QUALITY PORTFOLIOS AND FUNDING LIQUIDITY CRISES

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Abstract

This paper shows that the quality minus junk (*QMJ*) factor and quality-sorted portfolios contain information about funding liquidity crisis. There is a strong and positive relation between the behavior of the *QMJ* factor and the intensity of funding liquidity crises. This is the case even if we control for the profitability factor, the St. Louis Fed Financial Stress Index, and the market portfolio return. However, we do not find the same significant relation with respect to market liquidity crises. Moreover, the quality-based volatility bound is a strong predictor of the probability of future funding liquidity recessions. Investment performance improves when we explicitly incorporates the predictability embedded in quality-sorted portfolios.

This version: March 14, 2017

Keywords: quality pricing; market illiquidity; funding illiquidity; flight-to-liquidity; forecasting funding illiquidity crisis

JEL classification: G11, G12, G01

The author thanks Frank Fabozzi, Belén Nieto, and anonymous referee for their useful comments and suggestions. The author also acknowledges financial support from the Spanish Ministry of Economics and Competitiveness through grant ECO2015-67035-P, the Generalitat Valenciana research grant PROMETEOII/2013/015 and the Bank of Spain.

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1. Introduction

Quality pricing and the corresponding investment strategies are receiving increasing attention among practitioners and academics. A recent line of research due to Asness, Frazzini and Pedersen (2014, AFP hereafter) identifies a quality stock as an asset for which investors would be willing to pay a high price. Their quality minus junk factor (*QMJ* hereafter), that 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 (2014) is that the *QMJ* factor displays large realized returns during downturns, which suggests that the quality-based factor does not exhibit bad-times risk. In particular, they plot the risk-adjusted returns of the *QMJ* factor against market excess returns and show that the quality factor presents a mild positive convexity, which suggests that the *QMJ* factor benefits from flight-to-quality during financial and economic crises. The surprising relatively 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 and French (1993) 3-factor alpha, and 4-factor alpha, which includes the momentum factor (*MOM*) of Carhart (1997), and relatively small idiosyncratic risk. As AFP (2014) argue, this evidence presents a very serious challenge to risk-based rational explanations of asset pricing.

These striking results motivate our research. This paper investigates the sources of the flight-to-quality argument of AFP (2014). What is behind the surprising good performance of the *QMJ* factor during recessions? What is the major macroeconomic driver of the *QMJ* factor during crises? What is the role of market-wide liquidity crisis in the behavior of quality-based portfolios? What is the information embedded in quality-sorted portfolios regarding future economic activity and aggregate liquidity crises?

To this end, it is important to distinguish between alternative liquidity concepts. Funding liquidity means the ease access to financing, which implies low borrowing, and short-sale constraints and low margin requirements. On the other hand, market liquidity is the ease of trading an asset, which means simultaneously low bid-ask spreads and high depth. Since the recent great financial recession, funding liquidity is becoming a key source of aggregate risk among new recent papers on asset pricing. Brunnermeier and Pedersen (2009) model the liquidity spiral with interconnections between market and funding liquidity using the channel of margin requirements, and Garleanu and Pedersen (2011) show how precisely leverage constraints (or funding constraints) affect asset prices. The empirical evidence supports the presence of funding liquidity across a wide range of securities.

The main contribution of this paper is to show that flight-to-quality really means flight-to-funding liquidity but not necessarily flight-to-market liquidity. Thus, flight-to-funding liquidity seems to be the main macroeconomic driver behind the behavior of quality versus junk firms during or before recessions. Moreover, the uncertainty embedded in quality-sorted portfolios is able to predict the probability of funding illiquidity crises, even controlling for well-known predictors. We finally analyze the consequences of this predictability for investment strategies regarding alternative quality-sorted portfolios.

This paper is organized as follows. Section 2 discusses some related literature. Section 3 presents the data and analyzes the exposure of the *QMJ* factor and quality-sorted portfolios to factor risks. Section 4 discusses the relation between the *QMJ* factor and both, aggregate market and funding liquidity, while Section 5 reports the relation of aggregate liquidity to alternative quality-sorted portfolios. Section 6 shows evidence about the forecasting ability of quality regarding future funding liquidity crises, and discuss the information contained in quality-based portfolios. Section 7 discusses some investment implications of predictability, and Section 8 concludes the paper.

2. Related Measures and Issues: Quality, Profitability and Size

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. 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. In addition, gross profitability is strong and negatively correlated with value, which suggests that quality-profitability strategies provide a hedge to value strategies. This author proposes a profitability factor (profitable minus unprofitable, *PMU*), which follows the procedure of Fama and French (1993) to construct their *HLM* factor. Fama and French (2015) show that a five-factor model that expands their popular three-factor model with profitability (robust minus weak, *RMW*) and investment (aggressive minus conservative, *CMA*) factors explains anomalies associated with low betas, low share repurchases, and low volatility assets relative to high betas, high repurchases, and high volatility securities. Their profitability factor is operating profitability, which is revenues minus costs of goods sold, minus selling (general and administrative) expenses, minus interest expenses, divided by book equity. From July 1963 to December 2012, on annual basis, the *PMU* and *RMW* premia are 4.11% and 3.12%, respectively and the correlation coefficient is 0.494.

Novy-Marx (2014) identifies commonalities across some of the best-known strategies, and runs a performance horse race between the competing specifications. He shows that only gross profitability present significant excess return when analyzed on individual basis, and has the largest Fama and French (1993) 3-factor alpha.

Unfortunately, the analysis of Novy-Marx (2014) does not include the quality definition of AFP (2014). These authors understand quality as the willingness to pay a high price for quality stocks, which means precisely that these are stocks which are simultaneously safe (low required rate of return), profitable (high return on equity), growing (high cash flow growth), and well managed (high dividend payout ratio). The factor is long the top 30% high-quality stocks and shorts the bottom 30% junk stocks. As in Fama and French (1993), in order to control for size, they do this within the universe of large stocks and similarly within the universe of small stocks. From 1963 to 2012, the average annualized risk premium of the *QMJ* factor is 4.19%. The correlation coefficients are 0.436 and 0.743 with the *PMU* and *RMW* factors, respectively. Figure 1 shows the behavior over time of the three quality factors using the average monthly returns for a given year in the available sample.[1] The three factors tend to move together with different degrees of commonality with the only exception of the *RMW* factor during 1982.

In addition, Asness, Frazzini, Israel, Moskowitz, and Pedersen (2016) show that controlling for quality and junk resurrects the controversial size effect. This effect has shown to vary considerably through time. These authors show that the variability of the size effect is largely due to the volatile performance of small, low quality stocks. They run time series regressions of the small minus big (*SMB*) factor of Fama and French (1993) on several asset pricing specifications and during alternative sample periods.

[1] The *PMU* factor is from the web-page of Robert Novy-Marx. It is only available until December 2012.

They show that the alphas of the *SMB* factor become positive, and highly significant once they control for the *QMJ* factor. These results are robust to different sample periods. The time-varying behavior of the size premium is largely explained by the performance of quality and junk. To ignore the effects of quality and junk is the reason of the unstable performance of the size effect. Given that junk stocks are highly illiquid, they also check the robustness of these results to illiquidity and illiquidity risk factors. Interestingly, even in the presence of these potential liquidity effects, the size effect is again rescued by the *QMJ* factor. In any case, as pointed out by Asness, Frazzini, Israel, Moskowitz, and Pedersen (2016), it seems that quality helps clarify the relation between size and the cross-section of average return. Then, an important question is why do average returns vary by the quality of the company? This paper does not try to answer this relevant but extremely complex issue. This research simply discusses the behaviour of the *QMJ* factor during funding liquidity crises, and provides evidence about the information contained in the simultaneous time-series and cross-sectional behavior of quality-sorted portfolios regarding future funding liquidity stressed periods.

