00	0.00	(0.00)	(0.01)

Table 19: Univariate regressions for individual group measures: Macroeconomic and monetary variables

This table reports the adjusted R-squared values from univariate regressions of the individual liquidity groups on a series of macroeconomic and monetary variables. When the sign of the slope coefficient is contrary to what is expected (first column) the adjusted R-squared value is featured between brackets. The sample size is dependent on the available data series (and mentioned in the left column).

	sign	L_t	**Bid-A**	**Roll**	**Return**	**Fong**	**Etick**	**Amihud**	**Volume**	**Flow**
Coincident Index (n=408)	-	0.00	0.07	0.00	(0.09)	0.00	(0.03)	(0.03)	(0.03)	0.00
Capicity Utilization (n=552)	-	0.06	0.11	0.00	(0.01)	0.01	0.01	0.01	0.00	0.00
Labor Market Conditions (n=449)	-	0.05	0.12	0.02	(0.00)	0.01	0.00	0.00	(0.00)	0.00
CS HP Real ΔYOY (n=408)	-	0.07	0.01	0.00	0.01	0.00	0.02	0.00	0.00	(0.00)
Interest Rate FFR (n=624)	+	0.12	0.02	0.06	0.18	0.02	0.51	0.08	0.07	(0.00)
Term Spread 10Y-FFR (n=624)	-	0.04	(0.00)	(0.02)	0.03	(0.11)	0.06	0.15	0.13	(0.02)
Term Spread 10Y-2Y (n=451)	-	0.08	(0.00)	(0.01)	0.16	(0.09)	0.16	0.25	0.21	(0.01)
M2 Real Mgap (n=598)	-	0.07	(0.00)	(0.02)	0.09	(0.07)	0.18	0.17	0.17	(0.00)
ER US Euro ΔYOY (n=168)	-	0.26	0.00	0.03	0.02	0.03	0.04	0.02	-0.01	(-0.01)
ER R TW Broad ΔYOY (n=408)	+	0.09	0.00	0.00	0.04	(0.01)	0.01	0.04	0.02	(0.00)
ER US UK ΔYOY (n=408)	-	0.06	0.00	(0.00)	0.04	(0.00)	0.01	0.01	0.01	0.00

Figure 1: Market Liquidity Index - Time-varying Weights

This figure plots our market liquidity index with the basic weights and the time-varying weights. The time series are monthly, and run from January 1962 until December 2013. The dotted lines denote episodes of financial pressure. The bars denote NBER recessions.

