Turnover: Liquidity or Uncertainty?

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Abstract

The paper shows that turnover proxies for firm-specific uncertainty, not liquidity risk. I show that turnover is unrelated to several alternative measures of liquidity risk and that liquidity risk factors cannot explain why higher turnover predicts lower future returns. I show that, because high turnover firms have high uncertainty, high turnover firms beat the CAPM when aggregate volatility increases. All else equal, when uncertainty and aggregate volatility increase in recessions, the risk of real options drops and the value of real options increases. This effect should be stronger for high uncertainty (high turnover) firms and firms with abundant real options. I find that the aggregate volatility risk factor explains why higher turnover predicts lower future returns. I also find that the negative relation between turnover and future returns is stronger for firms with high market-to-book, or bad credit rating, or high leverage, and these regularities are also explained by the aggregate volatility risk factor.

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1 Introduction

The asset-pricing literature has long treated turnover (trading volume over shares outstanding) as a proxy for liquidity or liquidity risk[1]. The well-established negative cross-sectional relation between turnover and future returns (henceforth - the turnover effect) is then interpreted as the evidence of liquidity premium, since high turnover stocks are thought to be more liquid and to have lower liquidity risk.

The microstructure literature, on the other hand, uses turnover as a proxy for firm-specific uncertainty or investor disagreement (see, e.g., Harris and Raviv, 1993, Blume, Easley, and O'Hara, 1994). Turnover is found to be high if prices fluctuate a lot, if traders disagree about the firm value, or if they receive a lot of information about the firm (see, e.g., Karpoff, 1987, and references therein). In asset-pricing applications, the proponents of this view use turnover as a measure of uncertainty and show, for example, that several anomalies are stronger for high turnover firms (see Lee and Swaminathan, 2000, Jiang, Lee, and Zhang, 2005). However, if turnover measures uncertainty, the negative relation between turnover and future returns is puzzling.

In this paper I show that in asset pricing applications we can view turnover as a measure of firm-specific uncertainty rather than liquidity and still reconcile this view with the lower expected returns of high turnover firms. The mechanism is similar to the one in Johnson (2004) and Barinov (2009a). More uncertainty about the assets behind a valuable real option (e.g., growth options, the call option created by leverage) reduces the risk of the real option by making its value less responsive to the changes in the underlying asset value. The beta of a real option is, by Ito's lemma, the product of the underlying asset beta and the option value elasticity with respect to the underlying asset value. While changes in the uncertainty about the underlying asset do not influence its beta, they do make the elasticity and, hence, the real option's beta smaller.

Both aggregate volatility and firm-specific uncertainty are high during recessions (see the results in Campbell et al., 2001, and Barinov, 2009b). According to the previous paragraph, when firm-specific uncertainty increases, the risk exposure of real options declines. All else equal, the lower risk exposure means lower expected return and higher stock price. Hence, during volatile periods real options lose less value than what the CAPM predicts.

[1]See, e.g., Datar, Naik, and Radcliffe (1998), Rouwenhorst (1999), Eckbo and Norli (2002, 2005), and Avramov and Chordia (2006).

Also, holding everything else equal, real options increase in value when the uncertainty about the underlying asset increases[2]. These two effects of uncertainty on real options are stronger for high uncertainty firms (the formal proof is available from the author upon request). Hence, high uncertainty (high turnover) firms with valuable real options should outperform the CAPM during volatile times.

Campbell (1993) and Chen (2002) show that investors would require a lower risk premium from the stocks, the value of which correlates least negatively with aggregate volatility news, because these stocks provide additional consumption precisely when investors have to cut their current consumption for consumption-smoothing and precautionary savings motives. Ang, Hodrick, Xing, and Zhang (2006) confirm this prediction empirically and coin the notion of aggregate volatility risk. They show that the stocks with the least negative sensitivity to aggregate volatility increases have abnormally low expected returns. This paper builds on this literature and shows that high turnover firms have low expected returns because they have high uncertainty, and the high uncertainty makes them a hedge against aggregate volatility risk.

Because in my story firm-specific uncertainty impacts the firm's aggregate volatility risk through real options, I predict that, if turnover measures uncertainty, the turnover effect will be greater for the firms with valuable real options. For example, the turnover effect should be stronger the firms with high market-to-book, which have abundant growth options. Also, because of the existence of risky debt, one can view equity as a call option on the assets. Both leverage and credit rating can measure how close this option is to being at the money, and therefore how option-like the equity is. I predict that the turnover effect is stronger for highly levered firms and firms with bad credit rating, because the equity of these firms is more option-like. I also predict that the difference in aggregate volatility risk between high and low turnover firms will increase with leverage and market-to-book and decrease with credit rating, thus explaining why the turnover effect increases with leverage and market-to-book and decreases with credit rating[3].

I start with showing that high turnover firms tend to have significantly higher firm-specific uncertainty than low turnover firms. This conclusion applies to such measures of

[2] A recent analysis by Grullon, Lyandres, and Zhdanov (2008) suggest that changes in firm-level uncertainty have a substantial effect on the value of real options.

[3] The theory appendix at http://abarinov.myweb.uga.edu/Theory.pdf contains the formal derivation of the predictions in these three paragraphs.

uncertainty as idiosyncratic volatility, analyst disagreement, analyst forecast error, and volatility of earnings and cash flows. On the other hand, turnover is unrelated to several important measures of liquidity and liquidity risk, such as the Pastor and Stambaugh (2003) liquidity beta or the Sadka (2006) factor loadings.

The main empirical result of the paper is that high turnover firms have negative aggregate volatility risk exposure, and low turnover firms have positive aggregate volatility risk exposure. The difference in aggregate volatility risk can completely explain the turnover effect.

I also find, consistent with the aggregate volatility risk story that works through real options, that the turnover effect strengthens as either leverage or market-to-book increase, or as credit rating decreases. The difference in exposure to aggregate volatility risk between low and high turnover firms increases with both leverage and market-to-book and decreases with credit rating. The aggregate volatility risk factor (the FVIX factor) explains why the turnover effect is stronger for the firms with high market-to-book, or high leverage, or bad credit rating.

I study several competing explanations of the turnover effect. I try to explain the turnover effect using the Pastor and Stambaugh (2003) factor, the Sadka (2006) factor, and the factor based on the Amihud (2002) illiquidity measure. I find that neither of these factors can help in explaining why high turnover firms have low expected returns. I also find no overlap between the liquidity factors and the the FVIX factor I use to explain the turnover effect.

I also consider the possibility that the turnover effect is mispricing. If this is the case, I expect it to be stronger for the firms with high short sale constraints. I do find that the turnover effect is stronger for the firms with low institutional ownership, but this pattern in the turnover effect is completely explained by the FVIX factor.

I also expect that if the turnover effect is mispricing, it will disappear in a couple of years. If the FVIX factor picks up similar mispricing and this is the reason why the FVIX factor explains the turnover effect, the link between turnover and FVIX betas should also disappear in a couple of years. I look at the turnover effect for five years after the firms were sorted on turnover. I find that the turnover effect lasts for at least five years after the portfolio formation, and its aggregate volatility risk explanation works in all five years. Both results suggest that the turnover effect is not mispricing.

Lastly, I perform several robustness checks. I first show that the result that high turnover firms beat the CAPM when aggregate volatility increases (especially if the high turnover firms have high market-to-book, or high leverage, or bad credit rating, or low institutional ownership) still hold if I replace the FVIX factor by the change in the VIX index, which is the variable the FVIX factor is mimicking.

I also look at the turnover effect and its aggregate volatility risk explanation in the NYSE/AMEX and NASDAQ subsample. I find that the turnover effect is present in both subsamples, and the FVIX is able to explain it in both subsamples as well. I also look at the industry-adjusted turnover and unexpected turnover (computed using the coefficients from the firm-level regression of the firm turnover on the average turnover in the market). I find that while the turnover effect remains only in equal-weighted returns when I look at the industry-adjusted turnover and unexpected turnover, higher industry-adjusted and unexpected turnover is associated with lower aggregate volatility risk both in equal-weighted and value-weighted returns.

There are two important caveats about my results. First, my results do not imply that high turnover firms gain value when aggregate volatility increases. I only show that high turnover firms beat the CAPM when aggregate volatility increases, that is, their losses in bad times and their risk are smaller than what the CAPM says. This is the sense in which high turnover firms have low aggregate volatility risk, and this is the reason why these firms have negative CAPM alphas.

Second, the focus of the paper is the use of turnover in asset pricing. I am not trying to claim that turnover is completely unrelated to liquidity or that turnover should never be used as a proxy for liquidity. The point of the paper is that in asset pricing applications we should view turnover as a proxy for firm-specific uncertainty and aggregate volatility risk, not as a proxy for liquidity risk.

The main conclusion of the paper that turnover is not a good measure of liquidity risk has important implications. For example, in a related paper (Barinov, 2010a) I consider the liquidity explanation of the new issues puzzle in Eckbo and Norli (2005). Eckbo and Norli (2005) show that a turnover-based factor, long in low turnover firms and short in high turnover firms, can explain the low returns to IPOs and SEOs. Eckbo and Norli (2005) interpret the negative loadings of new issues on this factor as the evidence that new issues have low liquidity risk.

I revisit their findings and find that the smallest growth firms, which is the group 50% of IPOs and 25% of SEOs come from, have large and negative loadings on the turnover factor. I also find that the smallest IPOs and SEOs have the most negative turnover factor betas. These results are hard to interpret as the evidence of the hedging ability of small growth firms and small IPOs against liquidity risk, since this conclusion is not supported by any other liquidity measure. However, the negative turnover factor betas of small growth firms and small IPOs make perfect sense if one assumes that turnover proxies for uncertainty, because the uncertainty about firm value usually decreases with size. The hypothesis that the turnover factor of Eckbo and Norli (2005) picks up aggregate volatility risk is confirmed empirically: the FVIX factor is able to explain the new issues puzzle, the stronger new issues puzzle for small firms, and the apparent underperformance of small growth firms.

In another related paper (Barinov, 2010b) I resolve the apparent puzzle in Chordia, Subrahmanyam, and Anshuman (2001), who find that turnover variability, which they interpret as the measure of variations in liquidity, is negatively related to future returns. I do not find any evidence that the variability in turnover is positively associated to variability in other liquidity measures, such as price impact and exposure to changes in aggregate liquidity. What I do find is that high turnover variability is synonymous to high firm-specific uncertainty and low aggregate volatility risk. Firms with high turnover variability beat the CAPM when aggregate volatility increases unexpectedly, and this fact can explain why high turnover variability is associated with lower expected returns in cross-section.

The paper proceeds as follows: Section 2 describes the data sources. Section 3 looks at the relation between turnover and various measures of liquidity and uncertainty. Section 4 tests my main empirical hypotheses that the negative relation between turnover and future returns is explained by aggregate volatility risk. Section 5 looks at the ability of several liquidity factors to explain the turnover effect and the mispricing explanation of the turnover effect. Section 6 performs robustness checks, and Section 7 summarizes the findings and concludes.

2 Data

The data in the paper come from CRSP, Compustat, IBES, and the CBOE indexes databases. The sample period is from January 1964 to December 2006. I define turnover as trading volume divided by shares outstanding (both from CRSP). NASDAQ turnover is divided by two to control for the double counting. A firm is classified as a NASDAQ firm if its CRSP events file listing indicator - exchcd - is equal to 3. In the paper, I use an annual measure of turnover, which is the average monthly turnover in the previous calendar year (at least 5 valid observations are required). Firm size is also from CRSP and is shares outstanding times price.

My proxy for expected aggregate volatility is the old VIX index. It is calculated by CBOE and measures the implied volatility of one-month options on S&P 100, available from January 1986 to December 2006. I get the values of the VIX index from CBOE data on WRDS. Using the old version of the VIX gives me a longer data series compared to newer CBOE indices.

I define FVIX, my aggregate volatility risk factor, as a factor-mimicking portfolio that tracks the daily changes in the VIX index. I regress the daily changes in VIX on the daily excess returns to the six size and book-to-market portfolios (sorted in two groups on size and three groups on book-to-market). The fitted part of this regression less the constant is the FVIX factor. I cumulate returns to the monthly level to get the monthly return to FVIX. All results in the paper are robust to changing the base assets from the six size and book-to-market portfolio to the ten industry portfolios (Fama and French, 1997) or the five portfolios sorted on past sensitivity to VIX changes (Ang, Hodrick, Xing, and Zhang, 2006). The daily returns to the six size and book-to-market portfolios and the ten industry portfolios come from Kenneth French website[4].

I compute market-to-book and leverage from Compustat data. Market-to-book is market value of equity (item #25 times item #199) over the sum of book equity (item #60) and deferred taxes (item #74). Leverage is long-term debt (Compustat item #9) plus short-term debt (Compustat item #34) divided by equity value (Compustat item #25 times Compustat item #199). Credit rating is as reported by Standard and Poor's (item #280 in the Compustat annual file). The numeric credit rating is increasing in credit

[4]http://mba.tuck.dartmouth.edu/pages/faculty /ken.french/

risk: 1=AAA, 2=AA+, 3=AA, ... , 21=C, 22=D. Higher numerical value of credit rating therefore means higher risk of default. When I sort firms on market-to-book, or leverage, or credit rating at the end of the year, I use their value from the fiscal year ending no later than June of the sorting year.

I use several proxies for firm-specific uncertainty - idiosyncratic volatility, analyst forecast dispersion, analyst forecast error, and the variances of earnings and cash flows. I define idiosyncratic volatility as the standard deviation of the Fama-French model residuals. The Fama-French model is fitted to daily data for each firm-month with at least 15 non-missing observations. The data on Fama-French factors are from Kenneth French's website.

I measure the variance of earnings and the variance of cash flows using the quarterly data from the past twelve quarters (at least four valid observations are required). The earnings per share (item #11 from the quarterly Compustat tapes) are scaled by the stock price (item #14). The cash flows are operating income before depreciation (item #21) less the change in current assets (item #40) plus the change in current liabilities (item #49) less the change in short-term debt (item #45) plus the change in cash (item #36). The cash flows are scaled by average total assets (item #44) in the past two years.

