A Unified Market Liquidity Measure

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Abstract

We introduce a novel method to aggregate the different dimensions of liquidity into a single 'unified' market-wide liquidity measure. The weights for the multiple dimensions are time-varying and depend on three components: the correlation between groups, the pressure conveyed through the measure, and their conditional variance. Our liquidity measure 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 even has some predictive power for future growth rates. Finally, our methodology allows to gauge the individual importance of each liquidity group over time.

Keywords: Liquidity; Trading Volume; Transaction Costs; Pricing Impact; Effective Spread; Financial Crises; Macro-financial Linkages

JEL Classification: G01, G12, G14, E44

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1 Introduction

Liquidity is a well-known concept in financial[1] and monetary[2] economics. It has a strong intuitive appeal and its disappearance, causing panic[3], can often be linked with well-known crisis events. Moreover, liquidity has played a prominent role in the asset pricing literature over the past decades.[4] "Investors should worry about a security's performance and tradability both in market downturns and when liquidity dries up" (Acharya and Pedersen, 2005, p. 405). However, despite its intuitive appeal, liquidity is an unobservable, endogenous and multidimensional concept (Amihud et al., 2005). Hence, the shapes and guises which liquidity can take on are numerous, time-varying and often impalpable. These three features are central in understanding our novel approach in constructing a comprehensive, all-encompassing market liquidity measure.

Firstly, due to the fact that we are considering a latent variable, a precise and concise definition is impossible, and the literature is littered with multiple, often vaguely-defined notions of liquidity (De Nicolò and Ivaschenko, 2009). Hence, it can only be approximated through the measurement of liquidity-related quantities or proxies (Hallin et al., 2011). But because of its elusive and slippery nature (Kyle, 1985; Pástor and Stambaugh, 2003) these empirical measures can be markedly disparate (Næs et al., 2011), often relying on different methodologies.

Secondly, closely linked with the previous characteristic, liquidity is a multidimensional concept (Fong et al., 2014; Pástor and Stambaugh, 2003; Amihud et al., 2005). Most acquainted are the three quintessential dimensions advanced by Kyle (1985), namely depth, resilience and tightness, which all add up to a general feeling of liquidity. These traits describe the ability of trading a substantial amount of assets, quickly, at low cost, and at a reasonable price (Brennan et al., 2012; Harris, 2003).[5] However, underlying the ease of converting an asset into cash (the ease of trading a security) are many different cost components and potential frictions (Hallin et al., 2011; Amihud et al., 2005), some of which are explicit and easy to

[1]e.g. Sadka (2006); Mitchell et al. (2007); Roll et al. (2007); Chordia et al. (2008); Han and Lesmond (2011); Avramov et al. (2015).

[2]e.g. Kiyotaki and Moore (2012); Pedersen (2009); Bruno and Shin (2014).

[3]See Keynes (1936, p. 160) on the soothing effect of liquidity on financial markets: "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".

[4]e.g. Amihud and Mendelson (1986); Bekaert et al. (2007); Chordia et al. (2009); Asparouhova et al. (2010); Lee (2011); Brennan et al. (2012); Lou and Shu (2014).

[5]Gorton (2012, p. 48) points that "market 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."

measure, while others are more subtle. These costs include the bid-ask spread, market-impact costs, delay and search costs, and brokerage commissions and fees (Amihud and Mendelson, 2006). A more comprehensive list is included in Table 1. The search for the true meaning of liquidity has resulted into an intricate and multi-layered concept, reminiscent of Polycephalic creatures in ancient mythology. Hence, it is unfeasible for one single measure to capture all of the layers conveyed within liquidity (Amihud et al. 2005; Hallin et al. 2011). As a result, low correlations between different individual measures do not necessarily entail that one is inferior to the other. Instead, they could simply be gauging different dimensions (Liang and Wei, 2012). Moreover, there is evidence that even different frequencies capture different phenomena (Vayanos and Wang, 2012). Unsurprisingly, we notice little consensus on the efficacy of many of the commonly used liquidity proxies. Many authors simply apply a whole spectrum of liquidity measure in their analysis to advance a broader view of liquidity (Lam and Tam, 2011; Keene and Peterson, 2007), as each proxy is considered to have its specific strengths and weaknesses, instead of being mere substitutes (Lesmond, 2005; Vayanos and Wang, 2012).

Finally, adding to the complexity, liquidity is endogenous. It arises as the outcome of trading patterns in financial markets. Hence, liquidity depends on the total volatility of the financial system (Chordia et al., 2011). 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". More broadly, the concept of liquidity is closely entwined with its macro-finance surroundings through many different concepts, including sentiment (Baker and Wurgler, 2006), optimism (Tetlock, 2007), the economic environment (Hameed et al., 2010; Næs et al., 2011; Rösch and Kaserer, 2013), monetary policy (Goyenko and Ukhov, 2009) and the state of the economy (Watanabe and Watanabe, 2008). Moreover, it has leading and lagging relations with credit ratings (Odders-White and Ready, 2005; Avramov et al., 2009), and strong interlinkages with the interbank market (Nyborg and Östberg, 2014). Hence, when we apply the Lucas critique (1976) to financial markets, and more specifically to the multi-layered concept of liquidity, different economic environments (with disparate shocks hitting the economy) can influence the importance and even the ability of the liquidity measures to provide a clear picture of the underlying threats.

We want to address these unique features head on, and introduce a novel multidimensional market liquidity measure which reunites the individual strengths of different groups of liquidity measures. Thus, our main goal is to construct a measure that embodies the investor's general feeling about the liquidity (based on all of the potential underlying costs, frictions and asymmetries) of the US stock market.[6] We build on the recent developments made on financial crisis indicators (Oet et al., 2011; Holló et al., 2012). Firstly, we construct eight separate groups of individual liquidity measures by taking together measures that characterize similar dimensions of liquidity. Next, we apply the portfolio approach (Illing and Liu, 2006) in order to aggregate these groups of liquidity. We allow for the time-varying correlations to determine the individual importance of every class of liquidity, as similarities over the various measures indicate that several dimensions are picking up the same signal. Up to this point, we merely provide an alternative aggregation method by applying the portfolio approach instead of more classical common factor or principal component methodologies (Korajczyk and Sadka, 2008; Hallin et al., 2011). However, we expand the existent methodology, not solely relying on the commonality across liquidity groups, by also allowing for idiosyncratic elements to affect the multidimensional or unified liquidity measure through a time-varying weighting scheme, whenever a specific group hints at extreme pressure relative to its peers. Because of the discordant backgrounds of each liquidity measure, it is not unimaginable that a single or several specific measures pick up a signal that the others ignore. Only incorporating the different dimensions as weighted by their correlations would imply that we neglect such signals (as is the case with the common factor or principal component methodology). Finally, we adjust our time-varying weights, by making the assumption that volatile liquidity groups attract more investor attention than tranquil groups, which would increase the importance of the former.[7]

Our multi-layered liquidity measure succeeds well in identifying episodes of financial crisis and recessions over a long sample period from 1957 to 2013. It is closely linked with several well-established crisis indicators, and produces comparable signal-to-noise ratios. Moreover, the novel measure exhibits a close relation with various financial and macroeconomic variables. We can additionally unravel real spillovers from liquidity droughts, even assigning some forward looking power (in the spirit of Næs et al. (2011)) for our liquidity measure above and beyond classical forecasting variables. These features are relatively more robust and significant than for the existing liquidity proxies, thus reinforcing our belief that it is important to

[6] We decide to perform our aggregate method on the market as a whole, because of the increasing importance of commonality in liquidity across stocks (Chordia et al., 2000; Huberman and Halka, 2001; Hasbrouck and Seppi, 2001; Kamara et al., 2008; Brockman et al., 2009; Rösch and Kaserer, 2013), and because of its importance in a macroeconomic framework. However, our approach can readily be extended to the aggregation of different liquidity measures on a stock-specific level. The latter construct would be useful to incorporate in an asset pricing framework.

[7] We apply two methodologies, one by using the class specific volatility as a shrinkage factor, and another by augmenting the weighting scheme with the volatility values. Both techniques seem quite robust.

take into account all of the liquidity dimensions. Moreover, our measure is easily applicable and can be computed for long samples, as well as for many countries.

Whereas our analysis primarily consists of an aggregation method apt to handle the specific challenges surrounding liquidity, it also allows for a comprehensive inspection of the importance of the constituent liquidity groups over time, and more specifically during episodes of financial stress. We uncover that the spread and etick groups are the main protagonist during these turbulent periods. Depending on the type of crisis, one (or both) of these groups appears in combination with the amihud, roll and fong measure. Moreover, with the exception of the fong group, these are exactly the groups that perform well in unraveling the univariate relations with macroeconomic, financial, and crisis variables. In contrast, the flow, return and volume group seem to be more valuable in understanding liquidity during tranquil times. Hence, unifying these separate properties of each liquidity group allows for the construction of a proxy which is better equipped to handle different states of the economy.

This paper is organized as follows. Section 2 explores some strands of closely related literature, whereas section 3 describes the construction method of our multifaceted or unified liquidity measure. Next, we examine how our liquidity measure behaves over the business cycle and during financial stress in Section 4, including its interlinkages with macroeconomic and financial variables. Within this section we also gauge the importance of the separate liquidity groups. Finally, Section 5 provides some concluding remarks.

2 Literature

Our approach is similar in vein to a number of recent studies. Liu (2006) introduces a new measure that encompasses several dimensions of liquidity, including the mostly ignored aspect of trading speed. He uncovers high correlation between his novel measure and more traditional measures, which he interprets as evidence for its multidimensional property. A more explicit way of combining different attributes can be found in Holden (2009), where integrated models (combining manifold attributes) and multi-factor models (linear combinations of simpler models) have the potential of diversifying away imperfectly-correlated error terms.

Next to the outright construction of new measures, several authors have attempted principal component and common factor analyses, to crystallize the different features of liquidity into one single measure. Lesmond (2005) employs a factor analysis to unveil whether a single liquidity factor is being captured by any, or all, of four traditional unidimensional liquidity estimators, as he is doubtful that an individual measure can capture all of the potential liquidity features. Due to concerns about scale differences between the liquidity estimators, he applies a maximum likelihood factor.

Accordingly, in the context of market liquidity, Korajczyk and Sadka (2008) attempt to assess an overall market liquidity measure based on several liquidity measures via principal component methods. Their study focuses on combining information from various sources to form a common facet of asset liquidity. Similar in vein, but technically divergent is the analysis of Hallin et al. (2011). Through a Generalized Dynamic Factor Model (with block structure to provide a data-driven definition of unobservable market liquidity and to assess the complementarity of two observed liquidity measures) they succeed in identifying commonality over different liquidity measures.

