Turnover: Liquidity or Uncertainty?

Abstract

I show that turnover is unrelated to several alternative measures of liquidity risk and in most cases negatively, not positively, related to liquidity. Consequently, neither liquidity nor liquidity risk explain why higher turnover predicts lower future returns. I find that the aggregate volatility risk factor explains why higher turnover predicts lower future returns. The paper shows that the negative relation between turnover and future returns is stronger for firms with option-like equity and this regularity is also explained by the aggregate volatility risk factor.

Key words: liquidity; idiosyncratic volatility; uncertainty; turnover; aggregate volatility risk

1. Introduction

The asset-pricing literature has long treated turnover (trading volume over shares outstanding) as a proxy for liquidity or liquidity risk (see, e.g., Datar et al. 1998, Rouwenhorst 1999, Eckbo and Norli 2005, and Avramov and Chordia 2006). The well-established negative cross-sectional relation between turnover and future returns (henceforth, the turnover effect) is then interpreted as evidence of the 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 et al. 1994). Turnover is found to be high if prices fluctuate greatly, if traders disagree about firm value, or if they receive a greater amount of information about the firm. 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, e.g., Lee and Swaminathan 2000, Jiang et al. 2005).

However, if turnover measures uncertainty, the negative relation between turnover and future returns is puzzling. Furthermore, most microstructure models suggest that more uncertainty indicates less liquidity, making the liquidity view of turnover and the uncertainty view of turnover natural competitors.

In this paper, I show that in asset-pricing applications, one 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. I find that high turnover firms, as other high uncertainty firms, tend to outperform firms with similar CAPM/Fama-French betas when expected aggregate volatility increases. Therefore, high turnover firms are hedges against aggregate volatility risk and, as such, should have negative CAPM/Fama-French alphas.

Campbell (1993) and Chen (2002) show that investors would require a lower risk premium from stocks, the value of which correlates least negatively with innovations to aggregate volatility, because these stocks provide additional consumption precisely when investors have to cut their current consumption for consumption-smoothing and precautionary savings motives. Ang et al. 2006 confirm this prediction empirically and coin the notion of aggregate volatility risk. They find that stocks with the least negative sensitivity to aggregate volatility increases have abnormally low expected returns. My 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.[1]

The reason why high uncertainty firms have lower aggregate volatility risk and earn lower expected returns is twofold. First, holding all else equal, real options increase in value when the uncertainty about the underlying asset increases.[2] This is helpful in recessions, when both firm-specific uncertainty and aggregate volatility increase (see Barinov 2012, Duarte et al. 2012). Therefore, real options are hedges against aggregate volatility risk, and even more so are the

[1] The hypothesis that high uncertainty firms earn low returns because they are hedges against aggregate volatility risk was successfully tested in Barinov (2011) (the aggregate volatility risk factor explained the idiosyncratic volatility effect of Ang et al. 2006) and in Barinov (2012) (the aggregate volatility risk factor explained the analyst disagreement effect of Diether et al. 2002).

[2] A recent analysis by Grullon et al. (2012) suggests that changes in firm-level uncertainty have a substantial effect on the value of real options.

real options on high-uncertainty assets, which makes uncertainty negatively related to aggregate volatility risk and to expected returns.

Second, high firm-specific uncertainty (and therefore high turnover) is negatively related to aggregate volatility risk through a mechanism similar to the one in Johnson (2004) and Barinov (2011). 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 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 uncertainty about the underlying asset do not influence its beta, they do make the elasticity, and hence, the real option's beta, smaller.

When both aggregate volatility and firm-specific uncertainty increase, 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. This effect again works through the firm-specific uncertainty and is therefore close to zero for low uncertainty firms and stronger for high uncertainty firms (the formal proof is available from the author upon request). Hence, high uncertainty (high turnover) firms should hedge against aggregate volatility risk, and this hedging ability should explain their negative alpha.[3]

Because in my theory 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 firms with valuable real options. For example, the turnover effect should be stronger for firms with high market-to-book which have abundant growth options. Also, due to

[3]The aggregate volatility risk explanation of the turnover effect is broader than the conditional CAPM that is implied by the second channel linking firm-specific uncertainty and aggregate volatility risk. While I do predict that market betas of high uncertainty (high turnover) firms decline in recessions, the conditional CAPM overlooks the fact that lower betas in recessions also mean smaller losses in recessions. Also, the first channel (higher uncertainty in recessions makes real options perform better than other assets of comparable risk) is completely outside of the conditional CAPM. Therefore, my explanation of the turnover effect is a version of the intertemporal CAPM (henceforth, ICAPM), and as such, calls for the inclusion of the aggregate volatility risk factor.

the existence of risky debt, one can view equity as a call option on the assets. I predict that the turnover effect is stronger for firms with bad credit ratings, as the equity of these firms is more option-like. In addition, the difference in aggregate volatility risk between high and low turnover firms will increase with market-to-book and decrease with credit rating.

The empirical work is organized in four sections. Section 3 shows that higher turnover implies higher effective spread. The results on the link between turnover and price impact are mixed, and liquidity risk appears unrelated to turnover. I contend that in portfolio sorts, several popular liquidity risk factors, including the Pastor and Stambaugh (2003) factor and the Sadka (2006) factor, cannot explain the turnover effect. In cross-sectional regressions, the liquidity measures do not subsume the turnover effect either.

In Section 4, I use the aggregate volatility risk factor, FVIX, to explain the turnover effect. FVIX is the factor-mimicking portfolio that mimics changes in the VIX index.[4] Before proceeding with the use of FVIX to explain the turnover effect, Section 4.1 demonstrates that turnover is strongly related to several measures of uncertainty based on returns, analyst forecasts, and actual cash flows.

Section 4.2 holds the main empirical result of the paper. I find that high/low turnover firms have positive/negative FVIX betas. Additionally, both in portfolio sorts and in Fama-MacBeth (1973) regressions, the FVIX factor can explain the turnover effect.

Consistent with the aggregate volatility risk explanation of the turnover effect that works through real options, I find that in the cross-section, the turnover effect strengthens as market-to-book increases or as credit rating deteriorates. The difference in exposure to FVIX between low and high turnover firms also increases with market-to-book and decreases with credit rating.

[4] In untabulated results, available upon request, I show that FVIX has all three properties of a valid volatility risk factor: it is tightly correlated with the change in VIX, it earns a large and significantly negative risk premium, and it is able to predict future volatility, as Chen (2002) suggests a volatility risk factor should do. I also document a strong comovement between firm-specific uncertainty and aggregate volatility, as well as evidence that the firm-specific uncertainty is more sensitive to changes in aggregate volatility for high turnover firms.

The FVIX factor thus explains why the turnover effect is stronger for firms with high market-to-book or bad credit rating. The result holds using numerous measures of option-likeness, both in double sorts and cross-sectional regressions.

Section 5 considers the possibility that the turnover effect is mispricing, as Lee and Swaminathan (2000)[5] and Nagel (2005) hypothesize, or that it picks up the effects of attention. If this is the case, I expect the turnover effect to be stronger for firms with high short-sale constraints or low attention. In equal-weighted (but not value-weighted) returns, the turnover effect is stronger for firms with low institutional ownership (IO), or with high probability to be on special or low analyst following, but these patterns in the turnover effect are explained by the FVIX factor. Earnings announcement returns are also considered as an alternative test of the mispricing hypothesis. I find that the turnover effect is not concentrated at earnings announcements, both overall and for firms with higher limits to arbitrage. My conclusion is that the turnover effect is not mispricing or an attention effect.

My paper is related to Lee and Swaminathan (2000), who also find that turnover is weakly related to firm size and the level of stock price. In this paper, I use more direct measures of liquidity, such as effective spread and price impact, and liquidity risk to show that turnover is not related to liquidity. My paper is also related to Johnson (2008) and the literature summarized therein, which shows, both theoretically and empirically, that in time-series, trading volume is unrelated to liquidity. The notable difference in this paper is that I examine the cross-sectional relation between turnover and liquidity and its implications for the ability of turnover to predict returns in the cross-section.

The main conclusion of the paper that turnover is not a good measure of liquidity has impor-

[5] While the main result of Lee and Swaminathan is that momentum is stronger for high turnover firms, they also show that high turnover firms share common characteristics with growth firms. They conclude that the turnover effect is likely to be mispricing possibly similar to the value effect. My paper extends this idea by showing that the turnover effect is explained by the same risk – aggregate volatility risk – that explains the value effect in Barinov (2011).

tant implications. In a related paper (Barinov 2013), I resolve the apparent puzzle in Chordia et al. (2001), who find that turnover variability, which they interpret as the measure of variations in liquidity, is negatively related to future returns. Consistent with the uncertainty interpretation of turnover in this paper, I find that high turnover variability is synonymous to high firm-specific uncertainty and low aggregate volatility risk exposure, and these facts can explain why higher turnover variability is associated with lower expected returns in the cross-section.

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 2010. Turnover is trading volume divided by shares outstanding (both from CRSP). Following Gao and Ritter (2010), the NASDAQ turnover is adjusted to eliminate double-counting. I divide the NASDAQ turnover by 2.0 prior to January 2001, by 1.8 for the rest of 2001, by 1.6 for 2002–2003, and leave it unchanged thereafter. Firms are classified as NASDAQ firms if the exchcd historical listing indicator from the CRSP events file is equal to 3. Following Datar et al. (1998), a quarterly measure of turnover is used, which is the average monthly turnover in the previous quarter. The results are robust to measuring turnover at other frequencies, from one month to one year.

The 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 2010. The values of the VIX index are from CBOE data on WRDS. Using the old version of the VIX provides a longer data series compared to newer CBOE indices.

I define FVIX, the aggregate volatility risk factor, as a factor-mimicking portfolio that tracks the daily changes in the VIX index. Following Ang et al. (2006), the daily changes in VIX are regressed on the daily excess returns to the five portfolios sorted on past sensitivity to VIX changes. The fitted part of this regression less the constant is my aggregate volatility risk factor

(FVIX factor). The daily returns to FVIX are then cumulated to the monthly level. All results in the paper are robust to changing the base assets from the five portfolios sorted on past sensitivity to VIX changes to the ten industry portfolios (Fama and French 1997) or the six size and book-to-market portfolios (Fama and French 1993).

The rest of the variables are defined in the sections in which they are discussed.

3. Turnover, Liquidity, and Liquidity Risk

3.1. Turnover and Liquidity

Table 1 tests whether higher turnover is associated with higher liquidity and lower liquidity risk. To ensure that the measures of liquidity and liquidity risk do not pick up the effects of other variables on turnover, Table 1 introduces several controls. The choice of control variables follows Chordia et al. (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.

Table 1 also uses several controls for visibility: market-to-book, firm age, the number of analysts following the firm, 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 firm risk, which can be another determinant of turnover, the regressions add to the list of controls the market beta in the previous 60 months and firm leverage.

