Funding Liquidity Risk and the Cross-Section of Stock Returns

Jean-Sébastien Fontaine
Bank of Canada
René Garcia
EDHEC Business School
Sermin Gungor
Bank of Canada

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Abstract

Theory predicts that frictions in the funding markets of intermediaries should transmit to the cross-section of equities. Stocks that experience low returns when funding becomes scarce should exhibit higher illiquidity, higher volatility and ultimately higher risk premium. In this paper, we document this mechanism empirically. We show that the illiquidity and volatility of individual portfolios are positively associated with the value of funding liquidity, a measure of funding scarcity, while the portfolio returns are negatively correlated. In addition, the cross-section dispersion of illiquidity, volatility, and returns widens when funding conditions deteriorate. We find that this risk is priced. The funding liquidity risk premium explains the cross-section of returns across liquidity-, volatility-, and size-sorted portfolios. Overall, our results provide strong support for the prediction that funding liquidity plays a significant role in the determination of equity liquidity, volatility, and risk premium.

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The second author is a research fellow at CIRANO and CIREQ.
Correspondence: J-S. Fontaine, Bank of Canada, 234 Wellington, Ottawa, Canada, K1A 0G9.
jsfontaine@bankofcanada.ca.

Introduction

Funding liquidity is a significant driver of market liquidity and volatility. The value of funding liquidity, or the shadow cost of capital for financial intermediaries, varies over time and signals periods of high uncertainty, as captured by high implied volatilities across financial indices. Vayanos (2004) proposes an equilibrium model in which assets differ in their liquidity and where the stochastic volatility of asset payoffs captures the magnitude of uncertainty. In Brunnermeier and Pedersen (2009), tightness in funding conditions leads traders to avoid capital-intensive positions in high-margin securities, which lowers market liquidity and induces higher volatility. Therefore, funding liquidity shocks may affect equity volatility and illiquidity and may ultimately affect valuation via the risk premium if these shocks occur in states where economic conditions or investment opportunities are deteriorating.

Fontaine and Garcia (2012) propose a measure of funding liquidity based on small apparent deviations from arbitrage in a panel US Treasury bonds. Although small, these deviations follow from frictions in the funding market. Fontaine and Garcia (2012) find that variations in the value of funding affect asset growth in the shadow banking sector and that an increase in the value of funding liquidity predicts risk premia across a wide range of fixed income markets. In this paper, our objective is to measure the role of funding liquidity in the cross-section of equity risk premia.

Since several theories of limits to arbitrage suggest that funding liquidity, market liquidity and volatility are interrelated, we form portfolios based on illiquidity and volatility. We sort individual equities by market illiquidity according to the Amihud (2002) measure, which is the average ratio over a month of absolute daily returns over daily trading volume. We also sort individual equities by their past realized volatility to form 10 equally-weighted portfolios. We find that funding liquidity shocks increase the dispersion of liquidity and volatility portfolios. Moreover, consistent with the model of Brunnermeier and Pedersen (2009), we provide evidence that funding shocks increase the volatility dispersion within the liquidity-sorted portfolios.

Not only funding liquidity shocks impact market liquidity and volatility of equities, they also generate a funding risk premium in the cross-section of returns of volatility and liquidity portfolios. We show that the pattern of risk premia across portfolios matches almost exactly the pattern of betas for both sets of portfolios. More formally, we run asset pricing tests with cross-sectional regressions of the average returns on the betas of the illiquidity or volatility portfolios. The innovations in the funding liquidity factor alone explain a large percentage of the cross-sectional variation for both sets of portfolios (65% of the liquidity-sorted portfolios and 85% of the volatility-sorted portfolios). Adding the market and the Fama-French factors add only marginally to the explanatory power. The price of risk is robustly estimated at -2, which translates into a risk premium of 2% for a beta of -1. Overall our findings provide a strong support for the theoretical implications of Vayanos (2004) and Brunnermeier and Pedersen (2009) when the tightness of funding conditions is measured by innovations in the funding liquidity factor.

Apart from these direct tests built upon the theoretical implications of the asset pricing models with funding frictions, we may want to verify how the funding innovations are related to the usual portfolios sorted on size, book-to-market value, and momentum. This will give us the opportunity to compare our measure to the leverage factor measure used in Adrian et al. (2013) since they chose these traditional portfolios as test assets. Adrian et al. (2013) use broker-dealer financial leverage to proxy for the stochastic discount factor that reflects the marginal utility of wealth in different states of the economy. They find that shocks to broker-dealer leverage explain alone the average returns of portfolios sorted on industry, size, book-to-market, and momentum. Since they document a strong correlation between leverage growth and broker-dealer asset growth, they suggest that leverage is a good proxy for funding liquidity, as the ability of brokers-dealers to borrow corresponds to the amount borrowed. However, this interpretation is challenged by their finding of a lack of correlation between leverage shocks and shocks to the Pastor and Stambaugh (2003) liquidity factor, since theory predicts that funding liquidity and market liquidity are interrelated. Consistently with Adrian et al. (2013) we find that the leverage factor explains less than 10% of the cross-section of average returns of our illiquidity portfolios. Since our measure of funding liquidity shocks explains well the cross-section of liquidity portfolios and supports the theoretical pro-cyclical leverage or margin spiral, one may wonder whether the broker-dealer leverage is a good proxy for tightness of funding conditions.

Our results confirm that the Fama-French size and book-to-market portfolios have a negative exposure to changes in funding conditions and that this risk is negatively priced in the cross-section. This risk is different from the leverage factor of Adrian et al. (2013), which comes also as a significant risk factor in our sample. A closer look at the size or book-to-market portfolios taken separately shows clearly the difference between the two factors. The leverage factor explains by itself 85% of the cross-section of the book-to-market portfolios but only 1% of the size portfolios, while it is the reverse for the changes in funding liquidity. The latter explains 72% of the size portfolios but only 9% of the book-to-market portfolios. This is consistent with both the high correlation between the leverage factor and asset growth, and the high commonality of securities between the size and the illiquidity portfolios. However, the price of risk of funding liquidity innovations is in all cases estimated at a robust value close to -2.

In Figure 1, we plot the quarterly series of the funding liquidity factor, its innovations and the leverage factor of Adrian et al. (2013). The funding liquidity innovations series and the leverage factor series move in opposite directions at the beginning of the sample (in particular in the 1987 market crash and the 1994 Mexican peso crisis). However, leverage has tended to move together with funding conditions in the latter part of the sample (in particular at the beginning of the last financial crisis and also in the LTCM 1998 crisis), perhaps because previous commitment or concerns of financial intermediaries about their reputations delayed their response to funding conditions in terms of leverage. Therefore, it suggests that the funding liquidity measure and the leverage factor may complement each other in capturing the state of funding conditions.

When the momentum factor is introduced along with the three Fama-French factors to make up the Carhart four-factor model of asset pricing, the adjusted R^2 for the volatility portfolios is 84% compared to 83% for the ΔFL alone, while for the liquidity portfolios it is 90% compared to 65% for the ΔFL alone. However, if we augment the Carhart model by the ΔFL factor, the latter is not at all significant. This result leads us to look more closely at the relation between portfolios sorted on the momentum factor and the funding liquidity factor. Based on our empirical findings and the literature that aims at finding a risk-based explanation to momentum returns, we conclude that some of the momentum premia are due to liquidity risk.

Our findings reinforce the recent supporting evidence for the theory of Brunnermeier and Pedersen (2009) relating funding liquidity to market liquidity in other asset markets. Using the same measure of funding liquidity as in this paper, Fontaine and Garcia (2012) find that an increase in the value of funding liquidity predicts lower risk premia for on-the-run *and* off-the-run bonds but higher risk premia on LIBOR loans, swap contracts and corporate bonds. Franzoni et al. (2012) provide evidence of a link between private equity returns and overall market liquidity through a funding liquidity channel measured by changes in credit standards.

A larger literature has explored the link between asset returns and aggregate market liquidity risk in various markets and with various measures of liquidity. For stock returns, Pastor and Stambaugh (2003) show that aggregate liquidity risk is a priced factor. Their measure is based on daily price reversals and relies on the principle that order flow accentuates return reversals when liquidity is lower. Acharya and Pedersen (2005) derive a simple model for liquidity risk, which is a CAPM for returns net of illiquidity costs where illiquidity is measured by the Amihud (2002) measure as in this paper. They show that the model has a good fit for portfolios sorted on liquidity, liquidity variation, and size, but that it cannot explain the cross-sectional returns associated with the book-to-market effect. These results are consistent with our findings but are based on aggregate market liquidity risk. The Sadka (2006) measure is a market aggregate of the price impacts at the individual stock level. He shows that the cross-section of returns on portfolios sorted on momentum and post-earnings-announcement drift are well explained by the market-wide variations of the variable part of this price impact. Further evidence has been put forward for other asset markets[1].

The rest of the paper is organized as follows. The next section discusses briefly the theoretical literature on funding liquidity, its links to market liquidity and volatility, and flight to liquidity episodes. We also summarize the literature on the empirical measures of both funding liquidity and market liquidity. In Section II we describe how we construct illiquidity and volatility portfolios, describe the daily dataset on individual equities and the criteria chosen to include them in the study, and explain how quarterly data are constructed for conducting the asset pricing tests. The empirical results on the pricing of illiquidity and volatility portfolios are reported and discussed in Section III. Section IV conducts other pricing tests on portfolios sorted on size and book-to-market, while Section V analyzes the empirical links between funding liquidity and momentum. A discussion of our empirical findings with respect to the implications of asset pricing models with funding frictions is included in Section VI. Section VII concludes with the remaining challenges and promising avenues.

[1] See in particular Chordia et al. (2005), Beber et al. (2008), and Li et al. (2009) for bond markets, Longstaff et al. (2005), Bongaerts et al. (2011) and Longstaff et al. (2011) for credit derivative markets, and Boyson and Stulz (2010) and Sadka (2010) for hedge funds.

I Funding Liquidity and Asset Pricing

To capture how liquidity affects asset prices, Vayanos (2004) suggests to measure the liquidity premium between two assets of very similar characteristics but different liquidity. He cites the difference between a just-issued (on-the-run) thirty-year Treasury bond and a thirty-year bond issued three months ago (off-the-run). The two bonds have very similar cash flows but the on-the-run bond is much more liquid that the off-the-run one. Fontaine and Garcia (2012) extract this latent liquidity premium by estimating a term structure model from a panel of pairs of U.S. Treasury securities, where each pair has similar cash flows but different ages. This strategy is consistent with the existence of an on-the-run premium in the short-run but also with the evidence that older bonds are less liquid. Therefore, estimates of the liquidity factor will be obtained through price differentials that can be attributed to differences in age. They demonstrate that this age-based measure can be interpreted as a measure of the value of funding liquidity[2].

