Characteristic liquidity, systematic liquidity and expected returns

M. Reza Baradarannia[a,*], Maurice Peat [b]

[a,b] Business School, The University of Sydney, Sydney 2006, Australia

Abstract: We investigate whether the effect of liquidity on equity returns can be attributed to the liquidity level, as a stock characteristic, or a market wide systematic liquidity risk. We develop a CAPM liquidity-augmented risk model and test the characteristic hypothesis against the systematic risk hypothesis for the liquidity effect. We find that the two-factor systematic risk model explains the liquidity premium and the null hypothesis that the liquidity characteristic is compensated irrespective of liquidity risk loadings is rejected. This result is robust over 1931-2008 data and sub-samples of pre-1963 and post-1963 data both in the time-series and the cross-sectional analysis. The findings demonstrate that the liquidity augmented CAPM approach is the correct way to incorporate the liquidity risk.

*Corresponding author.
 E-mail address: rezab@econ.usyd.edu.au.

1. Introduction

Liquidity affects equity prices: illiquid stocks have higher returns than liquid stocks. There are two common hypotheses for the liquidity effect. One considers liquidity as a stock characteristic, and the premium for this characteristic (liquidity level) has been investigated (e.g. Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Hasbrouck, 2009). In these studies, the analysis includes control variables that account for the differences that can be explained by the different cash flows, and then tests whether the price differential that is unexplained by the control variables is significantly related to differences in liquidity level of the stocks. From this point of view, the liquidity premium is the rational response by investors in an efficient market in order to be compensated for bearing transaction costs and frictions underlying illiquidity (e.g. Amihud and Mendelson, 1986). The result is lower prices and higher expected returns for illiquid stocks relative to the liquid stocks. This premium is not due to a systematic risk, but the characteristics of the stocks.

The second hypothesis for the liquidity effect states that the high expected returns for illiquid stocks are compensation for a market level (systematic) liquidity risk. It is based on the idea that, as liquidity varies over time, and because there is commonality in liquidity, the market liquidity risk should also be priced. Accordingly, because liquidity varies over time, risk-averse investors require compensation for being exposed to the liquidity risk. Studies based on this hypothesis generally define and construct a common risk factor that is related to liquidity, and investigate the risk premium for the sensitivity of stock returns to that liquidity-based factor (Pastor and Stambaugh (2003), Acharya and Pedersen (2005) and Liu (2006, 2010)).

Some studies have tried to connect these two lines of research in liquidity-equity pricing, and have examined the relationship between liquidity as a characteristic and liquidity as a systematic risk factor in equity asset pricing, but the results have not been conclusive. For

example, Watanabe and Watanabe (2008) take the innovation in liquidity shocks as the liquidity risk factor and show that systematic liquidity captures the effect of characteristic liquidity. However, Korajczyk and Sadka (2008) extract the liquidity common factor, using the Asymptotic Principal Components (APC) approach, and report a cross-sectional premium for the level of liquidity after controlling for the liquidity systematic risk. Liu (2010) constructs a liquidity-related return factor, defined as the returns of a zero-cost portfolio, and shows that systematic liquidity picks up the effect of characteristic liquidity.

However, past research that has examined the returns of liquidity-sorted portfolios (as in Watanabe and Watanabe (2008) and Liu (2010)) has not been able to distinguish the systematic risk hypothesis from the characteristics model in equity-liquidity pricing tests[1]. The reason for this is that the liquidity characteristic is associated with co-variation in returns, and therefore the liquidity loadings may capture co-variation in returns that is not due to liquidity risk but to the liquidity characteristics. In other words, the co-variation between the illiquid stocks may not be the result of a liquidity risk factor, but reflect the fact that illiquid stocks tend to have similar properties due to operating in the same industries or related businesses. For example, let's focus on periods in which industries have become relatively (il) liquid because of the market-wide (il) liquidity. When liquidity characteristic-based portfolios are formed in order to pick up the co-variation related to the market-wide liquidity risk, the captured variation has been always present in the industry, but for the moment happens to be related to the market-wide, common source of liquidity risk. Hence, the liquidity premium seems to be associated to the covariance of returns with a common liquidity risk factor, when in fact it is due to the liquidity characteristic of the stocks. Thus, to

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[1] As Daniel and Titman (1997) and Davis et al. (2000) point out, the set-up in which the test portfolios are formed based on sorted characteristics, does not have enough power to distinguish characteristics models from the risk models in asset pricing tests.

discriminate between these two cases we need to apply a method that separates the firms that are illiquid, but that do not behave like illiquid firms by loading on liquidity factor.

We use the triple-sort portfolio construction suggested by Daniel and Titman (1997) and Davis et al. (2000) in order to isolate the variation in liquidity-related co-variation from the changes in liquidity level. More specifically, we apply a new liquidity measure, the effective tick developed by Holden (2009), and employ a time-series regression on portfolios over a long sample period of 1926–2008 to test the risk model against the characteristics model for the liquidity premium. We first establish a liquidity-equity pricing risk model that includes only the market factor and the liquidity factor. Our liquidity factor is the returns on mimicking arbitrage portfolio, which is long in illiquid stocks and short in liquid stocks, and it is neutral to the market factor. We show that this two-factor model can explain the expected returns over a long data sample period from 1931 to 2008, and also sub-samples of pre- and post-1963. The use of a long time series enhances the power of our asset pricing tests. We then test the characteristics hypothesis versus this two-factor risk model by using a triple-sorting of stocks on size, liquidity level and liquidity loading both in time series and in the cross section. We show that the liquidity premium can be attributed more to the systematic risk than the liquidity level.

This finding is in contrast with that of Acharya and Pedersen (2005) who find weak evidence that liquidity risk is important over and above the effects of market risk and the level of liquidity. However, as Acharya and Pederson (2005) acknowledge their results are estimated imprecisely because of collinearity between liquidity and liquidity risk. We mitigate the collinearity issue by triple-sorting approach and distinguish statistically the relative return impacts of liquidity level and liquidity risk. Nevertheless our results is consistent with finding of Papavassiliou (2013) who shows that in the framework of Acharya

and Pederson (2005) and in the Greece market, the level of liquidity, rather than the liquidity risk, is an irrelevant variable in asset pricing.

This paper contributes to the current literature by investigating whether the liquidity premium is due to the liquidity characteristic or the systematic liquidity risk. We show that the liquidity effect can be explained by a two-factor risk model. This provides evidence for practitioners and academia to treat liquidity as a systematic factor in their pricing models and cross-sectional analysis. The paper is summarised as follows. Section 2 reviews the liquidity measure and its construction. Section 3 presents a description of the data and variable constructions. The two-factor risk model is proposed in Section 4 and tested in Section 5. Section 6 tests the characteristics hypothesis against the risk hypothesis for the liquidity effect. Section 7 offers the concluding remarks.

2. The measure of liquidity

The liquidity measure that we have used in our study is Effective Tick4 (henceforth EFFT), developed by Holden (2009). It is the daily proxy for the effective spread, and includes two attributes of the daily data: price clustering on trading days, and reported quoted spreads for no-trade days. The proxy has two components corresponding to each of these attributes. The first component, effective tick, based on the observable price clustering, is a proxy for the effective spread. The second component is the average quoted spread from any no-trade days that exist, and enriches effective tick by incorporating the information related to no-trade days. First we review the effective tick and then conclude by reviewing the EFFT estimator. Effective tick is based on the idea that the effective spread on a particular day equals the increment of the price cluster on that particular day. For example, on a $1/8 fractional price grid, if the spread is $1/4, the model assumes that prices end on even-eights, or quarters. Thus, if odd-eight transaction prices are observed, one must infer that the spread

must be $1/8. This implies that the simple frequency with which closing prices occur in particular price clusters (in a time interval) can be used to estimate the corresponding spread probabilities and, hence, infer the effective spread for that interval. For example, on a $1/8 fractional price grid, the frequency with which trades occur in four, mutually exclusive price cluster sets (odd $1/8s, odd $1/4s, odd $1/2s, and whole dollars), can be used to estimate the probability of a $1/8 spread, $1/4 spread, $1/2 spread, and a $1 spread, respectively. There are similar clusters of special prices on a decimal price grid (off pennies, off nickels, off dimes, off quarters, and whole dollars) that can be used to estimate the probability of a penny spread, nickel spread, dime spread, quarter spread and whole dollar spread, respectively. In order to construct the effective tick proxy for a time interval, the first step is to compute the frequency of each price cluster within that time interval. Take S_t as the realisation of the effective spread at the closing trade of day t and assume that S_t is randomly drawn from a set of possible spreads S_j (for example in $1/8 fractional price grid, $S_1 = \$1/8$ spread, $S_2 = \$1/4$ spread, $S_3 = \$1/2$ spread and $S_4 = \$1$ spread) with corresponding probabilities γ_j , where $j=1,2,\ldots,J$ and $S_1 < S_2 < \ldots < S_J$. Let N_j be the observed number of trades on prices corresponding to the jth spread using only positive-volume days in the time interval. The observed probabilities of trade prices (F_j), corresponding to the jth spread is

$$F_j = \frac{N_j}{\sum_{j=1}^{J} N_j} \qquad j=1,2,..,J \qquad (1)$$

Let U_j be the unconstrained probability of the jth spread. The unconstrained probability of the jth effective spread is

$$U_j = \begin{cases} 2F_j & j = 1, \\ 2F_j - F_{j-1} & j = 2,3,...,J-1, \\ F_j - F_{j-1} & j = J. \end{cases} \qquad (2)$$

and the constrained probability[2] of the jth spread (γ_j) is

$$\hat{\gamma}_j = \begin{cases} Min\left[Max\left\{ U_j, 0 \right\}, 1 \right], & j = 1, \\ Min\left[Max\left\{ U_j, 0 \right\}, 1 - \sum_{k=1}^{j-1} \hat{\gamma}_k \right], & j = 2,3,...,J. \end{cases} \qquad (3)$$

