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

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Abstract

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

Keywords: systemic liquidity, asset prices, market state, time-series quantile regression.

JEL Codes: G01, G11, G12

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1. Introduction

Long-Term Capital Management's related events at the end of 90's reminded us that investors have a marked preference for liquidity (Amihud et al., 2005). In episodes of extreme turmoil, when liquidity appears to vanish from financial markets, investors engage in fire sales and financial intermediaries seem to renounce their function as purveyors of liquidity for the rest of the economic and financial system (Hameed et al., 2010)[1]. During these periods of market liquidity dry-ups, risk aversion leads investors to rebalance their portfolios towards less risky and more liquid assets, episodes referred to, respectively, as flights-to-quality and flights-to-liquidity (Baele et al., 2013; Beber et al., 2008). In contrast, when the market scenario and associated economic conditions are stable and optimistic, investors generally experience excess liquidity, leading them to rebalance their portfolios towards riskier and less liquid assets, with search-for-yield considerations in mind (Kiendrebeogo, 2016; Fratzscher et al., 2018)[2]. Both, flight-to-liquidity and search-for-yield are naturally associated with extreme market conditions, that is, bad and good, respectively.

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

To test our hypothesis we build upon Fama & French's (1993) traditional three-factor model augmented with the bid/ask based liquidity factor recently proposed by Abdi & Ranaldo

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

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

(2017)[3]. We conduct our estimations using quantile regressions, but rather than focusing on the cross-sectional effects (i.e. the cross-sectional liquidity premia associated with different portfolios at a given time insofar as they are illiquid or sensitive to a market-wide liquidity factor), we fit quantile regressions to time-series returns.

By adopting this strategy we are able to isolate the effects of liquidity on different parts of the stock return distribution over time, which in turn, are naturally related to different market states. Notice, however, that the definition of 'market state' can be elusive. Cooper et al. (2004), for instance, define a good (bad) market state based on the average market return over the preceding three years. Thus, depending on whether this average is positive or not, the market state is considered good or bad. Pagan & Sossounov (2003) and Edwards et al. (2003) define market states by locating turning points and the duration of peaks and troughs. According to these authors, a bad market state starts with a peak, i.e. a local maximum within an 8-month wide window, and ends with a trough, i.e. a local minimum.

However, these definitions are unnecessarily arbitrary given that the window widths are unjustified and selecting them may involve the cherry picking of results. Worse, they may also be misleading. What is deemed a bad market state, for example, might simply be a sequence of bad market results observed over a short number of days within an otherwise perfectly functioning and regular market presenting an average performance. Such misinterpretations can arise because markets are extremely volatile, as the constant appearance of unexpected bubbles and crashes reminds us time and again. For this reason, identifying a market state as an ex-post general trend in the data seems inappropriate in our context. Indeed, such trends might revert very quickly – within a matter of days, even – as the literature on momentum pricing and trading has documented extensively (Daniel and Moskowitz, 2016) and, therefore, it is necessary to seek alternative definitions of the market state.

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

[3] Available online at: https://sbf.unisg.ch/en/lehrstuehle/lehrstuhl_ranaldo/homepage_ranaldo/research-material

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

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

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

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

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

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

An important precedent of the present study, and one that merits attention, is the contribution of Watanabe and Watanabe (2007). These authors analyze the time-varying role of liquidity as a factor explaining asset prices. They find that cross-sectional liquidity betas vary over time, resulting in two distinct liquidity states: one of high liquidity betas, characterized by high volatility and a large liquidity risk premium (which is extremely short-lived), and another of low liquidity betas, which is more stable and houses a lower risk price for liquidity. They attribute the changing role of liquidity as a factor in the cross-section of the returns to changing levels of trader uncertainty about their trading counterparties (i.e. preference uncertainty), and proxy this in their estimations with trading value (the greater the uncertainty, the higher the trading value). Related studies include Longstaff (2004) and Gibson and Mougeot (2004), who also highlight a changing relationship between market-wide liquidity and asset prices conditioning on market sentiment and the probability of future recession, respectively. Unlike this closely related line in the literature, our emphasis is placed on the market price itself. Hence, our definition of a market state is broader and more general: a good market state is related to a good return realization and a bad market state to a bad realization (in the same spirit as Cooper et al. 2004). Because it depends on the return quantile, instead of on a specific variable (which might be correlated with other variables outside the model and subject, therefore, to criticisms of omitted confounding variables), we consider our approach more appropriate to tackle the problem we seek to analyze here. We also analyze a continuum of states, which allows us to identify when and how liquidity is priced by the market, which is novel for the literature.

The rest of the paper is organized as follow. In section 2 we describe the methods employed to test our hypothesis. In Section 3 we describe our data. In Section 4 the empirical results are discussed and robustness checks are provided. Finally, Section 5 concludes.

2. Methodology

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

2.1. Systemic Liquidity

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

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

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

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

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

$$s_{\widehat{monthly\ corrected}} = \sqrt{max\left\{4\frac{1}{N}\sum_{t=1}^{N}(c_t - \eta_t)(c_t - \eta_{t+1}), 0\right\}}, \tag{2}$$

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

Finally, the monthly systemic liquidity risk indicator can be calculated as the equally weighted average of this monthly spread of individual stocks.