Brunnermeier and Pedersen (2009) propose a model that links the ease with which traders can obtain funding with an asset's market liquidity. As long as the traders' capital is abundant, the funding constraint is not binding and market liquidity is not affected by marginal changes in capital and margins. When traders hit their capital constraints, they reduce their positions and market liquidity is reduced. Funding liquidity is then more important for pricing than fundamentals. Financial intermediaries that set margins are unsure whether price changes are driven by fundamental

[2]To link their measure to funding conditions, Fontaine and Garcia (2012) present evidence at three successive levels of aggregation. First, they relate the liquidity value to the expected benefits of holding a more liquid security, where benefits are measured by a common component in repo spreads. Second, they trace the linkages of funding liquidity to the shadow banking sector, a large non-bank component of the intermediation system that relies heavily on short-term funding to finance long-lived illiquid assets. Third, they study the relationship between the value of funding liquidity and broader measures of funding conditions, such as variations of non-borrowed reserves of commercial banks at the Federal Reserve or changes in the rate of growth of M2 (to capture the tightness of the supply of funds to intermediaries), after controlling for a broad range of financial and economic variables.

news or by liquidity shocks, and volatility is time varying. Indeed, a liquidity shock will lead to price volatility, and financial intermediaries will increase their margins in anticipation of a higher future volatility. Moreover, the model explains flight to quality, when speculators' capital shrinks, they provide liquidity to low-volatility stocks with lower margins. This increases the liquidity differential between high-volatility and low-volatility securities.

To test empirically these theoretical implications, we need to rank securities by their market liquidity and their volatility. Several measures have been used in the literature for market liquidity. The most widely used is the Amihud (2002) illiquidity ratio, which provides a good measure of price impact[3]. For an individual stock, the illiquidity ratio ($ILLIQ_{id}$) is given by:

$$ILLIQ_{id} = \frac{|R_{id}|}{DVOL_{id}} * 10^6 \quad (1)$$

where R_{id} is the return on a stock i on day d and $DVOL_{id}$ is the dollar value of trading volume on the same day. This measure can be aggregated over securities and time to obtain a portfolio illiquidity measure at the desired frequency. For volatility, we adopt the concept of realized volatility. For example, we use the standard deviation of daily returns over the month when using the monthly frequency. The realized volatility for a portfolio is the average volatility of all stocks in the portfolio. The next section describes the original data, the time aggregation, the portfolio formation and the risk factors used in the study.

[3]Goyenko et al. (2009) compare the various liquidity measures used in empirical studies and suggest other measures better able to capture both spreads and price impact. They conclude that the Amihud (2002) illiquidity ratio ia a good proxy for price impact.

II Data and Portfolio Formation

The funding liquidity measure in Fontaine and Garcia (2012) is a monthly measure starting in 1986[4]. Our sample will end in December 2011, therefore including the recent financial crisis. To build portfolios based on illiquidity and volatility, we start from daily data on individual stocks and build aggregated measures over firms and time.

A Daily data

Our daily stock data comprises returns and trading volumes for individual stocks traded in the NYSE and AMEX markets[5] for the 26-year period from January 1986 to December 2011. These are all the stocks for which the data is available in the Center for Research Securities Prices (CRSP). To be included in the sample, a stock must meet the following the criteria:

1. Ordinary common stock (CRSP share codes 10 and 11). The sample excludes ADRs, SBIs, REITs, certificates, units, closed-end-funds, companies incorporated outside the U.S., and Americus Trust components.

2. Traded in NYSE or AMEX.

3. The stock must have a price between \$5 and \$1000.

4. Each stock is required to have 150 days of observations over the previous year.

5. Each stock is required to have at least 10 days of data in each month.

[4]Before 1986, interest income had a favorable tax treatment compared to capital gains and investors favored high-coupon bonds. In that period, interest rates rose steadily and recently issued bonds had relatively high coupons and were priced at a premium both for their liquidity and for their tax benefits. The resulting tax premium cannot be disentangled from the liquidity premium using bond ages. Green and Ødegaard (1997) confirm that the tax premium mostly disappeared when the asymmetric treatment of interest income and capital gains was eliminated following the 1986 tax reform.

[5]Nasdaq stock are excluded from the sample because their trading volume is significantly higher compared to NYSE and AMEX stocks due to interdealer trades.

B Portfolio formation

The monthly liquidity and volatility portfolios are obtained by sorting stocks into decile portfolios based on their previous year-end illiquidity ratio and realized volatility, respectively. The illiquidity ratio for portfolio p with N stocks is defined as

$$ILLIQ_{pt} = \frac{1}{N}\sum_{i=1}^{N}\frac{|R_{it}|}{DVOL_{it}} * 10^6 \tag{2}$$

where t denotes a month. The realized volatility for a portfolio is the average volatility of all stocks in the portfolio.

C Quarterly data

An important aspect of our study is to compare our measure of funding liquidity to the leverage factor proposed by Adrian et al. (2013). To construct their factor, they use aggregate quarterly data on the levels of total financial assets and total financial liabilities of security broker-dealers as captured in Table L.129 of the Federal Reserve Flow of Funds. Therefore, we compute the measure of broker-dealer (BD) leverage as

$$Leverage_t^{BD} = \frac{TotalFinancialAssets_t^{BD}}{TotalFinancialAssets_t^{BD} - TotalLiabilities_t^{BD}} \tag{3}$$

The leverage factor is then computed as the seasonally adjusted log changes in the level of broker dealer leverage

$$LevFact_t = [\Delta ln(Leverage_t^{BD})]^{SA} \tag{4}$$

The seasonal adjustment follows the procedure in Adrian et al. (2012). It is done in real time using quarterly seasonal dummies. In Figure 1 we plot the quarterly series of leverage factor, as well as our funding liquidity factor and its innovations.

While the funding liquidity innovations series and the leverage factor series move in opposite directions in the beginning of the sample (in particular in the 1987 market crash and the 1994 Mexican peso crisis), they have tended to move together in the latter part of the sample (in particular at the beginning of the last financial crisis and also in the LTCM 1998 crisis). Therefore, it suggests that the new measure may at least complement the leverage factor measure.

Therefore, we will conduct our empirical study at the quarterly frequency. We convert all the monthly return data for our portfolios into quarterly frequency by compounding the monthly values over each quarter. The illiquidity ratio is aggregated over a quarter by taking simple average. The quarterly value of funding liquidity is its monthly value at the end of each quarter. The Fama-French 25 size and book-to-market sorted portfolio and the size sorted decile portfolios are from Kenneth French's data library, as well as the quarterly Fama-French three factors, (excess return on the market, size, and book-to-market factors). The monthly momentum factor and the one-month T-bill rate are also extracted from the same data library and compounded to the quarterly frequency.

III Funding Liquidity and Illiquidity and Volatility Portfolios

In this section, we will test the theoretical implications of the Adrian et al. (2013) model and investigate the empirical links between funding liquidity, market liquidity, volatility and flight to quality. First, we will test if the funding liquidity risk is priced in the cross-section of liquidity-sorted and volatility-sorted portfolios. Then we will evaluate the illiquidity and volatility sensitivity of each of these portfolios to changes in funding conditions. Finally, we will consider periods of tight or loose funding conditions to evaluate the effects on these portfolios in terms of returns, illiquidity and volatility.

A Pricing of Illiquidity and Volatility Portfolios

To investigate whether the funding liquidity risk is priced in the cross-section of returns of illiquidity and volatility portfolios we proceed as usual in two steps. First we run a set of time-series regressions:

$$r_{it} = \alpha_i + \beta_i^{\Delta FL} \Delta FL_t + \beta_i^{MKT} MKT_t + \varepsilon_{it} \tag{5}$$

in which we add the funding liquidity innovations to the market as a risk factor. In Panels (a) and (b) of Table 1, we report the betas and the R^2 of these first-stage regressions. For both sets of portfolios and all portfolios, we observe a negative exposure to funding changes, and a declining pattern in absolute magnitude from the most volatile to the least volatile and from the most illiquid to the least illiquid. The funding-liquidity beta of the most illiquid portfolio is equal to -3.05, compared to a beta of -0.28 for the most liquid portfolio. For volatility, the funding beta goes from a value of -2.64 for the most volatile to a value of -1.32 for the least volatile. Note that market betas are mostly flat across liquidity-sorted portfolios and, therefore, cannot explain the returns spread between illiquid and liquid portfolios. The coefficients of regression range from 60% for the least volatile portfolio to more than 90% for the most liquid portfolio.

Figure 2 shows that the risk loadings with respect to funding innovations align with the average returns (adjusted for the market risk) of the liquidity and volatility portfolios. Clearly, the pattern of risk premiums across portfolios match almost exactly the pattern of $\beta_i^{\Delta FL}$, and the price of risk (the slope) is close to -2. This is confirmed by the results of the Fama-MacBeth cross-sectional regressions in Table 2. In this table we report the estimated prices of risk for various asset pricing models and for liquidity-sorted, volatility-sorted, and liquidity-sorted and volatility-sorted taken together, respectively in Panels (a), (b) and (c). For the pricing models, we report first on the left-hand side of the table the estimated coefficients of the CAPM, the three-factor Fama-French model (FF3), the univariate leverage factor of Adrian et al. (2013) (LevFct), and our funding-liquidity innovations factor (ΔFL). On the right-hand side we report the estimated prices of risk for the first three asset pricing models (CAPM, FF3, LevFct) augmented by ΔFL.

For the liquidity-sorted portfolios, the $\beta^{\Delta FL}$s explain alone 65% of the cross-section of returns, compared to 85% for the three Fama-French factors. For the augmented FF3 model the R^2 increases to 88%. The price of risk is estimated at -2.45 for the ΔFL alone and -1.89 for the FF3 augmented by ΔFL. It is significant in both cases, and the α is not significantly different from zero. The LevFct does not explain at all the cross-section of the liquidity-sorted portfolios. The price of risk is insignificant in all configurations. This is consistent with the results mentioned in Adrian et al. (2013). For the volatility portfolio, the R^2 of the FF3 model and of the ΔFL are very large and almost identical (86.5% and 83% respectively). The value estimated for the price of the liquidity risk is again close to -2, but the statistical significance decreases a bit compared to the liquidity portfolios. The LevFct comes in with the wrong sign. When both sets of portfolios are pooled together, the funding-liquidity augmented FF3 model explains 81% of the cross-sectional variation and the ΔFL beta is the most significant regressor. The price of risk is again estimated at a value of -2. The LevFct explains only 3% of the cross-sectional variation in average returns.

B Sensitivity to Funding Conditions

In Table 3,we report the estimated sensitivities of changes in illiquidity or volatility of each portfolio to changes in funding conditions (ΔFL). We run the following regressions:

$$\Delta ILLIQ_{it} = \gamma_{0,i} + \gamma_i \Delta FL_t + \xi_{it} \quad (6)$$

$$\Delta VOL_{it} = \gamma_{0,i} + \gamma_i \Delta FL_t + \xi_{it} \quad (7)$$

Panel(a) summarizes the results of the liquidity regressions. Only the most illiquid and the most volatile show a market sensitivity to changes in funding conditions. This tends to support the reinforcement of shocks to funding liquidity through market liquidity and volatility spiraling effects. In Adrian et al. (2013) a margin spiral occurs if margins are increasing in illiquidity. A funding shock will then lower market liquidity, leading to higher margins. Moreover, when funding conditions affect negatively the capital of financial intermediaries, they tend to provide liquidity in low-volatility securities (with lower margins) that require less capital, increasing the liquidity differential between high-volatility and low-volatility stocks[6]. No such differentiated effects are apparent in the volatility regressions. The coefficients are more or less uniform across liquidity portfolios. However, the high-volatility securities tend to react more than low-volatility securities.

