The Quality Premium with Leverage and Liquidity Constraints

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This version: September 10, 2020

Abstract

This research analyzes the causes of the quality premium, one of the most intriguing and successful investment strategies in equity markets. While previous research has argued that psychological biases explain the performance of the quality minus junk factor, our paper analyzes a leverage constraint explanation within a rational risk-based framework. The quality factor is multidimensional in nature, which suggests that a combination of risk, frictions, and behavioral biases is a reasonable explanation. Once we incorporate margin requirements and liquidity restrictions, we find that tighter conditions result in a higher intercept and a lower slope for the empirically implemented capital asset pricing model when using 10 quality-sorted portfolios. Our paper shows that, indeed, not only behavioral biases explain quality, but also market frictions account for its performance.

Keywords: Margin requirements; quality premium; funding constraints; liquidity constraints; security market line

JEL classification: C12, G14, N22

The authors acknowledge financial support from the Ministry of Science, Innovation, and Universities through grant PGC2018-095072-B-I00. In addition, Gonzalo Rubio acknowledges financial support from Generalitat Valencia grant Prometeo/2017/158, and Ana González-Urteaga acknowledges financial support from the Ministry of Economics and Competitiveness through grants ECO2016-77631-R (AEI/FEDER.UE), PID2019-104304-GB-I00 and UPNA Research Grant for Young Researchers, Edition 2018. We also thank Belén Nieto for helpful suggestions. Any errors are entirely our own.

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1. Introduction

Quality pricing and the associated investment strategies are receiving increasing attention among practitioners and academics.[1] A recent line of research undertaken by Asness, Frazzini and Pedersen (2019, AFP hereafter) identifies a quality stock as an asset for which investors would be willing to pay a high price, which means that these stocks are simultaneously safe (low beta), profitable (high return on equity), growing (high cash flow growth), and well managed (high dividend payout ratio). As Alquist, Frazzini, Ilmanen, and Pedersen (2020) point out when discussing the facts and fictions of low-risk strategies, AFP (2019) focus on a broad composite or umbrella series of three subgroups, namely profitability, growth, and safety to construct a risk factor using the Fama and French (1993) dollar-neutral weighting scheme. The authors' quality minus junk (QMJ hereafter) factor, which buys high-quality stocks and shorts low-quality (junk) stocks, earns significant risk-adjusted returns not only in the U.S. market, but also in 24 other countries. In addition, the striking finding of AFP is that the QMJ factor displays large realized returns during downturns, which suggests that the quality-based factor does not exhibit bad-times risk. The surprising and extremely good performance of the QMJ factor in bad economic times implies that high-quality stocks are hedging assets, and consequently, they should have relatively low average returns during long sample periods. On the contrary, the factor displays positive Fama-French (1993) three- and four-factor alphas, the latter including Carhart's (1997) momentum factor (MOM), and a positive Fama-French (2015) five-factor alpha with relatively low

[1] Interestingly, this is the case even though, as shown by Frazzini, Kabiller, and Pedersen (2018), quality investing is one the key factors behind Warren Buffet's extraordinary historical performance. At least since Graham (1973), there has been a long industry tradition regarding quality strategies. However, there are multiple ways of understanding quality and, consequently, several practical and competing quality strategies. For example, Novy-Marx (2013) shows that gross profitability, a simple quality definition, which is the difference between a firm's total revenues and the costs of goods sold, scaled by assets is a powerful metric predicting the relative average return behavior of stocks. The Fama-French (2015) profitability factor is operating profitability, which is revenues minus the costs of goods sold, minus selling (general and administrative) expenses, minus interest expenses, divided by book equity.

idiosyncratic risk. As AFP argue, this evidence presents a very serious challenge to rational risk-based explanations of asset pricing.

These striking results motivate our research. Why do high-quality stocks have lower beta values but higher average returns than junk portfolios? Relative to other strategies, which rely on a single characteristic such as beta, value, profitability, or momentum, quality is multidimensional in nature. This suggests that it is difficult to conceive a unified explanation for its performance. A first possibility is that quality stocks could be exposed to an unidentified risk factor. On other hand, Bouchard, Ciliberti, Landier, Simon, and Thesmar (2016) strongly argue in favor of psychological biases to explain quality performance. They show that analysts pay deficient attention to classic profitability indicators, generating forecast errors that are systematically and negatively correlated with quality indicators. The information obtained from profitability information is badly weighted by analysts when forming their expectations.[2] Our research focuses on a third possibility closely related to risk compensation arguments: we analyze whether the leverage constraint hypothesis of Frazzini and Pedersen (2014), further explored by Jylha (2018), Chen and Lu (2019), Asness, Frazzini, Gormsen and Pedersen (2019), and Alquist et al. (2020), who focus their analysis on low-risk strategies, helps explain the puzzling behavior of high- versus low-quality stocks.[3] Note that the low-risk and quality strategies share the safety dimension. However, the multidimensional nature of quality makes necessary to investigate whether quality can also be explained, at least partially, by the leverage constraint hypothesis. Although, some overlaps with the explanation of low-risk

[2] Bouchard et al. (2016) employ cash-flows over assets as the measure of quality.

[3] Asness et al. (2019) argue that leverage constraints are both a limit to arbitrage for the low-risk effect, but simultaneously can cause the low-risk effect. Moreover, they recognize that the low-risk effect could also be explained by the lottery preferences theory of Barberis and Huang (2008), empirically investigated by Bali, Brown, Murray, and Tang (2019). They propose the betting against correlation approach to disentangle both theories and they document a stronger evidence for leverage constraints.

strategies may be expected, it does not mean that the leverage constraint hypothesis should not be investigated in the framework of quality. On the contrary, in this paper we argue that we should analyze whether the performance of combining well managed firms with high cash-flow growth, high profitability, and low-risk, is also related to leverage and liquidity constraints. These borrowing restrictions and liquidity frictions have not been explicitly analyzed or even directly considered as the drivers of quality performance. This is the key contribution of this paper. In fact, we do find a robust support for the leverage constraint hypothesis, also sustained for both market and funding liquidity restrictions.

Frazzini and Pedersen (2014), following Black's (1972) seminal paper, show that the slope of the leveraged constrained capital asset pricing model (CAPM) is lower than the slope of the classic unconstrained CAPM. Indeed, the intercept and slope of the CAPM under leverage constraints depend on the tightness of investors' borrowing constraints. Jylha (2018), using the minimum initial margin requirement set by the Federal Reserve Board in its Regulation T between 1934 and 1974, finds strong empirical support for the hypothesis that leverage constrained investors help explain why the slope of the security market line is flatter than the theoretical slope under the classic unconstrained CAPM. Using a similar empirical approach, with the Federal Reserve (FED) initial margin requirement from July 1957 to December 1974 and a synthetic margin from January 1975 to August 2017, we show that the quality premium depends significantly on leverage constrains. Beyond margin effects on the quality premium, we report evidence showing that quality performance also depends on funding liquidity restrictions and market-wide illiquidity. We first analyze the cross-sectional variation of 10 quality-sorted portfolios using the classic CAPM framework. In other words, we estimate monthly time series of the intercept and the slope of the security market line with the excess returns of 10 quality portfolios as the test assets. Then, we regress the intercept and slope estimates on the margin requirements. We find that the intercept (slope) is positively (negatively) related to the initial margin requirements, as predicted by Frazzini and Pedersen (2014) and as reported by Jylha (2018), using 10 portfolios sorted by market beta from 1934 to 1974. Moreover, the intercept is significantly affected by funding liquidity, but not by market illiquidity, while the slope is significantly related to both funding liquidity and market-wide illiquidity. Our results suggest that borrowing and liquidity restrictions explain, at least partially, the extraordinary behavior of quality-based investment strategies. We do not argue that this friction-based explanation is the only reason behind the success of the quality approach. Behavioral reasons could perfectly be part of the explanation. However, it is also the case that behavioral biases are not the only reason. A rational risk-based explanation under funding constraints also accounts for the impressive performance of quality investment.

This paper is organized as follows. Section 2 presents the data and motivates the research question. Section 3 describes the estimation of the synthetic margin requirements, given the theoretical framework, and Section 4 presents the empirical results with margin requirements. Section 5 discusses the simultaneous effects of funding liquidity, market-wide illiquidity, and margin requirements. Section 6 presents a robust analysis displaying some international evidence. We conclude the paper in Section 7.

2. Historical Performance of the QMJ Factor

2.1 Data

Data on both the QMJ factor and the 10 quality-sorted portfolios are obtained from the AQR Capital Management's database (www.aqr.com). Data on the Fama-French (1993) three-factor model with excess market returns, small minus big (SMB), and high-value minus low-growth (HML) and on the Fama-French (2015) five-factor model, with additional profitability (RMW) and investment aggressiveness (CMA) factors, together with Carhart's (1997) momentum factor (MOM), are downloaded from Kenneth French's database (http://mba.tuck.darmouth.edu). The betting against beta (BAB) factor of Frazzini and Pedersen (2014) is also downloaded from AQR Capital Management. The BAB factor is the return differential between leveraged low-beta stocks and de-leveraged high-beta stocks. Frazzini and Pedersen show that leverage constraints are strong and significantly reflected in the return provided by this factor. Indeed, they argue that the positive and highly significant risk-adjusted returns relative to traditional asset pricing models shown by portfolios sorted by the level of market beta are explained by shadow cost-of-borrowing constraints.

