Analyst Disagreement and Aggregate Volatility Risk

Alexander Barinov

Terry College of Business
University of Georgia
E-mail: abarinov@terry.uga.edu
http://abarinov.myweb.uga.edu/

This version: July 2009

Abstract

The paper explains why firms with high dispersion of analyst forecasts earn low future returns. These firms beat the CAPM in the periods of increasing aggregate volatility and thereby provide a hedge against aggregate volatility risk. I show that both aggregate volatility and analyst disagreement increase during recessions. The increase in analyst disagreement causes real options to respond to higher aggregate volatility by a lower decline in value than what the CAPM predicts. First, all else equal, real options increase in value when disagreement about the underlying asset value goes up, and this effect increases with the level of disagreement. Second, higher disagreement means that real options become less sensitive to the underlying asset value and, therefore, less risky.

I find empirically that the aggregate volatility risk factor can explain the abnormal return differential between high and low disagreement firms. I also find that this return differential is higher for the firms with abundant real options (growth firms and low credit rating firms), and this fact can be explained by aggregate volatility risk. Aggregate volatility risk is also capable of explaining why the link between analyst disagreement and future returns is stronger for the firms with low institutional ownership and high short sale constraints, but not why the link between analyst disagreement and future returns is stronger for illiquid firms.

JEL Classification: G12, G13, G32, E44, D80, M41
Keywords: Aggregate volatility risk, analyst disagreement, analyst forecasts, real options, mispricing

1 Introduction

Diether, Malloy, and Scherbina (2002) established the puzzling analyst disagreement effect - the negative cross-sectional relation between analyst forecast dispersion and future returns. This negative relation is puzzling, because it appears that investors are paying a premium for bearing additional uncertainty about future earnings. Diether, Malloy, and Scherbina (2002) suggest that the analyst disagreement effect is created by short sale constraints: as was first argued by Miller (1977), in the presence of short sale constraints only the most optimistic investors trade, and the stocks become overpriced. More disagreement means more overpricing and lower future returns, because if disagreement is high, optimistic investors are more optimistic, and pessimistic investors are kept out of the market by short sale constraints.

In this paper, I propose a risk-based explanation of the analyst disagreement effect. I hypothesize that investors tolerate the negative CAPM alphas of the highest disagreement firms because these firms tend to beat the CAPM during the periods of increasing aggregate volatility. The mechanism that partially saves high disagreement firms from losses in volatile periods works through real options. First, both average and median analyst disagreement increase when aggregate volatility goes up (see Section 3 for the empirical evidence). Higher disagreement during periods of high aggregate volatility means that the value of real options becomes less sensitive to the value of the underlying asset and the real options become therefore less risky precisely when risks are high. This effect is stronger for the firms with higher initial level of disagreement. Hence, I predict that firms with high level of analyst disagreement and valuable real options will have procyclical market betas and will suffer smaller losses when aggregate volatility increases and the risk and expected returns of all firms go up.

Second, all else equal, real options increase in value when disagreement about the value of the underlying asset increases (see Grullon, Lyandres, and Zhdanov, 2007, for empirical evidence). That makes their reaction to the increases of aggregate volatility (usually coupled with increases of disagreement) less negative. I show that this effect is also stronger for high disagreement firms. The empirical prediction is the same: high disagreement firms, especially if they possess valuable real options, tend to lose less value

than other firms with similar market betas when aggregate volatility and average analyst disagreement both increase.

Abnormally good performance during aggregate volatility increases is a desirable thing. Campbell (1993) creates a model where increasing aggregate volatility is synonymous with decreasing expected future consumption. Investors would require a lower risk premium from the stocks the value of which correlates positively with aggregate volatility news, because these stocks provide additional consumption precisely when investors have to cut their current consumption for consumption-smoothing and precautionary savings motives. Chen (2002) adds in the precautionary savings motive and concludes that the positive correlation of asset returns with aggregate volatility changes is desirable, because such assets deliver additional consumption when investors have to consume less in order to boost precautionary savings. Ang, Hodrick, Xing, and Zhang (2006) confirm this prediction empirically and coin the notion of aggregate volatility risk. They show that the stocks with the most positive sensitivity to aggregate volatility increases have abnormally low expected returns and that the portfolio tracking expected aggregate volatility earns a significant risk premium. This paper builds on this literature and shows that high disagreement firms have low expected returns because they are a hedge against aggregate volatility risk.

An important feature of my aggregate volatility risk story is that the story is conditional on the market risk. Because the market return is strongly negatively correlated with aggregate volatility (the correlation between the market factor and the change in the VIX index is -0.626), any stock with a positive beta, including high disagreement stocks, will react negatively to increases in expected aggregate volatility. My prediction is that high disagreement firms react less negatively to aggregate volatility increases than what the CAPM predicts. This is the reason why these firms have negative CAPM alphas. I do not predict, however, that high disagreement firms will go up in value when aggregate volatility increases.

Johnson (2004) employs a similar idea in his attempt to explain the analyst disagreement effect. He creates a model that focuses on the real option created by leverage and shows that for a levered firm the equity value becomes less elastic with respect to the value of total assets, which means a lower expected equity return. Johnson (2004) uses cross-sectional regressions to show that the analyst disagreement effect increases with leverage

and is absent for all-equity firms. This empirical result is disputed by Sadka and Scherbina (2007) and Avramov, Chordia, Jostova, and Philipov (2009), who show that the sign of the product of leverage and analyst disagreement is not robust to reasonable changes in the sample composition.

My paper extends Johnson (2004) in several important dimensions. First, I add the time-series dimension to the story and show that the reduced sensitivity to value of the underlying asset and reduced risk of real options because of higher disagreement happens during tough economic times, when lower risk and lower losses are particularly welcome. Second, I notice another interaction of disagreement and real options: because, all else equal, the value of an option increases in volatility, real options of high disagreement firms offer partial protection against losses in the times of high volatility and disagreement. Third, I conclude that the analyst disagreement effect can be explained by the aggregate volatility risk factor, thus extending the characteristic-based regressions in Johnson (2004) to a formal asset-pricing test of the two-factor ICAPM. Fourth, I generalize the story to all real options, including growth options, which allows to overcome the fragility of the interaction between leverage and the analyst disagreement effect.

The empirical tests of my hypothesis use the FVIX factor, a factor-mimicking portfolio that tracks daily changes in the VIX index, my proxy for expected aggregate volatility. The VIX index measures the implied volatility of the options on the S&P 100 index, and therefore it is a direct measure of the market expectation of aggregate volatility. Ang, Hodrick, Xing, and Zhang (2006) show that at the daily frequency VIX behaves like a random walk, which means that its change is a valid proxy for innovation in expected aggregate volatility, the variable of interest in the ICAPM context.