Are these effects more pronounced at times of high funding liquidity costs? This is the question addressed by Table 4. We report the conditional averages of the returns, illiquidity and volatility when funding liquidity cost is low (Panel(a)) or high (Panel(b)). The differential in these quantities between low and high funding liquidity cost is reported in Panel(c). For liquidity portfolios, the answer is yes since for the least liquid portfolios, their illiquidity worsens when funding conditions become tighter. In terms of returns, all portfolios have higher average returns because of the funding liquidity premium. The volatility of liquidity portfolios is also uniformly higher when the funding liquidity cost is high.

[6]The coefficient of the least volatile portfolio seems at odds with respect to the other low-volatility portfolios.

For the volatility, the most significant differences are for the most volatile portfolios where both returns and illiquidity increase in bad times. Therefore, the implication of the theoretical is again supported. The most volatile stocks become more illiquid in bad times and the average returns are higher due to the illiquidity premium.

IV Funding Liquidity and Size and Value Portfolios

We have seen that the leverage factor proposed by Adrian et al. (2013) does not explain the cross-section of returns of liquidity and volatility portfolios. However, Adrian et al. (2013) make a strong case for the capacity of their factor to explain the cross-section of size and value portfolios. In their sample (1968Q1-2009Q4) the leverage factor alone explains more than 70% of the cross-section of the 25 size and book-to-market portfolios, while the three-factor Fama-French model explains about 68%. Given that they interpret the leverage factor as a measure of funding conditions through the balance sheet positions of brokers-dealers, we need to see how our measure of funding liquidity innovations behaves with respect to these portfolios and whether it complements the leverage factor in explaining the cross-section of size and value portfolios. Therefore, we proceed as before in two stages.

First, we run time-series regressions of portfolio returns on the liquidity factor (ΔFL or LevFct) and the market to compute the betas. The results for ΔFL are reported in Table 5. All portfolios except the largest low-value portfolios have a negative exposure to the liquidity factor, as it was the case for the liquidity and volatility portfolios. There seems to be a reasonable variation among the portfolio betas for ΔFL. In Figure 3 we plot in panel(a) these betas against the market-risk adjusted returns. The slope is negative as it should be and the portfolio betas seem to spread above and below the line. In Panel (b) we plot the equivalent betas for the leverage factor against also the risk-adjusted returns. The slope is positive and the betas seem to be a bit more concentrated around the center.

Second, to see if the funding liquidity innovations or the leverage factor are priced risks we run cross-sectional regressions. As for the liquidity and volatility portfolios we estimate and test the CAPM, the three-factor Fama-French model (FF3), the univariate leverage factor of Adrian et al. (2013) (LevFct), and our funding-liquidity innovations factor (ΔFL), as well the first three asset pricing models (CAPM, FF3, LevFct) augmented by ΔFL. We report the estimated prices of risk, alphas and R^2 in Table 6. In Panel (a), we conduct the tests with the usual double-sorted five-by-five size and book-to-market portfolios except that we take out the small-growth portfolio as done in Adrian et al. (2013) and other studies. The estimated prices of risk of LevFct and ΔFL have the right sign but they are not statistically significant. The single-liquidity-factor models LevFct and ΔFL explain 27% and 22% of the cross-section of returns respectively. When considered together they keep their sign and explain 29% of the variation in average returns but the prices of risk are not significant. To gain power we consider the double-sorted ten-by-ten size and book-to-market portfolios. The estimated prices of risk are now significant when the liquidity factors are considered alone. The magnitude of the price of risk -1.9 is similar to what we obtained before. When the two liquidity factors are taken together, the leverage factor remains statistically significant, but the estimated value of the price of risk for ΔFL is halved and it is not statistically significant any longer. We can conclude that the two liquidity factors have some element in common and that size and book-to-market portfolios are favoring more the leverage factor than the innovations in funding liquidity.

To better understand the difference between the two factors, we examine in Table 7 the pricing of the single-sorted size portfolios and book-to-market portfolios, ten of each category. The results are striking. For the size portfolios, the leverage factor does not any explanatory power and the price of risk has the wrong sign, as opposed to the funding liquidity innovations that explains almost 70% of the cross-section of returns. The price of risk is estimated at -2.46 with a t-statistic of -2.66. In comparison the FF3 model has an adjusted R^2 of 78%. When the FF3 model augmented with the ΔFL factor it raises to almost 90%. The price of risk is still strongly significant. For the book-to-market portfolios, the single-leverage factor model explains close to 85% of the cross-section of returns, way above an adjusted R^2 of around 50% for the FF3 model. In the single-ΔFL factor, the price of risk is estimated at -1.61 and is borderline significant at a 5% level, but it explains a small percentage of the cross-section. When added to the FF3 model the funding liquidity factor becomes very significant but its price of risk doubles.

To complement these results, we form sets of 30 portfolios by adding to the 10 liquidity portfolios and 10 volatility portfolios either the 10 size portfolios or the 10 book-to-market portfolios. Results of the cross-sectional regressions for these two sets are reported in Table 8. Panel (a) contains the estimated prices of risk for the 30 portfolios including size. The ΔFL factor explains by itself 67% of the variation in returns, close to the 74% of the FF3 model. The price of risk estimated value is close to -2 and is statistically significant, even after controlling for the three Fama-French factors. For the 30 portfolios including book-to-market, the leverage factor explains by itself 25% of the cross-sectional variation in returns, compared to 7% for the ΔFL factor. However the latter is still close to significant in the augmented FF3 model.

To summarize, the cross-section of returns of the size portfolios is very well explained by the ΔFL factor but not at all by the leverage factor, while the leverage factor is the best factor explaining the cross-section of returns of the book-to-market portfolios, with a marginal role for the liquidity innovations. This distinction was not apparent in Adrian et al. (2013). How to interpret these results? Several papers in the literature have stressed that illiquid securities tend to have a small capitalization (see for example Acharya and Pedersen (2005)). In our sample, we verified that the illiquidity and size portfolios share many of the same securities. Therefore our findings regarding the size portfolios are not surprising for the leverage factor since they did not explain the cross-section of returns of the liquidity portfolios either. For the value portfolios, the strong explanatory power of the leverage factor may be due to its high correlation with asset growth[7].

V Funding Liquidity and Momentum

We have shown in the previous sections that the factor based on funding liquidity innovations explains very well the cross-section of returns of portfolios sorted on liquidity and volatility. We have also documented that when funding liquidity costs are high, the illiquidity of the least liquid portfolios worsens, the volatility of liquidity portfolios is uniformly higher, and the most volatile stocks become more illiquid. All these implications are consistent with the theoretical models of Vayanos (2004) and Adrian et al. (2013). In our empirical tests we have controlled for the usual three Fama-French risk factors. We have been silent about the momentum factor and have not estimated a four-factor model as in Carhart (1997). Whether the momentum factor is a reward for risk is controversial. However, Adrian et al. (2013) include momentum portfolios in their test assets and estimate Carhart models as benchmark for their single-leverage factor model. In this section, we explore in various dimensions how momentum and funding liquidity are related. We relate our findings to the literature aiming at explaining momentum profits.

[7] Adrian et al. (2013) report a correlation of 0.73 between their leverage factor and asset growth.

A Carhart Models

In Table 9, we estimate and test four-factor models where a momentum factor is added to the three Fama-French factors, for volatility and liquidity portfolios. The adjusted R^2 for the volatility portfolios is 84% compared to 83% for the ΔFL alone, while for the liquidity portfolios it is 90% compared to 65% for the ΔFL alone. Based on these findings we could conclude that the performance of the funding liquidity model is robust to the inclusion of the momentum factor, as in Adrian et al. (2013) for their leverage factor. However, if we augment the Carhart model by the ΔFL factor, the latter is not at all significant any longer. Remember that this was not the case for the three-factor Fama-French (FF3) model. Therefore, we need to look more closely at the relation between portfolios sorted on the momentum factor and the funding liquidity factor.

B Funding Liquidity Risk in Momentum Portfolios

In Table 9, we confirm that ΔFL is not a priced risk for momentum portfolios nor for the set of 30 portfolios sorted on liquidity, volatility and momentum. In Table 10, we proceed as before and measure the loadings of the momentum portfolios on the ΔFL factor in time-series regressions including the market returns. The betas are all negative but their magnitude is much larger for the loser portfolios (average of -4.10 for 1, 2 and 3) than for the winner portfolios (average of - 2.06 for portfolios 8, 9 and 10). Panel (a) of Figure 2b compares the average returns of momentum-sorted portfolios with their funding liquidity betas. The loser portfolios, with the most negative betas, also exhibits the lowest average returns. This suggests that momentum profits remain a puzzle. But note that the same pattern of betas emerges for the leverage factor in Panel (b), where the absence of the loser portfolios would create a negative price of risk, which is inconsistent with an explanation based on the intermediaries' funding constraints.

In terms of asset pricing tests, the price of risk is not significantly different from zero for the single-factor liquidity models (LevFct and ΔFL) but as seen on the graph the sign is positive for both measures. When we augment the FF3 model with ΔFL, we obtain a surprising result. The coefficient of ΔFL is negative, large in absolute value (close to -6), and strongly significant (t-stat of -4). In fact, the coefficients of the size and value factors absorbs the puzzle posed by the loser portfolios and allow the ΔFL betas to increase significantly the adjusted R^2 that jumps to 90% from less than 50%. This result is mechanical and not economically meaningful.

VI Discussion

In the recent empirical literature on cross-sectional asset pricing[8], a number of papers have considered liquidity risk in one form or another as a potential risk factor and have linked their results to the theoretical literature on limits of arbitrage and funding frictions. The measures of liquidity and the test assets vary among papers. We have amply compared our empirical findings to the results in Adrian et al. (2013) who use the balance sheet of financial intermediaries to measure the tightness of funding conditions. They interpret their results as supporting evidence of the view that leverage represents funding constraints based on the correlation of their leverage factor with funding constraint proxies such as volatility, the Baa-Aaa spread, asset growth, and a betting-against-beta factor[9]. Using the same aggregate liquidity measure as in Acharya and Pedersen (2005) based on the Amihud (2002) individual illiquidity measure, Akbas et al. (2010) propose an explanation of the value premium based on time-varying liquidity risk. They show that small value stocks have higher liquidity exposures than small growth stocks in worst times, and that small growth stocks have higher liquidity exposures than small value stocks in best times. They conclude

[8] See the survey by Goyal (2012).