2.2 Performance of Quality-Sorted Portfolios

In this section, we characterize and analyze the performance of the QMJ factor. Figure 1 shows the cumulative growth of 100 U.S. dollars invested in the QMJ factor from January 1965 to August 2017. The most salient feature of Figure 1 is the behavior of the QMJ factor during U.S. recessions. In all cases, the QMJ factor exhibits impressive hedging behavior. To analyze its risk-adjusted performance, we simply run regressions with alternative asset pricing models, included the CAPM, the Fama-French three- and five-factor models, and these models augmented with the MOM and BAB factors. Following Asness, Frazzini, Israel, and Moskowitz (2015), we use the HML factor with monthly price updates in the book-to-market ratio rather than the original Fama-French (1993) HML factor.[4]

The time series regressions are given by alternative specifications of the following model:

$$
\begin{aligned}
QMJ_t &= \alpha_q + \beta_{q,m} MRP_t + \beta_{q,smb} SMB_t + \beta_{q,hml} HML_t + \beta_{q,rmw} RMW_t \\
&\quad + \beta_{q,cma} CMA_t + \beta_{q,mom} MOM_t + \beta_{q,bab} BAB_t + \varepsilon_t \ ,
\end{aligned} \tag{1}
$$

where MRP is the excess return of the market portfolio, or the market risk premium. Table 1 reports the alphas, and the risk-factor loadings for the alternative models.[5] The QMJ factor has highly positive and significant alphas in all models. The strong alpha performance ranges from 64 to 39 basis points per month for the Fama-French three-factor model augmented by MOM, and the Fama-Franch five-factor model, respectively. The adjusted R^2 values increase from approximately 29% for the CAPM to 52% for the Fama-French three-factor set of models, and to 77% for the Fama-French five-factor group. The QMJ factor has relatively large negative market, size, and value exposures and a strong positive profitability exposure. Overall, the QMJ dynamic factor delivers impressive performance.

3. Initial Margin Requirements

If high-quality stocks have relatively low betas and investors on quality want positions with higher risk, the obvious simultaneous strategy is to leverage their investment borrowing in the risk-free asset and buying additional stocks with high-quality characteristics. However, under borrowing constraints imposed by margin requirements, the maximum leverage position is limited. The alternative is to invest in junk stocks with high betas. Hence, relative to the unconstrained CAPM, this creates a higher

[4] This is the HML Devil factor proposed by Asness and Frazzini (2013), available from (www.aqr.com).
[5] These results are consistent with the performance reported by AFP (2019) using data from July 1957 to December 2016.

demand for junk stocks precisely during tighter leverage conditions, increasing their prices and lowering their expected returns. Note, of course, that this is exactly the intuition behind the model of Frazzini and Pedersen (2014) and the empirical tests of Jylha (2018) regarding the behavior of high- versus low-beta assets to explain why the slope of the empirically implemented CAPM is lower than the slope of the theoretical unconstrained CAPM.

The CAPM with the margin constraints of Gàrleanu and Pedersen (2011) and Frazzini and Pedersen (2014), employed in Jylha's (2018) research as the reference model, is given by

$$E\left(R^{e}_{j,t+1}\right) = \psi m + \beta_j \left[E\left(R^{e}_{m,t+1}\right) - \psi m \right] , \tag{2}$$

where $E\left(R^{e}_{j,t+1}\right)$ is the expected excess return over the risk-free rate of any asset or portfolio *j*, $E\left(R^{e}_{m,t+1}\right)$ is the expected excess market return, ψ is the average shadow price of the initial margin requirement faced by the investor's optimal decision problem, and *m* is the initial margin requirement when all investors are assumed to confront the same margin requirement. This research analyzes whether the leverage constraint hypothesis embedded in expression (2) captures, at least partially, the risk-adjusted quality premium.

As Jylhä (2018) shows, a key issue is to have the appropriate proxy for margin requirements. The usual proxies measure the cost of leverage rather than the constraint on maximum borrowing. Jylha employs the minimum level of the initial margin requirement by the Federal Reserve Board, which is only available from October 1934 to January 1974. Unfortunately, quality-sorted portfolio data are readily available only since July 1957. This creates an additional difficulty, given the short time series of coincident periods between margin and quality-sorted data.

As pointed out in the introduction, using the Federal Reserve Board data, Jylhä (2018) shows a positive and significant relation between the initial margin requirement and the change in the lagged margin credit. This evidence motivates the estimation of a margin-mimicking variable or synthetic margin by projecting the initial margin requirement series from July 1957 to December 1974 onto a set of instruments and using the estimated coefficients to obtain a longer time series of instrumented margin requirements from January 1975 to August 2017.

Given the evidence reported by Jylha (2018), an obvious instrument is lagged margin credit. We employ six-month-lagged changes in margin debt, which is the debt of security brokers and dealers downloaded from www.finra.org/investors/learn-to-invest/advanced-investing/margin-statistics. In addition, we use a set of variables that have been shown to be strong predictors of future real activity and future stock market returns, as well as a cycle indicator based on risk aversion. Gilchrist and Zakrajsek (2012) show the forecasting power of the term structure of credit spreads for future output growth. They argue that there is a pure credit component orthogonal to macroeconomic conditions that accounts for a large part of the predictive capacity of credit spreads. It therefore seems natural to employ the default spread, calculated as the difference between Moody’s yield on Baa corporate bonds and the 10-year government bond yield, as a potentially relevant control variable. Both yields are obtained from the Federal Reserve Statistical Release. The most popular predictor of future equity returns is the aggregate dividend yield. As discussed in Cochrane (2017), the time-varying behavior of the expected market risk premium has a clear correlation with the business cycle. Cochrane shows that, indeed, the log of the dividend yield is a strong forecaster of the future market risk premium and, could therefore serve as a potential state variable to forecast real activity.[6]

We also employ the Hansen–Jagannathan (1991) volatility bound as an additional predictor. Nieto and Rubio (2014) propose a method of extracting future real activity information from optimally combined size-sorted portfolios. Specifically, they show that a size-based volatility bound of the stochastic discount factor (SDF) is a powerful in-sample and out-of-sample predictor of future industrial production growth. We estimate the monthly volatility bound of the model-free SDF with overlapping five-year sub-periods of monthly data from 10 size-sorted equity portfolios. The monthly estimated volatility corresponds to the average level of the risk-free interest rate for each of the five-year sub-periods. The time-varying behavior of this instrument is illustrated in Figure 2, which shows that the volatility bound is indeed a leading economic indicator. Note that this procedure does not depend on any consumption-based SDF specification, so the potential predictive relation does not depend on any given consumption dynamics. Finally, we employ the estimated surplus consumption ratio of Campbell and Cochrane (1999), who employ habit preferences to obtain a macro-finance asset pricing model with time-varying risk aversion. We collect data on monthly seasonally adjusted aggregate real per-capita consumption expenditures of non-durables and services from the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/). The estimation of surplus consumption closely follows the procedure described by Campbell and Cochrane (1999), which assumes a random walk process for consumption, and an autoregressive process for the log surplus consumption ratio, allowing for a sensitivity function that captures how surplus reacts to innovations in consumption growth. The time-varying behavior of surplus consumption is shown in

[6] The dividend yield in logs is computed from the original series on Robert Shiller's website (http://www.econ.yale.edu/~shiller/).

Figure 3. It illustrates that surplus consumption is a well-behaved business cycle indicator.

Table 2 shows the ordinary least squares OLS regression of the initial margin requirements on the set of instruments using data from August 1960 to December 1974 with heteroskedasticity- and autocorrelation-consistent (HAC) standard error *t*-statistics.[7] Note that we employ lagged margin debt growth in the regressions. All coefficient estimators are strongly significant with an adjusted *R*-squared of 45.2%. Figure 4 shows the real initial margin requirements set by the FED via Regulation T, and the fitted margins obtained from the previous regression. It illustrates that our synthetic model strongly captures the rise and falls of margin requirements. Henceforth, given this evidence, we combine the real initial margin requirements set by the FED from July 1957 to December 1974 and the synthetic margin estimated with the proposed mimicking model from January 1975 to August 2017.

The full sample period of the combined data is next divided into three non-overlapping subsamples classified by the level of the margin requirement. The low-tightness requirement includes 182 observations with a margin of 50% up to and including 70%, the medium-tightness requirement includes 358 observations with a margin is from 70% up to and including 87%, and the high-tightness requirement includes 182 observations with a margin from 87% up to and including 98.7%.