Then, the effective tick proxy is calculated as the probability-weighted average of each effective spread size divided by the average price ($\bar{p}_i$) in time interval i :

$$EffectiveTick_i = \frac{\sum_{j=1}^{J} \hat{\gamma}_j s_j}{\bar{p}_i} \qquad (4)$$

Holden (2009) incorporates the average of the quoted spreads in no-trade days into the effective tick estimator and concludes the EFFT. EFFT for the time interval i is the probability weighted average of the effective estimator and the average of the quoted spreads from no-trade days:

$$EFFT_i = \hat{\mu} \times (EffectiveTick_i) + \frac{\begin{cases} (1 - \hat{\mu}) \frac{1}{NTD} \sum_{t=1}^{NTD} NQS_t & when\ NTD \rangle 0, \\ 0 & when\ NTD = 0 \end{cases}}{\bar{P}_i} \qquad (5)$$

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[2] This probability assumes a higher frequency on higher rounded increments which is true in large sample. However, in small samples reverse price clustering may be realised that causes the unconstrained probability of one or more effective spread sizes to go above 1 or below zero. Thus, constraints are added to generate proper probabilities.

where NQS$_t$ is the quoted spread computed by using reported bid and ask quoted prices on no-trade days, and $\hat{\mu}$ is the estimated probability of a trading day given by

$$\hat{\mu} = \frac{TD}{TD + NTD} \qquad (6)$$

where TD and NTD are the number of trading days and no-trade days over the time interval, respectively.

Inclusion of the reported quoted spreads from no-trade days within EFFT improves the effective tick estimator by incorporating the information about the no-trade days. This is particularly important when there are considerable numbers of no-trade days within the time interval because it can capture the corresponding illiquidity of the stock for that time interval.

The method to compute EFFT in a decimal pricing system is slightly different from that explained here, which is suitable for fractional pricing grids. In Appendix A, we explain how to calculate EFFT under the decimal pricing regime. Holden (2009) and Goyenko et al. (2009) report a high correlation between this proxy and high-frequency and low-frequency benchmarks. They also show that this measure performs better against the high-frequency benchmarks than other available low-frequency proxies (such as Hasbrouck's (2009) Gibbs estimate) for liquidity and/or transaction costs.

3. Data

Daily transaction data (price, returns adjusted for splits and dividends, volume, high/ask, low/bid[3]) from the CRSP daily file from December 31st, 1925 until December 31st, 2008 for

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[3] High/ask (low/bid) means the highest (lowest) trade price on a trading day or the closing ask (bid) price on a non-trading day (Holden, 2009).

all the stocks listed in NYSE are employed to estimate the monthly EFFT. Monthly returns and other required data to compute characteristics for the stocks are downloaded from the CRSP monthly file. Data for Fama and French's (1993) three factors (market, size and value) were downloaded from French's website (French, 2010).

To be included in the monthly cross-sectional analysis a stock must satisfy the following selection criteria suggested by Amihud (2002), Hasbrouck (2009) and Holden (2009).

1- It is an ordinary common share (CRSP codes 10 and 11) traded at the beginning and end of the year.

2- It must have enough trading days – at least two days – in a month to estimate EFFT.

3- Its return and market capitalisation data for at least 10 months in each year are available from CRSP.

4- It has monthly data on return and market capitalisation at the start and end of the year.

The first criterion restricts our sample to those stocks usually used in asset pricing studies. The second condition ensures that enough data is used to estimate EFFTs. The third condition makes the estimated parameters more reliable. The forth criterion provides data required for the portfolio construction according to our asset pricing methodology. The selection is made based on information in the CRSP event file.

In addition to the above criteria, following Chalmers and Kadlec (1998), we eliminate Berkshire Hathaway and Capital Cities because of their unwieldy stock prices. We follow Hasbrouck (2006 and 2009) and do not remove penny stocks (as in Amihud, 2002) since this may bias our analysis towards the liquid stocks. Also, as suggested by Fama and French (1992), we exclude financial firms because they usually have high leverage. While high leverage is normal for these companies, in non-financial firms it is generally a sign of distress. This exclusion guarantees homogeneity across the stocks.

This screening process yields on average 3035 stocks. The NYSE introduced a decimal pricing regime by applying the new regime to some pilot firms from 28 Auguest, 2000, and then completely switched to decimal grids on 29 January, 2001. We eliminate the pilot firms that started to be quoted and traded based on the decimal pricing system between August 28, 2000 and the final switching of NYSE to the decimal regime on January 29, 2001. Since estimation of EFFT is based on tick sizes, this elimination makes the computation of EFFTs across the stocks, in each month, consistent. This filtering removes 88 pilot firms.

For each stock-month, EFFT is calculated at the end of the month using daily trade data. According to the price regimes of the NYSE used over our sample period, the approach used to compute EFFT is slightly different. From January 1926 to January 2001, during which NYSE was using a fractional price grid, price increments as small as $1/64 are used. Accordingly, following Holden's (2009) suggestion for the application of EFFT on a fractional price grid, we assume that there are seven possible daily bid-ask spreads ($1/64, $1/32, $1/16, $1/8, $1/4, $1/2 and $1). Therefore, there are seven mutually exclusive price cluster sets (odd sixty-fourths, odd thirty-seconds, odd sixteenths, odd eighths, odd quarters, odd halves and whole dollars) corresponding to each spread. From February 2001 to December 2008, during which the NYSE had a decimal pricing system, tick sizes are $0.01, $0.05, $0.10, $0.25 and $1. Therefore the possible spreads are $0.01, $0.05, $0.10, $0.25 and $1. The corresponding price cluster sets are off-pennies, off- nickels, off-dimes, off quarters, and whole dollars[4]. For each stock-month, we calculate the frequency of each price cluster, the number of no-trade days, the average trade price from trading days, and the average of the

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[4] Off-pennies are penny price points that are not nickels, dimes, or any higher clusters: namely, where the last digit of the price is 1, 2, 3, 4, 6, 7, 8, or 9. Off-nickels are nickel price points that are not dimes, quarters, or any higher clusters: namely, where the last two digits of the price are 05, 15, 35, 45, 55, 65, 85, or 95. And so on (Holden, 2009).

quoted spreads in no-trade days. Then, we follow equations 1 to 6 for the stocks under the fractional price system to compute the monthly EFFTs. For those under the decimal regime, we follow the same equations with one exception. Instead of using Equation 3 to compute the unconstrained probabilities of the effective spreads, we employ Equation A-1 in Appendix A.

Table 1 reports descriptive statistics of EFFT, size, as the market capitalisation of the equity of the firm, and returns for the whole period of 1926–2008. In each month, averages of the variables across the stocks are calculated. This results in a time-series of averages for 996 months. Means, medians, and standard deviations of these time-series are then computed over the sample period. The average of monthly effective spread (EFFT) is approximately 1.24%. The size variable displays considerable skewness and its distribution is skewed to the right. Therefore, in our cross sectional analysis we use a relative measure for size (the log market capitalisation relative to the median), as suggested by Hasbrouck (2009), to ensure the stationarity of the size time-series. This relative measure is constructed at the end of the month as follows. If m_{jt} indicates the natural logarithm of the equity market capitalisation of the stock j at the end of the month, the log relative market capitalisation is the difference between m_{jt} and the cross-sectional median of the natural logarithm of the equity market capitalisation of all the stocks computed in the month. The log size relative to the median captures the cross-sectional variation while removing the non-stationary long-run components.

[Insert Table 1 about here]

Figure 1 graphs the time-series of the cross-sectional means of EFFTs, as the measure of illiquidity, over the period from January, 1926 to December, 2008. Aggregate illiquidity exhibits considerable variation over the time. The peaks are associated with economic and financial events.

The highest values are found immediately after the 1929 crash and during the Great Depression (December 1929–March 1933). Another period of great illiquidity, before World War II, starts in early 1937 and continues more and less up until 1943. The illiquid market during this period (1937 to 1943) coincides with the 1937–1938 recession and World War II economic downturn. The first post-World War II period of illiquidity occurs over the recession of 1972–1975. This period is associated with several events: the oil embargo, the collapse of the world's monetary system and the consequences of the Watergate scandal (Liu, 2006). Liquidity starts decreasing again after the market crash in October 1987. It is exacerbated during the Persian Gulf War in 1990 and reaches its second-lowest level since the end of World War II in January 1991. Another decline in liquidity begins in 1997 and lasts until the end of 2001. This period includes several events: the Asian financial crisis (1997), the Russian default (1998), the collapse of the US hedge fund LTCM (1998), the burst of the internet bubble (2000) and the 9/11 terrorist attacks (2001).

4. Two-factor risk model

We test the characteristics hypothesis versus the risk hypothesis for the liquidity effect. We propose the following CAPM model augmented by a liquidity factor as the risk model:

$$E(R_i) - R_f = \beta_i^m \left[E(R_m) - R_f \right] + \beta_i^l E(LIQ) \tag{7}$$

Where R_i is the return on asset i, R_f is the risk-free rate of return, and R_m is the return of the value-weight market portfolio. LIQ is the mimicking liquidity factor, and β_i^m and β_i^l are market beta and liquidity beta, respectively.

This model can be categorised as Merton's (1973) intertemporal asset pricing model with two state factors; market and liquidity. A number of studies (e.g. Pastor and Stambaugh, 2003; Acharya and Pederen, 2005 and Liu, 2006) have provided evidence that shows that liquidity is a good candidate to be a state variable. The idea is that financial distress can be one of the factors that make a stock less liquid. Therefore, liquidity risk should be able to capture, to some extent, distress risk.