[9] Frazzini and Pedersen (2011) build a factor that goes long leveraged low beta securities and short high beta securities and show that it should co-move with funding constraints.

that these results are consistent with a flight-to-quality explanation for the countercyclical nature of the value premium. We need to refine our analysis by conditioning on the level of funding liquidity to verify if the same is true with exposures to funding liquidity. Engle et al. (2012) use the order book for the U.S. Treasury securities market to study the joint dynamics of liquidity and volatility during flight-to-safety episodes. They show that market depth declines sharply and price volatility increases during the crisis and on flight-to-safety days. They use market depth that is the quantity of securities available for purchase and sale to measure liquidity.

Acharya and Pedersen (2005) are the closest to our paper in terms of empirical strategy since they form portfolios by sorting securities on liquidity, liquidity variations and size. They also find that illiquid securities have high liquidity risk, a result consistent with flight to liquidity in periods of illiquid markets, and that results are very similar for liquidity and size portfolios. They find in particular that a security with high average illiquidity tends to have high commonality in liquidity with market liquidity, high return sensitivity to market liquidity, and high liquidity sensitivity to market returns. It remains to be investigated whether this commonality is due to the presence of funding liquidity that affects all three elements of market liquidity. Conditioning on funding liquidity level or innovations may help in distinguishing statistically the relative impacts of each element on returns.

To better understand the relation between momentum returns and funding liquidity risk, we turn to the existing literature that aims at finding a risk-based explanation to momentum returns. Let us start with liquidity risk. The most recent paper on the topic by Asness et al. (2013) concludes that momentum loads either negatively or zero on liquidity risk[10]. So momentum strategies do well when liquidity cost is high, which is consistent with our puzzle since winners should have lower returns if they were providing hedging value. They pool several asset classes and different markets

[10]They also find that value loads positively on liquidity risk, which means that value strategies do worse when liquidity is poor.

and use a number of measures for funding liquidity risk such as the U.S. Treasury-Eurodollar (TED) spread, a global average of TED spreads, and LIBOR-term repo spreads, along with market liquidity measures mentioned earlier to compute an illiquidity index. They also find that the importance of liquidity risk rises sharply after the liquidity crisis, suggesting that the effects are time-varying and are conditional on the relative tightness of funding conditions. Previously, Sadka (2006) had used a market aggregate of the price impacts at the individual stock level and showed that the cross-sections of returns on portfolios sorted on momentum and post-earnings-announcement drift are well explained by the market-wide variations of the variable part of this price impact. Pastor and Stambaugh (2003) show that their liquidity risk factor accounts for half of the profits to a momentum strategy over the period 1966 to 1999. Another strand of literature shows that momentum profits are stronger in small stocks[11]. Avramov et al. (2007) show that momentum profitability is large and significant among low-grade firms but nonexistent among high-grade firms. Recently, Mahajan et al. (2012) show that momentum profits are linked to innovations in aggregate default risk. They show that momentum returns are conditional on high economy-wide default shocks, which is also consistent with our results. They measure aggregate default risk as innovations in the yield spread between Moody's CCC corporate bond index and the 10-year U.S. Treasury bond. This yield spread is well explained by our measure of funding liquidity. This literature tour tends to establish from various angles a link between illiquidity or funding liquidity risk and momentum returns, which explains to some extent our empirical findings that the momentum factor explains the cross-section of returns of liquidity and volatility portfolios. Panel (b) in Figure 1 shows the complex dynamic relationship between ΔFL and long-short momentum portfolio returns. At times, the two series move in the same direction, at other times in opposite directions. A more thorough analysis of these co-movements

[11] See in particular Hong et al. (2000) and Fama and French (2011).

conditional on the level of funding liquidity is needed.

We have considered funding liquidity shocks and not the level of funding liquidity as a source of risk. In first-stage regressions of portfolio returns on the level and the innovations of funding liquidity factor for different portfolio sorts, estimates for the funding liquidity factor level are almost always insignificant. In contrast, the coefficients on funding liquidity changes are always very significant. However, the level of funding liquidity value is an important conditioning variable to capture episodes of funding tensions on the market. We used it in Section III to study the sensitivity of liquidity and volatility portfolios to the state of funding conditions. We should pursue this investigation for value and momentum portfolios.

Finally, Chen and Petkova (2012) decompose aggregate market variance (which is linked to the aggregate liquidity measure of Pastor and Stambaugh (2003)) into an average correlation component and an average variance component. They show that only the latter commands a negative price of risk in the cross section of portfolios sorted by idiosyncratic volatility (IV), therefore providing a risk-based explanation behind the IV puzzle. We need to investigate if the spread in loadings of IV-sorted portfolios to our funding liquidity factor is large enough to explain the difference in average returns between high and low IV stocks.

VII Conclusion

In this paper, we focus on measuring the effect of funding constraints in the cross-section of equity liquidity, volatility and risk premium. Several theoretical models emphasizes the role of funding market frictions in linking together a stock's volatility, liquidity and valuations. Fontaine and Garcia (2012) proposed a measure of funding liquidity value based on apparent arbitrage opportunities in the Treasury market which can be attributed to funding market frictions. Building on this measure, we show that funding shocks increase the dispersion of illiquidity across liquidity-sorted portfolios, increase the dispersion of volatility across volatility-sorted portfolios and, consistent with theory, we provide evidence of the cross-effect – that funding shocks increase the dispersion of illiquidity across volatility-sorted portfolios.

Our results provide strong supportive evidence for limits-to-arbitrage theories based on frictions in the intermediation mechanism. We also provide a partial answer to what Adrian et al. (2013) identified as a challenge to their results. Namely, that the leverage of broker-dealer appears to be unrelated to the cross-sectional liquidity or to a liquidity risk factor. We argue that our measure of funding liquidity value complement their proxy based on leverage, especially in the recent history where leverage tended to increase in the early phase of a financial crisis.

Our results are also consistent with several papers linking momentum profits to episodes with high liquidity risk. Though, the approach in this paper is based on unconditional cross-section tests, these existing results suggest that a fuller analysis of momentum profits and returns to other strategies should condition on the level funding liquidity risk.

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Table 1: **Time-Series Regressions – Liquidity and Volatility Portfolios**
Time-series regression of portfolios returns on funding liquidity changes, ΔFL_t and market returns, MKT_t: $r_{it} = \alpha_i + \beta_i^{\Delta FL} \Delta FL_t + \beta_i^{MKT} MKT_t + \varepsilon_{it}$. Panel (a) displays results for liquidity-sorted decile portfolios, with t-statistics in parenthesis. Panel (b) displays results for volatility-sorted decile portfolios. Quarterly data, Q2/1986 - Q4/2011.

Panel (a) Liquidity-Sorted Decile Portfolios

	Illiquid	2	3	4	5	6	7	8	9	Liquid
$\beta^{\Delta FL}$	-3.05	-3.01	-2.28	-2.10	-2.22	-2.25	-2.04	-1.76	-1.39	-0.28
	(-3.47)	(-2.97)	(-2.26)	(-2.22)	(-2.57)	(-3.11)	(-2.98)	(-2.67)	(-2.54)	(-0.78)
β^{MKT}	0.71	0.85	0.90	0.94	0.92	0.88	0.95	0.94	0.83	0.86
	(11.4)	(11.9)	(12.6)	(13.9)	(14.9)	(17.1)	(19.5)	(20.1)	(21.4)	(33.9)
R^2	64.3%	65.1%	66.4%	70.4%	73.4%	78.6%	82.3%	82.8%	84.4%	92.7%

Panel (b) Volatility-Sorted Portfolios

	Most Vol.	2	3	4	5	6	7	8	9	Least Vol.
$\beta^{\Delta FL}$	-2.64	-2.75	-2.52	-2.23	-1.94	-2.07	-2.03	-1.39	-1.40	-1.32
	(-2.24)	(-2.91)	(-3.07)	(-2.72)	(-2.46)	(-2.78)	(-3.03)	(-2.24)	(-2.29)	(-2.05)
β^{MKT}	1.19	1.07	1.00	1.01	0.93	0.85	0.83	0.76	0.67	0.50
	(14.3)	(15.9)	(17.2)	(17.3)	(16.7)	(16.1)	(17.5)	(17.2)	(15.6)	(11.6)
R^2	71.3%	76.0%	78.7%	78.5%	77.1%	76.2%	79.1%	78.0%	74.7%	60.4%

Table 2: **Pricing Volatility and Liquidity Portfolios**
Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions for liquidity-sorted decile portfolios (Panel a), volatility-sorted decile portfolios (Panel b), and the combination of volatility and liquidity-sorted portfolios (Panel c). Quarterly data, Q2/1986 - Q4/2011.

Panel (a) Liquidity-Sorted Portfolios

	CAPM	FF3	LevFct	ΔFL	Augmented by ΔFL		
α	15.71	-4.03	5.65	-3.40	4.23	-3.81	-1.73
	(3.63)	(-3.99)	(1.99)	(-0.75)	(0.95)	(-3.74)	(-0.41)
ΔFL				-2.45	-2.30	-1.89	-2.76
				(-2.75)	(-2.59)	(-2.74)	(-3.00)
LevFct			65.70				-56.29
			(1.31)				(-1.23)
MKT	-6.39	10.57			1.46	9.85	
	(-1.16)	(2.81)			(0.25)	(2.63)	
SMB		7.13				6.71	
		(3.04)				(2.85)	
HML		6.30				5.96	
		(2.03)				(1.92)	
R^2	3.33%	89.30%	8.42%	68.69%	80.93%	91.92%	73.69%
$\bar{R}^2$	-7.41%	85.73%	-3.03%	64.78%	76.16%	87.87%	66.17%

Panel (b) Volatility-Sorted Portfolios

	CAPM	FF3	LevFct	ΔFL	Augmented by ΔFL		
α	2.87	-0.58	15.21	2.70	2.76	-0.70	6.12
	(0.93)	(-0.53)	(2.60)	(0.89)	(0.89)	(-0.65)	(2.30)
ΔFL				-1.34	-1.98	-1.87	-1.04
				(-1.61)	(-2.47)	(-1.39)	(-1.36)
LevFct			-73.67				-29.31
			(-1.69)				(-1.09)
MKT	7.45	9.09			3.79	8.41	
	(1.49)	(2.49)			(0.81)	(2.33)	
SMB		3.30				3.48	
		(1.38)				(1.47)	
HML		3.71				3.50	
		(1.21)				(1.14)	
R^2	50.64%	89.86%	48.75%	84.94%	88.65%	91.42%	91.37%
$\bar{R}^2$	45.15%	86.48%	42.35%	83.06%	85.81%	87.13%	88.91%

Panel (c) Liquidity and Volatility-Sorted Portfolios

	CAPM	FF3	LevFct	ΔFL	Augmented by ΔFL		
α	3.83	-0.95	12.90	1.12	2.96	-1.21	2.09
	(1.35)	(-1.06)	(2.75)	(0.39)	(1.01)	(-1.42)	(0.82)
ΔFL				-1.63	-2.32	-2.00	-1.56
				(-2.12)	(-2.90)	(-2.62)	(-2.12)
LevFct			-40.42				-8.19
			(-1.43)				(-0.38)
MKT	6.62	8.52			2.82	7.97	
	(1.36)	(2.33)			(0.63)	(2.18)	
SMB		4.98				4.98	
		(2.19)				(2.19)	
HML		4.59				4.46	
		(1.52)				(1.47)	
R^2	21.49%	81.01%	7.90%	69.23%	81.87%	84.67%	69.80%
$\bar{R}^2$	17.36%	78.01%	2.78%	67.52%	79.86%	81.26%	66.24%

Table 3: **Sensitivity of Volatility and Illiquidity to Funding Liquidity**

Slope coefficient estimates in regressions of changes in portfolios' illiquidity on funding liquidity innovations, $\Delta ILLIQ_{it} = \gamma_{0,i} + \gamma_i \Delta FL_t + \xi_{it}$ (Panel a) and of changes of portfolios volatility on funding liquidity innovations, $\Delta VOL_{it} = \gamma_{0,i} + \gamma_i \Delta FL_t + \xi_{it}$, (Panel b). Portfolio 1 is the least liquid or the most volatile, and portfolio 10 is the most liquid or the least volatile portfolio. Estimates are multiplied by 100. Quarterly data, Q2/1986 - Q4/2011.

