Liquidity Risk and the Beta Premium

Gong, Cynthia ; Luo, Di; Zhao, Huainan

Published in:
Journal of Financial Research

DOI:
10.1111/jfir.12263

Publication date:
2022

Author accepted manuscript: Gong, C, Luo, D & Zhao, H 2022, 'Liquidity Risk and the Beta Premium', Journal of Financial Research, vol. 44, no. 4, pp. 789 - 814. https://doi.org/10.1111/jfir.12263

Liquidity Risk and the Beta Premium

Cynthia M. Gong[a], Di Luo[b,*], and Huainan Zhao[c]

[a] School of Business and Economics, Loughborough University, Loughborough, LE11 3TU UK. M.C.Gong@lboro.ac.uk

[b] Business School, University of Southampton, Highfield Campus, Southampton, SO17 1BJ, UK. d.luo@soton.ac.uk

[c] School of Business and Economics, Loughborough University, Loughborough, LE11 3TU, UK. H.Zhao6@lboro.ac.uk

We thank Erik Devos (the Editor) and an anonymous referee for their insightful comments and suggestions. We are grateful to Joonki Noh (the discussant) and Daniel Huberand (the discussant) and conference participants at the Financial Management Association (FMA) 2020 meeting, British Accounting and Finance Association 2021 meeting, and French Finance Association (AFFI) 2021 international conference for their helpful comments and suggestions. We are grateful to the financial support from the National Natural Science Foundation of China (Grant No.71991473 and No.71671076).

*Correspondence: Dr. Di Luo, Business School, University of Southampton, Highfield Campus, Southampton, SO17 1BJ, UK. Email: d.luo@soton.ac.uk

Liquidity Risk and the Beta Premium

Abstract

As opposed to the "low beta low risk" convention, we show that low beta stocks are illiquid and exposed to high liquidity risk. After adjusting for liquidity risk, low beta stocks no longer outperform high beta stocks. Although investors who "bet against beta" earn a significant beta premium under the Fama–French three- or five-factor models, this strategy fails to generate any significant returns when liquidity risk is accounted for. Our work helps understand the beta premium from a new liquidity-risk perspective, and draws useful implications for both fund and corporate managers.

JEL classification: G12; G14; G30

Keywords: Liquidity risk; Beta premium; Cross-sectional stock returns

1 Introduction

Based on the conventional Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965), beta fully captures the risk exposure: low beta stocks are regarded as safer securities and investors are content with low returns for holding low beta stocks.

Despite this broadly held convention, the relation between beta and realized stock returns is rather weak or even negative. Studies such as Friend and Blume (1970), Black et al. (1972), and Frazzini and Pedersen (2014) show that low beta stocks actually earn higher returns than high beta stocks (i.e., the beta premium), which challenges the "low beta low risk" perception and questions beta's ability in capturing systematic risk.

The empirical difficulties facing the CAPM have been very well discussed in Roll's critique. Roll (1977) argues that: "The theory is not testable unless the exact composition of the true market portfolio is known and used in the tests" (Page 130); while a true market portfolio should also include all other assets such as bonds, properties, commodities, and human capital (Roll, 1977, Lustig et al., 2013, and Doeswijk et al., 2020). Since the stock market ignores other components of aggregate wealth, it is, clearly, an imperfect proxy for the true market portfolio, and, consequently, the CAPM performs poorly against many market anomalies. Further, given the beta estimation depends on the particular market proxy used, an imperfect proxy of the market portfolio is likely to cause biases in beta estimation. As a result, the beta itself is being criticized as a risk measure (Roll, 1977), which can be one of the reasons for the observed beta premium.[1]

[1] Recent studies offer different explanations for the beta premium. Savor and Wilson (2014) highlight the importance of the macroeconomic news announcements in the relation between beta and returns. Antoniou et al. (2015) investigate the role of investor sentiment in an attempt to explain the relation between beta and returns. Bali et al. (2016) and Cederburg and O'Doherty (2016) show that conditional betas help explain the beta premium. Hong and Sraer (2016) incorporate aggregate disagreement in the

Thus, it is clear that, empirically, the market beta alone is not a complete measure of risk. Liu (2006) argues that the CAPM (and the Fama-French three-factor model) does not account for the liquidity premium (i.e., the liquidity risk to which a security is exposed); and neglecting the liquidity factor omits an important source of priced risk and contaminates the risk measure.[2] Motivated by Roll's (1977) critique and Liu's (2006) study, we test whether the beta premium can be explained by the liquidity risk.

In our study, we first plot the scale of liquidity risk for each of the beta decile portfolios based on three liquidity risk measures, namely, the Pastor and Stambaugh's (2003), Liu's (2006), and Sadka's (2006) measures. We observe a monotonic relation between beta and liquidity risk: low beta stocks are accompanied by high liquidity risk. Investors are likely to require high compensation for holding these low beta stocks due largely to their high liquidity risk exposure. We, therefore, conjecture that liquidity risk may play a significant role in explaining the inverse relationship between beta and stock returns.

[Figure 1 about here]

By examining the NYSE/AMES/NASDAQ data from 1963 to 2017, we confirm the power

---

CAPM to generate a downward-sloping Security Market Line. Bali et al. (2017) attribute the beta premium to lottery demand. Jylhä (2018) highlights the role of margin requirements in the relation between beta and returns. Giglio and Xiu (2019) show that the inverse relation between beta and returns is due to omitted factors. Giorgi et al. (2019) show that the low-minus-high beta premium is driven by the medium-minus-high beta premium while the low-minus-medium beta premium is small. Lou et al. (2019) find that the beta premium is present intraday rather than overnight.

[2] Prior evidence shows that liquidity risk plays an important role in explaining asset prices and liquidity is an important source of priced risk for asset pricing. For example, Amihud and Mendelson (1986), Brennan et al. (1998), Amihud (2002), and Corwin and Schultz (2012) show that illiquid stocks earn higher returns than liquid stocks. Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Liu (2006), Sadka (2006), and Amihud and Noh (2020) show that high liquidity risk stocks command higher risk premium than low liquidity risk stocks. Bekaert et al. (2007), Lee (2011), and Chaieb et al. (2018) highlight the role of liquidity risk in international stock markets. Hendershott et al. (2020) show that illiquidity due to stock market closure affects the relation between beta and stock returns.

of liquidity risk in explaining the beta premium. We find that, after adjusting for the two risk sources (market and liquidity as in the LCAPM of Liu (2006)), the beta premium is no longer significant. Yet, non-liquidity-adjusted models such as the CAPM, the Fama–French three-factor model (FF3FM), the momentum-extended FF3FM, and the Fama and French five-factor model (FF5FM) are unable to explain the beta premium.

Further, we test our hypotheses on portfolios based on bivariate independent sorts of market beta and one of our four liquidity measures. We find that the beta premiums are insignificant, under the FF3FM, momentum-extended FF3FM, and FF5FM, in the high liquidity sub-samples, while become significant in the low liquidity sub-samples. Hence, the beta premiums only appear in portfolios of low-liquidity stocks. This indicates that the commonly-used asset pricing models work well in situations of high stock liquidity, but facing difficulties in circumstances of low liquidity.

We perform a series of robustness tests to check the above results. We use alternative beta measures such as the Vasicek beta (Vasicek, 1973) and the Fama and French beta (Fama and French, 1992); we use alternative portfolio holding period by holding the portfolio for the subsequent 12 months following Cederburg and O'Doherty (2016); we divide the sample equally into two sub-periods; and we test sub-samples of NYSE/AMEX and NASDAQ stocks separately. We also test whether liquidity risk can explain the correlation component of beta premium (Asness et al., 2020). Our results are consistent throughout these tests.

Building on the evidence from portfolio sorts, we perform the Fama–MacBeth (1973) regression analysis to simultaneously control for CAPM beta and some common firm characteristics. We find that low (high) beta stocks generate significant high (low) returns (i.e., the beta premium) in the cross-section, after controlling for the common firm characteristics (i.e., size, book-to-market, momentum, operating profitability, and asset growth). However, the beta premium no longer exists after controlling for liquidity risk.

Next, we investigate the component of CAPM beta (instead of beta itself) in the cross-sectional returns following Bali et al. (2017). The component, which is the residual from regressing beta on liquidity, has no significant power in predicting returns. That is, after removing the liquidity component from beta, we observe no predictability of beta on returns. This further confirms that liquidity plays an important role in the relation between returns and beta.

Further, we test whether the stock liquidity is simply picking up variation in stock returns due to a funding constraint (Frazzini and Pedersen, 2014) or lottery-demand characteristics (Bali et al., 2017). We find that the CAPM beta remains significant after controlling for funding liquidity, which suggests that funding liquidity is not the same as stock liquidity. In terms of the effect of lottery characteristics, the beta is either insignificant or marginally significant depends on which lottery proxies are used. This suggests that the effect of lottery characteristics on beta premium is not very consistent.

Finally, we provide evidence on why liquidity risk explains the beta premium by examining the pricing ability of liquidity risk relative to other risk factors following recent advances in asset pricing tests such as Kan et al. (2013), and Gospodinov et al. (2014). We find that the liquidity risk premium, the premium relating to the covariance between stock returns and the liquidity risk factor are significant in general. This suggests that liquidity risk does matter in explaining the cross-section of stock returns and adds significant explanation power to the beta premium.

Our work draws practical implications to both fund and corporate managers. While the CAPM beta is widely used as a measure of systematic risk, we show that low-beta stocks are not necessarily less risky given their high liquidity risk. Since many funds build low-beta trading strategies to take advantage of the beta premium (Cederburg and O'Doherty, 2016), fund managers ought to understand the role of liquidity risk in delivering such a strategy. Our results also have the potential to be used in corporate financial decision-making. Graham and Harvey (2001) and Jacobs and Shivdasani (2012) show that 70% to 90% of firms use CAPM to estimate their costs of capital. Our evidence suggests that the CAPM beta, the key input for cost-of-capital estimation, can be misleading. A low-beta project can be associated with high liquidity risk, and, hence, its actual cost of capital can be much higher, which implies a lower NPV of the project.

The remainder of the paper proceeds as follows. Section 2 describes the data and methods. Section 3 reports the main empirical results and performs various robustness tests. Section 4 concludes the paper.

2 Data and Methodology

Our sample contains NYSE/AMEX/NASDAQ ordinary common stocks (i.e., stocks with a CRSP share code 10 or 11) over 07/1963–06/2017.[3] We collect data on monthly stock returns, daily returns, daily trading volumes, daily prices per share from CRSP.[4] We measure the monthly market capitalizations of sample stocks using price per share and the number of shares outstanding from CRSP. Using COMPUSTAT annual data, we follow Davis et al. (2000) to

[3] The American Stock Exchange (AMEX) is included in COMPUSTAT data from 1962 (Novy-Marx, 2013).

[4] We make adjustments to delisting returns. If a delisted stock's delisting return is missing, we follow Shumway (1997) and Shumway and Warther (1999) and assume a delisting return of -1 for delisting due to liquidation (CRSP delisting codes 400–490), -0.33 for performance-related delisting (CRSP codes 500 and 520–584), and zero otherwise.

calculate firms' book equity values.[5] We also calculate the book-equity-deflated operating profitability (OP) and the total asset growth rate (AG) as in Fama and French (2015).

We estimate the beta (β^{CAPM}) from the CAPM:[6]

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i^{CAPM} f_{MKTRF,d} + \varepsilon_{i,d} \tag{1}$$

where $R_{i,d}$ is the return of stock i on day d, $R_{f,d}$ is the risk-free rate on day d, and $f_{MKTRF,d}$ is the market factor on day d. We estimate β_i^{CAPM} at the end of each month over the prior 12 months.

We use four illiquidity measures, DV, LM, RV, and TO, to explore the multi-dimension of liquidity: trading quantity, the impact of trading on price, and trading speed. Specifically,

(i) DV is the negative dollar volume measure of Brennan et al. (1998), defined as the daily dollar volume averaged over the prior 12 months.

(ii) LM is the trading discontinuity measure of Liu (2006), defined as the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months,

$$LM = \left[Number\ of\ zero\ daily\ volumes\ in\ prior\ 12\ months + \frac{1/(\textit{12-month turnover})}{20{,}000}\right] \times \frac{(21 \times 12)}{NoTD} \tag{2}$$

where *12-month turnover* is the sum of daily turnover (in percentage) over the prior 12 months, $NoTD$ is the total number of exchange trading days over the

[5] In using COMPUSTAT annual data, we assume that they are available to the public five months after the fiscal year-end date.