Even though all of the above mentioned techniques have their particular merits, we have to advance several remarks concerning their adaptation to this specific setting. Firstly, several of these methodologies yield an unobservable "systematic" liquidity measure, and leave no room for any measure-specific idiosyncrasy. They count heavily on the commonality over the different liquidity measures as the sole feature which concerns the investor. Such an approach is quite restrictive, as for example the return of a specific stock could also be influenced by a purely idiosyncratic liquidity measure[8], which should therefore be kept in the equation.[9]

Secondly, these methodologies only provide a purely statistical (black box) solution for performing the aggregation exercise. There is no economic intuition behind the assemblage of the different pieces. Moreover, the selection of the included variables 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.[10]

Lastly, many of these studies commence by standardizing the raw liquidity measures, which are then aggregated through arithmetic averaging, principal component

[8] 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.

[9] Up to a certain point, our methodology (applying time-varying correlations) provides an alternative aggregation method to the more traditional principal component and common factor techniques, and similarly focuses on the systematic components. However, we extend this procedure and also 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.

[10] In contrast, our portfolio approach provides a more transparent way of performing the aggregation exercise. Moreover, we try to incorporate the full array of liquidity measures.

technique and common factor analysis. Holló et al. (2012) warn that standardized variables might be sensitive to irregular observations, as many customary liquidity measures violate the assumption of being normally distributed. Applying the principle component analysis might further exacerbate the problem, as this technique is also vulnerable to the presence of outliers.[11]

The recent state of the art liquidity literature also performs horse races in order to single out the most accomplished liquidity measure, as opposed to lumping all of the liquidity measures together in order to accommodate for the different liquidity dimensions.[12] Interestingly, these studies provide valuable insight in the adequacy of low frequency proxies in capturing the features of intraday data, thus legitimizing the use of low frequency measures. However, there are also some drawbacks to this methodology.

Firstly, high frequency data is only available for a relatively short period of time in the US[13], and is simply unobtainable for most other countries (Corwin and Schultz, 2012; Hasbrouck, 2009). In contrast, their low frequency counterparts can be formulated dating back eighty years in the US, and are available for various durations across countries around the world (Holden, 2009). When considering asset pricing tests, or similarly when performing macroeconomic analysis, researchers need to rely on long time series, to ameliorate the power of their tests (Amihud et al., 2005). More specifically, the limited availability of the high frequency data might raise questions about the stability of the results while performing these horse races. When comparing short timespans, the results might be driven by the underlying forces and shocks in the economy which can change over time (Lucas Jr, 1976). Hence, different periods might reward alternating winners, as other dimension become more important, or fade away over time.

Secondly, high-frequency benchmarks have a similar multidimensional nature comparable to its low frequency equivalent. Hence, performing the horse races only allows comparison within every dimension, resulting in a within-dimension winner, in contrast to an overall (across-dimensions) superior measure.[14] Our multidimensional

[11] We rely on conversion into order statistics using an empirical cumulative distribution function, which also provides the advantage of delivering stationary and more consistent series of the different liquidity groups.

[12] Most well-known examples are Holden (2009), Goyenko et al. (2009) and Fong et al. (2014). Moreover, Hasbrouck (2004) and Corwin and Schultz (2012) also compare their measures with high-frequency benchmarks.

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

[14] For example, Holden (2009) employs the percent effective spread and the percent quoted spread as high-frequency benchmark. Goyenko et al. (2009) relies on two spread benchmarks and three price impact benchmarks. Fong et al. (2014) suggests four high-frequency percent-cost

aggregation method might therefore also be useful (to unveil the latter) for the intra-daily measures.

Finally, the use of high frequency data has its own specific micro-structural problems ranging from inventory concerns to finding a suitable aggregation interval for order flows (Chordia et al., 2011).

3 Statistical Design

3.1 Basic Setup and Data

Albeit many authors refer to the multiple dimensions of liquidity, there are few attempts at integrating this feature in an all-encompassing measure. Most of the state of the art literature refutes to running horse races in order to find the first best liquidity measure amongst its competitors. In contrast, we present a novel unified market liquidity estimator which crystallizes the disparate liquidity groups into a single value, and thus embodies the investor's general feeling about liquidity in the US stock market. We build on the recent advances made on financial crisis indicators (Oet et al., 2011; Holló et al., 2012), and apply an advanced portfolio approach (Illing and Liu, 2006) to perform the aggregation of the separate liquidity groups.

Constructing our unified market liquidity measure consists of different steps. Initially, we standardize the rudimentary liquidity measures by converting them into order statistics using their empirical cumulative distribution function (CDF). Next, the twenty-one individual liquidity measures are grouped according to their dimension. This results in eight separate liquidity groups. Finally, we reach our unified market liquidity measure by taking into account the time-varying correlations between the different groups, but simultaneously allowing for (volatility-adjusted) time-varying weights across groups. More precisely, we implement two extensions to the traditional portfolio approach which better fit to the needs of the liquidity context under examination. Firstly, we augment our model by incorporating time-varying weights based on the relative liquidity pressures for each dimension of liquidity. This allows us to take into account the idiosyncratic signals of specific liquidity groups. Secondly, we adjust our time-varying weights to take into account the volatility of the particular group. The underlying idea is that highly volatile liquidity measures grab more attention, and hence have more impact. Practically,

benchmarks and one high-frequency cost per volume benchmark. Corwin and Schultz incorporates TAQ effective spreads. Hasbrouck (2004) simply refers to estimates derived from detailed trade and quote data.

we apply two variations on this theme which have a very similar relative impact. On the one hand we apply a ‘shrinkage factor’ to dampen the tranquil episodes, and on the other hand we incorporate an ‘augmentation factor’ reinforcing volatile outburst. Figure 1 gives a schematic overview of the different steps. The next subsections explain and motivate each step in detail.

3.1.1 Data

In our analysis, we incorporate twenty-one liquidity proxies representing eight different spheres of liquidity, based on spread measures, Roll measures, (zero) returns measures, Fong measures, effective tick measures, Amihud measures, volume measures and order flow measures.[15] All measures are expressed as such to denote illiquidity, and all measures are constructed on a monthly frequency. For this purpose, we use daily data from the CRSP database, ranging from 1957 to 2013.[16] We include series on prices (high, low, bid and ask), shares outstanding, shares traded and volume. An extensive survey on the construction of every individual liquidity measure can be found in Table 2. We create market aggregates for each proxy by constructing market capital weighted averages of the stock-specific liquidity measures for the five hundred stocks represented in the S&P500 in that particular month.[17]

3.1.2 Ordering

The rudimentary liquidity measures are standardized by converting them into order statistics using their empirical cumulative distribution function (CDF). This process is particularly critical for liquidity proxies because of differences in the unit of measurement as well as in their scale (Lesmond, 2005; Vayanos and Wang, 2012). Moreover, this transformation makes the liquidity measures robust to the influx of new information (Holló et al., 2012). We apply several alternative ordering techniques. Firstly, the ordering is done based on the full sample. Next, we apply subsamples based on changes in the underlying minimal tick size of the US stock exchange.[18] Finally, we apply a rolling window method in which the ordering for each

[15]Of course, our list of liquidity proxies is not exhaustive. However, we have good reasons to limit our set to these variables, as it allows for long data series (hence leaving out Chordia et al., 2009), is robust for different trading periods (therefore excluding the LOT measure) and is robust at least on monthly (preferably on a daily) basis (for that reason excluding Hasbrouck, 2009).

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

[17]We perform robustness tests with equally weighted alternatives, but this does not change our results in a meaningful manner.

[18]We get three subsamples: the first from the start of the sample up to June 1997 (change in the tick size from one sixteenth to one eight; the first time in history that an exchange had modified the minimum tick size); the second from July 1997 till February 2001 (change in tick size from

day is based on the last five years preceding that day (which shortens the sample to 1962-2013, as we lose the first five years of observations). This last approach accommodates the idea that investors have short memory. When gauging the particular impact of a liquidity measure, they would therefore mainly look at the short term window of the past five years.[19] Moreover, this 'short memory' feature alleviates the potential problem of event reclassification which is prevalent with measures whose empirical setup thoroughly banks on stable distributional features, as is customary in limited samples (Holló et al., 2012). Additionally, we achieve a more sensible representation of liquidity over time by evaluating the variable in relation to its immediate environment. After all, over long samples, many liquidity measures show dramatic drops simply due to their construction method (often due to an increase in the activity on the stock market in recent decades), indicating that recent illiquidity pressures are negligible in comparison to historic ones. However, for the present day investor these (seemingly understated) liquidity events embody very real treats.

Finally, this local evaluation leads the variables not only to be consistent, but also stationary. Table 3 highlights that standard unit root tests cannot reject the hypothesis that several liquidity groups based on the full sample ordering technique contain unit roots. More specifically, the returns, fong, etick, amihud and volume groups appear to be non-stationary.[20] However, these groups all exhibit stationary time series when we apply a more local ordering, through breakpoints or with a five year rolling window. The latter has the additional advantage that we do not have to exogenously administer the breakpoint dates, which can provide additional difficulties as additional data is added to the time-series.[21] Hence, for the remainder of the paper, we use the rolling window ordering method.

3.1.3 Liquidity Groups

In a next step, the measures for the eight separate liquidity groups, denoted by $l_{i,t}$, are then formed by taking the simple arithmetic mean of the individual measures

one sixteenth to one cent on the NYSE; this happens for all stocks in April 2001, but the choice between the two dates does not change the results); the final from March 2001 onwards till 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, and Holden (2009) similarly does so in the construction of the effective tick measure.

[19] Admittedly, the time frame of five years could be seen as arbitrary. However, the measure is robust for a time frame of ten years. The only difference is that the liquidity groups exhibit less volatility, and thus feature comparatively less idiosyncratic pressure with the ten year alternative.

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

[21] Moreover, as breakpoints differ across countries, this methodology does not allow a uniform approach for cross-country comparison.

$z_{i,j,t}$ belonging to each group ($i = 1, \ldots, 8$):

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

with n the number of individual measures belonging to each group and t the time period. Index j refers to the individual measure of a specific liquidity group. The formation of the groups is based on the underlying dimension. A more detailed account can be obtained in Figure 1.

3.2 Time-Varying Correlations (Portfolio Approach)

We reach our multidimensional or unified market liquidity measure L_t by applying the portfolio approach to the eight groups, i.e.

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

where C_t denotes the matrix of time-varying cross-correlations (measured with exponentially weighted moving averages with a decay factor of .94), l_t the vector of liquidity group measures and w_t the vector of weights attached to the liquidity groups, which are set equally up to this point.[22] The rationale behind this approach is that every market liquidity measure can theoretically be broken down into a systematic component and its idiosyncratic counterpart (Korajczyk and Sadka, 2008). On the one hand, the different liquidity groups might represent imperfect proxies of the same true underlying concept of liquidity (Amihud et al., 2005; Lesmond, 2005). On the other hand, they might gauge different dimensions of liquidity that are interconnected with each other (thus measuring closely related concepts). By using the portfolio approach, an individual liquidity group affects our unified liquidity measure to the extent that they are correlated with the other liquidity groups. When several groups simultaneously indicate a dry spell in liquidity, we want them to receive relatively more weight, as this would point towards several dimensions picking up the same signal or characteristic.[23] This is accounted for by our matrix C_t. Hence, up to this point, we simply provide an alternative to the more traditional principal component and common factor analysis (Korajczyk and Sadka, 2008; Hallin et al.,

[22] $w_t \circ l_t$ represents the Hadamard-product, i.e. element-by-element multiplication of the vector of weights and the vector of liquidity group measures.