2.2 Liquidity-Adjusted Three-Factor Model

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

$$r_{it} - r_{ft} = \beta_1^L Liq_t + \beta_2(r_{mt} - r_{ft}) + \beta_3(SMB)_t + \beta_4(HML)_t + \varepsilon_{it}, \tag{3}$$

where $(r_{it} - r_{ft})$ gives the monthly excess returns on 25 U.S. portfolios sorted according to size and book-to-market value (BE/ME) quintiles; the excess return on a broad market portfolio is denoted as $(r_{mt} - r_{ft})$, hereinafter (RMKT); r_{ft} is the risk-free rate, proxied by the one-month treasury bill rate; ε_{it} is the error term, assumed to be independent with zero mean and variance σ^2. The factors (SMB) and (HML) are portfolios, mimicking the risk factor in returns related to size and book-to-market equity, respectively. The (SMB) factor is constructed as the difference between the average returns on small- and big-stock portfolios (small minus big) with the same weighted-average book-to-market ratio. The (HML) factor is referred to as a value premium between the average returns on portfolios with high book-to-market and low book-to-market stocks (high minus low) with the same weighted average size[4], Liq_t denotes the systemic liquidity risk measure, which is not an asset or a portfolio, rather it is the equally weighted average of the monthly spread of individual stocks. The coefficient β_1^L captures the sensitivity of excess returns on systemic liquidity in the market. The inclusion of a systemic liquidity risk factor would appear to be appealing to the asset pricing literature, especially after recent liquidity dry-ups in financial markets. Using factor models, Pastor and Stambaugh (2003), Martinez et al. (2005) and Acharya & Pedersen (2005) have previously provided evidence that the level of aggregate liquidity is a priced risk factor when explaining expected stock returns[5].

2.3 Quantile Regression

Here we adopt Koenker & Bassett Jr's (1978) quantile regression technique (see also Koenker & Hallock, 2001). Quantile regressions provide insights into the impact of explanatory variables on the entire conditional distribution of the response variable. In this setting, conditional quantile regressions are linear in parameters for each selected quantile. We explore how systemic liquidity risk affects the different quantiles of excess returns of 25 value-weighted U.S. portfolios, sorted by size and book-to-market ratio. Moreover, we interpret the excess return quantiles as different market states, i.e. positive vs. negative abnormal returns as extreme scenarios, which leads directly to a comprehensive analysis of systemic liquidity risk scenarios.

Ando & Tsay (2011) and Allen & Powell (2011), among others, undertake studies of the emerging field of quantile regression and factor models, but do not explore the effects of systemic liquidity as a nonlinear priced risk factor. Applying a quantile regression method to factor models is similar to using a risk assessment tool, such as VaR (value-at-risk) or the ES (expected shortfall), except that we are not solely concerned with tail losses of the return distribution but also with how systemic liquidity risk relates to returns in normal times and periods when the market is in a good (bad) state, coinciding with extreme tail events.

[4] See Fama & French (1992), Fama & French (1993) and Fama & French (1996) for details about factor construction and description.
[5] Pastor & Stambaugh (2003) construct an aggregate liquidity measure based on volume-related price reversals which then is incorporated into Fama & French's (1993) three-factor model. Acharya & Pedersen (2005) adjust a CAPM with the illiquidity measure proposed by Amihud (2002).

Eq. (3) relates to the conditional mean scenario of excess returns and exposure to aggregate liquidity risk. To investigate excess returns across its conditional distribution, the time-series quantile liquidity-adjusted factor model for quantile τ can be written as follows:

$$r_{it} - r_{ft} = \beta(\tau)x_i + \varepsilon_i(\tau), \tag{4}$$

where all quantile parameters are displayed in a vector $\beta(\tau) = \{\beta_1^L(\tau), \beta_2(\tau), \beta_3(\tau), \beta_4(\tau)\}$ and all factors in a $N \times 4$ matrix, denoted as $x_i = \{Liq_t, RMKT_t, SMB_t, HML_t\}$. We further assume that the vector of error terms conditioned on the parameter matrix is zero, $Q_\tau(\varepsilon_{it|xi} = 0)$. We can then specify the τth conditional quantile function as follows:

$$Q_y((\tau)|x_i) = \beta(\tau)x_i. \tag{5}$$

To obtain an estimate $\hat{\beta}(\tau)$ of the unknown coefficient(s) for the τth quantile, the following function is minimized:

$$\hat{\beta}(\tau) = argmin \sum_i^n \rho_\tau((r_{it} - r_{ft}) - \beta_\tau x_i), \tag{6}$$

where $\rho_\tau(\mu) = \mu(\tau - I(\mu < 0))$ with $0 < \tau < 1$ is a check function with asymmetric weights, which depend on the quantile selected. While we collect all quantile estimates in a set $\Phi = \{\beta_1^L(\tau), \beta_2(\tau), \beta_3(\tau), \beta_4(\tau)\}$, we only report in the results section below the liquidity betas, $\beta_1^L(\tau)$, for every quantile[6]. The liquidity-adjusted three-factor model is estimated as a conditional quantile function at a range of quantiles, $\tau = (0.1 - 0.95)$, in 0.05 intervals. By so doing, we observe a transition between market states, from the negative tail of the return distribution, $\tau = (0.1)$, to extreme positive market scenarios, $\tau = (0.95)$.

3. Data

The portfolios used in our calculations include stocks from NYSE, AMEX and NASDAQ, and are constructed on a monthly basis from July of year t to June of year $t+1$, spanning the period July 2000-December 2016. Subtracting the risk-free rate from the returns, the excess returns on 25 portfolios denote the dependent variable in a time-series setting. The measure

[6] We do not provide estimates of the factor-portfolios (three factors) as they have been widely documented in the respective literature and extensively studied in other studies, see, for example, Fama & French (2016). The results are, nevertheless, available upon request.

for systemic liquidity risk was retrieved from the authors' webpage[7]. We standardized the liquidity measure to obtain comparable estimates with respect to the coefficients of the three factors commonly used in the literature (see Figure A1). Data on the portfolios and the three factors were retrieved from Kenneth French's webpage[8]. We also include some robustness exercises: we expand the sample to cover a period ranging from July 1960 to December 2016 and, second, we examine 30 U.S. industry portfolios, similarly retrieved from Kenneth French's webpage, employing the same procedure as for the 25 value-weighted portfolios.