Analyst forecast dispersion is the standard deviation of all outstanding earnings-per-share forecasts for the current fiscal year scaled by the absolute value of the outstanding earnings forecast (zero-mean forecasts and forecasts by only one analyst excluded). Analyst forecast error (computed for both one-quarter-ahead and one-year-ahead earnings forecast) is the absolute value of the difference between the mean analyst forecast (outstanding for each month) and the actual future earnings figure. The difference is scaled by the absolute value of actual earnings. The data on analyst forecasts and actual earnings are from IBES.

3 Determinants of Turnover

3.1 Descriptive Statistics

3.1.1 Returns and Firm Characteristics

In Table 1, I report the descriptive statistics across the turnover quintiles. The turnover quintiles are formed using NYSE (exchcd=1) breakpoints and are rebalanced annually. The first row of Panel A show the raw equal-weighted returns in the year after portfolio formation. I confirm the previous findings starting with Datar, Naik, and Radcliffe (1998) that high turnover stocks earn lower returns than low turnover stocks. In my sample period the low minus high differential is 49 bp per month, t-statistic 1.85. As we will see in Table 4, the differential is much wider in the CAPM alphas and the Fama-French alphas. From Panel A, it seems that neither low turnover firms nor high turnover firms stand out as having extremely high or extremely low returns.

In the next three rows of Panel A I report the Fama-French betas of the turnover quintile portfolios in the year after portfolio formation. I find that high turnover firms have higher market betas, higher size betas and lower HML betas than low turnover firms. The difference in the betas between low and high turnover stocks is around 0.5, which suggests that both the CAPM and the Fama-French model view high turnover firms as being riskier that low turnover firms. This is the source of the puzzling turnover effect from Datar, Naik, and Radcliffe (1998): if high turnover firms are riskier, why their average returns are lower?

In the rest of Table 1, I look at the firm characteristics in each turnover quintiles that are observable by investors at the portfolio formation date. In the next row of Panel A I find that high turnover firms have higher median market-to-book. Market-to-book increases monotonically from 1.386 in the lowest to 1.806 in the highest turnover quintile, suggesting that sorting on turnover implies sorting on growth options. I also find that leverage is flat across turnover quintile at about 0.23 (23% of the median firm's market value belong to the debtholders). Credit rating of low and high turnover is also very similar, but for both of them it is at BB+ to BB, much worse than the median rating of BBB+ to BBB of the firms with intermediate levels of turnover. Hence, we can tentatively conclude that the call option created by debt is more important for high turnover firms than for an average firm in the economy. The fact that high turnover firms have more valuable growth options and more option-like equity implies that high turnover firms will be a good hedge against aggregate volatility risk if they have high uncertainty.

3.1.2 Turnover and Uncertainty

In Panel B of Table 1, I look at the uncertainty measures across the turnover quintiles. I find that all uncertainty measures I look at are significantly higher for high turnover firms, consistent with my idea that turnover is strongly and positively correlated with firm-specific uncertainty.

For example, the median idiosyncratic volatility increases from 1.5% per day in the lowest turnover quintile to 2.2% per day in the highest volatility quintile (an increase of 46%, t-statistic for the difference 5.78). Similarly, for the median firm in the lowest turnover quintile the standard deviation of the analyst earnings forecast is 3.4 cents per $1 of EPS, and for the median firm in the highest turnover quintile the same standard deviation is 5.7 cents per $1 of EPS (an increase of 68%, t-statistic for the difference 4.61).

Quite similar picture emerges when I look at the quarterly forecast error, which monotonically increases with turnover, starting at 11.1 cents per $1 of EPS in the lowest turnover quintile and going all the way to 18.2 cents per $1 of EPS in the highest turnover quintile (an increase of 64%, t-statistic for the difference 8.89).

Overall, Panel B shows the following properties of high turnover firms: their stock prices vary more, analysts disagree more about their earnings and analyst make bigger mistakes predicting their earnings. This evidence supports my hypothesis that turnover is a good proxy for firm-specific uncertainty.

3.1.3 Turnover and Liquidity

In the first two rows of Panel C, I look at the relation between turnover and price impact. The first measure of price impact is the Amihud (2002) illiquidity measure, which is the average ratio of absolute return to dollar volume. Large positive values of the Amihud (2002) measure mean greater price impact and lower liquidity.

The second measure of price impact is the Pastor and Stambaugh (2003) gamma. The gamma is the slope from the firm-level regression of returns on yesterday's signed volume. High price impact means temporary price pressure today and a bounce back of the price tomorrow. Hence, large negative values of the Pastor and Stambaugh (2003) gamma mean large price impact and low liquidity.

I do not find any relation between the price impact measures and turnover except for the large upward spike in the lowest turnover quintile. While the spike is consistent with the view that the lowest turnover firms are less liquid, because they have higher price impact, there are three other possible views on this evidence.

First, the negative relation between turnover and the Amihud (2002) illiquidity measure is partly mechanical (and it is therefore surprising we do not see it in the other quintiles), because dollar volume is in the numerator of turnover and in the denominator of the Amihud measure.

Second, as Amihud (2002) and Harris and Raviv (1993) point out, price impact measures are also inverse measures of disagreement. If all investors agree on the interpretation of the arriving information (which is more likely to happen for high uncertainty firms), prices will move with little volume, which will mean low turnover and high price impact measures. Thus, the low price impact for low turnover firms may just mean that low turnover firms have low disagreement and are not necessarily less liquid.

Third, the spike in the price impact in the lowest turnover quintile can probably be a pure size effect, since the median size across the turnover quintiles follows the same pattern (see the last row of Panel A): flat (at about \$500 mln) in four quintiles and a sharp downward spike (to \$113 mln) in the lowest turnover quintile.

Also, as we will see later in Table 4, the turnover effect comes equally from the positive alphas of low turnover firms and the negative alphas of high turnover firms. While the higher price impact in the lowest turnover quintile can potentially explain the former, the flat price impact in the other four turnover quintiles does not help in explaining the latter.

In the last three rows of Panel C, I look at the exposure of the turnover quintile portfolios to aggregate liquidity risk. I use three non-traded factors from Amihud (2002), Sadka (2006), and Pastor and Stambaugh (2003). The Amihud factor is the innovation to the market-wide average of the Amihud illiquidity measure. The Sadka factor is the innovation to the market-wide average of a price impact measure, calculated from intraday transaction data. The Pastor-Stambaugh non-traded factor is the innovation to the market-wide average of the Pastor and Stambaugh (2003) gamma. I multiply the Amihud factor by -1 to bring it in line with the Sadka factor and the Pastor-Stambaugh factor, which measure liquidity.

The data on all liquidity factors except for the Amihud factor are from CRSP. To compute the Amihud factor, I take the average daily ratio of the return-to-volume ratio for each firm-month (at least 15 observations are required) and then for each month take the average of the monthly averages across all firms. The innovation is from the AR(1) model fitted to the latter average.

The positive loadings on the liquidity factors mean liquidity risk. The positive loading means negative returns when market liquidity declines unexpectedly. The loadings on the liquidity factors are measured in the year after the quintiles formation by regressing monthly returns to quintile portfolios on the three Fama-French (1993) factors and the liquidity factor.

In Panel C, I see only weak evidence that higher turnover means lower liquidity risk. In fact, the only liquidity factor, for which I observe significant difference in the liquidity risk of high and low turnover firms, is the Sadka factor. For the other two factors, the loadings are essentially flat.

Overall, Panel C extends the results of Lee and Swaminathan (2000) that turnover is only weakly related to other liquidity measures. While Lee and Swaminathan (2000) focus on firm characteristics, such as price level and bid-ask spread, I look at the sensitivity to aggregate liquidity movements and conclude that high turnover firms do not hedge against them either. I also find in Panel B strong evidence that turnover is positively related to firm-specific uncertainty. The bottom line from Table 1 is that sorting on turnover is more likely to pick up firm-specific uncertainty than liquidity risk.

3.2 Multiple Regressions

Table 1 presented the univariate analysis of the turnover determinants. However, as the evidence in Table 1 and prior research suggest, turnover is correlated with many firm characteristics. In order to see clearly, which role each of them plays, in Table 2 I resort to Fama-MacBeth (1973) regressions of turnover on a set of lagged uncertainty variables, a set of lagged liquidity risk measures, and lagged controls.

My focus in this paper is the association of turnover with the measures of uncertainty and the measures of liquidity risk. To make sure that these measures do not pick up the effects of other variables on turnover, in the multiple regressions in Table 2 I introduce several controls. In the choice of the control variables I generally follow Chordia, Huh, and Subrahmanyam (2007).

The first two controls are the positive return (equal to the monthly return if it is positive and zero otherwise) and the negative return (equal to the monthly return if it is negative and zero otherwise). The asymmetric relation between turnover and past return controls for the disposition effect and the effect of short sale constraints on trading.

I also throw in several variables that control for visibility: market-to-book, firm's age, and firm market cap. The market cap together with another variable, stock price, also controls for microstructure effects (stocks with small size and/or low price are costly to trade, for example, due to higher relative bid-ask spread).

To control for the firm's risk, which can be another determinant of turnover, I add as a control the market beta in the previous 60 months and the firm's leverage. I also include in the list of controls the number of analysts following the firm and the dummy variable equal to one if the stock is in S&P 500, two more proxies for visibility and information asymmetry.

The coefficients on the control variables (untabulated) are consistent with prior research. I find that turnover increases after large variations in past returns, and positive returns have a larger impact. I also find that turnover is higher for larger firms, growth firms, firms with high stock price, mature firms, and members of S&P 500. Turnover is also higher for the firms with higher leverage, higher beta, higher market-to-book, and greater analyst following.

In Panel A of Table 2, I add to the controls the uncertainty variables: idiosyncratic volatility, analyst disagreement, analyst forecast error, and the variance of cash flows and earnings. The uncertainty variables are transformed into ranks confined between zero and one. I rank all firms in my sample in the ascending order on the variable in question and then assign to each firm its rank instead of the ranking variable, with zero assigned to the firm with the lowest value of the variable. I then divide the rank by the number of firms with valid observations in each month less one, to make sure the rank is between zero and one.

The convenience of using the ranks is three-fold. First, using ranks eliminates of the extreme skewness of the uncertainty variables - the skewness of the ranks is zero by construction. Second, ranks minimize the impact of outliers. Third, since the ranks are between zero and one, the coefficients in Table 2 can be easily interpreted as the difference in turnover (the percentage of market cap changing hands each month) between the firm with the lowest and the highest value of the variable.

The estimates from Panel A of Table 2 suggest that all five uncertainty measures I use have a significant impact on turnover. First, the respective coefficients are highly significant with t-statistics exceeding 5. Second, and most importantly, the magnitude of the coefficients is quite plausible and economically large. According to the estimates from Panel A, the monthly turnover of the firms with the highest uncertainty is higher than the monthly turnover of the firms with the lowest uncertainty by 20% to 60% of the shares outstanding.

In Panel B of Table 2, I perform the same exercise using the same set of controls for the measures of liquidity risk. The measures of liquidity risk are also ranks confined between zero and one. I use the five measures of liquidity risk from Panel C of Table 1. The first one is the Amihud (2002) price impact measure (absolute return to volume ratio, higher if the price impact is higher and liquidity is lower). If turnover is a good proxy for liquidity, the coefficient in the regression of turnover on the Amihud (2002) measure should be negative.

In Panel B I find that the coefficient on the Amihud measure is negative and significant, but its magnitude is too large to be plausible. The coefficient suggests that the difference in turnover between the firms with the lowest and the highest price impact is 240% to 430% of the shares outstanding per month, depending on whether the Amihud measure is used in the regression alone or with other liquidity measures. Compared to the average turnover in my sample - 10% of shares outstanding per month - these numbers are unbelievably huge.

The second price impact measure is the Pastor and Stambaugh (2003) gamma. The gamma is the coefficient from the regression of the firm's return on the lagged signed volume. The gamma measures the temporary price impact by looking at how large will be the price bounce back in the next day. Hence, a large and negative gamma means greater price impact and lower liquidity. Therefore, if turnover proxies for liquidity, the coefficient in the regression of turnover on the gamma has to be positive.

The evidence in Panel B of Table 2 is mixed: when the gamma is used alone, it is positive and significant, indicating that higher turnover means lower price impact. When the gamma is used with other measures of liquidity, the coefficient is negative and insignificant. Also, the coefficient on the gamma is quite small, suggesting that the difference in turnover between the most negative and the least negative gamma firms is about 1% of shares outstanding per month. I conclude therefore that the link between the gamma and turnover is most likely non-existent.

The next three liquidity measures are the return sensitivities to innovations in aggregate liquidity. The measures of the innovations in aggregate liquidity are the Pastor and Stambaugh (2003) non-traded factor, the Sadka (2006) non-traded factor, and a similar factor based on the innovation to the cross-sectional average of the Amihud (2002) price impact measure. I measure the loadings on these factors at the firm level by running each firm-month the regression of the firm's return in the past 36 months on the three Fama-French (1993) factors and one of the liquidity factors. The positive loadings mean negative returns when liquidity unexpectedly declines, which constitutes liquidity risk. If turnover proxies for liquidity risk, the association between turnover and liquidity factor loadings should be negative.

This is generally not what I find in Panel B of Table 2. The only loading with the negative coefficient (significant at the 10% level) is the loading on the Sadka factor (note how its significance and importance declines compared to Panel C of Table 1 after I control for other determinants of turnover). However, the magnitude of the coefficient suggests that the firms with the highest liquidity risk have the turnover only by 3% of shares outstanding per month smaller than the firms with the lowest liquidity risk, which means that the link between liquidity risk and turnover is economically insignificant. Moreover, the coefficient on the Sadka factor loading becomes significantly positive when other liquidity measures are controlled for, suggesting the possibility that high turnover firms may have higher, not lower liquidity risk after all.

To sum up, Table 2 strongly suggests that sorting firms on turnover would produce a strong sorting on uncertainty, but the evidence that sorting firms on turnover would produce a sorting on liquidity or liquidity risk is scarce. In fact, Panel B suggests that high turnover firms have slightly higher liquidity risk. The only measure of liquidity that is higher for high turnover firms is the Amihud (2002) price impact measure, but even for this measure the results look unreliable. Therefore, the evidence in Table 2 supports my assertion that in asset pricing applications turnover should be used as a proxy for uncertainty, not liquidity or liquidity risk.