We develop a mimicking liquidity factor, LIQ, based on the EFFT liquidity measure using common stocks listed on the NYSE. Breeden (1979) suggests that state variables in Merton's (1973) intertemporal asset pricing model can be replaced by mimicking portfolios. Mimicking portfolios have been used as economic factors in number of studies. For example, Breeden et al. (1989) used this method to make proxies for aggregate consumption with which to test their consumption asset pricing model. Fama and French (1996) construct SMB and HML mimicking portfolios to capture distress common risk. In liquidity asset pricing, Liu (2006) builds up a liquidity factor using this method. His liquidity factor is the monthly profits from buying one dollar of equally weighted low-liquid portfolio and selling one dollar of equally weighted high-liquid portfolio.

However, there is a reservation to using Liu's liquidity factor. In order to form liquidity portfolios, Liu sorts the stocks based on only their liquidity measures. Since liquid stocks usually have lower market beta than illiquid stocks, liquidity factors that result from ranking solely based on liquidity can be affected by the market betas and not represent the distress attributed to the liquidity. We remedy this issue in our liquidity factor, LIQ. The construction of LIQ is similar to the construction of SMB in Fama and French (1993).

At the end of June of each year, all NYSE common stocks are ranked based on their CAPM beta computed using the previous three to five years. Three portfolios based on the breakpoints for the bottom 30 percent, middle 40 percent, and top 30 percent of the values of

beta for the NYSE stocks on CRSP are constructed: low beta, neutral beta and high beta. Then, within each beta portfolio, stocks are sorted based on their EFFT at the end of June and three additional portfolios are constructed: high liquid, medium liquid and low liquid. The breakpoints are the bottom 30 percent, middle 40 percent, and top 30 percent of the values of EFFT for the stocks in the sample. The nine portfolios are rebalanced at the end of June of each year based on the prior year's information. The mimicking liquidity factor, LIQ, is the monthly average return on the three (equally weighted) low-liquid portfolios minus the monthly average return on the three (equally weighted) high-liquid portfolios:

LIQ= (Lbeta/iLiq+Mbeta/iLiq+ Hbeta/iLiq)/3 –(Lbeta/Liq+Mbeta/Liq+Hbeta/Liq)/3

In other words, LIQ is the performance of a mimicking portfolio that is long in low-liquid firms and short in high-liquid firms.

One issue is whether market-wide liquidity constructed using EFFT measure captures real economic conditions. As we show in Appendix B, aggregate EFFT is affected by market condition: liquidity declines when and after the market performs poorly. This suggests that market liquidity does indeed capture the aggregate state of the economy.

Table 2 reports summary statistics for liquidity factor, LIQ, its underlying portfolios and the Fama–French three factors, RM-RF, SMB and HML. The values are presented for July 1931 to December 2008 (panel A) and two subsamples of July 1931-December 1962 (panel B) and July 1963-December 2008 (Panel C). We break the sample in 1963 to compare the results of pre-1963 data, for which there is lack of research in liquidity-equity pricing, and those of post-1963.

The monthly mean of the liquidity premium, LIQ, for the whole sample period is 0.42 percent (*t*-statistic = 3.28). The liquidity premium for the first part of the sample, July 1931–December 1962, is 0.56 (*t*-statistic = 2.31), while it is less for the second part of the sample (July 1963–December 2008), 0.3 (*t*-statistic = 2.06). Thus, there is a strong liquidity premium

in average returns. These large average LIQ returns for the full sample and subsamples are vital for tests of our hypothesis. The power of our tests would be low if the average LIQ return was small. The reason is that when the LIQ return is low, the characteristics model predicts that LIQ loadings (β_i^l) that are unrelated to the liquidity characteristic do not affect average returns. On the other hand, the risk model predicts that differences in LIQ loadings produce small changes in average returns.

[Insert Table 2 about here]

However, premiums with regards to RM-RF, HML and SMB over the subsamples are not consistently strong. There is strong market premium, RM-RF, of 0.57 percent per month (*t*-statistic = 3.25) for the full sample of July 1931–Decmeber 2008. Nevertheless, the monthly average market premium is larger and stronger over the pre-1963 period than the market premium for the later period of post-1963. The average value of the market premium is 0.83 percent per month (*t*-statistic = 2.51) for the sample period of July 1931–December 1962, while it is 0.36 (*t*-statistic = 1.79) for the sample period of July 1963–December 2008. Moreover, the results from the full sample suggest that there are value (0.42 percent per month, *t*-statistic = 3.59) and size (0.29 percent, *t*-statistic = 2.61) premiums, whereas this is not the case in the subsamples. It seems that the premium of value (high BE/ME) stocks over the growth stocks is more pronounced over the July 1963–December 2008 period (0.42 percent per month, *t*-statistic = 3.19) than over the July 1931-December 1962 period (0.40 percent per month, *t*-statistic = 1.76). The monthly average of the size premium, SMB, for the pre-1963 period is 0.35 (*t*-statistic = 1.91), while it is 0.22 (*t*-statistic = 1.53) over the post-1963 sample.

Over the entire sample, the Pearson correlations in panel A show that the liquidity factor (LIQ) is positively correlated with SMB at 0.67. This value is 0.63 for the early period (panel B) and 0.69 for the later period (panel C). These correlations confirm the positive relationship between size and liquidity documented in the literature. The correlation between LIQ and HML is not consistent over the samples. While it is low (0.33) over the whole period (panel A) and also the later period (0.16), it is high (0.53) over the early period. These inconsistencies in HML correlations with LIQ and also high correlation between SMB and LIQ have motivated us to replace SMB and HML in the Fama–French three-factor framework with LIQ, and propose and test the two-factor model (Equation 7).

The correlations between LIQ and RM-RF are low over the whole period (0.19), the pre-1963 subsample (0.29) and post-1963 subsample (0.11). This suggests that LIQ captures covariations beyond that of market factor.

Table 2 also shows that there is a reliable liquidity premium in average returns of both low risk stocks (with low market beta) and high risk stocks (with high market beta). Over the full sample of July 1931 to December 2008, the liquidity premium for low beta stocks (the average Lbeta/illiq-Lbeta/Liq return) and high beta stocks (the average Hbeta/illiq-Hbeta/Liq return) are very similar. The former is 0.42 percent per month and the latter is 0.48.

In the returns for the early period of July 1931–December 1962, the liquidity premium for risky stocks (Hbeta/illiq − Hbeta/liq), 0.36 percent per month, is lower than the liquidity premium for low risk stocks (Lbeta/illiq − Lbeta/liq), 0.76 percent per month. However, for the later period of July 1963–December 2008, the liquidity premium for low risk stocks (0.15 percent per month) is lower than that of the risky stocks (0.58 percent per month).

5. Empirical test of the two-factor risk model:

We are interested to test the characteristics model hypothesis against the risk model hypothesis for the liquidity effect. To do so, we first need to show that our risk model can explain the expected returns. We show here that the CAPM model augmented by the liquidity factor is a good approximation for stock expected returns.

We test model 7 on nine portfolios constructed based on size and liquidity. We control for size as there is a positive correlation between size and liquidity. Testing on two-level portfolios is a typical method documented by Fama and French (1993, 1996) and has been widely used in empirical asset pricing research.

At the end of June of each year, we rank all the stocks according to their size value and construct three portfolios based on the breakpoints for the bottom 33 percent, middle 34 percent, and top 33 percent of the values of market capitalisation: Small (S), Medium (M) and Big (B). Then, within each size portfolio, stocks are sorted based on their EFFT, available at the end of June, into three additional portfolios: Liquid, Medium liquid and illiquid (L, M, iL). The breakpoints are the bottom 33 percent, middle 34 percent, and top 33 percent of the values of EFFT for the stocks in the sample. The nine portfolios (S/L, S/M, S/iL, M/L, M/M, M/iL, B/L, B/M and B/iL) are equally weighted portfolios and rebalanced at the end of June of each year.

We, then, estimate the following two-factor model for each of the nine portfolios over the full sample period of July 1931–December 2008 and over the subsamples of pre-1963 and post-1963 periods:

$$R_{it} - R_{ft} = \alpha_0 + \beta_i^m (R_{mt} - R_{ft}) + \beta_i^l LIQ_t + e_{it} \qquad (8)$$

where R_{it} is the equally weighted monthly return on portfolio i and R_{mt} is value-weight monthly return on all NYSE, AMEX, and Nasdaq stocks. R_{ft} is the one-month Treasury bill rate and LIQ_t is the monthly liquidity factor. The t-statistics are based on the heteroskedasticity consistent standard errors of White (1980).

Table 3 summarises the results. The results show that sorting on size and then liquidity generates strong orderings on the LIQ risk loadings (β_i^l). The post-formation LIQ loadings increase with EFFT in all the sample periods. The spread between the LIQ loadings in small stock portfolios over the whole period is 1.04, while it is around 0.43 in medium and 0.37 in large stock portfolios. The spreads for liquidity loadings for each size portfolio are about a similar magnitude over the subsamples. They are 1.15, 0.49 and 0.41 in small, medium and large stock portfolios, respectively, over the pre-1963 period. The spreads between the liquidity loadings over the post-1963 period are 0.95, 0.39 and 0.28, in small, medium and large stock portfolios, respectively. As we see the spread sizes for pre-1963 are higher than those of post-1963. Since one source of the power in our tests comes from the size of the spread in liquidity loadings, the inclusion of pre-1963 data in our asset pricing analysis enhances the power of our tests.