Table 3 shows the average annualized return differential between high- and low-quality decile portfolios and the QMJ factor for the alternative partitions and the full sample period. The results are consistent with the predictions of the leverage constraint hypothesis. Tighter leverage constraints result in a higher-quality, low-beta return

[7] We also employ the term premium, calculated as the difference between long- and short-term government bond yields, the growth of industrial production, and the realized monthly volatility of the stock market estimated with daily returns within a month. None of these variables turned out to be statistically different from zero.

premium. Low-beta (high-quality) assets tend to have higher returns than high-beta (low-quality) assets, especially under tighter conditions. Analogous results are found for the QMJ factor. The Sharpe ratios follow a similar pattern. Recall that high-quality stocks have much lower betas than junk stocks. During the full sample period, the betas of high- and low-quality stocks are 0.918 and 1.345, respectively. The betas for the three alternative subperiods with low, medium, and high margin requirements are, respectively, 0.965, 0.915, and 0.885 for high-quality stocks and 1.228, 1.285, and 1.548 for low-quality stocks. Beta differentials increase with tighter conditions.

Table 4 shows the results for alphas estimated by the CAPM and by the three-factor Fama-French (1993) model augmented with Carhart's (1997) momentum factor. As before, we employ the HML-Devil factor of Asness and Frazzini (2013) rather than the original HML factor of Fama and French (1993). In all panels, the reported beta refers to the market beta, independent of whether the CAPM or the multi-factor model is used. The results are striking. We find that tighter leverage constraints result in positive, significant, and higher alphas for high- relative to low-quality portfolios. This is the case for both the CAPM and Fama-French models. The risk-adjusted behavior of quality stocks seems to be closely linked to leverage constraints. The market betas of the return differentials between extreme quality portfolios, and the QMJ factor are also related to the level of leverage tightness. The higher the leverage constraints, the more negative the market betas of high- minus low-quality portfolios.

4. Cross-Sectional Variation of Quality-Sorted Stocks and Effects of Leverage Constraints

Capital asset pricing models under leverage constraints establish that their intercepts and slopes depend on the tightness of investors' leverage constraints. More precisely, the tighter the leverage constraint, the higher the intercept and the lower the slope, which results in a flatter security market line.

In this section, we employ an extended version of the empirical strategy followed by Jylha (2018) with low- and high-beta stocks using, in our case, high- and low-quality stocks. We employ the 10 quality-sorted portfolios constructed by AQR Capital Management. We first estimate the ex-ante market betas of the 10 quality-sorted portfolios using the past 36 months on the excess market portfolio return. Then, for every month, we estimate the cross-sectional relation between the portfolio' ex ante betas and the realized returns of the 10 quality portfolios, as follows:

$$R^{e}_{j,t} = \lambda_{0t} + \lambda_{mt}\beta_{j,t-1} + \varepsilon_{j,t} \ , \ \ j = 1, \ldots,10 \ , \qquad (3)$$

where, under the leveraged constrained CAPM, as shown in equation (2), λ_{0t} is the nonnegative shadow price of the leverage constraint times the required margin, and λ_{mt} is the market risk premium minus the shadow price times the margin in month *t*. This is the well-known Fama-MacBeth (1973) procedure that yields a monthly series of intercepts and slopes. Recall that the final estimates of the intercept and slope are the averages of the estimated intercept and slopes of expression (3). Panel A of Table 5 presents the empirical results for the full sample period and for the three subperiods ranked by the level of leverage constraints. For the overall sample period, the average estimated intercept and average slope are 0.011, with a *t*-statistic of 4.5, and -0.0057, with a *t*-statistics of -2.05, respectively. Although the relation between the estimates of the cross-sectional regression and tightness across subperiods is not monotonic, it is important to note that the intercept is basically zero under low tightness conditions but becomes positive and highly significant under the highest leverage constraint scenario. Similarly, the slope coefficient is zero under weakest leverage constraints and becomes negative and statistically different from zero under higher margin requirements. Overall, the results are consistent with the leverage constraint hypothesis.

The research design employed in Panel A of Table 5 separately estimates the intercept and slope in each tightness partition. This procedure could lead to inefficient estimates given the relatively small sample size. As a robustness check, we repeat the analysis using the full sample period to regress excess returns for the 10 quality-sorted portfolios on the market beta, but also on their ex-ante beta associated with interactions of the market return with margin requirements. The idea is to isolate the effect of variation in leverage constraints on the estimated coefficients over the full sample period. In the new two-step cross-sectional regression procedure with full sample data we first estimate the monthly betas for each quality portfolio:

$$R_{jt}^{e} = \beta_0 + \beta_{jm} R_{mt}^{e} + \beta_{jm,mgn}\left(R_{mt}^{e} \times MGN_t\right) + \varepsilon_t \,, \tag{4}$$

where $\beta_{jm,mgn} = Cov\left(R_{jt}^{e}, R_{mt}^{e} \times MGN_t\right) \Big/ Var\left(R_{mt}^{e} \times MGN_t\right)$. In the second step we run the monthly cross-sectional observations with the 10 quality-sorted portfolios:

$$R_{jt}^{e} = \lambda_0 + \lambda_m \beta_{jm,t-1} + \lambda_{m,mgn} \beta_{jm,mgn,t-1} + e_t \,. \tag{5}$$

The results are reported in Panel B of Table 5. To be consistent with the hypothesis of leverage constraints, and with the results presented in Panel A, the risk premium associated with the interaction beta must be negative and statistically different from zero. Indeed, this is the case. The estimated coefficient is -0.005 with a *t*-statistic of -2.24.

These results motivate the following informative test of the effects of leverage constraints on the behavior of quality portfolios. We regress the estimated intercepts and slopes on the initial margin requirement using the full sample period between 1957 and 2027:

$$\hat{\lambda}_{0t} = \alpha_1 + \beta_1 MGN_t + u_{1t} \quad (6)$$

$$\hat{\lambda}_{mt} = \alpha_2 + \beta_2 MGN_t + u_{2t} \; , \quad (7)$$

where $\hat{\lambda}_{0t}$ and $\hat{\lambda}_{mt}$ are the cross-sectional estimators of the intercept and market risk premium estimated for every month, respectively, and MGN_t is the margin requirement at month *t*. We also run regressions (6) and (7) using the excess market return and the SMB, HML, and MOM factor returns as controls. Given the theoretical predictions of the constrained CAPM, the coefficient $\hat{\beta}_1$ should be nonnegative and the coefficient $\hat{\beta}_2$ should be nonpositive. Note that the shadow price of the leverage constraint is the Lagrange multiplier in the optimization problem to obtain the theoretical constrained CAPM. This implies that, if $\hat{\beta}_1$ and $\hat{\beta}_2$ are not statistically different from zero, the leverage constraint is nonbinding relative to the quality portfolios, and, therefore, we can conclude that leverage restrictions do not affect the pricing of quality stocks.

Table 6 shows the results for the full sample period between July 1957 and August 2017 without and with controls for both the intercept and the slope. The estimated coefficient of the margin in the intercept without (with) controls is equal to 0.056 (0.034), while the effect of margins on the slope is -0.051 (-0.034). All estimated coefficients are statistically different from zero, although the *t*-statistics tend to decrease slightly in absolute terms when we employ HAC standard errors. Overall, the results show that margin requirements, that is, leverage constraints, flattens the empirically implemented security market line when quality-sorted portfolios are used. In addition, the constrained CAPM also predicts that $\beta_1 = -\beta_2$. We also follow Jylha (2018) to test this prediction by estimating expressions (6) and (7) simultaneously in a seemingly unrelated regression. We perform a Wald test for the coefficient restriction. The associated *F*-statistics strongly suggest that the restriction cannot be rejected. Given the magnitudes of the estimated coefficients shown in Table 6 and the negative correlation coefficient between the estimates of the intercept and slope, which is equal to -0.81, the fact that we cannot reject $\hat{\beta}_1 = -\hat{\beta}_2$ is certainly not surprising.

5. **Cross-Sectional Variation of Quality-Sorted Stocks and Effects of Leverage and Liquidity Constraints**

Our previous evidence suggests that periods of tighter leverage constraints are associated with a higher intercept and a lower slope of the empirically implemented CAPM for quality-sorted stocks. This result is certainly consistent with the quality premium being at least partially explained by leverage constraints. In this section, we extend this line of research to incorporate the effects of market-wide illiquidity and funding liquidity on the behavior of quality-sorted portfolios.

We employ the aggregate liquidity risk factor (PSL) of Pastor and Stambaugh (2003). Data on this factor is downloaded from Lubos Pastor's database (http://faculty.chicagobooth.edu/lubos.pastor/research/). In addition, we employ a market-wide illiquidity measure (MIL) closely inspired by the effective bid-ask spread proposed by Abdi and Ranaldo (2017), but with the slight modification suggested by Abad, Nieto, Pascual, and Rubio (2020). Under the assumptions that the efficient price follows a geometric Brownian motion and trade directions are independent of the efficient price, Abdi and Ranaldo (2017) show that the squared effective spread (S^2) can be obtained using the close log-price (C) and the average of the high (H) and low (L) log-prices, or "mid-range" (Mid) for two consecutive days, as follows

$$S^2 = 4E\left[\left(C_d - Mid_d\right)\left(C_d - Mid_{d+1}\right)\right]. \tag{8}$$

The effective spread is estimated for every stock j and day d as $S_{j,d}^{2} = 4\left(C_{j,d} - Mid_{j,d}\right)\left(C_{j,d} - Mid_{j,d+1}\right)$. The practical implementation of equation (8), however, requires us to decide how to handle days without observable (H, L, and C) prices, zero price changes ($H = L = Cd$), and/or negative spread estimates.[8] Abad et al. (2020) choose to treat all these cases as missing values. [9]

As the main proxy for funding liquidity, we employ the measure of Chen and Lu (2019), who propose a new market-based measure of funding liquidity estimated from the time series and cross-section of stock returns: it is the return spread of two market-neutral betting-against-beta portfolios that are constructed with high- and low-margin stocks. These data are downloaded from Andrea Lu's database https://fbe.unimelb.edu.au/our-people/staff/finance/andrea-lu.