4 Turnover and Aggregate Volatility Risk

4.1 Characteristic-Based Tests

4.1.1 Hypotheses and Controls

My main hypothesis is that in cross-section high turnover predicts low future returns because high turnover means high firm-specific uncertainty. Relative to the assets with the same market betas, the real options of high uncertainty firms increase in value and have lower risk during volatile periods, which means that these firms have low aggregate volatility risk. Because firm-specific uncertainty makes real options hedges against aggregate volatility risk, I also hypothesize that the effect of turnover on future returns is stronger for the firms with abundant real options: highly levered firms and firms with high market-to-book. In cross-sectional regressions of returns on lagged firm characteristics I should see a significant negative coefficient for the product of market-to-book and turnover and the product of leverage and turnover. The negative relation between turnover and returns should disappear when either of the products is present.

The empirical problem with testing these hypotheses is that there are many confounding effects in the data. First, leverage and market-to-book are strongly negatively correlated both for mechanical and economic reasons. First, leverage and market-to-book have to be negatively correlated, because the market cap is in the numerator of market-to-book and the denominator of leverage. Second, value firms tend to have low leverage because they are often distressed firms, and distressed firms are highly levered, or because firms with few growth options take on a lot of debt to mitigate the free cash flow problem. Therefore, if the product of either market-to-book and turnover or leverage and turnover is used alone in the cross-sectional regressions, it will pick up both conflicting effects and the coefficient on the product will be biased towards zero.

Second, turnover is positively associated with size, and the dependence of returns on the interaction of turnover and market-to-book can run against the well-known dependence of the value effect on size (see, e.g., Loughran, 1997). My prediction is that the turnover effect is stronger if market-to-book is high, that is, the product of turnover and market-to-book is negatively associated with future returns. The value effect, i.e. the negative relation between market-to-book and future returns, is stronger for small firms (Loughran, 1997), so the product of market-to-book and size should be positively related to returns. If there is no relation between market-to-book and the turnover effect on returns, I would expect that the product of market-to-book and turnover is positively related to future returns, because turnover would just substitute for size. If there is no relation between leverage and the turnover effect on future returns, I would expect to find that the product of turnover and leverage is negatively related to future returns, just as my hypothesis predicts, but only because turnover is positively related to size, and leverage is negatively related to market-to-book. Therefore, not controlling for the product of size and market-to-book would artificially make the product of market-to-book and turnover too weak and the product of leverage and turnover too strong.

4.1.2 Results and Interpretation

All these confounding effects make me choose the multiple regression framework to test whether the turnover effect depends on market-to-book and leverage. In Table 3, I run Fama-MacBeth (1973) regressions of monthly returns on lagged stock characteristics. The controls I use in all regressions are the current month market beta, the previous year size, and the previous year market-to-book. All firm characteristics, except for the market beta, are percentage ranks scaled to be between 0 and 1. Using percentage ranks mitigates the impact of outliers and allows to interpret the coefficients as the difference in returns between the firms with the lowest and the highest value of the variable.

I first confirm that the previous year turnover does predict current returns. The first column estimates the return differential between the firms with the lowest and the highest turnover at 0.756% per month, reasonably close to what it actually is in Table 1 and Table 4. The turnover coefficient is highly significant.

Contrary to my hypothesis, in the second column I find that the product of market-to-book and turnover is insignificant and turnover retains significance in its presence. As discussed above, the lack of apparent relation between future returns and the product of turnover and market-to-book can be because the product runs against the well-known relation between size and the value effect.

In the third column, I add the product of size and market-to-book that should capture this relation. Once the relation between size and the value premium is controlled for, the product of turnover and market-to-book becomes significant, and the turnover coefficient drops by two thirds compared to the first column and becomes insignificant. The coefficient on the product of market-to-book and turnover implies that, holding everything else constant, the turnover effect varies from 0.294% per month for the firms with the lowest market-to-book to 0.294%+0.89%=1.184% per month for the firms with the highest market-to-book.

In unreported results, I also try omitting the product of turnover and market-to-book and keeping the product of size and market-to-book only. I find that the product of size and market-to-book does not eliminate the significance of turnover, so, as hypothesized, it is the interaction of turnover and market-to-book that explains the turnover effect.

In the fourth column, I test whether there is an interaction between the turnover effect and leverage. The coefficient on the product of leverage and turnover is negative and significant, and turnover itself loses significance in the presence of the product. The coefficient on the product implies that the turnover effect varies from 0.456% per month for the lowest leverage firms to 0.456%+0.58%=1.136% per month for the highest leverage firms, consistent with my hypothesis that the turnover effect is stronger for highly levered firms.

As I mentioned earlier, the product of turnover and leverage can proxy for the well-known relation between size and the value premium. In the fifth column I show that it is partially true, because the coefficient on the product drops by 14% and becomes marginally significant when I add the product of size and market-to-book.

Because market-to-book and leverage are negatively related, and the products of both with turnover are negatively related to future returns, having both products in one regression should reinforce their significance. This is what I find in column six, where the products of market-to-book and leverage with turnover are both highly significant and larger than in the previous columns. It does not change in column seven, where I add the product of size and market-to-book, which additionally strengthens the product of market-to-book and turnover and has no impact on the product of leverage and turnover.

Summing up the results in Table 3, I conclude that, consistent with my story, the turnover effect is significantly stronger for the firms with valuable real options (highly levered firms and growth firms). It appears that the interaction of turnover and real options can produce the variation in the turnover effect on returns of about 60-90 bp per month and leave insignificant the remaining part of the turnover effect.

4.2 Covariance-Based Tests

4.2.1 Turnover Effect and Aggregate Volatility Risk

The main prediction of my paper is that high turnover firms have low aggregate volatility risk, because they are high uncertainty firms. The firm-specific uncertainty makes real options hedges aggregate volatility risk, so the best hedges should be the firms with high levels of both. While the previous subsections brought some evidence in favor of the last prediction, a more direct test of the model is to verify that, first, the pattern in the abnormal returns across turnover quintiles is aligned with a similar pattern in the aggregate volatility risk factor betas, and second, that the interactions between real options and turnover in Table 3 can also be traced back to the difference in aggregate volatility risk.

In Table 4, I look at the turnover quintiles from Table 1 and consider the CAPM, the Fama-French model, the ICAPM with the market factor and the aggregate volatility risk factor (the FVIX factor), and the Fama-French model augmented with FVIX. The sample period is from January 1986 to December 2006 because of the availability of the VIX index, which is my proxy for expected aggregate volatility.

The first row of Panel A reports the value-weighted CAPM alphas for the new sample period and confirms that in the last 21 years of data going long in low turnover stocks and short in high turnover stocks yields a sizeable abnormal return (58 bp per month, t-statistic 2.15). Panel B shows that the turnover effect is even stronger in equal-weighted returns at 1.61% per month, t-statistic 5.88.

In the next row, I show that controlling for aggregate volatility risk eliminates the turnover effect in value-weighted returns and materially reduces the turnover effect in equal-weighted returns. The value-weighted alpha differential between low and high turnover firms declines to -15 bp per month, t-statistic -0.73. The equal-weighted ICAPM alphas of low and high turnover firms still differ by 0.94% per month, t-statistic 4.37, but this is by 42% smaller than the difference in the CAPM alphas.

The key to the success of the ICAPM in explaining the turnover effect is the FVIX beta of the highest turnover quintile (0.797, t-statistic 8.82, in value-weighted returns, 1.114, t-statistic 8.81, in equal-weighted returns). By construction, the FVIX factor is the combination of the base assets with the most positive correlation with VIX changes (VIX is my proxy for expected aggregate volatility). Therefore, the positive FVIX beta of high turnover firms means that these firms beat the CAPM when aggregate volatility increases, i.e. buying them and short-selling the firms with the same market beta would create a hedge against aggregate volatility risk.

In value-weighted returns, I also observe a significant aggregate volatility risk exposure for low turnover firms (FVIX beta -0.502, t-statistic -7.2), which brings the low minus high differential in FVIX betas to -1.299, t-statistic -11.5. The similar FVIX beta differential in equal-weighted returns is -1.194, t-statistic -11.6.

Looking at the Fama-French model and the Fama-French model with FVIX brings me to similar conclusions: higher turnover means lower aggregate volatility risk, and the return differential between low and high turnover firms can be at least partly explained by the fact that high (low) turnover firms beat (trail) the CAPM when aggregate volatility unexpectedly increases.

To sum up, the strong and monotonic increase in FVIX betas from highest to lowest turnover firms and the considerable differential in the FVIX betas between the extreme turnover portfolios shows that turnover is strongly associated with aggregate volatility risk, and this association can completely explain the turnover effect without appealing to liquidity or liquidity risk.

This is the main point of the paper: in asset pricing tests, we need not interpret high turnover as high liquidity or low liquidity risk in order to explain the turnover effect. We can interpret turnover as uncertainty, which is more consistent with the relation between turnover and the measures of liquidity and uncertainty, and still reconcile this interpretation of turnover with the negative relation between turnover and expected returns, because higher turnover (higher uncertainty) means lower aggregate volatility risk.

4.2.2 Turnover Effect and Growth Options

In Panel A of Table 5, I look at the equal-weighted returns to the turnover arbitrage portfolio across market-to-book deciles. The turnover arbitrage portfolio buys the firms in the lowest turnover quintile and shorts the firms in the highest turnover quintile. This strategy is followed separately in each market-to-book quintile. I make the sorting into turnover quintiles conditional on size to mitigate the confounding effects described in Section 4.1.1.

My story has it that turnover proxies for uncertainty. As prior research (Barinov, 2009a, Barinov, 2009b) shows, high uncertainty firms beat the CAPM in the periods of increasing aggregate volatility if they have valuable growth options. I predict therefore that the turnover effect significantly increases with market-to-book. I also predict that the ICAPM with FVIX explains the turnover effect in all market-to-book quintiles, and that the FVIX beta of the turnover arbitrage portfolio becomes more negative as market-to-book increases.

The evidence in Panel A is consistent with the above hypotheses. The CAPM alphas of the turnover arbitrage portfolio increase from 81 bp per month, t-statistic 2.89, in the value quintile to 161 bp per month, t-statistic 5.44, in the growth quintile (t-statistic for the difference 2.92). The CAPM alphas suggest that the turnover effect is indeed stronger for the firms with abundant growth options, consistent with my interpretation of turnover as a measure of uncertainty.

After I control for aggregate volatility risk, the alpha differential between the turnover arbitrage portfolios in the value subsample and in the growth subsample declines to 30 bp per month, t-statistic 1.24. The key to explaining the alpha differential are the FVIX betas of the turnover arbitrage portfolio. The FVIX betas monotonically increase in magnitude from the value subsample to the growth subsample (t-statistic for the difference 9.85). The increase means that, compared with exploiting the turnover effect in the value subsample, exploiting the turnover effect in the growth subsample implies greater underperformance of the CAPM when aggregate volatility increases. Hence, I conclude that, consistent with my story, aggregate volatility risk indeed explains why the turnover effect is stronger for growth firms.

4.2.3 Turnover Effect and Equity as a Call Option on the Assets

In Panel B of Table 5, I repeat the analysis in Panel A using leverage sorts instead of market-to-book sorts. To control for the negative relation between leverage and market-to-book and the consequent confounding effect of size (see Section 4.1.1 for discussion), I make the leverage sorts conditional first on size and then on market-to-book. To make this double conditioning feasible, I have to use the breakpoints from the whole CRSP universe instead of the NYSE only sample.

I do not find any pattern in the CAPM alphas of the turnover arbitrage portfolio. Even worse, in the ICAPM the FVIX betas of the turnover arbitrage portfolio, if anything, go against my hypothesis: they start at -1.587, t-statistic -4.19, in the lowest leverage quintile and decline to -0.981, t-statistic -4.76, in the highest leverage quintile (the difference is insignificant with t-statistic 1.28).

However, it turns out that the conditional sorting does not really destroy the negative relation between leverage and market-to-book. The lowest leverage quintile still has average market-to-book of 5.57, versus the average market-to-book of 4.01 for the highest leverage quintile. I attempt to control for the difference in the market-to-book by looking at the FVIX betas of the turnover arbitrage portfolio in the augmented Fama-French model, where the HML factor can help in controlling for the market-to-book effects.

In the Fama-French model in Panel C I do find that the turnover effect is stronger for highly levered firms. The difference is 93 bp per month, t-statistic 1.94. After I add the FVIX factor to the Fama-French model, the difference in the alphas goes down to 68 bp per month, t-statistic 1.26.

The FVIX betas of the turnover arbitrage portfolio also line up with my predictions. The FVIX betas start at 0.107, t-statistic 0.1, in the lowest leverage quintile and increase to -1.826, t-statistic -2.6, in the highest leverage quintile. It means that short-selling high turnover firms exposes the investor to larger-than-expected losses during aggregate volatility increases only if leverage is high and the real option created by leverage is valuable, exactly as my story predicts.

In Panel C, I use a different measure of the importance of the real option created by leverage - credit rating. For the firms with good credit rating, the limited liability and the fact that extreme losses happen at the cost of debtholders, is not an important consideration. For the firms with bad credit rating, equity is more option-like, because the probability that assets will be less than debt (i.e., that the option will be in the money) is much higher. Credit rating is also less correlated with market-to-book than leverage, since in the case of leverage the correlation is partly mechanical - the market cap is in the numerator of market-to-book and the denominator of leverage. I still make the sorts on credit rating conditional on market-to-book, to eliminate any association between the two.

In the CAPM, I find that the turnover effect is significantly stronger for the firms with worse credit rating, for which the option created by the existence of risky debt is more important. The CAPM alphas of the turnover arbitrage portfolio from -19 bp per month, t-statistic -0.84, in the best credit rating group to 71 bp per month, t-statistic 2.02 in the worst credit rating group. The difference in the alphas is significant with t-statistic 2.22.