I find that the two-factor ICAPM with the market factor and the FVIX factor explains 50% to 90% of the analyst disagreement effect, leaving the rest insignificant. The FVIX betas suggest that high disagreement firms beat the CAPM and low disagreement firms trail the CAPM when expected aggregate volatility increases unexpectedly. This conclusion is supported by the supplemental test that yields the same result using the changes in the VIX index directly, and by the conditional CAPM test that shows that the riskiness of buying low disagreement firms and shorting high disagreement firms increases sharply in recessions.

Consistent with my hypothesis, I also find that the analyst disagreement effect is stronger for the firms with higher market-to-book and lower credit rating. This dependence of the analyst disagreement effect on real options measures is perfectly explained by the FVIX factor, confirming that the hedging power of high disagreement firms against aggregate volatility risk increases with the value of real options these firms have. I corroborate the FVIX results by replacing FVIX by the change in VIX and by looking at the conditional CAPM betas: the low minus high disagreement portfolio indeed underperforms the CAPM in volatile periods by a greater amount, if this portfolio is formed in the growth firms subsample, and the beta of the low minus high disagreement portfolio increases more in recessions in the growth subsample.

Because of the strong negative correlation between leverage and market-to-book, which means that highly levered firms have few growth options, I fail to find similar results using market leverage instead of credit rating, inconsistent with Johnson (2004), but consistent with Sadka and Scherbina (2007) and Avramov, Chordia, Jostova, and Philipov (2009).

The evidence that the analyst disagreement effect increases with market-to-book and this increase can be explained by aggregate volatility risk is new to the literature. The fact that the analyst disagreement effect is stronger for the firms with lower credit rating is known from Avramov, Chordia, Jostova, and Philipov (2009). My contribution is to link this fact to aggregate volatility risk rather than to investors' failure to fully acknowledge the higher default risk of high disagreement firms.

Several recent papers try to show that the analyst disagreement effect is caused by short sale constraints. Nagel (2005) shows that the analyst disagreement effect is concentrated among the stocks with the lowest level of institutional ownership. Nagel (2005) concludes that this evidence speaks in favor of the mispricing explanation based on short sales constraints, as proposed by Diether, Malloy, and Scherbina (2002). Boehme, Danielsen, and Sorescu (2006) demonstrate that the strength of the analyst disagreement effect increases with their proxy for short sale constraints that combines short interest and the dummy variable for the existence of traded options.

In this paper, I show that the relation between the analyst disagreement effect and both institutional ownership and short-sale constraints can be explained by aggregate volatility

risk. The strategy of buying low disagreement firms and shorting high disagreement firms has the largest exposure to the aggregate volatility factor if followed in the subsample of firms with the lowest institutional ownership or the highest probability to be on special. I confirm the result with FVIX by using the VIX changes instead, and additionally corroborate it by showing that the market beta of the strategy buying low disagreement firms and shorting high disagreement firms is more countercyclical if this strategy is followed in the sample of the firms with the lowest institutional ownership or the highest probability to be on special.

In the case of probability to be on special, I find the natural positive association between analyst disagreement and the price for shorting the stock. Hence, sorting on the probability that this price will be high is similar to sorting on disagreement twice. Naturally, the second-pass sort on disagreement creates a wider spread in disagreement, expected returns, and aggregate volatility risk exposure if performed among the firms with sizeable levels of analyst disagreement.

In the case of institutional ownership, the story is that institutional investors are trying to maintain a trade-off between hedging against aggregate volatility risk and buying high disagreement firms (which is the way to hedge against aggregate volatility risk), because they like the hedge, but dislike idiosyncratic volatility. As a result, institutional ownership is positively associated with analyst disagreement for low disagreement stocks (institutional investors are buying the hedge against aggregate volatility risk while the hedge is cheap in terms of additional idiosyncratic volatility), but institutional ownership is negatively associated with analyst disagreement for high disagreement firms (institutional investors are trying to avoid additional idiosyncratic volatility even if it means lower aggregate volatility risk). Hence, for low disagreement firms low institutional ownership is the sign of high aggregate volatility risk, and among high disagreement firms the ones with the lowest institutional ownership have the highest disagreement and the lowest aggregate volatility risk. Thus, the aggregate volatility risk differential between low and high disagreement firms should be the largest among low institutional ownership firms. This risk differential creates the large analyst disagreement effect for the firms neglected by institutional investors first documented by Nagel (2005).

To conclude, I show that in the case of the analyst disagreement effect the conventional

proxies to short sale constraints in fact proxy for aggregate volatility risk. This evidence not only leads us to rethink the evidence that the analyst disagreement effect is related to short sale constraints, but also suggests that the other known relations between anomalies and the proxies for short sale constraints may have similar aggregate volatility risk interpretation.

Sadka and Scherbina (2007) argue that the analyst disagreement effect is mispricing, but this mispricing is impossible to exploit because of low liquidity and high trading costs. Their main evidence is that the analyst disagreement effect is present only in the subsample of firms with large price impact. They corroborate this result by showing that the analyst disagreement effect is stronger among small stocks and that it usually becomes insignificant after six to nine months. I confirm their findings in my sample and check if aggregate volatility risk can be responsible for these regularities. I find little evidence that the FVIX factor can explain the relation between the strength of the analyst disagreement effect and the liquidity proxies. However, while aggregate volatility risk cannot explain the analyst disagreement effect in the top illiquidity quintile and the bottom size quintile, the FVIX factor is essential for explaining the sizeable analyst disagreement effect in the other parts of the sample.

The paper proceeds as follows: Section 2 discusses the data sources, Section 3 tests the necessary condition of my story that analyst disagreement increases during recessions and periods of high volatility, and Section 4 uses the aggregate volatility risk factor to explain the analyst disagreement effect and its behavior in event time. Section 5 looks at the relation between the analyst disagreement effect and several measures of real options and establishes that this relation can be explained by aggregate volatility risk. Section 6 looks at the alternative explanations of the analyst disagreement effect and shows that aggregate volatility risk can explain the relation of the analyst disagreement effect to short sale constraints proxies, but not to illiquidity proxies. Section 7 corroborates all results in the paper by, first, replacing FVIX with changes in VIX and, second, by looking at conditional CAPM market betas. Section 8 summarizes the results and concludes.

2 Data

The data in the paper come from CRSP, Compustat, IBES, and the CBOE indexes databases. The sample period is from January 1986 to December 2006. The firms with the price of $5 or less are excluded from the sample. Analyst forecast dispersion is the standard deviation of all outstanding earnings-per-share forecasts for the current fiscal year scaled by the absolute value of the average outstanding earnings forecast (zero-mean forecasts and forecasts by only one analyst excluded). The data on analyst forecasts are from IBES.