Table 1 looks at the association between turnover and two groups of liquidity measures. The first group — the Gibbs measure (see Hasbrouck 2009), the Roll (1984) measure, and the estimate of effective spread from Corwin and Schultz (2012) — can be generally described as spread measures. The second group — the Amihud (2002) measure and the Pastor and Stambaugh (2003) gamma — are often considered measures of price impact. This grouping, however, is loose, because the Roll measure and the Gibbs measure can also pick up price impact. Technically, the Roll measure estimates the next-day bounce-back in prices, as does the Pastor-Stambaugh gamma; and the Gibbs measure assesses the average price response to a buy/sell trade, similar to the Amihud measure.

The liquidity variables (as well as all other control variables) are transformed into ranks confined between zero and one. In each month, all firms in my sample are ranked in the ascending order on the variable in question and then I 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 ensure the rank is between zero and one.

The convenience of using ranks is threefold. First, using ranks eliminates 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 1 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 highest values of the variable.[6]

The first three columns of Panel A consider the relation between turnover and the three spread measures, used separately. The spread measures should be lower for more liquid firms. If turnover proxies for liquidity, one should observe a negative association between turnover and the spread measures. However, Panel A presents the opposite evidence: all slopes from the regressions of turnover on the spread measures (and controls) are positive and highly significant. The magnitude of the slopes also suggests that high turnover firms are materially less liquid than

[6]Note that the dependent variable, turnover, is *not* transformed into ranks. Therefore, the cross-sectional regressions in Table 1 do not become rank regressions and standard OLS can be applied.

low turnover firms. According to Panel A of Table 1, the turnover of firms with the highest spreads is 4–8% (of the market cap per month) greater than the turnover of firms with the lowest spread. This variation in turnover is comparable to the difference in turnover between the 25th and the 75th turnover percentiles (0.6% vs. 7.5%).

The positive relation between turnover and effective bid-ask spreads is puzzling if one views turnover as a liquidity measure, but expected if turnover is viewed as an uncertainty measure. As most models of spread suggest, higher uncertainty implies for the market-maker larger expected losses from trading with an informed investor, and the market-maker compensates for these expected losses by setting a higher spread for high uncertainty stocks. If high turnover firms are high uncertainty stocks (see Section 4.1 and Table 5), it is not surprising that high turnover stocks have higher effective spreads.

The last two columns of Panel A turn to the price impact measures. The Amihud measure is the price reaction to current volume, and its higher values indicate lower liquidity. The Pastor-Stambaugh gamma is the price bounce-back caused by the prior day's volume, and its higher (less negative) values signal higher liquidity. Hence, if higher turnover means higher liquidity, turnover has to be negatively associated with the Amihud measure and positively associated with the Pastor-Stambaugh gamma.

The last two columns show that the signs of the respective slope coefficients are consistent with the hypothesis that firms with higher turnover are more liquid. However, when we turn to the magnitudes of the coefficients, the existence of the link between turnover and price impact becomes suspect. The slope on the Pastor-Stambaugh gamma is statistically insignificant and its magnitude suggests that the difference in turnover between the highest and the lowest price impact firms is only 0.3% (of market cap per month).

The slope on the Amihud measure is, to the contrary, too large. It suggests the turnover differential of 58% (of market cap per month) between firms with the lowest and highest price impact, which is twice greater than the difference in turnover between the 5th and the 95th turnover percentiles.

The likely source of the extreme slope on the Amihud measure is the fact that turnover and the Amihud measure are mechanically negatively related, since volume is in the numerator of turnover and the denominator of the Amihud measure. Unfortunately, the mechanical link with volume is characteristic of all price impact measures, since by definition, price impact measures the response of prices to trading. For example, Goyenko et al. (2009), the broadest-to-date study of different measures of price impact, runs a horse race between 12 alternative price impact measures, among which 11 (with the exception of the Pastor-Stambaugh gamma) are ratios with trading volume either in the numerator or in the denominator.

Panel B of Table 1 looks at the coefficients from one single regression that uses all liquidity measures together. Panel B shows that, expectedly, some spread measures become weaker when all measures are used at once. However, the spread measure from Corwin and Schultz (2012) and the Gibbs measure remain both economically and statistically significant. The slope on the Amihud price impact measure does not change and remains unusually large, and the slope on the Pastor-Stambaugh price impact flips sign, but remains statistically insignificant.

The positive relation between turnover and effective spread (and the mixed evidence on the relation of turnover and price impact) undermine the liquidity explanation of the turnover effect. For example, Datar et al. (1998) argue, in the spirit of the Amihud and Mendelson (1986) model, that more actively trading investors will hold stocks with lower trading costs, and therefore turnover can be used as a proxy for trading costs, if the latter are hard to estimate. This logic implicitly assumes that investors do not care about the identity of the firm they trade, only about trading costs. An alternative view of the trading process is presented in Harris and Raviv (1993), who argue that disagreement creates trade, and investors have more incentive to trade in high uncertainty stocks, which are also likely to have higher trading costs.

Datar et al. (1998) do not test the validity of turnover as a proxy for trading costs, and my test of such validity in this subsection leads to the conclusion that high turnover firms have higher, not lower trading costs. This result cannot be explained by low quality of the available trading cost measures, because the error-in-variables problem can only make a coefficient insignificant, but cannot make it flip sign. I conclude therefore that the turnover effect is not a manifestation of compensation for liquidity in expected returns.

3.2. Turnover Effect and Liquidity

While Table 1 suggests little evidence that high turnover firms are more liquid, and hence liquidity is unlikely to contribute to explaining the low expected returns to high turnover firms, it is of interest to examine how turnover and the liquidity variables interact in Fama-MacBeth (1973) regressions with returns on the left-hand side.

Table 2 presents the results of such regressions with standard asset pricing controls used alongside turnover and liquidity measures. The controls include market beta, size (controls for the size effect), market-to-book (controls for the value effect), cumulative return between months t-2 and t-12 (controls for momentum), and return in the previous month (controls for the short-term reversal of Jegadeesh (1990)). All explanatory variables are ranks between zero and one, such that the slopes represent the return differential between firms with the highest and lowest values of the explanatory variable.[7]

The first column shows that in the full sample (between January 1964 and December 2010), the turnover effect is strong and significant at 82.5 per month,[8] t-statistic 3.69, even after controlling for other known anomalies.

The next three columns show that the spread measures are positively, though weakly, related to returns. The "spread effect" is about 20–30 bp per month, but at most, marginally significant.

[7]The results are robust to replacing ranks by raw or log values of the explanatory variables.
[8]The slope on the rank variable is the difference in expected returns between firms with the highest and lowest values of the variable.

The turnover effect declines by 10–15 bp per month when one controls for the effective spread measures, but stays statistically and economically significant.

The fifth column reveals a marginally significant negative relation between the Amihud measure and expected returns and stronger turnover effect controlling for the Amihud measure. Further analysis shows that the driver of this counterintuitive result is the close mechanical correlation between the Amihud measure and turnover. In unreported results, I find that the Amihud measure is positively, though insignificantly, related to expected returns when used without turnover.

The sixth column shows an expectedly negative, but weak relation between the Pastor-Stambaugh gamma and expected returns (higher, less negative values of the gamma indicate higher liquidity). The turnover effect is unaffected by controlling for the gamma.

Column 7 uses all liquidity measures in one regression and shows that even then, the turnover effect is still at 64.6 bp per month, t-statistic 2.30.

The results in Table 2 demonstrate that the turnover effect survives after controlling for several well-known anomalies and liquidity measures, which suggests that the turnover effect is a strong and important anomaly unrelated to liquidity.

3.3. Turnover and Liquidity Risk

Table 3 looks at the relation between turnover and liquidity risk using the loadings on three non-traded and three traded liquidity factors. The non-traded factors are innovations to the market-wide average price impact. The difference between the factors is the price impact measure used: the Pastor-Stambaugh gamma, the Sadka (2006) permanent variable measure (similar to the Kyle (1985) lambda), and the Amihud measure.[9] Following the tradition of the liquidity risk literature, all factors are multiplied by -1 to ensure that they measure liquidity and positive

[9] These non-traded liquidity factors were used by Pastor and Stambaugh (2003), Sadka (2006), and Acharya and Pedersen (2005), respectively.

loadings on the factors signify liquidity risk.[10]

The traded Sadka and Amihud factors are the factor-mimicking portfolios that mimic the respective non-traded factors. To create the factor-mimicking portfolio, I regress the respective innovation to the market-wide average price impact (i.e., the non-traded factor) on the excess returns to the base assets (the two-by-three sorts on size and book-to-market from the website of Kenneth French). The fitted part of the regression less the constant is the return to the factor-mimicking portfolio.

The traded Pastor-Stambaugh factor is defined, following Pastor and Stambaugh (2003), as the value-weighted return differential between the top and bottom deciles sorted based on the expected loading on the non-traded Pastor-Stambaugh factor.

The positive loadings on all liquidity factors imply negative returns when liquidity unexpectedly declines, which constitutes liquidity risk. If higher turnover signals lower liquidity risk, the association between turnover and liquidity factor loadings should be negative.

A cursory look at Table 3 results in the first observation that the signs of the slopes are evenly split between positive and negative. While the only significant ones (for the traded Amihud factor) are negative, the magnitude of the slopes is not economically large. The slopes suggest that the difference in turnover between firms with the lowest and the highest liquidity risk is between -0.4% and 0.8% (the percentage points are the fraction of market cap changing hands each month). Therefore, I conclude that the relation between turnover and liquidity risk is essentially nonexistent.

3.4. Turnover Effect and Liquidity Risk

The previous subsection suggests that turnover is largely unrelated to liquidity risk. This subsection confirms that liquidity risk factors cannot explain the turnover effect. To that end, Table 4 sorts firms into quintiles based on average turnover in the previous quarter and estimates the

[10] The Pastor-Stambaugh and Sadka factors are from WRDS. WRDS reports their values multiplied by -1.

alphas and liquidity betas of the quintile portfolios.[11]

Table 4 uses the same three traded liquidity risk factors as Table 3: the Pastor-Stambaugh (2003) traded factor and the two factor-mimicking portfolios that mimic the Sadka (2006) non-traded factor and the non-traded factor from Acharya and Pedersen (2005), which is based on the market-wide average of the Amihud (2002) measure. In unreported results, I find that the risk premium of these factors varies from 60 bp per month in the case of the Pastor-Stambaugh factor to 20 bp per month in the case of the factor-mimicking portfolios.

The first row of Table 4 documents the turnover effect in the Fama-French alphas. The turnover effect is highly significant at around 35–40 bp in both equal-weighted and value-weighted returns. The turnover effect comes almost exclusively from the negative alphas of high turnover firms.