After I control for the FVIX factor, the difference in the alphas declines to 39 bp per month, t-statistic 1.05. The FVIX beta of the turnover arbitrage portfolio increase in magnitude from -0.02, t-statistic -0.16, among the firms with the best credit rating to -0.933, t-statistic -5.69, among the firms with the worst credit rating. The FVIX betas show that exploiting the turnover effect means more exposure to aggregate volatility risk if the option-like nature of equity is more important, consistent with my hypothesis that the turnover effect is created by the interaction of firm-level uncertainty and real options.

5 Alternative Explanations of the Turnover Effect

5.1 Turnover Effect and Liquidity Risk

The previous sections present two pieces of evidence suggesting that in asset pricing applications turnover should be used as a proxy for uncertainty and aggregate volatility risk, rather than as a proxy for liquidity and liquidity risk. First, I find that turnover is strongly correlated with uncertainty measures, but the relation between turnover and liquidity risk is weak to non-existent. Second, I find that, consistent with the hypothesis that turnover proxies for uncertainty, aggregate volatility risk explains the turnover effect and its dependence on the measures of real options predicted by the uncertainty story.

In this section, I take a different approach to showing that turnover is unrelated to liquidity risk. In Table 6, I sort firms into quintiles on the two measures of liquidity risk - the loadings on the Pastor-Stambaugh (2003) non-traded factor and the loadings on the Sadka (2006) non-traded factor - and one measure of liquidity, the Amihud (2002) price impact measure. I find that the sorts produce a significant spread in abnormal returns. The alphas of the firms with the lowest and the highest liquidity risk differ by 20 bp to 60 bp per month, all differences statistically significant, depending on the measure of liquidity risk I use and whether I use the CAPM or the Fama-French model to compute the alphas. I conclude therefore that the liquidity measures I use create a sizeable spread in liquidity risk.

In the next pair of rows I estimate the ICAPM with the FVIX factor. The point of this exercise is to show that FVIX does not substitute for liquidity risk, and therefore the evidence that FVIX explains the turnover effect means that liquidity risk is not necessary to explain the turnover effect. I find that the alpha differential between the firms with the lowest and the highest liquidity risk does not change when I control for FVIX. I also find that the FVIX betas of the highest and the lowest liquidity risk firms are about the same. I conclude that FVIX is unrelated to the most popular measures of liquidity risk, and the ability of FVIX to explain the turnover effect comes from a different source, thus aggravating the doubts that the sorts on turnover pick up liquidity risk.

I then form the liquidity factor following Eckbo and Norli (2002, 2005). I sort firms on turnover into top 30%, medium 40%, and bottom 30%. The sorting is performed separately for the firms below and above the median NYSE market cap. I then go long in the low turnover firms and short in the high turnover firms separately for each size group and then take a simple average return to the two low minus high strategy. This is the turnover factor Eckbo and Norli refer to as LMH.

In the last pair of rows, I look at the two-factor model with the market factor and LMH and fit this model to the liquidity risk quintiles. If turnover picks up liquidity risk, the LMH factor should explain the difference in the alphas in the sorts on liquidity or liquidity risk in Table 6.

The results in Table 6 suggest that it is not the case. The alpha differential between the firms with the lowest and the highest liquidity risk does not change when I control for the turnover factor. Also, the turnover factor betas of the most liquid and the least liquid firms are not significantly different. I conclude therefore that LMH (and turnover) are unlikely to pick up liquidity risk, since LMH is not helpful in explaining the return spread in the sorts on liquidity risk.

In Table 7, I take a different approach. I go back to the turnover quintiles from Table 4 and try to explain the turnover effect by throwing in the liquidity factors, which are the return differentials between the firms with the highest and the lowest liquidity risk reported in the rightmost column of Table 6. If the turnover effect is related to liquidity risk, the liquidity factors should help to explain it and produce positive liquidity betas (risk) for low turnover firms and negative liquidity betas (hedge) for high liquidity firms.

Table 7 shows that all three liquidity factors I derive from Table 6 are pretty useless in explaining the turnover effect. The Pastor and Stambaugh factor even suggests (in value-weighted returns) that low turnover firms have lower liquidity risk than high turnover firms and makes the turnover effect a bit stronger.

The liquidity factor based on the Amihud measure seems to explain the value-weighted alpha of the high turnover firms and make the value-weighted turnover effect insignificant, but this apparent success is driven primarily by the increased standard errors of the alphas. Moreover, I do not find that the loadings on the Amihud factor differ significantly across turnover quintiles. In equal-weighted returns, the Amihud factor has no effect on the equal-weighted alphas of the same turnover quintile portfolios.

The tradable version of the Sadka factor seems to work in the value-weighted returns, explaining the turnover effect and producing the significant spread in the liquidity betas across the turnover quintile. However, in equal-weighted returns the Sadka factor fails to produce a sizeable reduction in the turnover effect or a sizeable spread in the liquidity betas between high and low turnover firms.

The conclusion from Table 7 is that the alternative liquidity factors seem incapable of explaining the turnover effect. This evidence suggests that the turnover effect comes from a source other than liquidity risk, thus supporting my hypothesis that in asset pricing applications turnover should be used as a proxy for uncertainty and aggregate volatility risk.

5.2 Turnover Effect and Mispricing

An alternative view of the turnover effect is that it represents mispricing. The proponents of this view generally agree that turnover captures uncertainty/disagreement rather than liquidity and use the Miller (1977) story to predict that higher disagreement combined with short sale constraints creates overpricing. Miller (1977) argues that in the presence of short sale constraints the stock prices reflect the average valuation of the optimists, and this average increases with uncertainty/disagreement.

Nagel (2005) shows that the turnover effect is stronger for the firms with low institutional ownership (henceforth IO). This evidence is consistent with mispricing story if one views IO as a proxy for the amount of shares available to sell short. For the firms with low IO, the supply of shares for short sales is small and the cost of short sale is likely to be high. Therefore, the firms with high turnover and low IO are likely to be the most overpriced, because they have the highest disagreement and are the hardest ones to short, and this is the reason why the turnover effect is stronger for low IO firms.

In Table 8 I look at the returns to the turnover arbitrage portfolio across the IO quintiles. To make sure that I do not capture any size effects, I make IO orthogonal to size by regressing the logistic transformation of IO on log size and its square and taking the residual from this regression as the measure of IO.

My hypothesis is that aggregate volatility risk can explain why the turnover effect is stronger for the firms with low IO. I hypothesize that institutions avoid firms with very high turnover because high turnover means high uncertainty and big possible swings in prices. I predict that institutions also avoid firms with very low turnover because low turnover means high price impact, or because low turnover means high aggregate volatility risk, or because low turnover means low uncertainty and a smaller edge for informed traders.

I show (results not tabulated to save space) that the low IO subsample indeed includes the firms with both very high turnover and very low turnover. Therefore, sorting firms on turnover produces a wider spread in turnover (and aggregate volatility risk) in the low IO subsample.

In Table 8, I first confirm that the turnover effect is greater for the low IO firms. The difference in the CAPM alphas of the turnover arbitrage portfolio between the lowest and the highest IO quintiles is 82 bp per month, t-statistic 2.1, in value-weighted returns, and 100 bp per month, t-statistic 3.29, in equal-weighted returns.

I then find, consistent with my hypothesis, that sorting firms on turnover in low IO subsample produces a larger spread in aggregate volatility risk. The FVIX betas of the turnover arbitrage portfolio change from -0.93 (-0.65) in the highest IO quintile to -1.66 (-1.60) in the lowest IO quintile in value-weighted (equal-weighted) returns.

After I control for the FVIX factor, I find that difference in the turnover effect between low IO firms and high IO firms is reduced to 40.5 bp per month, t-statistic 1.19, and 46.4 bp per month, t-statistic 1.89, respectively. Hence, the stronger turnover effect in the low IO subsample is perfectly explained by aggregate volatility risk and therefore cannot be used as the evidence that the turnover effect is mispricing.

It is also worth pointing out that the Miller story is only capable of explaining the negative alphas of the high turnover firms. According to Table 4, the turnover effect comes equally from the negative alphas of high turnover firms and the positive alphas of low turnover firms, and the FVIX factor, in contrast to the Miller story, can explain both.

In Table 9, I perform another test of the mispricing explanation of the turnover effect. I hypothesize that if the turnover effect is mispricing, the mispricing should be eventually corrected and the turnover effect should disappear in a year or two. For example, suppose that the turnover effect of about 6% per month (see Panel A of Table 4) is mispricing that lasts only for one year. The trading costs of buying low turnover firms and shorting high turnover firms can well be greater than 6%. In this case, the turnover effect will not represent an arbitrage opportunity and will dissipate only gradually. If the turnover effect is mispricing that lasts at the same level for 6%, the trading costs will have to be greater than 12% to eliminate the arbitrage opportunity.

In Table 9, I look at the turnover effect in the first six months after portfolio formation, in the next six months after portfolio formation, in the second year after portfolio formation, and so forth up to five years. If the turnover effect is mispricing, it should disappear by the end of year five. If the turnover effect has a risk-based explanation (e.g., aggregate volatility risk), it will become weaker with time as the turnover becomes a stale proxy for current risks, but most likely will stay significant even in year five.

In Table 9, I see that the turnover effect in both equal-weighted and value-weighted returns stays significant in all years up to year five, and probably further. It is hard to imagine that if the turnover effect was all mispricing, it would last that long. On the other hand, the evidence in Table 9 suggests that at least part of the turnover effect is likely to be mispricing. The turnover effect declines by half after the first six months. In value-weighted returns, it stays at this new level of around 35 bp per month till year five. In equal-weighted returns, the turnover effect undergoes another decline by half at the end of year two, and then stays at this level of around 55 bp per month till year five. The FVIX betas do not make the jump at the time points when the turnover effect is halved, suggesting that the turnover effect declines at these time points for the reasons unrelated to aggregate volatility risk.

Interestingly, the FVIX factor is only able to explain completely the equal-weighted turnover effect after year two. Before that, adding FVIX substantially diminishes the equal-weighted turnover effect, but leaves it significant. In value-weighted returns, FVIX is capable of explaining the turnover effect even in the first six months after the portfolio formation. I conclude therefore that the risk-based part of the turnover effect is about 35-55 bp per month, and the rest can be mispricing.

To sum up, the evidence in this section suggests that while there is limited amount of evidence that the turnover effect is mispricing, this is not the whole story about the turnover effect. Furthermore, in many cases (Table 8, value-weighted returns in Table 9) controlling for aggregate volatility risk completely explains the turnover effect and makes the mispricing stories redundant.

6 Robustness Checks

6.1 The Anomalies and the Exposure to Aggregate Volatility Changes

6.1.1 Estimation

The previous sections of the paper established three main results. First, I have shown that high turnover firms react to unexpected increases in aggregate volatility less negatively than the firms with the same market beta, and the reverse is true about low turnover firms. Second, I found that the difference in reaction of high and low turnover firms to increasing aggregate volatility is the greatest for the firms with valuable real options (high market-to-book, high leverage, bad credit rating). Third, I found that this difference is also greater for the firms with low institutional ownership.

The method in the paper was to use FVIX, the factor-mimicking portfolio that tracks daily changes in expected aggregate volatility. I measure expected aggregate volatility using the VIX index. By construction, FVIX is the combination of the base assets (six portfolios from 2-by-3 sorts on size and market-to-book) that has the highest correlation with VIX changes. I add FVIX to the CAPM and interpret the positive FVIX betas as the evidence that the portfolio on the left hand side hedges against aggregate volatility risk. The positive FVIX beta means that when aggregate volatility unexpectedly increases, the portfolio loses value less than other portfolios with comparable market betas.

In this section, I replace the FVIX portfolio by changes in VIX. This is a more direct test of my hypothesis that when aggregate volatility increases, high turnover firms beat the CAPM. In this section I switch to daily frequency, because at the daily frequency the change in VIX is a better proxy for unexpected changes in expected aggregate volatility.

In Table 10 I regress the daily returns to the test assets on the daily excess return to the market and either the daily change in VIX (regression (1)) or the daily return to FVIX (regression (2)) and report the slope on the VIX change ($\beta_{\Delta VIX}$) and the slope on FVIX (β_{FVIX}). I use FVIX in the daily regressions to verify that the results in Table 10 are not driven by the change in the observation frequency and the FVIX betas are roughly the same in daily returns and monthly returns.

$$Ret = \alpha + \beta_{MKT} \cdot MKT + \beta_{\Delta VIX} \cdot \Delta VIX \tag{1}$$

$$Ret = \alpha + \beta_{MKT} \cdot MKT + \beta_{FVIX} \cdot FVIX \tag{2}$$

In Table 10, I look at five test assets that go on the left-hand side of the regressions above. First, I look at the portfolio that buys the firms from the lowest turnover quintile and short sells the firms from the highest turnover quintile (the Turn portfolio). Second, I look at two portfolios that buy the Turn portfolio formed in the highest market-to-book (leverage) quintile and short the Turn portfolio formed in the lowest market-to-book (leverage) quintile. These portfolios are denoted as Turn MB and Turn Lev, respectively. Last, I look at the two portfolios that buy the Turn portfolio formed in the lowest credit rating (institutional ownership) quintile and short the Turn portfolio formed in the highest credit rating (institutional ownership) quintile. These portfolios are denoted as Turn Cred and Turn Inst, respectively.

6.1.2 Results and Interpretation

In the first row of Table 10 I find that the Turn portfolio indeed underperforms the CAPM when aggregate volatility increases, since its loading on the VIX change is negative and significant. The underperformance suggests that high turnover firms react less negatively to aggregate volatility increases than low turnover firms, consistent with my story that turnover proxies for firm-level uncertainty and aggregate volatility risk.

The evidence for the Turn MB portfolio is mixed. In value-weighted returns its loading on the VIX change is negative, but almost exactly zero, but in equal-weighted returns it is sizeable and significant. However, the daily FVIX betas of the Turn MB portfolio are negative and significant in both equal-weighted and value-weighted returns.

Consistent with the evidence in Panel B of Table 5, the Turn Lev portfolio has positive loadings on the VIX change because of the mechanical negative correlation between leverage and market-to-book. When I look at credit rating, my alternative measure of the importance of the real option created by the existence of risky debt, I find that the Turn Cred portfolio loads negatively on the change in VIX. However, the loading is very close to zero for equal-weighted returns and marginally significant for value-weighted returns.