Panel (a) Liquidity Regressions

	Worse	2	3	4	5	6	7	8	9	Best
Liq. port.	30.8	7.4	4.2	1.6	0.8	0.4	0.2	0.1	0.05	0.01
t-stat.	(2.31)	(2.16)	(3.28)	(2.59)	(3.37)	(3.48)	(3.42)	(3.36)	(3.63)	(3.39)
R^2	5.0%	4.4%	9.6%	6.2%	10.1%	10.7%	10.4%	10.1%	11.5%	10.2%
Vol. port.	8.2	11.6	4.7	4.2	-0.8	1.3	1.9	0.1	-0.1	9.1
t-stat.	(1.49)	(2.39)	(1.31)	(1.13)	(-0.54)	(0.39)	(0.70)	(0.04)	(-0.05)	(1.76)
R^2	2.2%	5.4%	1.7%	1.3%	0.3%	0.2%	0.5%	0.0%	0.0%	3.0%

Panel (b) Volatility Regressions

	Worse	2	3	4	5	6	7	8	9	Best
Liq. port.	0.49	0.58	0.62	0.52	0.55	0.62	0.57	0.60	0.61	0.64
t-stat.	(4.62)	(3.94)	(4.42)	(3.66)	(3.68)	(4.29)	(3.70)	(3.86)	(4.11)	(4.20)
R^2	17.4%	13.3%	16.2%	11.7%	11.8%	15.4%	12.0%	12.9%	14.3%	15.0%
Vol. port.	0.77	0.70	0.64	0.64	0.64	0.55	0.52	0.53	0.47	0.43
t-stat.	(4.59)	(4.69)	(4.05)	(4.06)	(4.10)	(3.71)	(3.29)	(4.03)	(3.50)	(3.76)
R^2	17.3%	17.9%	14.0%	14.0%	14.3%	12.0%	9.7%	13.8%	10.8%	12.3%

Table 4: **Conditional Average Liquidity and Volatility**

Average illiquidity and volalitity of liquidity-sorted and volatility-sorted decile portfolios conditional on the lagged value of funding liquidity being in the bottom 30% (low FL_{t-1}) or the top 30% (high FL_{t-1}). Portfolio 1 is the least liquid or most volatile, and portfolio 10 is the most liquid or least volatile. The illiquidity ratio and volatility are multiplied by 100. Quarterly data, Q2/1986 - Q4/2011.

Panel (a) Low FL_{t-1}

	Liquidity Portfolios			Volatility Portfolios		
	Returns	Illiqu.	Vol.	Returns	Illiqu.	Vol.
1	13.52	382.51	3.72	10.45	104.49	5.11
2	12.35	66.09	3.82	6.16	54.86	4.39
3	10.78	22.15	3.77	8.18	52.89	4.08
4	7.94	9.44	3.66	7.76	36.13	3.78
5	9.08	3.79	3.51	8.51	37.72	3.52
6	9.27	1.88	3.38	6.87	41.25	3.26
7	6.02	1.07	3.39	7.62	31.95	3.08
8	6.74	0.58	3.34	7.23	33.19	2.85
9	6.01	0.28	3.15	8.05	32.50	2.58
10	0.38	0.10	3.02	10.87	44.99	2.20

Panel (b) High FL_{t-1}

	Liquidity Portfolios			Volatility Portfolios		
	Returns	Illiqu.	Vol.	Returns	Illiqu.	Vol.
1	13.90	475.23	4.40	21.69	117.07	5.66
2	17.38	76.23	4.40	19.10	74.84	5.07
3	15.92	28.16	4.31	14.35	58.99	4.70
4	15.48	11.35	4.18	14.33	49.22	4.37
5	15.05	5.29	4.08	12.66	39.10	4.14
6	13.62	2.57	3.96	13.07	49.66	3.89
7	13.27	1.27	3.91	12.65	43.25	3.66
8	12.58	0.67	3.85	11.09	32.26	3.33
9	9.88	0.64	3.68	9.69	38.65	3.08
10	10.69	0.12	3.57	9.28	56.74	2.55

Panel (c) High FL_{t-1} - Low FL_{t-1}

	Liquidity Portfolios			Volatility Portfolios		
	Returns	Illiqu.	Vol.	Returns	Illiqu.	Vol.
1	0.38	92.72	0.67	11.24	12.57	0.55
2	5.03	10.13	0.57	12.94	19.98	0.68
3	5.14	6.01	0.53	6.17	6.10	0.62
4	7.53	1.91	0.52	6.57	13.09	0.59
5	5.97	1.50	0.58	4.14	1.38	0.62
6	4.35	0.69	0.58	6.20	8.41	0.63
7	7.25	0.20	0.53	5.03	11.30	0.58
8	5.84	0.09	0.52	3.86	-0.93	0.47
9	3.87	0.06	0.53	1.64	6.14	0.51
10	10.32	0.02	0.55	-1.59	11.75	0.36

Table 5: **Time-series CAPM regressions augmented by ΔFL_t**

Time-series regression of size and book-to-market portfolios returns on the funding liquidity innovations, ΔFL_t and the market returns, MKT_t: $r_{it} = \alpha_i + \beta_i^{\Delta FL} \Delta FL_t + \beta_i^{MKT} MKT_t + \varepsilon_{it}$. Quarterly data, Q2/1986 - Q4/2011.

	$\beta^{\Delta FL}$					β^{MKT}					R^2				
	Small	2	3	4	Big	Small	2	3	4	Big	Small	2	3	4	Big
Low	-1.89	-0.12	0.42	1.03	0.84	1.51	1.39	1.31	1.23	0.98	72.3%	82.2%	83.2%	84.9%	88.3%
	(-1.33)	(-0.13)	(0.49)	(1.37)	(1.62)	(15.01)	(20.44)	(21.36)	(22.96)	(26.65)					
2	-2.30	-1.31	-0.70	-1.60	-0.42	1.23	1.12	1.07	0.96	0.89	73.4%	78.8%	84.2%	82.6%	87.4%
	(-2.02)	(-1.49)	(-1.00)	(-2.36)	(-0.83)	(15.19)	(17.93)	(21.71)	(20.03)	(24.85)					
3	-2.44	-2.08	-1.95	-2.20	-1.06	1.01	0.98	0.87	0.95	0.82	72.3%	77.1%	74.4%	79.7%	79.7%
	(-2.49)	(-2.51)	(-2.45)	(-2.92)	(-1.68)	(14.55)	(16.63)	(15.43)	(17.87)	(18.35)					
4	-3.03	-2.04	-2.10	-2.07	-1.50	0.93	0.92	0.92	0.91	0.81	67.1%	69.6%	70.6%	77.8%	74.3%
	(-2.90)	(-2.15)	(-2.26)	(-2.73)	(-2.04)	(12.52)	(13.70)	(13.98)	(16.91)	(15.55)					
High	-3.34	-2.8	-1.89	-2.69	-2.21	1.08	1.05	0.89	0.96	0.83	66.7%	66.7%	63.2%	71.4%	65.4%
	(-2.74)	(-2.37)	(-1.79)	(-2.80)	(-2.31)	(12.48)	(12.65)	(11.89)	(14.04)	(12.28)					

Table 6: **Pricing Size and Book-to-Market Portfolios**
Cross-section asset pricing tests based on two-stage Fama-MacBeth regressions for size and value portfolios. Panel (a) displays results for 5 × 5 double-sorted Fama-French portfolios but excluding the small-growth portfolios and Panel (b) displays results for the 10 × 10 double-sorted Fama-French portfolios. Quarterly data, Q2/1986 - Q4/2011.

Panel (a) 5 × 5 Size and Book-to-Market Double-Sorts

	CAPM	FF3	LevFct	ΔFL	Augmented by ΔFL		
α	10.46	0.05	6.18	3.52	7.11	0.26	4.24
	(1.70)	(0.05)	(1.45)	(0.82)	(1.21)	(0.029)	(1.07)
ΔFL				-0.83	-0.92	-0.84	-0.50
				(-1.07)	(-1.16)	(-1.26)	(-0.56)
LevFct			26.11				19.07
			(1.07)				(0.68)
MKT	-2.29	6.46			-0.40	6.15	
	(-0.33)	(1.77)			(-0.06)	(1.69)	
SMB		2.42				2.44	
		(1.08)				(1.08)	
HML		3.95				3.53	
		(1.18)				(1.01)	
R^2	3.41%	54.75%	30.19%	25.71%	39.91%	56.09%	35.16%
$\bar{R}^2$	-0.79%	48.84%	27.01%	22.33%	34.44%	48.10%	28.99%

Panel (b) 10 × 10 Size and Book-to-Market Double-Sorts

	CAPM	FF3	LevFct	ΔFL	Augmented by ΔFL		
α	27.82	19.89	1.93	-4.64	9.82	18.83	-2.42
	(2.65)	(4.51)	(0.40)	(-0.67)	(1.47)	(4.72)	(-0.37)
ΔFL				-1.87	-1.40	-1.05	-1.09
				(-2.09)	(-1.84)	(-1.35)	(-1.49)
LevFct			99.54				75.55
			(2.65)				(3.11)
MKT	-18.52	-16.88			-4.95	-13.75	
	(-1.89)	(-2.47)			(-0.70)	(-2.42)	
SMB		5.82				4.22	
		(1.94)				(1.58)	
HML		2.47				-2.60	
		(0.52)				(-0.67)	
R^2	16.11%	69.90%	46.70%	35.79%	41.32%	75.01%	52.16%
$\bar{R}^2$	15.27%	68.98%	46.16%	35.13%	40.13%	73.99%	51.18%

Table 7: **Pricing Size-Sorted Portfolios and Book-to-Market-Sorted Portfolios**
Cross-section asset pricing tests based on two-stage Fama-MacBeth regressions for size and value portfolios. Panel (a) displays results for 10 size-sorted (excluding Nasdaq stocks) and Panel (b) displays results for 10 portfolios sorted by book-to-market. Quarterly data, Q2/1986 - Q4/2011.