[Insert Table 3 about here]

Moreover, the average number of firms over the sample period in each portfolio is quite large, though it is smaller for pre-1963 than for post-1963. On average there are a minimum of 42 firms in portfolios during the July 1931–December 1963 period and 110 firms during the July 1963–December 2008 period. Therefore, the inclusion of pre-1963 data does not

affect the power of tests because of the relatively fewer number of stocks compared to the later period.

The two-factor model (Equation 7) holds if the intercept estimate is not significantly different from zero. The results for each of the nine portfolios over the whole sample of July 1931–December 2008 and also the subsamples of pre- and post-1963 show that alpha is indistinguishable from zero. The adjusted R^2 is more than 86 percent for the tests over the whole period and more than 90 percent over the pre-1963 period. It is at least 82 percent over the post-1963 period. However, in order to test the model, it is imperative to see if the intercept estimate across all portfolios is not statistically different from zero. We report the *F*-statistic of Gibbons, Ross and Shanken (GRS) (1989) for each sample in Table 3. The GRS test can not reject the null hypothesis that the intercept is indistinguishable from zero over the whole sample (*p*-value = 0.72) as well as pre-1963 (*p*-value = 0.43) and post-1963 (*p*-value = 0.30) periods.

This is a striking result as it shows that a simple two-factor model based on market and liquidity factors can explain the expected returns, and it is robust across different portfolios and sample periods. The common factor model used widely in academia and in practice is the Fama–French three-factor model. Their model is based on market factor, and SMB and HML factors as the common risk factors. However, the estimate results in Fama and French (1993, 1996) and also Davis et al. (2000) show that the three factor model has difficulty in explaining average returns, particularly over the pos-1963 period. The two-factor model, suggested in the present paper, replaces SMB and HML with a liquidity factor that can explain the average returns. More importantly, it makes economic sense for the liquidity factor to be regarded as a common risk factor, rather than HML.

Since the two-factor model can explain the average returns of the portfolios formed on size and liquidity characteristics, it is a sound risk model against which we test the predications of the characteristics model.

6. Liquidity systematic risk versus liquidity level- time-series analysis

The two-factor risk model suggests that alpha in Equation 8 is zero for all assets. The characteristics model says that when liquidity loadings of stocks do not move with their corresponding liquidity level, the alpha must be non-zero. Therefore, we are interested to induce variation in the liquidity loadings that is independent of liquidity level so that we can differentiate the risk model from the characteristics model. In order to generate this variation, we adopt the triple-sorting approach originally used by Daniel and Titman (1997) and Davis et al. (2000) to isolate variation in loadings of the Fama–French three factors from the corresponding characteristics variables

At the end of June of each year, we sort all the stocks based on their market capitalisations and construct three portfolios (small, medium and big) based on the breakpoints for the bottom 33 percent, middle 34 percent, and top 33 percent of the values of market capitalisation for the NYSE stocks on CRSP. Then, within each size portfolio, we rank the stocks based on their liquidity level (EFFT) and form three portfolios (Liquid, Medium liquid and illiquid) based on the breakpoints for the bottom 33 percent, middle 34 percent, and top 33 percent of the values of EFFT for the stocks in the sample. Finally, in each of the 9 size-liquidity portfolios, stocks are sorted based on their liquidity loadings. Liquidity loadings for each stock are estimated via the two-factor (LIQ-augmented CAPM) model for each stock using previous three to five years. Three portfolios based on the breakpoints for the bottom 33 percent, middle 34 percent, and top 33 percent of the values of

liquidity loadings for the stocks within each size-liquidity portfolios are constructed: Low-liquidity beta (Lliqbeta), Medium-Liquidity beta (Mliqbeta) and High-liquidity beta (Hliqbeta). Thus, in total we form 27 portfolios sorted based on size, liquidity as a characteristic, and liquidity beta. The portfolios are equally weighted and produce variation in the liquidity risk loadings independent of the size and liquidity characteristics of the portfolios. We test the characteristics model against the risk model by analysing the returns of the arbitrage portfolio of Hliqbeta-Lliqbeta. This portfolio is the difference between the returns on the high liquidity beta portfolios of a size-liquidity group minus the returns on the low liquidity beta portfolios of the same size-liquidity group, averaged across the nine size-liquidity groups.

Table 4 reports the summary statistics of the portfolios and also the estimates of the two-factor model for the period of 1931–2008. The results are similar for the periods of pre-1963 and post-1963 and have not been reported for brevity.

Each of the 27 portfolios has, on average, at least 23 stocks. This provides enough diversification within each portfolio for the purpose of our analysis. In almost all size-liquidity groups, the third-pass sort on liquidity loadings produce strong variations in post-formation LIQ risk loadings and weak variations in liquidity level. The exceptions are the small and medium portfolios in illiquid groups, for which the variation in liquidity level is large, but we have substantial variation in post-formation liquidity loadings in other 25 portfolios, which is enough to reassure us of the power of our test.

In Table 4, Excess Returns represents the post-formation monthly average of the excess return for each portfolio. In each of the nine size-liquidity groups, the excess return on the high liquidity beta portfolios is higher than the excess return on the low liquidity beta. Also the intercept is not distinguishable from zero in almost all of the 27 portfolios. The exceptions are three portfolios (M/M/Mliqbeta, S/L/Lliqbeta and S/L/Mliqbeta). These results are in line

with the liquidity risk hypothesis that predicts higher returns for the assets with higher systematic liquidity risk, and suggests that the two factors of liquidity and market can explain the results. However, our formal test of the characteristics hypothesis versus risk hypothesis for liquidity effects is based on the intercepts in estimates of Equation 8 for the Hliqbeta-Lliqbeta. Hliqbeta-Lliqbeta is the average of the differences between the returns on the Hliqbeta and the Lliqbeta portfolios of the nine size-liquidity groups.

[Insert Table 4 about here]

Table 5 shows estimates of the Hliqbeta-Lliqbeta regression for several periods. The two-factor model suggests that the intercepts must be zero. The alternative hypothesis of the characteristics model says that since the positive Liq loadings for Hliqbeta-Lliqbeta are largely unrelated to the liquidity level, as a characteristic, they do not affect the expected return. Thus, the characteristics model predicts that the intercepts in the Hliqbeta-Lliqbeta regressions are negative, to offset the positive return premiums implied by the product of the positive LIQ loadings and the positive expected LIQ return.

[Insert Table 5 about here]

The results in Table 5 show that the intercepts are both economically and statistically not different from zero over the entire sample period of July 1931–Decmber 2008 (*t*-statistic = 0.05), the early period of July 1931–December 1962 (*t*-statistic = 0.28), and the later period of July 1963–December 2008(*t*-statistic = 0.25). These results confirm the two-factor risk model. Table 5 also shows the average Hliqbeta-Lliqbeta return and its *t*-statistic for various periods. The liquidity beta premium over the entire sample is 0.2 percent (*t*-statistic = 2.29). The average return of the arbitrage portfolio over the pre-1963 is 0.12 percent, though it is

not statistically significant (t-statistic = 0.56). For the post-1963 period, the average return is 0.2 percent (t-statistic = 1.69). In a one-sided test (relevant when the alternative is the positive expected return predicted by the three-factor risk model), this average return is different from zero at the 0.05 level. However, the most precise evidence and the best single test of the characteristics model against the risk model is provided over the entire sample. In the tests for the 78-year period, the risk model outperforms the characteristics model. The risk model explains the average returns (the intercept is both economically and statistically equal to zero) and R^2 is 31 percent, whereas the characteristics model under-predicts the arbitrage portfolio return by 20 basis points per month (t-statistic = 2.29).

7. Liquidity systematic risk versus liquidity level- cross-sectional analysis

In this section, we test the two-factor risk model (1) in the cross-section of equity returns and then investigate to see if there is a liquidity characteristic premium which cannot be explained by the two-factor model. The pricing procedure is based on the OLS two-pass cross-sectional regression method but we follow Cochrane (2005) (pp. 241-243) and Hasbrouck (2009) and use the GMM estimation approach to avoid the error in estimation of risk factor loadings common in the two-pass regression estimates.

The asset pricing models that we test here are based on the two-factor model (1) modified to allow for characteristics and several specifications as follows.

$$E(r_i) = \delta_0 + \gamma'\beta_i + \delta' Z_i \tag{9}$$

where $E(r_i)$ is excess return relative to the risk free rate for asset i, β_i is the vector of loadings with respect to k factors that includes market risk factor and liquidity risk factor. γ is a vector of risk factor premia. Z_i is the vector of M characteristics that include liquidity level and

relative size (the log market capitalisation relative to the cross-sectional median), as the control variable, and δ is a vector of slopes for the characteristics. In order to estimate the coefficients of (9) we estimate the equation 10 using the monthly data of 27 triple sorted portfolios that we have constructed in June of each year and were explained in detail in section 6.

$$r_{it} = R_{it} - R_{ft} = \delta_0 + \gamma' \beta_i + \delta' Z_{it} + \varepsilon_{it} \qquad (10)$$

where R_{it} is the equally-weighted monthly return on portfolio i in month t, and R_{ft} is the one-month Treasury bill rate. Z_{it} is the vector of portfolio characteristics that are computed at the end of the June using the information available from July of the preceding year. The characteristics are liquidity level, $EFFT_{it}$, and relative size, R_size_{it}. $EFFT_{it}$ for portfolio i in month t is computed at the end of the past June as the average of the portfolio monthly EFFTs over the prior 12 months. R_size_{it} for portfolio i in month t is the average of the log relative market capitalisations over all firms in portfolio i and measured at the end of the past June. As it is explained in detail in section 3, the log relative market capitalisation for a stock in a month is the log market capitalisation of a firm relative to the cross-sectional median of all firms in the sample in that month.