In the last row of Table 10, I find that the Turn Inst portfolio loads negatively on the VIX change both in equal-weighted and value-weighted returns. It confirms my result in Section 5.2 that the turnover effect is stronger for low IO firms because exploiting it in this subsample means greater underperformance in the periods of increasing aggregate volatility.

Overall, the evidence from the loadings on the VIX change goes in the right direction, but remains shaky, since the loadings lose significance or become marginally significant either in equal-weighted or in value-weighted returns. That contrasts sharply with the daily FVIX betas, which have the same sign as the loadings on the VIX change, but are highly significant and comparable in magnitude with the monthly FVIX betas in the previous tables.

The higher significance of the FVIX betas leads me to believe that the loadings on the VIX change are sometimes insignificant because of the error-in-variables problem. The factor-mimicking procedure filters out the part of the VIX change that is orthogonal to all six size and book-to-market portfolios. This part of the VIX change is most likely noise, and it is responsible for about a half of the variance of the VIX change.

Another confirmation that the loadings on the VIX change are contaminated by the error-in-variables problem is their magnitude. The magnitude implies that the arbitrage portfolios in Table 10 lose about 2.5 bp per each point increase in VIX. During recessions, VIX increases by 20 to 40 points, which means that buying low turnover firms and selling high turnover firms would result to at most 1% additional loss in recessions on top of what the CAPM predicts.

For comparison, when I regress the excess market return on the VIX change, I find that the market portfolio loses about 13 bp for each one-point increase in VIX (at most 5% as the VIX changes from its expansion level to its recession level). Both the numbers in Table 10 and the number for the market portfolio are much smaller than the real losses suffered by stocks as the economy goes all the way from expansion to recession.

The valuable information in the loadings on the change in VIX is the relative importance of the difference in aggregate volatility exposure. For example, it appears that when aggregate volatility increases, the value-weighted Turn portfolio posts the returns that are by 26% lower than the CAPM prediction. In the rightmost column of the left panel of Table 10, the market beta of the value-weighted Turn portfolio is -0.69, and if we believe that the market portfolio loses "around 13 bp" per each point increase in VIX, we would predict from the CAPM that the Turn portfolio should gain "$0.69 \cdot 13 = 8.9$ bp" per each point increase in VIX. The loading on the change in VIX for the value-weighted Turn portfolio is -0.024, which means that when VIX goes up by one point, the Turn portfolio trails the CAPM prediction by "2.4 bp", or cuts the gain promised by the CAPM from

"8.9 bp" to "6.5 bp", or by 26%. (The returns in this paragraph are in quotation marks to underscore that I am interested solely in their relative, not absolute values).

Similar calculations for other portfolios in Table 10 show that, according to the CAPM, all these portfolios are set to gain from VIX increases because their market betas are negative, but the gain is 10% to 60% smaller than what the CAPM predicts because of the negative loadings on the VIX change. For some portfolios, the gain is even turned into a loss. For example, according to the CAPM, the equal-weighted Turn Inst portfolio should be gaining "about 5.1 bp" for each point of the VIX increase, but instead loses "2 bp" because of its large and negative loading on the VIX change.

The observation that the arbitrage portfolios that try to exploit the turnover effect do not lose during increases in aggregate volatility, but rather gain much less than what the CAPM would predict, is an important one. It is consistent with moderate differential in average raw returns to low and high turnover firms (see Table 1). The real puzzle of the turnover effect is not why the implied trading strategy is very profitable (it is not), but rather why this strategy, which has strongly negative market beta, earns clearly non-negative average return. The negative loading of the turnover arbitrage portfolios on the change in VIX helps to explain the positive CAPM alphas by pointing out that the negative market beta severely overstates the performance of the turnover arbitrage portfolios in hard times. Rather than being good, this performance is quite close to zero, which makes the non-negative average returns of the turnover arbitrage portfolios much less puzzling.

6.2 Look-Ahead Bias?

When I construct the FVIX factor - the portfolio that mimics the daily changes in VIX - I run one regression using all available observations. This is a common thing to do since the classic paper by Breeden, Gibbons, and Litzenberger (1989). The benefit of using the single regression is that doing so significantly improves the precision of the estimates. The potential drawback is that the results may suffer from the look-ahead bias. Indeed, in 1986 investors could not run the factor-mimicking regression of the daily VIX changes on the excess returns to the six size and book-to-market portfolios using the data from 1986 to 2006. The common defense here is that in 1986 investors are very likely to be much more informed about how to mimic changes in expected aggregate volatility than the econometrician. Allegedly, investors had an idea about what the current expected aggregate volatility and its change are long before the VIX index became available. Hence, by 1986 they probably had years and even decades of experience of mimicking the innovations to expected aggregate volatility (unobservable to the econometrician before 1986). Assuming that the weights in the FVIX portfolio are stable through time, it is possible that in 1986 investors already knew the weights that the econometrician was able to figure out only by the end of 2006.

In this subsection I revisit all results in the paper making the conservative assumption that the information set of investors is the same as the information set of the econometrician. I perform the factor-mimicking regression of the daily change in VIX on the excess returns to the six size and book-to-market portfolios using only the past available information. That is, if I need the weights of the six size and book-to-market portfolios in the FVIX portfolio in January 1996, I perform the regression using the data from January 1986 to December 1995. I then multiply the returns to the six size and book-to-market portfolios in January 1996 by the coefficients from this regression to get the FVIX return in January 1996. Then in February 1996 I run a new regression using the data from January 1986 to January 1996, etc. The resulting version of FVIX is a tradable portfolio immune from the look-ahead bias. I call this portfolio FVIXT.

In Panel A of Table 11 I compare FVIX and FVIXT using the sample from January 1991 to December 2006. I set aside the first five years (1986-1990) as the learning sample - the investors and the econometrician learn how to mimic the changes in VIX using these first five years of data.

First of all, Panel A shows that FVIX and FVIXT are very similar to each other. The correlation between them (see the last column of Panel A) is 0.939. The correlation between FVIXT and the change in VIX is 0.496, whereas the correlation between FVIX and the change in VIX is 0.542. FVIX comes closer to mimicking the change in VIX, because it uses superior information, but the difference is not large.

Second, the in 1991-2006 sample, I find that the factor premium of FVIXT is even larger than the factor premium of FVIX: the average raw return (the CAPM alpha) of FVIX is -1.13% per month, t-statistic -4.51 (-0.7% per month, t-statistic -2.95), versus the average raw return (the CAPM alpha) of FVIXT of -2.02% per month, t-statistic -4.22 (-1.28% per month, t-statistic -2.72). The average return and the CAPM alpha of FVIXT do look extreme, but they are also expectedly noisier.

In Panel B of Table 11, I reestimate the ICAPM for the five arbitrage portfolios from Table 10 replacing FVIX by FVIXT and using the sample from January 1991 to December 2006. If the results in the previous sections are not influenced by the look-ahead bias, the ICAPM with FVIXT in 1991-2006 should produce the same alphas as the ICAPM with FVIX in 1991-2006. In untabulated results, I find that the ICAPM with FVIX produces similar alphas in 1986-2006 and 1991-2006. The FVIXT betas should be about twice smaller than FVIX betas in 1991-2006, because the factor premium of FVIXT is twice larger than the factor premium of FVIX, and again, in untabulated results I find that the FVIX betas are similar in 1986-2006 and 1991-2006.

In the left column of each part of Panel B (the left part looks at value-weighted returns, the right part considers equal-weighted returns), I report the CAPM alphas in 1991-2006. I find that the turnover effect and its association with market-to-book, credit rating, and institutional ownership are still there in the shorter sample, and the alphas of the five arbitrage portfolios are significant (with the expected exception of the Turn Lev portfolio) and hover around 1% per month, in some instances climbing as high as 1.5% and 2% per month. The CAPM alphas in 1991-2006 are quite close to the CAPM alphas in 1986-2006, hence FVIXT has the same distance to go as FVIX in the rest of the paper.

In the middle columns of both parts of Panel B I show that FVIXT works as well as FVIX in the rest of the paper. The vast majority of the alphas become insignificant after I control for FVIXT and they are reduced to the close vicinity of zero. The few exceptions when the alphas remain significant (but are reduced by about a half compared to the CAPM alphas) are common to both the ICAPM with FVIX and the ICAPM with FVIXT.

In the right columns I report the FVIXT betas of the five anomalous portfolios and find that all FVIXT betas are sizeable, negative, and significant (the only exceptions are the Turn Lev portfolios and the value-weighted Turn Cred portfolio), just as the respective FVIX betas in the rest of the paper. The magnitude of the FVIXT betas is indeed twice smaller than the magnitude of the FVIX betas, reflecting the difference in the factor risk premiums.

I conclude therefore that the results in the paper are not contaminated by the potential look-ahead bias in FVIX. I can achieve very similar results using the fully tradable version of FVIX that uses only the information available to the econometrician in each moment of time. I prefer the full-sample version of FVIX because it is less noisy and using it allows me to keep five more years of data (1986-1990) that I have to forego to the learning sample if I have to use the tradable version of FVIX.

6.3 Alternative Definitions of Turnover

In this subsection I briefly describe the untabulated results of the attempts to make sure that the turnover effect and its aggregate volatility risk explanation are robust to reasonable variations in research design. First, I split the sample into NYSE/AMEX (exchcd=1 and exchcd=2) firms and NASDAQ (exchcd=3) firms. The NASDAQ turnover is usually, but not always, double counted, and the crude adjustment of dividing the NASDAQ turnover by two I use in the previous sections may not be sufficient. Sorting NYSE/AMEX firms and NASDAQ firms separately is a simple way to make sure that I am comparing comparable variables.

I find that the turnover effect is strong and significant both in the NYSE/AMEX subsample and the NASDAQ subsample irrespective of whether I look at equal-weighted or value-weighted returns. The FVIX factor explains the turnover effect completely in value-weighted returns and materially reduces it in equal-weighted returns both for the NYSE/AMEX firms and the NASDAQ firms. I also find that in the NASDAQ subsample both the turnover effect and its aggregate volatility risk explanation are twice stronger than in the NYSE/AMEX subsample, which is consistent with my hypothesis that the turnover effect and its aggregate volatility risk explanation are stronger for the firms with abundant real options (the firms on NASDAQ generally have higher market-to-book and lower credit rating).

One can argue that only unexpected turnover reflects uncertainty/disagreement. Indeed, if the turnover jumps at an announcement day, we can interpret its magnitude as a proxy for the amount of information in the announcement and the amount of disagreement about this information. But if the turnover is high day after day, it most likely reflects the fact that the stock is cheap to trade and investors use it, say, for portfolio rebalancing. Therefore, one hypothesis can be that if turnover is indeed proxying for uncertainty/disagreement, a measure of unexpected turnover will create a stronger turnover effect and have a stronger link with aggregate volatility risk.

In untabulated results, I use two measures of what is close to unexpected turnover at the annual level. First, I look at the industry-adjusted turnover, defined as the firm-level turnover less the median turnover of the firms in the same industry in the same year. The firms are classified by industry using the Fama-French (1997) 30-industry classification. The industry-adjusted turnover presumably captures only the abnormally high turnover caused by firm-specific factors, and therefore can be a better measure of firm-level uncertainty than raw turnover.

I also look at the unexpected turnover defined as the residual from the market model for turnover. For each firm-month, I use the prior 36 months of turnover data for this firm and regress the firm's turnover on the average turnover in the market. I use the coefficients from this regression run in the previous 36 months to determine the unexpected turnover in the current firm-month. This is a slightly different view on the unexpected turnover, because the benchmark is not the industry, but instead the trading activity in the whole market and the usual responsiveness of the firm's turnover to the average trading activity in the market.

I sort firms on both measures of unexpected turnover and discover that the turnover effect is about the same in the sorts on industry-adjusted turnover as in the sorts on the raw turnover in Table 4. The spread in the FVIX betas in the sorts on industry-adjusted turnover is sizeable and significant, but almost twice smaller than the similar spread in Table 4. In the sorts on the regression-based unexpected turnover the turnover effect is twice smaller, though still significant, and the difference in the FVIX betas between low and high turnover firms is even smaller than in the sorts on industry-adjusted turnover, but still significant.

The fact that both the turnover effect and its association with aggregate volatility risk exist when I look at the measures of unexpected turnover is reassuring, but the fact that both the turnover effect and its association with aggregate volatility risk are weaker in the sorts on unexpected turnover is surprising. I suspect that at the annual level even expected turnover can be a good measure of uncertainty/disagreement. For example, if the firm exists in a high uncertainty industry, the industry-level uncertainty will still create a hedge against aggregate volatility risk both for this firm and all other firms in the industry. The median turnover in the high uncertainty industry is likely to be high, picking up the industry-level uncertainty, and deducting this median turnover from the firm-level turnover does not make the remaining part of turnover a better measure of uncertainty or aggregate volatility risk, just as my empirical results would suggest.

7 Conclusion

This paper shows that turnover is related to firm-specific uncertainty and the consequent hedging ability against aggregate volatility risk and unrelated to liquidity and liquidity risk. High turnover firms have much higher idiosyncratic volatility, analyst forecast dispersion, analyst forecast errors, and the variance of earnings and cash flows than low turnover firms. On the other hand, the link between turnover and the measures of price impact is weak and unreliable, and the link between turnover and the measures of liquidity risk is non-existent.

The reason why higher uncertainty implies lower expected returns is two-fold. First, as the uncertainty about the underlying asset increases, the value of the real option becomes less sensitive to changes in its value. The beta of the option equals the beta of the underlying asset times the sensitivity of the option's value to the changes in the underlying asset's value. The beta of the underlying asset does not change with firm-specific uncertainty. The decrease in the sensitivity of the real option value to the value of the underlying asset means that the beta of the real option decreases in firm-specific uncertainty. This drop in risk exposure is particularly useful in the periods of high aggregate volatility, when firm-specific uncertainty and expected risk premium are high and consumption is low. Second, the increase in firm-specific uncertainty in the periods of high aggregate volatility means an increase in the real option value, and this effect is most pronounced for high uncertainty firms.