[23] Amihud et al. (1990, pp. 65-66) already acknowledged that "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."

2011), solely relying on the systematic liquidity elements to perform the aggregation.

Table 4 provides some summary statistics for the time-varying correlations of each specific group measure with the seven other group measures. Panel A highlights values for the mean, standard deviation and the interquartile ranges (IQ). Panel B shows sample averages for the full sample period ($n = 624$), but also differentiates between the crisis periods[24] ($n = 111$) and tranquil times ($n = 513$). The interquartile values in Panel A show that correlations shift considerably over time. Panel B reveals though that the timing does not exactly correspond with the crisis periods. Possibly the correlations only change after such events. Overall, the results justify the use of time-varying cross-correlations in our methodology.

3.3 Time-Varying Weights

3.3.1 Methodology

Up to this point, we have mainly followed the approach by Holló et al. (2012). However, we customize the existing approach to better fit the needs of the liquidity context that we are examining. As our groups consist of imperfect proxies that gauge the same concept from different viewing points (fundamental and distinct aspects of illiquidity, as pointed out by Vayanos and Wang (2012)), it is possible that a single or several specific measures pick up a signal that the other groups (because of their specific construction method) do not pick up on. Merely incorporating the different dimensions as weighted by their correlations would imply that we interpret this signal as noise, and hence would be weighted less relative to the other groups. However, if this signal is strong, it could be hinting at an important feature that the other groups are not able to pick up on. We would therefore also like to account for these idiosyncratic signals, in our weighting scheme. For this purpose, we enhance our model by incorporating time-varying weights based on the relative illiquidity pressures in every group.[25] The weighting function $w_{i,t}$ of group i at time t is modeled as an exponential function of the deviation of the group-specific liquidity

[24]Crisis periods are defined as historic financial stress events (as explained in Section 4.1), combined with the recession periods during the sample from January 1962 up to December 2013.

[25]The CISS methodology only incorporates fixed weights for the full sample, based on the impact of each group on the economy. However, this could introduce endogeneity issues in the identification of the importance of every group.

value $l_{i,t}$ at time t minus an arbitrary threshold T[26]:

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

This function ensures that higher deviations (which point at stronger signals or higher pressure) get higher weights. We force the weights to sum to one over the different groups, and are therefore only interested in the relative pressures which are present in our system of liquidity groups. If all the groups are similarly exceeding their threshold, they simply receive equal weights.

3.3.2 Volatility Adjustment

We also include another explicit aspect of investor behavior based on the literature about limited attention (Kahneman, 1973) and the use of heuristics (Gigerenzer, 2008).[27] Closer to our story, there are several studies examining limited attention in the stock market (Corwin and Coughenour, 2008; Huang and Liu, 2007). With the full spectrum of information, we cannot expect an individual investor to pick up all the relevant signals to make his decision. We suspect that signals that are more volatile will also attract more attention.[28] More specifically, investors will be affected more by episodes of high relative idiosyncratic pressure in a specific group, if this relative pressure reveals itself in an irregular, unexpected manner. For example, if the illiquidity pressure in the group is comparatively high, this would yield a high weight in the previous setting. But if it has been that high for the past five months, then the investor would be accustomed to that stance, and would have already taking the necessary precautionary steps, thus being less affected by it lingering. In contrast, a similar amount of pressure, brought about virulently, with high volatility, will bring about a more pronounced impact. Attention grabbing "liquidity groups" may have a similar impact as attention grabbing stocks ('all that glitters'), when there are many to choose from (Barber and Odean, 2008). We therefore adjust our weighting function to take into account the volatility of the particular group.[29]

[26] As our liquidity proxies are between zero and one, imagine a 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.

[27] We do not want to construct an abstract theoretical construct that relates to the real life investor experience, as for example Goyenko et al. (2009) remark that there is little evidence that any liquidity measure is related to the investor experience.

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

[29] The downside is that the weights of the groups do not sum up to one, due to the shrinkage, so we lose some comparability with the previous weighting schemes. However, this approach is

Using volatility as a weighting factor for different groups is not uncommon. For example Gerdesmeier et al. (2011) apply weights based on the volatility of different asset classes in setting up their early warning indicator. Practically, we apply two variations on this theme which have a very similar relative impact. Firstly, we apply a 'shrinkage factor' to dampen the tranquil episodes:

$$ws_{i,t} = \frac{exp(l_{i,t} - T) * \sigma^2_{i,t}}{\sum_{i=1}^{8} exp(l_{i,t} - T)}$$

where $\sigma^2_{i,t}$ is the volatility (measured with exponentially weighted moving averages with a decay factor of .94) of liquidity measure $l_{i,t}$ of group i at time t. Secondly, we built an alternative version where volatility interacts with the liquidity measure itself, leading to a volatility augmented approach:[30]

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

According to this model, volatility outbursts are reinforced for higher levels of illiquidity. Both volatility-adjusted weighting functions $ws_{i,t}$ and $wa_{i,t}$ allow us to account for the heuristic approach many investors rely on.[31]

3.3.3 Descriptive Statistics

To get a full understanding of the different weighting functions, we look closely at the dynamics of our unified liquidity measure and the underlying time-varying weighting schemes. Table 5 reports the average values for our unified liquidity measure based on the four different weighting schemes, namely fixed weights w, basic time-varying weights $w_{i,t}$, volatility shrinkage time-varying weights $ws_{i,t}$ and volatility augmented time-varying weights $wa_{i,t}$. We present the average values over the full sample period, but also differentiate between crisis periods and tranquil times (as explained in Section 3.2). As the different construction methods do not allow a clear-cut comparison across methodology for the absolute values, we merely focus on the relative changes (expressed as percentage) in the average illiquidity values for the different weighting options. Moving from the full sample to the tranquil subsample, illiquidity values based on $w_{i,t}$, $w_{i,t}$, and $wa_{i,t}$ exhibit comparable fluctuations whereas the drop for their $ws_{i,t}$ based counterpart is comparatively larger.

intuitively appealing and yields the most powerful results.

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

[31] An additional feature for future work could be to allow the threshold to change for up and down markets.

This difference is even more pronounced when we switch from the full sample to the turbulent sub-period. While this increase is above fifty percent for the $ws_{i,t}$ methodology, it only amounts to thirty-three percent with the other options. This suggests that the preferred volatility shrinkage methodology succeeds best at capturing the expected pattern of higher relative illiquidity values during crisis times (and conversely lower values during tranquil times) in comparison with its full sample counterpart. For the remainder of the paper, we focus on this specific application of our unified liquidity measure, unless we mention it explicitly.

A more detailed understanding of the driving forces for the above mentioned shifts can be obtained by looking more closely at the dynamics in the underlying time-varying weighting schemes. This allows us to unravel how our unified liquidity measure is built up (for the different alternatives), and how the importance of the different groups can shift over time. In Table 6 we can clearly distinguish three different trends among the weights of the constituent groups. Firstly, for some groups these weights markedly increase during the crisis timespan, and decrease (slightly) during the tranquil period. This is most pronounced for the spread, 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. The third group merely consists of the order flow, which is visibly unaffected but the different subsamples. These results are further refined in Section 4.4 where we analyze in detail which groups contribute more/less during well-known historic episodes of financial stress.

4 Evaluation

4.1 Identifying Financial Stress

4.1.1 Financial Stress Events

Since the eighties, we have witnessed several market crisis which were closely associated with liquidity spirals, focusing the attention of researchers and policymakers towards understanding the dynamics of liquidity (Brennan et al., 2012; Liang and Wei, 2012). Figure 2 displays our unified market liquidity measure together with the NBER recessions and a list of episodes that are linked with financial pressure.[32] Many of the upswings in illiquidity systematically coincide with market downturns,

[32]The list is based on Hubrich and Tetlow (2015), who document financial events affecting the US Economy from 1986 till 2012, which we expand for our full dataset.

consistent with the existing literature (Chordia et al., 2001; Jones, 2002; Amihud and Mendelson, 2006; Næs et al., 2011). Chronologically, we can discern following major events.[33] Firstly, we can discern a brief episode of domestic political unrest in 1970, matched with a spike in illiquidity. The second major hike in the multi-dimensional liquidity measure corresponds with the oil embargo in November 1973. Moreover, illiquidity remained relatively high in the seventies (Chordia et al., 2001; Jones, 2002). Thirdly, 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), which was followed with a debt crisis in Latin American. Fourthly, we highlight the stock market collapse in October 1987, during which the financial markets were highly illiquid (Grossman and Miller, 1988; Brennan et al., 2012). The crash was partly attributable to a decline in investors' awareness of the general market liquidity in comparison to pre-crash level (Amihud et al., 1990). Fifthly, after witnessing spurts of illiquidity during the Iraq invasion (and ensuing recession) as well as during the Mexican Peso crisis, we reach the Asian crisis in 1997, shortly thereafter succeeded by the collapse of Long Term Capital Management (LTCM) combined with the Russian debt crises. Both of these events can be separately discerned by means of our liquidity proxy (Chordia et al., 2001; Lesmond, 2005). Sixthly, a remarkable feature about the tech bubble burst in 2000 is that the illiquidity levels already skyrocketed just before the recession really kicked in. Finally, the most recent financial crisis 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). Concerns about liquidity kept global equity markets tumbling until March 2009. Hence, shortage or abundance of liquidity can ravage or buttress stock markets (Liang and Wei (2012)).

The behavior of liquidity during financial distress highlights that market liquidity evaporates when it is most necessary, during market turmoil and in periods of crisis. Market risk and liquidity risk seem therefore to be closely connected, with investors simultaneously being hit by both factors (Rösch and Kaserer, 2013). Our multifaceted liquidity measure succeeds well in capturing these rich dynamics and succeeds proficiently in identifying historical episodes of financial stress.

Table 7 shows that our constructed liquidity measure also has some rapport with other well-known crisis indicators. Certainly, during the past decades, market crises seem to have been closely associated with financial pressures and liquidity spirals (Liang and Wei, 2012). The regression results reported underpin what we presented

[33]We merely want to provide the reader some examples, as we do not want to dissect this anecdotal analysis in too many details.

visually in Figure 2. However, this relation does not hold uniformly over all the incorporated crisis measures. Whereas liquidity seems to be connected to certain elements of the Cleveland Financial Stress Index (CFSI), namely the contribution of the interbank or funding markets (CFSI-IB-FUND) and the interbank liquidity spread (CFSI-IB-LIQ), this relation cannot be retrieved with the overall CFSI itself.[34] However, our unified market liquidity measure does show kinship with the concepts of the National Financial Conditions Index (NFCI), the Kansas City Financial Stress Index (KCFSI)[35], Smoothed U.S. Recession Probabilities (REC P), the St. Louis Fed Financial Stress Index (SLFSI), Aruoba-Diebold-Scotti business conditions index (ADSBCI)[36] and the Financial Stress index measured by the International Monetary Fund (IMF FSI).[37]

4.1.2 Signal-to-Noise Ratio

Even though our unified liquidity measure is merely constructed with the goal of capturing all of the dimensions of liquidity simultaneously and hence not primarily set up to retrieve financial stress events, we can use the close association between such events and the disappearance of liquidity as a general indication of its performance.[38] In order to uncover the historic dates necessary for the calculation of our signal-to-noise ratios, we follow Christensen and Li (2014) in describing a financial stress event as the moment when the financial stress index (FSI) exceeds an extreme value:

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

where μ_{FSI} is the sample mean of the FSI and σ_{FSI} the sample standard deviation. However, as we do not want to be reliant on a single financial stress index, we apply this methodology to several well-known FSI's.[39] In order to detect the stress events,

[34]Similarly, there is no significant relation with the Flight-to-Safety measure constructed by Baele et al. (2015).