3. The Returns of the *QMJ* Factor, High Quality Stocks, and Junk Stocks

3.1 Data

Data on both the *QMJ* factor and the 10 quality-sorted portfolios are obtained from the AQR Capital Management Database (www.aqr.com). Data on the Fama and French factors used in their 3-factor and 5-factor models and on the *MOM* factor are downloaded from Kenneth French database (http://mba.tuck.darmouth.edu), while data on the market liquidity risk factor (*ILLIQ*) is from Lubos Pastor Database (http://faculty.chicagobooth.edu/lubos.pastor/research/). As the main proxy for funding liquidity we employ the Betting against Beta (*BAB*) factor of Frazzini and Pedersen

(2014), which 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. These authors show that leverage constraints are strong and significantly reflected in the return provided by this factor. Indeed, Frazzini and Pedersen (2014) 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. Finally, as a measure of financial distress, we employ St. Louis Fed Financial Stress Index. This index measures the degree of financial stress in the market and is constructed from 18 series: seven interest rate series, six yield spreads, and five other indicators. Each of these variables captures some aspect of financial stress. In this regard, it is a broader measure of financial credit risk or financial stress than the default premium. As was learned from the Great Recession, financial stress can arise from dimensions other than the default spread. The serious difficulties of financial institutions in providing funding, especially to finance short-term liabilities, encourage the use of financial stress indicators that also employ funding liquidity-related aspects of the economic situation. By construction, the average value of the index is equal to zero. Thus, zero reflects normal financial market conditions. Values below zero suggest below-average financial stress, and values above zero indicate above-average financial stress. We obtain this index from http://www.stlouisfed.org/newsroom/financial-stress-index/.

3.2 The Performance of Quality-Sorted Portfolios

In this section, we characterize and analyze the performance of the *QMJ* factor, and the two extreme portfolios, which are only-long high quality stocks, and only-long junk stocks. We simply run regressions with alternative asset pricing models, included the

CAPM, the Fama-French 3-factor model, the Fama-French 5-factor model, and these models augmented with the *MOM* factor of Carhart (1997), the *BAB* factor of Frazzini and Pedersen(2014), and *ILLIQ* factor of Pastor and Stambaugh (2003)

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

$$\begin{aligned} QMJ_t = \alpha_q + \beta_{q,mkt} R^e_{mt} + \beta_{q,smb} SMB_t + \beta_{q,hml} HML_t + \beta_{q,rmw} RMW_t \\ + \beta_{q,cma} CMA_t + \beta_{q,mom} MOM_t + \beta_{q,bab} BAB_t + \beta_{q,illiq} ILLIQ_t \end{aligned} \quad , \quad (1)$$

where R^e_m is the excess return of the market portfolio. Panel A of Table 1 reports the alphas, and the risk-factor loadings for the alternative models.[2] The *QMJ* factor has highly significant alphas in all models. The strong performance ranges from 62 to 28 basis points per month for the Fama and French 3-factor model to the Fama-Franch 5-factor model augmented with *MOM* and *BAB*, respectively. The adjusted R^2 increases from, approximately, 28% for the CAPM, to 49% for the Fama-French 3-factor set of models, and to 78% for the Fama and French 5-factor group. As in AFP (2014), the *QMJ* factor has negative market, size, and value exposures. This suggests that the factor is long low-beta, large, and growth stocks. On top of that, even controlling for the Fama and French 5-factor model, the *QMJ* factor is long high momentum and leveraged low-beta stocks. However, the market liquidity factor risk of Pastor and Stambaugh (2003) is not statistically different from zero. As expected, the *QMJ* factor is also long profit and conservative (from the investment point of view) stocks. Of course, this evidence also implies that the factor is short high beta, small, value, low momentum, low profit, and aggressive stocks. Overall, the *QMJ* dynamic factor delivers an impressive performance.

[2] Some of the evidence displayed in this section has already been examined by AFP (2014). However, for completeness, and in order to clarify what is behind the *QMJ* factor, and the corresponding high quality and low quality (junk) portfolios, we decided to report our own results. In any case, the results using the Fama and French 5-factor model and the *BAB* factor are not in the AFP paper.

Panel B of Table 1 reports the performance and characteristics of the extreme high quality portfolio. As before, all alphas are positive and highly significant. The adjusted R^2 is around 92% for all specifications under the Fama and French set of models, while the R^2 for the CAPM is slightly lower. The market beta is approximately 0.90, and the portfolio loads positively on large, growth, high profit, and high momentum stocks. The exposures to the *CMA* factor and measures of aggregate illiquidity are clearly much more debatable from the statistical point of view. Finally, Panel C of Table 1 contains the results with respect to the portfolio of extreme low-quality-junk stocks. The portfolio has a very poor performance, with highly significant and negative alphas. The R^2 is slightly higher for the Fama and French 5-factor familiy. The market beta is around 1.21 for the models with a higher explanatory fit, and the portfolio loads positively on small, value, low profit, aggressive, low momentum, and high de-leveraged beta stocks.

As AFP (2014) note, as long as quality stocks have negative performance during bad economic times, this evidence would not be necessarily consistent with quality stocks being underpriced. Unfortunately, this is not the case. These authors show that quality stocks have a strong performance during crisis suggesting a flight-to-quality phenomenon. The lack of understanding of this surprising performance of quality stocks is disturbing.

4. Quality and Flight to Market and Funding Liquidity

This section analyzes how the *QMJ* factor relates to alternative measures of aggregate illiquidity. The idea is to understand the flight-to-quality argument of AFP (2014). In other words, what is the major macroeconomic driver of the extraordinary performance of the *QMJ* factor during or before economic crisis? More precisely, we analyze the role of market and funding aggregate liquidity on the flight-to-quality argument.

The econometric specification runs regressions with monthly returns from January 1986 to December 2012 of the following form:

$$\begin{aligned} QMJ_t = a + b_1 RMW_t + b_2 ILLIQ_t + b_3 BAB_t + b_4 FSI_t + b_5 ILLIQ_t * DPSL_t \\ + b_6 BAB_t * DBAB_t + b_7 R_{mt} + \varepsilon_t \end{aligned} , \qquad (2)$$

where *FSI* is the St. Louis Fed Financial Stress Index.[3] In addition, *DPSL* and *DBAB* are dummy variables, which take the value of 1 if the market and funding illiquidity variables are higher than two times the corresponding standard deviation, and zero otherwise. Note that these are months in which the economy experienced highly negative illiquidity shocks.[4] Finally, R_{mt} is the rate of return of the market portfolio. Table 2 reports OLS *t*-statistics in parentheses, and HAC-based *t*-statistics in brackets.

The specification in equation (2) controls for profitability. Both, Novy-Marx (2014) and AFP (2014) show that profitability is the key component of alternative measures of quality. Moreover, Panel A of Table 1 displays a very strong relation between *QMJ* and *RMW*. Estimated coefficients associated with the *RMW* factor show the highest precision among all risk factors. The *t*-statistic is approximately 30, independently of the specification employed in the regressions. Indeed, the first column of Table 2 shows that the adjusted R^2 is 67% when we explain the returns of the *QMJ* exclusively with the profitability factor.

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[3] This index is available from January 1994 onwards. Our regressions go back until January 1986. We obtain a synthetic *FSI* by a projection of the *FSI* from January 1994 to December 2012 on VIX, *TED*, and the default spread. The OLS coefficients are then used to construct the synthetic financial stress index from January 1986 to December 1993. The default spread is the difference between Moody's yield on Baa corporate bonds and the 10-year government bond yield. *TED* is the difference between the three-month Treasury bill and LIBOR rates. As Frazzini and Pedersen (2014) argue, *TED* is a measure of funding conditions. High *TED* spreads suggests higher tightness funding constraints. The ultimate reason behind this behavior is that higher *TED* spreads imply that banks decrease credit availability. The spread is obtained from daily Treasury bill and LIBOR data from the Federal Reserve of St-Louis FRED database. VIX is the CBOE Volatility Index.

[4] The number of stressed market liquidity and funding liquidity months represent 7.4% and 11.8% of the full sample, respectively.