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

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

In Section 5 I use three real options proxies: market-to-book, leverage, and credit rating. I compute market-to-book and leverage from Compustat data. Market-to-book is market value of equity (item #25 times item #199) over the sum of book equity (item #60) and deferred taxes (item #74). Leverage is long-term debt (Compustat item #9) plus short-term debt (Compustat item #34) divided by market value of equity (Compustat item #25 times Compustat item #199). Credit rating is as computed by Standard and

Poor's (item #280 in the Compustat annual file). The numeric credit rating is increasing in credit risk: 1=AAA, 2=AA+, 3=AA, ... , 21=C, 22=D. Higher credit rating therefore means higher risk of default. When I sort firms on credit rating, market-to-book, or leverage at the end of the year, I use their value from the fiscal year ending no later than June of the sorting year.

I use two liquidity measures: size and the price impact measure from Amihud (2002). Size is shares outstanding times price from the CRSP monthly returns file. Low size implies low liquidity. The Amihud (2002) illiquidity measure is the ratio of absolute return to dollar volume averaged separately for each firm-year. Firms with less than 200 valid return observations in a year and the stock price of less than \$5 at the end of the previous year are excluded. The higher is the Amihud measure, the higher are the price impact and trading costs, which means lower liquidity.

I use two measures of short sale constraints - residual institutional ownership, $RInst$, and the estimated probability to be on special, $Short$. I define institutional ownership for each firm-quarter as the sum of institutional holdings from Thompson Financial 13F database, divided by the shares outstanding from CRSP. If the stock is on CRSP, but not on Thompson Financial 13F database, it is assumed to have zero institutional ownership. Following Nagel (2005), I drop all stocks below the 20th NYSE/AMEX size percentile and measure residual institutional ownership for the remaining stocks as the residual from

$$log(\frac{Inst}{1-Inst}) = \gamma_0 + \gamma_1 \cdot log(Size) + \gamma_2 \cdot log^2(Size) + \epsilon \tag{1}$$

The estimated probability to be on special is defined as in D'Avolio (2002) and Ali and Trombley (2006)

$$Short = \frac{e^y}{1+e^y}, \tag{2}$$

$$y = -0.46 \cdot log(Size) - 2.8 \cdot Inst + 1.59 \cdot Turn - 0.09 \cdot \frac{CF}{TA} + 0.86 \cdot IPO + 0.41 \cdot Glam \tag{3}$$

Equation (3) uses the coefficients estimated by D'Avolio (2002) for a short 18-month sample of short sale data. Ali and Trombley (2006) use the same formula to estimate the probability to be on special for the intersection of Compustat, CRSP, and Thompson Financial populations. They show that the estimated probability is closely tied to other short sale constraint measures in different periods.

In (3) $Size$ is defined as shares outstanding times the price per share and measured in millions, $Inst$ is institutional ownership, $Turn$ is turnover, defined as the trading volume over shares outstanding, CF is cash flow[1], TA are total assets (Compustat item #6), IPO is the dummy variable equal to 1 if the stock first appeared on CRSP 12 or less months ago, and $Glam$ is the dummy variable equal to 1 for three top market-to-book deciles.

To estimate the conditional CAPM in Section 7, I employ four commonly used conditioning variables: the dividend yield, the default premium, the risk-free rate, and the term premium. I define the dividend yield, (DIV_t), as the sum of dividend payments to all CRSP stocks over the previous 12 months, divided by the current value of the CRSP value-weighted index. The default spread, (DEF_t), is the yield spread between Moody's Baa and Aaa corporate bonds. The risk-free rate is the one-month Treasury bill rate, (TB_t). The term spread, ($TERM_t$), is the yield spread between ten-year and one-year Treasury bond. The data on the dividend yield and the risk-free rate are from CRSP. The data on the default spread and the term spread are from FRED database at the Federal Reserve Bank at St. Louis.

3 Analyst Disagreement in Time-Series and Cross-Section

3.1 Analyst Disagreement, Aggregate Volatility, and the Business Cycle

In this subsection, I show that analyst disagreement increases when aggregate volatility is high and the economy is in recession. This empirical fact is necessary to make the prediction that high analyst disagreement firms are hedges against aggregate volatility risk: my story has it that their value responds less negatively to aggregate volatility increases, because the value of their growth options drops less due to a simultaneous increase in the uncertainty about the underlying asset.

[1]Following D'Avolio (2002) and Ali and Trombley (2006) I define cash flow as operating income before depreciation (Compustat item #178 plus Compustat item #14) less non-depreciation accruals, which are change in current assets (Compustat item #4) less change in current liabilities (Compustat item #5) plus change in short-term debt (Compustat item #34) less change in cash (Compustat item #1).

The related evidence (see, e.g., Campbell, Lettau, Malkiel, and Xu, 2001) is that the idiosyncratic volatility of the average firm is higher during the NBER-defined recessions and is strongly positively correlated with realized market volatility. In this subsection, I extend these results to analyst disagreement using expected aggregate volatility instead of realized one. The first measure of expected aggregate volatility is the VIX index, which is the implied volatility of the one-month options on S&P 100. The second measure is the TARCH(1,1) market volatility forecast. The TARCH(1,1) model is estimated using monthly returns to the CRSP value-weighted index. The TARCH(1,1) model is a modification of GARCH(1,1) that allows for the asymmetric volatility response to negative returns[2].

In Figure 1 I look at the dynamics of the average analyst disagreement and the analyst disagreement of the median firm. The shaded regions are NBER recessions. It is visible in the picture that both the average and the median disagreement tend to increase during recessions, lagging behind by a few months, because some analyst forecasts are stale and analyst forecasts on average lag stock prices.

In Table 1, I provide formal evidence to corroborate Figure 1. In the first rows of Panel A (average analyst disagreement) and Panel B (analyst disagreement of the median firm) I regress the logs of the respective variables on the recession dummy that takes the value of 1 in periods NBER marks as recessions, and 0 otherwise. The average dispersion of analyst forecasts is higher in recessions by 17% to 29% (t-statistics from 1.81 to 2.50), depending on whether we take the contemporaneous value of the recession dummy or lag it by several quarters to account for stale forecasts. The strongest relation between average analyst disagreement and the recession dummy exists when the recession dummy is lagged by three quarters. The dispersion of analyst forecasts for the median firm also increases significantly during recessions - by 17% to 19% (t-statistics from 2.45 to 3.95).