The risk factor loadings for each portfolio in (10) are the estimated coefficients in Equation 8. In order to avoid errors in estimated loadings we employ GMM approach suggested by Cochrane (2005) and estimate equations 8 and 10 simultaneously. The GMM slope estimates of equation 10 are equivalent to those estimated from a two-pass regression procedure in which loading betas are estimated using OLS time-series regression (8) over the sample and then used as the independent variables in the pooled OLS regression of equation 10. However, the standard errors of the estimated slopes in GMM approach are corrected for errors in beta estimations. Also, Cochrane (2005) shows that under the normality assumption

these standard errors are asymptotically equivalent to those heteroskedasticity-corrected ones constructed using Shanken (1992) correction method.

The moment conditions we used in our GMM estimation are identical to those employed by Hasbrouck (2009) in his empirical pricing analyses. The moment conditions used to estimate equations 8 and 10 at the same time in a general form are

$$
\begin{bmatrix}
E(r_t - \alpha - \beta f_t) \\
E\left[(r_t - \alpha - \beta f_t)f_t'\right] \\
E\left[\beta'(r_t - \delta_0 - \beta\gamma - Z_t\delta)\right] \\
E\left[Z_t'(r_t - \delta_0 - \beta\gamma - Z_t\delta)\right]
\end{bmatrix}
=
\begin{bmatrix}
0 \\
0 \\
0 \\
0
\end{bmatrix}
\tag{11}
$$

where r_t is a vector of excess returns ($R_t - R_{ft}$) for N portfolios. β is a N×K matrix of factor loadings, f_t is a vector of K risk factors, α is a vector of N intercepts. Z_t is a N×M matrix of characteristics. The top two moment conditions are N(1+K) equations that exactly identify the same number of α and β as the time-series OLS. The bottom two moment conditions are K+M equations that exactly identify the same number of unknowns δ_0, γ and δ.

We test the model in equation (10) for several specifications and the results are provided in Table 6. First, the CAPM and the two-factor model (1) are tested (specifications 1 and 2 in Table 6). Then, we add liquidity level to the two-factor model in specification 3 to examine characteristics hypothesis versus systematic hypothesis for the liquidity effect, and finally we include relative size as the control characteristics variable in specification 4.

Table 6 reports estimates of the above specifications over three sample periods: 1) the entire sample, from July 1931 to December 2008; 2) pre-1963, from July 1931 to December 1963; 3) post-1963, from July 1963 to December 2008. The first 5 years of the sample are used to estimate pre-ranking betas for portfolio formation and also liquidity risk factor (LIQ) construction.

[Insert Table 6 about here]

The results from the entire sample, panel A, show that the intercept in specification 1 is significant (*t*-statistic= 4.52) indicating that CAPM is not able to explain the cross-sectional returns. This is not a new result as previous literature has documented that CAPM does not hold empirically. However, when we add the liquidity factor in specification 2, the intercept becomes insignificant (*t*-statistic=0.06), and there are premia on betas relative to the market factor (*t*-statistic=4.56) and the liquidity factor (*t*-statistic=2.53). This confirms the two-factor model (1) in the cross-section. When we add liquidity level as the characteristics in specification 3, the significance level of the point estimate relative to the liquidity factor is attenuated but still significant (*t*-statistic= 2.13) at the 5 percent level over the entire sample. However, the premium for the liquidity level, as a characteristic, is not significant (*t*-statistic=0.36). These results show that liquidity risk factor captures systematic risks beyond those of market risk factor and that it explains liquidity-related co-variation in returns independent of liquidity level. The findings are barely changed when we control for the relative size in the specification 4; liquidity risk is priced in the two factor model while there is no premium for the liquidity characteristic. The premium for the liquidity factor found in specification 6 is 0.41 (*t*-statistic=2.00) percent or 41 basis points.

The results from the subsamples are very similar to those reported above for the entire sample. Significant intercepts in specifications 1 and insignificant ones in specifications 2 in panels A and B indicate that liquidity-augmented CAPM risk model explains variation of returns better than the CAPM. Moreover, the premium for liquidity risk factor in specification 3 is marginally significant in both sub-samples. However, this premium becomes insignificant when we include the liquidity level in the model in specification 3.The result in specification 4 is slightly different in the subsamples. While the premium for the liquidity risk is significant over the pre-1963 subsample, it is insignificant for post-1963

subsample. However, in both sub-samples the *t*-statistic for the slope of the liquidity beta is higher than that of the liquidity level suggesting liquidity risk is more important than the liquidity characteristics in explaining the cross section of returns.

In above cross-sectional analysis we have used liquidity level, EFFT, as the proxy for the liquidity characteristics. We repeat all above analyses using the idiosyncratic EFFT, as the proxy for the liquidity characteristics, which is the error term in the time-series regression of EFFT level on the liquidity risk factor, LIQ. The results are barely modified and reported in the appendix C.

In summary, the cross sectional results show that the risk model outperforms the characteristics model and that the two-factor model is able to explain the cross-sectional variations in expected returns. These findings are robust to several specifications and over different sub-samples.

8. Conclusion

In this paper we have shown that market wide liquidity risk is priced in a two-factor asset pricing framework. We have further demonstrated that the hypothesis that liquidity risk is characteristic rather than market wide cannot be supported.

We developed a liquidity augmented CAPM model where the liquidity factor is constructed using portfolios which are neutral with respect to loadings of the market factor. The Holden (2009) low frequency liquidity measure, EFFT, was adopted as a proxy for intraday effective spread and computed using daily data. The liquidity premium (which is neutral with respect to size effects) in average returns for July 1931–December 2008 is 0.42 percent per month (*t*-statistic=3.28). We show that when portfolios are formed from independent sorts of stocks on size and the liquidity level measure (EFFT), the two-factor

model cannot be rejected by the GRS F-test. We also test the two factor model in the cross-section using GMM approach and we show that the model holds over the entire sample of 1931-2008 and subsamples of pre and post 1963. The intercepts are statistically indifferent from zero in all specifications tested in the cross sectional analyses.

To investigate whether the liquidity premium is due to the liquidity characteristic or the systematic liquidity risk we isolate the variation in liquidity loadings from the variation in liquidity levels by using a triple-sorting approach based on size, liquidity level and liquidity loadings. The liquidity risk loading determines expected returns of arbitrage portfolios of Hliqbeta-Lliqbeta according to the two factor risk model, irrespective of the liquidity characteristic. This result is robust over the sample of 78 years from 1931 to 2008, and sub-samples of pre- and post-1963. The intercept in the Hliqbeta-Lliqbeta two-factor regression is close to zero both economically and statistically over the different samples. The results of the cross-sectional analysis over the entire sample also confirm that liquidity characteristic does not have significant predictive power beyond the liquidity risk in the two-factor framework. The implication of this study is important for both academics and practitioners; it provides clear guidance on the impact of liquidity on expected returns and demonstrates that the liquidity augmented CAPM approach is the correct way to incorporate this risk factor.

Appendices:

Appendix A: Computation of EFFT in the decimal pricing system

This section presents the general formula for the EFFT, which works on any decimal (or fractional) price grid. It is based on Appendix A in Holden (2009) and also his example on his website[5].

In a fractional price grid, the price increments overlap completely between adjacent spread levels. For example, all wholes are halves, all halves are quarters, all quarters are eighths, all eighths are sixteenths, etc. However, this does not hold in the decimal system. In the decimal price grid under consideration, all dollars are quarters, all dimes are nickels, and all nickels are pennies, but quarters are different. Two quarters are dimes ($0.50, $1.00) and two quarters are not dimes ($0.25, $0.75). The latter two quarters overlap with nickels (two spread layers down), but not dimes (one spread layer down). Holden (2009) suggests a way to identify and track these overlaps in computing EFFT.

Based on his approach for the decimal system, it is assumed that the possible effective spreads (the s_j 's) are $0.01, $0.05, $0.10, $0.25, and $1.00 and $J = 5$.

Let A_j be the *total* number of (trade) prices corresponding to the jth spread ($j =1, 2,$K$, J$). For prices, there are 100 pennies, 20 nickels, 10 dimes, 4 quarters, and 1 dollar, so $A_1 =100$, $A_2 = 20$, $A_3 =10$, $A_4 = 4$, and $A_5 =1$.

Holden defines *special* price increments for the jth spread as price increments that can be generated by the jth spread, but not by any larger spreads. Let B_j be the number of special prices and corresponding to the jth spread ($j =1, 2,$K$, J)$. Also let O_{jk} be the number of price increments for the jth spread ($j =1, 2,…$K$, …, J)$ that *overlap* the price increments of the kth

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[5] www.kelly.iu.edu/cholden

spread and do *not overlap* the price increments of any spreads between the *j*th spread and the *k*th spread. Table A-1 summarises the A_j, B_j, and O_{jk} variables under the decimal price regime.

Table A-1: A_j, B_j and O_{jk} for a decimal price grid

j	Corresponding spread	A_j	B_j	O_{jk}
1	$0.01	100	80	
2	$0.05	20	8	$O_{21}=20$
3	$0.10	10	8	$O_{31}=0$, $O_{32}=10$
4	$0.25	4	3	$O_{41}=0$, $O_{42}=2$, $O_{43}=2$
5	$1.00	1	1	$O_{51}=0$, $O_{52}=0$, $O_{53}=0$, $O_{54}=1$

Then, the general formula for the unconstrained probability of the *j*th spread is

$$U_j = \begin{cases} \left(\dfrac{A_1}{B_1}\right)F_1 & j=1 \\ \left(\dfrac{A_j}{B_j}\right)F_j - \sum_{k=1}^{j-1}\left(\dfrac{O_{jk}}{B_k}\right)F_k & j=2,3,...,J \end{cases} \tag{A1}$$

The rest of the effective tick computation is the same as the fraction grid case in the body of the text.