Column 2 of Table 2 adds the *FSI* to the previous specification. Even controlling for profitability, we conclude that the returns of *QMJ* tends to increase when the *FSI* goes up (during financially stressed economic times). This is an alternative way of analyzing the behavior of *QMJ*, which is consistent with the evidence reported by AFP (2014). Note that the positive relation between *QMJ* and *FSI* is statistically significant in most specifications. Columns 3 and 4 add market illiquidity and funding illiquidity, respectively. Market-wide illiquidity is proxied by the Pastor and Stambaugh (2003) aggregate liquidity risk factor, and funding liquidity by the *BAB* factor. It turns out that only market illiquidity seems to explain significantly the returns of the *QMJ* factor. Higher market-wide illiquidity shocks are positive and significantly related to the quality factor. This empirical evidence remains when we add, in columns 5 and 6, the *FSI* to the previous specifications. Column 7 contains the results with market-wide illiquidity, the *FSI*, and an interactive term, which takes the value of 1 only when market illiquidity is especially high. It turns out that market illiquidity is no longer statistically significant, and only the interactive term is positive and significant. The *FSI* losses precision when we employ HAC standard errors. We conclude that market-wide illiquidity is only relevant to explain the *QMJ* factor during periods of extreme highly market illiquidity shocks. Column 8 reports a similar specification but now using funding liquidity rather than market liquidity. Note that the returns of the *BAB* factor are negatively correlated with *TED* –correlation of -0.28–, and with *ILLIQ* –correlation of -0.14. The way in which Frazzini and Pedersen (2014) construct the *BAB* factor implies that low or negative returns of this factor are times of poor funding liquidity or high leverage constraints. Contrary to market-wide illiquidity, we now obtain that funding liquidity has an overall relation with the *QMJ* factor. The coefficient associated with *BAB* is negative and significant. This is true even if we control for the more extreme negative funding liquidity shocks and the *FSI* in the regression. The extreme negative shocks have a strong effect on the quality factor, but it is also true that the more stressed the overall funding liquidity conditions are the higher the return of the *QMJ* factor. The strong evidence of the relevance of funding liquidity conditions on the quality minus junk dynamic factor remains the same even if we control for the market portfolio return in the last column of Table 2. Indeed, the results in the last column show that when we add the market return to the full specification with funding liquidity, both the *BAB* factor and the cross interactive term, which reflects strong negative illiquidity shocks, are statistically significant and with the right sign, while the *FSI* factor remains positive and significantly different from zero. As a matter of fact, when we control for the market portfolio return in all other columns, the evidence is even more favorable to funding liquidity relative to market liquidity. The Pastor and Stambaugh (2003) illiquidity factor is not longer statistically different from zero in columns (3) and (5), but the *BAB* factor becomes significantly different from zero in column (4), and negative and with a *t*-statistic of -1.60 in column (6).

We conclude that, when we control for profitability and the financial stress conditions in the market, funding liquidity has a significant impact on the behavior of the *QMJ* factor. Importantly, this is the case for both extreme funding illiquidity conditions and over the full sample period and. Even more important, these effects become even stronger when we control for the market portfolio return. On the other hand, market-wide illiquidity losses statistical significance when we control for the market return. Overall results suggest that dynamic quality investment strategies hedge bad funding liquidity market conditions.[5]

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[5] These results do not seem to be a consequence of severe multicollinearity problems. The correlation coefficients are -0.112, -0.271, and -0.207 between *ILLIQ* and *BAB*, *ILLIQ* and *FSI*, and *BAB* and *FSI*, respectively.

Table 3 contain a similar evidence when we proxy funding liquidity with the *TED* spread rather than with the *BAB* factor. The specification in Column 1 controls exclusively for profitability. In this case, funding illiquidity becomes positive and statistically significant. As before, the returns of the *QMJ* portfolios rise with funding liquidity restrictions. The evidence becomes much weaker when we also control for overall financial stress in column 2 using the *FSI*. Next column displays the results with *TED*, the *FSI*, and an interactive term, which takes the value of 1 only when funding illiquidity is especially high. *TED* losses significance and funding liquidity restrictions are relevant only under especially restrictive economic periods in terms of funding availability. Surprisingly, when we add the market return in the regressions, extreme funding liquidity times lose significance, but *TED* remains positive and statistically different from zero. In one case or another, it seems that, as before, the behavior of the *QMJ* portfolio is positively related to funding liquidity restrictions when we approximate these restrictions with the *TED* spread.

5. Extreme and Intermediate Quality Portfolios and Flight to Market and Funding Liquidity

In this section, we complement the evidence regarding the behavior over time of the *QMJ* dynamic factor relative to aggregate funding liquidity with a cross-sectional analysis within the set of ten quality-sorted portfolios. Panel A of Table 4 analyzes the relation between funding liquidity and three alternative portfolios, which are the difference between the returns of the highest quality (quality 10) and the lowest quality (quality 1) portfolios, the difference between the following categories (quality 9 minus quality 2), and between the returns of intermediate quality portfolios (quality 6 minus quality 5). Given the previous results, our conjecture is that funding liquidity, financial stress, and extreme funding liquidity conditions are particularly related to the differential returns of extreme quality portfolios, and less so to differences in returns of intermediate portfolios. Indeed this is actually the case. The adjusted R^2 declines monotonically with the three alternative portfolios. The R^2 for the extreme portfolio case (quality 10 minus quality 1) is approximately 60%. The R^2 rapidly declines to 34% for the difference between portfolios 9 and 2, and it becomes negligible for the intermediate portfolios. The coefficients associated with the *RMW* factor, funding liquidity, proxied by the *BAB* factor, the *FSI* and the extreme funding liquidity conditions are strongly significant for the extreme portfolios, and in all cases with the right sign. Similar results are obtained for portfolios 9 and 2, although the magnitude of the estimates of the coefficients associated with the independent variables tend to be much lower than for the extreme portfolios. Finally, the results for the intermediate portfolios are very poor, although the *BAB* remains statistically different from zero. As in the previous section, funding liquidity seems to be an important factor to explain the differential returns between high quality and low quality portfolios. High quality portfolios tend to behave extremely well under funding illiquidity stressed economic conditions.

Panel B of Table 4 reports similar evidence with respect to market-wide illiquidity. The results show that the differential return behavior of quality portfolios is not related to market-wide illiquidity. High quality portfolios do not seem to behave differently from a statistical point of view when the market confronts extreme market illiquidity conditions. The behavior of quality portfolios is associated with funding liquidity and much less with market-wide liquidity.

6. Forecasting the Probability of Funding Illiquidity Crisis

Given the importance of funding liquidity crisis for the behaviour of quality portfolios, I define a funding liquidity crisis as those months in which the *BAB* factor (negative) return is higher than two times the corresponding standard deviation. In this section, I focus just on predicting funding illiquidity crisis or funding illiquidity-recession economic times. I simply employ several probit model specifications for forecasting the binary variable that is one if there is a funding illiquidity crisis in the subsequent τ months, and zero otherwise. In particular, I consider 9 probit specifications depending upon the predictors we include in the probit regressions. The general specification of the model is given by the following expression:

$$P\left(DBAB_{t,t+\tau}=1\right)=\Phi\left(\beta_0+\beta' PRED\right) \tag{3}$$

where $DBAB_{t,t+\tau}$ is the dummy variable that takes on a value of 1 if and only if there is a funding illiquidity recession, proxied by the *BAB* factor, at some point during months $t+1$ through $t+\tau$, *PRED* is a vector of five alternative predictors available at time *t*, and $\Phi(\cdot)$ is the standard normal cumulative distribution function.