[35]Albeit, only at a higher significance level.

[36]All these financial stress indicators and (business or financial) condition indices were obtained from the FRED database, which is provided by the St. Louis Fed.

[37]Gibson and Mougeot (2004) also find evidence that the time-varying liquidity risk premium in the U.S. stock market is associated with a recession index.

[38]However, the occurrence of illiquidity with such stress events does not necessarily have to be simultaneous. The dynamics in liquidity could have a leading or lagging pattern, depending on the type of event, and underlying causes.

[39]We employ the following stress indices: the St. Louis Fed Financial Stress Index (STLFSI), the Kansas City Financial Stress Index (KCFSI), the Cleveland Financial Stress Index (CFSI), the International Monetary Fund U.S. Financial Stress Index (IMF FSI); in combination with the following condition indices: the National Financial Conditions Index (NFCI), the Bloomberg Financial Conditions Index (BFCI), the Citi financial conditions index (CFCI) and the Aruoba-

we set $k = 1.5$, similar to Christensen and Li (2014).[40] In our analysis, we focus on the signal-to-noise ratio, as well as the number of financial stress events which were distinguished correctly, and similarly the number of no stress events unraveled appropriately. When we analyze the data, the following four situations can be discerned, as described in Panel A of Table 8: a financial stress event signaled by our measure (A), a financial stress event not signaled by our measure (C), a no financial stress event miscorrectly signaled as stress event (B), and a no financial stress event correctly not being signaled (D). The signal-to-noise ratio can then be summarized by [B/(B+D)]/[A/(A+C)], the number of crisis events signaled correctly by [A/(A+C)], and the number of non-crisis events signaled correctly by [D/(D+B)].

Panel B of Table 8 compares the signal-to-noise ratio for our unified market liquidity measure with those for two established financial conditions indicators, more specifically the National Financial Conditions Index (NFCI) and the Aruoba-Diebold-Scotti business conditions index (ADSBCI).[41] The values are similar to the NFCI index, and slightly worse than the ADSBCI. We can therefore conclude that our measure performs comparatively well.[42] We have to keep in mind that our liquidity construct only takes into account one very specific market, namely the stock market (S&P500 stocks), it merely incorporates a very limited amount of data series on these stocks, and it is not designed with the aim of detecting crisis events, but solely with the purpose of unraveling illiquidity. In contrast, the financial conditions index looks at very many different markets, and combines the information of many data series, specifically in order to optimally detect the specific conditions of the economy.

Panel C of Table 8 examines the signal-to-noise ratios for the several different weighting methods underlying our liquidity measure. The liquidity measure with the volatility adjusted weights ($ws_{i,t}$ and $wa_{i,t}$) perform relatively better than their more basic counterparts.[43] Hence, this provides additional evidence that the volatility corrections are valuable extensions in constructing a sensible liquidity measure.

Diebold-Scotti business conditions index (ADSBCI). We identify the stress events based on each of these indices and then evaluate an observation to contain financial stress when the average exceeds .5, hence when at least half of the available indices for that observation hint at stress.

[40] Alternatively, Illing and Liu (2006) set $k = 2$, whereas Cardarelli et al. (2009) apply $k = 1$. However, these adjustments do not change the identified crisis moments profoundly.

[41] We limit our comparison to the ADSBCI and the NFCI, as these have long-running data series.

[42] As a robustness test, we perform a similar exercise with dates based on anecdotal evidence, as given by the important historical financial stress events discussed in Section 4.1.1. For our unified measure and NFCI the results are still comparable. In contrast, the ADSBCI is slightly superior in this setting. These results can be obtained from the authors upon request.

[43] Similarly, we perform this exercise with the anecdotal dates. The results are comparable, with the distinction of the $ws_{i,t}$ now also being superior to $wa_{i,t}$, thus reaffirming our choice as the preferred metric.

4.2 Link with Financial and Macroeconomic Variables

In this section, we examine the basic comovement of our unified market liquidity measure with a large number of financial and economic variables (as conducted in Baele et al., 2015; and specifically for liquidity measures in Brennan et al. (2012)). We learn that our measure behaves in accordance to general financial and macroeconomic theory and intuition. 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. The results are summarized in Tables 9 to 11.

When looking at the comovement of illiquidity with confidence indicators (see Panel A of Table 9), we retrieve the expected negative relation, where higher illiquidity coincides with lower levels of confidence (Baker and Stein, 2004). This relation holds for the business tendency survey, consumer opinion survey and inventory sentiment index. The sign is different for the inventory sentiment index, as an increase in this index leads to a greater degree of discomfort with current levels of inventory. Similarly, we would expect illiquidity to match with higher uncertainty. However, we cannot retrieve a significant relationship in this context (see Panel B of Table 9).

"A number of empirical studies have found that thin speculative markets are ceteris paribus more volatile than deep ones" (Pagano, 1989, p. 269). More recently, Brennan et al. (2012) unravel that their market wide illiquidity proxies are significantly positively correlated with TED spread as well as with implied market volatility measure (VIX).[44] In a similar vein, Nyborg and Östberg (2014) report that the market share of volume for more liquid stocks expands with Libor-OIS spread, above and beyond what can be explained by the VIX.[45] Correspondingly, on a stock specific level, Han and Lesmond (2011) report a robust positive correlation between idiosyncratic volatility and liquidity. The same type of interdependence between liquidity and total volatility is highlighted in Chordia et al. (2009). We detect a similar positive relation between illiquidity and the market specific variants of implied volatility, with the highest adjusted R-squared for the market indices most closely related to the construction of our unified market liquidity index (see Panel A of Table 10). The same story holds for the TED spread, as well as for the different modalities of the option adjusted spreads (ranging from AAA to higher yielding spreads), as visualized in Panel B of Table 10.

When we examine the relation of our market liquidity measure with measures indicating the capacity of the economy, we get a mixed picture (see Table 11).

[44]Both values are typically associated with funding liquidity (Asness et al., 2013)

[45]The market share of volume of more liquid stocks is also increasing in the VIX itself.

Whereas the linkages between illiquidity and the growth proxies are robust and even forward-looking (see next section), the evidence for particular variables seem weaker. For example, with the coincident index, there seems no clear-cut association. However, for capital utilization and (on a higher significance level) for labor market conditions, we do retrieve a closer relation. A potential reason for the weaker bond might be that these variables are more sluggish, and we should thus build in richer dynamics to get the true linkages. House prices have played an important role during financial crises (Case and Shiller, 2003), and are quintessential in identifying financial cycles (Borio, 2014). Hence, it is no surprise that higher illiquidity seems to coincide with lower levels of house price inflation. Evaluating the connection with monetary policy[46], we can discern that higher illiquidity is associated with higher short term interest rates. Moreover, higher illiquidity levels concur with a flattening yield curve. When incorporating monetary aggregates in our analysis, we rely on the concept of real money gap, based on the construction method by Calza et al. (2003), and implemented by Hofmann (2009) and Drescher (2011). As such, we retrieve the real money gap proxy from a recursive long-run M3 demand function. Illiquidity seems to be negatively connected with the real money gap.[47] Because financial crises usually coincidence with flights to home and flights to safety, we also examine the relationship with exchange rates. Both for the US-Euro as for the US-UK exchange rate, there seems to be a flight to home effect, where higher illiquidity levels concur with higher relative values for the US dollar. The same effect is measurable through the real trade-weighted exchange rate (towards a broad range of currencies).[48]

4.3 Impact on Future Economic Growth

Both De Nicolò and Ivaschenko (2009) and Næs et al. (2011) hint at the potential of illiquidity to affect the real economy. More specifically, illiquidity is presumed to have a forward looking effect on a country's growth opportunities. Hence, we incorporate an update of the empirical exercise featured in Næs et al. (2011), and look at the forecasting abilities of illiquidity on future economic performance, in a multivariate setting, with a number of control variables.[49] In Table 12, we conduct an in-sample forecasting exercise where we gauge the effect of illiquidity on the one-quarter ahead industrial production growth (Panel A), as well as on the one-quarter

[46] Goyenko and Ukhov (2009) advance that monetary policy shocks can impact stock and bond market illiquidity.

[47] Our results are robust for estimates of the monetary overhang and the change in p-star.

[48] 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.

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

ahead industrial production gap measure, constructed using a HP filter (Panel B).[50] Our results are comparable with Næs et al. (2011), as we detect that higher illiquidity levels lead to lower growth levels.[51]

To further investigate the causality of the relation, we apply Granger causality tests, to analyze whether the impact on future growth rates is generated by illiquidity, and not vice versa. Table 13 reports p-values for the Granger Causality tests between brackets. A value below .05 implies proof in support of Granger causality. We find consistent evidence for our unified liquidity measure Granger causing output growth, while the reverse causality is not present.[52] 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 spread measure.

We get a similar outcome when performing a simple Vector Autoregressive estimation with 5 lags (based on the lag selection criteria), and a choleski ordering consisting of our unified market liquidity measure, year-on-year money growth, federal funds rate, month-on-month CPI inflation, and year-on-year industrial productions growth. A shock in illiquidity leads to a lower rate of growth in industrial production. The impulse response functions are summarized in Figure 3.

To complement our previous in-sample analysis in Table 12, we perform a small out-of-sample forecasting exercise for economic growth. Table 14 presents the out-of-sample forecasting performance for future economic growth over different horizons, respectively 3, 6 and 9 months. We estimate our forecasting models through a rolling window technique (Næs et al. (2011)). The initial estimation sample is set to 45 years (1962-2007) in order to obtain stable estimation parameters. The out of sample estimation covers the period 2008-2013. We evaluate our model, which includes term spread, excess market return, corporate bond yield and our unified liquidity measure, and compare this to a benchmark model without liquidity. We report the relative mean squared forecasting error and the relative out-of-sample R-squared value for our four different unified liquidity measures. Despite the full-fledged crisis period, the model which incorporates liquidity performs markedly better at fore-

[50]We use industrial production as proxy for output, since we conduct our analysis on a monthly level.

[51]Our unified market liquidity measure seems even capable of explaining a markedly higher proportion of variation of future growth values than its unidimensional counterparts, indicating that incorporating our novel methodology might improve on capturing the existent macroeconomic relations. These results can be requested from the authors.

[52]This causal relation is absent for the unified liquidity measure with the basic time-varying weighting function, and the causality even reverses (with output growth Granger causing illiquidity) for the fixed weight alternative. This further supports our model using time-varying weights combined with the volatility shrinkage.

casting out of sample, than a model that neglects liquidity.[53] Moreover, the results are comparatively robust for the different forecasting horizons ($h = 3, 6, 9$).