Panel (a) 10 Size Portfolios

	CAPM	FF3	LevFct	ΔFL	Augmented by ΔFL		
α	17.00	-3.12	11.22	-3.48	6.36	-3.29	-1.94
	(3.82)	(-3.33)	(3.65)	(-0.72)	(1.10)	(-3.55)	(-0.40)
ΔFL				-2.46	-2.28	-2.59	-2.43
				(-2.66)	(-2.48)	(-3.95)	(-2.62)
LevFct			-15.92				-20.95
			(-0.62)				(-0.83)
MKT	-7.77	10.08			-0.89	9.30	
	(-1.29)	(2.70)			(-0.13)	(2.49)	
SMB		6.63				6.24	
		(2.87)				(2.70)	
HML		5.25				5.30	
		(1.70)				(1.72)	
R^2	3.59%	83.38%	1.13%	71.90%	84.23%	91.58%	74.79%
$\bar{R}^2$	-7.13%	77.84%	-11.23%	68.38%	80.29%	87.37%	67.59%

Panel (b) 10 Book-to-Market Portfolios

	CAPM	FF3	LevFct	ΔFL	Augmented by ΔFL		
α	25.91	-3.44	2.15	-2.39	18.41	-0.14	-3.06
	(4.61)	(-2.54)	(0.38)	(-0.45)	(3.62)	(-0.07)	(-0.57)
ΔFL				-1.61	-2.09	-4.22	-1.01
				(-1.82)	(-2.74)	(-3.28)	(-1.13)
LevFct			111.95				110.32
			(3.42)				(3.34)
MKT	-14.52	8.02			-13.40	4.61	
	(-2.29)	(2.19)			(-2.12)	(1.91)	
SMB		2.82				0.01	
		(1.15)				(0.00)	
HML		10.32				6.24	
		(3.05)				(1.75)	
R^2	37.65%	61.57%	85.49%	9.02%	90.83%	68.22%	87.32%
$\bar{R}^2$	30.72%	48.76%	83.68%	-2.35%	88.54%	52.34%	83.70%

Table 8: **Pricing Liquidity, Volatility, Size and Value**

Cross-section asset pricing tests based on two-stage Fama-MacBeth regressions for liquidity, volatility, size and value portfolios. Panel (a) displays results for 3x10 portfolios sorted by volatility, liquidity and size (excluding Nasdaq stocks) while Panel (b) displays results for 3x10 portfolios sorted by volatility, liquidity and book-to-market. Quarterly data, Q2/1986 - Q4/2011.

Panel (a) 30 Volatility, Liquidity, and Size Portfolios

	CAPM	FF3	LevFct	ΔFL	Augmented by ΔFL		
α	4.38	-0.39	12.27	0.06	3.26	-1.08	1.13
	(1.58)	(-0.45)	(3.09)	(0.02)	(1.13)	(-1.39)	(0.37)
ΔFL				-1.82	-2.45	-2.19	-1.76
				(-2.37)	(-2.98)	(-3.50)	(-2.28)
LevFct			-31.20				-9.94
			(-1.54)				(-0.52)
MKT	6.10	7.87			2.20	7.54	
	(1.24)	(2.14)			(0.49)	(2.05)	
SMB		5.59				5.50	
		(2.47)				(2.43)	
HML		4.02				4.36	
		(1.32)				(1.44)	
R^2	12.51%	76.15%	4.55%	67.79%	81.56%	82.90%	68.59%
$\bar{R}^2$	9.50%	73.69%	1.15%	66.64%	80.25%	80.46%	66.26%

Panel (b) 30 Volatility, Liquidity, and Value Portfolios

	CAPM	FF3	LevFct	ΔFL	Augmented by ΔFL		
α	11.71	-1.66	5.31	5.57	10.12	-1.50	-0.07
	(2.75)	(-1.59)	(1.07)	(1.45)	(2.34)	(-1.47)	(-0.02)
ΔFL				-0.70	-2.47	-1.41	-1.00
				(-0.84)	(-3.24)	(-1.82)	(-1.25)
LevFct			68.17				74.48
			(2.34)				(2.81)
MKT	-1.92	7.60			-6.12	7.05	
	(-0.34)	(2.11)			(-1.13)	(1.95)	
SMB		2.00				1.64	
		(0.80)				(0.67)	
HML		10.86				10.45	
		(3.35)				(3.23)	
R^2	1.75%	58.05%	28.02%	10.56%	64.63%	59.56%	42.34%
$\bar{R}^2$	-1.64%	53.71%	25.45%	7.36%	62.10%	53.78%	38.07%

Table 9: **Carhart Models**

Cross-section tests of 4-factors Cahart asset pricing models based on two-stage Fama-MacBeth regressions for liquidity, volatility, and momentum portfolios. Portfolio 1 contains the least liquid, most volatile and loser stocks, while portfolio 10 contains the most liquid, least volatile and winner stocks. Quarterly data, Q2/1986 - Q4/2011.

					Augmented by ΔFL			
	VOL	LIQ	MOM	VOL+LIQ+MOM	VOL	LIQ	MOM	VOL+LIQ+MOM
α	-1.51	-2.46	-0.24	-0.89	-2.04	-2.44	-0.1	-0.94
	(-1.53)	(-3.23)	(-0.45)	(-1.41)	(-2.08)	(-3.05)	(-0.23)	(-1.44)
ΔFL					0.94	-0.59	-0.1	1.18
					(0.83)	(-0.83)	(-0.19	(1.04)
MKT	8.07	8.36	6.53	7.10	8.69	8.31	6.48	7.73
	(2.21)	(2.28)	(1.84)	(1.97)	(2.39)	(2.26)	(1.78)	(2.10)
SMB	5.21	5.25	2.68	3.28	5.63	5.23	2.6	4.15
	(2.20)	(2.33)	(1.12)	(1.35)	(2.35)	(2.31)	(1.14	(1.83)
HML	3.36	4.51	2.02	4.49	3.97	4.48	7.2	4.13
	(1.09)	(1.49)	(0.66)	(1.31)	(1.29)	(1.47)	(1.99	(1.25)
MOM	7.41	9.16	7.00	6.99	8.02	9.12	7.0	6.70
	(2.08)	(2.63)	(1.94)	(1.94)	(2.27)	(2.61)	(1.99	(1.88)
R^2	88.52%	93.20%	97.97%	74.83%	89.04%	93.21%	97.97	77.91%
$\bar{R}^2$	83.42%	90.18%	97.06%	71.35%	82.18%	88.97%	96.71	73.97%

Table 10: **Funding Liquidity Risk in Momentum Portfolios**

Time-series and cross-section results for momentum portfolios. Panel (a) displays results from time-series regression of returns on funding liquidity changes, ΔFL_t, and market returns, MKT_t: $r_{it} = \alpha_i + \beta_i^{\Delta FL} \Delta FL_t + \beta_i^{MKT} MKT_t + \varepsilon_{it}$. Panel (b) displays results from cross-section asset pricing tests based on two-stage Fama-MacBeth regressions. Quarterly data, Q2/1986 - Q4/2011.

Panel (a) Time-series analysis

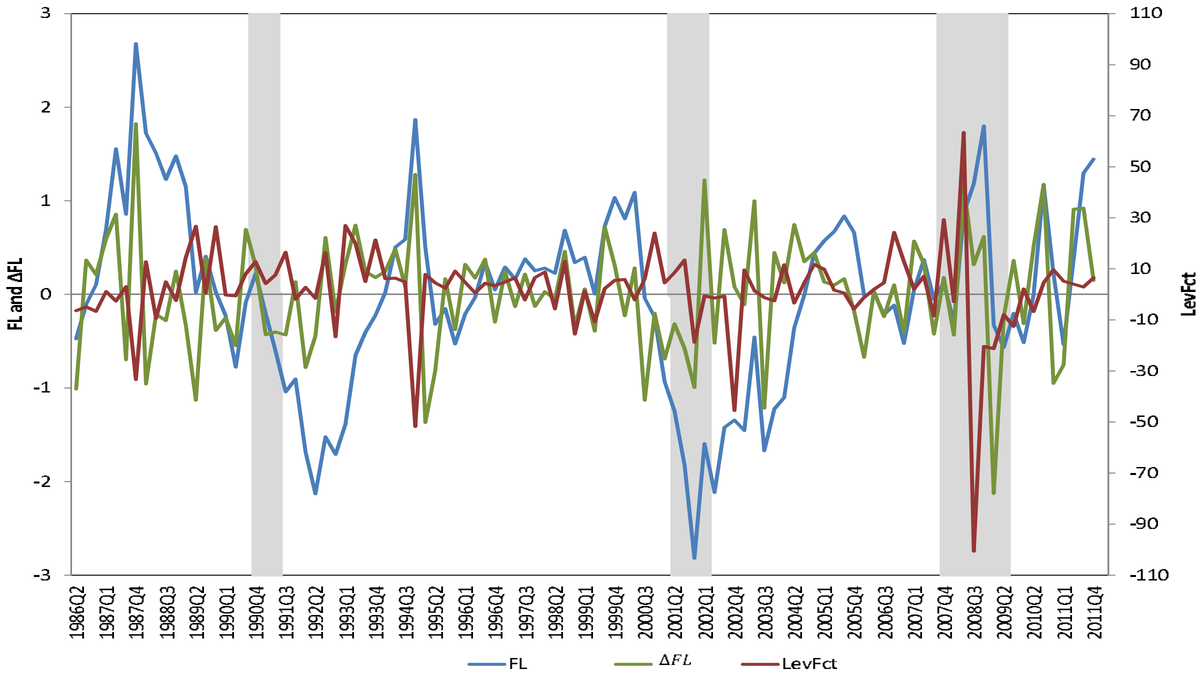
	Loser	2	3	4	5	6	7	8	9	Winner
$\beta^{\Delta FL}$	-5.25	-3.87	-3.20	-2.83	-2.34	-2.44	-2.24	-1.98	-2.22	-1.97
	-2.11	-2.77	-2.97	-3.22	-3.03	-3.36	-3.14	-2.85	-2.51	-1.65
β^{MKT}	1.59	1.20	1.05	0.96	0.91	0.89	0.87	0.90	0.96	1.25
	9.01	12.09	13.70	15.44	16.56	17.23	17.25	18.31	15.23	14.73
R^2	51.41%	65.47%	70.68%	75.23%	77.39%	78.91%	78.77%	80.36%	74.03%	71.92%