[6] Bali et al. (2017) use the same method.

prior 12 months, and 20,000 is chosen so that $0 < \frac{1/(\textit{12-month turnover})}{20{,}000} < 1$ for all sample stocks. The factor $21 \times 12/NoTD$ standardizes the number of one-month trading days in the market to 21, which makes the LM values comparable over time. The LM measure captures the probability of no trading. Large LM (i.e., very infrequent trading) indicates low liquidity.

(iii) RV is the price impact measure of Amihud (2002), defined as the daily absolute-return-to-dollar-volume ratio averaged over the prior 12 months.[7]

(iv) TO is the negative turnover measure of Datar et al. (1998), defined as the daily turnover averaged over the prior 12 months.[8]

Table 1 provides descriptive statistics for the main variables. Because of the different recording methods on trading volumes between NYSE/AMEX and NASDAQ stocks, we report the statistics separately for the two groups.[9] For NYSE/AMEX stocks, the average β^{CAPM} is 0.792 over 1963–2017; while it is 0.673 for NASDAQ stocks over 1984–2017.[10] In line with Bali et al. (2017), β^{CAPM} is positively correlated with firm size (*MV)* and negatively correlated with book-to-market (*BM*). The correlation between β^{CAPM} and asset growth rate (AG) is positive, meaning that firms with high beta stocks have more investment opportunities.

Consistent with our conjecture, β^{CAPM} is negatively correlated with all four illiquidity measures. In other words, low β^{CAPM} stocks tend to have lower trading volumes,

[7] Similar to Amihud (2002), the calculation of RV requires that there are at least 80% non-missing daily trading volumes available in the prior 12 months. Also, the calculation of RV excludes zero trading volumes.

[8] We use negative dollar volume and turnover so that stocks with high DV and TO are less liquid than those with low DV and TO. Constructions of DV, LM, and TO require no missing daily trading volumes in the prior 12 months.

[9] Compared with NYSE/AMEX stocks, trading volumes of NASDAQ stocks are inflated due to intra-dealer transactions.

[10] For NASDAQ stocks, daily trading volume data became available from the beginning of November 1982.

slower trading speed, and larger price impact than high β^{CAPM} stocks, which indicates that low β^{CAPM} stocks tend to be more illiquid.

[Table 1 about here]

3 Empirical results

3.1 Return predictability of beta

We use two common approaches to examine the return predictability of CAPM beta (β^{CAPM}): portfolio analysis and Fama and MacBeth (1973) cross-sectional regression analysis. To perform the portfolio analysis, we form equal-weighted portfolios at the end of each month and hold them for the subsequent one month following Bali et al. (2017).[11]

We measure portfolio performance based on several commonly used asset pricing models including the Fama–French (1993) three-factor model (FF3FM), the Carhart (1997) momentum-extended FF3FM, the Fama–French (2015) five-factor model (FF5FM), and the Liu (2006) liquidity-augmented capital asset pricing model (LCAPM).[12] Specifically, we run the following time-series regressions:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t} \tag{3}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t} \tag{4}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t} \tag{5}$$

[11] In our robustness test, we also form equal-weighted portfolios at the end of June each year and hold the portfolios for the subsequent 12 months following Cederburg and O'Doherty (2016).

[12] We also use the CAPM benchmark, which does not subsume the beta premium. We skip the CAPM adjusted results to preserve space.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t} \qquad (6)$$

where $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{SMB,t}$ is the month-t value of the Fama–French (FF) size factor, $f_{HML,t}$ is the month-t value of the FF book-to-market factor, $f_{WML,t}$ is the month-t value of the momentum factor, $f_{RMW,t}$ is the month-t value of the FF profitability factor, $f_{CMA,t}$ is the month-t value of the FF investment factor, and $f_{LF,t}$ is the month-t value of the Liu (2006) liquidity factor.[13]

Table 2 reports the performance of the decile portfolios sorted by β^{CAPM}.[14] In general, risk-adjusted returns under the FF3FM, momentum-extended FF3FM, and FF5FM decrease from low- to high-β^{CAPM} portfolios, which generates a significant beta premium. Specifically, the β^{CAPM} premiums are 0.988% (t = 5.66), 0.741% (t = 4.01) and 0.621% (t = 3.39) per month under the FF3FM, momentum-extended FF3FM, and FF5FM, respectively. It is worth noting that all the β^{CAPM} premiums have t-statistics above 3, which is the t-cutoff point recommended by Harvey et al. (2016).[15] These findings are consistent with Cederburg and O'Doherty (2016) and Bali et al. (2017).

In contrast, the LCAPM adjusted return, i.e., the intercept of Equation (6), is insignificant across all the β^{CAPM} decile portfolios. The loadings on the liquidity risk factor show that liquidity beta decreases steadily from low- to high-β^{CAPM} portfolios. Figure 1 exhibits this monotonic pattern under the liquidity-augmented model. The low-β^{CAPM} portfolio's loading on

[13] We obtain the one-month T-Bill rates, excess market returns, size, book-to-market, momentum, profitability, and investment factors from Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[14] t-statistics are based on White (1980) heteroskedasticity-consistent standard errors. Results are qualitatively similar with Newey-West standard errors.

[15] Harvey et al. (2016) propose t-cutoff values of 2.78 and 3.39, and argue that a newly discovered factor should have a t-statistic above 3.

the liquidity risk factor is the highest (0.635, t = 7.79) and the high-β^{CAPM} portfolio's loading on the liquidity risk factor is the lowest and even negative at -0.492 (t = -4.04), generating a highly significant difference of 1.127 (t = 15.09) between the two. This is in line with our conjecture that low-β^{CAPM} firms are exposed to high liquidity risk as compared to high-β^{CAPM} firms. After adjusting for the LCAPM, all $\hat{\alpha}$s in β^{CAPM} decile portfolios turn insignificant. Further, low-β^{CAPM} firms no longer exhibit abnormal performance relative to high-β^{CAPM} firms, leading to an insignificant beta premium. This evidence suggests that liquidity risk plays a key role in explaining the beta premium.

[Table 2 about here]

Further, we test our hypotheses on portfolios based on bivariate independent sorts of market beta and one of our four liquidity measures (*LM*, *DV*, *RV*, and *TO*). Specifically, we independently double-sort stocks into three liquidity (using one of the liquidity measures) and three market beta-based portfolios (3×3) at the end of each month. We form equal-weighted portfolios and hold them for the subsequent one month. To preserve space, we report the results based on one of the liquidity measures only (i.e., *LM* of Liu (2006)).[16]

Table 3 shows that the beta premiums are insignificant under the FF3FM, momentum-extended FF3FM, and FF5FM in the low *LM* (i.e., high liquidity) sub-samples, while become significant in the high *LM* (i.e., low liquidity) sub-samples. Hence, the beta premiums only appear in portfolios of low-liquidity stocks. This indicates that the commonly-used asset pricing models work well in situations of high stock liquidity, but facing

[16] In untabulated results, we find that the results are, nevertheless, similar under the other three liquidity measures (*DV*, *RV*, and *TO*).

difficulties in circumstances of low liquidity.

Finally, we use the GRS test of Gibbons et al. (1989) to examine the pricing errors of the asset pricing models. We find that the GRS estimates are 5.518 (p-value=0.000), 5.218 (p-value=0.000), 3.220 (p-value=0.001), and 1.587 (p-value=0.115) for the FF3FM, momentum-extended FF3FM, FF5FM, and LCAPM, respectively. This suggests that the LCAPM yields smaller pricing errors than other models and the GRS test cannot reject the null that the LCAPM alphas are jointly equal to zero. These results again suggest that liquidity risk plays a significant role in explaining the beta premium.

[Table 3 about here]

3.2 Robustness tests

3.2.1 Alternative beta measures

We employ two alternative beta measures to check the robustness of our results. First, following Vasicek (1973) and Liu et al. (2018), we estimate the Vasicek CAPM beta (VCK^{Beta}) as

$$VCK_i^{Beta} = \omega \times \beta_i^{CAPM} + (1 - \omega) \times 1 \tag{7}$$

where

$$\omega = \frac{1/\sigma^2\left(\beta_i^{CAPM}\right)}{1/\sigma^2\left(\beta_i^{CAPM}\right) + 1/\sigma^2(\beta^{CAPM})} \tag{8}$$

$\sigma\left(\beta_i^{CAPM}\right)$ is the standard error of β_i^{CAPM} and $\sigma^2(\beta^{CAPM})$ is an estimate of the cross-sectional variance of true betas. $\sigma^2(\beta^{CAPM})$ is estimated as

$$\sigma^2(\beta^{CAPM}) = \sigma^2_{CS}(\beta_i^{CAPM}) - \overline{\sigma^2(\beta_i^{CAPM})} \tag{9}$$

where $\sigma^2_{CS}(\beta_i^{CAPM})$ is the cross-sectional variance of β_i^{CAPM} and $\overline{\sigma^2(\beta_i^{CAPM})}$ is the cross-sectional mean of $\sigma^2(\beta_i^{CAPM})$.

Second, following Bali et al. (2016) and Liu et al. (2018), we estimate the Fama and French (1992) beta (FF^{Beta}) as

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_{i,0} f_{MKT,d} + \beta_{i,1} f_{MKT,d-1} + \varepsilon_{i,d} \tag{10}$$

where $R_{i,d}$ is the return of stock *i* on day *d*, $R_{f,d}$ is the risk-free rate on day *d*, $f_{MKT,d}$ is the market factor on day *d*, and $f_{MKT,d-1}$ is the market factor on day *d - 1*. Following the summed slope method of Dimson (1979), $FF^{Beta} = \beta_{i,0} + \beta_{i,1}$ which is estimated at the end of each month over the prior 12 months.

We form equal-weighted portfolios at the end of each month based on VCK^{Beta} and FF^{Beta}. Results are reported in Panels A and B of Table 4. We hold the portfolios for the subsequent one month. Our results show that the VCK^{Beta} and FF^{Beta} premiums are still significant under the FF3FM, momentum-extended FF3FM, and FF5FM, while the LCAPM again captures the beta premium.

[Table 4 about here]

3.2.2 Alternative holding period

We form equal-weighted portfolios at the end of June each year and hold the portfolios for the subsequent 12 months following Cederburg and O'Doherty (2016). We calculate the monthly portfolio returns over the 12-month holding period based on the decomposed buy-and-hold method of Liu and Strong (2008):[17]

$$R_{p,\tau} = \sum_{i=1}^{N} \frac{\omega_i \prod_{t=1}^{\tau-1}(1 + R_{i,t})}{\sum_{j=1}^{N} \omega_j \prod_{t=1}^{\tau-1}(1 + R_{j,t})} R_{i,\tau}\,, \tau = 2, \cdots, 12;\ R_{p,1} = \sum_{i=1}^{N} \omega_i R_{i,1} \qquad (11)$$

where $R_{p,\tau}$ is the month-τ return of the portfolio in the 12-month holding period, $R_{i,t}$ is the month-t return of stock i, N is the number of stocks in the portfolio, and ω_i is the portfolio weight in stock i.

Table 5 shows that the beta premiums remain highly significant at 0.653% (t = 4.99), 0.514% (t = 3.71), and 0.377% (t = 2.98) per month under the FF3FM, momentum-extended FF3FM, and FF5FM, respectively. However, the LCAPM subsumes the beta premium.

[Table 5 about here]

3.2.3 Sub-period and sub-sample analyses

Further, we conduct both sub-period and sub-sample analyses. For the sub-period test, we evenly divide the full sample into two sub-periods (07/1963–06/1990 and 07/1990–06/2017). For each sub-period, we form β^{CAPM} decile portfolios at the end of each month and hold them for the subsequent one month. Table 6 reports the sub-period results. It shows that the beta premium exists

[17] With Equation (11), the calculations of the decomposed buy-and-hold returns do not involve rebalancing the portfolio weights and constituents over the 12-month holding period. Our results are, however, qualitatively similar to the results from using conventional (rebalancing) method.

in both sub-periods. The LCAPM, once again, captures the beta premium over the second sub-period, suggesting that liquidity risk plays a role in explaining the return predictability of CAPM beta.

[Table 6 about here]

For the sub-sample analyses, we test the β^{CAPM} premium separately based on the NYSE/AMEX sample and the NASDAQ sample to examine whether our results are driven by the inclusion of relatively small and illiquid NASDAQ stocks. Table 7 presents the results for NYSE/AMEX sample over 1963–2017 (Panel A) and for NASDAQ stocks over 1974–2017 (Panel B), respectively.[18] For the NYSE/AMEX sample, the β^{CAPM} premiums are significant at 0.841% (t = 4.67), 0.635% (t = 3.17), and 0.754% (t = 3.94) per month under the FF3FM, momentum-extended FF3FM, and FF5FM, respectively. Panel B shows consistent results for NASDAQ stocks. In contrast, the LCAPM, again, explains the performance of the β^{CAPM} decile portfolios within both the NYSE/AMEX and the NASDAQ samples.