In the next rows I regress the log of analyst forecast dispersion on the log of the VIX index values. Table 1 shows that 1% increase in the VIX index triggers about 0.3% increase in the average analyst forecast dispersion (t-statistics exceed 3). The increase in the median analyst forecast dispersion is about 0.1% per each 1% increase in VIX (insignificant). In untabulated results I find that during NBER-marked recessions VIX is higher, on average,

[2]See Glosten, Jagannathan, and Runkle (1993) for more details about TARCH models.

by 30 to 50% than during expansions, which means that analyst disagreement is higher then by 5 to 15%, consistent with the results in the previous paragraph.

The reaction of the analyst disagreement to changes in the forecasted market volatility from TARCH(1,1) model is smaller and hovers around 0.1% to 0.15% for each 1% increase in the forecasted volatility. The t-statistics for both average and median between 2.0 and 2.5. The smaller slopes are likely due to the fact that the TARCH volatility fluctuates more than VIX and in recessions it is higher than in booms by 60 to 100%.

Overall, I document statistically significant and economically sizeable relation of analyst disagreement to business cycle and expected aggregate volatility. Analyst disagreement is 20% higher in recessions and increases substantially when expected aggregate volatility is high. This evidence lends firm empirical ground to my story. I hypothesize that high disagreement firms with valuable real options are good hedges against increases in expected aggregate volatility because of their ability to transform higher firm-specific uncertainty into lower risk and higher value. The missing link was the positive relation between expected aggregate volatility and analyst disagreement, and this relation is established in this section.

3.2 Descriptive Statistics across the Analyst Disagreement Quintiles

In Table 2 I present the descriptive statistics for analyst disagreement quintiles. I first sort all firms into the disagreement quintiles using NYSE breakpoints. NYSE firms are defined as the firms for which the exchcd listing indicator from the CRSP events file is equal to 1 at portfolio formation. I follow the tradition in the literature and exclude the firms with the price of $5 or less on the date of portfolio formation. Then I compute the median of each firm characteristic in Table 2 separately for each quintile on the date when the quintile portfolio was formed. Quintile portfolios are rebalanced monthly.

The firm characteristic fall into three categories: the measures of real options, the liquidity measures, and the proxies for short sale constraints. In the first group, I look at market-to-book, market leverage, and the credit rating. The numerical credit rating reported in the table is increasing in default risk: AAA=1, AA+=2, ..., C=21, D=22. I

treat leverage and credit rating as two complementing indicators of how close to the money the real option created by leverage is. Default can be likely both because the company has a lot of debt or because its financial health is poor.

I find that median market-to-book increases by about a half and median market leverage decreases by about a half as I go from the highest disagreement firms to the lowest disagreement firms. High disagreement firms tend to be distressed firms with limited growth prospects. The credit rating confirms it: its median increases monotonically from 7 (A-) in the lowest disagreement quintile to almost 12 (BB) in the highest disagreement quintile. This is consistent with the evidence in Avramov, Chordia, Jostova, and Philipov (2009).

The second group of firm characteristics measures liquidity. I look at size (in billion dollars) and the price impact measure of Amihud (2002), also known as the Amihud illiquidity ratio. The Amihud measure is the ratio of absolute return to dollar volume (in millions) averaged across each firm-year. Stocks are required to have at least 200 non-missing return and volume observations to compute the Amihud measure. In Table 2, I multiply the Amihud measure by 100 millions, making the figures the percentage change in stock price in response to trading $1 million of the stock in a day.

The relation between size and disagreement is slightly non-monotonic: median size peaks at $736 million in the second lowest disagreement quintile, followed by $614 in the lowest disagreement quintile. This contrasts with the median size in the highest disagreement quintile, $294 million, the decrease of more than two times from the lowest disagreement quintile. The difference in size suggests that high disagreement firms are relatively illiquid.

This conclusion is supported by the Amihud price impact measure that follows a U-shape pattern closely mirroring the inverted U-shape pattern in size. For the median firm in the second-lowest disagreement quintile pushing $1 million (0.14% of total firm capitalization) through the market during a single day would move the prices by about 1.9%. For the median firm in the highest disagreement quintile trading the same $1 million of daily trading volume (0.34% of the total firm capitalization) would move the prices by about 4.4%. The median price impact declines monotonically from the second-lowest to

the highest disagreement quintile, but jumps up in the lowest disagreement quintile to almost 3.2% price reaction to $1 million of daily trading volume (0.16% of the total firm capitalization).

The third group of firm characteristics measures short sale constraints. Here I look at the institutional ownership (percentage of shares outstanding held by institutional investors), residual institutional ownership (orthogonalized to size following Nagel, 2005, see equation (1)), and the probability to be on special, estimated using (2) and (3) as suggested by Ali and Trombley (2006). Being on special is synonymous to having to pay high fees for shorting the stock[3].

I find that the variation in institutional ownership across the disagreement quintiles is small: institutions hold 47.4% of the median firm in the highest disagreement quintile and 51.9% of the median firm in the lowest disagreement quintile. The residual ownership is completely flat across the disagreement quintile, suggesting that the variation in institutional ownership is driven primarily by size.

The lack of relation between institutional ownership and analyst disagreement is surprising, because institutions are believed to stay away from high uncertainty stocks (see, e.g., Shleifer and Vishny, 1997). I believe that the lack of relation between institutional ownership and analyst disagreement can be explained by the fact that institutional investors acknowledge the ability of high disagreement firms to hedge against aggregate volatility risk and find this feature desirable. However, all else equal, they also prefer lower disagreement stocks, consistent with the argument in Shleifer and Vishny (1997). Therefore, in the low disagreement subsample institutional investors tend to choose higher disagreement firms, because the price of the hedge (in terms on additional uncertainty) is low. In the high disagreement subsample, the aversion to idiosyncratic volatility wins, and institutional investors choose lower disagreement firms. Hence, the correlation between institutional ownership and analyst disagreement should be positive if disagreement is low and negative if disagreement is high, but it can well be zero on average.

[3]When the stock is sold short, the party that sells it short (the borrower) borrows the stock from the party that owns it (the lender) and immediately sells it. The proceeds (plus a 2% margin) are deposited with the lender, and the lender pays the borrower the risk-free rate less the short sale fee on the deposit. If the stock is on special, the fee is larger than the risk-free rate, and the sum left with the lender declines with time.

I confirm this hypothesis by performing independent double sorts on institutional ownership and analyst disagreement (results not reported to save space). In the lowest disagreement quintile, the median of my analyst disagreement measure is 15.1% (t-statistic 10.32) higher in the highest institutional ownership quintile than in the lowest institutional ownership quintile. In the highest disagreement quintile, however, the reverse is true: the median disagreement measure is 10.1% (t-statistic 4.33) higher in the lowest institutional ownership quintile.