Appendix B: Aggregate liquidity as a state factor

In this section, we examine to what extent the market level liquidity measured by aggregate EFFT captures the real market conditions. The aggregate EFFT at the end of month t ($MEFFT_t$) is the average of individual EFFTs across all stocks at the end of month t:

$$MEFFT_t = \frac{1}{N_t} \sum_{i=1}^{N_t} EFFT_{i,t} \qquad\qquad (B1)$$

where $EFFT_{i,t}$ is the liquidity measure for stock i computed at the end of month t and N_t is the number of stocks eligible for our sample at the end of month t.

We use the equally-weighted CRSP NYSE/AMEX/NASDAQ index returns to describe the economic conditions. We follow the approach suggested by Liu (2006) and run the regressions of MEFFT on market returns and vice-versa at lags 3, 6, 9 and 12 over the period 1927–2008. The estimates are reported in Table B-1. The results show that aggregate liquidity depends on past market performance, but the opposite relation is not significant. Moreover, the negative relation between market returns and aggregate EFFT suggests that liquidity declines after the poor market conditions. This is in line with the results of Liu (2006) and Korajczyk and Sadka (2008), who document that returns predict liquidity, but the converse does not hold. These regression results are consistent with what would be observed during an economic crisis. As we explained in detail at the end of data section (Section 3), large declines in aggregate liquidity follow economic and financial events over the last century. For example, consider the low liquidity over periods 1929–1933 (Great Depression), 1937–1943 (1937 recession and World War II), 1972–1975 (oil embargo and collapse of the world's monetary system), 1987–1991(market crash 1987 and Persian Gulf War) and 1997–2001 (1997 Asian financial crisis, Russian default and collapse of LTCM). In all these events liquidity is related to the market performance simultaneously or with a time lag.

Table B-1: Regression analysis on aggregate liquidity and market returns

Panel A:	$MEFFT_t = \alpha_0 + \alpha_1 R_{m,t-x}$			
	Lags			
	X=3	X=6	X=9	X=12
Intercept	0.0147	0.0137	0.0137	0.0138
	(21.19)	(21.02)	(20.79)	(20.77)
$R_{m,t-x}$	-0.0179	-0.0145	-0.0163	-0.0185
	(-2.55)	(-1.92)	(-2.13)	(-2.61)
Adjusted R^2	0.02	0.02	0.02	0.03

Panel B:	$R_{m,t} = \beta_0 + \beta_1 MEFFT_{t-x}$			
	Lags			
	X=3	X=6	X=9	X=12
Intercept	0.0004	0.0070	0.0032	-0.0011
	(0.07)	(1.17)	(0.61)	(-0.17)
$MEFFT_{t-x}$	0.7087	0.2145	0.4980	0.8077
	(1.27)	(0.45)	(1.22)	(1.66)
Adjusted R^2	0.006	0.0006	0.002	0.007

Numbers in parentheses are *t*-statistics and adjusted by Newey-West method using five lags.

Appendix C: Cross-sectional analysis using idiosyncratic liquidity

In this section, we use orthogonalised EFFT, as the proxy for the liquidity characteristic, and repeat all the cross-sectional analyses conducted in section 6. Orthogonalised liquidity, denoted *EFFT_orth* for each stock month, is the error term in the following time-series regression.

$$EFFT_{it} = \alpha_0 + \beta_i LIQ_t + \varepsilon_{it} \qquad (C1)$$

where $EFFT_{i,t}$ is the liquidity of the stock *i* measured at the end of month *t*. $LIQ_{i,t}$ is the liquidity risk factor constructed using the procedure described in the text and ε_{it} is the error term. In order to conduct our cross-sectional analyses we compute the $EFFT\_orth_{i,t}$ for each

of 27 portfolios constructed in section 6. $EFFT\_orth_{i,t}$ for portfolio i in month t is computed at the end of the past June as the average of the portfolio monthly $EFFT\_orth$s over the prior 12 months. We use $EFFT\_orth_{i,t}$ instead of $EFFT_{i,t}$ in equation 10 and repeat the GMM estimations conducted in section 6. Table C-1 reports the results.

Table C-1: Cross-sectional analysis using orthogonalised liquidity level as the liquidity characteristic

	Specification			
Variable	1	2	3	4
Panel A: 07/1931 -12/2008				
Intercept	0.0097	0.0057	-0.0881	-0.3398
	(4.52)	(0.06)	(-0.67)	(-0.89)
β_i^m	0.0035	0.3294	0.5057	0.2104
	(1.03)	(4.56)	(4.48)	(1.33)
β_i^l		0.3577	0.3576	0.4183
		(2.53)	(2.32)	(2.00)
EFFT			0.5496	0.9174
			(0.32)	(0.47)
R_Size				0.022
				(0.80)
Panel B: 07/1931 - 06/1963				
Intercept	0.0121	0.0091	-0.0845	-0.3623
	(3.09)	(0.07)	(-0.38)	(-0.67)
β_i^m	0.0035	0.3281	0.5111	0.2088
	(0.60)	(2.44)	(2.34)	(1.13)
β_i^l		0.3565	0.3672	0.4622
		(1.78)	(1.51)	(2.26)
EFFT			0.5486	0.9164
			(0.26)	(0.39)
R_Size				0.0307
				(0.89)
Panel C: 07/1963 - 12/2008				
Intercept	0.0078	0.0036	-0.091	-0.3328
	(3.64)	(0.03)	(-0.56)	(-0.59)
β_i^m	0.0037	0.3301	0.5022	0.2087
	(1.11)	(3.98)	(3.91)	(0.84)
β_i^l		0.3583	0.3526	0.4012
		(1.75)	(1.65)	(1.09)
EFFT			0.5501	0.9181
			(0.18)	(0.21)
R_Size				0.0207
				(0.44)

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Table 1: Summary statistics for the stocks.

The summary statistics of the monthly cross-sectional means for NYSE stocks from January, 1926 to December, 2008 (996 months) are shown. For each month, the mean of each variable is computed across the stocks, which resulted in a time-series of means. The table presents the summary statistics for this time-series. For each firm-month: Return is adjusted for splits and dividends, as reported in CRSP monthly stocks file. The liquidity proxy, EFFT, is estimated from daily data. Size is the market value of the equity of the firm in billions of dollars. Mean and median of Returns and EFFT are in percent. The sample is all non-financial firms listed in NYSE and drawn from the CRSP. Selection criteria have been explained in the text.

Variable	Mean	Std Dev	Median
Return	1.17	0.072	1.4
EFFT	1.24	0.007	1.1
Size (in $ Billion)	1.5108	2.3508	0.4380

Table 2: Properties of the systematic risk factors

The table represents summary statistics of the Fama–French three factors, liquidity factor, LIQ, and its underlying portfolios.

LIQ is constructed as follows. At the end of June of each year t, stocks are ranked based on their CAPM beta computed using the previous three to five years and three portfolios are constructed: low beta, neutral beta and high beta. The breakpoints are the bottom 30 percent, middle 40 percent, and top 30 percent of the values of beta for the NYSE stocks. Then, within each of the beta portfolios, stocks are sorted based on their EFFT at the end of June into three additional portfolios: high liquid, medium liquid and low liquid portfolios. The breakpoints are the bottom 30 percent, middle 40 percent, and top 30 percent of the values of EFFT for the stocks in the sample. The nine portfolios are rebalanced at the end of June of each year. The mimicking liquidity factor, LIQ, is constructed as the monthly profits from taking a long position on the three (equally weighted) low-liquid portfolios (Lbeta/iLiq, Mbeta/iLiq, Hbeta/iLiq) and a short position on the three (equally weighted) high-liquid portfolios (Lbeta/Liq, Mbeta/Liq, Hbeta/Liq). RM-RF, SMB and HML are market, size and book-to-market factors obtained from French's (2010) website.

The table reports the summary statistics of the monthly percent returns of the six portfolios underlying LIQ factor as well as the monthly percent returns of four factors. The values are reported over three samples: panel A: from July 1931 to December 2008, panel B: from July 1931 to December 1962, panel C: from July 1963 to December 2008.

	RM-RF	SMB	HML	LIQ	Lbeta/Liq	Lbeta/iliq	Mbeta/Liq	Mbeta/iliq	Hbeta/Liq	Hbeta/iliq
Panel A: 07/1931-12/2008: 930 months										
Ave	0.57	0.29	0.42	0.42	0.87	1.29	1.05	1.40	0.98	1.46
Std	0.05	0.03	0.04	0.04	0.05	0.07	0.06	0.09	0.09	0.11
t-statistics	3.25	2.61	3.59	3.28	5.58	5.82	5.22	5.01	3.44	4.12
Pearson correlations:										
SMB	0.27									
HML	0.00	-0.01								
LIQ	0.19	0.67	0.33	1.00						
Panel B: 07/1931-12/1962: 378 months										
Ave	0.83	0.35	0.40	0.56	0.72	1.48	1.10	1.66	1.17	1.53
Std	0.07	0.04	0.04	0.05	0.06	0.09	0.08	0.11	0.11	0.14
t-statistics	2.51	1.91	1.76	2.31	2.41	3.32	2.79	2.91	2.05	2.15
Pearson correlations:										
SMB	0.27									
HML	0.44	0.22								
LIQ	0.29	0.63	0.53	1.00						
Panel C: 07/1963-12/2008: 510 months										
Ave	0.36	0.22	0.42	0.30	0.96	1.11	1.00	1.18	0.76	1.34
Std	0.05	0.03	0.03	0.03	0.04	0.05	0.05	0.06	0.06	0.08
t-statistics	1.79	1.53	3.19	2.06	5.65	4.93	4.65	4.26	2.68	3.74
Pearson correlations:										
SMB	0.28									
HML	-0.38	-0.20								
LIQ	0.11	0.69	0.16	1.00						

Table 3: Two-factor regressions for nine size- and liquidity-sorted portfolios

The table reports the coefficients of the regression of nine portfolios which are the intersection of size and liquidity groups. At the end of June of each year *t*, stocks are ranked based on their market capitalisation. Three portfolios based on the breakpoints for the bottom 33 percent, middle 34 percent, and top 33 percent of the values of market capitalisation for the NYSE stocks are constructed: Small, Medium, and Big (S, M and B). Within each size portfolio, stocks are sorted based on their EFFT at the end of June into three additional portfolios: Liquid, Medium liquid and illiquid (L, M, iL). The breakpoints are the bottom 33 percent, middle 34 percent, and top 33 percent of the values of EFFT for the stocks in the sample. The nine portfolios (S/L, S/M, S/iL, M/L, M/M, M/iL, B/L, B/M and B/iL) are rebalanced at the end of June of each year.