Panel (b) Price of risk from cross-sectional regressions

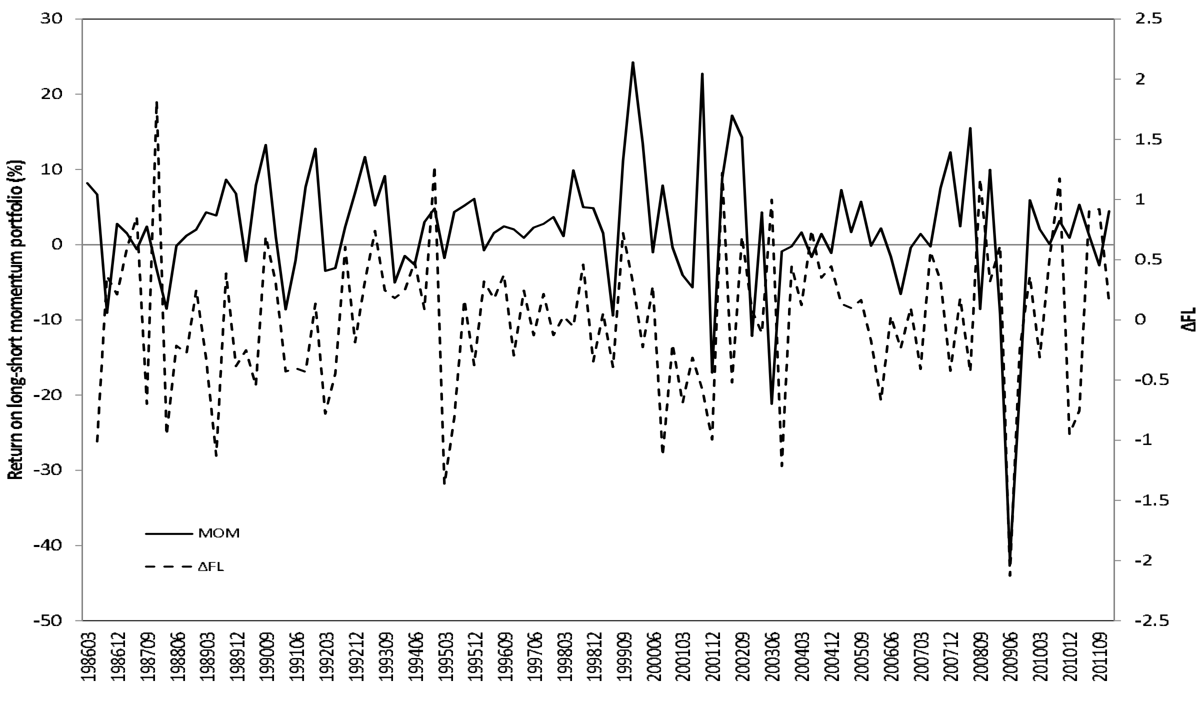
	CAPM	FF3	LevFct	ΔFL	Augmented by ΔFL		
α	12.14	6.16	7.75	14.83	11.16	5.60	38.61
	2.10	3.01	1.08	2.90	2.17	2.87	3.05
ΔFL				0.78	0.55	-5.80	3.30
				0.77	0.57	-4.05	2.17
LevFct			24.18				-126.65
			0.50				-2.25
MKT	-2.75	5.38			-0.62	1.82	
	-0.38	1.47			-0.10	0.48	
SMB		-1.03				-3.24	
		-0.37				-1.10	
HML		-5.02				-2.71	
		-1.44				-0.83	
R^2	6.44%	60.37%	11.93%	32.19%	10.03%	93.22%	65.03%
$\bar{R}^2$	-3.96%	47.16%	0.92%	23.71%	-12.47%	89.83%	55.04%

Figure 1: The Value of Funding Liquidity

(a) ΔFL and Broker-Dealer Leverage



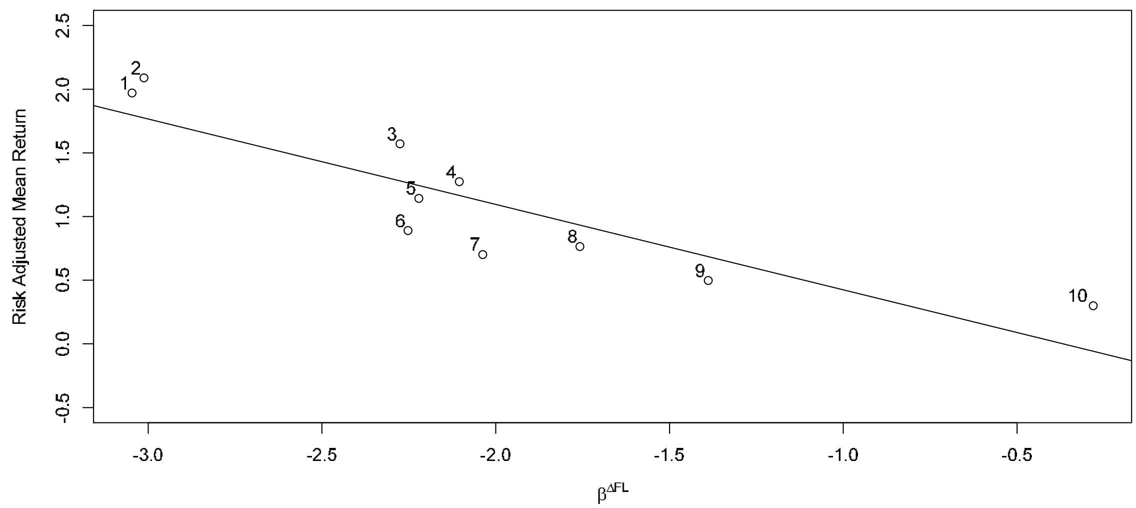
(b) ΔFL and Long-Short Momentum Portfolio Returns



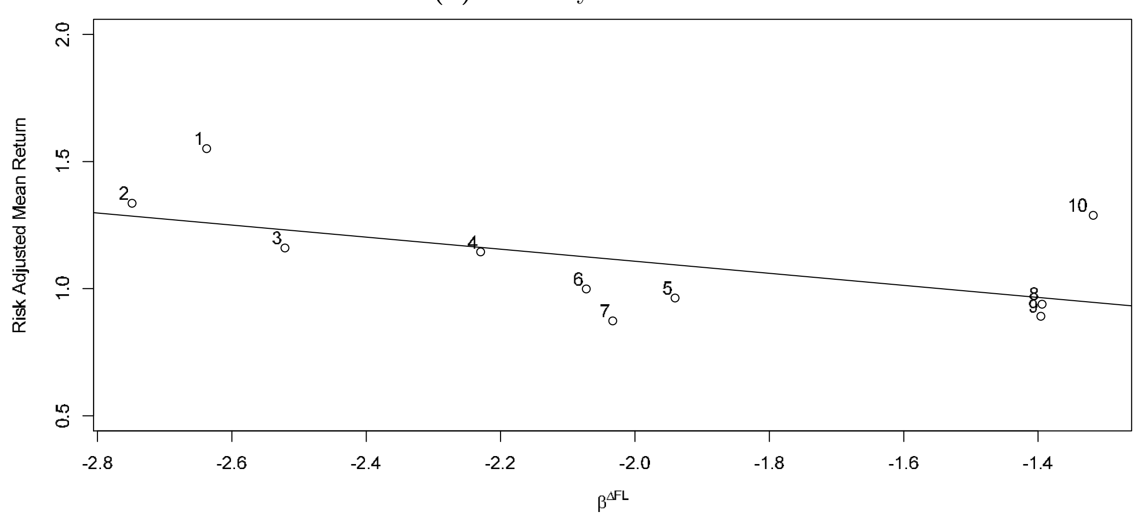
Panel (a) compares the value of funding liquidity from Fontaine and Garcia (2012), (FL), its changes, (ΔFL), and the leverage factor (LevFct) from Adrian et al. (2013). NBER recessions are shaded. Panel (b) compares changes in the value of funding liquidity, (ΔFL), with the returns on a long-short momentum portfolio. Quarterly data from Q2/1986 to Q4/2011.

Figure 2: Risk-Adjusted Returns and Funding Risk in Liquidity and Volatility Portfolios

(a) Liquidity Portfolios



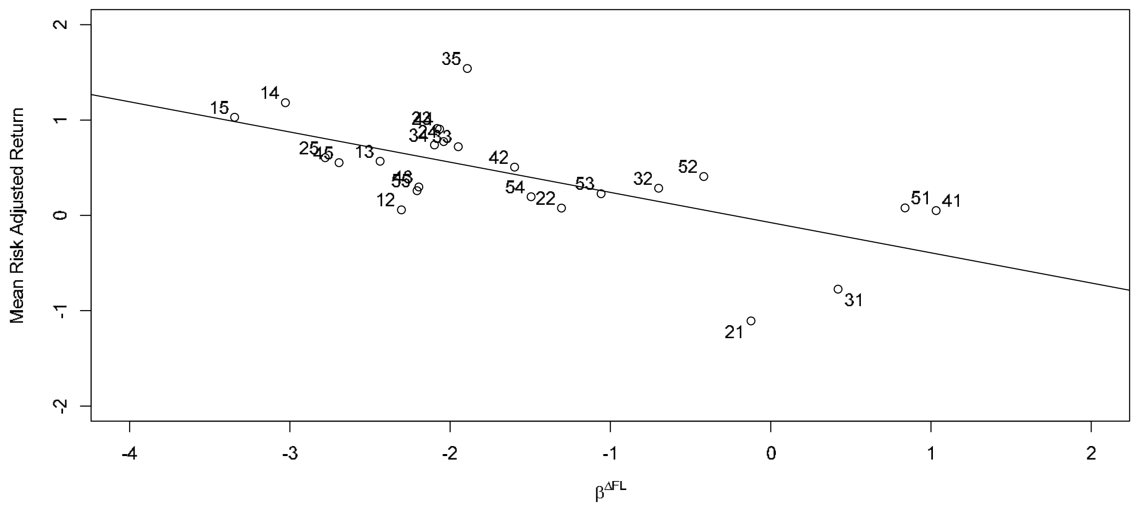
(b) Volatility Portfolios



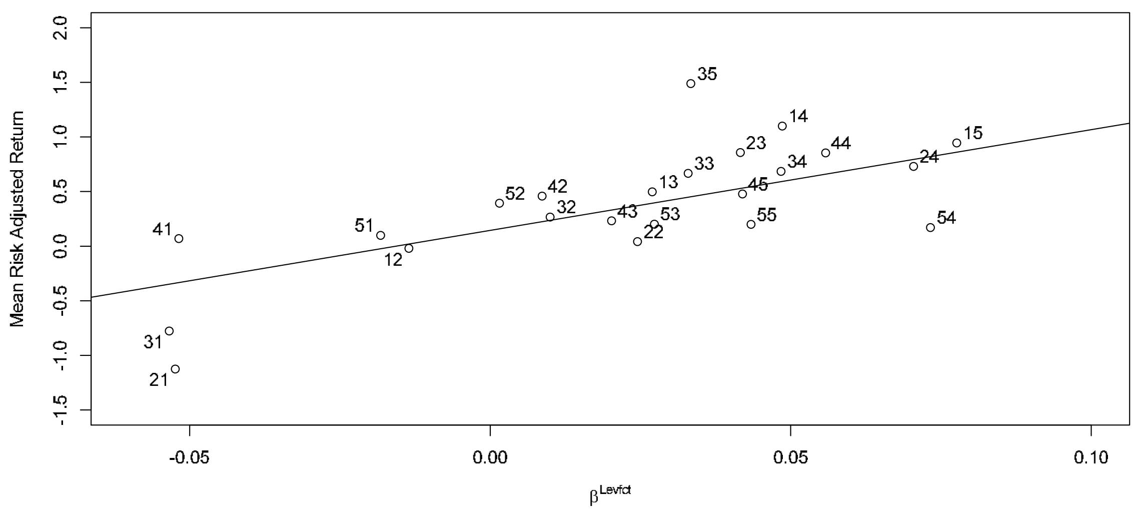
Average risk-adjusted returns and funding liquidity beta, $\beta^{\Delta FL}$, for liquidity-sorted (Panel a) and volatility-sorted (Panel b) decile portfolios. Funding liquidity betas are obtained from the regressions $r_{it} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta FL} \Delta FL_t + \varepsilon_{it}$ and risk-adjusted return are computed as $r_{it} - \beta_i^{MKT} MKT_t$. Portfolio 1 is the least liquid or most volatile and portfolio 10 is the most liquid or least volatile. Quarterly data, Q2/1986 - Q4/2011.