However, with probability to be on special I get a clearer picture confirming that high disagreement firms can indeed be short-sale constrained, as Diether, Malloy, and Scherbina (2002) suggest. The probability to be on special monotonically increases from the median of 3.7% in the lowest disagreement quintile to the median of 7.7% in the highest disagreement quintile. The relation between analyst disagreement and the probability to be on special is so strong that double sorts on these two variables can turn out to be similar to sorting on analyst disagreement twice. If this is the case, the relation between the analyst disagreement effect and short sale constraints in Boehme, Danielsen, and Sorescu (2006) can potentially be explained by aggregate volatility risk.

4 Analyst Disagreement Effect and Aggregate Volatility Risk

4.1 Explaining the Analyst Disagreement Effect

The central idea of the paper is that the negative relation of analyst disagreement to future returns (the analyst disagreement effect) can be explained by aggregate volatility risk. I argue that high disagreement firms beat the CAPM during the periods of increasing aggregate volatility for two reasons. First, higher disagreement means lower sensitivity of the real options value to the value of the underlying asset and therefore lower risk. When aggregate volatility increases, the simultaneous increase in analyst disagreement (see the evidence in the previous section) mutes the corresponding increase in risk and consequent decrease in value. This effect is naturally stronger for high disagreement firms with abundant real options. Second, real options themselves, holding all else equal, benefit

from the increase in disagreement, and even more so if they are initially written on high disagreement assets.

The transformation of high firm-specific uncertainty (proxied by analyst disagreement) into lower risk of real options can be understood using the fact that the beta of real options is, by Ito's lemma, the product of the underlying asset beta and the option value elasticity with respect to the underlying asset value. While changes in the firm-specific uncertainty do not influence the beta of the underlying asset, they do make the elasticity and, hence, the growth options beta smaller. The decline in elasticity comes from the well-known fact that the option delta decreases in volatility.

My primary test of whether aggregate volatility risk can explain the analyst disagreement effect is fitting the two-factor ICAPM with the market factor and the aggregate volatility factor to the analyst disagreement quintile portfolios. I expect to find that the CAPM alpha differential between high and low disagreement firms disappears once I control for the aggregate volatility risk factor. The loadings of the analyst disagreement quintile portfolios on the aggregate volatility risk factor should also reveal the exposure of low disagreement firms to aggregate volatility risk and the ability of high disagreement firms to hedge against it.

I form the aggregate volatility risk factor (the FVIX factor) as the zero-investment portfolio that tracks daily changes in expected aggregate volatility. I regress the daily changes in the VIX index on the daily excess returns to the six size and book-to-market portfolios (sorted in two groups on size and in three groups on book-to-market). The regression uses all data from January 1986 to December 2006, which is the period when the VIX index is available. The FVIX factor is the fitted part of the regression less the constant. To obtain the monthly values of FVIX, I cumulate its daily returns. All results in the paper are robust to using other base assets instead of the six size and book-to-market portfolios, such as the 10 industry portfolios (from Fama and French, 1997) or the aggregate volatility sensitivity quintiles (from Ang, Hodrick, Xing, and Zhang, 2006).

Ang, Hodrick, Xing, and Zhang (2006) use a very similar factor-mimicking portfolio. The only difference is that they perform the factor-mimicking regression of VIX changes on the excess returns to the base assets separately for each month. Clearly, the estimates

of six or seven parameters using 22 data points are not too precise, and it is especially true about the constant, which varies considerably month to month. This variation adds noise to their version of FVIX, and the imprecise estimation of the constant makes the FVIX factor premium small and insignificant. In unreported results I find that the Ang, Hodrick, Xing, and Zhang (2006) version of FVIX is significantly correlated with my version of FVIX and produces the betas of the same sign if used instead of my FVIX. However, the use of the Ang, Hodrick, Xing, and Zhang (2006) version of FVIX in asset-pricing tests is problematic because of the noise in it and the small factor premium.

In unreported results, I look at the factor premium of FVIX. FVIX is a zero-investment portfolio that yields positive return when expected aggregate volatility increases, thus hedging against aggregate volatility risk. Therefore, FVIX has to earn significantly negative return even after other sources of risk have been controlled for. Consistent with that, the raw return to FVIX is -1.01% per month (t-statistic -4.35), and the CAPM alpha of FVIX is -56 bp per month (t-statistic -3.0).

Barinov (2009) shows that the ICAPM with the market factor and the FVIX factor beats the Fama-French model in pricing several portfolio sets. The ICAPM with FVIX also explains the puzzling underperformance of the smallest growth stocks and new issues. The FVIX factor is therefore a strong and important factor with broad applications.

In Table 3, I look at the alphas and FVIX betas of the analyst disagreement quintiles. The first three rows confirm the evidence in Diether, Malloy, and Scherbina (2002) that analyst disagreement is negatively related to future returns. The CAPM and Fama-French (1993) alpha differential between the bottom and top disagreement quintiles is about 70 bp in equal-weighted returns and about 50 bp in value-weighted returns, all highly significant.

In the next two rows I show that in the ICAPM with the market factor and the FVIX factor this return differential declines by about a half and becomes insignificant in equal-weighted returns and is completely wiped away in value-weighted returns. The reason is the large spread in FVIX betas, which vary, for equal-weighted returns, from 0.557, t-statistic 3.81, in the highest disagreement quintile, to -0.201, t-statistic -2.32, in the lowest disagreement quintile. The positive FVIX betas of high disagreement firms means that these firms react more positively to aggregate volatility increases than what the CAPM

predicts, and therefore high disagreement firms are less risky than what the CAPM says, which explains their negative CAPM alphas.

In the last two rows, I augment the Fama-French (1993) model with the FVIX factor. The FVIX factor performs the same way as it performs in the CAPM, reducing the equal-weighted Fama-French alpha by about 40% and completely wiping away the value-weighted differential in Fama-French alpha. The FVIX betas, in equal-weighted returns, vary from -1.603, t-statistic -9.28, for the lowest disagreement quintile, to 0.443, t-statistic 2.76, for the highest disagreement quintile. The spread in the FVIX betas is wider than in the case of the ICAPM, because the CAPM alpha of the FVIX portfolio is larger than its Fama-French alpha.

Overall, Table 3 shows that, as predicted by my story, higher analyst disagreement means lower aggregate volatility risk, which explains the negative relation between the dispersion of analyst forecasts and future returns documented by Diether, Malloy, and Scherbina (2002). First, I show that adding the FVIX factor to either the CAPM or the Fama-French model explains the return differential between the firms with the lowest and the highest analyst disagreement. Second, I find that the highest disagreement firms tend to significantly outperform the prediction of the CAPM or the Fama-French model when aggregate volatility increases, hedging in this way against aggregate volatility risk.

4.2 Analyst Disagreement Effect in Event Time

Diether, Malloy, and Scherbina (2002) show that the negative relation between analyst forecast dispersion and future returns declines by 50% and becomes insignificant after six months. They argue that the quick dissipation of the analyst disagreement effect suggests that it is mispricing that is corrected fairly quickly.