I employ five predictors of funding illiquidity recessions: the volatility (bound) of the stochastic discount factor estimated with quality- and size-sorted portfolios, the default spread, the term spread, and the leverage factor. Nieto and Rubio (2014) suggest that financial uncertainty predict future real activity. Indeed, their paper shows that changes in the uncertainty embedded in stock prices are a powerful indicator of future economic growth. However, it is also the case that the information contained in the market capitalization of trading assets is a key issue for optimally detecting the impact of financial uncertainty in future real activity. In particular, Nieto and Rubio (2014) analyze the capacity of the size-based model-free Hansen and Jagannathan (1991) (HJ hereafter) volatility bound to predict future economic growth. They find that the volatility bound is a powerful in-sample and out-of-sample predictor of future industrial production growth. The asymmetric sensitivities of small and large companies through the business cycle explain their findings. Given the findings of the previous sections, we use the volatility of the stochastic discount factor based on quality-sorted portfolios to forecast future illiquidity recessions. This exploits the simultaneous time series and cross-sectional information embedded in the quality-sorted portfolios. For comparison, we also employed the size-based volatility bound suggested by Nieto and Rubio (2014). We estimate the monthly HJ volatility bound of the model-free stochastic discount factor with overlapping sub-periods of five years of monthly data from the 10 quality-sorted equity portfolios, using

$$\sigma(M) \geq \left[(1_N - E(M)E(R))' V^{-1} (1_N - E(M)E(R)) \right]^{1/2}, \tag{4}$$

where M is a stochastic discount factor satisfying the first-order pricing equations

$$1 = E_t\left[M_{t+1} R_{jt+1}\right],$$

$$E_t\left[M_{t+1}\right] = 1/R_{ft+1},$$

where 1_N and $E(R)$ are an N-vectors of ones and average gross returns, and N equals 10 in our empirical exercise, respectively; V^{-1} is the inverse of the variance–covariance matrix of returns; and R_f is the gross risk-free rate. The monthly estimated volatility corresponds to the average level of the risk-free interest rate for each of the five-year sub-periods. This procedure does not depend on any particular consumption-based stochastic discount factor specification, so the potential predictive relation does not depend on any given consumption dynamics. Moreover, the estimation does not impose a linear specification of the stochastic discount factor, which would be consistent with the typical factor models employed in finance, like the CAPM or the Fama and French pricing models. In this sense, the volatility bound given by expression (4) is a powerful, real time, predictor of future economic activity.

The term spread, measured as the difference between the interest rates on long and short maturity government debt, is probably the most common financial leading indicator of real activity. Among many others, Estrella and Hardouvelis (1991), Estrella and Mishkin (1998), Stock and Watson (2003), and Ang, Piazzesi, and Wei (2006), show the significant predictive content of the spread for production growth, including its capacity to forecast a recession indicator in probit regressions. Additionally, there is a growing body of literature exploring the transmission of credit conditions into the real economy. Among other papers, Mueller (2009) and Gilchrist, Zankov, and Zakrajsek (2009) show the forecasting power of the term structure of credit spreads for future output growth. These authors argue that there is a pure credit component orthogonal to macroeconomic conditions that accounts for a large part of the predicting capacity of credit spreads. Finally, we also employ the leverage factor proposed by Adrian, Etula and Muir (2014), which is the seasonally adjusted log changes in the level of broker-dealer leverage and is downloaded from Tobias Adrian' web page.[6] Adrian, Moench, and Song Shin (2014) test four alternative intermediary asset pricing models, employing either book or market values from either broker-dealers or commercial banks as aggregate risk factors. These authors show that the model specification based on broker-dealer book leverage performs relatively well in comparison to other intermediary pricing models. On top of that, both Adrian, Moench, and Song Shin (2014), and Muir (2014) show that leverage is a strong predictor of the market excess return.

The empirical results are shown in Panels A, B, and C of Table 5 for horizons $\tau = 3$, 6, and 12 months, respectively. These tables contain the coefficient estimates, the

[6] Given that we employ monthly data from 1986 to 2013, we employ the alternative measure of the leverage factor at monthly frequency also suggested by Adrian, Etula and Muir (2014).

Mc Fadden R^2, and the Bayes Information Criterion (BIC) from the maximum likelihood estimation of the probit regressions at the alternative horizons. In parentheses, we report the *t*-statistics constructed from the Newey-West standard errors. At the shortest horizon, we find that, independently of the regression specification employed, the quality-based volatility bound is always positive and strongly significant. In fact, it seems to be higher and estimated with more precision that the size-based volatility bound suggested by Nieto and Rubio (2014). Similarly the default spread is also positive and highly significant. On other hand, the term spread does not seem to predict the probability of illiquidity-linked recessions, and the leverage factor losses significance when we include the default spread and the size-based volatility bound. At the intermediate horizon, the results are practically identical. Both the quality-based volatility bound and the default spread are positive and highly significant. The only exception is that at the six-month horizon, the size-based volatility bound remain positive and statistically different from zero even when we include simultaneously, the quality-based bound, the default spread, and the leverage factor. Finally, at the longest horizon, the quality-based volatility bound consistently remains as a powerful probability predictor of funding liquidity crisis. On the other hand, the size-based bound and the default spread lose forecasting ability. However, the term spread becomes a strong predictor with the right sign at the 12-month horizon. In any case, when we combine all predictors together, we find that this the best model with the quality-based volatility bound, and the default and term spreads as significant predictors. Interestingly, the size-based volatility bound losses statistical significance. Taking all this evidence together, it seems that the time series and cross-sectional information embedded across the 10 quality-sorted portfolios is a strong predictor of funding liquidity crises. When the quality-based volatility bound rises, we find that the probability of future funding liquidity crises significantly increases. Figure 2 displays the temporal behaviour of the quality-based volatility bound together with funding liquidity recessions represented by the black bars. We observe that there is a clear tendency of the quality-based volatility bound to increase in front of funding liquidity crises. Interestingly, this behavior seems to be reinforced in recent years.

7. The Effects of Predicting Financial Crisis on the Performance of Quality, Value and Momentum Strategies

Current practices on portfolio management trade, among others, on factors such as momentum, value, and quality. Momentum refers to purchasing recent winners and short-selling recent losers. Value means buying stocks with high ratios of fundamental value to market value, and sell those with the opposite characteristics. As Pedersen (2015) discusses, momentum complements value investing but it is also the case that quality complements both value and momentum investing. For instance, the combination of value and quality investing leads to the so called "quality at reasonable price" type of investment strategies.

In this section, we compare value, momentum, and quality investment strategies using a conditionally rather than an unconditionally approach. The objective of the analysis is to point out how different is the behaviour of momentum, value, and quality strategies when we forecast future funding liquidity crisis. Indeed, our evidence shows how defensive the quality investing strategy is relative to either value or momentum investments. When we employ a conditional performance evaluation, we suggest that any portfolio's risk is determined not only by the covariance of its return with the return of a contemporaneous factor like the market portfolio, but by that covariance conditional on a state variable that captures time-varying risk premium. In our case, we assume that this variation is attributable to the time variation in future financial crisis predicted by our forecasting variable. In other words, a given portfolio is more or less risky depending on how correlates with the market in bad times, where bad times are periods for which the state variable predicts a funding liquidity crisis. From the previous section, the forecasting variable is the volatility of the stochastic discount factor embedded in ten quality-sorted portfolios.

We run the following conditional regressions using the FF five-factor model extended with momentum,

$$\begin{aligned} R^{e}_{jt+1} = {} & \alpha_{j} + \beta_{jm} R^{e}_{mt+1} + \beta_{jm,\sigma(M)} \left[R^{e}_{mt+1} \sigma_{t}(M) \right] + \beta_{jsmb} SMB_{t+1} + \beta_{jhml} HML_{t+1} \\ & + \beta_{jrmw} RMW_{t+1} + \beta_{jcma} CMA_{t+1} + \beta_{jmom} MOM_{t+1} + \varepsilon_{t+1} \end{aligned} \tag{5}$$

It is important to note that we introduce a dynamic behaviour on the market risk premium by scaling the market excess return by the predictor variable. This variable appears in brackets in equation (5). The idea is to analyze how different the cross-beta, $\beta_{jm,\sigma(M)}$, coefficient is between high quality and either high value or high momentum portfolios. We show the results in Table 6. As expected, the performance of high (low) quality stocks presents a positive (negative) and significant alpha. The portfolio that goes long on high quality stocks and shorts low quality stocks has an even higher alpha and, similarly, the *QMJ* factor has a positive and significant risk-adjusted average return. A more relevant result is that either the high momentum or the high value portfolios have higher alphas than the high quality portfolio. Overall, the performance of both momentum and value seem to be stronger than the high quality stocks. Indeed, a portfolio that buys high quality and sells high momentum has a surprising poor average performance with an annualized negative alpha of -4.7%. We obtain a similar finding for a portfolio that goes long on quality and short on value.