For each portfolio, the following two-factor model is estimated

$$R_{it} - R_{ft} = \alpha_0 + \beta_i^m (R_{mt} - R_{ft}) + \beta_i^l LIQ_t + e_{it}$$

Where R_{it} is the equally weighted monthly return on portfolio *i* and R_{mt} is value-weight monthly return on all NYSE, AMEX, and NASDAQ stocks. R_{ft} is the one-month Treasury bill rate and LIQ_t is the monthly liquidity factor. *T*-statistics (in parentheses) are adjusted by the White (1980) method.

Firms represents the rounded average number of firms in the portfolio. EFFT is the average of the stock EFFTs in a portfolio and in percentage. Size is the value-weighted average of the stock market capitalisations in a portfolio and in millions of dollars. Excess return is the monthly average of the excess return for each portfolio. *F*-statistics and *p*-values are the results of GRS (Gibbons, Ross and Shanken, 1989) test over each sample period.

	firms	EFFT	Size	Excess returns	α_0	β_i^m	β_i^l	Adj-R^2
7/1931-12/2008								
S/L	82	1.091	116.19	0.92	0.0008 (0.80)	1.19 (35.16)	0.47 (10.30)	0.86
S/M	84	1.689	88.90	1.08	0.0001 (0.11)	1.25 (36.82)	0.91 (19.84)	0.90
S/iL	80	3.967	58.98	1.42	0.0011 (1.22)	1.17 (44.94)	1.51 (27.37)	0.93
M/L	86	0.652	427.92	0.76	0.0007 (0.91)	1.16 (45.73)	0.12 (3.73)	0.89
M/M	89	0.852	380.03	0.84	0.0003 (0.40)	1.19 (43.73)	0.32 (9.48)	0.90
M/iL	86	1.383	354.52	0.80	-0.0007 (-0.87)	1.18 (53.93)	0.55 (19.57)	0.91
B/L	85	0.369	5929.40	0.57	0.0001 (0.33)	1.03 (59.10)	-0.14 (-7.57)	0.94
B/M	88	0.524	3760.55	0.60	-0.0001 (-0.14)	1.05 (65.55)	-0.02 (-1.25)	0.94
B/iL	85	0.824	2710.36	0.69	-0.0003 (-0.57)	1.09 (55.94)	0.23 (8.81)	0.92
GRS test results	*F*-statistic=0.69			*p*-value = 0.72				
7/1931-12/1962								
S/L	44	1.386	14.42	1.13	-0.0006 (-0.36)	1.38 (31.62)	0.31 (4.51)	0.90
S/M	44	2.132	12.09	1.44	-0.0008 (-0.56)	1.42 (34.27)	0.82 (14.13)	0.94
S/iL	42	4.998	8.45	1.92	0.0011 (0.73)	1.26 (35.93)	1.46 (17.00)	0.94
M/L	47	0.800	48.90	0.95	-0.0005 (-0.44)	1.29 (42.75)	-0.01 (-0.13)	0.93
M/M	48	1.063	43.97	1.08	-0.0012 (-1.08)	1.34 (44.05)	0.23 (5.24)	0.94
M/iL	47	1.765	40.66	1.08	-0.0013 (-1.08)	1.28 (43.73)	0.48 (13.34)	0.94
B/L	47	0.431	709.31	0.76	-0.0009 (-1.43)	1.06 (39.43)	-0.16 (-5.88)	0.97
B/M	49	0.622	300.82	0.81	-0.0009 (-1.43)	1.10 (48.47)	-0.05 (-1.86)	0.97
B/iL	47	1.085	198.55	0.97	-0.0013 (-1.68)	1.17 (60.20)	0.25 (8.89)	0.96
GRS test results	*F*-statistic = 1.00			*p*-value = 0.43				
7/1963-12/2008								
S/L	112	0.856	198.75	0.72	0.0016 (1.46)	0.97 (31.02)	0.58 (12.68)	0.82
S/M	116	1.338	151.22	0.76	0.0007 (0.65)	1.03 (34.39)	0.92 (15.24)	0.86
S/iL	110	3.155	99.95	1.00	0.0010 (0.97)	1.06 (34.50)	1.53 (27.17)	0.91
M/L	118	0.535	735.56	0.60	0.0013 (1.40)	1.00 (39.24)	0.20 (5.38)	0.83
M/M	121	0.683	652.80	0.64	0.0014 (1.43)	0.99 (38.79)	0.35 (8.52)	0.84
M/iL	118	1.081	609.30	0.57	-0.0001 (-0.13)	1.06 (40.63)	0.59 (13.21)	0.86
B/L	116	0.318	10162.93	0.42	0.0007 (1.12)	0.99 (50.31)	-0.14 (-5.14)	0.90
B/M	119	0.446	6570.01	0.42	0.0006 (0.78)	0.98 (48.40)	-0.02 (-0.81)	0.89
B/iL	115	0.617	4750.11	0.46	0.0006 (0.76)	0.96 (39.70)	0.14 (3.44)	0.86
GRS test results	*F*-statistic=1.19			*p*-value = 0.30				

Table 4: Two-factor regressions for portfolios based on size, EFFT and liquidity loadings

The table reports the coefficients of the regression of 27 portfolios sorted on size, EFFT and liquidity loadings. At the end of June of each year t, stocks are ranked based on their market capitalisation.

Three portfolios based on the breakpoints for the bottom 33 percent, middle 34 percent, and top 33 percent of the values of market capitalisation for the NYSE stocks are constructed: Small, Medium, and Big (S, M and B). Then, within each size portfolio, stocks are sorted based on their EFFT at the end of June into three portfolios: Liquid, Medium liquid and Illiquid (L, M, iL). The breakpoints are the bottom 33 percent, middle 34 percent, and top 33 percent of the values of EFFT for the stocks in the sample. In each of the nine portfolios, (S/L, S/M, S/iL, M/L, M/M, M/iL, B/L, B/M and B/iL) stocks are sorted based on their liquidity loadings. Liquidity loadings for each stock are estimated via the two factor (LIQ-augmented CAPM) model for each stock using the previous three to five years. Three portfolios based on the breakpoints for the bottom 33 percent, middle 34 percent, and top 33 percent of the values of liquidity loadings for the stocks within each size-EFF portfolios are constructed: Low liquidity beta, Medium Liquidity beta and High liquidity beta (Lliqbeta, Mliqbeta, Hliqbeta). In total, 27 portfolios are formed. The following two-factor model is estimated for each portfolio

$$R_{it} - R_{ft} = \alpha_0 + \beta_i^m (R_{mt} - R_{ft}) + \beta_i^l LIQ_t + e_{it}$$

Where R_{it} is the equally weighted monthly return on portfolio i and R_{mt} is value-weight monthly return on all NYSE, AMEX, and NASDAQ stocks. R_{ft} is the one-month Treasury bill rate and LIQ_t is the monthly liquidity factor. T-statistics (in parentheses) are adjusted by the White (1980) method. Firms is the rounded average number of firms in the portfolio. EFFT is the average of the stock EFFTs in a portfolio and in percentage. Size is the value-weighted average of the stock market capitalisations in a portfolio and in million dollars. Excess return is the monthly average of the excess return for each portfolio.