The next rows add the liquidity factors to the Fama-French model and report the alphas and liquidity betas of the turnover quintile portfolios. I find that none of the three liquidity factors can explain the turnover effect. According to the Pastor-Stambaugh betas, high turnover firms have, if anything, higher liquidity risk than low turnover firms. However, the difference in liquidity risk is insignificant both statistically and economically. This is consistent with the evidence from cross-sectional regressions in Table 3. Likewise, the Sadka factor betas are unrelated to turnover, again supporting the conclusions in Table 3.

The only factor that shows a negative relation between turnover and liquidity risk is the Amihud traded factor. The last two rows of Table 4 show that high turnover firms have significantly lower liquidity betas than low turnover firms. However, two caveats are in order. First, the spread in the Amihud betas in the turnover sorts is economically small. The factor premium of the Amihud factor is also relatively low (20 bp per month, statistically significant), and therefore,

[11] The firms are sorted into quintiles using NYSE breakpoints. Firms with a stock price below $5 at the portfolio formation date are omitted from the sorts. The results are robust to including firms with stock price below $5 back into the sample, using the breakpoints for the entire CRSP population or looking at the NYSE/AMEX firms and NASDAQ firms separately.

the Amihud factor can explain at most 10 bp per month of the 40-bp-per-month turnover effect. Second, the Amihud factor appears to explain the alphas that do not need an explanation and not to explain those that require one. For example, the Amihud factor betas suggest that low turnover firms are exposed to liquidity risk, but the Fama-French alphas of these firms are small and insignificant, whereas high turnover firms, with large and significantly negative Fama-French alphas, do not exhibit any visible hedging power against liquidity risk.[12]

The conclusion from Table 4 is that the liquidity risk factors cannot explain the turnover effect. This evidence suggests that the turnover effect comes from a source other than liquidity risk, thus indirectly supporting my hypothesis that in asset-pricing applications, turnover should be used as a proxy for uncertainty and aggregate volatility risk.

4. Turnover Effect and Aggregate Volatility Risk

4.1. Turnover and Firm-Specific Uncertainty

The main empirical hypothesis behind the aggregate volatility risk explanation of the turnover effect is the hypothesis that turnover is positively related to uncertainty. Table 5 runs regressions similar to those in Tables 1 and 3, with the same controls and several measures of firm-specific uncertainty: idiosyncratic volatility (IVol),[13] analyst disagreement (Disp),[14] analyst forecast error (Error),[15] and the volatility of cash flows and earnings (CVEarn and CVCFO).[16]

[12]One concern about the results above is that, due to the right skewness of turnover, the bottom turnover deciles may not have much variation in turnover and hence, their exposure to liquidity risk is similar (but less than that of the top turnover quintile). If this is the case, the lack of dispersion in turnover across the turnover quintiles may be the reason behind the lack of relation between turnover and liquidity risk in Table 4. In untabulated findings, I look at median turnover across turnover quintiles and find that while the difference in turnover between quintiles one and four is comparable to the similar difference between quintiles four and five, turnover increases fivefold between quintiles one and four. This indicates that the cross-section of turnover in the quintile sorts is rich enough to elicit a relation between turnover and liquidity risk, if one exists.

[13]Idiosyncratic volatility is the standard deviation of residuals from the Fama-French (1993) model, fitted to the daily data for each firm-month.

[14]Analyst disagreement 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 (the data are from IBES).

[15]Analyst forecast error is the absolute value of the difference between the one-year-ahead consensus forecast and actual earnings divided by actual earnings.

[16]Earnings/cash flows volatility is measured by the coefficient of variation (standard deviation over the average) of quarterly earnings/cash flows (from Compustat quarterly) in the past 12 quarters.

The estimates from Panel A of Table 5, which use each uncertainty measure separately, suggest that all five uncertainty measures have a significant impact on turnover. First, the respective coefficients are highly significant with t-statistics exceeding 3.0. Second, the magnitude of the coefficients is plausible and economically large. According to the estimates from Panel A, the monthly turnover of firms with the highest uncertainty is higher than monthly turnover of firms with the lowest uncertainty by approximately 4% of shares outstanding (for comparison, the difference in the turnover between the 25th and the 75th turnover percentiles is around 7%). The only coefficient that differs in magnitude is the loading on idiosyncratic volatility, which suggests that the monthly turnover of the firm with the lowest and the firm with the highest idiosyncratic volatility is different by more than 10% of shares outstanding.

Panel B uses all uncertainty measures in the same regression and yields similar conclusions. The slopes remain economically and statistically significant, even though they are generally smaller than in Panel A, signifying the expected overlap between the uncertainty measures.

In untabulated results, I add to Panels A and B all liquidity measures from Table 1 and find that all slopes, both on liquidity and uncertainty, remain unaffected. The only two slopes that are visibly different are the slope on idiosyncratic volatility (declines, but remains stronger than any other slope in Panel B) and the slope on effective bid-ask spread (becomes more positive after controlling for uncertainty). I also replace the liquidity controls with controls for liquidity risk from Table 3 (results untabulated) and find no intersection between uncertainty measures and liquidity risk measures.

I conclude that sorting firms on turnover will implicitly strongly sort them on firm-specific uncertainty, and second, that the sorting on turnover/uncertainty will not produce sorting on liquidity or liquidity risk (in fact, it will produce an inverse sorting on liquidity, making the turnover effect harder to explain).

4.2. Turnover Effect: Single Sorts

The main prediction of the paper is that high turnover firms have low exposure to aggregate volatility risk, because they are high uncertainty firms. Table 6 looks at the turnover quintile portfolios as formed in Section 3.4 and Table 4 (the sample excludes stocks with a share price below $5 on portfolio formation date). The sample period is from January 1986 to December 2010 due to availability of VIX and FVIX.

The first three rows of Table 6 report the alphas from the CAPM, the Fama and French (1993) model, and the Carhart (1997) model. The turnover effect is significant at about 35–40 bp per month in value-weighted returns and about 50–75 bp per month in equal-weighted returns. It can also be observed that the turnover effect is driven primarily by the negative alphas of the highest turnover quintile, consistent with the aggregate volatility risk explanation, which focuses on high uncertainty firms.

The next two rows show that controlling for aggregate volatility risk exposure eliminates the turnover effect both in value-weighted and equal-weighted returns. To save space, I report the alphas and the FVIX betas from the two-factor ICAPM with the market factor and FVIX.[17] Augmenting the Fama-French model or the Carhart model with FVIX brings about very similar results. Also, since the CAPM produces the largest estimates of the turnover effect, the FVIX factor has the longest distance to cover if used in the two-factor ICAPM.

I find that the ICAPM alpha differential between low and high turnover firms is materially smaller and statistically insignificant in both value-weighted and equal-weighted returns. Neither of the turnover quintiles, including the highest turnover quintile, has a significant ICAPM alpha.

The explanation is the FVIX betas, which change, for example, in Panel A, from -0.566, t-statistic -4.42, in the lowest turnover quintile to 0.915, t-statistic 3.92, in the highest turnover quintile. Since, by construction, the FVIX factor tends to earn positive returns when aggregate

[17]Please refer to footnote 4 for more information on FVIX as an ICAPM factor.

volatility increases, the positive FVIX beta of high turnover firms signals that these firms are a hedge against aggregate volatility risk.

The strong and generally 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 exposure, and this association can explain the turnover effect.

This is the central point of my paper: in asset pricing tests, one need not interpret high turnover as high liquidity or low liquidity risk exposure in order to explain the turnover effect. One 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 exposure to aggregate volatility risk.

4.3. Fama-MacBeth Regressions

Table 7 performs firm-level Fama-MacBeth regressions to corroborate the results in Table 6 and verify their robustness to the inclusion of stocks with a share price below $5 back into the sample. As in Table 4, the regressions use several common controls that control for the size effect, value effect, momentum, and the short-term reversal of Jegadeesh (1990). The sample is from January 1986 to December 2010 due to the availability of VIX and FVIX.

The first column of Table 7 confirms the turnover effect in the shorter sample at 50.7 bp per month, t-statistic 2.76, close to what Panel B of Table 6 reports. The second column adds the loading on the VIX change estimated separately for each firm-month using daily data. The loading on the VIX change is estimated in the regression with the market factor and the VIX change used as explanatory variables.

In the presence of the loading on VIX, the turnover effect declines by two-thirds and becomes insignificant. The risk premium on the loading on the VIX change is significant and economically sizeable at -26.9 bp per month (more positive returns in response to VIX increases mean lower risk), which lends further support to aggregate volatility risk being the explanation of the turnover effect.

The third column replaces the loading on the VIX change by the FVIX beta. The FVIX beta is estimated in the two-factor ICAPM with the market factor and FVIX, separately for each firm-month, using monthly returns in the past 36 months. The impact on the turnover variable is the same: its coefficient is reduced by two-thirds and becomes insignificant. Also, the risk premium on the FVIX beta is -91.8 bp per month and statistically significant.

The fourth column confirms the existence of the turnover effect in the sample that includes stocks with prices below \$5. The turnover effect is estimated to be slightly larger than in the sample that excludes such stocks, at 0.76% per month.

The fifth and sixth columns control for the loading on the VIX change and the FVIX beta, respectively, and yield the same conclusions as the second and third columns. The turnover effect is reduced by more than one-half, to a statistically insignificant number, after controlling for aggregate volatility risk. The risk premiums for the loading on the VIX change and the FVIX beta are also not impacted by the inclusion of stocks priced below \$5.

4.4. Turnover Effect in the Cross-Section

4.4.1. Option-Like Equity, Turnover Effect, and Aggregate Volatility Risk in Cross-Sectional Regressions

My explanation of the turnover effect assumes that the turnover effect works through real options: higher uncertainty/turnover make real options less exposed to aggregate volatility risk. The natural prediction is then that the turnover effect is stronger for more option-like firms.

In Panel A of Table 8, I test the this prediction by running Fama-MacBeth regressions of returns on turnover, several alternative measures of equity option-likeness, their product with turnover, and the standard controls from Tables 2 and 7 (the coefficients on the controls and the measures of option-likeness are suppressed for brevity). I expect the product of turnover and proxies of option-likeness to have a negative slope, i.e., the negative relation between turnover and expected returns will be stronger if equity is more option-like. I also expect that turnover itself will have a smaller slope in the presence of the product (as compared to the turnover effect of 82.5 bp per month in Table 2).

Panel A uses four measures of real options suggested by Grullon et al. (2012). Two of them, the reciprocal of the book equity (1/BE) and the ratio of R&D to total assets (RD/TA), measure growth options. Another two are general measures of firm convexity: "SUE flex" is the slope from the firm-by-firm regression, using the data from quarters t-1 to t-20, of earnings announcement returns on SUE squared (controlling for the level of SUE). "TVol Sens" is the sensitivity of firm returns to changes in total firm-specific volatility, from firm-specific regressions, using the data from months t-1 to t-60, of returns on the market return and the change in volatility.

I also use three additional measures of option-likeness: market-to-book (probably the most widely used measure of growth options), credit rating[18] and O-score of Ohlson (1980), both of which measure distress and the consequent importance of the option-likeness created by leverage.