From our point of view, the most relevant result that helps understanding the hedging behaviour of quality investing is the opposite sign of the cross-beta coefficient when we go long on either high momentum, high value, or high quality. The results are given in column 3 of Table 6. When the iterative term between the predictor of funding liquidity crisis and the market goes up, indicating a forthcoming crisis but still a positive market return, the return on quality significantly increases. However, both the return on high momentum and high value significantly decrease. The coefficient on the scaled $\sigma(M)$ factor is positive and statistically different from zero in all cases in which we go long in quality, and it becomes negative and significant when we buy either momentum or value. This suggests that momentum and value investing become riskier than quality when the market predicts a funding liquidity crisis. The behaviour of high quality stocks suggests a flight-to-funding liquidity. The investment implication is that we should tilt our portfolios toward quality investing whenever there are signals of funding illiquidity shocks.

We next analyze the performance of alternative investment strategies based on the behaviour of the funding liquidity crisis predictor as shown in Figure 2. We report the results in Table 7. The Sharpe ratio of the market portfolio return is 0.33 for the overall sample period. If we invest in a portfolio with 90% on high quality stocks and 10% on the market, the Sharpe ratio increases to 0.76. In the third column of Table 7, we show the performance of a conditionally strategy consisting of 75% on quality and 25% on the market, but the strategy changes towards a higher percentage on quality whenever the predictor of a future funding liquidity crisis increases. During those times, the portfolio invests 90% on quality and 10% on the market. The Sharpe ratio becomes as high as 0.92. Finally, in the last column of Table 7 we consider the case for which we invest 75% on quality and 25% on the market with a tilt towards quality when we observe a decreasing probability of a funding liquidity crisis. This strategy puts the same weight on quality as in our previous case, but time we tilt towards quality for precisely the opposite reasons. As expected, the Sharpe ratio becomes 0.80, which is relatively much lower than in the previous strategy given that we do not take advantage of the positive performance of quality stocks during the months for which a funding liquidity crisis is building up.

8. Conclusion

The combination of positive and significant risk-adjusted average returns, independently of the asset pricing models employed, and the extraordinary performance of high- versus low-quality stocks during economic downturns represents a puzzling result for financial economics. This paper investigates the macroeconomic risk that high-quality stocks really hedge during bad economic times. The results suggest that the flight-to-quality argument of AFP (2014) really means flight-against-to-funding liquidity crises. The investment strategy following the dynamic *QMJ* factor or going long on high-quality stocks seems to be especially appropriate during funding illiquidity events but much less during market-wide illiquidity episodes. On top of that, one key characteristic of high- versus low-quality stocks is their strong and significant forecasting capacity of funding liquidity crises. The main driver of this forecasting ability relates to the information contained in the simultaneous time series and cross-sectional behaviour of quality-sorted portfolios. The behaviour of the volatility bound of the stochastic discount factor obtained with quality-sorted portfolios is consistent with the formal forecasting capacity of future funding illiquidity events observed with the *QMJ* factor. We finally show that performance can be improved by tilting our portfolio towards high quality stocks whenever there is an increasing probability of a funding liquidity crisis.

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Table 1. Panel A: The performance of the Quality Minus Junk factor (*QMJ*)
July 1963-December2015

	α	β_1 *Market*	β_2 *SMB*	β_3 *HML*	β_4 *RMW*	β_5 *CMA*	β_6 *MOM*	β_7 *BAB*	β_8 *P&S*	*Adj.* R^2
CAPM	0.0050 (6.13)	-0.2825 (-15.61)	-	-	-	-	-	-	-	27.9
FF 3-Factor	0.0062 (8.86)	-0.2462 (-14.76)	-0.3410 (-14.57)	-0.1881 (-7.41)	-	-	-	-	-	47.7
FF 3 + MOM	0.0054 (7.73)	-0.2302 (-13.85)	-0.3418 (-14.90)	-0.1598 (-6.28)	-	-	0.0857 (5.24)	-	-	49.8
FF 5-Factor	0.0033 (7.17)	-0.1908 (-16.75)	-0.1648 (-10.32)	-0.2573 (-11.55)	0.7080 (30.13)	0.2294 (6.86)	-	-	-	78.0
FF 5 + MOM	0.0030 (6.39)	-0.1841 (-16.29)	-0.1680 (-10.68)	-0.2308 (-10.18)	0.6949 (29.83)	0.2077 (6.25)	0.0499 (4.63)	-	-	78.7
FF 5 + MOM + BAB	0.0028 (6.05)	-0.1890 (-16.66)	-0.1724 (-10.99)	-0.2473 (-10.66)	0.6757 (28.12)	0.1929 (5.78)	0.0420 (3.81)	0.0472 (3.00)	-	79.1
FF 5 + MOM + ILLIQ	0.0030 (6.34)	-0.1820 (-15.40)	-0.1671 (-10.58)	-0.2306 (-10.17)	0.6961 (29.75)	0.2077 (6.25)	0.0499 (4.63)	-	0.0049 (0.59)	78.7

Panel A of this table shows the risk-adjusted excess returns, the factor loadings and the adjusted R^2 of the quality minus junk (*QMJ*) portfolio associated with alternative asset pricing models. The explanatory variables are the monthly returns from the excess return of the market portfolio (*Market*), size (*SMB*), book-to-market (*HML*), momentum (*MOM*), profitability (*RMW*), investment aggressiveness (*CMA*), betting-against-beta (*BAB*), and the Pastor and Stambaugh (2003) market liquidity risk factor (*ILLIQ*). Returns and alphas are in monthly percent, and *t*-statistics are shown in parentheses

Table 1. Panel B: The performance of long-only quality investment
July 1963-December2015

	α	β_1 *Market*	β_2 *SMB*	β_3 *HML*	β_4 *RMW*	β_5 *CMA*	β_6 *MOM*	B_7 *BAB*	β_8 *P&S*	*Adj.* R^2
CAPM	0.0014 (2.22)	0.9212 (67.19)	-	-	-	-	-	-	-	87.8
FF 3-Factor	0.0029 (5.70)	0.8910 (73.67)	-0.1392 (-8.20)	-0.3120 (-16.96)	-	-	-	-	-	91.9
FF 3 + MOM	0.0026 (5.02)	0.8971 (73.29)	-0.1395 (-8.26)	-0.3011 (-16.08)	-	-	0.0329 (2.73)	-	-	92.0
FF 5-Factor	0.0023 (4.71)	0.8974 (74.82)	-0.0949 (-5.65)	-0.2733 (-11.64)	0.1990 (8.04)	-0.0522 (-1.48)	-	-	-	92.8
FF 5 + MOM	0.0021 (4.25)	0.9011 (74.80)	-0.0967 (-5.77)	-0.2586 (-10.70)	0.1918 (7.72)	-0.0642 (1.81)	0.0276 (2.40)	-	-	92.9
FF 5 + MOM + BAB	0.0022 (4.34)	0.9030 (74.17)	-0.0951 (-5.65)	-0.2525 (-10.15)	0.1989 (7.18)	-0.0587 (1.64)	0.0305 (2.58)	-0.0174 (-1.03)	-	92.9
FF 5 + MOM + ILLIQ	0.0021 (4.14)	0.9080 (72.23)	-0.0937 (-5.58)	-0.2582 (-10.70)	0.1958 (7.87)	-0.0643 (-1.82)	0.0276 (2.40)	-	0.0166 (1.87)	92.9