[Table 7 about here]

3.3 The decomposition of beta

The CAPM beta, as argued by Asness et al. (2020), can be decomposed into two components: correlation and volatility. The correlation part captures the effect of systematic risk without the effect of idiosyncratic volatility (Liu et al., 2018). In this sub-section, we examine whether

[18] Data for NASDAQ stocks became available from 1973.

liquidity risk is able to explain the correlation premium.[19] Specifically, we estimate the correlation as the correlation between the three-day log returns of the stock and three-day log returns of the market using daily returns over five years. We use five years' data since correlations tend to move slowly (Asness et al., 2020).

We form equal-weighted portfolios at the end of each month based on *Corr* and hold the portfolios for the subsequent one month. Table 8 shows that the correlation premiums are 0.611% (t = 3.66), 0.437% (t = 2.49), and 0.636% (t = 3.55) per month under the FF3FM, momentum-extended FF3FM, and FF5FM, respectively. However, the correlation premium becomes insignificant (-0.048%, t = -0.28) under the LCAPM.

[Table 8 about here]

3.4 Fama–MacBeth (1973) regressions

In this sub-section, we perform the Fama–MacBeth (1973) cross-sectional regression analysis as follows:

$$R_{i,t+m} - R_{f,t+m} = \gamma_0 + \gamma_1 \beta^{CAPM}{}_{i,t} + \gamma_2 MV_{i,t} + \gamma_3\, B/M_{i,t} + \gamma_4 MOM_{i,t} + \gamma_5 OP_{i,t} + \gamma_6 AG_{i,t} + \gamma_7 L_{i,t} + \epsilon_{i,t+m} \quad (12)$$

where $R_{i,t+m}$ is stock i's return in month $t + m$ (m = 1, 2, ..., 12), $R_{f,t+m}$ is the risk-free rate for

[19] Asness et al. (2020) show that the volatility premium can be explained by the Fama-French five-factor model (FF5FM) while the correlation premium cannot. We, thus, focus on the correlation premium in our study. In untabulated results, we find that the volatility premium can also be explained by the LCAPM.

month $t + m$, $\beta^{CAPM}{}_{i,t}$ is stock i's CAPM beta estimated at the end of month t, $MOM_{i,t}$ is the buy-and-hold return of stock i over month t - 11 to month t - 1, $L_{i,t}$ is stock i's liquidity proxy measured at the end of month t (i.e., one of the four liquidity measures used in the paper). Other regressors are the market capitalization $MV_{i,t}$, book-to-market ratio $B/M_{i,t}$, operating profitability $OP_{i,t}$, and asset growth rate $AG_{i,t}$. Each regressor is, then, standardized to have a mean of one and a variance of one (e.g., Green et al. (2017)).

Table 9 presents the Fama–MacBeth regression results. Consistent with the results of portfolio sorts, the regression exhibits strong return predictability of β^{CAPM} : low (high) β^{CAPM} predicts high (low) returns for the next one month, after controlling for market capitalization, book-to-market ratio, momentum, operating profitability, and asset growth. Coefficients on control variables are, in general, significant and as expected. When adding liquidity as a control, the β^{CAPM} loses its power in predicting stock returns. The coefficient estimations of all four illiquidity proxies are in line with previous literature.[20] This evidence suggests that liquidity risk explains returns better than CAPM beta.

[Table 9 about here]

Since β^{CAPM} is correlated with liquidity (see Table 1), if liquidity can explain beta anomaly, then beta premium can be eliminated after removing the effect of liquidity on CAPM beta. Following Bali et al. (2017), we regress β^{CAPM} on each of the four illiquidity proxies each month to obtain the residual term, β^{CAPM*} , which is essentially the component of β^{CAPM} that is orthogonal to the illiquidity proxy. We, then, use β^{CAPM*} in the following Fama–MacBeth (1973)

[20] See, for example, Lewellen (2015) and Green et al. (2017).

cross-sectional regressions:

$$R_{i,t+m} - R_{f,t+m} = \gamma_0 + \gamma_1 \beta^{CAPM*}{}_{i,t} + \gamma_2 MV_{i,t} + \gamma_3\, B/M_{i,t} + \gamma_4 MOM_{i,t} + \gamma_5 OP_{i,t} + \gamma_6 AG_{i,t} + \epsilon_{i,t+m} \quad (13)$$

Table 10 presents the Fama–MacBeth regression results. We find that the coefficients of β^{CAPM*} become insignificant, which implies that β^{CAPM} has no significant power in predicting returns after removing the liquidity effect. Thus, the predictability of β^{CAPM} on stock returns is attributed to liquidity.

[Table 10 about here]

In untabulated results, we also examine the predictability of illiquidity proxies on returns after removing the CAPM beta effect. Specifically, in each month, we regress L on β^{CAPM} to obtain the residual term, L^*, which is the component of illiquidity proxies that is orthogonal to CAPM beta. We, then, use L^* in the following Fama–MacBeth (1973) cross-sectional regressions:

$$R_{i,t+m} - R_{f,t+m} = \gamma_0 + \gamma_1 L^*{}_{i,t} + \gamma_2 MV_{i,t} + \gamma_3\, B/M_{i,t} + \gamma_4 MOM_{i,t} + \gamma_5 OP_{i,t} + \gamma_6 AG_{i,t} + \epsilon_{i,t+m} \quad (14)$$

We find that the coefficients of L^* are highly significant in general, which implies that the illiquidity proxies predict returns after removing the β^{CAPM} effect.

Further, we test whether the stock liquidity is simply picking up variation in stock returns due to a funding constraint (Frazzini and Pedersen, 2014) or lottery-demand characteristics (Bali et al., 2017). Following Bali et al. (2017), we estimate a stock's exposure to funding liquidity (β^{TB}) as

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i^{TB} f_{TB,d} + \varepsilon_{i,d} \tag{15}$$

where $R_{i,d}$ is the return of stock *i* on day *d*, $R_{f,d}$ is the risk-free rate on day *d*, and $f_{TB,d}$ is the 3-month treasury bill rate on day *d*. We estimate β_i^{TB} at the end of each month over the prior 12-month period.

Next, we use three proxies to capture the lottery-demand characteristics. Following Bali et al. (2011), we measure the lottery demands of a stock (*MAX*) as the average of the five highest daily returns during a month. Following Kumar (2009), Han and Kumar (2013), and Bali et al. (2017), we also use idiosyncratic volatility (*IVOL*) and idiosyncratic skewness (*ISKEW*) to proxy for the lottery feature of a stock. Specifically, we estimate *IVOL* and *ISKEW* in month *t* as the standard deviation and skewness of the residuals from regressing stock's excess returns on the Fama-French (1993) three factors

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_{i,m} f_{MKT,d} + \beta_{i,s} f_{SMB,d} + \beta_{i,h} f_{HML,d} + \varepsilon_{i,d} \tag{16}$$

where $R_{i,d}$ is the return of stock *i* on day *d*, $R_{f,d}$ is the risk-free rate on day *d*, $f_{MKT,d}$ is the market factor on day *d*, $f_{SMB,d}$ is the Fama–French size factor on day *d*, and $f_{HML,d}$ is the Fama–French book-to-market factor on day *d*.

Finally, we estimate the liquidity beta using the Liu (2006) model as

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_{i,m} f_{MKT,d} + \beta_{i,l} f_{LF,d} + \varepsilon_{i,d} \tag{17}$$

where $R_{i,d}$ is the return of stock i on day d, $R_{f,d}$ is the risk-free rate on day d, $f_{MKT,d}$ is the market factor on day d, and $f_{LF,d}$ is the liquidity factor on day d. We estimate the liquidity beta $\beta_{i,l}$ at the end of each month over the prior 12-month period.

Table 11 presents the results. In terms of the effect of funding liquidity, it shows that β^{CAPM} remains significant after controlling for funding liquidity (β_i^{TB}). In untabulated results, we find that all our liquidity measures remain significant after controlling for funding liquidity. This suggests that funding liquidity is not the same as stock liquidity. In terms of the effect of lottery characteristics, it shows that β^{CAPM} is either insignificant or marginally significant depends on which lottery proxies are used. This suggests that the effect of lottery characteristics on beta premium is not very consistent. Finally, consistent with our main results, β^{CAPM} turns insignificant after controlling for the liquidity beta of Liu (2006).

[Table 11 about here]

3.5 Pricing ability of risk factors

In this sub-section, we provide further evidence on why liquidity risk is able to explain the beta premium by examining the pricing ability of liquidity risk factor relative to other risk factors. We conduct our assessments based on several testing procedures including recent methods by Kan et al. (2013) and Gospodinov et al. (2014).

Firstly, we follow Kan et al. (2013)'s approach to examine the pricing ability of risk factors by looking at both factor's loading and covariance risk. Specifically, Kan et al. (2013) point out that examining whether a factor makes an incremental contribution to a multi-factor model's goodness-of-fit is different from testing whether the factor is priced. They argue that, in a multi-factor model, it is important to test the significance of covariance risk (the covariance between asset return and a risk factor of interest). If the coefficient of the covariance is significantly different from zero, then the factor makes an incremental contribution to the model's overall explanatory power.

To conduct the above tests, we test the pricing ability of risk factors using 25 portfolios formed with β^{CAPM} and also expand these portfolios with industry portfolios. Specifically, we sort sample stocks into 25 β^{CAPM} portfolios at the end of each month starting from 1963. We hold the 25 portfolios for one month and calculate their equal-weighted monthly returns. In addition, we expand the 25 β^{CAPM} portfolios with five industry portfolios as in Gomes et al. (2009). This is because that although Fama–French 25 *MV-B/M* portfolios are commonly used in asset pricing tests, Lewellen et al. (2010) point out that the *MV-B/M* portfolios have a strong factor structure, and a number of pricing models have already included the size and/or book-to-market factors. One way to mitigate this problem is to use testing portfolios sorted by other characteristics or by industry other than *MV-B/M* portfolios (Lewellen et al., 2010).

With the 30 testing portfolios, we run the following cross-sectional regression to test whether a factor loading in a multi-factor asset pricing model is priced:

$$R_{i,t} - R_{f,t} = \gamma_0 + \sum_{k=1}^{K} \gamma_k \hat{\beta}_{i,k} + e_{i,t}, \tag{18}$$

where $R_{i,t}$ is the month-t return of testing portfolio i, $R_{f,t}$ is the risk-free rate for month t, $\hat{\beta}_{i,k}$ is the loading estimate of portfolio i on risk factor k, and γ_k is the price of beta risk with respect to risk factor k. We estimate the factor loadings for each testing portfolio by running the following time-series regression using data over the full sample period (1963–2017):[21]

$$R_{i,t} - R_{f,t} = \alpha_0 + \sum_{k=1}^{K} \beta_{i,k} f_k + \varepsilon_{i,t}, \tag{19}$$

where f_k denotes the value of the k^{th} risk factor ($k = 1, 2, ..., K$).

Following Kan et al. (2013), we also run the following cross-sectional regression to estimate the price of covariance risk:

$$R_{i,t} - R_{f,t} = \lambda_0 + \sum_{k=1}^{K} \lambda_k \widehat{Cov}(R_i, f_k) + e_{i,t}, \tag{20}$$

where $\widehat{Cov}(R_i, f_k)$ stands for the estimate of the covariance between returns of asset *i* and the k^{th} risk factor f_k, and λ_k stands for the price of covariance risk associated with the k^{th} risk factor f_k. For each testing portfolio, we estimate its return covariances with *K* risk factors using data over the full sample period (1963–2017).

If γ_k in Equation (18) and λ_k in Equation (20) are statistically significant, then the risk factor *k* has significant pricing power. To test the significance of γ_k and λ_k, we use not only the conventional Fama–MacBeth *t*-statistic (t_{FM}) but also the Shanken (1992) *t*-statistic (t_S), the Jagannathan and Wang (1996) *t*-statistic (t_{JW}), and the Kan et al. (2013) *t*-statistic (t_{KRS}). t_S adjusts for the errors-in-variables problem. t_{JW} corrects the sampling errors in the estimated betas or covariances. t_{KRS} takes into account the issue of potentially misspecified models.