3.1. Summary statistics

Table 1 presents the mean excess returns and the standard deviation for 25 stock portfolios sorted according to the criteria of size and book-to-market value[9]. The mean excess returns lie within a wide range, from seven basis points (b.p.) to 114 b.p. per month. For the size quintiles, an increasing trend is detected in excess returns from the lowest to the highest BE/ME portfolios with differences ranging from 103 b.p. for the smallest quintile to 28 b.p. for the largest. Although not monotonic, average excess returns tend to decrease from the lowest to the highest size quintile for all but the lowest BE/ME quintile. We further note that for all but the highest BE/ME quintile, the standard deviations decrease from the small to the big stock portfolios. Table A1 reports an extended overview of the summary statistics, including three further moments and minimum and maximum values of mean excess returns. We observe that most portfolios (22 out of 25) are left skewed and have a kurtosis above 3. The null hypothesis of the Jarque-Bera (JB) test is rejected in all cases, confirming non-normality for all portfolios.

[7] https://sbf.unisg.ch/en/lehrstuehle/lehrstuhl_ranaldo/homepage_ranaldo/research-material
[8] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/datalibrary:html
[9] These portfolios are updated monthly - see Kenneth French's webpage.

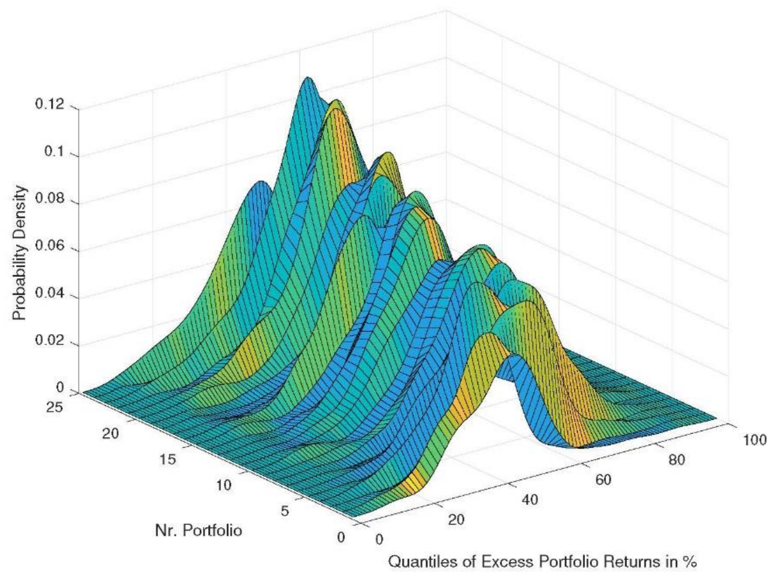
Table 1: Descriptive Statistics: Excess returns on 25 equity portfolios sorted on ME and BE/ME

	Book-to-Market (BE/ME) Quintiles									
Size Quintile	Low	2	3	4	High	Low	2	3	4	High
	Mean					Standard Deviation				
Small	0.07	0.79	0.78	1.09	1.10	8.6	7.49	6.00	5.89	6.14
2	0.44	0.87	0.96	0.91	0.92	7.24	5.91	5.50	5.54	6.68
3	0.37	0.87	0.89	0.99	1.14	6.67	5.31	5.18	5.30	6.17
4	0.57	0.83	0.74	0.93	0.70	6.06	4.98	5.31	5.15	6.36
Big	0.24	0.52	0.63	0.29	0.52	4.30	4.19	4.27	5.37	6.56

Note: This table reports the mean and the standard deviation of the excess returns of 25 U.S. portfolios from July 2000 to December 2016, 204 observations. The value-weighted monthly percent on the portfolios are calculated from July of year t to June of t+1.

Figure 1 shows the kernel density function for the 25 excess portfolio returns. The x-axis denotes the portfolio number while the y-axis shows the excess return quantiles. Median returns coincide with the 50th quantile on this scale. We observe return distributions with differentiated features in terms of tail shapes, skewness and kurtosis. For this reason, we perform a comprehensive examination of each distribution conditional on market, value, growth and liquidity factors, by means of quantile regression. Quantile regression provides a much better overall description of this broad range of conditional distributions than is provided by traditional linear regression. Moreover, it does not impose symmetries in the way that factors are allowed to impact on the portfolios returns, be it in the cross-section or in the time-series dimensions.

Figure 1. Density function of 25 excess portfolio returns



This figure shows the probability density function of the 25 U.S. excess portfolio returns, sorted by (i) size and (ii) book-to-market value, from July 2000 to December 2016.