4.4 Evaluation of Individual Groups

4.4.1 Importance of Constituent Liquidity Groups

We link back the properties of our multidimensional liquidity measure to its founding elements in Table 15 by analyzing the correlation of our measure with the individual group measures (Panel A), together with the results for the unconditional variance decomposition of our measure into the underlying group measures (Panel B). Panel A indicates that the most important associations can be found with the etick group, followed by the spread, roll, fong and order flow groups (which are comparable). The return and volume group generally have low correlations with our unified liquidity measure. Panel B reports the results for the unconditional variance decomposition. Firstly, we convey the unconditional variance decomposition making abstraction of the covariance terms ('Var1' and 'Var2' provide two separate options in this context[54]). However, we also calculate the unconditional variance decomposition including the covariance terms ('Cov'). All three techniques give a general idea on the influence of each underlying group on our multidimensional liquidity measure. In this exercise, the etick, roll and spread group seem to be the most important. Admittedly, our framework lacks a theoretical framework, a feature it shares with most of the empirical work on liquidity, and with the widespread crisis measures which provided us with the inspiration to take on this exercise (Vayanos and Wang, 2012; Chordia et al., 2009). A theoretical foundation could provide valuable insights, not only for our understanding of the financial concept, but also in its interlinkages with the macroeconomic world, especially in the financial and monetary world we have come to live in (Borio, 2014). However, in this particular setting, we merely aspire to create a measure, which takes into account all of the dimensions of liquidity (allowing a sensible aggregation), and which is not susceptible to any fad or fashion concerning the particular measures.

4.4.2 Contributions of the Constituent Liquidity Groups to Stress Events

This section analyzes the contributions of the constituent liquidity groups for specific historic crisis moments. A supplementary feature of our methodology is that it does

[53]This improvement is most pronounced for our preferred volatility shrinkage methodology.

[54]Whereas for the latter methodology the weights are treated as being exogenous; this is not the case for the former.

not only allow to aggregate the different liquidity groups into a unified measure, but also allows us to gauge the individual importance of each group over time, and more specifically during periods of financial stress.[55] To give a comprehensive overview, we group the historic stress events based on their most important contributing liquidity groups. This classification allows us to discern some general characteristics that these events might have in common. The results are reported in Figure 4. Each panel groups stress events of a specific type which relates to a certain category of liquidity group measures.

Firstly, in Panel A, we focus on the category that contains the spread, etick, amihud groups as its main protagonists, and which entails the following dates: The 1966 credit crunch (10/1966), the peak during the first oil shock (10/1974) and the Iraq invasion (08/1990).[56] These periods were characterized by some sort of foreign contamination (increase in spending due to the Vietnam war, the Yom Kippur war, and the Iraq Invasion). Similarly, they all witnessed a credit crunch[57] and are related to a stock market crash (only 1990 saw a mini crash). Moreover, these specific episodes of financial stress were preceded by a tightening of the Federal Reserve rate. Finally, we can discern no (1966) or only a slight (1990) recession, except for 1974 when there was a severe recession.[58]

The second class (Panel B) most prominently features the spread, etick, fong group, and portrays the peak of the 1970s crisis (06/1970), the peak during the 1980s crisis (04/1980)[59] and the Tech Bubble burst (03/2000). Interestingly, there was a credit crunch both in 1970 and 1980 (1982), but not in 2000, as this event seems to have a slightly different physiology than its peers. Additionally, there was a stock market crash in 1970 and 2000, however, not in 1980 or 1982. Furthermore, each of these crisis periods tends to occur after a tightening of the Federal Reserve rate. Finally, there was no banking crisis, nor a major recession.[60] Admittedly, this specific class of events shows close resemblance with the first cluster, both for the features of these events (credit crunch, Fed tightening, stock market crash; only the

[55]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 (2013). Hence, our analysis mainly builds on their classification and interpretation of these events.

[56]The peak during the Russian crisis (08/1998) could also be added to these events, but only has the spread and amihud group as its main protagonists.

[57]Albeit for 1998 the not full blown credit crunch might explain a divergent pattern.

[58]Both the event in 1974 and in 1990 are also associated with a banking crisis (although this was minor for 1974).

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

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

foreign component disappears), as well as for the most important groups it contains (the spread and etick group now simply go together with the fong group, instead of with the Amihud group). Hence, both can be seen as subclasses of a more general class of events.

For the third category (Panel C), the lion's share of the contributions can be attributed to the spread and roll group. This composition seems useful to describe the 1987 stock market crash (10/1987), the decline of LTCM (05/1998)[61] and AIG-Lehman (09/2008). We can observe a minor[62] or a more full-fledged (during the 2008 financial crisis) stock market crash. We cannot ascertain any underlying recession for earlier crises (1987 and 1998), in comparison to their more recent counterpart (which featured a major recession, banking crisis and housing bust). A subcategory of these events, more specifically focusing on their aftermath, can be constructed by grouping together the aftermath of the 1987 stock market crash (corresponding with its peak in illiquidity, 01/1988), together with the aftermath of the 2008 financial crisis (the TALF announcement, 11/2008; the stress test announcement 02/2009). The composition (see Panel D) is logically very similar to the above mentioned events, only with the addition of the etick group. Hence, this cluster again shows a close association with the first two groups, where the etick and spread groups are similarly playing a prominent role, but this time together with the roll group.

Finally, in Panel E, we describe a more dispersed category which contains the returns, fong, etick, and order flow group[63], which is useful for describing 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 (the dollar declines against major currencies in 1977, the second oil shock in 1979, and huge losses on the Mexican stock market in 1994 leading to rebalancing portfolios). However, there were no severe disruptions of the financial markets, and no real domestic stock market crash. Moreover, we cannot observe any tightening of the Federal reserve rate. Finally, there was no recession associated with these events.[64] Hence, we could potentially describe these events as being the least impactful.

The most prominent liquidity groups in our analysis of historical crisis events, are the spread group, closely followed by the etick group. Both groups seem to feature

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

[62]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.

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

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

prominently at times when the financial stress skyrockets. These protagonists are often combined with the roll, fong and amihud group, which tend to be useful at portraying specific subclasses with their own characteristics.[65] In contrast, the flow, returns and volume group seem to be less important liquidity categories when examining these crisis events specifically. 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.

Of course, these categories can, to a certain extent, be considered as being anecdotal or somewhat arbitrary. Moreover, many characteristics of these financial pressure episodes can be debated upon, and have been the focus of numerous academic studies. However, our only purpose is to show that specific liquidity groups are more important during financial stress periods than others, and that there are some similarities over time between different stress events. For this objective, our current distinction between the different types of crisis events or their underlying causes should be sufficient.[66] Finally, our results might be mainly driven by the construction method of our unified liquidity measure. Logically, as portrayed in Table 6, the most prominent groups during financial stress events are also the groups that exhibit the largest increase in weights when comparing the full sample with the sub-period of stress (and conversely the groups least prominent during the crisis events, are those which exhibit the largest increase in their weights when comparing the full sample with the tranquil period).[67] However, we find proof that our conclusions are not solely model-dependent. The univariate regressions for the eight liquidity groups (which will be discussed in Section 4.4.3) show us that the liquidity groups which have strong interlinkages with many confidence and uncertainty; spread and volatility; crisis; productivity; monetary and exchange rate variables (which can be mainly retrieved with the spread and etick group, but to a lesser extent also with the roll and amihud group) coincide with the protagonist liquidity groups during the financial stress events, as mentioned in our pie charts.[68] Hence, the contributions

[65]Due to presence of the two dominant groups, these subclasses tend to have many similarities.

[66]We acknowledge that the groups can be formed differently. However, this would not fundamentally change the conclusion of this section. The same holds for different identification methods, criteria and definitions of the financial stress events.

[67]The only special case is the fong group, which features prominently in at least two of the crisis categories. An explanation can be that the fong group (which has increasing weights during the tranquil period in comparison to the full sample) succeeds in capturing liquidity movements during tranquil periods, but also plays its part in certain crisis events. Both aspects might also explain its prominent role in the variance decomposition or the decomposition based on the group contribution.

[68]But 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.

of the different groups into our unified model, simply reflect their intrinsic qualities, and our model seems to perform the aggregation in a desirable fashion. We can therefore conclude that specific groups are better equipped at capturing the more volatile episodes in liquidity, while others are more useful to model its relative tranquil counterparts. Hence, if we would solely focus on a subgroup of them, we would have to sacrifice on the richer dynamics we can portray within our framework.

4.4.3 Univariate Regressions for Constituent Liquidity Groups

Similarly to our analysis in Section 4.2, we again look at linkages between the liquidity measure (but now for the underlying groups) and the following four main categories: confidence and uncertainty indices; spread and volatility measures; crisis indicators; productivity and monetary/exchange rate variables. The main results are summarized in Tables 16 to 19. We report the R-squared for the univariate regressions. Moreover, whenever the coefficients have a counterintuitive sign, we add brackets to the R-squared value.

The spread and the etick group perform best at untangling the univariate relations, posting comparable and at times higher R-squared values than the unified measure.[69] However, the spread group is not able to unravel the monetary interlinkages, while the etick group shows little or no connections with the option-adjusted spreads and productivity subcategories. The performance of the roll and amihud group is more mixed. Whereas the former unveils a close relation with the option-adjusted spreads, variants of implied volatility as well as with some crisis indicators, the latter succeeds for the monetary, and some of the implied volatility and crisis variables. However, both perform worse in detecting relationships with many of the other categories. Finally, the fong, volume and order flow groups exhibit many counterintuitive signs and feeble relations with the investigated categories, which should normally be closely linked to liquidity. A possible explanation might be that these groups mainly seem important for liquidity during tranquil times, and hence are not able to catch the richer dynamics necessary to unravel such connections.

[69] For several of these categories, the spread and etick group show an even higher R-squared value than for our unified liquidity measure. 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. Hence, its performance, de facto, has to be comparable with its building blocks. It cannot suddenly outperform them. In contrast, it will often be outperformed by many of its constituent elements, as it incorporates all of the different qualities (for example, necessary to identify illiquidity both during stress events and tranquil times). However, whereas the underlying groups perform inadequately in at least one or several of the categories we are investigating, the unified measure finds all of the expected monetary, macroeconomic, financial and crisis linkages consistently over all of the domains.

Moreover, their relationship with the investigated categories might have changed over time, leading to the lack of coherent interlinkages. Because of its multidimensional properties our novel market liquidity measure succeeds better in catching a much broader array of dynamics with its macroeconomic surroundings than its unidimensional siblings, where interlinkages are more confined to certain subcategories.