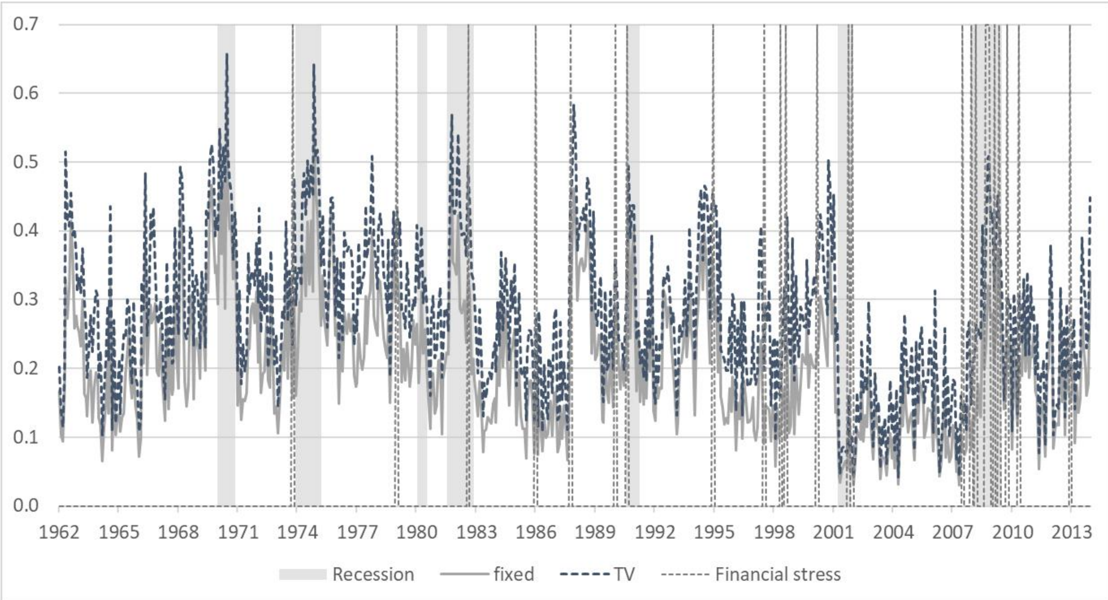


Figure 2: Market Liquidity Index - Volatility Adjustment

The figure plots the effects of the volatility adjustment for our market liquidity index by starting off with the time-varying weighting scheme and then applying the two volatility adjustments: Shrinkage and augmentation. The time series are monthly, and run from January 1962 until December 2013. The dotted lines denote episodes of financial pressure. The bars denote NBER recessions.

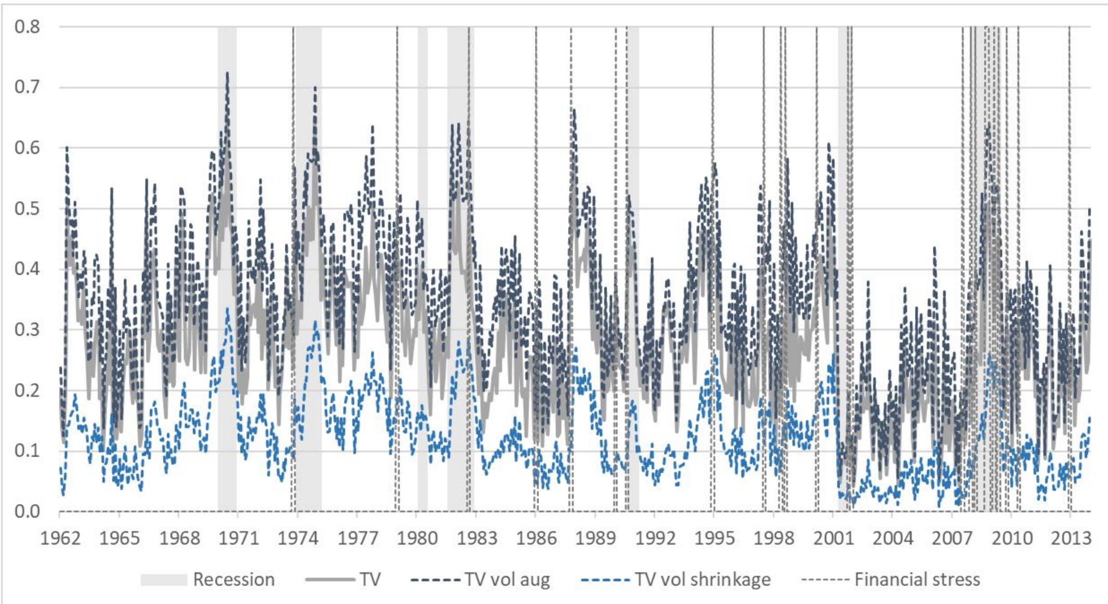


Figure 3: Market Liquidity Index and Financial Stress

This figure plots our market liquidity index (constructed with the volatility shrinkage weighting method). The time series is monthly, and runs from January 1962 until December 2013.The dotted lines denote episodes of financial pressure. The bars denote NBER recessions.