Table 7 shows the correlation coefficients among the alternative proxies for the margin (MGN), market-wide illiquidity (MIL) and the liquidity factor (PSL), the funding liquidity factor (FLS) of Chen and Lu (2019), and the BAB factor of Frazzini and Pedersen (2014). It is important to note that the correlation coefficients between margin requirements and market illiquidity/liquidity are higher than those with respect to funding liquidity measures. Given the construction of both measures, we find a negative correlation between the market-wide illiquidity of Abdi and Ranaldo (2017) and the aggregate liquidity of Pastor and Stambaugh (2003). Finally, the correlation between the funding liquidity of Chen and Lu (2019) and the BAB factor is also positive and relatively high. Note that the way in which the FLS factor is constructed

[8] Negative spread estimates are a common disadvantage of low-frequency illiquidity metrics. Corwin and Schultz (2012), for example, report that 29% of daily spread estimates are negative when using their own metric. Abad et al. (2020) obtain negative effective spread estimates for 30.7% of the days, on average across stocks. Abdi and Ranaldo (2017) provide no statistics on this issue. It is important to note that Nieto (2018) shows that the accuracy of Corwin and Schultz's spread estimator improves by considering the data for no-trading days and days with negative values to be missing.

[9] We thank the authors for letting us use their data.

implies that it decreases when market funding liquidity declines, which explains the positive correlation reported in Table 7 between the FLS and BAB factors. For further illustration, Figure 5 shows the behavior of the market-wide illiquidity (MIL) measure constructed by Abad at al. (2029) together with the NBER recession dates. Note the high peaks of market-wide illiquidity during recessions, the crash of October 1987, and the Asian and Russian crises of 1997-1998.

Table 8 shows the results of regressing the QMJ factor on the alternative measures of margin requirements and liquidity, using the Fama-French (2015) factors with the HML-Devil as additional controls:

$$\begin{aligned} QMJ_t &= \alpha_q + \beta_{q,m} MRP_t + \beta_{q,smb} MIL_t + \beta_{q,hml} MGN_t + \beta_{q,rmw} FLS_t \\ &+ \beta_{q,cma} BAB_t + \beta_{q,cs} Controls_t + \varepsilon_t \end{aligned} \quad . \qquad (9)$$

In all specifications, we use the market risk premium (MRP) as an independent variable. Surprisingly, the results show that the inclusion of either market-wide illiquidity, margin requirements, or both strongly diminishes the positive and significant alpha performance of the QMJ factor reported in Table 1. The results tend to show negative alphas, although the relatively bad performance is not statistically different from zero. Note the positive factor loading of both market-wide illiquidity and margin requirements, which is consistent with the hedging behavior of the QMJ factor. Funding liquidity as proxied by the FLS factor is not statistically different from zero, and it has no impact over and above market-wide illiquidity and margin requirements. On the contrary, the BAB factor has a significant impact on the results. Table 9 shows the results when we employ Pastor and Stambaugh's (2003) aggregate liquidity instead of Abdi and Ranaldo's (2017) market-wide illiquidity. Unlike the significant effect of market-wide illiquidity, the loading of the PSL metric is never statistically different from zero. As before, margin requirements and the BAB factor do have a significant effect on the performance of the QMJ factor. In any case, recall from Table 1 that the BAB factor by itself is not able to subtract the positive performance on the QMJ factor. It is only when this factor is combined with market-wide illiquidity or margin requirements that performance becomes non-significant.

In our final analysis, we run regressions (6) and (7) with margin requirements, adding either market-wide illiquidity or aggregate liquidity, as well as funding liquidity metrics:

$$\hat{\lambda}_{0t} = \alpha_1 + \beta_{11} MGN_t + \beta_{12} MIL_t + \beta_{13} PSL_t + \beta_{14} FLS_t + u_{1t} \quad (10)$$

$$\hat{\lambda}_{mt} = \alpha_2 + \beta_{21} MGN_t + \beta_{22} MIL_t + \beta_{23} PSL_t + \beta_{24} FLS_t + u_{1t} \ . \quad (11)$$

Given the availability of data, Table 10 shows the results for the period between July 1963 and August 2017, except when we employ the funding liquidity factor, which is available only from January 1965 onwards. In all specifications, and regarding margin effects, we find similar results to those already reported in Table 6. Recall that the theoretical predictions of the constrained CAPM imply that the coefficient $\hat{\beta}_{11}$ should be nonnegative and the coefficient $\hat{\beta}_{21}$ should be nonpositive. The statistically significant estimated coefficient of the margin in the intercept ranges from 0.065 to 0.070. On the other hand, the margin coefficient associated with the slope is always negative, ranging from -0.030 to -0.063, and statistically different from zero except when we control for funding liquidity proxied by the FLS factor. Moreover, and unlike the intercept, market-wide illiquidity/liquidity is statistically significant with the expected negative/positive sign, depending on whether market-wide illiquidity or aggregate liquidity is used. Overall, the results show that margin requirements, that is, leverage constraints, flatten the empirically implemented security market line when quality-sorted portfolios are used. However, although this is clearly the case with respect to the intercept, for which the margin coefficient is highly significant and positive, the case of the slope seems to be slightly more complex. In this case, funding liquidity takes the role of margin requirements with the correct sign and, even more important, market-wide illiquidity plays a consistent and critical role in flattening the slope of the empirically implemented CAPM.

6. An International Robustness Analysis

The international evidence on the effects leverage constrains and funding liquidity on the QMJ factor is also missing. We next provide a first approximation to this issue, which we use as a robustness check and complementary evidence of our previous results.

In a rather general setting, Malkhozov, Mueller, Vendolin, and Venter (2018), analyze the role of funding-restricted investors across developed capital markets. Using the measure of the tightness of funding constraints proposed by Hu, Pan, and Wang (2013), which is calculated as the average squared deviation of government bond yields from a fitted yield curve, and beta-sorted equity portfolios, they show that higher funding illiquidity is associated with a flatter security market line across the analyzed countries. In other words, Malkhozov et al. (2018) find that the BAB strategy in high-illiquid countries outperforms the BAB strategy in low-illiquidity countries. As other literature, this evidence is directly related to low-risk investments, but not to the multidimensional QMJ factor.

We employ the QMJ factor from the U.S. and four international geographical areas, namely, Global, Global Ex U.S., Europe, and Pacific. For the five areas we download the QMJ and BAB factors, as well as the excess market portfolio returns from the AQR Capital Management website from July 1993 to August 2017. As a proxy for funding liquidity, we employ the BAB factor.[10] For each area we rank the BAB returns (and we match them with the QMJ factor and excess market returns) from the lower to the higher returns. Then, we divide these series into four partitions of approximately the same number of observations. We take the two extreme partitions, where the partition with the lower BAB returns represents an economic period of low funding liquidity, while the partition with the higher BAB returns signals an economic period with high funding liquidity. Then, for each low and high funding liquidity observations separately, and the five geographical areas, we estimate the alphas using two alternative regressions:

$$QMJ_t = \alpha + \beta_1 BAB_t + \varepsilon_t \ ; t \in \ \textit{either Low FLiq or High Fliq} \qquad (12)$$

$$QMJ_t = \alpha + \beta_1 BAB_t + \beta_2 Rm_t^e + \varepsilon_t \ ; t \in \ \textit{either Low FLiq or High Fliq} \qquad (13)$$

Table 11 shows the results. The first two columns display the average and volatility of the BAB returns for the two extreme partitions and geographical areas. The magnitudes of the average BAB returns across all areas are similar and ranges from -2.20% for Global Ex U.S. to -2.99% for Europe and from 5.06% for Europe to 4.20% for the Global market for the low and high funding liquidity partitions, respectively. Volatilities are also similar. The next four columns present the performance of the QMJ factors across areas and funding liquidity levels. Our hypothesis, consistent with the leverage explanation, is that the QMJ factor should perform better when BAB is low or, in other words, with higher funding illiquidity (or higher tightness constraints). Overall, the results show that the QMJ factor displays a significantly better performance during periods of low funding liquidity. The evidence in the U.S. market corroborates the previous results reported in this paper. The annualized alphas during low funding

[10] Frazzini and Pedersein (2014) convincingly argue that the BAB is a reasonable proxy for funding liquidity.

liquidity episodes is positive and highly significant, while they become negative for periods of high funding liquidity.[11] The results for the four analyzed geographical areas show consistently that alphas in low funding liquidity times are higher than alphas in high funding liquidity periods. It is true however that, when using regression (12), alphas are not statistically significant, although in all cases alphas are numerically much higher when funding liquidity is low. When we control for the excess market return in expression (13), alphas are positive, statistically different from zero and always higher in periods of low funding liquidity.