Panel B of this table shows the risk-adjusted excess returns, the factor loadings and the adjusted R^2 of the long-only highest quality portfolio associated with alternative asset pricing models. The highest quality portfolio is portfolio 10 (P10) from the ten quality-sorted portfolios available from AQR Capital Management Database. The explanatory variables are the monthly returns from the excess return of the market portfolio (*Market*), size (*SMB*), book-to-market (*HML*), momentum (*MOM*), profitability (*RMW*), investment aggressiveness (*CMA*), betting-against-beta (*BAB*), and the Pastor and Stambaugh (2003) market liquidity risk factor (*ILLIQ*). Returns and alphas are in monthly percent, and *t*-statistics are shown in parentheses

Table 1. Panel C: The performance of long-only junk investment
July 1963-December2015

	α	β_1 *Market*	β_2 *SMB*	β_3 *HML*	β_4 *RMW*	β_5 *CMA*	β_6 *MOM*	β_7 *BAB*	β_8 *P&S*	*Adj.* R^2
CAPM	-0.0056 (-4.50)	1.4170 (50.89)	-	-	-	-	-	-	-	80.5
FF 3-Factor	-0.0068 (-6.84)	1.2966 (54.49)	0.6531 (19.55)	0.0942 (2.60)	-	-	-	-	-	87.8
FF 3 + MOM	-0.0058 (-5.81)	1.2765 (53.57)	0.6540 (19.89)	0.0586 (1.61)	-	-	-0.1078 (-4.60)	-	-	88.2
FF 5-Factor	-0.0032 (-3.96)	1.2194 (61.00)	0.4520 (16.13)	0.2035 (5.20)	-0.8119 (-19.68)	-0.4013 (-6.84)	-	-	-	92.3
FF 5 + MOM	-0.0028 (-3.38)	1.2111 (60.54)	0.4560 (16.38)	0.1706 (4.25)	-0.7957 (-19-29)	-0.3744 (-6.37)	-0.0619 (-3.24)	-	-	92.4
FF 5 + MOM + BAB	-0.0026 (-3.11)	1.2179 (60.46)	0.4620 (16.58)	0.1933 (4.70)	-0.7692 (-18.03)	-0.3540 (-5.97)	-0.0509 (-2.60)	-0.0650 (-2.33)	-	92.4
FF 5 + MOM + ILLIQ	-0.0028 (-3-35)	1.2092 (57.77)	0.4552 (16.27)	0.1705 (4.24)	-0.7969 (-19.23)	-0.3744 (-6.36)	-0.0619 (-3.24)	-	-0.0046 (-0.31)	92.4

Panel C of this table shows the risk-adjusted excess returns, the factor loadings and the adjusted R^2 of the long-only lowest quality portfolio associated with alternative asset pricing models. The highest quality portfolio is portfolio 1 (P1) from the ten quality-sorted portfolios available from AQR Capital Management Database. The explanatory variables are the monthly returns from the excess return of the market portfolio (*Market*), size (*SMB*), book-to-market (*HML*), momentum (*MOM*), profitability (*RMW*), investment aggressiveness (*CMA*), betting-against-beta (*BAB*), and the Pastor and Stambaugh (2003) market liquidity risk factor (*ILLIQ*). Returns and alphas are in monthly percent, and *t*-statistics are shown in parentheses

Table 2: Quality and flight to market and funding liquidity: *QMJ* with Pastor and Stambugh and *BAB* as proxies for market and funding liquidity, respectively
January 1986-December 2012

	QUALITY MINUS JUNK (*QMJ*)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.0013 (1.37) [1.06]	0.0008 (0.83) [0.70]	0.0014 (1.58) [1.27]	0.0014 (1.49) [1.09]	0.0010 (1.11) [0.96]	0.0007 (0.75) [0.60]	0.0002 (0.16) [0.13]	0.0029 (2.64) [2.37]	0.0049 (5.32) [5.13]
RMW	0.9124 (25.20) [15.32]	0.8950 (25.20) [15.92]	0.9015 (25.58) [17.01]	0.9277 (23.09) [14.86]	0.8901 (25.49) [17.36]	0.8890 (22.06) [16.41]	0.8947 (25.79) [16.79]	0.8841 (22.40) [17.99]	0.7955 (23.47) [29.26
P&S Market ILLIQ			0.0626 (4.44) [4.98]		0.0504 (3.49) [3.30]		0.0203 (1.07) [1.16]		
BAB Funding ILLIQ				-0.0236 (-0.88) [-0.61]		0.0086 (0.32) [0.28]		-0.0650 (-1.97) [-1.95]	-0.0840 (-2.91) [-3.00]
Financial Stress Index		0.0042 (4.21) [2.26]			0.0032 (3.20) [1.61]	0.0043 (4.11) [2.34]	0.0028 (2.77) [1.36]	0.0062 (5.44) [3.74]	0.0028 (2.84) [2.38]
DPSL*ILLIQ							0.0114 (2.45) [2.79]		
DBAB*BAB								-0.0153 (-3.78) [-2.87]	-0.0094 (-2.76) [-2.35]
Market									-0.2043 (-11.53) [-7.24]
Adj R^2 (%)	67.09	68.77	68.96	67.07	69.86	68.68	70.34	69.97	79.34

This table shows the coefficient estimates form regressions estimated with monthly data of the quality minus-junk (*QMJ*) portfolio on a constant, the profitability (*RMW*) factor from the Fama and French (2015) 5-factor model, the Pastor and Stambaugh (2003) market liquidity risk factor (*ILLIQ*), the Frazzini and Pedersen (2014) funding liquidity betting-against-beta factor (*BAB*), the St. Louis Fed Financial Stress Index (*FSI*), dummy variables (*DPSL* and *DBAB*), which take the value of 1 if the market and funding illiquidity variables are higher than two times the corresponding standard deviation, and zero otherwise, and the market portfolio return (*Market*). OLS *t*-statistics are shown in parentheses and *t*-statistics based on HAC standard errors are shown in brackets.

Table 3: Quality and flight to funding liquidity: *TED* as a proxy for funding liquidity January 1986-December 2012

QUALITY MINUS JUNK (*QMJ*)				
	(1)	(2)	(3)	(4)
Constant	-0.0042	-0.0022	-0.0010	0.0004
	(-2.60)	(-1.18)	(-0.53)	(0.27)
	[-2.23]	[-0.80]	[-0.39]	[0.23]
RMW	0.9052	0.8975	0.8589	0.7647
	(25.62)	(25.35)	(23.28)	(23.88)
	[16.50]	[16.13]	[18.50]	[29.58]
TED	0.8472	0.4965	0.4834	0.5483
Funding ILLIQ	(4.15)	(1.83)	(1.80)	(2.44)
	[3.03]	[1.32]	[1.25]	[1.93]
Financial Stress		0.0026	0.0045	0.0009
Index		(1.94)	(3.12)	(0.73)
		[1.01]	[1.94]	[0.51]
DTED*TED			0.0105	0.0036
			(3.21)	(1.28)
			[2.31]	[0.96]
Market				-0.2029
				(-11.42)
				[-7.73]
Adj R^2 (%)	68.73	69.00	69.91	78.83

This table shows the coefficient estimates form regressions estimated with monthly data of the quality minus-junk (*QMJ*) portfolio on a constant, the profitability (*RMW*) factor from the Fama and French (2015) 5-factor model, the Pastor and Stambaugh (2003) market liquidity risk factor (*ILLIQ*), the difference between the three-month Treasury Bill and LIBOR rates (*TED*), the St. Louis Fed Financial Stress Index (*FSI*), a dummy variable (*DTED*), which take the value of 1 if the funding illiquidity variable is higher than two times the corresponding standard deviation, and zero otherwise, and the market portfolio return (*Market*). OLS *t*-statistics are shown in parentheses and *t*-statistics based on HAC standard errors are shown in brackets.