It is also possible that the data on analyst disagreement become stale and the analyst disagreement effect on future returns weakens with time. If this is the case, I expect the FVIX betas also decline with time. However, if mispricing is behind part of the analyst disagreement effect, then the decline in FVIX betas will not be enough to explain the event-time decline in the analyst disagreement effect.

Table 4 shows the equal-weighted alphas and the FVIX betas, as well as raw returns, of the arbitrage portfolio long in the lowest disagreement quintile and short in the highest disagreement quintile. The analyst disagreement is measured one to twelve months ago, and the results are reported in the column with the respective number (e.g., column five has the results for the arbitrage portfolio that uses the disagreement quintiles formed five months ago).

In the first three rows of Table 4 I confirm the result of Diether, Malloy, and Scherbina (2002) that the negative relation between disagreement and future returns disappears in six to nine months. For example, the CAPM alpha of the low minus high disagreement portfolio starts at 76.5 bp per month, t-statistic 3.53, in the first month after portfolio formation, is still 44.5 bp, t-statistic 2.03, in the seventh month, but then declines to 37 bp, t-statistic 1.76, in the ninth month and 23 bp, t-statistic 1.15, in the twelfth month. The Fama-French alphas start a bit lower and decline a bit faster. The last column of Table 4 tests the hypothesis that the CAPM and Fama-French alphas of the low minus high disagreement portfolio in month one and month twelve are equal and rejects this hypothesis with t-statistics above 5, indicating significant decline in the alphas.

The ICAPM alpha of the low minus high disagreement portfolio and the alpha from the Fama-French model augmented with the FVIX factor are insignificant in all periods, suggesting that the mispricing story is redundant controlling for aggregate volatility risk. The only exception is the equal-weighted alpha from the Fama-French model with FVIX. The alpha starts 40 bp per month, t-statistic 2.4, in month one, but declines to 25 bp, t-statistic 1.48, in month two and never comes close to significance since then.

The FVIX betas in the ICAPM decline by about 20% (from -0.76 to -0.59, t-statistic for the difference -1.39) between month one and month twelve, but remain highly significant in month twelve. The same is true about the FVIX betas in the four-factor model with FVIX and the Fama-French factors. Given the CAPM alpha of the FVIX factor (-56 bp per month), the -0.17 decline in the FVIX beta is hardly enough to explain 10 bp of the 50 bp decline in the analyst disagreement effect between month one and month twelve. Consistent with that, the decline in the ICAPM alphas between month one and month twelve is highly significant with t-statistic 4.6, even though none of the ICAPM alphas per se is significant. The same is true about the decline in the FVIX betas from

the Fama-French model with FVIX (t-statistic for the difference between month one and month twelve is 4.74).

The overall conclusion from Table 4 is ambiguous. On the one hand, after I properly control for risk, I do not see any evidence of mispricing in any period. On the other hand, the aggregate volatility risk story cannot explain more than a quarter of the weakening of the analyst disagreement effect in event time. I conclude tentatively that both explanations could be at work, but the aggregate volatility risk takes a bigger part of the analyst disagreement effect than mispricing. I delay further exploration of the role of mispricing in creating the analyst disagreement effect until Section 6.

5 Analyst Disagreement Effect and Real Options

The main prediction of my story is that higher analyst disagreement lowers the exposure of real options to aggregate volatility risk. The natural prediction is that the analyst disagreement effect is stronger for the firms with abundant real options. Also, the difference in aggregate volatility risk exposure between high and low disagreement firms should be small for the firms with few real options and increase significantly as we look at more and more option-like firms.

In this section, I look at three measures of real options: market-to-book (which measures growth options), market leverage and credit rating (which measure the option created by risky debt and limited liability). I look at credit rating in addition to leverage for three reasons. First, the moneyness of the option created by leverage depends both on how much debt the firm has (leverage) and its financial health (credit rating). A relatively highly levered firm can be growing and prosperous, and its leverage-created option will have low value despite the high leverage.

Second, market-to-book and leverage are highly negatively correlated, both for mechanical reasons (market value of equity is in the numerator of market-to-book and in the denominator of leverage) and because firms with low levels of growth opportunities tend to choose higher levels of leverage. My story, however, predicts that the analyst disagreement effect and the hedging power of high disagreement firms will be higher for

both high market-to-book and high leverage firms. Therefore, the effect of market-to-book and the effect of leverage on the analyst disagreement effect and the FVIX betas as its explanation will work against each other. The correlation between market-to-book and credit rating is still negative (higher numerical credit rating means higher default risk), but much lower than the correlation between market-to-book and leverage, which means that for my purpose credit rating will be a cleaner proxy for the importance of the option created by leverage.

Third, Avramov, Chordia, Jostova, and Philipov (2009) show that the analysts disagreement effect exists only in the bottom two quintiles with the worst credit rating. These quintiles account for 4.5% of market capitalization and 26% of rated firms. Avramov, Chordia, Jostova, and Philipov (2009) use this evidence to argue that the analyst disagreement effect arises because investors fail to fully acknowledge the future losses of distressed firms. It is interesting to see whether the findings of Avramov, Chordia, Jostova, and Philipov (2009) can be explained by aggregate volatility risk, because my story makes a similar prediction that the analyst disagreement effect will be stronger for distressed firms, but the explanation is different.

5.1 Analyst Disagreement Effect and Market-to-Book

In Panel A of Table 5 I look at the analyst disagreement effect across market-to-book quintiles. The firms are sorted independently into five disagreement quintiles and five market-to-book quintiles. In both sorts the quintile breakpoints are from the NYSE only (exchcd=1) subsample. The sorting on market-to-book is conditional on leverage in order to control for the potential confusing effects stemming from the negative correlation between market-to-book and leverage (see the discussion above). The numbers I report in Panel A of Table 5 are the alphas and FVIX betas of the portfolio that buys the firms in the lowest disagreement quintile and shorts the firms in the highest disagreement quintile. This strategy is followed separately in each market-to-book quintile.

In the first row of Panel A I report the CAPM alphas. For value-weighted returns they vary from 23.8 bp per month, t-statistic 0.78, in the lowest market-to-book (value) quintile to 1.275% per month, t-statistic 3.43, in the highest market-to-book (growth) quintile. The

difference in the analyst disagreement effect between value and growth firms is significant with t-statistic of 2.25. In fact, in value-weighted returns the analyst disagreement quintile is small and insignificant everywhere except for the growth quintile.

In equal-weighted returns the analyst disagreement quintile is significant in all market-to-book groups, increasing from 45.5 per month, t-statistic 2.08, in the value quintile to 80.2 bp per month, t-statistic 2.49, in the growth quintile. However, the difference in the analyst disagreement effect between value and growth firms is insignificant (t-statistic 1.17).