[21] Estimating the betas over the entire sample period is similar to Lettau and Ludvigson (2001), Acharya and Pedersen (2005), and Sadka (2006).

Secondly, we follow the stochastic discount factor (SDF) framework of Gospodinov et al. (2014) to further test the pricing ability of risk factors. Specifically, Gospodinov et al. (2014) generalize the testing procedure of Kan et al. (2013) and others to allow for possible identification failure in a SDF framework. This approach is robust to the potential model misspecification in selecting risk factors and in determining whether the selected risk factors are priced.

Let $y_t(\mu) = \tilde{f}_t'\mu$ be a linear risk factor model, where $\tilde{f}_t' = [1, f_t']'$ and f_t is a vector containing the month-*t* values of $K - 1$ risk factors. To test the SDF parameters, μ, the pricing error of the risk factor model is defined as:

$$e(\mu) = E[x_t y_t(\mu) - q] \tag{21}$$

where x_t stands for the month-*t* payoffs of *N* assets and q for a vector of the costs of *N* assets.

To estimate the SDF parameters, μ, the mathematical problem is:

$$\min \hat{e}(\mu)'\hat{U}^{-1}\hat{e}(\mu) \tag{22}$$

where $\hat{U} = \frac{1}{T}\sum_{t=1}^{T} x_t x_t'$, $\hat{e}(\mu) = \hat{B}\mu - q$ and where $\hat{B} = \frac{1}{T}\sum_{t=1}^{T} x_t \tilde{f}_t'$. Solving the minimization problem above yields

$$\hat{\mu} = \left(\hat{B}'\hat{U}^{-1}\hat{B}\right)^{-1}\hat{B}'\hat{U}^{-1}q \tag{23}$$

Suppose that the null hypothesis is $\mu_i = \mu_i^*$. Gospodinov et al. (2014) propose two *t*-statistics for testing the pricing ability of risk factors: one assumes the correct model specification ($t_{GKR,c}$) and the other is based on model misspecification ($t_{GKR,m}$):

$$t_{GKR,c}(\hat{\mu}_i) = \frac{\hat{\mu}_i - \mu_i^*}{\sqrt{\iota_i'\hat{\Sigma}_{\mu_i}^0 \iota_i}} \tag{24}$$

and

$$t_{GKR,m}(\hat{\mu}_i) = \frac{\hat{\mu}_i - \mu_i^*}{\sqrt{\iota_i'\hat{\Sigma}_{\mu_i} \iota_i}} \tag{25}$$

where $\hat{\Sigma}_{\mu_i}^0$ is an estimator of $\Sigma_{\mu_i}^0 = (B'U^{-1}B)^{-1}B'U^{-1}SU^{-1}B(B'U^{-1}B)^{-1}, S = E[e_t(\mu^*)e_t(\mu^*)'], e_t(\mu^*) = x_t\tilde{f}'_t\mu^* - q$, ι_i is a vector with its i^{th} element equals one and zero otherwise, and $\hat{\Sigma}_{\mu_i}$ is an estimator of $\Sigma_{\mu_i} = (B'U^{-1}B)^{-1}B'U^{-1}e_t(\mu^*) + (B'U^{-1}B)^{-1}(\tilde{f}'_t B'U^{-1}x_t)e_t(\mu^*)U^{-1}x_t$.

Consider the 30 testing portfolios and the FF3FM, for example, *x* represents the excess returns of the 30 testing portfolios, q represents the original costs (which are equal to zero), and $y_t(\mu) = \mu_0 + \mu_1 f_{MKT,t} + \mu_2 f_{SMB,t} + \mu_3 f_{HML,t}$. The estimate of μ_k is expected to be negative, while the estimates of γ_k and λ_k are expected to be positive.

Table 12 reports the results on testing the pricing ability of risk factors. By looking at *t*-ratios of factor's loading, we find that, consistent with early studies such as Fama and French (1992), CAPM beta alone lacks the power to predict returns. In fact, the market factor loading is even negatively related to the cross-section of average returns, showing the beta anomaly.[22] The size factor, the book-to-market factor, the momentum factor, the profitability factor, and the investment factor are insignificant.

In contrast, the liquidity risk (i.e., the loading on the liquidity risk factor of the LCAPM) is significantly priced based on the FM t-ratio, the SH t-ratio, the JW t-ratio, and the KRS t-ratio. It suggests that investors are concerned about liquidity risk and require a high return for bearing such risk.

In terms of t-ratios of covariance risk, the coefficient of the covariance between stock returns and the liquidity risk factor is significantly positive no matter which t-ratio is used. This evidence indicates that the liquidity risk factor adds significant explanatory power to the cross-sectional variations of stock returns. However, the covariance risk, relative to the market factor, the book-to-market factor, the momentum factor, the profitability factor, and the investment factor does not exhibit any significant power in predicting stock returns.

Under the SDF framework, the two t-statistics ($t_{GKR,c}$ and $t_{GKR,m}$) of Gospodinov et al. (2014) show strong pricing ability for the liquidity risk factor, no matter whether the model is correctly specified or potentially mis-specified. However, the size factor under all models, the book-to-market factor and the investment factor under the FF5FM do not survive the Gospodinov et al. (2014) test. Overall, from the perspective of pricing ability of risk factors, this sub-section provides

[22] Jagannathan and Wang (1996), Lettau and Ludvigson (2001), and Petkova (2006) also report the negative estimates for the market risk premium.

further evidence on why liquidity risk is able to explain the beta premium.[23]

[Table 12 about here]

4 Conclusion

In this paper, we show that stocks of firms with low beta are less liquid and hence exposed to high liquidity risk than stocks of firms with high beta. After adjusting for liquidity risk, the predictive power of beta diminishes and the beta premium turns insignificant.

Because common asset pricing models, such as the Fama–French three- and five-factor models and momentum-extended Fama–French three-factor model, show limited success in accounting for the beta premium, we perform further analysis on the explanatory power of liquidity risk in asset pricing. That is, we conduct an exercise to evaluate empirically the pricing ability of the liquidity risk factor of the LCAPM in comparison with the other pricing factors. Based on recent technical advances together with traditional approaches on testing asset pricing models, we obtain consistent results that liquidity risk exhibits a robust pricing ability and significantly contributes to explaining the cross-section of expected stock returns.

Our work draws some practical implications for fund managers and corporate executives. While the CAPM beta is widely used as a measure of systematic risk, we show that low-beta stocks are not necessarily less risky given their high liquidity risk. Since many funds build beta trading strategies to take advantage of the beta premium, fund managers ought to understand the role of liquidity risk in delivering such a strategy. Our results also have the potential to be used in

[23] We obtain qualitatively similar results following the Giglio and Xiu (2019) three-pass method to estimate the risk premium.

corporate financial decision-making. Since most firms are still using CAPM to estimate their costs of capital, our evidence suggests that the CAPM beta, the key input for cost-of-capital estimation, can be misleading. A low-beta project can be associated with high liquidity risk, and, hence, its actual cost of capital is likely to be higher than what its beta suggests, implying a lower NPV of the project.

References

Acharya, V. V. and L. H. Pedersen (2005). Asset pricing with liquidity risk. *Journal of Financial Economics 77* (2), 375–410.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets 5* (1), 31–56.

Amihud, Y. and H. Mendelson (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics 17* (2), 223–249.

Amihud, Y. and J. Noh (2020). The pricing of the illiquidity factor's conditional risk with time-varying premium. *Journal of Financial Markets*, forthcoming.

Antoniou, C., J. A. Doukas, and A. Subrahmanyam (2015). Investor sentiment, beta, and the cost of equity capital. *Management Science 62* (2), 347–367.

Asness, C., A. Frazzini, N. J. Gormsen, and L. H. Pedersen (2020). Betting against correlation: Testing theories of the low-risk effect. *Journal of Financial Economics 135* (3), 629–652.

Bali, T. G., S. J. Brown, S. Murray, and Y. Tang (2017). A lottery-demand-based explanation of the beta anomaly. *Journal of Financial and Quantitative Analysis 52* (6), 2369–2397.

Bali, T. G., N. Cakici, and R. F. Whitelaw (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics 99* (2), 427–446.

Bali, T. G., R. F. Engle, and Y. Tang (2016). Dynamic conditional beta is alive and well in the cross section of daily stock returns. *Management Science 63* (11), 3760–3779.

Bekaert, G., C. R. Harvey, and C. Lundblad (2007). Liquidity and expected returns: Lessons from emerging markets. *Review of Financial Studies 20* (6), 1783–1831.

Black, F., M. C. Jensen, M. Scholes, et al. (1972). The capital asset pricing model: Some empirical tests. *Studies in the Theory of Capital Markets 81* (3), 79–121.

Brennan, M. J., T. Chordia, and A. Subrahmanyam (1998). Alternative factor specifications, security characteristics, and the cross-section of expected stock returns1. *Journal of Financial Economics 49* (3), 345 – 373.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance 52* (1), 57–82.

Cederburg, S. and M. S. O'Doherty (2016). Does it pay to bet against beta? On the conditional performance of the beta anomaly. *Journal of Finance 71* (2), 737–774.

Chaieb, I., V. R. Errunza, and H. Langlois (2018). Is liquidity risk priced in partially segmented markets? Working Paper.

Corwin, S. A. and P. Schultz (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *Journal of Finance 67* (2), 719–760.

Datar, V. T., N. Y. Naik, and R. Radcliffe (1998). Liquidity and stock returns: An alternative test. *Journal of Financial Markets 1* (2), 203–219.

Davis, J. L., E. F. Fama, and K. R. French (2000). Characteristics, covariances, and average returns: 1929 to 1997. *Journal of Finance 55* (1), 389–406.

Dimson, E. (1979). Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics 7* (2), 197–226.

Doeswijk, R., T. Lam, and L. Swinkels (2020). Historical returns of the market portfolio. *Review of Asset Pricing Studies 10* (3), 521–567.

Fama, E. F. and K. R. French (1992). The cross-section of expected stock returns. *Journal of Finance 47* (2), 427–465.

Fama, E. F. and K. R. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics 33* (1), 3–56.

Fama, E. F. and K. R. French (2015). A five-factor asset pricing model. *Journal of Financial Economics 116* (1), 1–22.

Fama, E. F. and J. D. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy 81* (4), 607–636.

Frazzini, A. and L. H. Pedersen (2014). Betting against beta. *Journal of Financial Economics 111* (1), 1–25.

Friend, I. and M. Blume (1970). Measurement of portfolio performance under uncertainty. *American Economic Review 60* (4), 561–575.

Gibbons, M. R., S. A. Ross, and J. Shanken (1989). A test of the efficiency of a given portfolio. *Econometrica 57* (5), 1121–1152.

Giglio, S. and D. Xiu (2019). Asset pricing with omitted factors. Working paper.

Giorgi, E. G. D., T. Post, and A. Yalçın (2019). A concave security market line. *Journal of Banking & Finance 106*, 65 – 81.

Gomes, J. F., L. Kogan, and M. Yogo (2009). Durability of output and expected stock returns. *Journal of Political Economy 117* (5), 941–986.

Gospodinov, N., R. Kan, and C. Robotti (2014). Misspecification-robust inference in linear asset-pricing models with irrelevant risk factors. *Review of Financial Studies 27* (7), 2139–2170.

Graham, J. R. and C. R. Harvey (2001). The theory and practice of corporate finance: Evidence from the field. *Journal of Financial Economics 60* (2-3), 187–243.

Green, J., J. R. Hand, and X. F. Zhang (2017). The characteristics that provide independent information about average us monthly stock returns. *The Review of Financial Studies 30* (12), 4389–4436.

Han, B. and A. Kumar (2013). Speculative retail trading and asset prices. *Journal of Financial and Quantitative Analysis 48* (2), 377–404.

Harvey, C. R., Y. Liu, and H. Zhu (2016). ... and the cross-section of expected returns. *Review of Financial Studies 29* (1), 5–68.

Hendershott, T., D. Livdan, and D. Rösch (2020). Asset pricing: A tale of night and day. *Journal of Financial Economics 138* (3), 635–662.

Hong, H. and D. A. Sraer (2016). Speculative betas. *Journal of Finance 71* (5), 2095–2144.

Jacobs, M. T. and A. Shivdasani (2012). Do you know your cost of capital? *Harvard Business Review 90* (7-8), 118–124.

Jagannathan, R. and Z. Wang (1996). The conditional CAPM and the cross-section of expected returns. *Journal of Finance 51* (1), 3–53.

Jylhä, P. (2018). Margin requirements and the security market line. *Journal of Finance 73* (3), 1281–1321.