Table 4: Quality and flight to liquidity: Extreme and intermediate quality portfolios January 1986-December 2012

Panel A Funding Liquidity	QUALITY 10 – QUALITY 1	QUALITY 9 – QUALITY 2	QUALITY 6 – QUALITY 5
	1	2	3
Constant	0.0066	0.0014	0.0009
	(3.10)	(0.69)	(0.65)
	[3.11]	[0.75]	[0.70]
RMW	1.4489	0.7349	-0.0541
	(18.72)	(10.08)	(-1.03)
	[15.76]	[6.76]	[-0.94]
BAB	-0.2525	-0.1463	-0.1163
Funding ILLQ	(-3.90)	(-2.40)	(-2.65)
	[-4.50]	[-2.45]	[-2.74]
Financial Stress Index	0.0089	0.0099	0.0001
	(4.00)	(4.74)	(0.09)
	[2.55]	[2.67]	[0.06]
	-0.0359	-0.0179	-0.0050
DBAB*BAB	(-4.53)	(-2.40)	(-0.93)
	[-3.82]	[-1.98]	[-0.84]
Adj R^2 (%)	60.16	33.53	3.13

Panel B Market Liquidity	QUALITY 10 – QUALITY 1	QUALITY 9 – QUALITY 2	QUALITY 6 – QUALITY 5
	1	2	3
Constant	0.0008	-0.0017	-0.0012
	(0.40)	(-0.97)	(-0.95)
	[0.36]	[-0.82]	[-0.92]
RMW	1.4021	0.6950	-0.1139
	(19.92)	(10.80)	(-2.45)
	[13.28]	[6.73]	[-1.72]
P&S	0.0420	0.0516	-0.0086
Market ILLIQ	(1.10)	(1.47)	(-0.34)
	[1.14]	[1.18]	[-0.31]
Financial Stress Index	0.0040	0.0068	-0.0005
	(1.91)	(3.58)	(-0.34)
	[0.93]	[1.56]	[-0.21]
	0.0068	0.0073	0.0132
DPSL*ILLIQ	(0.72)	(0.85)	(1.81)
	[0.68]	[0.64]	[1.35]
Adj R^2 (%)	57.85	33.66	2.73

Panel A of this table shows the coefficient estimates form regressions estimated with monthly data of the difference returns between alternative quality portfolios given by P10-P1, P9-P2, and P6-P5, obtained from the ten quality-sorted portfolios available from AQR Capital Management Database, on a constant, the profitability (*RMW*) factor from the Fama and French (2015) 5-factor model, the Frazzini and Pedersen (2014) funding liquidity betting-against-beta factor (*BAB*), the St. Louis Fed Financial Stress Index (*FSI*), a dummy variable (*DBAB*), which take the value of 1 if the funding illiquidity variable is higher than two times the corresponding standard deviation, and zero otherwise. OLS *t*-statistics are shown in parentheses and *t*-statistics based on HAC standard errors are shown in brackets. Panel B of this table reports similar results using the Pastor and Stambaugh (2003) market liquidity risk factor (*ILLIQ*) instead of using the *BAB* factor as a proxy for funding liquidity, and the corresponding market liquidity dummy (*DPSL*).

Table 5: Forecasting the probability of funding illiquidity crises
January 1986-December 2012

Panel A: Three-Month Horizon									
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SDF Volatility: Quality Portfolios	4.022 (4.82)			4.914 (5.19)	4.396 (4.81)	4.701 (4.91)	3.979 (4.68)	4.575 (4.79)	4.348 (4.77)
SDF Volatility: Size Portfolios		2.470 (3.64)			1.431 (2.15)				1.259 (1.89)
Default			55.447 (4.78)	64.527 (5.10)	59.295 (4.50)	65.446 (5.01)		59.541 (4.43)	54.813 (4.07)
Term						-10.05 (-0.83)		-10.42 (-0.87)	
Leverage Factor							-8.837 (-3.22)	-5.039 (-2.03)	-4.365 (-1.70)
Mc Fadden R^2 (%)	9.15	7.79	11.19	22.41	24.24	22.67	14.06	24.12	25.23
BIC	217.89	223.26	213.27	193.52	195.10	198.66	212.49	201.11	198.60

Panel B: Six-Month Horizon									
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SDF Volatility: Quality Portfolios	5.258 (5.41)			5.916 (5.58)	5.398 (5.20)	5.679 (5.34)	5.142 (5.30)	5.634 (5.37)	5.419 (5.25)
SDF Volatility: Size Portfolios		2.667 (3.97)			1.694 (2.59)				1.723 (2.55)
Default			40.405 (3.71)	49.418 (4.18)	43.311 (3.54)	50.561 (4.16)		49.479 (4.07)	43.959 (3.56)
Term						-9.747 (-1.01)		-9.891 (-1.02)	
Leverage Factor							-3.877 (-1.23)	-0.804 (-0.29)	0.558 (0.18)
Mc Fadden R^2 (%)	14.89	8.04	5.99	22.48	25.08	22.73	15.93	22.77	25.10
BIC	204.87	220.42	225.08	193.36	193.19	198.54	208.24	204.19	198.90

Panel C: Twelve-Month Horizon									
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SDF Volatility: Quality Portfolios	5.330 (5.51)			5.419 (5.62)	4.819 (5.10)	4.396 (4.49)	4.445 (4.45)	4.415 (4.47)	4.412 (4.49)
SDF Volatility: Size Portfolios		2.609 (3.94)			1.888 (2.80)				0.327 (0.37)
Default			13.145 (1.34)	15.791 (1.43)	11.734 (1.05)		27.660 (2.54)	26.909 (2.33)	25.987 (2.25)
Term						-42.51 (-4.18)	-50.55 (-4.56)	-50.51 (-4.57)	-46.15 (-3.50)
Leverage Factor								-0.668 (-0.23)	
Mc Fadden R^2 (%)	14.92	8.05	0.53	15.58	19.23	20.55	22.42	22.45	22.48
BIC	204.78	220.40	237.49	209.03	206.48	197.75	199.23	204.92	204.84

This table shows the coefficient estimates, Mc Fadden R, and Bayes Information criterion (BIC) from the maximum likelihood estimation of the probit regression at a horizon of 3-month, 6-month, 12-month horizons reported in Panels A, B and C, respectively. Below the estimates, in parentheses, this table reports the *t*-statistics constructed using Newey-West standard errors. The stochastic discount factor volatility (SDF) bound are estimated using either ten quality- or size-sorted portfolios with overlapping sub-periods of five years of monthly data, and the average level of the risk-free interest rate for each of the five-year sub-periods. The default spread is the difference between Moody's yield on Baa corporate bonds and the 10-year government bond yield. The term spread is the difference between the 10-year and one-month government bond yields, and the leverage factor is the seasonally adjusted log changes in the level of broker-dealer leverage from Tobias Adrian's web page.