The products of all seven measures with turnover have significantly negative slopes. The magnitude of the slopes is also economically large: the slopes suggest that the difference in the turnover effect between the most and the least option-like firms varies between 37 bp per month (sixth column, SUE flex) and 2.04% per month (fifth column, credit rating). Most of the coefficients estimate the difference to be between 0.6% and 1% per month.

Also, the slope on the turnover itself (which measures the turnover effect for the least option-like firms) is about one-half of the slope reported in the first column of Table 2, marginally significant in two cases (columns (1) and (4) of Panel A), and even flips sign in column (5).

[18] The credit rating is coded as 1=AAA, 2=AA+, 3=AA, ... , 21=C, 22=D, so higher credit rating is a worse credit rating. Credit rating is then divided by 22 to make sure it is between 0 and 1 as all other rank variables.

(Other columns fall in between.)

Overall, Panel A of Table 8 strongly supports the hypothesis that the turnover effect is stronger for firms with more option-like equity using a battery of alternative measures of equity option-likeness.

Panel B re-runs the regressions in Panel A using FVIX betas as the dependent variable (instead of returns). As in Panel A, only the slopes on turnover, measures of equity option-likeness (a different measure in each column), and their product with turnover are reported. Unreported are the slopes on other common asset-pricing controls: size, momentum, reversal, and market-to-book (slope on market-to-book is reported only in column (1)), as well as the slopes on the option-likeness measures.

Panel B of Table 8 aims to show that the hedging ability, and hence the FVIX beta of high turnover firms, increases as equity becomes more option-like. Therefore, in regressions of FVIX betas on firm characteristics, I expect FVIX betas to be positively related to the product of turnover and measures of equity option-likeness.

The evidence in Panel B confirms this hypothesis. The products of turnover with the measures of equity option-likeness are all positive and significant, and the magnitude of the slopes suggests that the FVIX beta differential between low and high turnover firms increases by 0.3 to 1.8 as one goes from firms with the least option-like equity to firms with the most option-like equity.

To sum up, Table 8 shows that the turnover effect is stronger for more option-like firms using a number of alternative measures of option-likeness. Also, the relation between the turnover effect and equity option-likeness in returns is mirrored by a similar relation in FVIX betas, which suggests that FVIX betas can explain why the turnover effect is stronger for option-like firms, as my theory predicts.[19]

[19] A referee suggested that the stronger turnover effect for more option-like firms may also be mispricing, because firms with abundant real options are more difficult to value. While the fact that the effect in returns (Panel A) is mirrored with a similar effect in FVIX betas (Panel B) is inconsistent with the hypothesis that the interaction between the turnover effect and option-likeness is 100% mispricing, it is still possible that the interaction is a

4.4.2. Turnover Effect and Growth Options

Panel A of Table 9 looks at the returns to the low-minus-high turnover portfolio across market-to-book deciles. The low-minus-high turnover portfolio buys firms in the lowest turnover quintile and shorts firms in the highest turnover quintile. This strategy is followed separately in each market-to-book quintile.

The goal of Table 9 is to illustrate a stronger turnover effect for growth firms and, most importantly, to illustrate that the link between the turnover effect and market-to-book has a risk-based explanation: aggregate volatility risk.

The first row of Panel A presents the CAPM alphas of the low-minus-high turnover portfolio across market-to-book quintiles. The evidence is mixed. On the one hand, consistent with the regressions in Table 8, the turnover effect is stronger for growth firms in value-weighted returns. The difference in the CAPM alphas of the low-minus-high turnover portfolios between value and growth firms is 85 bp, t-statistic 1.98, and the turnover effect is only significant in the top market-to-book quintile. On the other hand, the turnover effect is weaker overall in value-weighted returns. In equal-weighted returns, where it is stronger, the difference in the effect between value and growth firms is statistically insignificant at 31 bp per month.

The FVIX betas align better with my theory. The difference in FVIX betas between the low-minus-high turnover portfolios formed in the growth subsample and the value subsample is large and highly significant. The significant FVIX betas are confined to the two top market-to-book quintiles. Compared with exploiting the turnover effect in the value subsample, exploiting the turnover effect in the growth subsample implies greater losses when aggregate volatility increases. Of particular note is that in value-weighted returns, the difference in the alphas of the low-minus-

mixture of risk and mispricing. In untabulated results, I re-run the regressions in Panel A using returns at earnings announcements instead of usual monthly returns. If higher turnover for option-like stocks is mispricing, then this effect will be concentrated at earnings announcements, when the mispricing is corrected. The untabulated results show that there is no reliable evidence that turnover effect is more concentrated at earnings announcements for more option-like firms, inconsistent with the mispricing hypothesis.

high turnover portfolio is reduced from 85 bp per month in the CAPM to 1 bp per month in the ICAPM.

Thus, there is suggestive evidence that the turnover effect is related to market-to-book, and quite strong evidence that aggregate volatility risk can explain this relation, consistent with the evidence in Table 8.

4.4.3. Turnover Effect and Equity as a Call Option on the Assets

Panel B of Table 9 uses credit rating as a measure of the importance of the real option created by risky debt. For 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 firms with bad credit ratings, 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.[20]

The CAPM alphas in the first row of Panel B reveal that the turnover effect is significantly stronger for firms with worse credit rating, for which equity is more option-like. In equal-weighted returns, for example, the CAPM alphas of the low-minus-high turnover portfolio vary from -14.8 bp per month, t-statistic -0.86, in the best credit rating group to 58 bp per month, t-statistic 1.8 in the worst credit rating group.

After controlling for the FVIX factor, the difference in the equal-weighted alphas declines from 72.8 bp per month, t-statistic 2.16, to 39.1 bp per month, t-statistic 1.2, which indicates that aggregate volatility risk can explain why the turnover effect is stronger for firms with bad credit ratings. The value-weighted returns bring similar conclusions.

The FVIX betas of the low-minus-high turnover portfolio become more negative as credit rating deteriorates. In value-weighted returns, they change by -0.828, t-statistic -1.84, going

[20] Another intuitive measure of equity option-likeness would be leverage. However, leverage is mechanically and negatively related to market-to-book (market cap is in the numerator of market-to-book and in the denominator of leverage). Since both market-to-book and leverage are expected to be positively related to the strength of the turnover effect, the mechanical negative correlation between them will obscure the results. On the other hand, the negative correlation between market-to-book and credit rating is significantly lower, making credit rating a better measure of equity option-likeness.

from the firms with the best credit rating to those 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.

I conclude that there is a strong link between the turnover effect and option-likeness of equity due to the existence of risky debt, and this link can be explained by aggregate volatility risk, just as the regressions in Table 8 suggest.

5. Alternative Explanations of the Turnover Effect

5.1. Turnover Effect and Mispricing

An alternative view of the turnover effect (expressed, for example, in Lee and Swaminathan 2000 and Nagel 2005) is that it represents mispricing. The proponents of this view agree that turnover captures uncertainty/disagreement rather than liquidity and use the Miller (1977) theory to predict that higher disagreement combined with short-sale constraints creates overpricing. Miller (1977) argues that in the presence of short-sale constraints, stock prices reflect the average valuation of optimists, and this average increases with uncertainty/disagreement.

My theory of the turnover effect does not exclude the possibility that the turnover effect can be related to measures of short-sale constraints, however, any such relation should be explained by the FVIX factor. Also, the FVIX factor should be able to explain the turnover effect irrespective of the level of short-sale constraints.

Nagel (2005) shows that the turnover effect is stronger for firms with low institutional ownership (IO).[21] This evidence is consistent with the mispricing theory above if IO is viewed as a proxy for the amount of shares available to sell short. For low IO firms, the supply of shares for short sales is small and the cost of a short sale is generally high. Therefore, firms with high turnover and low IO are likely to be the most overpriced.

[21] To make sure that institutional ownership is not capturing any size effects, Nagel (2005) orthogonalizes IO to size by running cross-sectional regressions on IO on log size and its square and taking the residuals as residual IO. In this paper, I follow his example, but in the discussion refer to residual IO as simply IO for brevity.

In Panel A of Table 10, I look at returns to the low-minus-high turnover portfolio across IO quintiles. I confirm the Nagel (2005) result that the turnover effect is greater for low IO firms. The difference in the turnover effect between the lowest and highest IO quintiles is only significant in equal-weighted returns at 93 bp per month, t-statistic 3.45.

Controlling for FVIX, the difference in the turnover effect between low and high IO firms is reduced to 41 bp per month, t-statistic 1.64. The FVIX factor is also successful in explaining the turnover effect in the bottom two IO quintiles, where it is the strongest at over 1% per month. Hence, the stronger turnover effect in the low IO subsample is explained by aggregate volatility risk and does not necessarily point to the turnover effect as mispricing.

The reason why FVIX explains the dependence of the turnover effect on IO is that institutions avoid stocks with both high turnover and option-like equity due to their high volatility[22] and stocks with low turnover and non-option-like equity due to their high aggregate volatility risk. Thus, most stocks with extremely high and extremely low levels of turnover and equity option-likeness end up in the low IO group, and sorting firms on turnover in the low IO group produces a wider spread in turnover, FVIX betas, and expected returns. Untabulated results (available upon request) reveal that, indeed, the spread in turnover and market-to-book between extreme turnover quintiles is significantly wider for low IO stocks. Consistent with that, the last row of Panel A in Table 10 shows that the spread in FVIX betas between extreme turnover quintiles is also significantly wider for low IO stocks.

The prediction of the Miller theory is that the negative effect of disagreement on future returns is concentrated among stocks that are expensive to short. The data on shorting fees for a sufficiently long period and a sufficiently broad cross-section are impossible to obtain. The approach in Nagel (2005) is to use supply (IO) as a proxy for price: if the supply is high, then the price is likely to be low.

[22]As Shleifer and Vishny (1997) point out, portfolio managers are averse to idiosyncratic volatility because too much of their wealth is tied to the portfolio they manage and they feel underdiversified

Another approach would be to use an estimate of the cost of shorting. D'Avolio (2002) uses private data on shorting fees and performs a regression that estimates which variables determine the probability of the stock to be on special.[23] Ali and Trombley (2006) employ the same formula to estimate the probability to be on special for the intersection of Compustat, CRSP, and Thomson Financial populations. They show that the estimated probability is closely tied to other short-sale constraint measures in different periods.

Panel B of Table 10 looks at the turnover effect across quintiles from the sorts on the probability to be on special. I find that the turnover effect is reliably related to short-sale constraints only in equal-weighted returns, where the respective CAPM alpha differential is 67 bp per month, t-statistic 2.04.

Once one controls for aggregate volatility risk, the turnover effect disappears for both firms that are cheap to short and firms that are expensive to short. The ICAPM alphas of the low-minus-high turnover portfolios for firms with high and low probability to be on special are different by about 30 bp per month, t-statistics below 1; and in equal-weighted returns, the FVIX betas become significantly more negative for the low-minus-high turnover portfolios formed in the subsample with a higher probability to be on special.