When I add the FVIX factor in the second row, I no longer find any significant alphas in any market-to-book quintile both in equal-weighted and value weighted returns. The difference in the analyst disagreement effect between value and growth quintiles is reduced to zero even in value-weighted returns, where this difference declines from 104 bp per month, t-statistic 2.25, to mere 19.6 bp pr month, t-statistic 0.41.

The FVIX betas in the last row of Panel A provide the strongest evidence that the analyst disagreement effect is related to market-to-book. In equal-weighted returns, the FVIX beta of the low minus high disagreement portfolio starts at -0.314, t-statistic -2.07, in the value quintile and changes monotonically to -1.161, t-statistic -6.34, in the growth quintile, the difference being significant with t-statistic -6.12. In value-weighted returns, the FVIX beta of the low minus high disagreement portfolio follows the same monotonic pattern, changing from 0.199, t-statistic 1.51, to -1.29, t-statistic -5.98, with the t-statistic for the difference of -5.68. Since negative FVIX betas means underperformance during aggregate volatility increases, the values of FVIX betas reported above mean that buying low disagreement stocks and shorting high disagreement stocks results in greater exposure to aggregate volatility risk when one follows this strategy in the subsample of stocks with higher market-to-book (more growth options). In unreported results I observe, consistent with my story, that in the growth quintile the high aggregate volatility risk of this strategy comes primarily from shorting high disagreement firms with abundant growth options, which are the best hedges against aggregate volatility risk.

To sum up, in this subsection I present two new pieces of evidence: that the analyst disagreement effect increases with market-to-book and that this increase can be explained

by increasing aggregate volatility risk. Both pieces of evidence are consistent with my main hypothesis that the analyst disagreement effect is explained by aggregate volatility risk, because high analyst disagreement makes real options a hedge against aggregate volatility risk.

5.2 Analyst Disagreement Effect and Leverage

In Panel B of Table 5 I look at the analyst disagreement effect across leverage quintiles. As in Panel A, the double sorts are independent, the breakpoints are from the NYSE subsample, and the leverage sorts are conditional on market-to-book. The numbers in the table refer to the low minus high disagreement portfolio formed separately within each leverage quintile.

In the first row, I discover that the CAPM alphas are flat across the leverage quintiles. This is inconsistent with Johnson (2004), who finds that in cross-sectional regressions the strength of the analyst disagreement effect positively depends on leverage, but consistent with Sadka and Scherbina (2007) and Avramov, Chordia, Jostova, and Philipov (2009), who find that the Johnson result is not robust to reasonable changes in the sample (December 31 fiscal year end firms in Sadka and Scherbina, 2007, firms with credit rating in Avramov, Chordia, Jostova, and Philipov, 2009).

The lack of relation in the CAPM alphas between leverage and the analyst disagreement effect does not necessarily contradict my prediction that the analyst disagreement effect is stronger for the firms with valuable real options. Even though my leverage sorts are conditional on market-to-book, the median market-to-book in the lowest leverage quintile beats the median market-to-book in the highest leverage quintile by a factor of 1.5. Because of the strong negative relation between leverage and market-to-book, if leverage per se was unrelated to the analyst disagreement effect, in leverage sorts (which would be then just reverse sorts on market-to-book) we would see a negative relation between leverage and the analyst disagreement effect.

The more decisive evidence, as before, comes from the FVIX betas. The FVIX betas of the low minus high arbitrage portfolios become less negative as we move up the leverage quintiles, clearly contradicting my hypothesis that the exposure of the arbitrage portfolio

to aggregate volatility risk should increase with leverage. Most likely, the FVIX betas pick up the reverse sorting on market-to-book implied by the leverage sorts.

I conclude that the relation between leverage and the analyst disagreement effect, if anything, goes in the opposite way to what I predict. It is impossible to tell from Panel B whether that is because the real option created by leverage does not matter or because leverage and market-to-book are too tightly related. To discriminate between these two hypotheses I use another way to measure the real option created by leverage - the S&P credit rating.

5.3 Analyst Disagreement Effect and Credit Rating

In Panel C of Table 5 I look at the analyst disagreement effect across credit rating quintiles. The numerical credit rating is increasing in default risk (AAA=1, AA+=2, ..., C=21, D=22), so the top credit rating quintile consists of the most distressed firms. As in Panels A and B, the double sorts are independent, the breakpoints are from the NYSE subsample, and the credit rating sorts are conditional on market-to-book. The numbers in the table refer to the low minus high disagreement portfolio formed separately within each credit rating quintile.

I find (results not reported to save space) that the median market-to-book is flat across credit rating quintile except for a spike in the lowest credit rating (highest credit quality) quintile, the median market-to-book of which beats the median market-to-book in the highest credit rating (lowest credit quality) quintile by a factor of 1.5. Therefore, even sorting on credit rating conditional on market-to-book does not guarantee that I do not pick up the market-to-book effect on the analyst disagreement effect when I look at the relation between the analyst disagreement effect and credit rating.

In the top row of Panel C I observe that the equal-weighted CAPM alphas do line up with my prediction that the analyst disagreement effect should be the strongest for the firms with the worst credit rating. The analyst disagreement effect starts at 20 bp per month, t-statistic 0.82, in the lowest (best) credit rating quintile and stays insignificant in all quintiles except for the highest (worst) rating, where the analyst disagreement effect is 113 bp per month, t-statistic 2.27. The difference in the analyst disagreement effect

between the highest and the lowest credit rating quintiles is marginally significant with t-statistic 1.95.

The pattern in the CAPM alphas confirms very similar results in Avramov, Chordia, Jostova, and Philipov (2009), who look at raw returns and the Carhart model alphas instead and find that the analyst disagreement quintile exists in the two quintiles with the worst credit rating. The discriminating test between their story (investors' failure to acknowledge coming default losses) and my story (aggregate volatility risk) is to look at the FVIX betas, which I do in the bottom row of Panel C.

The bottom row of Panel C shows that the FVIX betas of the low minus high disagreement portfolio increase strongly and monotonically as one moves from the best credit rating firms (FVIX beta of 0.093, t-statistic 0.87) to the worst credit rating firms (FVIX beta of -0.547, t-statistic -2.72). The difference in the FVIX betas is highly significant with the t-statistic of -3.19.

Two more pieces of evidence support my view that the cross-sectional increase of the analyst disagreement effect with credit rating is explained by aggregate volatility risk. First, I notice that exploiting the analyst disagreement effect means significant exposure to aggregate volatility risk (negative FVIX beta) only in the highest (worst) credit rating quintile, which is the only one with significant analyst disagreement effect. Second, I do not find neither any significant difference in the ICAPM alphas, nor any significant ICAPM alphas across the credit rating quintile.