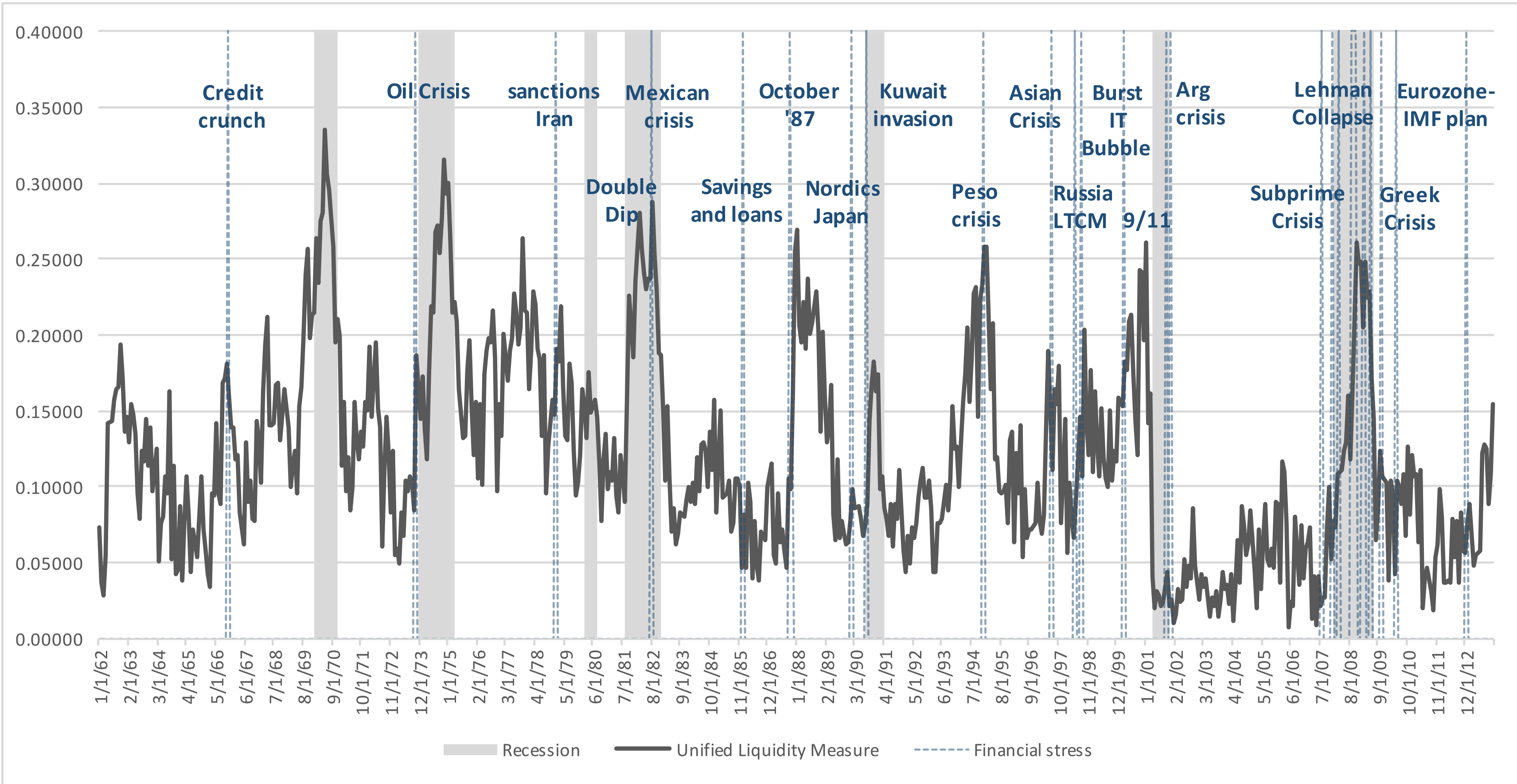
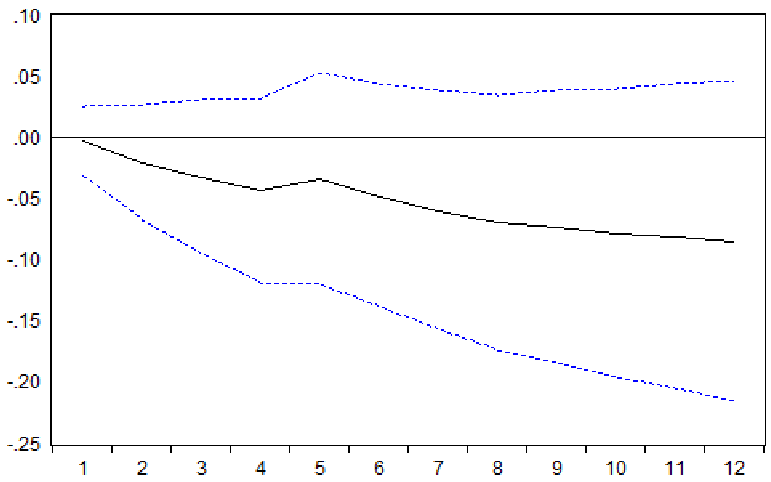