4. Results

4.1. Market return and systemic liquidity risk

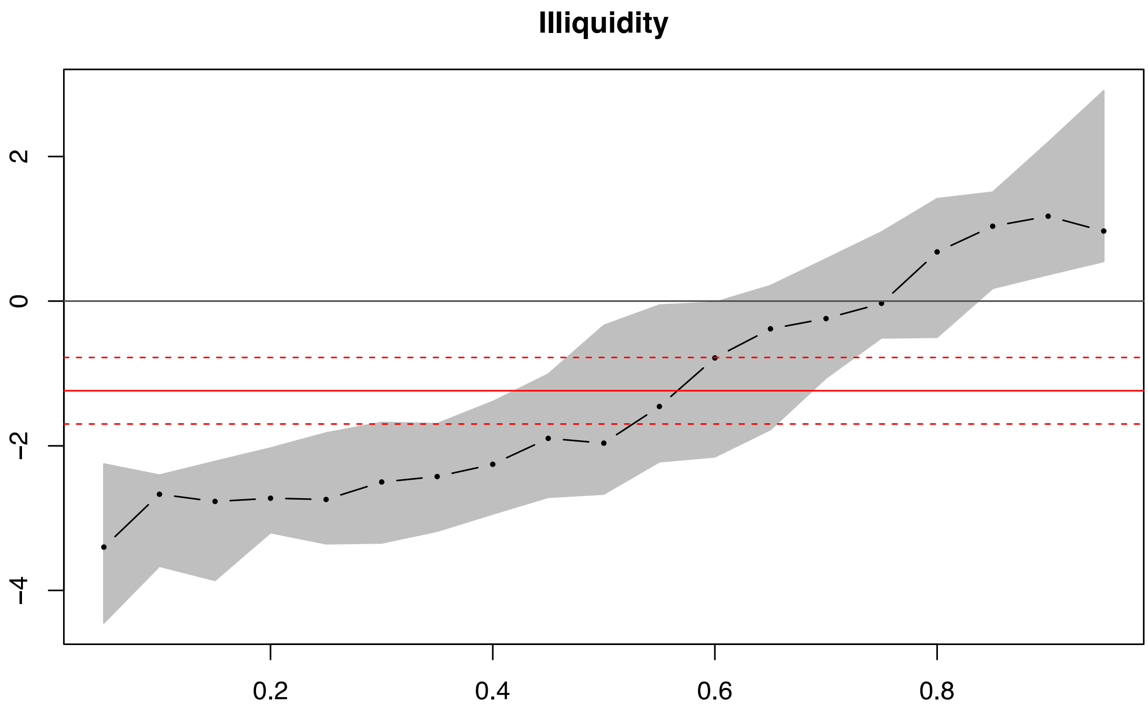
Figure 2 summarizes the effects of liquidity, proxied by Abdi & Ranaldo's (2017) liquidity index, on different quantiles of the excess stock return distribution over time. As is evident, the effects are highly nonlinear, ranging from negative to positive as market returns increase.

The linear effect of liquidity on returns is also apparent in the figure (as indicated by the solid red line accompanied by two parallel dotted lines representing the 95% confidence intervals of the regression). This effect is both negative and statistically significant, indicating that illiquidity reduces contemporaneous market returns. This outcome is consistent with findings in the literature that document a positive premia in the cross-section of the returns for assets that are more sensitive to market-wide liquidity risk (and for less liquid assets). In other words, a generalized increase in market liquidity risk forces invertors to rebalance their portfolio towards *more liquid* and *less risky* assets (flight-to-quality and flight-to-liquidity), which, in turn, depresses the contemporaneous prices of less liquid and riskier assets. Under constant expectations about the future cash flows of such assets, a reduction in contemporaneous prices is associated with an increase in their future expected returns. In this way, a positive cross-sectional relationship emerges between systemic liquidity risk and *expected market returns*, which is consistent with a negative time-series relationship between *contemporaneous returns* and liquidity risk.

However, Figure 2 also makes evident that the aforementioned story does not always hold. Indeed, when we examine the effects of market-wide liquidity risk under different quantiles of the market return – as captured by the dash-dotted black line and the associated bootstrapping confidence intervals of the quantile regressions (gray-shaded area) – a contrasting landscape emerges. On the one hand, the negative and expected effect of illiquidity on market returns is higher under very bad market states (quantiles below the 20^{th} percentile). Not only is this effect higher, it is also statistically different from the linear effect, as witnessed by the fact that the shaded bootstrapped confidence intervals do not include the linear effect below the 30^{th} percentile of the market returns. This means that the liquidity risk effect on market returns (and, therefore, the liquidity premium) is underestimated by the cross-sectional and linear models traditionally employed when the market state is bad.

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

Figure 2. Systemic Liquidity Effects on Excess Market Returns



Note: The figure shows the effects of liquidity on excess market returns from January 2000 to December 2016.

Finally, in the mid-range quantiles (between the 55th and 90th percentiles), the effect of market-wide liquidity risk on market returns is not statistically different from zero. Only between the 50th and the 60th percentiles can it not be statistically distinguished from the traditional linear effect.

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

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

4.2. *Testing for nonlinearity in the relationship between systemic liquidity and asset prices*

In this section, we conduct an exploratory analysis of the stability of the parameters in Fama and French's (1993) three-factor model augmented using a liquidity factor. The results are reported in Table 2. We estimated ten stability tests for each of the 25 portfolios in our sample, giving us 250 statistics and their respective critical values. To facilitate the reporting of these results, Table 2 only records the mean, maximum, minimum and standard deviation values across the 25 portfolios, for each set of statistics. More importantly, the table records the number of rejections of the null hypothesis, which in all cases correspond to the stability of the parameters. The ten statistics employed included three based on the cumulative sum of the regression, the recursive regression residuals, and the scores of each regression parameter – that is, OLS-Cusum, Rec-Cusum, and Score-Cusum, respectively, and two constructed using recursive OLS estimates of the regression coefficients and moving OLS estimates – that is, RE and ME, respectively. The remaining five included the test developed by Nyblom (1989) and Hansen (1992a; 1992b), the recursive Chow (Chow, 1960; Andrews and Ploberger, 1994) and three tests based on F-statistics: namely, SupF, AveF and ExpF. Procedures of this kind are well documented, for instance, in Zeileis (2005) or in the accompanying documentation of the 'strucchange' package in the statistical software R used to conduct the estimations (Zeiles, 2006).

As is evident, with the exception of two out of the three cusum-tests, in most instances the tests indicate the presence of unstable coefficients, with the number of null rejections rising above 16 and, most of the time, above 20 (out of 25 portfolios). We can conclude from this that a non-linear behavior continues to characterize the parameters in the four-factor model, which justifies the use of quantile regressions.