7. Conclusion

This paper studies the effect of leverage constraints on the relation between the market betas and expected returns of 10 quality-sorted portfolios. The quality strategy is a powerful investment approach that presents consistently positive and highly significant alphas with respect to the most popular asset pricing models. We understand quality as AFP (2019), such that high-quality stocks are simultaneously safe, profitable, growing, and well managed. It turns out that the QMJ factor presents not only positive and significant alphas, but also striking positive performance during bad times. Interestingly, high-quality stocks are low-beta assets with a high average return, while junk stocks are high-beta assets with a relatively low average return. However, it is key to note that the quality strategies are not only low-risk investments. This indicates the enormous challenge of risk-based rational explanations of frictionless asset pricing models, and the need to explore whether the leverage constraints hypothesis affects not only to low-risk strategies, but also to the more powerful quality factor investing.

[11] For the U.S., we repeat the analysis using TED instead of BAB. The results confirm that alphas are positive when TED is high (low funding liquidity), and they become negative when TED is low (high funding liquidity).

Our paper shows that margin requirements help explain, at least partially, the surprising behavior of quality stocks. Leverage constraints result in a flatter empirically implemented CAPM when 10 quality-sorted portfolios are used. The intercept of the security market line is positive and significantly related to margin requirements, while the slope is negative and significantly related to margins. Interestingly, leverage constraints accompanied by market-wide illiquidity and funding liquidity reinforce our findings. A behavioral view could certainty account for part of the striking performance of quality stocks; however, it does not seem to be either the only or the most important cause. Leverage and liquidity constraints seem to play a key rational role in the quality premium. The described market friction-based explanation, together with the behavioral biases of Bouchard et al. (2016), are two important pieces to understand the extraordinary performance of the QMJ factor. Future research should try to disentangle these theories and find separate evidence for both possibilities.

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Table 1. Performance of the QMJ factor, January 1965 to August 2017

	α	β_1 MRP	β_2 SMB	β_3 HML	β_4 RMW	β_5 CMA	β_6 MOM	β_7 BAB	*Adj.* R^2
CAPM	0.0052 (6.81)	-0.2760 (-16.12)	-	-	-	-	-	-	29.1
FF 3-Factor	0.0062 (9.65)	-0.2375 (-15.99)	-0.3065 (-13.03)	-0.2112 (-11.52)	-	-	-	-	52.0
FF 3 + MOM	0.0064 (9.56)	-0.2418 (-15.70)	-0.3081 (-13.08)	-0.2290 (-9.18)	-	-	-0.0221 (-1.06)	-	52.0
FF 5-Factor	0.0039 (8.38)	-0.1806 (-15.98)	-0.1584 (-9.08)	-0.1994 (-13.25)	0.5647 (25.72)	0.0918 (3.27)	-	-	76.6
FF 5 + MOM	0.0043 (9.21)	-0.1847 (-16.46)	-0.1585 (-9.19)	-0.2661 (-11.79)	0.5723 (26.26)	0.1472 (4.73)	-0.0637 (-3.93)	-	77.1
FF 5 + MOM + BAB	0.0043 (9.09)	-0.1883 (-16.63)	-0.1643 (-9.43)	-0.2747 (-12.00)	0.5533 (23.52)	0.1317 (4.13)	-0.0733 (-4.36)	0.0328 (2.11)	77.3

This table shows the risk-adjusted excess returns (α), the factor loadings, and the adjusted R^2 values of the QMJ portfolio factor of AFP associated with alternative asset pricing models. The explanatory variables are the monthly returns from the excess return of the market portfolio (MRP), size (SMB), book-to-market (HML), momentum (MOM), profitability (RMW), investment aggressiveness (CMA), and the betting-against-beta factor (BAB). The HML factor is the value factor with monthly price updates in the book-to-market ratio. The *t*-statistics are in parentheses.

Table 2. Determinants of the FED's initial margin requirements, August 1960 to December 1974

Determinants	Estimated Coefficients
Intercept	-0.135 (-0.76)
Volatility Bound SDF	0.387 (4.94)
(6-Months) Lagged Margin Debt Growth	-0.0003 (-8.93)
Surplus Consumption	1.662 (6.35)
Default Premium	-4.752 (-4.08)
Ln Price/Dividend	13.290 (2.73)
Adjusted R-Squared (%)	45.22

This table shows the results of regressing the FED's initial margin requirements from August 1960 throughout December 1974 on the SDF volatility bound of Hansen and Jagannathan (1991) estimated with 10 size-sorted portfolios, the six-month-lagged margin debt growth, the surplus consumption of the habit preference framework of Campbell and Cochrane (1999), the default premium defined as the difference between Moody's yield on Baa corporate bonds and the 10-year government bond yield, and the log of the price-dividend ratio from Shiller's webpage (http://www.econ.yale.edu/~shiller/data.htm). The level of the initial margin required on positions in listed U.S. equities from August 1960 to December 1974 was established by the Federal Reserve Board of Governors via Regulation T. The *t*-statistics for HAC-based standard errors are in parentheses.

Table 3: Portfolio returns by subperiods based on the level of margin requirements with the FED's initial margin (1957-1974) and synthetic margin (1975-2017) requirements

Annualized Excess Returns	Low Tightness Margin (0.50:0.70)	Medium Tightness Margin (> 0.70:< 0.87)	High Tightness Margin (>0.87:0.987)	Full Sample Period
High-Junk (Q10-Q1)	0.0244	0.0645	0.0963	0.0626
	(0.121)	(0.137)	(0.164)	(0.141)
	[0.202]	[0.470]	[0.589]	[0.444]
QMJ	0.0149	0.0517	0.0669	0.0441
	(0.057)	(0.067)	(0.102)	(0.075)
	[0.262]	[0.769]	[0.655]	[0.579]
Market Betas Low-Quality Q1	1.228	1.285	1.548	1.345
Market Betas High-Quality Q10	0.965	0.915	0.885	0.918

This table presents descriptive statistics for the return difference between two quality portfolios constructed with high- and low-quality stocks from 10 quality-sorted portfolios (Q10-Q1), and the QMJ factor of AFP for the full sample period and three non-overlapping subperiods classified by the level of the initial margin requirement. The low-tightness requirement includes 182 observations with a margin of 50% up to and including 70%, the medium-tightness requirement includes 358 observations with a margin from 70% up to and including 87%, and the high-tightness requirement includes 182 observations with a margin from 87% up to and including 98.7%. The full sample period is from July 1957 to August 2017. The months from July 1957 to December 1974 employ the available initial margin requirements set by the FED, and the months from January 1975 to August 2017 use the synthetic margin requirements obtained from the OLS regression estimates shown in Table 2 and the corresponding data on the determinants of the initial margin requirements. Average returns are shown in the first line. The standard deviations are in parentheses and the Sharpe ratios are in square brackets.

Table 4: Quality-based portfolio alphas by subperiods based on the level of margin requirements with the FED's initial margin (1957-1974) and synthetic margin (1975-2017) requirements

Panel A.1: High-Junk (Q10-Q1)	Low Tightness Margin (0.50:0.70)	Medium Tightness Margin (> 0.70:< 0.87)	High Tightness Margin (>0.87:0.987)	Full Sample Period (1957-2017)
Annualized Alphas (CAPM)	0.0296	0.0965	0.1363	0.0893
	(1.00)	(4.13)	(4.25)	(5.50)
Market Beta	-0.2625	-0.3702	-0.6628	-0.4272
	(-4.35)	(-8.34)	(-11.55)	(-13.84)
Adjusted R-squared (%)	9.02	16.10	42.25	20.91

Panel A.2: High-Junk (Q10-Q1)	Low Tightness Margin (0.50:0.70)	Medium Tightness Margin (> 0.70:< 0.87)	High Tightness Margin (>0.87:0.987)	Full Sample Period (1957-2017)
Annualized Alphas (3-Factor FF + MOM)	0.0785	0.1332	0.1524	0.1190
	(3.21)	(7.19)	(5.54)	(8.82)
Market Beta	-0.1978	-0.3492	-0.5288	-0.3506
	(-3.80)	(-9.97)	(-9.74)	(-13.38)
Adjusted R-squared (%)	49.44	55.32	59.95	52.50

Panel B.1: QMJ	Low Tightness Margin (0.50:0.70)	Medium Tightness Margin (> 0.70:< 0.87)	High Tightness Margin (>0.87:0.987)	Full Sample Period (1957-2017)
Annualized Alphas (CAPM)	0.0177	0.0690	0.0849	0.0602
	(1.29)	(6.17)	(4.70)	(7.18)
Market Beta	-0.1416	-0.2002	-0.4643	-0.2606
	(-5.07)	(-9.42)	(-14.39)	(-16.38)
Adjusted R-squared (%)	12.03	19.73	53.24	27.05