In untabulated results, I also perform an alternative test of the mispricing explanation that looks at the returns to high and low turnover firms at earnings announcements. If high (low) turnover firms are overpriced (underpriced), their prices will decrease (increase) as investors process the information in earnings. Since the earnings announcement returns are measured over three days around the announcement (5% of trading days in a quarter), the test does not suffer from the "bad-model problem" and can be viewed as a model-free estimate of the lower limit of the part of the turnover effect that can be explained by mispricing (e.g., if 30% of an anomaly is realized during earnings announcements, then at least 30% of the anomaly is mispricing).

[23] Being on special indicates that the shorting fee exceeds the current risk-free rate.

I track earnings announcement returns for four quarters after the portfolio formation and find no evidence that high turnover firms underperform low turnover firms at earnings announcements. The lack of price adjustment at earnings announcements suggests that both low and high turnover firms are fairly priced, as the previous section implies. I also look at earnings announcement returns in the double sorts on turnover and a measure of short-sale constraints from Table 10, and again find no visible relation between short-sale constraints and the concentration of the turnover effect at earnings announcements. This corroborates the results in Table 10 that the apparent link between the turnover effect and short-sale constraints can be explained by aggregate volatility risk.

5.2. Turnover Effect and Attention

One last hypothesis considered about the source of the negative relation between turnover and future returns is that turnover is a proxy for attention. Indeed, actively traded firms may attract more attention, and if attention increases the demand for the stock and decreases its expected return, as Merton (1987) suggests, turnover will be negatively related to future returns.

In Table 11, I perform double sorts on turnover and attention measures and hypothesize that, if the turnover effect is explained by attention and not by aggregate volatility risk, both the CAPM alphas and ICAPM alphas of the low-minus-high turnover portfolio will be stronger for low attention firms, for which the additional attention attracted to high turnover firms should matter more. If either of the alphas are not related to the attention measures, the conclusion is that the attention explanation of the turnover effect is redundant compared to the aggregate volatility risk explanation.

One example of such a test is the double sorting on turnover and IO discussed above, since IO can be used as a proxy for attention. As the previously stated, the turnover effect is indeed stronger for low IO firms, but the conclusion that the turnover effect is an attention phenomenon would be premature, because FVIX can successfully explain why the turnover effect depends on IO. Hence, one does not need the attention explanation to explain the turnover effect.

Likewise, looking at the alphas and FVIX betas of the low-minus-high turnover portfolios across analyst-following quintiles[24] in Panel A of Table 11, I find that the turnover effect is indeed stronger for firms with little analyst following (but only in equal-weighted returns). Also, the low-minus-high turnover portfolio has higher exposure to aggregate volatility risk (more negative FVIX betas) in the lowest analyst following quintile, and the ICAPM alphas of the low-minus-high turnover portfolio do not depend on analyst following. Thus, controlling for aggregate volatility risk, it appears that the attention theory does not explain the turnover effect.

In Panel B of Table 11, I look at the double sorts on turnover and the measure of price delay from Hou and Moskowitz (2005). Price delay, D, is defined as $D = 1 - \frac{R^2_{full}}{R^2_{short}}$, where R^2_{short} is the R-square from the firm-level regression of weekly firm returns on weekly market returns and R^2_{full} is the R-square from the same regression with four lags of the market return added. Though it appears that the price delay measure should capture liquidity, Hou and Moskowitz (2005) show that the priced part of the price delay measure is unrelated to liquidity, but is related to several (sometimes difficult to obtain) attention measures such as the number of employees, number of shareholders, proximity to the airport, etc. Therefore, the price delay measure appears a good and simple portmanteau statistic for attention.

In Panel B of Table 11, inconsistent with the attention explanation of the turnover effect, I find no strong relation between price delay and the turnover effect either in CAPM or ICAPM alphas. The exposure of the low-minus-high turnover portfolio to aggregate volatility risk is also unrelated to price delay. Thus, while there is limited evidence that the turnover effect depends on attention measures, in all such cases this link is explained by the difference in aggregate volatility risk, leaving the attention explanation with little significance.

[24] Following Lee and Swaminathan (2000), I orthogonalize to size the number of analysts following the stock, making my sorting variable residual analyst coverage, or excess coverage given the firm size.

6. Robustness Checks

6.1. Turnover Effect and Other Uncertainty Effects

In untabulated results, I run a horse race between turnover and uncertainty measures from Table 5 in the Fama-MacBeth regressions with returns as the dependent variable. On the one hand, I expect to find significant overlap between turnover and uncertainty measures, since Table 5 suggests they are tightly related, and the current paper is making the case that the turnover effect is an uncertainty effect. On the other hand, if either of the uncertainty measures (or a combination thereof) subsumes turnover in the Fama-MacBeth regressions, we can conclude that the turnover effect is not an independent anomaly and does not merit a separate explanation.

I find that, without controlling for turnover, the firm uncertainty measures are negatively related to expected returns, consistent with Ang et al. (2006) and Diether et al. (2002). The only exception is analyst forecast error, which is unrelated to future returns. Also, to the best of my knowledge, the negative relation between variability of earnings or cash flows and expected returns has not yet been documented in previous work.[25] In unreported results, I find that this latter effect is not subsumed by the idiosyncratic volatility discount of Ang et al. or the analyst disagreement effect of Diether et al.

Using turnover and the uncertainty measures in the same regressions makes both of them weaker, usually by 25–35%, but leaves both variables economically and statistically significant. For example, the idiosyncratic volatility discount of Ang et al. (2006) declines from 1.23% per month to 1.1% per month after I control for turnover, and the turnover effect declines from 76 bp per month to 50 bp per month after I control for idiosyncratic volatility. Hence, the evidence from the horse race regressions is consistent both with the fact that turnover is related to uncertainty and the hypothesis that the turnover effect is a strong independent anomaly that

[25] Haugen and Baker (1996) use a very similar measure of earnings variability as a predictor of expected returns, but do not report it in the number of "twelve most important factors." They do report though a negative relation between expected returns and a similarly defined variability of the cash-flow-to-price ratio.

merits a separate explanation.

6.2. Turnover Effect in Different Sample Periods

Due to the limited availability of the VIX index, the main analysis of the turnover effect in Section 4 uses data only from 1986–2010. Since this period is not very long, in untabulated tests I checked whether the turnover effect exists outside of this period and verified that it is not driven by a few data points inside the sample period.

I first look at the turnover effect in the longer 1964–2010 period and in the pre-Compustat era (1926–1963). Using cross-sectional regressions similar to Table 7, I estimate the turnover effect for the full sample at 76 bp per month in 1964–2010 and at 74.5 bp per month in 1926–1963, versus 65 bp per month in 1986–2010. Dropping stocks priced below $5 does not change my conclusion that the turnover effect is very similar in 1926–1963, 1964–1985, and 1986–2010.

Within 1986–2010, I tested whether the dot-com bubble period (2000–2002), characterized by high levels of turnover and volatility, is driving the turnover effect and its aggregate volatility risk explanation. The turnover effect weakens by only a few bp after the 2000–2002 period is removed, and the explanatory power of FVIX remains unchanged. The same results apply when I remove the most recent financial crisis (2007–2009) from the sample.

I also checked whether the horizon over which turnover is measured matters. The tests in the paper use quarterly measures of turnover, that is, average monthly turnover in the previous quarter. I experimented with using annual and monthly turnover. Annual turnover performs in the same manner as quarterly turnover. Using monthly turnover from the previous month results in weaker, but still significant turnover effect (45.7 bp per month, t-statistic 2.20, versus 65 bp per month, t-statistic 3.01). The weaker turnover effect with monthly turnover is due in part to more noise in the monthly turnover measure and partly due to microstructure issues, because using monthly turnover from two or three months ago makes the estimate of the turnover effect stronger and almost on par with the estimate that uses quarterly turnover.

6.3. Turnover Effect and Changes in VIX

The conclusion of the paper that high turnover firms perform relatively well when VIX increases is based on their FVIX betas. Here, I provide a more direct test of this statement by regressing the low-minus-high turnover portfolio on the change in VIX. Such regression will not produce an estimate of what part of the alpha of the low-minus-high portfolio is explained by the exposure to aggregate volatility risk, because the change in VIX is not directly tradable. However, it will corroborate the FVIX results and show that they are not an artefact of the chosen base assets or any other part of the factor-mimicking procedure.

In untabulated results (available upon request), I regress the returns to the low-minus-high turnover portfolio, formed in the full sample and in the subsamples where the turnover effect is the strongest (growth firms, distressed firms, short-sale constrained firms) on the market return and the change in VIX. I find that all those portfolios load negatively on the change in VIX, and even more so if the low-minus-high turnover portfolio is formed in the subsample where the turnover effect is stronger. The magnitude of the loading is economically sizeable and suggests that during periods of increasing VIX, the turnover portfolio will perform by about one-third worse than what the CAPM predicts.

6.4. Turnover Effect and Sentiment

Baker and Wurgler (2006, 2007) argue that mispricing of high uncertainty firms can be driven by economy-wide waves of sentiment. According to Baker and Wurgler (2007), high uncertainty firms should witness price increases when sentiment becomes more upbeat and investors are more inclined to make speculative bets. Since FVIX is sometimes viewed as a measure of economy-wide uncertainty and a "fear gauge," it is interesting to evaluate the potential overlap between FVIX and the sentiment factor of Baker and Wurgler.

In untabulated results, I run a horse race between FVIX and the sentiment factor by adding both, alone and together, to the Fama-French (1993) model fitted to the returns of the low-minus-high turnover strategy, and look at its betas. I find that there is virtually no overlap between FVIX and sentiment, since the FVIX betas of the low-minus-high turnover portfolio do not change controlling for contemporaneous changes in sentiment. Therefore, I conclude that FVIX does not appear to pick up any sentiment effects and the part of the turnover effect explained by FVIX is most likely risk rather than mispricing.

7. Conclusion

This paper shows that turnover is related to firm-specific uncertainty, unrelated to liquidity risk, and negatively rather than positively related to liquidity. High turnover firms have much higher idiosyncratic volatility, analyst forecast dispersion, analyst forecast errors, and variance of earnings and cash flows than low turnover firms. On the other hand, firms with higher turnover appear to have higher effective spread, the link between turnover and the measures of price impact is ambiguous and unreliable, and the link between turnover and the measures of liquidity risk is virtually nonexistent. In asset-pricing tests, neither liquidity measures nor liquidity risk factors can explain the lower expected returns to high turnover firms (the turnover effect).

I find that it is possible to reconcile the view of turnover as an uncertainty proxy and the turnover effect. I argue that real options of high uncertainty firms have relatively good performance when firm-specific uncertainty increases. The reason is twofold: first, as the uncertainty about the underlying asset increases, the value of the real option becomes less sensitive to changes in its value and therefore, the real option becomes less risky and, all else equal, its value increases. Second, the value of an option, in general, increases in the uncertainty about the underlying asset. Both effects are naturally stronger for high uncertainty firms.