Table 2. Structural change statistics

Test	*Rec-Cusum*	*Ols-Cusum*	*Score-Cusum*	*Chow*	*Nyblom-Han.*
Mean	0.935	0.962	2.010	5.876	2.917
Stad. Dev.	0.352	0.292	0.376	5.489	0.816
Min	0.384	0.571	1.253	0.808	1.339
Max	1.776	1.857	2.800	26.681	4.645
Null Rejections	**10**	**2**	**19**	**16**	**23**

Test	*SupF*	*AveF*	*ExpF*	*RE*	*ME*
Mean	64.67	32.193	29.057	2.052	1.624
Stad. Dev.	42.145	21.62	20.803	0.641	0.285
Min	14.878	8.955	5.371	0.921	1.115
Max	180.09	96.326	86.381	3.300	2.468
Null Rejections	**23**	**23**	**23**	**18**	**21**

We used ten tests of structural change in order to identify any possible instabilities in the 3-Factor (Panel A) and 4- Factor Models (Panel B). We used 25 value-weighted portfolios sorted by size and book-to-market value. Our sample for these estimations runs from 2000 to 2017. Rec-Cusum, Ols-Cusum and Score-Cusum are based on cumulative residuals of recursive, OLS and score estimates, respectively. RE and ME are based on recursive OLS estimates of the regression coefficients and moving OLS estimates, respectively. Chow and Nyblom-Hansen correspond to the statistics proposed by those authors. SupF, AveF and ExpF are tests of structural change based on F-statistics.

4.3. Value-growth portfolios and systemic liquidity

Our results for the 25 portfolios are reported in Figure 3. Panel A of the figure presents the liquidity betas of 25 portfolios sorted according to size and book-to-market criteria, for different quantiles of the time-series return distribution $\tau = \{0.05, 0.10, \ldots, 0.90, 0.95\}$. The x-axis denotes the portfolio (from small-low portfolios to big-high portfolios) and the y-axis corresponds to the quantiles. Lower quantiles are associated with negative returns and, therefore, with bad market states (darker shades through to red), while higher quantiles are associated with positive returns and, therefore, with good market states (lighter shades through to yellow). Panel B presents a binary visualization of the associated t-statistics of the quantile regressions, where 1 – depicted in black – indicates whether the respective liquidity estimate made in the same coordinates of Panel A is statistically different from zero and 0 – depicted in white, indicates just the contrary. The axes follow the same convention in both panels.

Figure 3 clearly shows the transition of the liquidity betas associated with the systemic liquidity factor across states (represented by different quantiles) and across portfolios and, at the same time, it indicates whether (and when) these effects are significant. We document a clear pattern across market states, but we are unable to extract a reliable pattern across portfolios. We find that systemic liquidity risk tends to produce an effect on portfolio returns, with estimates ranging from -1.3 to 2.6. The sign and significance of these effects clearly depend on the market state. On the one hand, the coefficients associated with the liquidity factor tend to be negative for bad market states and positive for good market states. This means that an increase in illiquidity when the market is experiencing losses hurts the portfolio performance and that an increase in illiquidity busts portfolio returns when the market is experiencing gains.

The effect of systemic liquidity risk on portfolio returns lying close to the median is, by general rule, statistically equal to zero. That is, around the median, $\tau = (0.5)$, with the exception of two portfolios, we do not find significant liquidity betas, suggesting that the market does not price systemic liquidity risk in regular times, when neither extreme losses nor gains are experienced. This result is consistent, for instance, with the findings of Watanabe & Watanabe (2007), who show that during ordinary transaction months, the pricing of illiquidity in the market is quite flat across portfolios. This contrasts with what these authors document for high liquidity states, when liquidity risk premia are disproportionately large, amounting to more than twice the value premium.

In episodes of extreme market turmoil, when the markets are experiencing significant and recurring losses, market-wide liquidity falls dramatically. The negative spirals documented in the literature as emerging between funding liquidity and market-wide liquidity may lead traders to engage in fire sales or precautionary transactions, as they seek to avoid expected margin calls. This situation is in turn accompanied by an increase in preference uncertainty, market sentiment and, in general, a deterioration in future economic outlooks on the part of market participants. All these reasons have been documented previously in the literature and are in line with an increasing appetite for safe and liquid assets (i.e. flight-to-quality and flight-to-liquidity). Moreover, they point to a contemporaneous reduction in market prices, following an increase in generalized market illiquidity. Such reductions are to be found in the left tail of the returns distribution, which correspond to its lowest quantiles. As can be observed in Figure 3, the lower the quantile, the higher is the negative impact of liquidity risk on the contemporaneous stocks returns (regardless of the market portfolio analyzed).

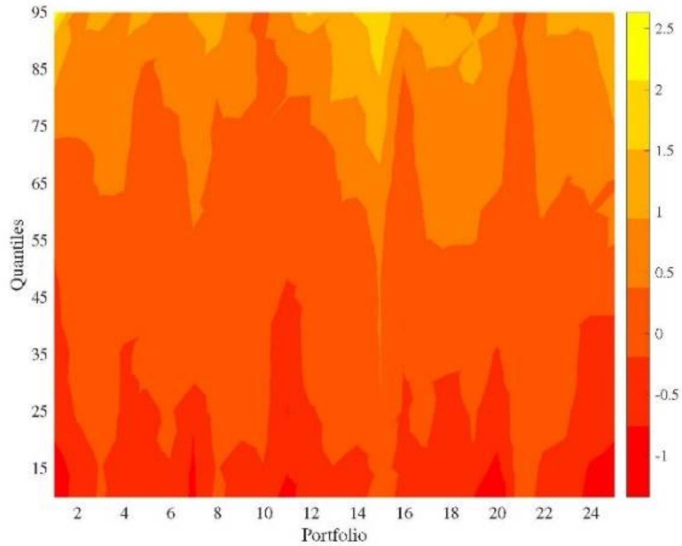
The positive in the right tail of the return distribution implies that when the market state is good (in the sense that positive and large returns are recorded), traders perceive liquidity as a relevant factor to inform their decisions about portfolio composition. In other words, exposure to the market-wide liquidity of a certain asset is valuable information priced by the market, in accordance with expectations in the literature. This situation is expected in a search-for-yield scenario[10], in which investors start to rebalance their portfolios in a diametrically opposite way to the strategy they adopt during a bad market state. Thus, they rebalance towards riskier and less liquid assets, which can provide greater returns. This is generally the case when market and funding liquidities are both perceived as sufficiently high and, therefore, traditional and safe assets yield unusually low gains, which traders aim to offset by resorting to less liquid and riskier assets. If market portfolios consist of these risker and less liquid assets, returns naturally increase, as traditional compensation for risk demands, at the same time as market-wide liquidity falls. This explains the positive time-series pattern that we observed for the highest quantiles of the market return distribution, which depicts a positive relationship between returns and systemic liquidity risk.