Kan, R., C. Robotti, and J. Shanken (2013). Pricing model performance and the two-pass cross-sectional regression methodology. *Journal of Finance 68* (6), 2617–2649.

Kumar, A. (2009). Who gambles in the stock market? *Journal of Finance 64* (4), 1889–1933.

Lee, K.-H. (2011). The world price of liquidity risk. *Journal of Financial Economics 99* (1), 136–161.

Lettau, M. and S. Ludvigson (2001). Resurrecting the (C)CAPM: A cross-sectional test when risk premia are time-varying. *Journal of Political Economy 109* (6), 1238–1287.

Lewellen, J. (2015). The cross-section of expected stock returns. *Critical Finance Review 4* (1), 1–44.

Lewellen, J., S. Nagel, and J. Shanken (2010). A skeptical appraisal of asset pricing tests. *Journal of Financial Economics 96* (2), 175–194.

Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. *Journal of Finance 20* (4), 587–615.

Liu, J., R. Stambaugh, and Y. Yuan (2018). Absolving beta of volatility's effects. *Journal of Financial Economics 128* (1), 1–15.

Liu, W. (2006). A liquidity-augmented capital asset pricing model. *Journal of Financial Economics 82* (3), 631–671.

Liu, W. and N. Strong (2008). Biases in decomposing holding-period portfolio returns. *Review of Financial Studies 21* (5), 2243–2274.

Lou, D., C. Polk, and S. Skouras (2019). A tug of war: Overnight versus intraday expected returns. *Journal of Financial Economics 134* (1), 192 – 213.

Lustig, H., S. Van Nieuwerburgh, and A. Verdelhan (2013). The wealth-consumption ratio. *Review of Asset Pricing Studies 3* (1), 38–94.

Newey, W. K. and K. D. West (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica 55* (3), 703–708.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics 108* (1), 1–28.

Pastor, L. and R. F. Stambaugh (2003). Liquidity risk and expected stock returns. *Journal of Political Economy 111* (3), 642–685.

Petkova, R. (2006). Do the Fama-French factors proxy for innovations in predictive variables? *Journal of Finance 61* (2), 581–612.

Roll, R. (1977). A critique of the asset pricing theory's tests part i: On past and potential testability of the theory. *Journal of Financial Economics 4* (2), 129–176.

Sadka, R. (2006). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics 80* (2), 309–349.

Savor, P. and M. Wilson (2014). Asset pricing: A tale of two days. *Journal of Financial Economics 113* (2), 171–201.

Shanken, J. (1992). On the estimation of beta-pricing models. *Review of Financial Studies 5* (1), 1–55.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance 19* (3), 425–442.

Shumway, T. (1997). The delisting bias in CRSP data. *Journal of Finance 52* (1), 327–340.

Shumway, T. and V. A. Warther (1999). The delisting bias in CRSP's Nasdaq data and its implications for the size effect. *Journal of Finance 54* (6), 2361–2379.

Vasicek, O. A. (1973). A note on using cross-sectional information in Bayesian estimation of security betas. *Journal of Finance 28* (5), 1233–1239.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica 48* (4), 817–838.

Table 1
Descriptive statistics

This table reports descriptive statistics and correlations for the following variables:
β^{CAPM}: CAPM beta;
MV: market capitalization, measured in millions of dollars;
B/M: book-to-market ratio;
OP: book-equity-deflated operating profitability;
AG: total asset growth rate;
DV: negative average daily dollar volume over the prior 12 months, where daily dollar volume is the number of shares traded on a day times the closing price on that day;
LM: standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months;
RV: daily ratio of the absolute return on a day to the dollar volume on that day averaged over the prior 12 months;
TO: negative daily turnover averaged over the prior 12 months;
At the end of each month in each year, we work out the cross-sectional mean and standard deviation for each of the above variables. This table reports the time-series averages of the cross-sectional estimates. Likewise, we compute the Spearman rank correlations of β^{CAPM} with other variables at the end of each month and report the time-series averages of the cross-sectional estimates. The sample includes NYSE/AMEX/NASDAQ ordinary common stocks.

	β^{CAPM}	*MV* ($m)	*B/M*	*OP* (%)	*AG* (%)	*DV* ($m)	*LM*	*RV* ($\times 10^6$)	*TO*
Panel A: NYSE/AMEX stocks over 6/1963–6/2017 (53 years)									
				Descriptive statistics					
Mean	0.792	2497.111	0.935	26.249	15.004	-14.722	8507.274	3.587	-0.367
Stdev	1.929	12761.404	1.204	665.052	114.335	68.410	23471.150	30.889	0.542
				Spearman correlation					
β^{CAPM}	1	0.273	-0.216	0.120	0.119	-0.414	-0.312	-0.552	-0.561
Panel B: NASDAQ stocks over 6/1984–6/2017 (33 years)									
				Descriptive statistics					
Mean	0.673	723.139	0.768	0.495	22.847	-8.518	25683.196	11.758	-0.574
Stdev	0.712	7820.593	1.482	3288.480	301.197	91.578	47629.556	269.633	0.862
				Spearman correlation					
β^{CAPM}	1	0.474	-0.311	-0.006	0.143	-0.606	-0.529	-0.614	-0.575

Table 2

Performance of decile portfolios sorted by β^{CAPM}

We form equal-weighted decile portfolios at the end of each month based on the CAPM beta (β^{CAPM} in Eq. (1)) and hold them for the subsequent one month. The symbol $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{SMB,t}$ is the month-t value of the Fama-French size factor, $f_{HML,t}$ is the month-t value of the Fama-French book-to-market factor, $f_{WML,t}$ is the month-t value of the momentum factor, $f_{RMW,t}$ is the month-t value of the Fama-French profitability factor, $f_{CMA,t}$ is the month-t value of the Fama-French investment factor, and $f_{LF,t}$ is the month-t value of the Liu (2006) liquidity factor. The testing period is 7/1963-6/2017 (648 months). The numbers in parentheses are t-statistics based on White (1980) heteroskedasticity-consistent standard errors.

	Low- β^{CAPM}	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*	*D9*	*High-* β^{CAPM}	*L-H*
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.379	0.309	0.221	0.161	0.142	0.021	-0.056	-0.183	-0.304	-0.610	0.988
	(3.22)	(3.13)	(2.37)	(2.04)	(2.05)	(0.31)	(-0.88)	(-2.51)	(-3.03)	(-4.27)	(5.66)
$\hat{\beta}_{i,m}$	0.561	0.621	0.723	0.809	0.884	0.980	1.057	1.169	1.297	1.521	-0.960
	(16.32)	(19.48)	(23.89)	(31.45)	(36.45)	(43.34)	(48.74)	(49.91)	(39.06)	(29.10)	(-14.75)
$\hat{\beta}_{i,s}$	0.803	0.635	0.706	0.728	0.772	0.821	0.903	0.980	1.076	1.262	-0.459
	(13.72)	(13.51)	(15.29)	(14.15)	(13.74)	(13.88)	(16.06)	(17.20)	(16.83)	(18.75)	(-6.30)
$\hat{\beta}_{i,h}$	0.277	0.363	0.377	0.355	0.363	0.353	0.311	0.213	0.065	-0.150	0.427
	(4.77)	(6.32)	(6.51)	(7.15)	(7.66)	(8.03)	(7.59)	(4.62)	(1.03)	(-1.87)	(4.70)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.458	0.406	0.319	0.266	0.238	0.138	0.081	-0.003	-0.038	-0.283	0.741
	(3.62)	(3.80)	(3.20)	(3.27)	(3.25)	(2.00)	(1.11)	(-0.03)	(-0.27)	(-1.84)	(4.01)
$\hat{\beta}_{i,m}$	0.544	0.600	0.701	0.786	0.864	0.954	1.027	1.130	1.239	1.450	-0.907
	(14.86)	(18.61)	(23.06)	(31.14)	(36.88)	(46.66)	(50.90)	(50.43)	(38.68)	(31.89)	(-14.61)
$\hat{\beta}_{i,s}$	0.804	0.637	0.708	0.730	0.774	0.824	0.905	0.984	1.082	1.268	-0.464
	(13.89)	(14.95)	(17.34)	(16.34)	(15.59)	(15.98)	(18.57)	(21.01)	(20.34)	(21.07)	(-6.64)
$\hat{\beta}_{i,h}$	0.246	0.324	0.338	0.313	0.325	0.306	0.257	0.142	-0.041	-0.280	0.525
	(4.08)	(5.69)	(5.81)	(6.64)	(7.47)	(7.74)	(6.48)	(3.02)	(-0.61)	(-3.73)	(5.85)
$\hat{\beta}_{i,w}$	-0.091	-0.112	-0.113	-0.122	-0.110	-0.135	-0.158	-0.207	-0.306	-0.375	0.284
	(-2.24)	(-3.57)	(-3.79)	(-4.14)	(-3.31)	(-4.23)	(-4.12)	(-3.84)	(-3.71)	(-5.64)	(4.42)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.450	0.315	0.189	0.141	0.111	0.004	-0.018	-0.070	-0.037	-0.171	0.621
	(3.56)	(3.06)	(1.94)	(1.62)	(1.46)	(0.06)	(-0.24)	(-0.73)	(-0.28)	(-1.14)	(3.39)
$\hat{\beta}_{i,m}$	0.550	0.618	0.732	0.814	0.888	0.975	1.034	1.124	1.207	1.391	-0.841
	(15.03)	(20.45)	(25.68)	(31.99)	(38.30)	(44.84)	(45.59)	(42.06)	(31.92)	(27.28)	(-12.94)
$\hat{\beta}_{i,s}$	0.750	0.638	0.726	0.744	0.806	0.856	0.917	0.956	0.977	1.058	-0.308
	(13.32)	(15.41)	(19.67)	(20.03)	(21.58)	(22.17)	(23.89)	(23.29)	(19.27)	(15.60)	(-4.29)
$\hat{\beta}_{i,h}$	0.118	0.265	0.226	0.208	0.227	0.238	0.242	1.190	0.134	-0.051	0.169
	(1.57)	(3.39)	(2.89)	(3.12)	(3.67)	(4.16)	(4.58)	(3.47)	(1.89)	(-0.52)	(1.48)
$\hat{\beta}_{i,r}$	-0.219	0.001	0.062	0.036	0.087	0.080	-0.003	-0.146	-0.459	-0.872	0.653
	(-3.17)	(0.02)	(1.15)	(0.57)	(1.44)	(1.30)	(-0.05)	(-1.97)	(-4.47)	(-7.24)	(5.17)
$\hat{\beta}_{i,c}$	0.105	0.020	0.116	0.100	0.062	0.000	-0.125	-0.249	-0.482	-0.603	0.708
	(0.90)	(0.24)	(1.46)	(1.32)	(0.91)	(0.01)	(-1.44)	(-2.22)	(-3.04)	(-3.81)	(4.28)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.048	0.077	0.008	0.010	0.042	-0.042	-0.041	-0.080	-0.051	-0.113	0.161
	(0.34)	(0.64)	(0.07)	(0.09)	(0.37)	(-0.35)	(-0.32)	(-0.54)	(-0.28)	(-0.51)	(0.97)
$\hat{\beta}_{i,m}$	0.999	0.963	1.074	1.128	1.186	1.271	1.322	1.394	1.445	1.557	-0.558
	(21.08)	(22.67)	(27.07)	(25.54)	(24.16)	(25.79)	(25.73)	(26.01)	(25.76)	(20.58)	(-8.44)
$\hat{\beta}_{i,l}$	0.635	0.541	0.535	0.454	0.404	0.362	0.261	0.118	-0.122	-0.492	1.127
	(7.79)	(8.26)	(8.38)	(7.03)	(6.37)	(5.29)	(3.49)	(1.43)	(-1.24)	(-4.04)	(15.09)

Table 3
Performance of portfolios independently sorted by β^{CAPM} and LM

We divide the sample of NYSE/AMEX/NASDAQ stocks independently into three β^{CAPM} and three LM -based equal-weighted sub-samples at the end of each month. We hold the portfolios for the subsequent one month. Stocks below the 40th percentile of LM of NYSE stocks are defined as "Low" LM. Stocks above the 60th percentile of LM of NYSE stocks are defined as "High" LM. Stocks below the 40th percentile of β^{CAPM} are defined as "Low" β^{CAPM} . Stocks above the 40th percentile but below 60th percentile of β^{CAPM} are defined as "Medium" β^{CAPM} . Stocks above the 60th percentile of β^{CAPM} are defined as "High" β^{CAPM} . The symbol $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{SMB,t}$ is the month-t value of the Fama-French size factor, $f_{HML,t}$ is the month-t value of the Fama-French book-to-market factor, $f_{WML,t}$ is the month-t value of the momentum factor, $f_{RMW,t}$ is the month-t value of the Fama-French profitability factor, $f_{CMA,t}$ is the month-t value of the Fama-French investment factor, and $f_{LF,t}$ is the month-t value of the Liu (2006) liquidity factor. The testing period is 7/1963-6/2017 (648 months). The numbers in parentheses are t-statistics based on White (1980) heteroskedasticity-consistent standard errors.