Panel B.2: QMJ	Low Tightness Margin (0.50:0.70)	Medium Tightness Margin (> 0.70:< 0.87)	High Tightness Margin (>0.87:0.987)	Full Sample Period (1957-2917)
Annualized Alphas (3-Factor FF + MOM)	0.0457	0.0903	0.0997	0.0731
	(3.95)	(9.62)	(5.77)	(9.90)
Market Beta	-0.1404	-0.2056	-0.3763	-0.2282
	(-5.69)	(-11.58)	(-12.26)	(-15.89)
Adjusted R-squared (%)	48.72	52.10	67.22	50.19

This table presents descriptive statistics for the return difference between two quality portfolios constructed with high- and low-quality stocks from 10 quality-sorted portfolios (Q10-Q1), and the QMJ factor of AFP for the full sample period and three non-overlapping subperiods classified by the level of the initial margin requirement. The low-tightness requirement includes 182 observations with a margin of 50% up to and including 70%, the medium-tightness requirement includes 358 observations with a margin from 70% up to and including 87%, and the high-tightness requirement includes 182 observations with a margin from 87% up to and including 98.7%. The full sample period is from July 1957 to August 2017. The months from July 1957 to December 1974 employ the available initial margin requirements set by the FED, and the months from January 1975 to August 2017 use the synthetic margin requirements obtained from the OLS regression estimates shown in Table 2 and the corresponding data on the determinants of the initial margin requirements. Panels A.1 and B.1 show the alphas relative to the CAPM, and Panels A.2 and B.2 show the alphas estimated from the four-factor model with the Fama-French factors plus momentum. The HML factor is the value factor with monthly price updates in the book-to-market ratio. *t*-statistics are in parentheses.

Table 5. Intercept and slope of the empirically implemented CAPM with 10 quality-sorted excess return portfolios across levels of initial margin requirements with the FED's initial margin (1957-1974) and synthetic margin (1975-2017) requirements

Panel A	Low Tightness Margin (0.50:0.70)	Medium Tightness Margin (> 0.70:< 0.87)	High Tightness Margin (>0.87:0.987)	Full Sample Period (1957-2917)
Intercept (λ_0)	0.0029 (0.41)	0.0219 (4.63)	0.0146 (4.39)	0.0110 (4.48)
Slope (λm)	-0.0011 (-0.14)	-0.0146 (-2.77)	-0.0091 (-1.95)	-0.0057 (-2.05)
Cross-Sectional *R*-squared (%)	0.656	79.5	72.3	75.0

Panel B	Intercept (λ_0)	Slope (λm)	Slope (λm,mgn)	Cross-Sectional *R*-squared (%)
Estimated coefficients (*t*-statistics)	0.0102 (4.11)	-0.0052 (-1.88)	-0.0050 (-2.24)	75.6

Panel A of this table shows the results of the cross-sectional regressions of the monthly excess returns of 10 quality-sorted portfolios on the previously estimated rolling market betas of the portfolios using the Fama-MacBeth (1973) two-steps procedure. We report the results for the full sample period and three non-overlapping subperiods classified by the level of the initial margin requirement. The low-tightness requirement includes 182 observations with a margin of 50% up to and including 70%, the medium-tightness requirement includes 358 observations with a margin from 70% up to and including 87%, and the high-tightness requirement includes 182 observations with a margin from 87% up to and including 98.7%. The full sample period is from July 1957 to August 2017. The months from July 1957 to December 1974 employ the available initial margin requirements set by the FED, and the months from January 1975 to August 2017 use the synthetic margin requirements obtained from the OLS regression estimates shown in Table 2, and the corresponding data on the determinants of the initial margin requirements. The *t*-statistics are in parentheses, and the *R*-squared values are the cross-sectional measure of the model's fit in terms of explaining the cross-section of monthly returns. Instead of using partitions, Panel B shows the results of the two-steps procedure using the full sample period with interaction effects between the market and the margin requirement levels. The second step is given by the following monthly cross-sectional regression:

$$R^e_{jt} = \lambda_0 + \lambda_m \beta_{jm,t-1} + \lambda_{m,mgn} \beta_{jm,mgn,t-1} + e_t \text{, where } \beta_{jm,mgn} = Cov\left(R^e_{jt}, R^e_{mt} \times MGN_t\right) \Big/ Var\left(R^e_{mt} \times MGN_t\right)$$

Table 6. Relation between the intercept and the slope of the empirically estimated CAPM with 10 quality-sorted portfolios, with the FED's initial margin (1957-1974) and synthetic margin (1975-2017) requirements

Full Sample Period, July 1957-August 2017	Intercept (λ_0)		Slope (λm)	
	Without Controls	With Controls	Without Controls	With Controls
Constant	-0.0307 (-1.79) [-1.71]	-0.0111 (-0.78) [-0.77]	0.0349 (1.78) [1.67]	0.0189 (1.36) [1.24]
Margin	0.0560 (2.45) [2.35]	0.0340 (1.89) [1.88]	-0.0513 (-2.10) [-1.89]	-0.0344 (-2.00) [-1.75]
Adjusted R-squared %	0.69	31.1	0.47	51.4

This table shows the results of the regression of the monthly intercept and slope from the empirically estimated CAPM on the FED's initial margin requirements, using the cross-section of 10 quality-sorted portfolio excess returns, and the Fama-MacBeth (1973) two-steps procedure. We report the results for the full sample period from July 1957 to August 2017. The months from July 1957 to December 1974 employ the available initial margin requirements set by the FED, and the months from January 1975 to August 2017 use the synthetic margin requirements obtained from the OLS regression estimates shown in Table 2, and the corresponding data on the determinants of the initial margin requirements. The *t*-statistics are in parentheses, and the *t*-statistics for HAC-based standard errors are in square brackets. In addition to margin requirements, regressions with controls employ the excess market return and the SMB, HML, and MOM factor returns. The HML factor is the value factor with monthly price updates in the book-to-market ratio.

Table 7. Correlation coefficients between the FED's initial margin (1965-1974) and synthetic margin (1975-2017) requirements, and market-wide and funding liquidity measures.

	MIL	PSL	FLS	BAB
MGN	0.288	0.106	-0.020	0.006
MIL	1	-0.260	-0.130	-0.163
PSL		1	0.190	0.183
FLS			1	0.289

This table shows the correlation between margin requirements (MGN), market-wide illiquidity (MIL), Pastor and Stambaugh's (2003) aggregate liquidity (PSL), Chen and Lu's (2019) traded funding liquidity measure from stock returns (FLS), and Frazzini and Pedersen's (2014) betting-against-beta factor (BAB).The market-wide illiquidity estimator of Abdi and Ranaldo (2017) is computed from daily close, high, and low prices using data from individual stocks traded on the NYSE, AMEX, and NASDAQ. We treat days without observables (high, low, and close prices), with no price changes (when the high, low, and close prices are equal), and/or with negative spread estimates as missing values.

Table 8. Panel A: Performance of the QMJ factor with liquidity (market-wide illiquidity and funding liquidity) and margin constraints, January 1965 to August 2017

QMJ	α	β_1 MRP	β_2 MIL	β_3 MGN	β_3 FLS	β_3 BAB	Adj. R^2
CAPM +MIL	-0.0003 (-0.12)	-0.2705 (-15.66)	0.2117 (2.14)	-	-	-	29.5
CAPM +MGN	-0.0090 (-1.50)	-0.2777 (-16.26)	-	0.0178 (2.38)	-	-	29.6
CAPM +MIL +MGN	-0.0103 (-1.69)	-0.2733 (-15.79)	0.1554 (1.50)	0.0143 (1.83)	-	-	29.7
CAPM +MIL +MGN +FLS	-0.0101 (-1.65)	-0.2710 (-15.12)	0.1506 (1.45)	0.0142 (1.83)	-0.0112 (-0.52)	-	29.7
CAPM +MIL +MGN +BAB	-0.0120 (-2.01)	-0.2616 (-15.32)	0.2618 (2.54)	0.0115 (1.50)	-	0.1234 (5.40)	32.8
CAPM +LIQ Controls +FF Controls	0.0010 (0.30)	-0.1871 (-16.50)	0.1120 (1.83)	0.0003 (0.08)	-	0.0399 (2.49)	77.3

This table shows the risk-adjusted excess returns (*α*), the factor loadings and the adjusted R^2 of QMJ) portfolio factor of AFP associated with alternative asset pricing models. The factors employed include margin requirements (MGN), market-wide illiquidity (MIL), Chen and Lu's (2019) traded funding liquidity measure from stock returns (FLS), and Frazzini and Pedersen's (2014) betting-against-beta factor (BAB).The market-wide illiquidity estimator of Abdi and Ranaldo (2017) is computed from daily close, high, and low prices using data from individual stocks traded on the NYSE, AMEX, and NASDAQ. We treat days without observables (high, low, and close prices), with no price changes (when the high, low, and close prices are equal), and/or with negative spread estimates as missing values. Other controls are the excess return of the market portfolio (MRP), size (SMB), book-to-market (HML), momentum (MOM), profitability (RMW), and investment aggressiveness (CMA) factors. The HML factor is the value factor with monthly price updates in the book-to-market ratio. The *t*-statistics are in parentheses.