5 Conclusions

Liquidity is an unobservable, endogenous and multidimensional concept. Hence, it is unfeasible for one single measure to capture all of the layers conveyed within liquidity. We want to address each of these challenges directly, and introduce a novel multidimensional market liquidity measure which unifies the individual strengths of the constituent liquidity groups. Albeit there are many authors that refer to the multiple dimensions of liquidity, there have been few attempts at integrating this feature in an all-encompassing measure. Most of the state of the art literature refutes to running horse races, in order to find the first best liquidity measure amongst its competitors. In contrast, our novel liquidity measure incorporates all of the individual groups through a mechanism of time-varying correlations and time-varying weights. We augment the latter with a volatility component to reflect the effects of limited investor attention. For this purpose, we build on the recent advances made on financial crisis indicators (Oet et al., 2011; Holló et al., 2012), and apply several extensions on the portfolio approach (Illing and Liu, 2006) to perform the aggregation of the separate liquidity groups.

Looking back over the sample period, our unified liquidity measure is capable of tracking episodes of financial strains. It is closely linked with several prominent crisis indicators. Moreover, it exhibits a close relation with its macro-financial surroundings. Additionally, we can detect spillovers to the real economy from liquidity droughts. These features are relatively more robust and meaningful than for the existing liquidity proxies, thus reinforcing our belief that it is important to take all of the liquidity dimensions into account. Finally, next to aggregating our constituent liquidity groups, our methodology also allows closer inspection of the importance of these groups over time, and specifically during crisis periods. The protagonists during these latter periods are mainly the spread and etick group.

Given the importance of illiquidity during downturns (due to the increasingly financial nature of our economy) and the endogenous nature of the concept, it is necessary to have such an all-encompassing measure, with respect to all of the existing layers and dynamics. Moreover, our measure is easily applicable and can be computed for long samples, as well as for many countries.

Interesting paths for future research would be to examine the performance of our multilayered liquidity measure in an asset pricing framework, by also constructing its counterpart on an asset-specific level. The same adaptations could be also done for high frequency data. Moreover, it would be useful to further examine the rich dynamics of liquidity with the macroeconomics surroundings, potentially building a more general theoretical framework. Moreover, our adaptation to the well-established portfolio approach could be useful for other markets as well, besides the stock market, and hence can be suitable for constructing more elaborate crisis or early warning indicators.

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

This table reports several typologies for the costs and frictions underlying the concept of liquidity.

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 different dimensions in our analysis

This table reports all of the different groups which are incorporated in the multidimensional liquidity measure. The table provides the most important formulas for their construction.

Reference	Proxy
1. Spread 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)	$\begin{cases} \sqrt{\frac{-Cov\left(\Delta P_t^{**}, \Delta P_{t+1}^{**}\right)}{\hat{\mu}}} & when\ Cov(\Delta P_t^{**}, \Delta P_{t+1}^{**}) < 0 \\ 0 & when\ Cov(\Delta P_t^{**}, \Delta P_{t+1}^{**}) > 0 \end{cases}$ $\Delta P_t^{*} = ar_t.P_{t-1}$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)	$Zeros = \frac{Number\ of\ days\ with\ zero\ return}{Number\ of\ trading\ days\ in\ month}$ $Zeros\ PV = \frac{Number\ of\ positve\ volume\ days\ with\ zero\ return}{Number\ of\ trading\ days\ in\ month}$
4. Fong Group	
Fong, Holden, Trzcinka (2013)	$FHT \equiv S = 2\sigma N^{-1}\left(\frac{1+Z}{2}\right)$ 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: $L_{HH}=\left[\left(P_{max}-P_{min}\right)/P_{min}\right]/\left[V/S*\bar{P}\right]$ V: total dollar volume, S: number of instruments outstanding $\overline{P}$: Average closing price of instrument
Breen, Hodrick, Korajczyk (2000)	$r_{i,t}^{AR}=\theta_t+\phi_t r_{i,t}+BHK_t sign(r_{i,t}^e)*vol_t+\epsilon_t$ $r_{i,t}^{AR}=\theta_t+\phi_t r_{i,t}+BHK_t sign(r_{i,t}^e)*turn_t+\epsilon_t$
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 (1998)	$SharesTraded/SharesOutstanding$
8. Order Flow Measures	
Pastor, Stambaugh (2003)	$r_{i,t+1}^e=\theta_t+\phi_t r_{i,t}+\gamma_t sign(r_{i,t}^e)*vol_t$ $r_{i,t+1}^e=\theta_t+\phi_t r_{i,t}+\gamma_t sign(r_{i,t}^e)*turn_t$

Table 3: Augmented Dickey-Fuller test: Testing stationarity of 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 group measures, according to the three ordering techniques (as explained in Section 3.1.2). '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.

	Spread	**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 group measures. Each column refers to the correlation of the specific group measure with the seven other group measures. Panel A highlights values for the mean, standard deviation and the interquartile ranges (IQ). Panel B shows sample averages for the full sample ('fs'), as well as for two sub-periods where we discern tranquil times ('tranq'), versus financial stress periods ('crisis'). Additionally, we convey the relative changes of the subperiods in comparison to the full sample.

Panel A: Descriptive statistics

	Spread	**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

	Spread	**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
%Δ	-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
%Δ	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 unified liquidity measure, respectively based on equal weights (w) and based on three different weighting schemes as explained in Section 3. w_i denotes the basic time-varying weighting scheme, while the other two include a volatility adjustment, respectively the shrinkage method (ws_i) and augmented method (wa_i). We report the results for the full samples ('fs'), as well as for two sub-periods where we discern tranquil times ('tranq'), versus financial stress periods ('crisis'). Additionally, we convey the relative changes of the subperiods in comparison to the full sample.

	w	w_i	ws_i	wa_i
fs	0.21	0.28	0.12	0.35
tranq	0.19	0.26	0.11	0.33
%Δ	-7%	-7%	-11%	-7%
crisis	0.27	0.37	0.18	0.46
%Δ	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 3. w_i denotes the basic time-varying weighting scheme, while the other two include a volatility adjustment, respectively the shrinkage method (ws_i) and augmented method (wa_i). We report the results for the full samples ('fs'), as well as for two sub-periods where we discern tranquil times ('tranq'), versus financial stress periods ('crisis'). Additionally, we convey the relative changes of the subperiods in comparison to the full sample.

Panel A: Spread and Roll

spread	w_i	ws_i	wa_i
fs	0.13	0.08	0.14
tranq	0.13	0.07	0.13
%Δ	-4%	-11%	-8%
crisis	0.16	0.13	0.20
%Δ	20%	57%	40%

roll	w_i	ws_i	wa_i
fs	0.13	0.07	0.13
tranq	0.13	0.07	0.13
%Δ	0%	-2%	0%
crisis	0.13	0.08	0.13
%Δ	1%	13%	4%

Panel B: Returns and Fong

ret	w_i	ws_i	wa_i
fs	0.12	0.06	0.12
tranq	0.13	0.07	0.13
%Δ	5%	9%	8%
crisis	0.09	0.04	0.07
%Δ	-23%	-45%	-41%

fong	w_i	ws_i	wa_i
fs	0.15	0.11	0.19
tranq	0.16	0.12	0.20
%Δ	3%	4%	5%
crisis	0.13	0.09	0.14
%Δ	-15%	-21%	-26%

Panel C: Etick and Amihud

etick	w_i	ws_i	wa_i
fs	0.12	0.06	0.11
tranq	0.11	0.05	0.10
%Δ	-4%	-13%	-9%
crisis	0.14	0.10	0.16
%Δ	21%	61%	43%

amih	w_i	ws_i	wa_i
fs	0.11	0.04	0.09
tranq	0.11	0.04	0.09
%Δ	-2%	-11%	-4%
crisis	0.12	0.07	0.11
%Δ	12%	54%	20%

Panel D: Volume and Order Flow

vol	w_i	ws_i	wa_i
fs	0.10	0.04	0.09
tranq	0.11	0.04	0.09
%Δ	2%	3%	4%
crisis	0.09	0.03	0.07
%Δ	-9%	-18%	-19%

flow	w_i	ws_i	wa_i
fs	0.13	0.08	0.13
tranq	0.13	0.08	0.13
%Δ	1%	0%	2%
crisis	0.13	0.08	0.12
%Δ	-4%	1%	-9%

Table 7: Univariate regressions for unified liquidity measure: Crisis indicators

This table reports estimated intercept and slope coefficients from regressions of our unified liquidity measure (constructed with the volatility shrinkage weighting method) on a number of widespread crisis indicators. We employ the following crisis indicators: the Cleveland Financial Stress Index (CFSI), the contribution of the interbank or funding markets (CFSI-IB-FUND), the interbank liquidity spread (CFSI-IB-LIQ) and the liquidity spread (CFSI-LIQ) to this index, the National Financial Conditions Index (NFCI), the Flight-to-Safety measure constructed by Baele et al. (2015) (FTS), the Kansas City Financial Stress Index (KCFSI), Smoothed U.S. Recession Probabilities (REC P), St. Louis Fed Financial Stress Index (STLFSI), the Aruoba-Diebold-Scotti business conditions index (ADSBCI) and the International Monetary Fund U.S. Financial Stress Index (IMF FSI). 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.

Crisis Indicators	$\hat{\alpha}$	$\hat{\beta}^{liq}$	$adjR^2$
CFSI (n=268)	-0.106 (0.626)	1.515 (0.502)	0.005
CFSI-IB-FUND (n=267)	4.528 (0.000)	17.150 (0.000)	0.255
CFSI-IB-LIQ (n=267)	0.790 (0.000)	8.777 (0.000)	0.325
CFSI-LIQ (n=267)	2.313 (0.000)	-4.665 (0.041)	0.074
NFCI (n=492)	-0.804 (0.000)	7.112 (0.000)	0.213
FTS (n=386)	0.012 (0.550)	0.169 (0.351)	0.008
KCFSI (n=287)	-0.645 (0.020)	6.722 (0.070)	0.151
REC P (n=559)	-0.108 (0.008)	1.850 (0.000)	0.213
STLFSI (n=241)	-0.715 (0.003)	8.131 (0.004)	0.265
ADSBCI (n=624)	-0.415 (0.007)	3.555 (0.014)	0.069
IMF FSI (n=349)	-2.611 (0.000)	22.701 (0.001)	0.185

Table 8: Signal-to-noise ratio

This table reports the results for the signal-to-noise ratio analysis. Panel A summarizes the methodology, based on Christensen and Li (2014), to calculate signal-to-noise ratios, as explained in Section 4.1.2. Panel B reports the signal-to-noise ratio, as well as the number of crisis respectively non-crisis events signaled correctly (in %), for our unified liquidity measure L_t, the National Financial Conditions Index (NFCI), and Aruoba-Diebold-Scotti business conditions index (ADSBCI). Panel C reports the same statistics for our unified liquidity according to the four different weighting schemes, as explained in Section 3. w refers to the constant weighting scheme; w_i denotes the basic time-varying weighting scheme; the other two include a volatility adjustment, respectively the shrinkage method (ws_i) and augmented method (wa_i).