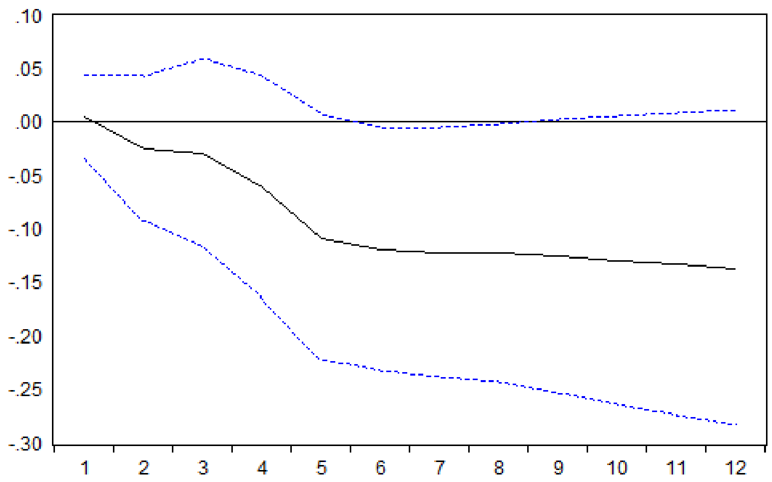
Figure 4: Impulse responses

This figure plots impulse responses of a VAR with 5 lags (based on lag selection criteria) and the following choleski ordering: market liquidity index, M3 (YoY money growth), federal funds rate, CPI (MoM CPI inflation), IP growth (YoY industrial production growth). The panels show the effect of a shock in illiquidity on respectively inflation (CPI), federal funds rate, IP growth and M3.