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

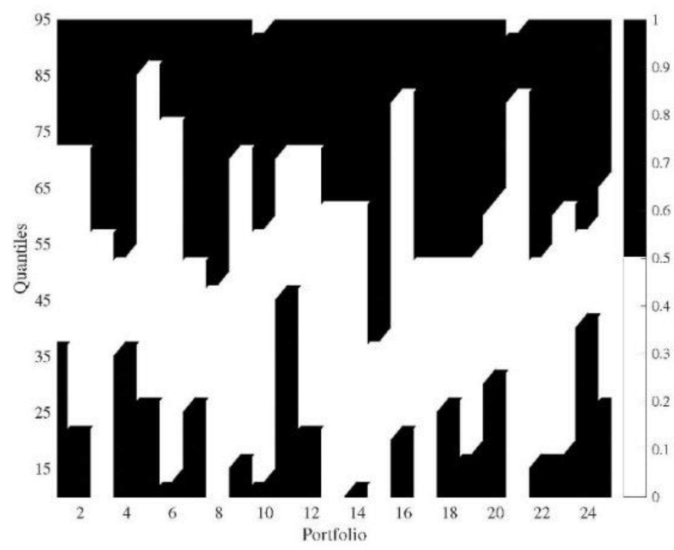
[10] Kiendrebeogo (2016) and Fratzscher et al. (2018) study this phenomenon in relation to the excess liquidity produced by the quantitative easing policies implemented by the Federal Reserve after the Global Financial Crisis.

Figure 3. Systemic Liquidity Betas according to market states

Panel A



Panel B



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

4.4. Industry portfolios and systemic liquidity risk

Table 3 reports the industry portfolios, sorted into 30 sectors, as commonly recognized in the literature. Figure 3 shows the liquidity betas and their corresponding t-statistics for each industry. The results show that some industries are more exposed to aggregate liquidity than others. For instance, with the exception of (3) Tobacco, (11) Construction, (13) Fabricated Products, (17) Mines and (27) Retail, all other industries display a negative sensitivity up to their 40^{th} quantile. Up to the 80^{th} quantile, the Steel Industry (12) shows an even more extreme negative sensitivity to market-wide liquidity risk. In contrast, the positive liquidity estimates show a similar magnitude for all 25 portfolios, sorted by size and book-to-market value. Only (3) Tobacco and (18) the Coal Industry seem to fall outside this range. However, for most industry portfolios there is statistical significance only for the upper quantiles, i.e. $\tau = 0.65 - 0.95$, coinciding with a bullish market state. At the other end of the spectrum, the lower quantiles, corresponding to a bearish market state, the excess portfolio returns of many industries do not seem to be statistically different from zero, i.e. (3) Tobacco, (4) Games, (5) Books, (7) Clothes, (11) Construction, (13) Fabricated Products, (17) Mines, (18) Coal and (25) Transportation. Similar to the 25 portfolios sorted by size and book-to-market value, we observe that for the median case the aggregate liquidity risk seems to be non-significant across all industries.

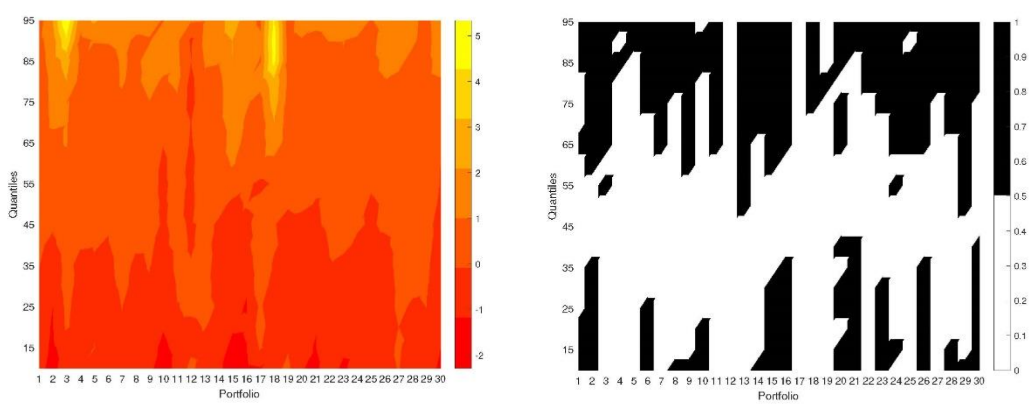
Table 3. 30 U.S. Industry Portfolio

Portfolio Nº	Industry	Portfolio Nº	Industry
1	Food	16	Aircraft, Ships
2	Beer	17	Mines
3	Tobacco	18	Coal
4	Games	19	Oil/Petroleum/Gas
5	Books	20	Utilities
6	Households	21	Telecommunication
7	Clothes	22	Personal/Business Services
8	Healthcare	23	Business Equipment
9	Chemicals	24	Paper/Business Supplies/Shipping Equip.
10	Textiles	25	Transportation
11	Construction	26	Wholesale
12	Steel	27	Retail
13	Fabricated Products	28	Gastronomy
14	Electrical Equipment	29	Finance
15	Automobiles	30	Other

Stocks from NYSE, AMEX and NASDAQ are assigned to industry portfolios based on a four-digit SIC code. For a more detailed description of the industry definition, see http://mba.tuck.dartmouth.edu/pages/faculty/ken.french-/data_library.html

Figure 4. Heatmap Beta – Industry Portfolios - Systemic Liquidity Risk - July 2000 to December 2016

(a) Heatmap - Liquidity Betas (b) Heatmap - Significance



5. Conclusion

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

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

During regular times, the market rarely prices liquidity risk. This shows that investors are less concerned about illiquidity in untroubled market states, corresponding to returns around the median. We also find that none of the portfolios, sorted by size and book-to-market value, exhibits any size effect, neither during up, down or normal market swings. Our robustness checks provide similar evidence across an extended sample period (from 1960 to 2017), and in a different portfolio formation (30 U.S. industries).