Prior research shows that firm-specific uncertainty comoves with aggregate volatility, and therefore, I conclude that high uncertainty firms, in particular high turnover firms, perform relatively well when aggregate volatility increases, i.e., have lower aggregate volatility risk. I also predict that this hedging ability is the greatest and the turnover effect is the strongest for firms with abundant real options.

Empirically, 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 turnover effect. I also show that the effect of turnover on future returns increases with market-to-book (and other measures of growth options) and decreases with credit rating (and other measures of equity option-likeness created by leverage). These cross-sectional patterns in the turnover effect are also explained by the FVIX factor.

In addition, the mispricing and attention explanations of the turnover effect are also examined. The turnover effect is stronger for firms with lower attention and higher limits to arbitrage, which would be consistent with the turnover effect being mispricing or an attention phenomenon. However, I also find that the stronger turnover effect for firms with lower attention and higher limits to arbitrage can be explained by the FVIX factor, which limits the role of the mispricing and the attention explanations.

References

Acharya, V., L. H. Pedersen. 2005. Asset pricing with liquidity risk. *J. of Financial Economics* **77**, 375–410.

Ali, A., M. A. Trombley. 2006. Short sales constraints and momentum in stock returns. *J. of Business Finance and Accounting* **33**, 587–615.

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

Amihud, Y. 2002. Illiquidity and stock returns: cross-section and time-series effects. *J. of Financial Markets* **5**, 31–56.

Ang, A., R. J. Hodrick, Y. Xing, X. Zhang. 2006. The cross-section of volatility and expected returns. *J. of Finance* **61**, 259–299.

Avramov, D., T. Chordia. 2006. Asset pricing models and financial market anomalies. *Review of Financial Studies* **19**, 1001–1040.

Baker, M., J. Wurgler. 2006. Investor sentiment and the cross-section of stock returns. *J. of Finance* **61**, 1645–1680.

Baker, M., J. Wurgler. 2007. Investor Sentiment in the Stock Market. *J. of Economic Perspectives* **21**, 129–151.

Barinov, A. 2011. Idiosyncratic volatility, growth options, and the cross-section of returns. Working paper, University of Georgia.

Barinov, A. 2012. Analyst disagreement and aggregate volatility risk. *J. of Financial and Quantitative Analysis*, forthcoming.

Barinov, A. 2013. Why does higher turnover variability predict lower expected returns? Working paper, University of Georgia.

Blume, L., D. Easley, M. O'Hara. 1994. Market statistics and technical analysis: the role of volume. *J. of Finance* **49**, 153–181.

Campbell, J. Y. 1993. Intertemporal asset pricing without consumption data. *American Economic Review* **83**, 487–512.

Carhart, M. 1997. On persistence in mutual fund performance. *J. of Finance* **52**, 57–82.

Chen, J. 2002. Intertemporal CAPM and the cross-section of stock returns. Working paper, University of Southern California.

Chordia, T., A. Subrahmanyam, V. R. Anshuman. 2001. Trading activity and expected stock returns. *J. of Financial Economics* **59**, 3–32.

Chordia T., S.-W. Huh, A. Subrahmanyam. 2007. The cross-section of expected trading activity. *Review of Financial Studies* **20**, 709–741.

Corwin, S. A., P. Schultz. 2012. A simple way to estimate bid-ask spreads from daily high and low prices. *J. of Finance* **67**, 719–759.

Datar, V. T., N. Naik, R. Radcliffe. 1998. Liquidity and stock returns: an alternative test. *J. of Financial Markets* **1**, 203–219.

D'Avolio, G. 2002. The market for borrowing stock. *J. of Financial Economics* **66**, 271–306.

Diether, K., C. Malloy, A. Scherbina. 2002. Differences of opinion and the cross-section of returns. *J. of Finance* **57**, 2113–2141.

Duarte, J., A. Kamara, S. Siegel, C. Sun. 2012. The common components of idiosyncratic volatility, Working paper, Rice University.

Eckbo, B. E., Ø. Norli. 2005. Liquidity risk, leverage, and long-run IPO returns. *J. of Corporate Finance* **11**, 1–35.

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

Fama, E. F., K. R. French. 1997. Industry costs of equity. *J. of Financial Economics* **43**, 153–193.

Fama, E. F., J. MacBeth. 1973. Risk, return, and equilibrium: empirical tests. *J. of Political Economy* **81**, 607–636.

Gao, X., J. R. Ritter. 2010. The marketing of seasoned equity offerings. *J. of Financial Economics* **97**, 33–52.

Goyenko, R., C. W. Holden, C. A. Trczinka. 2009. Do liquidity measures measure liquidity? *J. of Financial Economics* **92**, 153–181.

Grullon, G., E. Lyandres, A. Zhdanov. 2012. Real options, volatility, and stock returns. *J. of Finance* **67**, 1499–1537.

Harris, M., A. Raviv. 1993. Differences of opinion make a horse race. *Review of Financial Studies* **6**, 473–506.

Hasbrouck, J. 2009. Trading costs and returns for U.S. equities: estimating effective costs from daily data. *J. of Finance* **64**, 1445–1477.

Haugen, R. A., N. L. Baker. 1996. Commonality in the determinants of expected stock returns. *J. of Financial Economics* **41**, 401–439.

Hou, K., T. J. Moskowitz. 2005. Market frictions, price delay, and the cross-section of expected returns. *Review of Financial Studies* **18**, 981–1020.

Jegadeesh, N. 1990. Evidence of predictable behavior of security returns. *J. of Finance* **45**, 881–898.

Jiang, G., C. M. C. Lee, G. Y. Zhang. 2005. Information uncertainty and expected returns. *Review of Accounting Studies* **10**, 185–221.

Johnson, T. C. 2004. Forecast dispersion and the cross-section of expected returns. *J. of Finance* **59**, 1957–1978.

Johnson, T. C. 2008. Volume, liquidity, and liquidity risk. *J. of Financial Economics* **87**, 388–417.

Kyle, A. S. 1985. Continuous auctions and insider trading. *Econometrica* **53**, 1315–1336.

Lee, C. M. C., B. Swaminathan. 2000. Price momentum and trading volume. *J. of Finance* **55**, 2017–2069.

Merton, R. C. 1987. Presidential address: a simple model of capital market equilibrium with incomplete information. *J. of Finance* **42**, 483–510.

Miller, E. M. 1977. Risk, uncertainty, and divergence of opinion. *J. of Finance* **32**, 1151–1168.

Nagel, S. 2005. Short sales, institutional investors, and the cross-section of stock returns. *J. of Financial Economics* **78**, 277–309.

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

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

Roll, R. 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. *J. of Finance* **39**, 1127–1139.

Rouwenhorst, K. G. 1999. Local return factors and turnover in emerging stock markets. *J. of Finance* **54**, 1439–1464.

Sadka, R. 2006. Momentum and post-earnings-announcement drift anomalies: the role of liquidity risk. *J. of Financial Economics* **80**, 309–349.

Shleifer, A., and R. Vishny. 1997. The limits of arbitrage. *J. of Finance* **52**, 35–55.

Table 1. Turnover and Liquidity

Panel A: Liquidity measures used one-by-one

$$Turn_{t+1} = a + B \cdot Controls_t + C \cdot X_t,$$

$$X_t \in \{Spread_t;\ Roll_t;\ Gibbs_t;\ Amihud_t;\ Gamma_t\}$$

	Spread	Roll	Gibbs	Amihud	Gamma
Coef	0.080	0.038	0.052	-0.579	0.003
t-stat.	6.89	6.42	3.67	-7.62	1.49

Panel B: Liquidity measures used all together

$$Turn_{t+1} = a + B \cdot Controls_t + C \cdot X_t,$$

$$X_t = \{Spread_t;\ Roll_t;\ Gibbs_t;\ Amihud_t;\ Gamma_t\}$$

	Spread	Roll	Gibbs	Amihud	Gamma
Coef	0.049	0.008	0.063	-0.550	-0.004
t-stat.	5.81	2.87	5.22	-7.41	-1.78

Notes: The table presents Fama-MacBeth regressions of turnover (trading volume over shares outstanding, averaged within a quarter) on lagged measures of liquidity and lagged controls. *Spread*, *Roll*, and *Gibbs* measure effective bid-ask spread as percentage of the stock price and are described in Corwin and Schultz (2012), Roll (1984), and Hasbrouck (2009). *Amihud* and *Gamma* measure price impact as described in Amihud (2002) and Pastor and Stambaugh (2003). The annual measures are lagged by one year, the quarterly and monthly measures are lagged by one quarter. The controls used, but not reported, in every regression are positive/negative returns in the previous quarter (equal to the return if it is positive/negative, zero otherwise), market leverage, market-to-book, stock price, market cap, market beta in the past 60 months, firm age (number of months it appears in CRSP), and number of analysts following the firm (from IBES). All explanatory variables are transformed into rank variables between zero and one. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1964 to December 2010.

Table 2. Turnover, Liquidity, and Expected Returns

	1	2	3	4	5	6	7
Beta	0.333	0.354	0.328	0.351	0.352	0.362	0.288
t-stat.	5.64	7.81	5.58	7.36	7.47	6.63	5.04
Size	-0.373	-1.124	-0.468	-1.058	-1.018	-1.118	-0.930
t-stat.	-1.24	-4.03	-1.57	-3.09	-3.52	-1.73	-1.84
MB	-0.867	-0.770	-0.823	-0.874	-0.885	-0.663	-0.596
t-stat.	-3.54	-3.58	-3.51	-3.96	-4.34	-2.69	-2.83
Mom	1.835	1.290	1.568	1.195	1.158	1.473	1.449
t-stat.	8.31	4.81	7.02	4.56	4.43	5.18	6.14
Rev	-0.294	-0.380	-0.333	-0.423	-0.417	-0.287	-0.287
t-stat.	-2.39	-3.15	-2.67	-3.41	-3.46	-2.09	-2.23
Turn	-0.825	-0.649	-0.675	-0.723	-0.881	-0.718	-0.646
t-stat.	-3.69	-3.24	-3.12	-3.20	-2.63	-3.07	-2.30
Spread		0.328					-0.047
t-stat.		1.32					-0.78
Roll			0.238				0.077
t-stat.			1.69				0.36
Gibbs				0.319			0.114
t-stat.				1.69			0.72
Amihud					-0.695		-0.902
t-stat.					-1.85		-2.24
Gamma						-0.057	0.115
t-stat.						-0.90	0.42

Notes: The table presents results of firm-level Fama-MacBeth regressions run each month. The dependent variable is raw monthly return. Beta is lagged by one month, turnover is lagged by one quarter, size, market-to-book, and liquidity measures are lagged by one year. *Spread*, *Roll*, and *Gibbs* measure effective bid-ask spread as percentage of the stock price and are described in Corwin and Schultz (2012), Roll (1984), and Hasbrouck (2009). *Amihud* and *Gamma* measure price impact as described in Amihud (2002) and Pastor and Stambaugh (2003). All independent variables, except for market beta, are ranks between zero and one. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1964 to December 2010.