Both effects imply that high uncertainty firms, in particular high turnover firms, beat the CAPM when aggregate volatility increases, especially if these firms have valuable real options. Investors require lower risk premium from high uncertainty (high turnover) firms, because these firms deliver better-than-expected returns when investors have to cut consumption for consumption-smoothing (Campbell, 1993) and precautionary savings (Chen, 2002) motives. Hence, high turnover firms hedge against aggregate volatility risk, and this hedging ability increases with the amount of real options they have.

I find that low turnover firms load negatively and high turnover firms load positively on the FVIX factor that tracks changes in aggregate volatility. The difference in the FVIX betas is large enough to explain the negative relation between turnover and future returns (the turnover effect). Consistent with my view that turnover proxies for firm-specific uncertainty and the uncertainty reduces the firm's risk through real options, I find that the effect of turnover on future returns increases with leverage and market-to-book and decreases with credit rating. These cross-sectional patterns in the turnover effect are explained by the FVIX factor. The FVIX betas suggest that the ability of high turnover firms to beat the CAPM in the periods of increasing aggregate volatility indeed increases in market-to-book and leverage and decreases in credit rating.

While the FVIX factor does not need the help of liquidity factors to explain the turnover effect, I try the Pastor and Stambaugh (2003) factor, the Sadka (2006) factor, and the arbitrage portfolio based on the Amihud (2002) price impact measure as the potential explanatory factors for the turnover effect. I find that neither of these factors can explain the turnover effect and neither of these factors has an overlap with the FVIX factor that does explain the turnover effect. Moreover, I find that the low minus high turnover portfolio, suggested as a liquidity factor by Eckbo and Norli (2002, 2005) cannot explain the spread in returns produced by the sorts on the three liquidity measures above.

I also consider the mispricing explanations of the turnover effect and find that the turnover effect and its aggregate volatility risk explanation remain visible for five and more years after portfolio formation, apparently inconsistent with the mispricing story. Furthermore, the evidence that the turnover effect is stronger for the firms with low institutional ownership, while consistent with the mispricing story, can be explained by the FVIX factor.

I check the robustness of my results replacing the FVIX factor by the change in VIX, which is the variable it mimics, or using another variation of the factor-mimicking procedure to form the FVIX factor. I find that my main conclusion that high turnover firms beat the CAPM when aggregate volatility increases and that this is more true about high turnover firms with abundant real options is robust to these changes in research design. The main conclusion is also robust to sorting on turnover separately in the NYSE/AMEX subsample and the NASDAQ subsample, and to sorting on industry-adjusted and unexpected turnover.

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Table 1. Descriptive Statistics: Turnover Sorts

The table presents descriptive statistics for the turnover quintiles. Turnover, which is trading volume divided by shares outstanding (both from CRSP), is measured monthly and averaged in each firm-year (at least 5 valid observations are required). The turnover portfolios are rebalanced annually. NASDAQ (exchcd=3) turnover is divided by 2. The quintiles use NYSE (exchcd=1) breakpoints. The alphas and betas are computed using equal-weighted returns. The betas are from the Fama-French (1993) model.

All firm characteristics are medians measured at the portfolio formation month. Size is shares outstanding times price from the CRSP monthly returns file. Market-to-book is defined as equity value (Compustat item #25 times Compustat item #199) divided by book equity (Compustat item #60) plus deferred taxes (Compustat item #74). Leverage is long-term debt (Compustat item #9) plus short-term debt (Compustat item #34) divided by equity value (Compustat item #25 times Compustat item #199).

Idiosyncratic volatility is defined as the standard deviation of residuals from the Fama-French model, fitted to the daily data for each month (at least 15 valid observations are required). Analyst forecast dispersion (Disp) is the standard deviation of all outstanding earnings-per-share forecasts for the current fiscal year scaled by the absolute value of the outstanding earnings forecast (zero-mean forecasts and forecasts by only one analyst excluded). ErrQtr (ErrAnn) is analyst forecast error for one-quarter-ahead (one-year-ahead) earnings.

The Amihud (2002) Illiquidity measure (Illiq) is the average ratio of absolute return to dollar volume. The ratio is computed daily and averaged within each firm-year (firms with less than 200 valid return observations in a year and the stock price of less than \$5 at the end of the previous year are excluded). γ_{PS} is the firm return sensitivity to the firm previous day dollar volume times the sign of the previous date return. γ_{PS} is computed only for NYSE (exchcd=1) and AMEX (exchcd=2) shares. The dollar volume is scaled by the ratio of the current total market value of NYSE and AMEX shares to the total market value of NYSE and AMEX shares in January 1963.

The turnover quintile portfolios sensitivities to the Sadka factor (β_{Sadka}), the traded Pastor-Stambaugh factor (β_{PS}), and the Amihud factor (β_{Amihud}) are from the monthly regression of the portfolio returns on the three Fama-French factors and the respective liquidity factor. The Sadka (2006) non-traded factor is the innovations to the market-wide average of the variable (information-based) price impact (Kyle's λ). The Pastor-Stambaugh (2003) traded factor is the equal-weighted return differential between the top decile and bottom deciles of firms sorted on the return sensitivity to the innovation to the market-wide average of γ_{PS}. The Amihud (2002) illiquidity non-traded factor is the innovation to the monthly market-wide average ratio of absolute return to dollar volume (at least 15 valid return and volume observations within each firm-month are required).

The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1964 to December 2006 for all firm characteristics except for ErrQtr and ErrAnn (January 1984 - December 2006), Disp (January 1980 - December 2006), β_{PS} and β_{Amihud} (January 1971 - December 2006) and β_{Sadka} (January 1988 - December 2006).

Panel A. Turnover and Firm Characteristics

	Low	Turn2	Turn3	Turn4	High	L-H
Return	1.444	1.316	1.169	1.126	0.955	0.488
t-stat	*5.04*	*4.36*	*3.57*	*3.09*	*2.24*	*1.85*
$\boldsymbol{\beta}_{MKT}$	0.817	0.977	1.073	1.172	1.278	-0.461
t-stat	*22.3*	*32.6*	*35.3*	*34.0*	*28.6*	*-7.86*
$\boldsymbol{\beta}_{SMB}$	0.724	0.770	0.830	0.952	1.126	-0.403
t-stat	*11.0*	*14.1*	*13.1*	*11.5*	*14.5*	*-5.65*
$\boldsymbol{\beta}_{HML}$	0.545	0.329	0.302	0.244	-0.097	0.642
t-stat	*7.34*	*5.97*	*4.95*	*3.15*	*-1.07*	*7.67*
MB	1.386	1.544	1.573	1.606	1.806	0.420
t-stat	*10.9*	*11.8*	*10.7*	*10.8*	*12.3*	*3.74*
Lev	0.207	0.225	0.239	0.249	0.232	0.025
t-stat	*10.7*	*13.0*	*13.7*	*13.5*	*12.0*	*1.31*
Cred	11.614	8.886	8.591	9.568	11.477	-0.136
t-stat	*19.8*	*17.7*	*29.0*	*30.9*	*47.2*	*-0.24*
Size	113	426	535	532	505	392
t-stat	*7.05*	*3.00*	*3.14*	*3.24*	*2.99*	*2.41*

Panel B. Turnover and Uncertainty

	Low	Turn2	Turn3	Turn4	High	L-H
ErrQtr	0.111	0.117	0.123	0.143	0.182	0.071
t-stat	*26.5*	*21.5*	*20.5*	*19.7*	*17.3*	*8.89*
ErrAnn	0.088	0.091	0.104	0.122	0.171	0.082
t-stat	*20.9*	*19.2*	*18.2*	*18.5*	*14.6*	*8.55*
IVol	0.015	0.015	0.016	0.018	0.022	0.007
t-stat	*21.2*	*20.3*	*21.3*	*20.0*	*18.4*	*5.78*
Disp	0.034	0.033	0.038	0.045	0.057	0.023
t-stat	*7.91*	*7.57*	*6.56*	*6.77*	*6.50*	*4.61*

Panel C. Turnover and Liquidity

	Low	Turn2	Turn3	Turn4	High	L-H
Illiq	0.515	0.164	0.155	0.178	0.134	-0.382
t-stat	*4.45*	*3.19*	*2.92*	*2.63*	*2.65*	*-4.01*
$\boldsymbol{\gamma}_{PS}$	-0.300	-0.081	-0.102	-0.147	-0.108	0.192
t-stat	*-4.63*	*-3.71*	*-3.72*	*-3.27*	*-4.84*	*2.60*
$\boldsymbol{\beta}_{Sadka}$	0.105	-0.212	-0.349	-0.442	-0.964	1.069
t-stat	*0.49*	*-0.81*	*-1.29*	*-1.20*	*-2.34*	*2.84*
$\boldsymbol{\beta}_{PS}$	-0.011	-0.019	-0.016	-0.036	-0.048	0.036
t-stat	*-0.38*	*-0.64*	*-0.56*	*-1.15*	*-1.08*	*0.83*
$\boldsymbol{\beta}_{Amihud}$	-0.860	-0.930	-1.058	-0.915	0.249	-1.109
t-stat	*-1.41*	*-1.93*	*-2.31*	*-1.68*	*0.42*	*-1.41*

Table 2. Turnover, Liquidity, and Uncertainty

The table presents the Fama-MacBeth regressions of monthly turnover (dollar trading volume as a fraction of market capitalization) on the lagged measures of uncertainty, lagged measures of liquidity, and controls. The measures of uncertainty are idiosyncratic volatility of the firm's returns (IVol), standard deviation of analyst forecasts of one-quarter ahead earnings (Disp), analyst forecast error for one-quarter-ahead earnings (ErrQtr), the variance of earnings (VarEarn, measured during the past twelve quarters), and the variance of cash flows (VarCF, measured during the past twelve quarters). The detailed description of all variables are in the header of Table 1. IVol, Disp, and ErrQtr are lagged by one month compared to the turnover. VarEarn and VarCF are lagged by three months.

The measures of liquidity are the Amihud (Illiq) and Pastor-Stambaugh (γ_{PS}) price impact measures and the betas with respect to the Sadka (β_{Sadka}), Pastor-Stambaugh (β_{PS}), and Amihud (β_{Amihud}) economy-wide illiquidity factors. High values of all measures, except for the Pastor-Stambaugh gamma, mean illiquidity. The detailed description of all variables are in the header of Table 1. All variables, except for the Amihud illiquidity measure, are lagged by one month, the Amihud measure is lagged by one year.

The controls used, but not reported, in every regression are positive and negative returns in the previous month (equal to the return if it is positive/negative, zero otherwise), market leverage, market-to-book, stock price, market capitalization, market beta of the firm in the past 60 months, the firm's age (number of months it appears on CRSP), number of analysts following the firm. All controls, except for market-to-book and leverage, are lagged by one month, market-to-book and leverage are lagged by one year.

All explanatory variables are transformed into rank variables between zero and one. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is determined by the availability of the uncertainty and liquidity proxies (see the last paragraph in the header of Table 1). In Panel C, the sample period is from January 1988 to December 2006.

Panel A. Turnover and Uncertainty

	1	**2**	**3**	**4**	**5**	**6**
IVol	0.606					1.189
t-stat	*8.42*					*18.1*
Disp		0.252				0.152
t-stat		*7.01*				*4.69*
ErrQtr			0.345			0.193
t-stat			*10.7*			*7.77*
VarEarn				0.352		0.424
t-stat				*8.50*		*15.0*
VarCF					0.212	0.206
t-stat					*5.66*	*6.49*
Controls	YES	YES	YES	YES	YES	YES

Panel B. Turnover and Liquidity

	1	2	3	4	5	6
Illiq		-2.401				-4.322
t-stat		*-7.15*				*-8.40*
$\boldsymbol{\gamma}_{PS}$	0.011					-0.006
t-stat	*2.62*					*-1.20*
$\boldsymbol{\beta}_{PS}$			0.001			-0.013
t-stat			*0.08*			*-0.57*
$\boldsymbol{\beta}_{Sadka}$				-0.028		0.050
t-stat				*-1.80*		*3.04*
$\boldsymbol{\beta}_{Amihud}$					0.034	0.048
t-stat					*3.32*	*2.10*
Controls	YES	YES	YES	YES	YES	YES

Table 3. Turnover Effect and Real Options

The table presents the results of firm-level Fama-MacBeth regressions run each month. The dependent variable is raw monthly return. All independent variables, except for the market beta, are ranks with values between zero and one. All independent variables are from the previous calendar year, except for idiosyncratic volatility that is lagged by a month, and the market beta that is not lagged. Idiosyncratic volatility is defined as the standard deviation of residuals from the Fama-French model, fitted to the daily data for each firm-month (at least 15 valid observations are required). The market beta comes from the same regression. Turnover is trading volume divided by shares outstanding (both from CRSP). Turnover is measured monthly and averaged in each firm-year (at least 5 valid observations are required). Market-to-book is defined as equity value (Compustat item #25 times Compustat item #199) divided by book equity (Compustat item #60) plus deferred taxes (Compustat item #74). Leverage is long-term debt (Compustat item #9) plus short-term debt (Compustat item #34) divided by equity value (Compustat item #25 times Compustat item #199). The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1964 to December 2006.