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

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Appendix

Table A1

Descriptive Statistics: Excess Returns on 25 portfolios formed on ME and BE/ME

Size Quintile	(BE/ME) Quintiles Low	2	3	4	High	Low	2	3	4	High
	Variance					Skewness				
Small	74.09	56.1	36.01	34.74	37.32	0.40	0.48	-0.004	0.07	-0.47
2	52.55	35.01	30.27	30.73	44.63	-0.14	-0.34	-0.29	-0.52	-0.61
3	44.61	28.27	26.88	28.11	38.16	-0.37	-0.22	-0.23	-0.27	-0.44
4	36.8	24.81	28.27	26.57	40.45	-0.18	-0.48	-0.68	-0.65	-0.55
Big	18.52	17.58	18.3	28.89	43.14	-0.45	-0.4	-0.41	-1.09	-0.2
	Kurtosis					Jarque				
Small	5.21	6.88	3.68	4.35	3.8	47.12	136.63	4.03	15.74	13.08
2	3.83	4.27	3.61	4.1	4.23	6.69	17.93	6.16	19.85	25.7
3	4.16	3.98	3.62	4.23	4.16	16.22	9.99	5.12	15.52	18.29
4	4.98	4.65	5.87	4.93	4.47	34.56	31.29	86.54	46.33	28.99
Big	3.59	3.99	3.75	7.28	3.65	10.12	13.8	10.71	196.91	5.03
	Min					Max				
Small	-24.06	-20.37	-18.97	-15.77	-21.78	38.51	40.62	21.43	24.97	17.43
2	-22.61	-23.58	-18.69	-19.65	-21.71	27.74	17.08	16.34	16.24	19.00
3	-23.62	-18.35	-17.55	-20,00	-20.57	24.17	18.17	17.16	16.23	17.38
4	-20.06	-20.48	-25.35	-22.48	-21.95	25.79	15.85	16.87	14.36	16.96
Big	-14.47	-15.58	-13.16	-27.09	-17.22	10.18	11.00	12.63	15.62	23.61

Note: This table reports the mean and the standard deviation of the 25 U.S. portfolios between July 2000 and December 2016, and includes up to 204 observations.

Table A2

Summary statistics for the liquidity measure and three factors: July 2000 to December 2016

			Correlations			
	Mean	St.Dev.	Liq	RMKT	SMB	HML
Liq	0.09	1.06	1			
RMKT	0.36	4.45	-29.73	1		
SMB	0.31	3.38	-1.08	26.58	1	
HML	0.4	3.22	6.25	-5.22	-27.88	1

Note: Liq is the liquidity measure, RMKT is the excess return of a broad CRSP market portfolio; SMB (small minus big) is the difference between returns on the average returns on a small- and big-stock portfolio; HML (high minus low) is the value premium between the average returns on portfolios with high book-to-market value and low book-to-market value. All correlations are expressed in percentage points.

Table A3

Dependent variable: Excess returns on 25 portfolios formed on ME and BE/ME

	(BE/ME) Quintiles									
Size Quintile	Low	2	3	4	High	Low	2	3	4	High
10th Quantile										
			β^L					$t(\beta^L)$		
Small	-0.40	-0.19	0.00	-0.22	-0.31	**-2.79**	-1.63	-0.05	**-2.79**	**-3.98**
2	-0.01	-0.25	-0.15	-0.10	-0.02	-0.12	**-2.94**	-1.77	-1.40	-0.20
3	-0.34	-0.33	-0.10	-0.18	0.04	**-3.80**	**-3.55**	-1.17	**-1.97**	0.34
4	-0.04	-0.30	-0.40	-0.09	-0.07	-0.48	**-3.03**	**-3.74**	-0.95	-0.59
Big	-0.11	-0.25	-0.19	-0.45	-0.46	-1.69	**-2.72**	**-2.07**	**-4.52**	**-3.10**
25th Quantile										
			β^L					$t(\beta^L)$		
Small	-0.44	-0.12	0.01	-0.05	-0.20	**-3.82**	-1.49	0.08	-0.69	-2.94
2	-0.05	-0.14	0.01	-0.03	0.04	-0.63	**-2.03**	0.23	-0.44	0.57
3	-0.22	-0.16	0.04	0.05	0.02	**-2.76**	**-2.09**	0.55	0.71	0.28
4	-0.14	0.00	-0.13	0.01	-0.19	**-1.99**	0.04	-1.69	0.08	-1.82
Big	-0.002	-0.06	-0.08	-0.19	-0.09	-0.03	-0.87	-1.03	**-2.26**	-0.82
50th Quantile										
			β^L					$t(\beta^L)$		
Small	-0.33	0.06	-0.01	0.02	-0.12	**-3.03**	0.73	-0.18	0.36	-1.82
2	-0.02	0.04	0.05	0.01	-0.03	-0.31	0.60	0.75	0.20	-0.41
3	0.04	-0.04	0.03	0.01	0.14	0.56	-0.60	0.44	0.08	1.78
4	-0.03	-0.02	-0.08	-0.04	0.05	-0.47	-0.29	-1.10	-0.55	0.45
Big	0.07	0.16	-0.04	-0.08	0.08	1.14	2.41	-0.57	-1.04	0.76
75th Quantile										
			β^L					$t(\beta^L)$		
Small	-0.10	0.17	0.10	0.23	0.09	-0.82	1.94	1.49	**3.14**	1.29
2	0.08	0.10	0.18	0.09	0.04	0.87	1.28	**2.76**	1.30	0.60
3	0.19	0.16	0.05	0.12	0.34	**2.31**	**2.00**	0.64	1.75	**3.83**
4	0.12	0.25	0.09	0.11	0.16	1.62	**3.12**	1.10	1.23	1.49
Big	0.06	0.22	0.13	0.15	0.23	1.15	**3.27**	1.60	**2.13**	1.91
90th Quantile										
			β^L					$t(\beta^L)$		
Small	0.46	0.48	0.41	0.47	0.48	**2.82**	**4.03**	**4.76**	**5.26**	**5.65**
2	0.26	0.43	0.08	0.21	0.12	**2.57**	**4.15**	0.82	**2.68**	1.40
3	0.37	0.37	0.27	0.32	0.66	**3.91**	**3.81**	**2.68**	**3.09**	**5.59**
4	0.33	0.64	0.56	0.37	0.39	**3.32**	**5.68**	**4.95**	**3.29**	**3.17**
Big	0.16	0.52	0.37	0.23	1.05	**2.31**	**6.45**	**3.49**	**2.72**	**7.37**