Table 9. Panel A: Performance of the QMJ factor with liquidity (Pastor and Stambaugh's market liquidity and funding liquidity) and margin constraints, January 1965 to August 2017

QMJ	α	β_1 MRP	β_2 PSL	β_3 MGN	β_3 FLS	β_3 BAB	Adj. R^2
CAPM +PSL	0.0055 (6.31)	-0.2791 (-15.63)	0.0081 (0.62)	-	-	-	29.0
CAPM +PSL +MGN	-0.0086 (-1.41)	-0.2797 (-15.72)	0.0051 (0.39)	0.0175 (2.33)	-	-	29.5
CAPM +PSL +MGN +FLS	-0.0083 (-1.35)	-0.2767 (-15.12)	0.0063 (0.48)	0.0172 (2.30)	-0.0152 (-0.70)	-	29.5
CAPM +PSL +MGN +BAB	-0.0105 (-1.74)	-0.2659 (-15.05)	-0.0093 (-0.71)	0.0179 (2.44)	-	0.1158 (5.01)	32.1
CAPM +LIQ Controls +FF Controls	0.0010 (0.30)	-0.1843 (-15.86)	-0.0127 (-1.65)	0.0035 (0.81)	-	0.0384 (2.41)	77.3

This table shows the risk-adjusted excess returns (*α*), the factor loadings and the adjusted R^2 of QMJ) portfolio factor of AFP associated with alternative asset pricing models. The factors employed include margin requirements (MGN), Pastor and Stambugh's (2003) aggregate liquidity (PSL), Chen and Lu's (2019) traded funding liquidity measure from stock returns (FLS), and Frazzini and Pedersen's (2014) betting-against-beta factor (BAB). Other controls are the excess return of the market portfolio (MRP), size (SMB), book-to-market (HML), momentum (MOM), profitability (RMW), and investment aggressiveness (CMA) factors. The HML factor is the value factor with monthly price updates in the book-to-market ratio. The *t*-statistics are in parentheses.

Table 10. Relation between the intercept and the slope of the empirically estimated CAPM with 10 quality-sorted portfolios and the FED's initial margin (1963-1974) and synthetic (1975-2017) requirements

Full Sample Period, July 1963-August 2017	Intercept (λ_0)				Slope (λm)			
	Margin	Margin and MIL	Margin and PSL	Margin, MIL and FLS	Margin	Margin and MIL	Margin and PSL	Margin, MIL and FLS
Constant	-0.0438 (-2.20) [-2.09]	-0.0445 (-2.22) [-2.05]	-0.0400 (-1.99) [-1.93]	-0.0431 (-2.05) [-1.87]	0.0386 (1.69) [1.50]	0.0475 (2.07) [1.84]	0.0492 (2.14) [2.00]	0.0372 (1.58) [1.45]
Margin	0.0678 (2.75) [2.60]	0.0656 (2.54) [2.55]	0.0651 (2.64) [2.52]	0.0700 (2.61) [2.55]	-0.0551 (-1.95) [-1.67]	-0.0295 (-1.84) [-1.65]	-0.0627 (-2.22) [-2.00]	-0.0333 (-1.22) [-1.11]
MIL/PSL	-	0.0951 (0.27) [0.24]	0.0551 (1.30) [1.35]	-0.0365 (-0.10) [-0.09]	-	-1.1274 (-2.82) [-2.06]	0.1551 (3.20) [3.36]	-0.7892 (-1.99) [-1.85]
FLS	-	-	-	-0.1833 (-2.57) [-1.73]	-	-	-	0.4966 (6.22) [3.70]
R-squared (%)	1.00	0.86	1.11	1.74	0.43	1.49	1.82	6.97

This table shows the results of the regression of the monthly intercept and slope from the empirically estimated CAPM on the FED's initial margin requirements, using the cross-section of 10 quality-sorted portfolio excess returns, and the Fama-MacBeth (1973) two-steps procedure. We also report the regressions controlling for market-wide illiquidity (MIL), Pastor and Stambaugh's (2003) aggregate liquidity (PSL), and Chen and Lu's (2019) traded funding liquidity measure from stock returns (FLS). The market-wide illiquidity estimator of Abdi and Ranaldo (2017) is computed from daily close, high, and low prices using data from individual stocks traded on the NYSE, AMEX, and NASDAQ. We treat days without observables (high, low, and close prices), with no price changes (when the high, low, and close prices are equal), and/or with negative spread estimates as missing values. Given data availability, the full sample period ranges from July 1963 to August 2017, except when we employ funding liquidity (FLS), which is available from January 1965 onwards. The months from July 1957 to December 1974 employ the FED's available initial margin requirements, and the months from January 1975 to August 2017 use the synthetic margin requirements obtained from the OLS regression estimates shown in Table 2 and the corresponding data on the determinants of the initial margin requirements. The *t*-statistics for HAC-based standard errors are in square brackets.

Table 11. The performance of the QMJ factor across levels of funding liquidity: An international evidence, July 1993 to August 2017

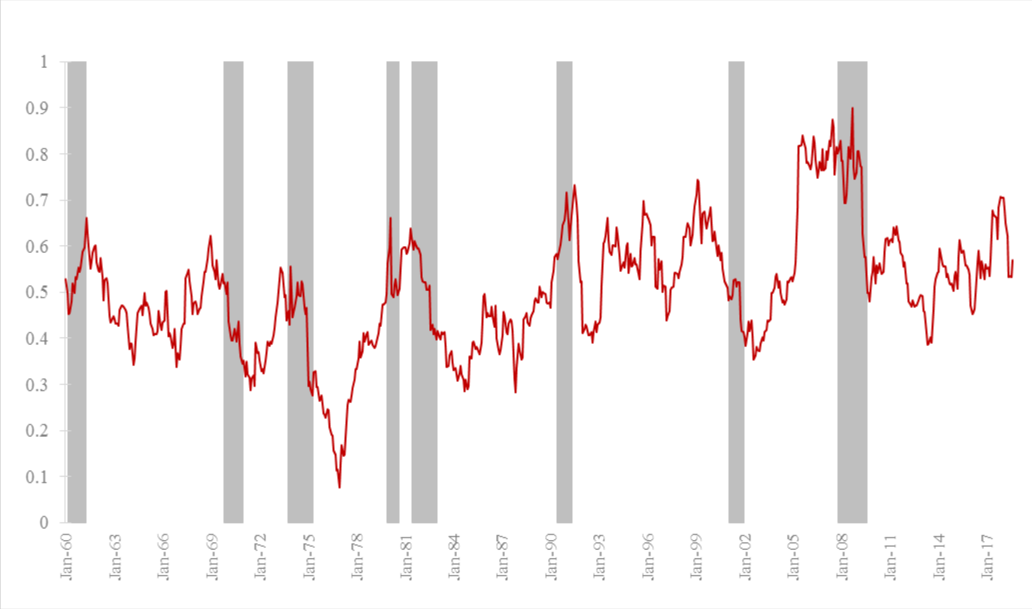
	Funding Liquidity (BAB)	Average Funding Liquidity	Volatility Funding Liquidity	Annualized Alpha QMJ1/	Adj R^2	Annualized Alpha QMJ2/	Adj R^2
US	Low FL	-0.0290	0.0278	0.1063 (3.25)	0.0776	0.1252 (4.64)	0.3749
	High FL	0.0444	0.0221	-0.1785 (-4.25)	0.1865	-0.0759 (-1.91)	0.3637
GLOBAL	Low FL	-0.0265	0.0242	0.0440 (0.81)	0.0748	0.0805 (2.38)	0.6422
	High FL	0.0420	0.0213	-0.0129 (-0.21)	0.1224	0.0611 (1.45)	0.7481
GLOBAL Ex US	Low FL	-0.0220	0.0164	0.0631 (0.91)	0.0295	0.0840 (1.57)	0.5578
	High FL	0.0423	0.0171	0.0150 (0.27)	0.0009	0.0469 (1.26)	0.4601
EUROPE	Low FL	-0.0299	0.0241	0.0891 (1.48)	0.1155	0.1036 (2.48)	0.5754
	High FL	0.0506	0.0221	0.0051 (0.06)	0.0558	0.0405 (0.70)	0.5044
PACIFIC	Low FL	-0.0289	0.0181	0.0774 (1.11)	0.1190	0.0881 (1.64)	0.4756
	High FL	0.0447	0.0189	0.0082 (0.09)	0.0082	0.0170 (0.25)	0.4035

In this table we employ the QMJ factor from the U.S. and four international geographical areas, namely, Global, Global Ex U.S., Europe, and Pacific. For the five areas we download the QMJ and BAB factors, as well as the excess market portfolio returns from the AQR Capital Management website from July 1993 to August 2017. As a proxy for funding liquidity, we employ the BAB factor. For each area we rank the BAB returns (and we match them with the QMJ factor and excess market returns) from the lower to the higher returns. Then, we divide these series into four partitions of approximately the same number of observations. We take the two extreme partitions, where the partition with the lower BAB returns represents an economic period of low funding liquidity, while the partition with the higher BAB returns signals an economic period with high funding liquidity. Then, for each low and high funding liquidity observations separately, and the five geographical areas, we estimate the alphas using two alternative regressions: 1/ $QMJ_t = \alpha + \beta_1 BAB_t + \varepsilon_t$ and 2/ $QMJ_t = \alpha + \beta_1 BAB_t + \beta_2 R^e_{mt} + \varepsilon_t$. The first two columns display the average and volatility of the BAB returns for the two extreme partitions and geographical areas. The next four columns present the performance of the QMJ factors across areas and funding liquidity levels.