Panel A: Four situations

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

Panel B: S/N for unified measure

	S/N	fin stress correct	No fin stress correct
L_t	0.13	0.34	0.95
NFCI	0.16	0.37	0.94
ADSBCI	0.05	0.56	0.97

Panel C: S/N for different weighting schemes

	S/N	fin stress correct	No fin stress correct
w	0.12	0.10	0.99
w_i	0.11	0.15	0.98
ws_i	0.13	0.34	0.95
wa_i	0.09	0.34	0.97

Table 9: Univariate regressions for unified liquidity measure: Confidence and uncertainty measures

This table reports estimated intercept and slope coefficients from univariate regressions of our unified liquidity measure (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 shows 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)	

Table 10: Univariate regressions for unified liquidity measure: Volatility and spread Measures

This table reports estimated intercept and slope coefficients from univariate regressions of our unified liquidity measure (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 shows 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 11: Univariate regressions for unified liquidity measure: Macroeconomic and monetary variables

This table reports estimated intercept and slope coefficients from univariate regressions of our unified liquidity measure (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 shows the adjusted R-squared. The values used for money are equilibrium values obtained through estimation of recursive money demand function. The last column shows the adjusted R-squared.

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

Table 12: Multivariate regressions for unified liquidity measure: Future economic growth

This table reports univariate regressions capturing the effect of the multidimensional liquidity measure 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 shows 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 13: 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 liquidity measure based on equal weights (w) and based on three different weighting schemes. w_i denotes the basic time-varying weighting scheme, while the other two include a volatility adjustment: ws_i is based on the shrinkage method; wa_i 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_i	1.81 (0.11)	1.80 (0.11)	EMR	7.83 (0.00)	1.86 (0.14)
ws_i	2.96 (0.01)	1.61 (0.16)	SPR	1.64 (0.18)	1.88 (0.13)
wa_i	2.07 (0.07)	1.52 (0.18)			

Table 14: 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 unified liquidity measure, and is compared to a benchmark forecasting model without liquidity. RMSE is the mean squared forecasting error of our model including the unified liquidity measure, relative to the mean squared forecasting error of the benchmark model exluding the unified liquidity measure. 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_i denotes the basic time-varying weighting scheme, while the other two include a volatility adjustment: ws_i is based on the shrinkage method; wa_i 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_i	0,93	0,14	0,93	0,13	0,98	0,04
ws_i	0,83	0,30	0,85	0,29	0,92	0,15
wa_i	0,91	0,18	0,88	0,22	0,92	0,16

Table 15: Unified liquidity measure: Correlation with liquidity groups and variance decomposition

This table shows the impact of each liquidity group in the unified liquidity measure. Panel A reports the average correlations of our unified market liquidity measure with the groups employed for the construction of the measure. P-values for the correlation test are reported between brackets. Panel B reports the results for the unconditional variance decomposition of the multidimensional liquidity measure into the underlying liquidity group measures. Firstly, we convey the unconditional variance decomposition making abstraction of the covariances ('Var1' and 'Var2' provide two separate options in this context). However, we also calculate the unconditional variance decomposition including the covariance terms ('Cov'). All three techniques gives a general idea on the influence of each underlying subgroup on our multidimensional liquidity measure.

	Spread	**Roll**	**Returns**	**Fong**	**Etick**	**Amihud**	**Volume**	**Flow**
Panel A: Correlation with liquidity group measures								
L_t	0.349	0.339	0.193	0.355	0.722	0.298	-0.150	0.321
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Variance decomposition								
Var1	0.192	0.097	0.146	0.239	0.149	0.060	0.056	0.061
Var2	0.178	0.097	0.132	0.299	0.135	0.042	0.034	0.082
Cov	0.183	0.122	0.081	0.191	0.320	0.087	-0.064	0.079

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 group measures 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 group measures 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 group measures 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	**Spread**	**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 group measures 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	**Spread**	**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: Statistical design of unified market liquidity measure

This figure gives a schematic overview of the different steps in the statistical design of our unified market liquidity measure.

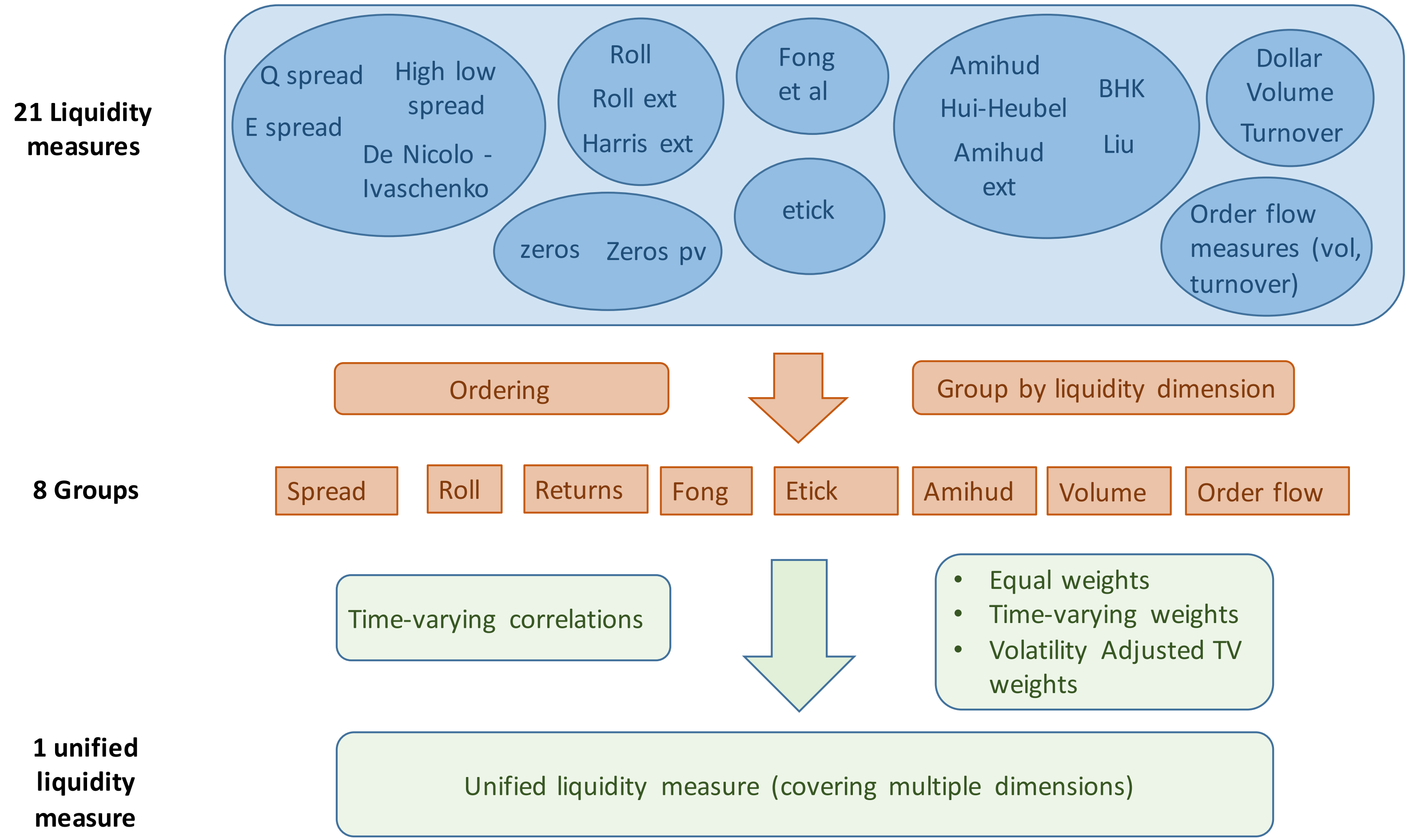


Figure 2: Unified market liquidity measure and financial stress events

This figure plots the unified market liquidity measure (constructed with the volatility shrinkage weighting method). The dotted lines denote financial pressure. The bars denote NBER recessions.

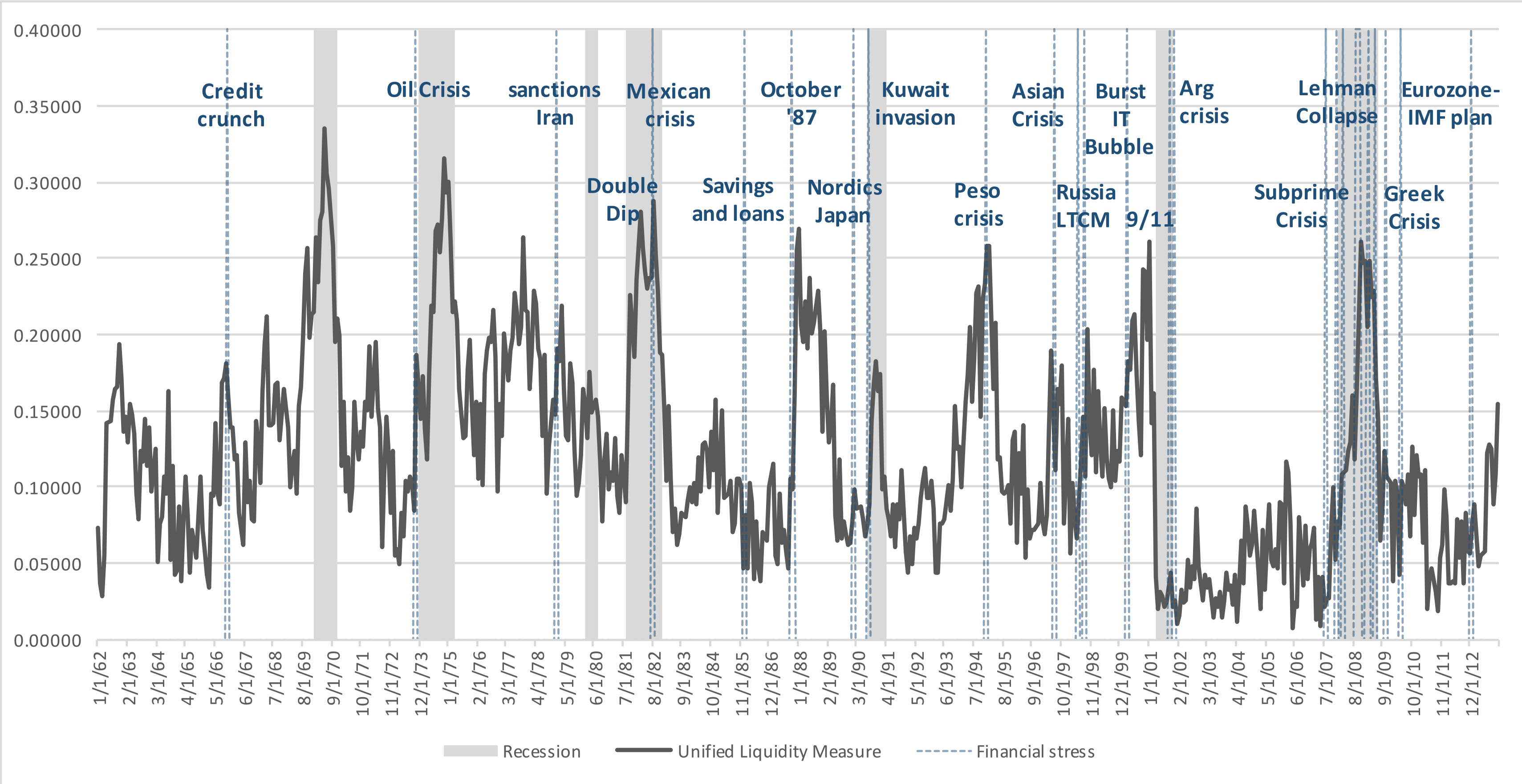
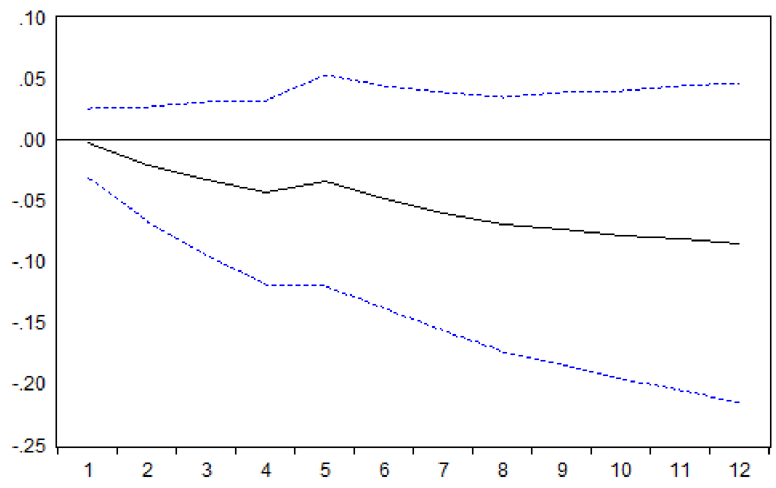