Note: The table shows the liquidity estimates for each of the 25 value-weighted portfolios sorted according to size and book-to-market quintiles. The sample runs from July 1960 to December 2016, and includes 1,088 observations. The first five columns show associated t-statistics for each coefficient. Each section reports the estimates for a particular quantile of the excess portfolio returns in ascending order.

Figure A1. Standardized systemic liquidity risk estimate from July 2000 to December 2016

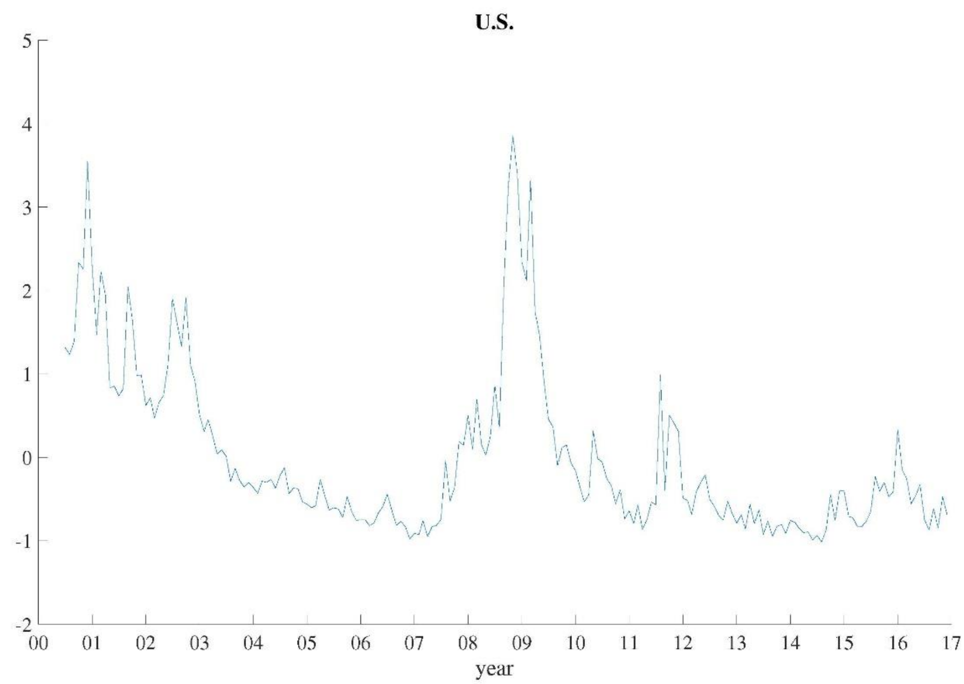
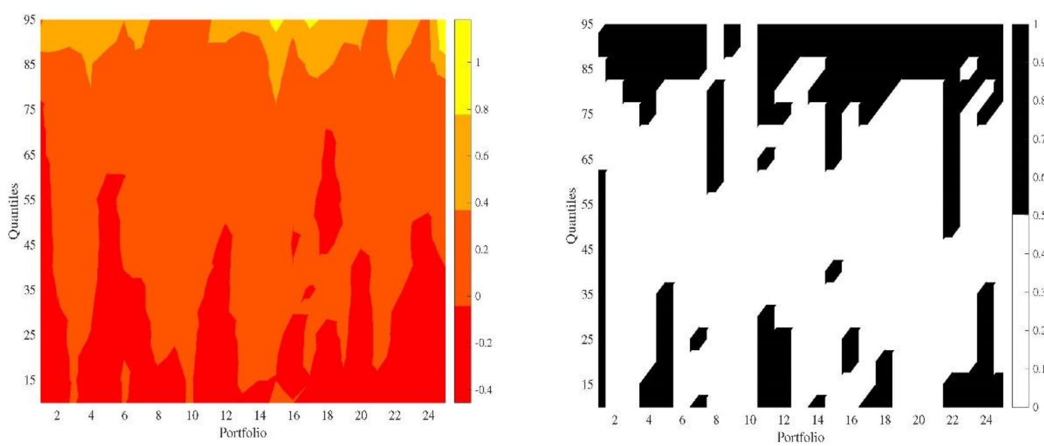


Figure A2. Liquidity Betas of the Three-Factor Model – July 1960 to December 2016



(a) Heatmap – Liquidity Betas

(b) Heatmap – Significance