Figure 3: Risk-Adjusted Returns, Funding Risk and Leverage in 5×5 Size and Value Sorted Portfolios

(a) Funding Liquidity Risk



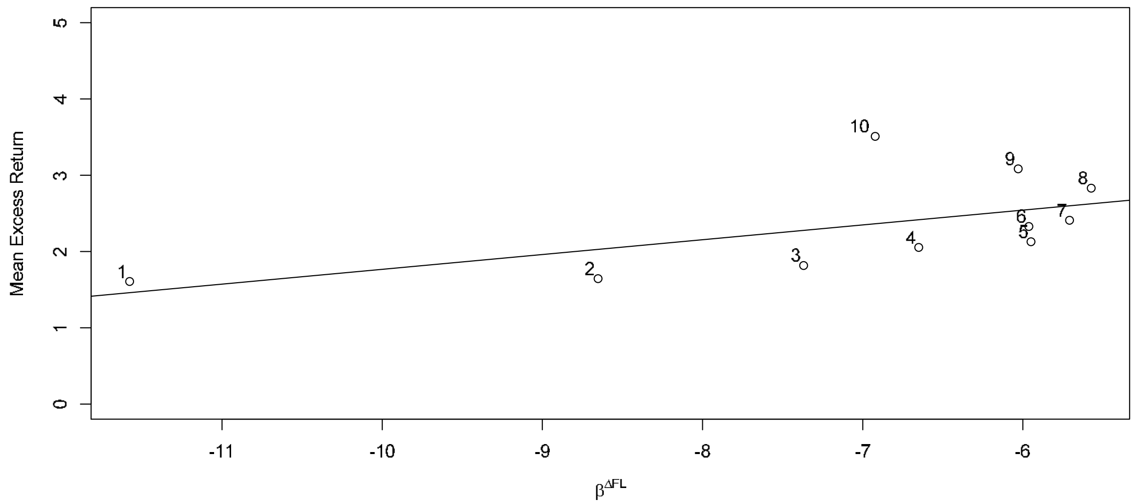
(b) Broker-Dealer Leverage



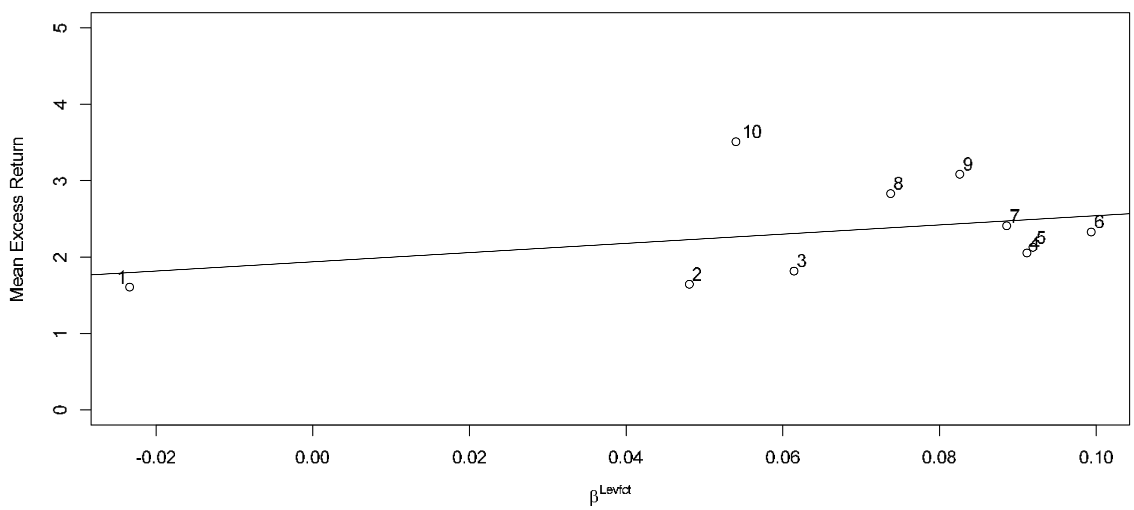
Panel (a) compares average risk-adjusted portfolio returns and funding liquidity beta, $\beta^{\Delta FL}$, for size and value portfolios from a 5×5 double-sort excluding the small growth portfolios. Panel (b) compares average risk-adjusted returns with leverage factor beta, β^{Lev}. Funding liquidity betas are obtained from the regression $r_{it} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta FL} \Delta FL_t + \varepsilon_{it}$ and leverage factor betas are obtained from the regressions $r_{it} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{Lev} LevFact_t + \varepsilon_{it}$. In each case, the risk-adjusted return are computed as $r_{it} - \beta_i^{MKT} MKT_t$. Portfolio 1 contains losers and portfolio 10 contains winner. Quarterly data, Q2/1986 - Q4/2011.

Figure 4: Risk-Adjusted Returns, Funding Risk and Leverage in Momentum Portfolios

(a) Funding Liquidity Risk



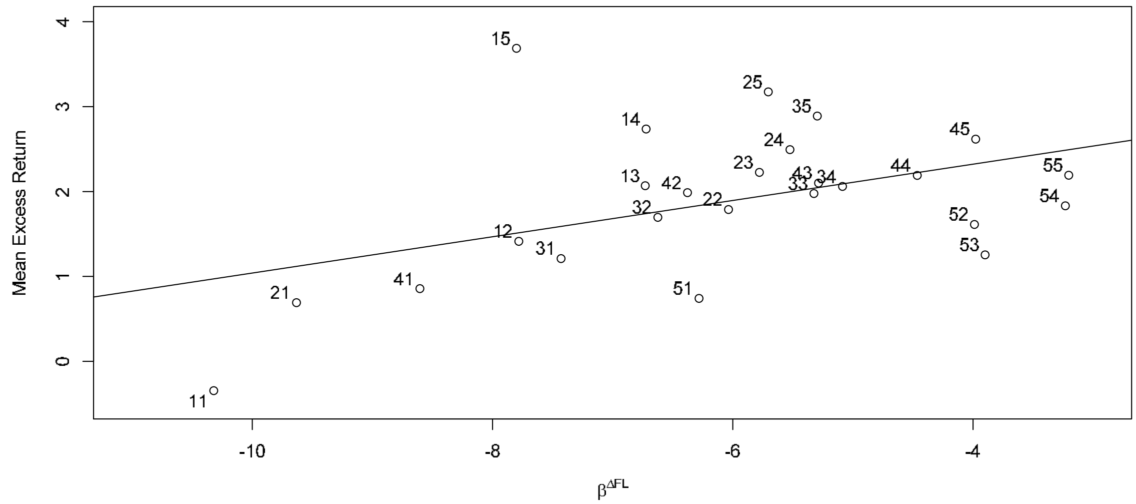
(b) Broker-Dealer Leverage



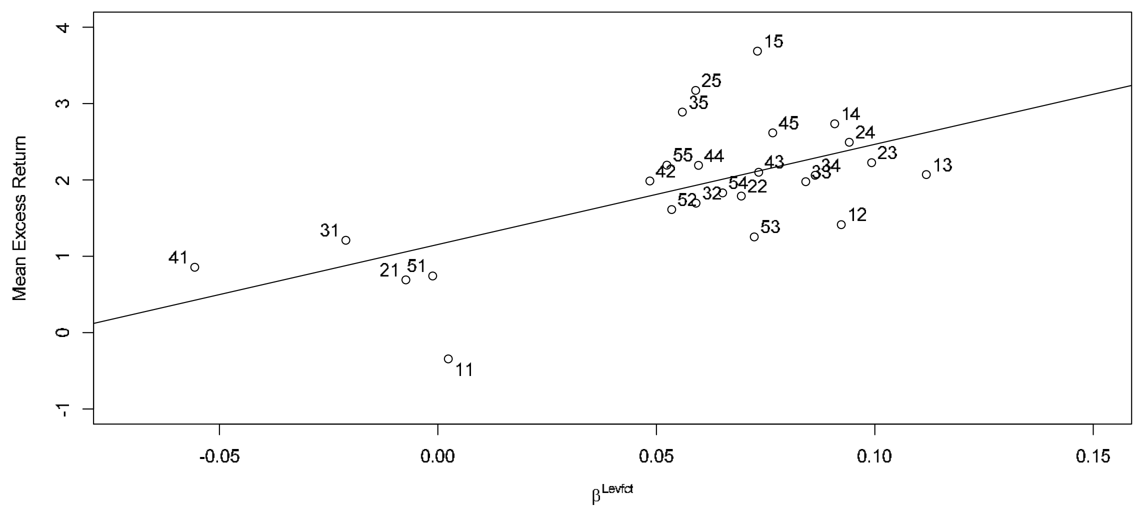
Panel (a) compares average risk-adjusted momentum portfolio returns and funding liquidity beta, $\beta^{\Delta FL}$. Panel (b) compares average risk-adjusted momentum portfolio returns and leverage factor beta, β^{Lev}. Funding liquidity betas are obtained from the regression $r_{it} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta FL} \Delta FL_t + \varepsilon_{it}$ and leverage factor betas are obtained from the regressions $r_{it} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{Lev} LevFact_t + \varepsilon_{it}$. In each case, the risk-adjusted return are computed as $r_{it} - \beta_i^{MKT} MKT_t$. Portfolio 1 contains losers and portfolio 10 contains winner. Quarterly data, Q2/1986 - Q4/2011.

Figure 5: Risk-Adjusted Returns, Funding Risk and Leverage in Size and Momentum Portfolios

(a) Funding Liquidity Risk



(b) Broker-Dealer Risk



Panel (a) compares average risk-adjusted returns and funding liquidity beta, $\beta^{\Delta FL}$, for size and momentum portfolios Panel (b) compares average risk-adjusted size and momentum portfolio returns and leverage factor beta, β^{Lev}. Funding liquidity betas are obtained from the regression $r_{it} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta FL} \Delta FL_t + \varepsilon_{it}$ and leverage factor betas are obtained from the regressions $r_{it} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{Lev} LevFact_t + \varepsilon_{it}$. In each case, the risk-adjusted return are computed as $r_{it} - \beta_i^{MKT} MKT_t$. Portfolio 1 contains losers and portfolio 10 contains winner. Quarterly data, Q2/1986 - Q4/2011.