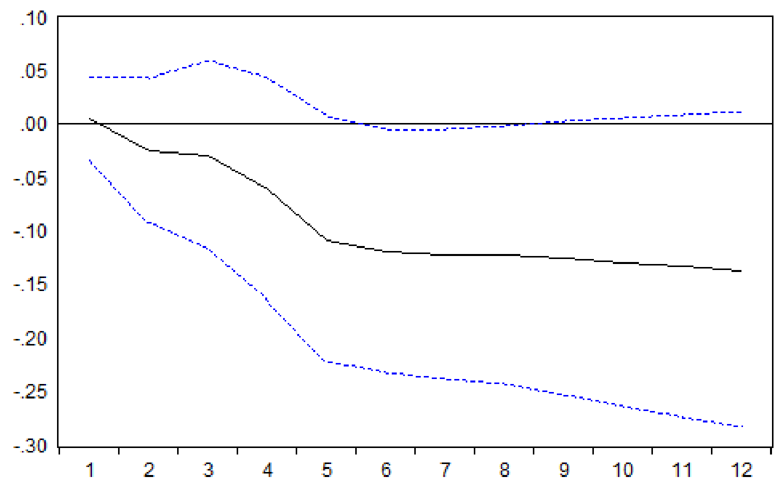
Figure 3: Impulse responses

This figure plots impulse responses of a VAR with 5 lags (based on lag selection criteria) and the following choleski ordering: unified liquidity measure, 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.

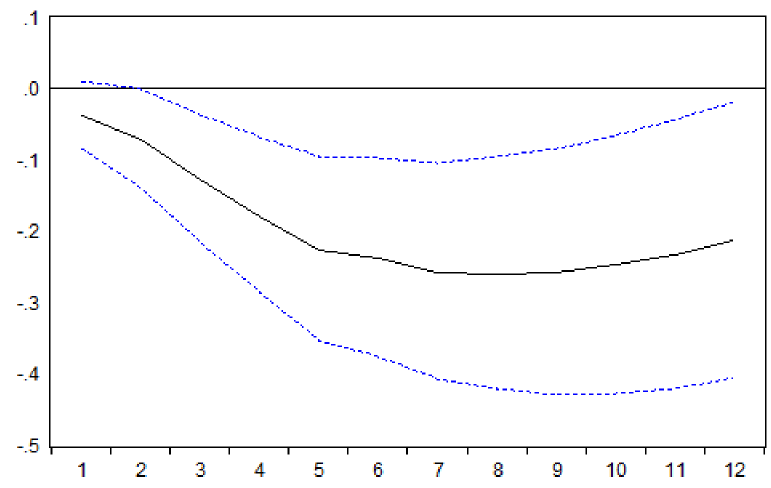
Panel A: Effect of illiquidity on CPI



Panel B: Effect of illiquidity on federal funds rate



Panel C: Effect of illiquidity on IP growth



Panel D: Effect of illiquidity on M3

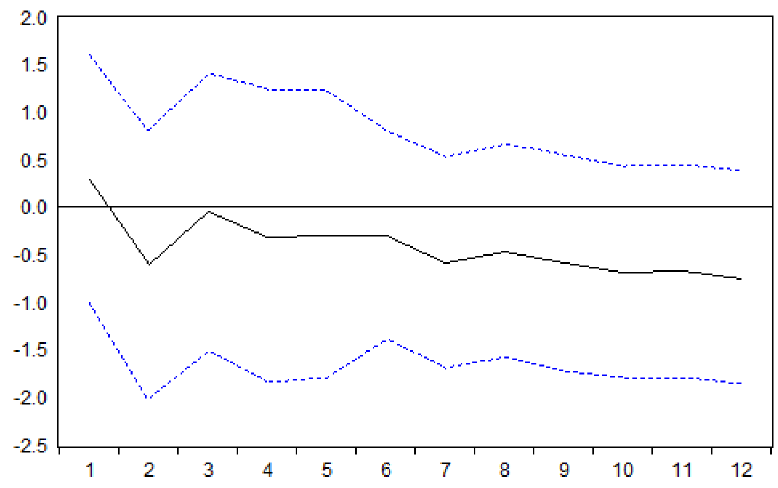
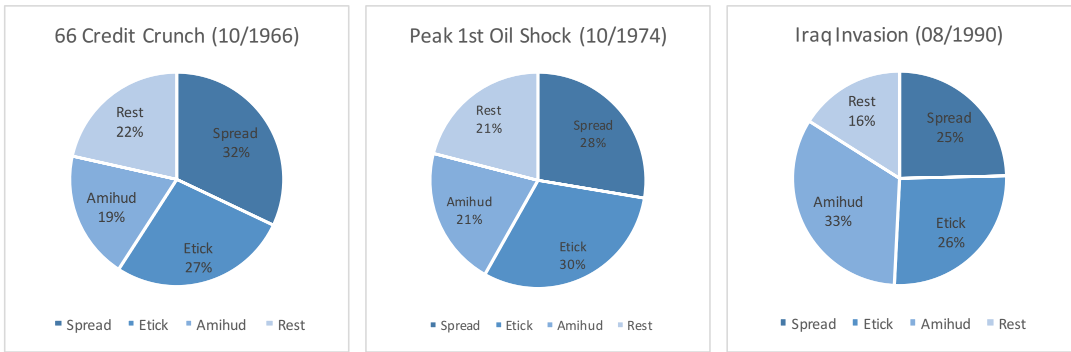


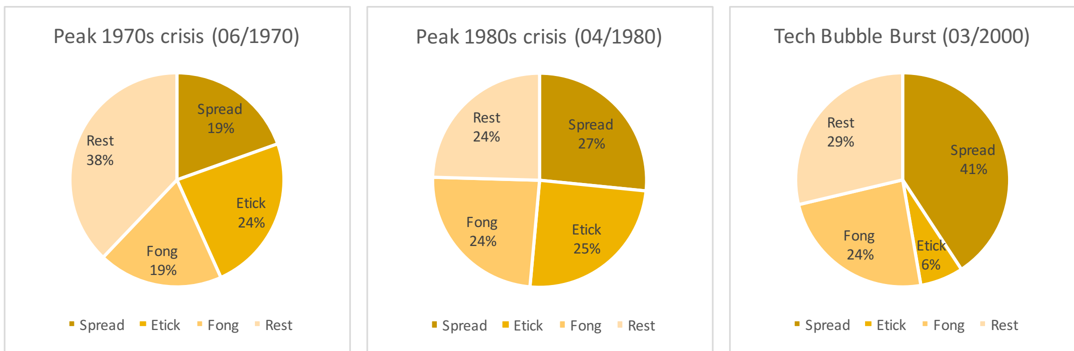
Figure 4: Decomposition of unified liquidity measure and financial crises

This figure shows the contribution of the individual liquidity group measures to our unified liquidity measure for specific historic stress events. Each panel groups stress events of a specific type which relates to a certain category of liquidity group measures.

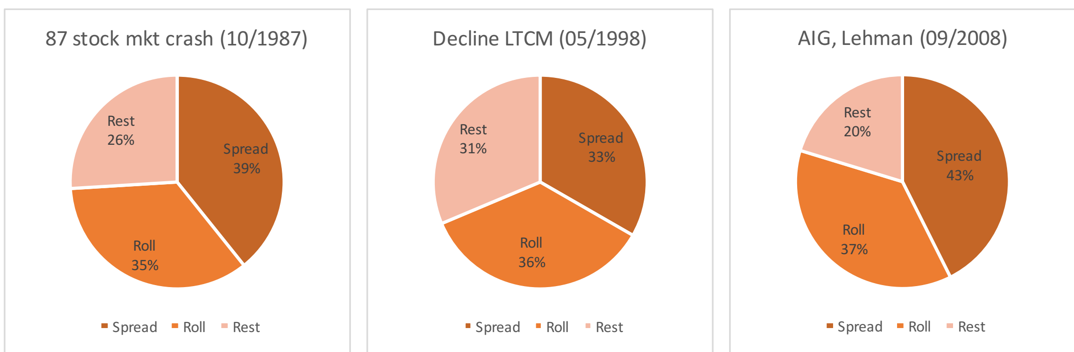
Panel A: Crisis Type 1



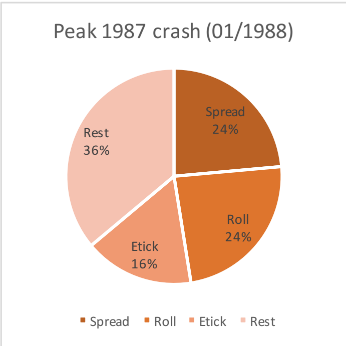
Panel D: Crisis Type 2

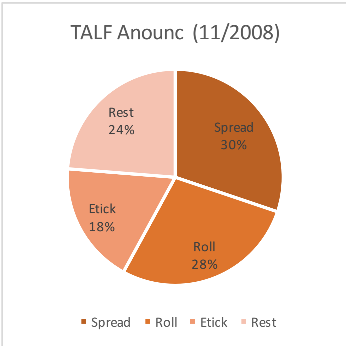


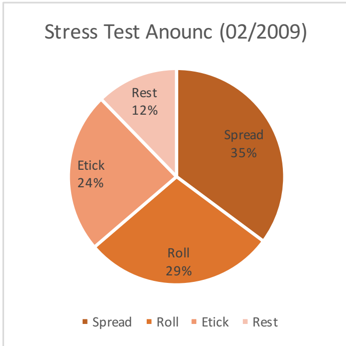
Panel C: Crisis Type 3A



Panel D: Crisis Type 3B







Panel E: Crisis Type 4