Table 3. Turnover and Liquidity Risk

Panel A: Liquidity risk measures used one-by-one

$$Turn_{t+1} = a + B \cdot Controls_t + C \cdot X_t,$$

$$X_t \in \{\beta_{PS};\ \beta_{Sad};\ \beta_{Ami};\ \beta_{PS-T};\ \beta_{Sad-T};\ \beta_{Ami-T}\}$$

	β_{PS}	β_{Sad}	β_{Ami}	β_{PS-T}	β_{Sad-T}	β_{Ami-T}
Coef	0.002	-0.005	-0.002	0.004	0.002	-0.008
t-stat.	0.62	-1.64	-0.96	0.98	0.53	-2.67

Panel B: Liquidity risk measures used all together

$$Turn_{t+1} = a + B \cdot Controls_t + C \cdot X_t,$$

$$X_t = \{\beta_{PS};\ \beta_{Sad};\ \beta_{Ami};\ \beta_{PS-T};\ \beta_{Sad-T};\ \beta_{Ami-T}\}$$

	β_{PS}	β_{Sad}	β_{Ami}	β_{PS-T}	β_{Sad-T}	β_{Ami-T}
Coef	-0.001	-0.004	-0.003	0.003	0.004	-0.006
t-stat.	-0.27	-1.15	-1.27	0.64	0.82	-2.02

Notes: The table presents Fama-MacBeth regressions of turnover (trading volume over shares outstanding, averaged within a quarter) on lagged measures of liquidity risk and lagged controls. The annual measures are lagged by one year, quarterly and monthly measures are lagged by one quarter. The controls used, but not reported, in every regression are positive/negative returns in the previous quarter (equal to the return if it is positive/negative, zero otherwise), market leverage, market-to-book, stock price, market cap, market beta in the past 60 months, firm age (number of months it appears in CRSP), and number of analysts following the firm (from IBES). Liquidity risk is measured by firm-level loadings on traded (subscript T) and non-traded factors. The factors are the traded and non-traded Pastor and Stambaugh (2003) factors, the non-traded Sadka (2006), and Amihud (2002) factors and their factor-mimicking portfolios. The liquidity factors are essentially innovations to average price impact. All explanatory variables are transformed into rank variables between zero and one. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2010.

Table 4. Turnover Effect and Liquidity Factors

Panel A: Value-weighted returns	Low	Turn2	Turn3	Turn4	High	L-H	Panel B: Equal-weighted returns	Low	Turn2	Turn3	Turn4	High	L-H
α_{FF}	0.084	0.033	-0.010	-0.088	-0.267	0.351	α_{FF}	0.026	-0.012	-0.060	-0.127	-0.395	0.421
t-stat.	1.32	0.58	-0.21	-1.23	-2.74	2.48	t-stat.	0.33	-0.21	-1.08	-2.34	-5.05	3.16
α_{PS}	0.106	0.020	-0.038	-0.122	-0.313	0.418	α_{PS}	0.047	-0.013	-0.085	-0.156	-0.413	0.460
t-stat.	1.46	0.31	-0.73	-1.70	-3.08	2.75	t-stat.	0.57	-0.20	-1.50	-2.75	-5.01	3.30
β_{PS-T}	0.016	0.002	-0.009	0.008	0.026	-0.009	β_{PS-T}	-0.012	-0.009	-0.011	0.012	0.050	-0.062
t-stat.	0.73	0.11	-0.54	0.38	0.71	-0.18	t-stat.	-0.65	-0.47	-0.51	0.69	1.87	-1.74
α_{Sadka}	0.113	0.075	-0.062	-0.124	-0.233	0.346	α_{Sadka}	-0.006	-0.089	-0.211	-0.278	-0.497	0.492
t-stat.	1.06	0.94	-0.95	-1.30	-1.81	1.68	t-stat.	-0.05	-0.98	-2.73	-3.64	-4.54	2.65
β_{Sad-T}	0.008	0.034	0.038	-0.009	-0.056	0.064	β_{Sad-T}	0.008	0.029	0.014	-0.001	-0.027	0.035
t-stat.	0.32	1.94	2.13	-0.38	-2.00	1.27	t-stat.	0.45	1.73	0.79	-0.06	-1.04	1.03
α_{Amihud}	0.053	0.012	-0.017	-0.108	-0.258	0.311	α_{Amihud}	-0.051	-0.078	-0.111	-0.172	-0.389	0.337
t-stat.	0.81	0.20	-0.32	-1.47	-2.57	2.14	t-stat.	-0.73	-1.39	-1.96	-2.94	-4.84	2.63
β_{Ami-T}	0.134	0.151	0.040	0.158	-0.067	0.201	β_{Ami-T}	0.431	0.427	0.312	0.310	-0.018	0.450
t-stat.	2.47	2.16	0.63	2.05	-0.73	1.99	t-stat.	6.61	4.66	3.52	2.91	-0.20	4.65

Notes: The table reports the alphas, liquidity betas, and FVIX betas for the turnover quintiles. The table presents Fama-French alphas (α_{FF}), the alphas (α_{PS}) and the liquidity betas (β_{PS-T}) from the four-factor model with the three Fama-French factors and the Pastor and Stambaugh traded factor, the alphas (α_{Amihud}) and the liquidity betas (β_{Ami-T}) from the four-factor model with the three Fama-French factors and the Amihud traded factor, and the alphas (α_{Sadka}) and the liquidity betas (β_{Sad-T}) from the four-factor model with the three Fama-French factors and the Sadka traded factor. The liquidity factors are described in the notes to Table 3. The turnover portfolios are rebalanced quarterly. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2010.

Table 5. Turnover and Uncertainty

Panel A: Uncertainty measures used one-by-one

$$Turn_{t+1} = a + B \cdot Controls_t + C \cdot X_t,$$

$$X_t \in \{IVol_t;\ Disp_t;\ Error_t\ CVEarn_t;\ CVCFO_t\}$$

	IVol	Disp	Error	CVEarn	CVCFO
Coef	0.116	0.040	0.039	0.044	0.043
t-stat.	5.19	3.94	5.67	7.84	9.55

Panel B: Uncertainty measures used all together

$$Turn_{t+1} = a + B \cdot Controls_t + C \cdot X_t,$$

$$X_t = \{IVol_t;\ Disp_t;\ Error_t\ CVEarn_t;\ CVCFO_t\}$$

	IVol	Disp	Error	CVEarn	CVCFO
Coef	0.130	0.016	0.017	0.030	0.028
t-stat.	8.37	3.41	6.45	9.06	8.22

Notes: The table presents Fama-MacBeth regressions of turnover (trading volume over shares outstanding, averaged within a quarter) on the lagged measures of uncertainty and lagged controls. The uncertainty variables are idiosyncratic volatility (*IVol*), analyst forecast dispersion (*Disp*), analyst forecast error (*Error*), coefficient of variability (standard deviation divided by average) of earnings (*CVEarn*) and cash flows (*CVCFO*). The annual measures are lagged by one year, quarterly and monthly measures are lagged by one quarter. The controls used, but not reported, in every regression are positive/negative returns in the previous quarter (equal to the return if it is positive/negative, zero otherwise), market leverage, market-to-book, stock price, market cap, market beta in the past 60 months, firm age (number of months it appears in CRSP), and number of analysts following the firm (from IBES). All explanatory variables are transformed into rank variables between zero and one. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1964 to December 2010.

Table 6. Turnover Effect and Aggregate Volatility Risk

Panel A: Value-weighted returns

	Low	Turn2	Turn3	Turn4	High	L-H
α_{CAPM}	0.120	0.073	0.021	-0.051	-0.299	0.419
t-stat.	1.91	1.12	0.45	-0.72	-2.32	2.39
α_{FF}	0.084	0.033	-0.010	-0.088	-0.267	0.351
t-stat.	1.32	0.58	-0.21	-1.23	-2.74	2.48
α_{ICAPM}	-0.075	-0.153	-0.141	-0.077	0.092	-0.167
t-stat.	-0.77	-1.38	-1.84	-0.90	0.58	-0.73
β_{FVIX}	-0.566	-0.684	-0.269	0.101	0.915	-1.481
t-stat.	-4.42	-3.39	-2.48	1.09	3.92	-4.32

Panel B: Equal-weighted returns

	Low	Turn2	Turn3	Turn4	High	L-H
α_{CAPM}	0.234	0.112	-0.036	-0.161	-0.523	0.757
t-stat.	1.18	0.70	-0.25	-1.19	-2.43	2.68
α_{FF}	0.035	-0.048	-0.156	-0.238	-0.474	0.510
t-stat.	0.31	-0.54	-1.94	-3.23	-4.40	2.76
α_{ICAPM}	0.327	0.182	0.082	0.030	-0.022	0.348
t-stat.	1.62	1.04	0.51	0.20	-0.09	1.31
β_{FVIX}	0.202	0.152	0.255	0.414	1.088	-0.886
t-stat.	1.47	1.44	2.87	4.02	3.25	-2.05

Notes: The table reports CAPM alphas, Fama-French alphas, ICAPM alphas, and FVIX betas for the turnover quintiles. FVIX is the factor-mimicking portfolio that tracks 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-quarter. The turnover portfolios are rebalanced quarterly. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2010.

Table 7. Cross-Sectional Regressions

	Price > $5			All firms		
	1	2	3	4	5	6
Beta	0.096	0.005	0.086	0.136	0.014	0.072
t-stat.	1.08	0.16	1.73	1.68	0.47	1.62
Size	-0.254	-0.089	-0.085	-0.830	-0.969	-0.988
t-stat.	-0.91	-0.21	-0.21	-2.23	-1.59	-1.62
MB	-0.771	-0.453	-0.470	-0.855	-0.742	-0.755
t-stat.	-3.62	-1.35	-1.41	-4.03	-2.14	-2.16
Mom	1.690	1.434	1.439	1.290	0.740	0.739
t-stat.	8.18	3.86	3.89	5.30	1.58	1.59
Rev	-0.299	-0.340	-0.333	-0.459	-0.469	-0.461
t-stat.	-2.66	-1.77	-1.75	-4.01	-2.34	-2.34
Turn	-0.507	-0.227	-0.293	-0.649	-0.271	-0.233
t-stat.	-2.76	-0.66	-0.87	-3.01	-0.80	-0.69
γ_{VIX}		-0.269			-0.308	
t-stat.		-2.21			-2.55	
β_{FVIX}			-0.918			-0.743
t-stat.			-3.20			-2.47

Notes: The table presents the results of firm-level Fama-MacBeth regressions run each month. The dependent variable is raw monthly return. Risk loadings are lagged by one month, turnover is lagged by one quarter, size and market-to-book are lagged by one year. All independent variables, except for the market beta, are ranks between zero and one. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2010.