	$Low\text{-}\beta^{CAPM}$	$Medium\text{-}\beta^{CAPM}$	$High\text{-}\beta^{CAPM}$	$L\text{-}H$
Panel A: Results of the *Low-LM* (High liquidity) sub-sample				
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\varepsilon_{i,t}$				
$\hat{\alpha}_i$ (%)	-0.306	-0.139	-0.424	0.118
	(-1.98)	(-1.73)	(-4.51)	(0.71)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,w}f_{WML,t}+\varepsilon_{i,t}$				
$\hat{\alpha}_i$ (%)	-0.213	-0.023	-0.152	-0.061
	(-1.24)	(-0.26)	(-1.32)	(-0.33)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,r}f_{RMW,t}+\beta_{i,c}f_{CMA,t}+\varepsilon_{i,t}$				
$\hat{\alpha}_i$ (%)	-0.194	-0.111	-0.153	-0.042
	(-1.18)	(-1.22)	(-1.34)	(-0.24)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,l}f_{LF,t}+\varepsilon_{i,t}$				
$\hat{\alpha}_i$ (%)	-0.277	-0.022	0.018	-0.295
	(-1.33)	(-0.17)	(0.11)	(-1.59)
Panel B: Results of the *High-LM* (Low liquidity) sub-sample				
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\varepsilon_{i,t}$				
$\hat{\alpha}_i$ (%)	0.303	0.174	-0.015	0.317
	(3.22)	(2.37)	(-0.17)	(3.28)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,w}f_{WML,t}+\varepsilon_{i,t}$				
$\hat{\alpha}_i$ (%)	0.418	0.293	0.164	0.254
	(4.19)	(3.88)	(1.69)	(2.30)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,r}f_{RMW,t}+\beta_{i,c}f_{CMA,t}+\varepsilon_{i,t}$				
$\hat{\alpha}_i$ (%)	0.308	0.151	0.086	0.222
	(3.11)	(1.88)	(0.85)	(2.23)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,l}f_{LF,t}+\varepsilon_{i,t}$				
$\hat{\alpha}_i$ (%)	0.030	0.033	-0.026	0.056
	(0.25)	(0.28)	(-0.15)	(0.53)

Table 4

Performance of decile portfolios sorted by the Vacisek beta (VCK^{Beta}) and the Fama and French beta (FF^{Beta})

We form equal-weighted decile portfolios at the end of each month based on the Vasicek beta (VCK^{Beta} in Eq. (7)) in Panel A and the Fama and French beta (FF^{Beta} in Eq. (10)) in Panel B and hold them for the subsequent one month. The symbol $R_{i,t}$ is the month-*t* return of portfolio *i*, $R_{f,t}$ is the risk-free rate for month *t*, $f_{MKT,t}$ is the month-*t* value of the market factor, $f_{SMB,t}$ is the month-*t* value of the Fama-French size factor, $f_{HML,t}$ is the month-*t* value of the Fama-French book-to-market factor, $f_{WML,t}$ is the month-*t* value of the momentum factor, $f_{RMW,t}$ is the month-*t* value of the Fama-French profitability factor, $f_{CMA,t}$ is the month-*t* value of the Fama-French investment factor, and $f_{LF,t}$ is the month-*t* value of the Liu (2006) liquidity factor. The testing period is 7/1963-6/2017 (648 months). The numbers in parentheses are *t*-statistics based on White (1980) heteroskedasticity-consistent standard errors.

Panel A: Results of the Vacisek beta (VCK^{Beta})

	Low- VCK^{Beta}	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*	*D9*	*High-* VCK^{Beta}	*L-H*
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.334	0.312	0.270	0.174	0.088	0.018	-0.100	-0.143	-0.341	-0.529	0.863
	(3.81)	(3.35)	(3.02)	(2.08)	(1.15)	(0.23)	(-1.23)	(-1.61)	(-3.22)	(-3.86)	(4.93)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.382	0.409	0.370	0.281	0.192	0.131	0.055	0.035	-0.080	-0.200	0.583
	(3.91)	(3.97)	(3.90)	(3.21)	(2.42)	(1.63)	(0.61)	(0.31)	(-0.56)	(-1.36)	(3.09)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.300	0.287	0.236	0.144	0.063	0.016	-0.027	0.026	-0.054	-0.107	0.407
	(3.18)	(2.91)	(2.52)	(1.60)	(0.76)	(0.19)	(-0.28)	(0.24)	(-0.41)	(-0.74)	(2.33)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.106	0.114	0.090	0.017	-0.040	-0.061	-0.137	-0.096	-0.130	-0.006	0.111
	(0.99)	(0.99)	(0.78)	(0.15)	(-0.33)	(-0.47)	(-0.94)	(-0.57)	(-0.68)	(-0.03)	(0.59)

Panel B: Results of the Fama and French beta (FF^{Beta})

	Low- FF^{Beta}	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*	*D9*	*High-* FF^{Beta}	*L-H*
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.347	0.262	0.235	0.157	0.087	-0.024	-0.018	-0.151	-0.276	-0.601	0.949
	(3.04)	(3.03)	(3.01)	(2.23)	(1.29)	(-0.37)	(-0.24)	(-1.82)	(-2.78)	(-4.03)	(5.47)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.411	0.334	0.324	0.246	0.188	0.100	0.159	0.051	-0.011	-0.246	0.656
	(3.42)	(3.62)	(4.03)	(3.48)	(2.76)	(1.60)	(1.79)	(0.45)	(-0.08)	(-1.48)	(3.50)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.386	0.233	0.184	0.105	0.050	-0.033	0.033	0.008	0.014	-0.132	0.519
	(3.18)	(2.55)	(2.18)	(1.38)	(0.69)	(-0.46)	(0.34)	(0.08)	(0.12)	(-0.84)	(2.83)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.043	0.027	0.038	0.032	0.004	-0.055	0.013	-0.050	-0.042	-0.133	0.176
	(0.31)	(0.25)	(0.36)	(0.28)	(0.03)	(-0.46)	(0.10)	(-0.32)	(-0.23)	(-0.56)	(0.96)

Table 5
Performance of decile portfolios sorted by β^{CAPM}: annual holding period

We form equal-weighted decile portfolios at the end of June each year based on the CAPM beta (β^{CAPM} in Eq. (1)) and hold them for the subsequent 12 months. The symbol $R_{i,t}$ is the month-*t* return of portfolio i, $R_{f,t}$ is the risk-free rate for month *t*, $f_{MKT,t}$ is the month-*t* value of the market factor, $f_{SMB,t}$ is the month-*t* value of the Fama-French size factor, $f_{HML,t}$ is the month-*t* value of the Fama-French book-to-market factor, $f_{WML,t}$ is the month-*t* value of the momentum factor, $f_{RMW,t}$ is the month-*t* value of the Fama-French profitability factor, $f_{CMA,t}$ is the month-*t* value of the Fama-French investment factor, and $f_{LF,t}$ is the month-*t* value of the Liu (2006) liquidity factor. The testing period is 7/1963-6/2017 (648 months). The numbers in parentheses are *t*-statistics based on White (1980) heteroskedasticity-consistent standard errors.

	Low-β^{CAPM}	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*	*D9*	*High-β^{CAPM}*	*L-H*
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.120	0.121	0.020	0.072	0.013	-0.020	-0.030	-0.149	-0.264	-0.534	0.653
	(1.42)	(1.87)	(0.32)	(1.19)	(0.22)	(-0.38)	(-0.58)	(-2.77)	(-4.04)	(-5.41)	(4.99)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.087	0.104	-0.022	0.019	-0.020	-0.053	-0.043	-0.134	-0.219	-0.427	0.514
	(0.98)	(1.54)	(-0.33)	(0.29)	(-0.33)	(-0.91)	(-0.79)	(-2.43)	(-2.98)	(-4.17)	(3.71)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.110	0.071	-0.033	0.036	-0.031	-0.054	-0.048	-0.123	-0.117	-0.267	0.377
	(1.28)	(1.06)	(-0.51)	(0.61)	(-0.54)	(-1.02)	(-0.96)	(-2.36)	(-1.81)	(-2.88)	(2.98)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	-0.138	-0.106	-0.180	-0.133	-0.156	-0.138	-0.090	-0.128	-0.151	-0.241	0.103
	(-1.32)	(-1.29)	(-2.00)	(-1.43)	(-1.59)	(-1.31)	(-0.78)	(-1.06)	(-1.06)	(-1.42)	(0.77)

Table 6

Performance of the β^{CAPM} portfolios: sub-period analysis

We form equal-weighted decile portfolios at the end of each month based on the CAPM beta (β^{CAPM} in Eq. (1)) and hold them for the subsequent one month. The symbol $R_{i,t}$ is the month-*t* return of portfolio *i*, $R_{f,t}$ is the risk-free rate for month *t*, $f_{MKT,t}$ is the month-*t* value of the market factor, $f_{SMB,t}$ is the month-*t* value of the Fama-French size factor, $f_{HML,t}$ is the month-*t* value of the Fama-French book-to-market factor, $f_{WML,t}$ is the month-*t* value of the momentum factor, $f_{RMW,t}$ is the month-*t* value of the Fama-French profitability factor, $f_{CMA,t}$ is the month-*t* value of the Fama-French investment factor, and $f_{LF,t}$ is the month-*t* value of the Liu (2006) liquidity factor. The numbers in parentheses are *t*-statistics based on White (1980) heteroskedasticity-consistent standard errors.

	Low-β^{CAPM}	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*	*D9*	*High-β^{CAPM}*	*L-H*
	Panel A: Results over 7/1963-6/1990 (324 months)										
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.073	0.096	0.106	0.015	0.035	-0.072	-0.156	-0.233	-0.327	-0.653	0.727
	(0.56)	(1.05)	(1.20)	(0.21)	(0.52)	(-1.11)	(-2.40)	(-3.14)	(-3.46)	(-4.54)	(3.53)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.075	0.166	0.180	0.105	0.113	0.033	-0.066	-0.166	-0.291	-0.666	0.741
	(0.53)	(1.63)	(1.82)	(1.29)	(1.52)	(0.48)	(-1.00)	(-2.12)	(-2.99)	(-4.24)	(3.17)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.100	0.083	0.100	0.035	0.049	-0.027	-0.064	-0.119	-0.132	-0.451	0.551
	(0.72)	(0.83)	(1.02)	(0.41)	(0.68)	(-0.38)	(-0.98)	(-1.58)	(-1.50)	(-3.22)	(2.63)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	-0.127	-0.021	-0.040	-0.078	-0.007	-0.079	-0.138	-0.153	-0.170	-0.423	0.296
	(-0.80)	(-0.17)	(-0.29)	(-0.56)	(-0.05)	(-0.50)	(-0.82)	(-0.84)	(-0.87)	(-1.74)	(1.56)
	Panel B: Results over 7/1990-6/2017 (324 months)										
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.684	0.534	0.358	0.316	0.258	0.133	0.059	-0.140	-0.314	-0.636	1.320
	(3.54)	(3.19)	(2.32)	(2.48)	(2.37)	(1.28)	(0.58)	(-1.17)	(-1.83)	(-2.72)	(4.95)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.800	0.647	0.469	0.433	0.365	0.259	0.215	0.086	0.038	-0.203	1.004
	(4.02)	(3.66)	(2.88)	(3.36)	(3.25)	(2.39)	(1.89)	(0.60)	(0.18)	(-0.92)	(3.76)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.875	0.610	0.359	0.324	0.245	0.139	0.127	0.032	0.077	-0.000	0.875
	(4.19)	(3.46)	(2.23)	(2.30)	(1.98)	(1.14)	(0.99)	(0.20)	(0.33)	(-0.00)	(3.02)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.201	0.185	0.077	0.160	0.171	0.076	0.131	0.063	0.088	0.143	0.058
	(0.84)	(0.87)	(0.38)	(0.88)	(1.02)	(0.44)	(0.69)	(0.27)	(0.28)	(0.38)	(0.20)

Table 7

Performance of the β^{CAPM} portfolios: sub-sample analysis

We form equal-weighted decile portfolios at the end of each month based on the CAPM beta (β^{CAPM} in Eq. (1)) and hold them for the subsequent one month. The symbol $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{SMB,t}$ is the month-t value of the Fama–French size factor, $f_{HML,t}$ is the month-t value of the Fama–French book-to-market factor, $f_{WML,t}$ is the month-t value of the momentum factor, $f_{RMW,t}$ is the month-t value of the Fama–French profitability factor, $f_{CMA,t}$ is the month-t value of the Fama–French investment factor, and $f_{LF,t}$ is the month-t value of the Liu (2006) liquidity factor. The numbers in parentheses are t-statistics based on White (1980) heteroskedasticity-consistent standard errors.