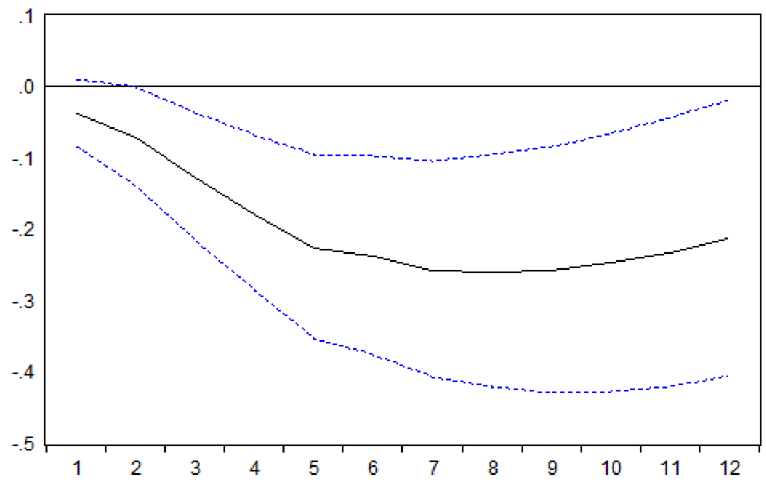
Panel A: Effect of illiquidity on CPI



Panel B: Effect of illiquidity on federal funds rate



Panel C: Effect of illiquidity on IP growth



Panel D: Effect of illiquidity on M3

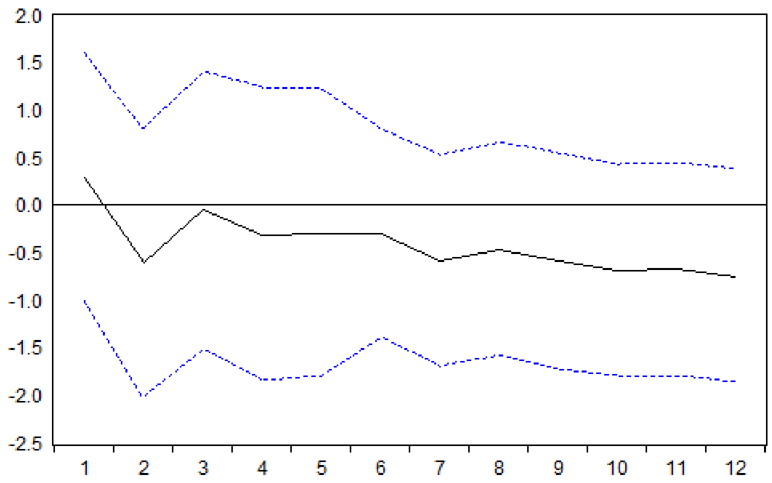
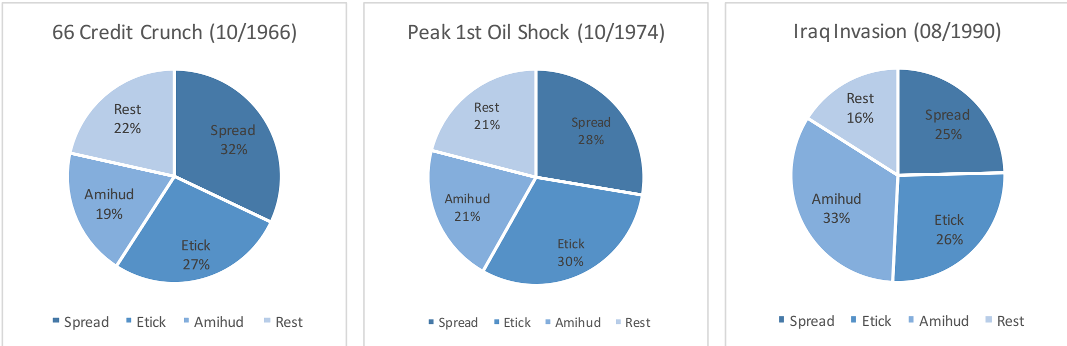


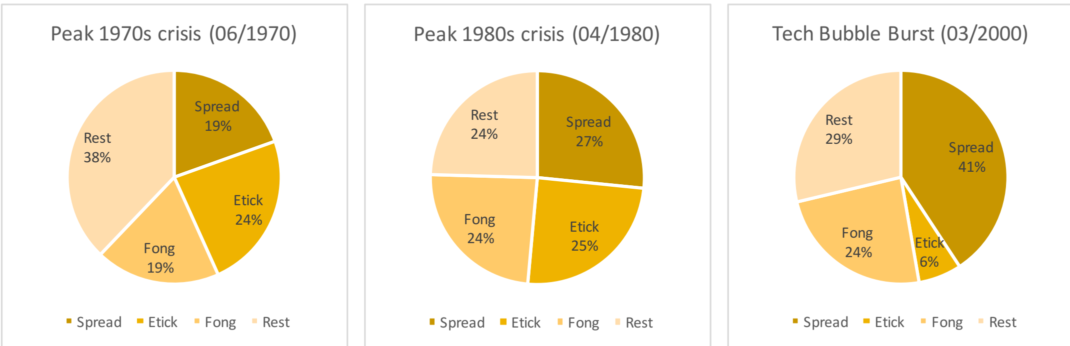
Figure 5: Decomposition of unified liquidity measure and financial crises

This figure illustrates the contribution of the individual liquidity group measures to our market liquidity index for specific historic stress events. Each panel clusters together stress events that can be explained by certain combinations of liquidity groups.