	firms	EFFT	Size	Excess Returns	α_0	β_i^m	β_i^l	Adj-R^2
Illiquid								
S/iL/Lliqbeta	23	2.571	84.01	0.985	-0.0003 (-0.27)	1.10 (31.19)	1.29 (25.19)	0.83
S/iL/Mliqbeta	24	3.171	66.01	1.112	0.0004 (0.36)	1.09 (30.15)	1.50 (24.57)	0.81
S/iL/Hliqbeta	23	4.801	61.84	1.511	0.0021 (1.38)	1.23 (25.01)	2.05 (17.82)	0.80
M/iL/Lliqbeta	25	0.990	517.36	0.756	0.0004 (0.47)	1.01 (32.46)	0.40 (9.08)	0.76
M/iL/Mliqbeta	26	1.121	479.63	0.797	0.0002 (0.22)	1.04 (40.22)	0.56 (13.51)	0.80
M/iL/Hliqbeta	25	1.509	447.27	0.844	-0.0009 (-0.77)	1.23 (36.01)	0.71 (13.43)	0.78
B/iL/Lliqbeta	25	0.603	5213.31	0.488	-0.0003 (-0.37)	0.89 (31.41)	-0.03 (-0.61)	0.72
B/iL/Mliqbeta	26	0.652	3512.42	0.643	0.0004 (0.54)	0.95 (41.20)	0.13 (3.74)	0.81
B/iL/Hliqbeta	25	0.798	2872.69	0.706	0.0000 (-0.05)	1.04 (43.11)	0.33 (8.52)	0.82
Medium liquid								
S/M/Lliqbeta	25	1.268	121.76	0.813	-0.0002 (-0.20)	1.03 (31.59)	0.79 (13.68)	0.80
S/M/Mliqbeta	25	1.379	104.47	1.017	0.0010 (0.96)	1.12 (16.45)	0.92 (31.08)	0.81
S/M/Hliqbeta	25	1.534	102.91	1.011	0.0001 (0.12)	1.22 (42.87)	0.97 (20.02)	0.81
M/M/Lliqbeta	26	0.689	553.84	0.738	0.0009 (0.95)	1.00 (27.15)	0.19 (3.95)	0.73
M/M/Mliqbeta	27	0.715	515.76	0.862	0.0017 (2.06)	1.03 (38.80)	0.28 (6.90)	0.80
M/M/Hliqbeta	26	0.771	493.99	0.947	0.0015 (1.55)	1.16 (41.17)	0.37 (9.22)	0.79
B/M/Lliqbeta	26	0.456	6481.72	0.555	0.0002 (0.27)	0.96 (37.78)	-0.14 (-4.03)	0.80
B/M/Mliqbeta	26	0.468	5078.87	0.590	0.0007 (1.04)	0.96 (40.70)	-0.03 (-0.84)	0.83
B/M/Hliqbeta	26	0.496	3504.29	0.734	0.0009 (1.36)	1.04 (51.07)	0.07 (2.53)	0.84
Liquid								
S/L/Lliqbeta	24	0.865	154.27	0.967	0.0026 (2.63)	0.99 (28.37)	0.41 (9.27)	0.74
S/L/Mliqbeta	25	0.920	150.24	0.968	0.0020 (2.04)	1.04 (31.97)	0.52 (13.22)	0.77
S/L/Hliqbeta	24	0.973	135.58	0.969	0.0007 (0.63)	1.21 (31.78)	0.63 (9.90)	0.75
M/L/Lliqbeta	25	0.557	613.95	0.714	0.0010 (1.15)	1.00 (34.09)	0.06 (1.38)	0.76
M/L/Mliqbeta	26	0.570	582.72	0.774	0.0016 (1.83)	0.98 (35.21)	0.13 (3.05)	0.77
M/L/Hliqbeta	25	0.575	540.81	0.733	0.0001 (0.07)	1.13 (46.43)	0.21 (5.07)	0.79
B/L/Lliqbeta	25	0.326	9336.34	0.541	0.0002 (0.35)	0.99 (40.94)	-0.26 (-8.57)	0.84
B/L/Mliqbeta	26	0.338	8610.34	0.639	0.0008 (1.44)	0.98 (42.63)	-0.09 (-2.43)	0.85
B/L/Hliqbeta	25	0.358	4999.59	0.633	0.0004 (0.58)	1.01 (53.59)	-0.02 (-0.61)	0.82

Table 5: Two-factor regressions for the arbitrage portfolio based on size, EFFT and liquidity loadings

At the end of June of each year *t*, stocks are ranked based on their market capitalisation. Three portfolios based on the breakpoints for the bottom 33percent, middle 34 percent, and top 33 percent of the values of market capitalisation for the NYSE stocks are constructed: Small, Medium, and Big (S, M and B). Then, within each size portfolio, stocks are sorted based on their EFFT at the end of June and three portfolios are constructed: Liquid, Medium liquid and illiquid (L, M, iL). The breakpoints are the bottom 33 percent, middle 34 percent, and top 33 percent of the values of EFFT for the stocks in the sample. In each of the nine portfolios, (S/L, S/M, S/iL, M/L, M/M, M/iL, B/L, B/M and B/iL) stocks are sorted based on their liquidity loadings. Liquidity loadings for each stock are estimated via the two factor (LIQ-augmented CAPM) model for each stock using the previous three to five years. Three portfolios based on the breakpoints for the bottom 33 percent, middle 34 percent, and top 33 percent of the values of liquidity loadings for the stocks within each size-EFFT portfolios are constructed: Low liquidity beta, Medium Liquidity beta and High liquidity beta (Lliqbeta, Mliqbeta, Hliqbeta). Therefore, 27 equally weighted portfolios are formed. The arbitrage portfolio return, Hliqbeta-Lliqbeta, is ((S/iL/Hliqbeta – S/iL/Lliqbeta) + (S/M/Hliqbeta – S/M/Lliqbeta) + (S/L/Hliqbeta – S/L/Lliqbeta) + (M/iL/HLiqbeta - M/iL/Lliqbeta) + (M/M/Hliqbeta - M/M/Lliqbeta) + (M/L/Hliqbeta – M/L/Lliqbeta) + (B/iL/Hliqbeta – B/iL/Lliqbeta) + (B/M/Hliqbeta - B/M/Lliqbeta) + (B/L/Hliqbeta - B/L/Lliqbeta))/9 .

The following two-factor model is estimated for each portfolio

$$(Hliqbeta - Lliqbeta)_t - R_{ft} = \alpha_0 + \beta_i^m (R_{mt} - R_{ft}) + \beta_i^l LIQ_t + e_{it}$$

where *(Hliqbeta-Lliqbeta)$_t$* is the return on portfolio *i* and R_{mt} is value-weight monthly return on all NYSE, AMEX, and NASDAQ stocks. R_{ft} is the one-month Treasury bill rate and LIQ_t is the monthly liquidity factor. *T-statistics* (in parentheses) are adjusted by the White (1980) method. Mean is the average of Hliqbeta-Lliqbeta returns and in percent.

	Mean	α_0	β_i^m	β_i^l	Adj-R^2
7/30-12/2008	0.2	0.000	0.14	0.29	0.31
	(2.29)	(0.05)	(7.36)	(10.35)	
7/30-12/62	0.12	0.001	0.16	0.37	0.25
	(0.56)	(0.28)	(2.06)	(5.79)	
7/63-12/2008	0.2	0.000	0.18	0.32	0.36
	(1.69)	(0.25)	(6.96)	(8.63)	

Table 6: Systematic liquidity and liquidity characteristic in the cross section

The table shows the results of the cross-sectional analysis of liquidity effects on 27 portfolios sorted on size, EFFT and liquidity loadings. Liquidity loadings for portfolio construction are estimated via the two factor (LIQ-augmented CAPM) model for each stock using the previous three to five years. The following two-factor model is estimated for each portfolio

$$R_{it} - R_{ft} = \alpha_0 + \beta_i^m (R_{mt} - R_{ft}) + \beta_i^l LIQ_t + e_{it}$$

where R_{it} is the equally weighted monthly return on portfolio i and R_{mt} is the value-weighted monthly return on all NYSE, AMEX, and NASDAQ stocks. R_{ft} is the one-month Treasury bill rate and LIQ_t is the monthly liquidity factor. The estimated liquidity and market factor loadings (β_i^m and β_i^l) are used in the following regression model

$$R_{it} - R_{ft} = \delta_0 + \lambda_m \beta_i^m + \lambda_{liq} \beta_i^l + \delta_{liq} EFFT_{it} + \delta_{size} R\_Size_{it} + u_{it}$$

where $EFFT_{it}$ is the measure for the illiquidity level for portfolio i in month t, computed at the end of the past June as the average of the portfolio monthly EFFTs over the prior 12 months. R_Size_{it} is the log relative market capitalisation which is the log market capitalisation relative to the cross-sectional median of log market capitalisations at the end of past June. Estimation of factor loadings in above first equation and the slopes in the second equations is done simultaneously using GMM method to avoid estimation error in the factor loadings. *T-statistics* are corrected for heteroskedasticity using GMM standard errors and reported in parentheses. The sample includes NYSE common stocks for the period of July 1931 to December 2008. The first 60 months are used to estimate pre-ranking betas to form 27 portfolios.

Variable	Specification			
	1	2	3	4
Panel A: 07/1931 -12/2008				
Intercept	0.0097	0.0057	-0.0945	-0.3467
	(4.52)	(0.06)	(-0.73)	(-0.88)
β_i^m	0.0035	0.3294	0.4972	0.2076
	(1.03)	(4.56)	(4.38)	(1.34)
β_i^l		0.3577	0.3496	0.4142
		(2.53)	(2.13)	(2.00)
EFFT			0.5372	0.9115
			(0.36)	(0.57)
R_Size				0.0245
				(0.82)
Panel B: 07/1931 - 06/1963				
Intercept	0.0121	0.0091	-0.0922	-0.3707
	(3.09)	(0.07)	(-0.42)	(-0.65)
β_i^m	0.0035	0.3281	0.4957	0.2042
	(0.60)	(2.44)	(2.30)	(1.11)
β_i^l		0.3565	0.3488	0.4579
		(1.78)	(1.37)	(2.23)
EFFT			0.5351	0.9086
			(0.27)	(0.35)
R_Size				0.0339
				(0.85)
Panel C: 07/1963 - 12/2008				
Intercept	0.0078	0.0036	-0.0957	-0.3399
	(3.64)	(0.03)	(-0.60)	(-0.58)
β_i^m	0.0037	0.3301	0.4988	0.2066
	(1.11)	(3.98)	(3.89)	(0.84)
β_i^l		0.3583	0.3509	0.3985
		(1.75)	(1.57)	(1.09)
EFFT			0.5385	0.9132
			(0.23)	(0.31)
R_Size				0.0234
				(0.45)

Figure 1: Cross-sectional averages of EFFTs.

This plot shows the time-series of the cross-sectional averages of the monthly percentage EFFTs (aggregate EFFT) for NYSE stocks over the period of January 1926 to December 2008. The sample is drawn from the CRSP population. Selection criteria have been explained in the text. For each firm-month, the transaction costs proxy, EFFT, is estimated from daily data. Then, the mean of the EFFTs across the stocks is computed for each month. This gives a time-series of means, displayed in the plot.