	Low-β^{CAPM}	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*	*D9*	*High-β^{CAPM}*	*L-H*
Panel A: NYSE/AMEX sample: 7/1963–6/2017 (648 months)											
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.256	0.124	0.147	0.122	0.078	-0.050	-0.098	-0.178	-0.327	-0.585	0.841
	(1.87)	(1.19)	(1.59)	(1.57)	(1.07)	(-0.71)	(-1.3)	(-2.34)	(-3.68)	(-4.31)	(4.67)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.374	0.232	0.231	0.193	0.170	0.051	0.008	-0.036	-0.126	-0.261	0.635
	(2.45)	(2.07)	(2.32)	(2.39)	(2.31)	(0.74)	(0.12)	(-0.43)	(-1.40)	(-1.78)	(3.17)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.287	0.070	0.050	0.004	-0.029	-0.169	-0.217	-0.281	-0.390	-0.467	0.754
	(1.90)	(0.63)	(0.51)	(0.05)	(-0.39)	(-2.48)	(-2.96)	(-3.87)	(-4.28)	(-2.98)	(3.94)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	-0.051	-0.079	-0.021	0.016	0.024	0.005	0.014	0.049	0.004	-0.005	-0.046
	(-0.33)	(-0.63)	(-0.17)	(0.15)	(0.22)	(0.04)	(0.11)	(0.32)	(0.02)	(-0.02)	(-0.26)
Panel B: NASDAQ sample: 7/1974–6/2017 (516 months)											
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.464	0.439	0.341	0.311	0.172	0.136	-0.017	-0.152	-0.307	-0.645	1.109
	(2.99)	(3.45)	(2.56)	(2.69)	(1.59)	(1.29)	(-0.14)	(-1.21)	(-2.14)	(-3.42)	(4.90)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.533	0.542	0.456	0.454	0.318	0.283	0.188	0.057	-0.020	-0.293	0.826
	(3.34)	(3.96)	(3.17)	(3.72)	(2.49)	(2.22)	(1.17)	(0.34)	(-0.12)	(-1.52)	(3.51)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.574	0.518	0.386	0.395	0.292	0.317	0.256	0.177	0.149	-0.056	0.630
	(3.49)	(3.79)	(2.80)	(3.00)	(2.24)	(2.44)	(1.63)	(1.09)	(0.93)	(-0.31)	(2.67)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.087	0.207	0.123	0.160	0.035	0.028	-0.064	-0.151	-0.134	-0.203	0.290
	(0.46)	(1.36)	(0.78)	(1.03)	(0.21)	(0.16)	(-0.32)	(-0.70)	(-0.54)	(-0.72)	(1.26)

Table 8
Performance of decile portfolios sorted by correlation (*Corr*)

We form equal-weighted decile portfolios at the end of each month based on correlation (*Corr*) and hold them for the subsequent one month. We estimate *Corr* as the correlation between the three-day log returns of the stock and three-day log returns of the market using daily returns for five years. The symbol $R_{i,t}$ is the month-*t* return of portfolio i, $R_{f,t}$ is the risk-free rate for month *t*, $f_{MKT,t}$ is the month-*t* value of the market factor, $f_{SMB,t}$ is the month-*t* value of the Fama–French size factor, $f_{HML,t}$ is the month-*t* value of the Fama–French book-to-market factor, $f_{WML,t}$ is the month-*t* value of the momentum factor, $f_{RMW,t}$ is the month-*t* value of the Fama–French profitability factor, $f_{CMA,t}$ is the month-*t* value of the Fama–French investment factor, and $f_{LF,t}$ is the month-*t* value of the Liu (2006) liquidity factor. The testing period is 7/1963–6/2017 (648 months). The numbers in parentheses are *t*-statistics based on White (1980) heteroskedasticity-consistent standard errors.

	Low-Corr	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*	*D9*	*High-Corr*	*L-H*
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.461	0.382	0.159	0.117	0.015	-0.026	-0.068	-0.057	-0.042	-0.150	0.611
	(3.38)	(3.24)	(1.44)	(1.37)	(0.24)	(-0.43)	(-1.35)	(-1.02)	(-0.72)	(-2.07)	(3.66)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.517	0.482	0.279	0.253	0.150	0.130	0.088	0.110	0.133	0.080	0.437
	(3.60)	(3.73)	(2.23)	(2.58)	(1.87)	(1.80)	(1.52)	(1.99)	(2.14)	(0.98)	(2.49)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.526	0.464	0.252	0.197	0.080	0.030	-0.032	-0.030	-0.022	-0.109	0.636
	(3.69)	(3.56)	(2.01)	(1.91)	(1.01)	(0.36)	(-0.48)	(-0.43)	(-0.32)	(-1.21)	(3.55)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.099	0.118	-0.035	0.013	-0.009	0.050	0.079	0.176	0.244	0.147	-0.048
	(0.52)	(0.61)	(-0.18)	(0.07)	(-0.06)	(0.33)	(0.58)	(1.41)	(2.29)	(1.44)	(-0.28)

Table 9
Cross-sectional regressions

We run the following regression each month over each 12-month period from July (t + 1) to next June (t + 12):

$$R_{i,t+m} - R_{f,t+m} = \gamma_0 + \gamma_1 \beta^{CAPM}{}_{i,t} + \gamma_2 MV_{i,t} + \gamma_3\, B/M_{i,t} + \gamma_4 MOM_{i,t} + \gamma_5 OP_{i,t} + \gamma_6 AG_{i,t} + \gamma_7 L_{i,t} + \epsilon_{i,t+m}$$

where $R_{i,t+m}$ is stock i's return in month $t + m$ (m = 1, 2, ..., 12), $R_{f,t+m}$ is the risk-free rate for month $t + m$, $\beta^{CAPM}{}_{i,t}$ is firm i's CAPM beta estimated over the prior 12-month period, $MV_{i,t}$ is stock i's market capitalization available at the end of June of each year, $B/M_{i,t}$ is stock i's book-to-market ratio available at the end of June of each year, $MOM_{i,t}$ is the buy-and-hold return of stock i over month t - 11 to month t - 1, $OP_{i,t}$ is stock i's book-equity-deflated operating profitability as defined in Fama and French (2015), $AG_{i,t}$ is stock i's annual total asset growth rate available at the end of June of each year, and $L_{i,t}$ is stock i's illiquidity proxy from month t - *11* to month t. We use four illiquidity proxies: the negative average daily dollar trading volume over the prior 12 months (*DV*), the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months (*LM*), the average daily absolute-return-to-dollar-volume ratio over the prior 12 months (*RV*), and the negative average daily turnover over the prior 12 months (*TO*). The calculation of RV requires that there are at least 80% of non-missing daily trading volumes available in the prior 12 months. The symbol $\hat{\gamma}_{\beta^{CAPM}}$ is the slope estimate on the CAPM beta, and similarly for others. Each regressor is transformed to have a mean of one and a standard deviation of one. For each regression, we use the maximum observations available for the regression. The numbers in parentheses are t-statistics. The intercept is not reported.

$\hat{\gamma}_{\beta^{CAPM}}$	$\hat{\gamma}_{MV}$	$\hat{\gamma}_{B/M}$	$\hat{\gamma}_{MOM}$	$\hat{\gamma}_{OP}$	$\hat{\gamma}_{AG}$	$\hat{\gamma}_{DV}$	$\hat{\gamma}_{LM}$	$\hat{\gamma}_{RV}$	$\hat{\gamma}_{TO}$
Fama and MacBeth (1973) estimates (%) over 7/1963–6/2017 (648 months)									
-0.183	-0.032	0.252	0.254	0.089	-0.275				
(-2.05)	(-1.62)	(6.36)	(4.09)	(1.87)	(-4.83)				
-0.144	0.004	0.241	0.282	0.231	-0.309	0.073			
(-1.62)	(0.19)	(6.00)	(4.42)	(3.33)	(-5.08)	(2.28)			
-0.116	-0.024	0.222	0.280	0.224	-0.308		0.115		
(-1.37)	(-1.26)	(5.65)	(4.37)	(3.28)	(-5.11)		(3.45)		
-0.133	-0.026	0.207	0.289	0.225	-0.299			0.426	
(-1.46)	(-1.35)	(5.57)	(4.59)	(3.53)	(-4.95)			(3.40)	
-0.047	-0.042	0.238	0.318	0.212	-0.279				0.253
(-0.60)	(-2.32)	(5.86)	(5.01)	(3.10)	(-4.91)				(5.37)

Table 10
Cross-sectional regressions with the component (β^{CAPM*})

We run the following regression each month over each 12-month period from July (*t + 1*) to next June (*t + 12*):

$$R_{i,t+m} - R_{f,t+m} = \gamma_0 + \gamma_1 \beta^{CAPM*}{}_{i,t} + \gamma_2 MV_{i,t} + \gamma_3 \, B/M_{i,t} + \gamma_4 MOM_{i,t} + \gamma_5 OP_{i,t} + \gamma_6 AG_{i,t} + \epsilon_{i,t+m}$$

where $R_{i,t+m}$ is stock *i*'s return in month $t + m$ (*m* = 1, 2, ..., 12), $R_{f,t+m}$ is the risk-free rate for month $t + m$, $\beta^{CAPM*}{}_{i,t}$ is firm *i*'s component CAPM beta over the prior 12-month period, $MV_{i,t}$ is stock *i*'s market capitalization available at the end of June of each year, $B/M_{i,t}$ is stock *i*'s book-to-market ratio available at the end of June of each year, $MOM_{i,t}$ is the buy-and-hold return of stock *i* over month *t - 11* to month *t - 1*, $OP_{i,t}$ is stock *i*'s book-equity-deflated operating profitability as defined in Fama and French (2015), and $AG_{i,t}$ is stock *i*'s annual total asset growth rate available at the end of June of each year. Each month we regress firm *i*'s CAPM beta (β^{CAPM}) on each of our four illiquidity proxies (*L*) to obtain the component of β^{CAPM} that is orthogonal to *L*. We use four illiquidity proxies: the negative average daily dollar trading volume over the prior 12 months (*DV*), the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months (*LM*), the average daily absolute-return-to-dollar-volume ratio over the prior 12 months (*RV)*, and the negative average daily turnover over the prior 12 months (*TO*). The calculation of *RV* requires that there are at least 80% of non-missing daily trading volumes available in the prior 12 months. The symbol $\hat{\gamma}_{\beta^{CAPM}}$ is the slope estimate on the CAPM beta, and similarly for others. Each regressor is transformed to have a mean of one and a standard deviation of one. For each regression, we use the maximum observations available for the regression. The numbers in parentheses are *t*-statistics. The intercept is not reported.