Table 8. Turnover Effect, FVIX Betas, and Real Options

Panel A: Turnover effect and real options

	MB	1/BE	RD/TA	O-score	Cred	SUE flex	TVol sens
Turn	-0.406	0.051	-0.483	-0.424	1.033	-0.232	-0.398
t-stat.	-1.76	0.14	-1.32	-1.67	2.44	-0.68	-1.61
Var	-0.486	-0.176	1.856	-0.129	0.373	0.227	0.309
t-stat.	-2.14	-0.42	3.83	-0.70	0.65	1.62	2.55
Turn×Var	-0.621	-1.937	-0.961	-0.665	-2.036	-0.369	-0.765
t-stat.	-1.99	-5.14	-1.99	-2.27	-2.08	-1.75	-3.83

Panel B: FVIX betas and real options

	MB	1/BE	RD/TA	O-score	Cred	SUE flex	TVol sens
Turn	1.538	1.206	0.803	-0.484	0.980	1.512	1.474
t-stat	8.23	4.81	4.49	-2.21	5.22	9.83	8.29
Var	0.389	0.521	0.361	4.311	0.090	-0.121	-0.047
t-stat	2.98	1.47	1.69	3.14	1.97	-1.55	-0.47
Turn×Var	0.422	0.969	1.789	1.478	0.368	0.284	0.479
t-stat	1.93	3.16	5.88	5.60	5.32	2.35	3.09

Notes: Panel A presents results of firm-level Fama-MacBeth regressions run each month. The dependent variable is raw monthly return. The explanatory variables are turnover, real option proxies, the product of turnover and real option proxies, and controls (as in Tables 2 and 7). Each column presents the results of a separate regression with the real option proxy from the name of the column. Panel B repeats the analysis in Panel A replacing returns (the dependent variable) with FVIX betas and dropping the CAPM beta from the list of controls. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2010.

Table 9. Turnover Effect, Real Options, and Aggregate Volatility Risk

Panel A: Turnover effect, market-to-book, and aggregate volatility risk

A1: Value-weighted returns

	Value	MB2	MB3	MB4	Growth	G-V
α_{CAPM}	-0.211	0.318	0.438	0.223	0.636	0.847
t-stat.	-0.61	1.38	1.67	0.71	1.83	1.98
α_{ICAPM}	-0.231	0.137	0.282	-0.378	-0.221	0.010
t-stat.	-0.72	0.56	0.93	-1.15	-0.68	0.02
β_{FVIX}	-0.059	-0.411	-0.381	-1.285	-1.829	-1.770
t-stat.	-0.18	-1.64	-1.41	-3.01	-3.10	-2.90

A2: Equal-weighted returns

	Value	MB2	MB3	MB4	Growth	G-V
α_{CAPM}	0.513	0.608	0.377	0.664	0.826	0.313
t-stat.	1.83	3.02	1.58	2.81	3.07	1.17
α_{ICAPM}	0.524	0.424	0.267	0.358	0.481	-0.042
t-stat.	2.01	2.25	1.10	1.64	2.37	-0.18
β_{FVIX}	0.019	-0.398	-0.253	-0.646	-0.718	-0.736
t-stat.	0.06	-1.82	-1.47	-2.38	-2.01	-2.99

Panel B: Turnover effect, credit rating, and aggregate volatility risk

B1: Value-weighted returns

	Best	Cr2	Cr3	Cr4	Worst	W-B
α_{CAPM}	-0.162	0.011	-0.202	-0.004	0.780	0.943
t-stat.	-0.59	0.03	-0.60	-0.01	1.85	1.69
α_{ICAPM}	-0.334	-0.498	-0.848	-0.471	0.231	0.565
t-stat.	-1.12	-1.60	-1.90	-1.31	0.56	1.09
β_{FVIX}	-0.377	-1.116	-1.417	-1.025	-1.204	-0.828
t-stat.	-1.92	-3.21	-2.97	-3.12	-2.48	-1.84

B2: Equal-weighted returns

	Best	Cr2	Cr3	Cr4	Worst	W-B
α_{CAPM}	-0.148	0.020	0.122	0.173	0.580	0.728
t-stat.	-0.86	0.09	0.49	0.70	1.80	2.16
α_{ICAPM}	-0.235	-0.186	-0.140	0.000	0.157	0.391
t-stat.	-1.28	-0.78	-0.54	0.00	0.48	1.20
β_{FVIX}	-0.189	-0.451	-0.573	-0.380	-0.927	-0.737
t-stat.	-1.76	-2.63	-4.00	-2.22	-2.00	-1.69

Notes: The table reports CAPM alphas, ICAPM alphas, and FVIX betas of the low-minus-high turnover portfolio across market-to-book (Panel A) and credit rating (Panel B) quintiles. The low-minus-high turnover portfolio is long in the lowest turnover quintile and short in the highest turnover quintile. The market-to-book 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. All quintiles use NYSE (exchcd=1) breakpoints. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2010.

Table 10. Turnover Effect and Short-Sale Constraints

Panel A: Turnover effect and institutional ownership

A1: Value-weighted returns

	Low	RI2	RI3	RI4	High	L-H
α_{CAPM}	0.619	0.850	0.284	0.472	-0.033	0.651
t-stat.	1.64	2.35	0.95	1.70	-0.13	1.64
α_{ICAPM}	-0.172	0.073	-0.379	-0.031	-0.480	0.307
t-stat.	-0.51	0.25	-1.39	-0.12	-1.73	0.99
β_{FVIX}	-1.717	-1.732	-1.430	-1.077	-1.007	-0.710
t-stat.	-3.10	-2.92	-3.28	-4.55	-3.55	-1.67

A2: Equal-weighted returns

	Low	RI2	RI3	RI4	High	L-H
α_{CAPM}	1.222	1.176	0.597	0.517	0.291	0.931
t-stat.	3.55	3.25	2.21	2.47	1.29	3.45
α_{ICAPM}	0.536	0.556	0.120	0.329	0.124	0.413
t-stat.	1.62	1.74	0.45	1.52	0.54	1.64
β_{FVIX}	-1.498	-1.359	-1.042	-0.403	-0.377	-1.121
t-stat.	-2.66	-2.57	-2.58	-1.69	-1.77	-2.97

Panel B: Turnover effect and probability to be on special

B1: Value-weighted returns

	Low	Sh2	Sh3	Sh4	High	H-L
α_{CAPM}	-0.096	0.246	0.156	0.433	0.438	0.533
t-stat.	-0.31	0.65	0.55	1.45	1.07	1.05
α_{ICAPM}	-0.503	-0.055	-0.280	0.017	-0.191	0.312
t-stat.	-1.62	-0.16	-0.91	0.06	-0.42	0.57
β_{FVIX}	-0.885	-0.653	-0.945	-0.902	-1.364	-0.479
t-stat.	-3.51	-1.50	-3.77	-2.59	-2.12	-0.76

B2: Equal-weighted returns

	Low	Sh2	Sh3	Sh4	High	H-L
α_{CAPM}	0.184	-0.163	0.024	0.573	0.856	0.672
t-stat.	0.80	-0.65	0.09	2.27	2.63	2.04
α_{ICAPM}	0.111	-0.309	-0.332	0.301	0.398	0.287
t-stat.	0.46	-1.18	-1.16	1.20	1.39	0.97
β_{FVIX}	-0.158	-0.317	-0.774	-0.589	-0.993	-0.835
t-stat.	-0.70	-1.25	-2.64	-1.65	-1.91	-2.22

Notes: The table reports CAPM alphas, ICAPM alphas, and FVIX betas for the low-minus-high turnover portfolio across IO quintiles and the probability to be on special quintiles. The low-minus-high turnover portfolio is long in the lowest turnover quintile and short in the highest turnover quintile. RI is residual IO, Sh is the probability to be on special (see Section 5.1 for detailed definitions). All quintiles use NYSE (exchcd=1) breakpoints. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2010.

Table 11. Turnover Effect and Attention Proxies

Panel A: Turnover effect and analyst following

A1: Value-weighted returns							A2: Equal-weighted returns						
	Low	An2	An3	An4	High	L-H		Low	An2	An3	An4	High	L-H
α_{CAPM}	1.110	0.787	0.230	0.414	0.801	0.310	α_{CAPM}	1.208	0.945	0.629	0.594	0.547	0.661
t-stat.	3.31	2.78	0.68	1.34	2.39	0.91	t-stat.	3.92	3.43	2.25	2.46	2.17	3.18
α_{ICAPM}	0.188	0.204	-0.431	-0.003	0.249	-0.061	α_{ICAPM}	0.591	0.450	0.113	0.303	0.337	0.254
t-stat.	0.57	0.78	-1.29	-0.01	0.79	-0.17	t-stat.	1.83	1.49	0.37	1.28	1.58	1.04
β_{FVIX}	-2.033	-1.284	-1.428	-0.911	-1.207	-0.826	β_{FVIX}	-1.378	-1.073	-1.114	-0.660	-0.445	-0.933
t-stat.	-4.71	-4.97	-4.66	-1.87	-3.29	-2.66	t-stat.	-3.01	-2.21	-2.48	-1.90	-1.51	-3.04

Panel B: Turnover effect and price delay

B1: Value-weighted returns							B2: Equal-weighted returns						
	Low	D2	D3	D4	High	H-L		Low	D2	D3	D4	High	H-L
α_{CAPM}	0.446	0.361	0.746	0.463	0.731	0.285	α_{CAPM}	0.427	0.349	0.334	0.661	0.852	0.425
t-stat.	1.81	1.42	2.67	1.47	2.10	0.86	t-stat.	1.77	1.55	1.43	2.44	2.65	1.55
α_{ICAPM}	-0.153	-0.266	0.084	-0.077	0.282	0.435	α_{ICAPM}	-0.059	-0.040	-0.041	0.280	0.384	0.443
t-stat.	-0.66	-1.06	0.25	-0.26	0.75	1.23	t-stat.	-0.25	-0.17	-0.17	0.95	1.09	1.48
β_{FVIX}	-1.300	-1.360	-1.437	-1.173	-0.974	0.325	β_{FVIX}	-1.054	-0.844	-0.813	-0.827	-1.016	0.038
t-stat.	-4.63	-5.81	-4.04	-2.42	-1.75	0.77	t-stat.	-4.12	-3.11	-2.55	-2.30	-1.87	0.10

Notes: The table reports CAPM alphas, ICAPM alphas, and FVIX betas for the low-minus-high turnover portfolio across quintiles sorted on the number of analysts following the firm in Panel A and the price delay measure from Hou and Moskowitz (2005) in Panel B. The low-minus-high turnover portfolio is long in the lowest turnover quintile and short in the highest turnover quintile. All quintiles use NYSE (exchcd=1) breakpoints. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2010.