	1	**2**	**3**	**4**	**5**	**6**	**7**
Beta	0.339	0.340	0.339	0.340	0.340	0.341	0.340
t-stat	*8.23*	*8.26*	*8.26*	*8.31*	*8.34*	*8.35*	*8.35*
Size	-0.875	-0.885	-1.557	-0.855	-1.366	-0.870	-1.494
t-stat	*-2.43*	*-2.45*	*-4.10*	*-2.41*	*-3.72*	*-2.45*	*-3.99*
MB	-0.986	-0.820	-1.040	-1.152	-1.522	-0.785	-0.955
t-stat	*-4.65*	*-3.90*	*-3.77*	*-6.35*	*-6.14*	*-3.72*	*-3.43*
Turn	-0.756	-0.603	-0.294	-0.456	-0.473	-0.015	0.274
t-stat	*-2.95*	*-2.35*	*-1.15*	*-1.40*	*-1.46*	*-0.04*	*0.79*
MB*Turn		-0.300	-0.890			-0.750	-1.320
t-stat		*-0.98*	*-2.96*			*-2.58*	*-4.51*
Lev*Turn				-0.580	-0.500	-0.710	-0.690
t-stat				*-2.20*	*-1.93*	*-2.69*	*-2.63*
MB*Size			1.290		0.980		1.180
t-stat			*3.69*		*2.89*		*3.40*

Table 4. Turnover Effect and Aggregate Volatility Risk

The table reports the alphas and the FVIX betas for the turnover quintiles. The following models are used for measuring the alphas and betas: the CAPM, the Fama-French model, the CAPM augmented with FVIX (ICAPM), and the Fama-French model augmented with FVIX (FF4). FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX, the implied volatility of one-month options on S&P 100. Turnover, which is trading volume divided by shares outstanding (both from CRSP), is measured monthly and averaged in each firm-year (at least 5 valid observations are required). The turnover portfolios are rebalanced annually. The sorts on turnover are conditional on size. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006.

Panel A. Value-Weighted Returns

	Low	Turn2	Turn3	Turn4	High	L-H
$\boldsymbol{\alpha}_{CAPM}$	0.255	0.216	-0.006	-0.037	-0.328	0.584
t-stat	*2.15*	*1.70*	*-0.06*	*-0.41*	*-1.86*	*2.15*
$\boldsymbol{\alpha}_{ICAPM}$	-0.028	-0.119	-0.155	-0.055	0.121	-0.149
t-stat	*-0.32*	*-1.11*	*-1.49*	*-0.70*	*0.79*	*-0.73*
$\boldsymbol{\beta}_{FVIX}$	-0.502	-0.594	-0.264	-0.033	0.797	-1.299
t-stat	*-7.20*	*-7.27*	*-2.82*	*-0.51*	*8.82*	*-11.5*
$\boldsymbol{\alpha}_{FF}$	0.074	0.068	-0.072	-0.063	-0.080	0.153
t-stat	*0.83*	*0.69*	*-0.81*	*-0.75*	*-0.54*	*0.74*
$\boldsymbol{\alpha}_{FF4}$	-0.030	-0.074	-0.153	-0.067	0.013	-0.043
t-stat	*-0.36*	*-0.83*	*-1.76*	*-0.82*	*0.08*	*-0.20*
$\boldsymbol{\beta}_{FVIX}$	-0.805	-1.098	-0.625	-0.034	0.717	-1.522
t-stat	*-4.54*	*-6.02*	*-3.83*	*-0.15*	*2.16*	*-3.94*

Panel B. Equal-Weighted Returns

	Low	Turn2	Turn3	Turn4	High	L-H
$\boldsymbol{\alpha}_{CAPM}$	0.725	0.228	-0.036	-0.272	-0.886	1.611
t-stat	*2.79*	*0.98*	*-0.16*	*-1.19*	*-3.37*	*5.88*
$\boldsymbol{\alpha}_{ICAPM}$	0.680	0.353	0.127	-0.018	-0.257	0.937
t-stat	*2.57*	*1.33*	*0.49*	*-0.07*	*-0.84*	*4.37*
$\boldsymbol{\beta}_{FVIX}$	-0.079	0.222	0.289	0.449	1.114	-1.194
t-stat	*-0.76*	*2.02*	*2.87*	*4.61*	*8.81*	*-11.6*
$\boldsymbol{\alpha}_{FF}$	0.409	0.048	-0.177	-0.359	-0.706	1.116
t-stat	*2.91*	*0.37*	*-1.50*	*-2.69*	*-4.00*	*5.22*
$\boldsymbol{\alpha}_{FF4}$	0.363	-0.001	-0.200	-0.373	-0.629	0.992
t-stat	*2.46*	*-0.01*	*-1.62*	*-2.70*	*-3.17*	*4.52*
$\boldsymbol{\beta}_{FVIX}$	-0.362	-0.380	-0.177	-0.104	0.599	-0.961
t-stat	*-1.31*	*-1.68*	*-0.74*	*-0.40*	*1.71*	*-3.27*

Table 5. Turnover Effect, Real Options, and Aggregate Volatility Risk

The table reports the alphas and betas of the turnover arbitrage portfolio across market-to-book (Panel A), leverage (Panel B), and credit rating (Panel C) quintiles. The following models are used for measuring the alphas and betas: the CAPM, the Fama-French model, the CAPM augmented with FVIX (ICAPM), and the Fama-French model augmented with FVIX (FF4). The turnover arbitrage portfolio is long in the lowest turnover quintile and short in the highest turnover quintile. The sorts on turnover and market-to-book are conditional on size, the sorts on leverage and credit rating are conditional on size and market-to-book. The market-to-book, leverage, and credit rating are from the previous fiscal year ending no later than in June, and from the fiscal year before that if the fiscal year end is between July and December. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006.

Panel A. Turnover Effect, Market-to-Book, and Aggregate Volatility Risk

	Value	**MB2**	**MB3**	**MB4**	**Growth**	**G-V**
$\boldsymbol{\alpha}_{CAPM}$	0.808	1.121	0.842	0.879	1.614	0.806
t-stat	*2.89*	*4.36*	*3.34*	*3.68*	*5.44*	*2.92*
$\boldsymbol{\alpha}_{ICAPM}$	0.579	0.743	0.304	0.365	0.878	0.299
t-stat	*2.01*	*2.67*	*1.31*	*1.63*	*3.75*	*1.24*
$\boldsymbol{\beta}_{FVIX}$	-0.405	-0.669	-0.953	-0.910	-1.304	-0.899
t-stat	*-3.64*	*-3.55*	*-7.30*	*-6.32*	*-11.8*	*-9.85*

Panel B. Turnover Effect, Leverage, and Aggregate Volatility Risk

	Low	**Lev2**	**Lev3**	**Lev4**	**High**	**L-H**
$\boldsymbol{\alpha}_{CAPM}$	0.333	0.161	0.813	0.684	0.750	0.417
t-stat	*0.78*	*0.39*	*1.78*	*1.69*	*1.81*	*0.86*
$\boldsymbol{\alpha}_{ICAPM}$	-0.562	-0.975	-0.107	0.023	0.196	0.758
t-stat	*-1.63*	*-3.28*	*-0.27*	*0.06*	*0.47*	*1.50*
$\boldsymbol{\beta}_{FVIX}$	-1.587	-2.013	-1.630	-1.172	-0.981	0.606
t-stat	*-4.19*	*-13.7*	*-8.48*	*-4.21*	*-4.76*	*1.28*
$\boldsymbol{\alpha}_{FF}$	-0.298	-0.621	0.370	0.447	0.634	0.932
t-stat	*-0.95*	*-2.10*	*0.97*	*1.20*	*1.62*	*1.94*
$\boldsymbol{\alpha}_{FF4}$	-0.284	-0.807	0.070	0.247	0.399	0.683
t-stat	*-0.83*	*-2.68*	*0.19*	*0.62*	*0.98*	*1.26*
$\boldsymbol{\beta}_{FVIX}$	0.107	-1.446	-2.326	-1.558	-1.826	-1.933
t-stat	*0.10*	*-2.71*	*-3.49*	*-1.81*	*-2.60*	*-1.70*

Panel C. Turnover Effect, Credit Rating, and Aggregate Volatility Risk

	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**W-B**
$\boldsymbol{\alpha}_{CAPM}$	-0.192	0.087	0.563	0.738	0.711	0.903
t-stat	*-0.84*	*0.39*	*2.02*	*2.83*	*2.02*	*2.22*
$\boldsymbol{\alpha}_{ICAPM}$	-0.203	0.131	0.342	0.683	0.184	0.387
t-stat	*-0.87*	*0.55*	*1.22*	*2.55*	*0.59*	*1.05*
$\boldsymbol{\beta}_{FVIX}$	-0.020	0.076	-0.391	-0.097	-0.933	-0.914
t-stat	*-0.16*	*0.51*	*-3.80*	*-0.83*	*-5.69*	*-7.23*

Table 6. Liquidity Sorts, Future Returns, and Aggregate Volatility Risk

The table reports the alphas, the FVIX betas, and the turnover betas for the liquidity quintiles. The following models are used for measuring the alphas and betas: the CAPM, the Fama-French model, the CAPM augmented with FVIX, and the CAPM augmented with the turnover factor (LMH). FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX, the implied volatility of one-month options on S&P 100. LMH is the portfolio that buys low turnover firms and shorts high turnover firms. This strategy is followed separately for the firms above and below the NYSE median market cap, and the simple average of the two returns is the return to LMH. The liquidity measures employed in the sorts are the loadings on the non-traded Pastor-Stambaugh factor (Panel A), the loadings on the non-traded Sadka factor (Panel B), and the Amihud price impact measure (Panel C). The detailed description of the liquidity factors is in the header of Table 1. Higher values of all measures mean higher levels of illiquidity. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006.

Panel A. Loadings on the Pastor-Stambaugh Factor, Future Returns, and Aggregate Volatility Risk

	Liquid	**PS2**	**PS3**	**PS4**	**Illiquid**	**I-L**
$\boldsymbol{\alpha}_{CAPM}$	-0.486	0.056	0.103	0.124	0.107	0.594
t-stat	*-3.55*	*0.58*	*1.41*	*1.55*	*0.96*	*3.14*
$\boldsymbol{\alpha}_{FF}$	-0.392	-0.008	0.025	0.051	0.151	0.543
t-stat	*-2.87*	*-0.09*	*0.41*	*0.69*	*1.33*	*2.86*
$\boldsymbol{\alpha}_{FVIX}$	-0.340	-0.109	-0.067	0.008	0.209	0.549
t-stat	*-2.32*	*-1.15*	*-1.13*	*0.10*	*1.80*	*2.85*
$\boldsymbol{\beta}_{FVIX}$	0.259	-0.291	-0.300	-0.204	0.180	-0.079
t-stat	*3.18*	*-3.97*	*-4.46*	*-2.64*	*2.14*	*-0.78*
$\boldsymbol{\alpha}_{LMH}$	-0.349	-0.076	-0.016	0.105	0.291	0.641
t-stat	*-2.44*	*-0.88*	*-0.25*	*1.16*	*2.70*	*3.29*
$\boldsymbol{\beta}_{LMH}$	-0.186	0.179	0.161	0.025	-0.249	-0.063
t-stat	*-4.55*	*4.72*	*3.86*	*0.42*	*-4.36*	*-0.97*

Panel B. Loadings on the Sadka Factor,
Future Returns, and Aggregate Volatility Risk

	Liquid	Sadka2	Sadka3	Sadka4	Illiquid	I-L
$\boldsymbol{\alpha}_{CAPM}$	-0.391	-0.076	0.180	0.142	0.008	0.399
t-stat	*-2.93*	*-0.81*	*1.97*	*1.87*	*0.08*	*2.90*
$\boldsymbol{\alpha}_{FF}$	-0.357	-0.156	0.112	0.128	0.048	0.405
t-stat	*-2.85*	*-1.74*	*1.39*	*1.79*	*0.49*	*2.82*
$\boldsymbol{\alpha}_{FVIX}$	-0.278	-0.232	0.030	0.049	0.075	0.352
t-stat	*-2.12*	*-2.66*	*0.40*	*0.59*	*0.77*	*2.49*
$\boldsymbol{\beta}_{FVIX}$	0.208	-0.286	-0.275	-0.170	0.123	-0.085
t-stat	*1.90*	*-4.32*	*-6.67*	*-2.41*	*1.48*	*-1.22*
$\boldsymbol{\alpha}_{LMH}$	-0.197	-0.153	0.082	0.050	0.100	0.296
t-stat	*-1.48*	*-1.77*	*1.01*	*0.57*	*1.08*	*1.99*
$\boldsymbol{\beta}_{LMH}$	-0.269	0.107	0.136	0.128	-0.127	0.142
t-stat	*-3.11*	*2.83*	*5.86*	*2.30*	*-2.20*	*2.16*

Panel C. Sorts on the Amihud Illiquidity Measure,
Future Returns, and Aggregate Volatility Risk

	Liquid	Ami2	Ami3	Ami4	Illiquid	I-L
$\boldsymbol{\alpha}_{CAPM}$	-0.076	0.075	0.125	0.144	0.204	0.280
t-stat	*-0.71*	*0.72*	*1.08*	*1.43*	*1.95*	*2.31*
$\boldsymbol{\alpha}_{FF}$	-0.157	-0.096	-0.083	-0.051	0.063	0.220
t-stat	*-1.81*	*-1.38*	*-1.04*	*-0.66*	*0.75*	*1.96*
$\boldsymbol{\alpha}_{FVIX}$	-0.192	-0.133	-0.129	-0.058	0.101	0.293
t-stat	*-2.36*	*-2.05*	*-1.84*	*-0.72*	*0.87*	*2.02*
$\boldsymbol{\beta}_{FVIX}$	-0.206	-0.370	-0.451	-0.358	-0.183	0.023
t-stat	*-2.09*	*-8.34*	*-8.32*	*-5.81*	*-1.69*	*0.12*
$\boldsymbol{\alpha}_{LMH}$	-0.075	-0.016	-0.006	0.039	0.137	0.212
t-stat	*-0.80*	*-0.17*	*-0.07*	*0.43*	*1.18*	*1.48*
$\boldsymbol{\beta}_{LMH}$	-0.001	0.124	0.178	0.141	0.091	0.092
t-stat	*-0.02*	*2.37*	*3.13*	*2.83*	*1.27*	*0.72*

Table 7. Turnover Effect and Liquidity Factors

The table reports the alphas, the liquidity betas, and the FVIX betas for the turnover quintiles. The table presents the CAPM alphas (α_{CAPM}), the alphas (α_{PS}) and the liquidity betas (β_{PS}) from the two-factor model with the market factor and the Pastor and Stambaugh traded factor, the alphas (α_{Amihud}) and the liquidity betas (β_{Amihud}) from the two-factor model with the market factor and the Amihud factor, and the alphas (α_{Sadka}) and the liquidity betas (β_{Sadka}) from the two-factor model with the market factor and the Sadka traded factor.