$\hat{\gamma}_{\beta^{CAPM*}DV}$	$\hat{\gamma}_{\beta^{CAPM*}LM}$	$\hat{\gamma}_{\beta^{CAPM*}RV}$	$\hat{\gamma}_{\beta^{CAPM*}TO}$	$\hat{\gamma}_{MV}$	$\hat{\gamma}_{B/M}$	$\hat{\gamma}_{MOM}$	$\hat{\gamma}_{OP}$	$\hat{\gamma}_{AG}$
Fama and MacBeth (1973) estimates (%) over 7/1963–6/2017 (648 months)								
-0.112				-0.045	0.247	0.282	0.204	-0.293
(-1.50)				(-2.56)	(6.03)	(4.38)	(3.10)	(-6.54)
	-0.080			-0.034	0.253	0.272	0.193	-0.298
	(-1.17)			(-1.80)	(6.11)	(4.21)	(3.00)	(-6.53)
		-0.089		-0.032	0.251	0.281	0.191	-0.294
		(-1.17)		(-1.65)	(6.11)	(4.40)	(2.98)	(-6.51)
			-0.004	-0.034	0.267	0.273	0.210	-0.306
			(-0.08)	(-1.84)	(6.36)	(3.94)	(3.09)	(-6.59)

Table 11
Cross-sectional regressions with additional controls

We run the following regression each month over each 12-month period from July (*t + 1*) to next June (*t + 12*):

$$R_{i,t+m} - R_{f,t+m} = \gamma_0 + \gamma_1 \beta^{CAPM}{}_{i,t} + \gamma_2 MV_{i,t} + \gamma_3 \, B/M_{i,t} + \gamma_4 MOM_{i,t} + \gamma_5 OP_{i,t} + \gamma_6 AG_{i,t} + \gamma_7 L_{i,t}$$
$$+\gamma_8 \beta^{TB}{}_{i,t} + \gamma_9 MAX_{i,t} + \gamma_{10} IVOL_{i,t} + \gamma_{11} ISKEW_{i,t} + \gamma_{12} \beta_{l,t} + \epsilon_{i,t+m}$$

where $R_{i,t+m}$ is stock *i*'s return in month *t* + *m* (*m* = 1, 2, ..., 12), $R_{f,t+m}$ is the risk-free rate for month *t* + *m*, $\beta^{CAPM}{}_{i,t}$ is firm *i*'s CAPM beta estimated over the prior 12-month period, $MV_{i,t}$ is stock *i*'s market capitalization available at the end of June of each year, $B/M_{i,t}$ is stock *i*'s book-to-market ratio available at the end of June of each year, $MOM_{i,t}$ is the buy-and-hold return of stock *i* over month *t - 11* to month *t - 1*, $OP_{i,t}$ is stock *i*'s book-equity-deflated operating profitability as defined in Fama and French (2015), and $AG_{i,t}$ is stock *i*'s annual total asset growth rate available at the end of June of each year. β^{TB} is a stock's exposure to 3-month treasury bill rate. *MAX* is the lottery demand. *IVOL* is the idiosyncratic volatility. *ISKEW* is the idiosyncratic skewness. β_l is the liquidity beta from Liu (2006) model. The symbol $\hat{\gamma}_{\beta^{CAPM}}$ is the slope estimate on the CAPM beta, and similarly for others. Each regressor is transformed to have a mean of one and a standard deviation of one. For each regression, we use the maximum observations available for the regression. The numbers in parentheses are *t*-statistics. The intercept is not reported.

$\hat{\gamma}_{\beta^{CAPM}}$	$\hat{\gamma}_{MV}$	$\hat{\gamma}_{B/M}$	$\hat{\gamma}_{MOM}$	$\hat{\gamma}_{OP}$	$\hat{\gamma}_{AG}$	$\hat{\gamma}_{\beta^{TB}}$	$\hat{\gamma}_{MAX}$	$\hat{\gamma}_{IVOL}$	$\hat{\gamma}_{ISKEW}$	$\hat{\gamma}_{\beta_l}$
Fama and MacBeth (1973) estimates (%) over 7/1963–6/2017 (648 months)										
-0.181	-0.032	0.272	0.208	0.068	-0.253	0.715				
(-2.10)	(-1.67)	(6.86)	(3.32)	(1.64)	(-6.58)	(0.83)				
-0.091	-0.051	0.270	0.216	0.044	-0.251		-0.303			
(-1.10)	(-3.03)	(7.55)	(3.81)	(1.12)	(-7.12)		(-4.38)			
-0.151	-0.037	0.242	0.249	0.065	-0.245			-0.045		
(-1.81)	(-2.29)	(7.01)	(4.63)	(1.68)	(-7.17)			(-0.58)		
-0.178	-0.034	0.260	0.252	0.063	-0.253				-0.093	
(-1.99)	(-1.71)	(6.38)	(4.07)	(1.52)	(-6.55)				(-4.72)	
-0.127	-0.033	0.246	0.248	0.065	-0.245					0.192
(-1.57)	(-1.89)	(6.47)	(4.20)	(1.58)	(-6.69)					(2.09)

Table 12
Pricing ability of risk factors

This table reports the risk price *t*-ratios, the price of covariance risk *t*-ratios following Kan et al. (2013) and the risk price *t*-ratios under the stochastic discount factor (SDF) framework based on the standard errors under correct model specification ($t_{GKR,c}$) and model misspecification ($t_{GKR,m}$) following Gospodinov et al. (2014). For the risk price and price of covariance risk tests, we apply different *t*-statistics: the FM *t*-ratio of Fama and MacBeth (1973), the SH *t*-ratio of Shanken (1992) with errors-in-variables adjustment, the JW *t*-ratio of Jagannathan and Wang (1996), and the KRS *t*-ratio of Kan et al. (2013) under potentially mis-specified models. Test models are the FF3FM, momentum-extended FF3FM, FF5FM, and LCAPM. The risk factors in FF3FM are the excess market returns, size factor, and book-to-market factor (Fama and French (1993)). The risk factors in the momentum-extended FF3FM are the excess market returns, size factor, book-to-market factor, and momentum factor. The risk factors in FF5FM are the excess market returns, size factor, book-to-market factor, profitability factor, and investment factor (Fama and French (2015)). The risk factors in LCAPM are the excess market returns and liquidity factor (Liu (2006)). We sort sample stocks into twenty-five β^{CAPM} portfolios at the end of each month starting from July 1963. We hold the twenty-five portfolios for one month subsequent to the portfolio formation and calculate their equal-weighted monthly returns over the one-month holding period. Test assets are the twenty-five β^{CAPM} portfolios plus five value-weighted industry portfolios of Gomes et al. (2009).

	t-ratios of factor's loading				*t*-ratios of covariance risk				SDF pricing ability	
	t_{FM}	t_S	t_{JW}	t_{KRS}	t_{FM}	t_S	t_{JW}	t_{KRS}	$t_{GKR,c}$	$t_{GKR,m}$
	$FF3FM: E(R_i - R_f) = \beta_{i,m}E(f_{MKT}) + \beta_{i,s}E(f_{SMB}) + \beta_{i,h}E(f_{HML})$									
f_{MKT}	-1.81	-1.80	-1.78	-1.77	-1.50	-1.49	-1.45	-1.45	-3.34	-3.10
f_{SMB}	0.53	0.52	0.52	0.53	1.20	1.19	1.20	1.20	0.42	0.41
f_{HML}	1.19	1.19	1.18	1.18	0.93	0.92	0.91	0.91	-2.12	-1.80
	$\text{Momentum} - \text{ext. FF3FM}: E(R_i - R_f) = \beta_{i,m}E(f_{MKT}) + \beta_{i,s}E(f_{SMB}) + \beta_{i,h}E(f_{HML}) + \beta_{i,w}E(f_{WML})$									
f_{MKT}	-0.63	-0.61	-0.56	-0.56	0.16	0.16	0.14	0.13	-3.26	-2.96
f_{SMB}	1.66	1.62	1.40	1.44	2.07	1.96	1.73	1.76	-0.41	-0.42
f_{HML}	1.52	1.47	1.43	1.44	1.92	1.82	1.62	1.60	-2.80	-2.29
f_{WML}	2.13	2.04	1.63	1.56	2.11	2.00	1.47	1.40	-2.23	-1.88
	$FF5FM: E(R_i - R_f) = \beta_{i,m}E(f_{MKT}) + \beta_{i,s}E(f_{SMB}) + \beta_{i,h}E(f_{HML}) + \beta_{i,r}E(f_{RMW}) + \beta_{i,c}E(f_{CMA})$									
f_{MKT}	-2.06	-2.03	-1.95	-1.94	-1.89	-1.83	-1.71	-1.64	-3.14	-2.89
f_{SMB}	1.07	1.05	1.04	1.01	1.89	1.83	1.86	1.82	-1.45	-1.27
f_{HML}	0.08	0.08	0.08	0.08	0.65	0.63	0.59	0.52	0.81	0.60
f_{RMW}	1.45	1.41	1.35	1.30	1.28	1.23	1.19	1.16	-2.60	-2.09
f_{CMA}	-0.72	-0.70	-0.69	-0.61	-0.93	-0.90	-0.86	-0.74	-1.26	-0.97
	$LCAPM: E(R_i - R_f) = \beta_{i,m}E(f_{MKT}) + \beta_{i,l}E(f_{LF})$									
f_{MKT}	0.43	0.43	0.42	0.42	1.55	1.51	1.52	1.51	-5.45	-5.34
f_{LF}	2.83	2.79	2.86	2.87	2.27	2.20	2.31	2.31	-5.93	-5.82

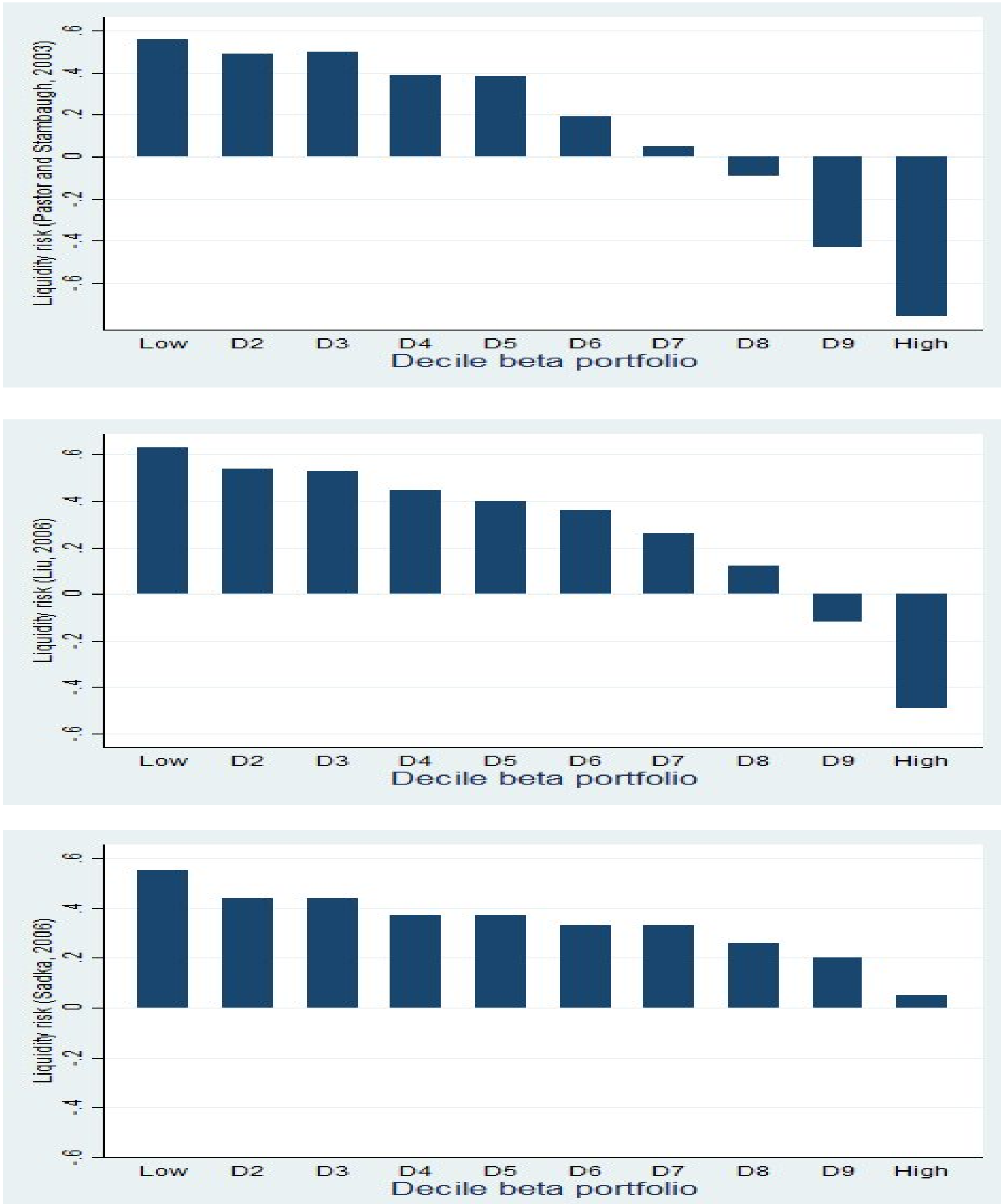

Figure 1. Liquidity Risk

This figure plots the liquidity risk of the CAPM beta (β^{CAPM}) decile portfolios. We form β^{CAPM} portfolios at the end of each month and hold them for the subsequent one month. We estimate the loading on the liquidity risk factor of Pastor and Stambaugh (2003), Liu (2006), and Sadka (2006).