Table 6. Panel A: The performance of quality portfolios
January 1970-December2012

Panel A. Volatility of Stochastic Discount Factor as the Predictor: One-Month Horizon									
	α	β_2 *Market*	β_3 $\sigma(M)R_m$	β_4 *SMB*	β_5 *HML*	β_6 *RMW*	β_5 *CMA*	β_6 *MOM*	*Adj.* R^2
High Quality	0.0021 (3.58)	0.7818 (15.26)	0.2085 (2.16)	-0.0937 (-4.76)	-0.2991 (-10.9)	0.1954 (6.91)	-0.0470 (-1.11)	0.0291 (2.28)	92.9
Low Quality	-0.0026 (-2.96)	1.3891 (17.87)	-0.3122 (-2.13)	0.4276 (14.32)	0.1951 (4.69)	-0.7969 (-18.6)	-0.2861 (-4.44)	-0.0727 (-3.75)	93.6
High Q Minus Low Q	0.0048 (4.35)	-0.6072 (-6.39)	0.5207 (2.91)	-0.5213 (-14.3)	-0.4942 (-9.71)	0.9923 (18.92)	0.2390 (3.04)	0.1018 (4.29)	75.7
QMJ	0.0037 (7.27)	-0.3535 (-8.04)	0.2990 (3.61)	-0.1992 (-11.8)	-0.2232 (-9.47)	0.6944 (28.60)	0.1774 (4.87)	0.0433 (3.94)	83.0
High MOM	0.0060 (7.05)	1.2900 (17.48)	-0.3262 (-2.35)	0.2915 (10.28)	0.0311 (0.79)	-0.1833 (-4.50)	-0.2748 (-4.50)	0.5728 (31.10)	92.4
High VALUE	0.0043 (4.11)	1.3890 (15.33)	-0.4682 (-2.74)	0.3441 (9.89)	0.9647 (19.89)	-0.0877 (-1.75)	-0.1037 (-1.38)	-0.0709 (-3.14)	87.4
H Qual Minus H Mom	-0.0039 (-3.61)	-0.5082 (-5.46)	0.5347 (3.05)	-0.3852 (-10.8)	-0.3302 (-6.62)	0.3786 (7.37)	0.2278 (2.95)	-0.5437 (-23.4)	64.9
H Qual Minus H Value	-0.0022 (-1.90)	-0.6072 (-6.11)	0.6767 (3.61)	-0.4378 (-11.5)	-1.2638 (-23.8)	0.2830 (5.16)	0.0566 (0.69)	0.1000 (4.03)	73.0
Panel B. Volatility of Stochastic Discount Factor as the Predictor: Three-Months Horizon									
	α	β_2 *Market*	β_3 $\sigma(M)R_m$	β_4 *SMB*	β_5 *HML*	β_6 *RMW*	β_5 *CMA*	β_6 *MOM*	*Adj.* R^2
High Quality	0.0021 (3.58)	0.7750 (15.33)	0.2198 (2.33)	-0.0942 (-4.79)	-0.3009 (-11.0)	0.1957 (6.92)	-0.0457 (-1.08)	0.0295 (2.31)	92.9
Low Quality	-0.0026 (-2.96)	1.400 (18.26)	-0.3301 (-2.31)	0.4284 (14.36)	0.1979 (4.76)	-0.7974 (-18.6)	-0.2881 (-4.48)	-0.0733 (-3.78)	93.6
High Q Minus Low Q	0.0047 (4.35)	-0.6250 (-6.67)	0.5499 (3.15)	-0.5226 (-14.3)	-0.4989 (-9.81)	0.9930 (18.96)	0.2424 (3.08)	0.1027 (4.33)	75.8
QMJ	0.0037 (7.24)	-0.3437 (-7.90)	0.2770 (3.42)	-0.2001 (-11.8)	-0.2255 (-9.55)	0.6946 (28.57)	0.1770 (4.84)	0.0434 (3.95)	83.0
High MOM	0.0060 (7.06)	1.2859 (17.65)	-0.3150 (-2.32)	0.2924 (10.32)	0.0337 (0.85)	-0.1836 (-4.51)	-0.2751 (-4.50)	0.5725 (31.07)	92.4
High VALUE	0.0043 (4.14)	1.2752 (14.18)	-0.2435 (-1.45)	0.3462 (9.90)	0.9664 (19.81)	-0.0914 (-1.21)	-0.1037 (-1.38)	-0.0691 (-3.04)	87.2
H Qual Minus H Mom	-0.0039 (-3.62)	-0.5109 (-5.56)	0.5347 (3.12)	-0.3866 (-10.8)	-0.3347 (-6.71)	0.3792 (7.38)	0.2294 (2.97)	-0.5430 (-23.4)	65.0
H Qual Minus H Value	-0.0022 (-1.94)	-0.5002 (-5.06)	0.4633 (2.52)	-0.4404 (-11.5)	-1.2673 (-23.6)	0.2830 (5.13)	0.0457 (0.55)	0.0986 (3.95)	72.7

This table shows the risk-adjusted excess returns, the factor loadings and the adjusted R^2 of alternative quality, momentum, and value portfolios when we allow for dynamic effects on the conditional performance through an interaction term between the market excess return and the one-month (three-months) lagged predictor of financial crisis. The predictor is the volatility of the (lower bound) stochastic discount factor estimated with 10 quality-sorted portfolios. The control variables are the monthly returns from the excess return of the market portfolio (*Market*), size (*SMB*), book-to-market (*HML*), profitability (*RMW*), investment aggressiveness (*CMA*), and momentum (*MOM*). Returns and alphas are in monthly percent, and *t*-statistics are shown in parentheses.

Table 7. The Performance of forecasting-based investments on quality portfolios January 1970-December 2012

Sharpe Ratios			
Market Excess Return	Full period: 90% Quality/ 10% Market	Increasing the probability of a funding liquidity crisis: 90% Quality/ 10% Market	Decreasing the probability of a funding liquidity crisis: 90% Quality/ 10% Market
0.329	0.758	0.915	0.800

This table shows annualized Sharpe ratios of four alternative investment strategies. The first column reports the performance of investing in the market in excess over the risk-free rate. The second column is the result of investing 90% on the QMJ factor and 10% on the market during the full sample period. The third column displays the strategy that invests 90% on quality and 10% on the market during periods for which the predictor of a future funding liquidity crisis increases, and 75% on quality and 25% on the market during the rest of the period. The fourth column shows the result for the opposite strategy. It invests 90% on quality and 10% of the market when the predictor of a funding liquidity crisis decreases, but otherwise invests 75% on quality and 25% on the market.

Figure 1: The profitability factors of Novy-Marx (*PMU*), Fama and French (*RMW*), and Asness, Frazzini, and Pedersen (*QMJ*)

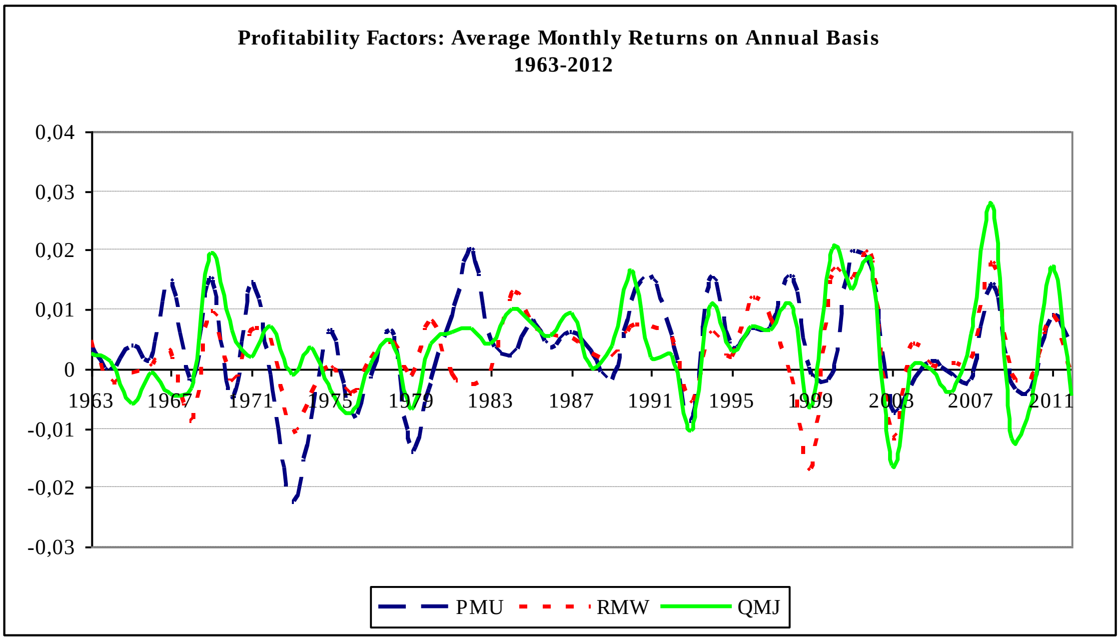

Figure 2: Volatility of the stochastic discount factor with quality-sorted portfolios and funding illiquidity crises