The Amihud factor is the value-weighted return differential between the top quintile and the bottom quintile of firms sorted on the average ratio of daily returns to daily trading volume (price impact) in the previous year. The Pastor-Stambaugh traded factor is the value-weighted return differential between the top decile and the bottom decile of firms sorted on the betas with respect to innovations in the Pastor-Stambaugh economy-wide illiquidity measure. The Sadka factor is the value-weighted return differential between the top quintile and the bottom quintile of firms sorted on the betas with respect to innovations in the Sadka economy-wide illiquidity measure. The Pastor-Stambaugh and Sadka betas are estimated from the monthly firm-level regressions of returns on the three Fama-French factors and the innovations in the Pastor-Stambaugh or Sadka illiquidity measure. The regressions use the data from the past 36 months (at least 12 valid observations are required).

The turnover portfolios are rebalanced annually. The sorts on turnover are conditional on size. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006.

Panel A. Turnover Effect and Liquidity Factors

	Value-Weighted Returns							Equal-Weighted Returns					
	Low	**Turn2**	**Turn3**	**Turn4**	**High**	**L-H**		**Low**	**Turn2**	**Turn3**	**Turn4**	**High**	**L-H**
$\boldsymbol{\alpha}_{CAPM}$	0.255	0.216	-0.006	-0.037	-0.328	0.584	$\boldsymbol{\alpha}_{CAPM}$	0.725	0.228	-0.036	-0.272	-0.886	1.611
t-stat	*2.15*	*1.70*	*-0.06*	*-0.41*	*-1.86*	*2.15*	**t-stat**	*2.79*	*0.98*	*-0.16*	*-1.19*	*-3.37*	*5.88*
$\boldsymbol{\alpha}_{PS}$	0.316	0.294	0.038	-0.021	-0.381	0.697	$\boldsymbol{\alpha}_{PS}$	0.809	0.278	0.018	-0.244	-0.895	1.704
t-stat	*2.78*	*2.65*	*0.44*	*-0.22*	*-2.11*	*2.61*	**t-stat**	*2.89*	*1.13*	*0.07*	*-1.01*	*-3.13*	*5.96*
$\boldsymbol{\beta}_{PS}$	-0.136	-0.177	-0.090	-0.009	0.105	-0.242	$\boldsymbol{\beta}_{PS}$	-0.062	-0.057	-0.062	-0.060	0.047	-0.109
t-stat	*-2.70*	*-3.24*	*-2.08*	*-0.42*	*1.32*	*-1.89*	**t-stat**	*-0.93*	*-0.67*	*-0.73*	*-0.65*	*0.33*	*-1.12*
$\boldsymbol{\alpha}_{Amihud}$	0.259	0.252	0.061	-0.006	-0.203	0.462	$\boldsymbol{\alpha}_{Amihud}$	0.688	0.235	0.001	-0.205	-0.761	1.449
t-stat	*1.93*	*1.85*	*0.68*	*-0.06*	*-1.08*	*1.55*	**t-stat**	*2.62*	*0.97*	*0.00*	*-0.83*	*-2.55*	*5.13*
$\boldsymbol{\beta}_{Amihud}$	-0.014	-0.129	-0.237	-0.112	-0.449	0.435	$\boldsymbol{\beta}_{Amihud}$	0.132	-0.022	-0.131	-0.237	-0.448	0.580
t-stat	*-0.08*	*-0.63*	*-2.26*	*-2.14*	*-1.37*	*0.88*	**t-stat**	*1.27*	*-0.14*	*-0.79*	*-1.12*	*-1.11*	*1.55*
$\boldsymbol{\alpha}_{Sadka}$	0.192	0.149	0.035	0.041	-0.171	0.363	$\boldsymbol{\alpha}_{Sadka}$	0.802	0.291	0.067	-0.204	-0.750	1.552
t-stat	*1.59*	*1.21*	*0.40*	*0.49*	*-0.93*	*1.30*	**t-stat**	*2.99*	*1.25*	*0.30*	*-0.89*	*-2.71*	*5.23*
$\boldsymbol{\beta}_{Sadka}$	0.134	0.140	-0.064	-0.139	-0.348	0.482	$\boldsymbol{\beta}_{Sadka}$	-0.182	-0.183	-0.205	-0.189	-0.349	0.166
t-stat	*2.58*	*1.93*	*-1.44*	*-2.88*	*-3.66*	*3.88*	**t-stat**	*-1.83*	*-1.44*	*-1.60*	*-1.23*	*-1.84*	*1.11*

Table 8. Turnover Effect and Short Sale Constraints

The table reports the CAPM alphas, the ICAPM alphas, and the FVIX betas for the turnover arbitrage portfolio across institutional ownership quintiles. The turnover arbitrage portfolio is long in the lowest turnover quintile and short in the highest turnover quintile. Inst is residual institutional ownership, defined as the residual from the logistic regression of institutional ownership on log size and its square. All quintiles use NYSE (exchcd=1) breakpoints. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006.

Panel A. Value-Weighted Returns

	Low	**Inst2**	**Inst3**	**Inst4**	**High**	**L-H**
$\boldsymbol{\alpha}_{CAPM}$	1.056	1.089	0.260	0.325	0.238	0.819
t-stat	*2.67*	*2.66*	*0.79*	*1.17*	*0.80*	*2.10*
$\boldsymbol{\alpha}_{ICAPM}$	0.118	0.170	-0.489	-0.144	-0.287	0.405
t-stat	*0.41*	*0.57*	*-1.42*	*-0.53*	*-0.97*	*1.19*
$\boldsymbol{\beta}_{FVIX}$	-1.662	-1.628	-1.327	-0.831	-0.929	-0.733
t-stat	*-11.7*	*-11.8*	*-6.59*	*-6.59*	*-5.80*	*-3.75*

Panel B. Equal-Weighted Returns

	Inst1	**Inst2**	**Inst3**	**Inst4**	**Inst5**	**1-5**
$\boldsymbol{\alpha}_{CAPM}$	1.616	1.845	1.022	0.939	0.617	1.000
t-stat	*4.51*	*5.03*	*3.50*	*4.21*	*2.61*	*3.29*
$\boldsymbol{\alpha}_{ICAPM}$	0.713	0.998	0.325	0.521	0.249	0.464
t-stat	*2.87*	*3.90*	*1.61*	*2.86*	*1.27*	*1.89*
$\boldsymbol{\beta}_{FVIX}$	-1.601	-1.501	-1.235	-0.740	-0.652	-0.949
t-stat	*-15.4*	*-11.4*	*-13.1*	*-5.41*	*-3.71*	*-5.08*

Table 9. Turnover Effect in Event Time

The table reports the CAPM alphas, the ICAPM alphas, and the FVIX betas of the portfolio long in low turnover firms and short in high turnover firms. FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX, the implied volatility of one-month options on S&P 100. Turnover, which is trading volume divided by shares outstanding (both from CRSP), is measured monthly and averaged in each firm-year (at least 5 valid observations are required). The names of the column indicate the period after portfolio formation in which the alphas and betas were measured. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006.

Panel A. Value-Weighted Returns

	1-6mo	**7-12mo**	**2 yr**	**3 yr**	**4 yr**	**5 yr**
$\boldsymbol{\alpha}_{CAPM}$	0.597	0.324	0.333	0.346	0.381	0.360
t-stat	*2.37*	*1.23*	*1.75*	*1.99*	*2.22*	*2.00*
$\boldsymbol{\alpha}_{ICAPM}$	-0.400	0.018	-0.243	-0.255	-0.273	-0.268
t-stat	*-1.18*	*0.06*	*-1.18*	*-1.27*	*-1.50*	*-1.44*
$\boldsymbol{\beta}_{FVIX}$	-1.424	-1.157	-1.223	-1.137	-1.117	-1.146
t-stat	*-9.06*	*-6.06*	*-10.1*	*-10.3*	*-9.64*	*-11.9*

Panel B. Equal-Weighted Returns

	1-6mo	**7-12mo**	**2 yr**	**3 yr**	**4 yr**	**5 yr**
$\boldsymbol{\alpha}_{CAPM}$	2.297	1.035	1.118	0.617	0.567	0.558
t-stat	*6.98*	*2.57*	*4.39*	*2.60*	*2.52*	*3.05*
$\boldsymbol{\alpha}_{ICAPM}$	1.287	0.626	0.606	0.152	0.088	0.147
t-stat	*4.31*	*2.20*	*2.39*	*0.68*	*0.41*	*0.80*
$\boldsymbol{\beta}_{FVIX}$	-1.226	-1.106	-0.907	-0.825	-0.848	-0.728
t-stat	*-8.29*	*-8.23*	*-6.02*	*-7.95*	*-7.85*	*-9.39*

Table 10. Turnover Effect and the Exposure to Aggregate Volatility Changes

The table reports the sensitivity to aggregate volatility changes of the anomalous arbitrage portfolios. The sensitivity is measured as the loading on the daily changes in VIX or on daily returns to FVIX in the regressions of the daily returns to the arbitrage portfolios on the daily excess return to the market portfolio and the change in VIX ($\beta_{\Delta VIX}$) or return to FVIX (β_{FVIX}). VIX is the implied volatility of one-month options on the S&P 100. FVIX is the stock portfolio that tracks daily changes in VIX.

The test assets are the portfolio long in the bottom turnover quintile and short in the top turnover quintile (Turn), the return differential between the Turn portfolio formed only in the growth (high leverage, worst credit rating) quintile and formed only in the value (low leverage, best credit rating) quintile - Turn MB (Turn Lev, Turn Cred), and the return differential between the Turn portfolio formed only in the lowest institutional ownership quintile and formed only in the highest institutional ownership quintile (Turn Inst).

Panel A looks at value-weighted returns, Panel B repeats the tests for equal-weighted returns. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006.

	Value-Weighted Returns				**Equal-Weighted Returns**		
	$\boldsymbol{\beta}_{\Delta VIX}$	$\boldsymbol{\beta}_{FVIX}$	$\boldsymbol{\beta}_{MKT}$		$\boldsymbol{\beta}_{\Delta VIX}$	$\boldsymbol{\beta}_{FVIX}$	$\boldsymbol{\beta}_{MKT}$
Turn	-0.024	-1.457	-0.687	**Turn**	-0.016	-0.853	-0.809
t-stat	*-3.16*	*-20.2*	*-19.2*	**t-stat**	*-1.87*	*-21.0*	*-34.0*
Turn MB	-0.004	-1.942	-0.323	**Turn MB**	-0.021	-1.101	-0.120
t-stat	*-0.36*	*-15.3*	*-6.77*	**t-stat**	*-2.60*	*-22.2*	*-4.45*
Turn Lev	0.094	0.961	0.386	**Turn Lev**	0.037	1.027	0.200
t-stat	*4.48*	*4.09*	*5.61*	**t-stat**	*4.40*	*19.9*	*7.40*
Turn Cred	-0.034	-1.029	*-0.45*	**Turn Cred**	*0.000*	*-0.679*	*-0.44*
t-stat	*-1.73*	*-9.12*	*-8.08*	**t-stat**	*-0.03*	*-8.83*	*-14.3*
Turn Inst	-0.071	-0.894	-0.395	**Turn Inst**	-0.024	-0.609	-0.083
t-stat	*-6.51*	*-6.86*	*-7.06*	**t-stat**	*-1.97*	*-8.25*	*-3.63*

Table 11. Turnover Effect and the Tradable Version of FVIX

Panel A compares the FVIX factor with its tradable version (FVIXT), for which the weights in the factor-mimicking portfolio are estimated using only past information. I report the correlations of FVIX and FVIXT with the change in VIX ($Corr(\Delta VIX, \cdot)$) and the correlation between FVIX and FVIXT ($Corr(FVIX, \cdot)$), as well as the average monthly returns and the CAPM alphas of both factors.

Panel B reports the ICAPM alphas and the FVIX betas of the five anomalous portfolios described in the heading of Table 10. The alphas and the FVIX betas are estimated using the tradable version of FVIX in the regression below:

$$Ret = \alpha + \beta_{MKT} \cdot MKT + \boldsymbol{\beta_{FVIXT}} \cdot FVIXT \tag{3}$$

The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1991 to December 2006.

Panel A. FVIX versus Tradable FVIX

	$\boldsymbol{Corr(\Delta VIX, \cdot)}$	**Return**	$\boldsymbol{\alpha_{CAPM}}$	$\boldsymbol{Corr(FVIX, \cdot)}$
FVIX	0.542	-1.132	-0.704	
t-stat	*8.90*	*-4.51*	*-2.95*	
FVIXT	0.496	-2.020	-1.276	0.939
t-stat	*7.87*	*-4.22*	*-2.72*	*37.5*

Panel B. Tradable FVIX instead of FVIX

Value-Weighted				**Equal-Weighted**			
	$\boldsymbol{\alpha_{CAPM}}$	$\boldsymbol{\alpha_{ICAPM}}$	$\boldsymbol{\beta_{FVIXT}}$		$\boldsymbol{\alpha_{CAPM}}$	$\boldsymbol{\alpha_{ICAPM}}$	$\boldsymbol{\beta_{FVIXT}}$
Turn	0.719	-0.065	-0.615	**Turn**	1.978	1.265	-0.559
t-stat	*2.25*	*-0.26*	*-7.53*	**t-stat**	*6.53*	*4.78*	*-10.6*
Turn MB	0.247	-0.415	-0.519	**Turn MB**	1.013	0.500	-0.402
t-stat	*0.58*	*-1.15*	*-5.44*	**t-stat**	*3.02*	*1.60*	*-5.49*
Turn Lev	0.868	1.232	0.286	**Turn Lev**	0.120	0.536	0.325
t-stat	*1.48*	*2.01*	*1.24*	**t-stat**	*0.33*	*1.55*	*5.13*
Turn Cred	1.509	1.189	-0.251	**Turn Cred**	1.724	1.130	-0.465
t-stat	*3.01*	*2.26*	*-1.51*	**t-stat**	*3.82*	*2.70*	*-3.56*
Turn Inst	1.101	0.528	-0.450	**Turn Inst**	1.071	0.421	-0.509
t-stat	*2.48*	*1.43*	*-5.15*	**t-stat**	*2.93*	*1.59*	*-5.12*