Figure 1. QMJ) factor, July 1965 to August 2017

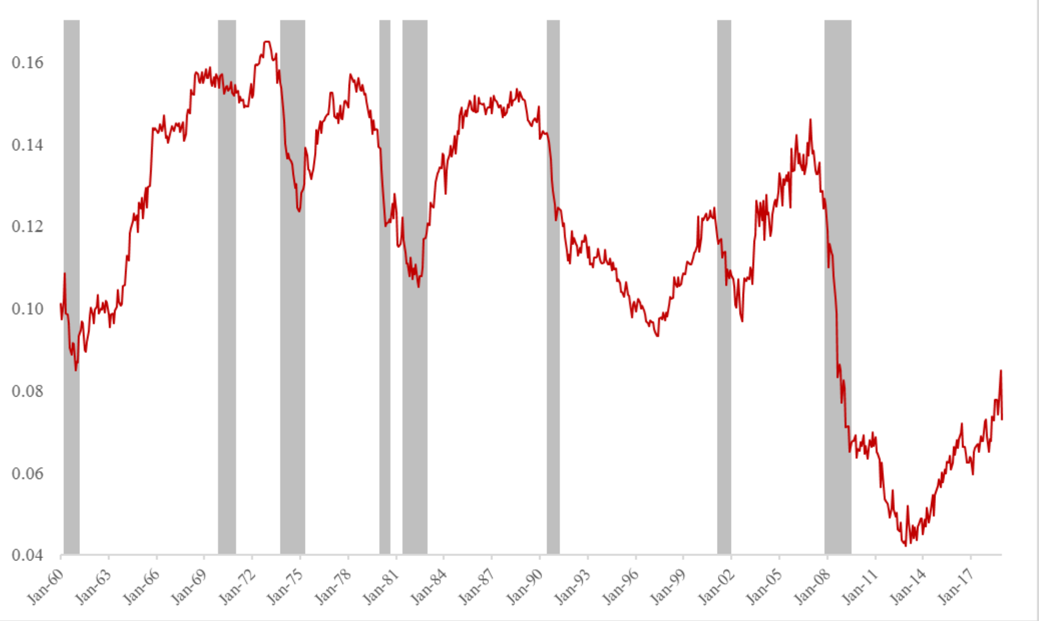
This figure shows the performance of an investment of 100 U.S. dollars in January 1965 in the QMJ factor of AFP. The grey recession bars indicate official U.S. National Bureau of Economic Research (NBER) recession dates.

Figure 2. Hansen-Jagannathan volatility bound estimated with 10 size-sorted portfolios, January 1960 to December 2018



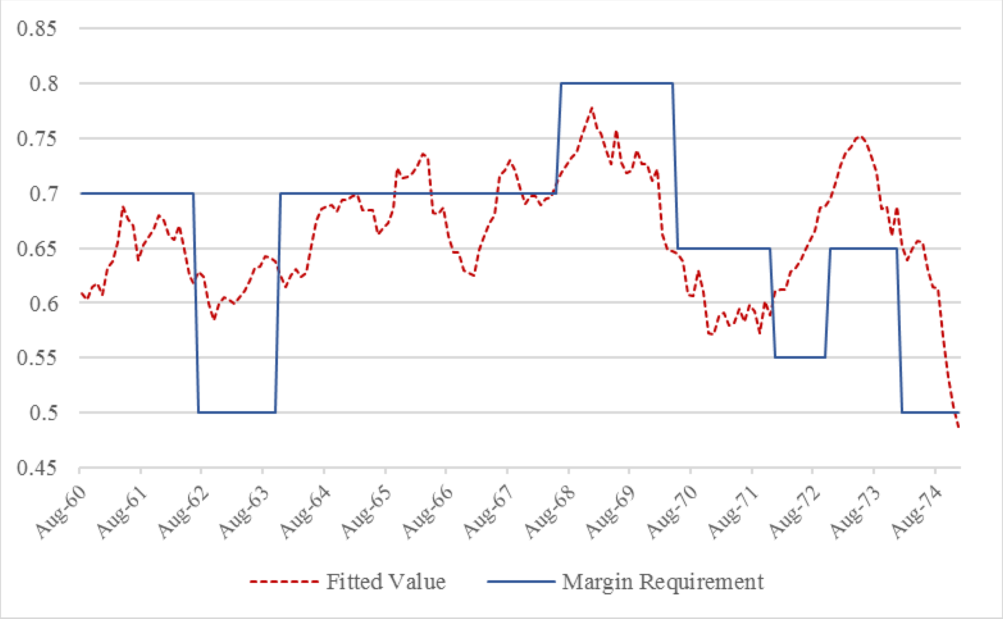
This figure shows the estimated monthly volatility bound of the model-free SDF with overlapping five-year sub-periods of monthly data from the 10 quality-sorted equity portfolios. The monthly estimated volatility corresponds to the average level of the risk-free interest rate for each of the five-year sub-periods. The grey recession bars indicate official U.S. National Bureau of Economic Research (NBER) recession dates.

Figure 3. Campbell-Cochrane surplus consumption ratio, January 1960 to December 2018



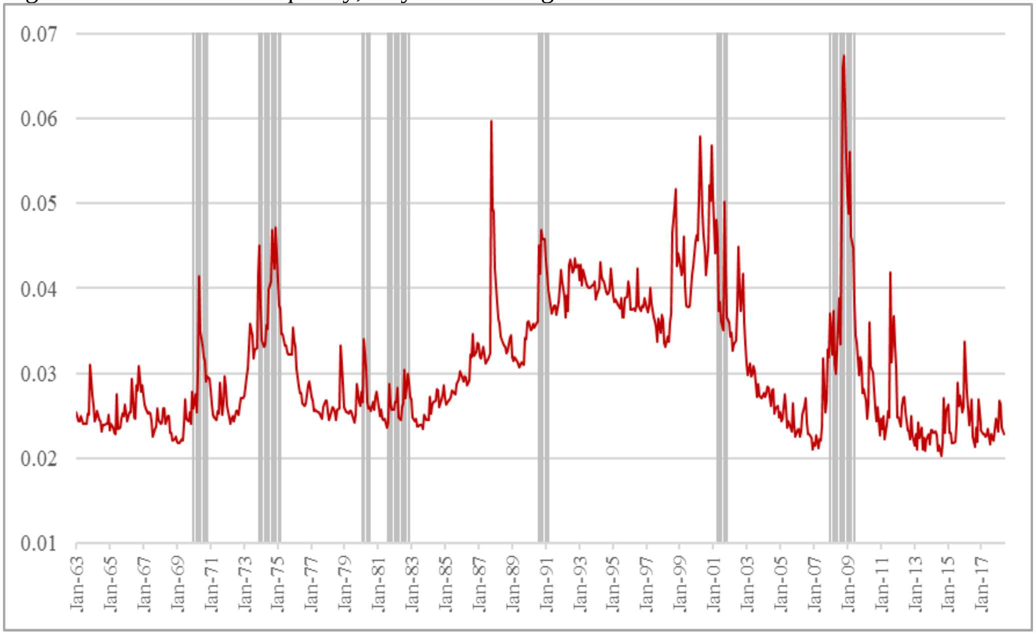
This Figure shows the surplus consumption ratio estimated from habit preferences with time-varying risk aversion. We assume a random walk process for consumption growth and an autoregressive process for the log surplus consumption ratio, allowing for a sensitivity function that captures the way surplus reacts to innovations in consumption growth. The grey recession bars indicate official U.S. National Bureau of Economic Research (NBER) recession dates.

Figure 4. Fitted versus real values for initial margin requirement, August 1960 to December 1974



This figure shows the initial margin levels required on positions in listed U.S. equities from August 1960 to December 1974, as established by the Federal Reserve Board of Governors via Regulation T, and the fitted value of the regression of the margin on the SDF volatility bound of Hansen and Jagannathan (1991), estimated with 10 size-sorted portfolios, the six-month-lagged margin debt growth, the surplus consumption of the habit preference framework of Campbell and Cochrane (1999), the default premium defined as the difference between Moody's yield on Baa corporate bonds and the 10-year government bond yield, and the log of the price-dividend ratio obtained from Shiller's webpage (http://www.econ.yale.edu/~shiller/data.htm).

Figure 5. Market-wide illiquidity, July 1963 to August 2017



This figure shows the market-wide illiquidity estimator of Abdi and Ranaldo (2017) computed by Abad et al. (2020) from daily close, high, and low prices using data from individual stocks traded on the NYSE, AMEX, and NASDAQ. We treat days without observables (high, low, and close prices), with no price changes (when the high, low, and close prices are equal), and/or with negative spread estimates as missing values. The grey recession bars indicate official U.S. National Bureau of Economic Research (NBER) recession dates.