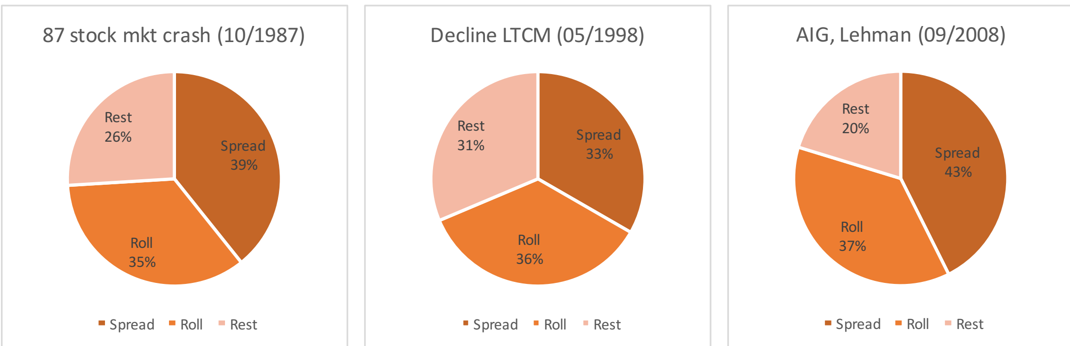
Panel A: Crisis Type 1



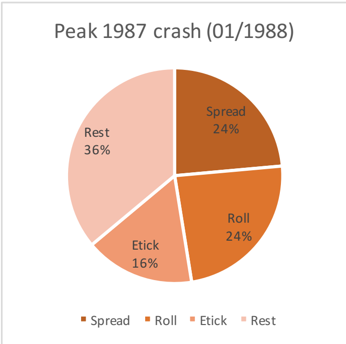
Panel D: Crisis Type 2

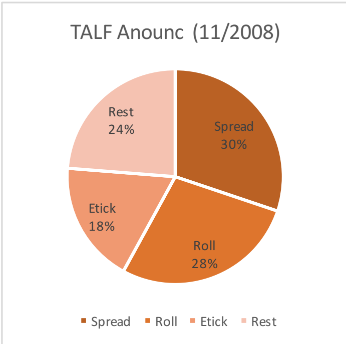


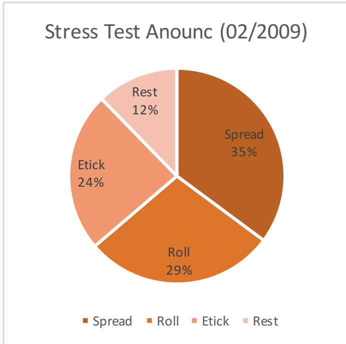
Panel C: Crisis Type 3A



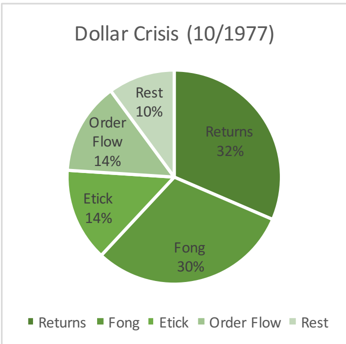
Panel D: Crisis Type 3B

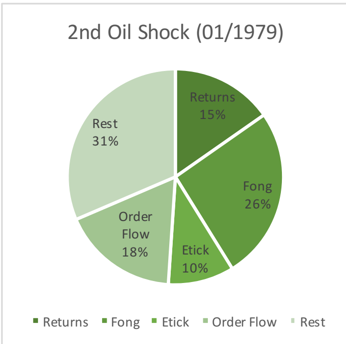


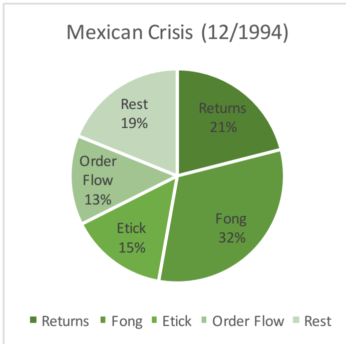




Panel E: Crisis Type 4







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