In value-weighted returns, where the relation between market-to-book and the analyst disagreement effect was the strongest (see Panel A), I find no relation between credit rating and the analyst disagreement effect, be it the CAPM alphas or the FVIX betas. Because of the negative correlation between credit rating and market-to-book, and the implied negative relation between credit rating and the analyst disagreement effect, the lack of relation between credit rating and the analyst disagreement effect in value-weighted returns does not necessarily contradict my story, but rather shows the power of the confounding relation between market-to-book and the analyst disagreement effect.

6 Alternative Explanations of the Analyst Disagreement Effect

The existing explanations of the analyst disagreement effect rely on the mispricing story of Miller (1977). Miler (1977) argues that if short sale constraints exist, higher disagreement leads to overpricing and lower future returns, because the pessimistic investors have to stay out of the market (they cannot sell short), and the average investor in the market is overoptimistic and suffers from the winner's curse. The overoptimism of the average investor is naturally higher when investors disagree more.

The existing empirical studies use different proxies for short sale constraints to show that the analyst disagreement effect is stronger when these constraints are more restrictive. Nagel (2005) finds that in cross-section the analyst disagreement effect increases when institutional ownership decreases. Boehme, Danielsen, and Sorescu (2006) find that the analyst disagreement effect is significantly stronger if their measure of short sale constraints is high. Sadka and Scherbina (2007) take a different approach and argue that the mispricing creating the analyst disagreement effect is not corrected because of high trading costs. Sadka and Scherbina (2007) show that the analyst disagreement discount is strong if the price impact measure from Sadka (2006) is high (indicating high trading costs) and non-existent if the Sadka (2006) price impact measure is low.

In this section, I use the aggregate volatility risk factor to explain these cross-sectional patterns in the magnitude of the analyst disagreement effect. My story says that the analyst disagreement effect exists because disagreement makes real options less exposed to aggregate volatility risk. It does not imply that in cross-section the analyst disagreement effect can be related only to measures of real options. What it does imply is that any variation in the analyst disagreement effect should be related to aggregate volatility risk.

6.1 Analyst Disagreement Effect and Residual Institutional Ownership

In Section 3.2, I demonstrated that institutional investors face a trade-off between aggregate volatility risk and firm-specific uncertainty. The portfolio managers are reluctant

to take on idiosyncratic volatility and to trade in stocks with uncertain value, because it introduces additional risk to their personal wealth, and this personal risk is hard to diversify. However, portfolio managers, as all investors, appreciate a hedge against aggregate volatility increases. The trade-off arises because firm-specific uncertainty (proxied by the analyst disagreement measure) creates the hedge against aggregate volatility risk, so it is hard to both have the hedge and bear low idiosyncratic volatility.

In results not reported to save space, I find that in the subsample of stocks with low analyst disagreement institutional investors tilt toward higher disagreement stocks in their search for the hedge against aggregate volatility risk. In the subsample of high disagreement stocks institutional investors tend to believe that the price of additional aggregate volatility hedge in terms of additional uncertainty is too high and tilt towards lower disagreement stocks. Empirically, in the lowest disagreement quintile, the median of my analyst disagreement measure is 15.1% (t-statistic 10.32) higher in the highest institutional ownership quintile than in the lowest institutional ownership quintile. In the highest disagreement quintile, however, the reverse is true: the median disagreement measure is 10.1% (t-statistic 4.33) higher in the lowest institutional ownership quintile.

Therefore, in double sorts on idiosyncratic volatility and analyst disagreement, the firms with the lowest level of both analyst disagreement and institutional ownership will have the highest level of aggregate volatility risk (which is the reason why institutional investors tend not to hold them). The firms with the highest level of analyst disagreement and the lowest level of institutional ownership will have the lowest level of aggregate volatility risk (and the highest level of analyst disagreement, which is the reason why institutional investors tend not to hold them too). Hence, the difference in aggregate volatility risk between high and low disagreement firms will be the greatest in the lowest institutional ownership group. That would explain the evidence in Nagel (2005) that the analyst disagreement effect is the strongest in this group of firms.

Nagel (2005) uses residual institutional ownership, that is, the residual from the logistic regression (1) of institutional ownership on the log of size and its square. In Panel A of Table 6 I look at the equal-weighted alphas and FVIX betas of the low minus high disagreement portfolio across the residual institutional ownership quintiles. Sorting on analyst disagreement is performed separately within each residual institutional ownership

quintile. All quintile breakpoints are from the sample of NYSE (exchcd=1) firms with the price greater than $5 and the market cap higher than the 20th NYSE/AMEX percentile at the portfolio formation date. The firms with the price smaller than $5 and the market cap lower than the 20th NYSE/AMEX percentile are excluded from the sample, because for such firms the lack of institutional ownership data in Thompson 13F database does not mean that the institutional ownership is zero.

In the first row of Panel A I find that the CAPM alpha of the low minus high disagreement portfolio are flat in four institutional ownership quintiles except for the lowest one. In the four quintiles, the alphas are around 60 bp per month, with t-statistics of 2.3 and higher, and in the lowest institutional ownership quintile, the alpha is 110 bp per month, t-statistic 3.61. The difference between the disagreement portfolio alphas in the lowest and the highest institutional ownership quintiles is 46.5 bp per month, t-statistic 1.83. The results are similar to Nagel (2005), who also finds that the analyst disagreement effect is significant in all institutional ownership quintiles, and the difference in the analyst disagreement effect between the lowest and the highest institutional ownership firms is economically large, but marginally significant (69 bp per month, t-statistic 1.92 in his Table 2).

In the next rows of Panel A I show that the relation between the analyst disagreement effect and institutional ownership is entirely due to aggregate volatility risk. In the highest institutional ownership quintile, the similar beta is -0.343, t-statistic -2.3. In the lowest institutional ownership quintile, the FVIX beta of the low minus high disagreement portfolio is -1.131, t-statistic -7.91, which means that buying low disagreement firms and shorting high disagreement firms exposes the investor to significantly higher aggregate volatility risk if this strategy is followed for the stocks with low institutional ownership. The t-statistic for the difference in the FVIX betas is -8.17, and the change in the FVIX betas is monotonic, consistent with my story. Also, the alphas of the low minus high disagreement portfolio are flat after I control for FVIX, and the alpha of the low minus high disagreement portfolio in the lowest institutional ownership quintile changes from 110 bp per month, t-statistic 3.61, to 46 bp per month, t-statistic 1.88.

I conclude that the relation between the analyst disagreement effect and residual institutional ownership is not the evidence that the analyst disagreement effect exists because

of short sale constraints, as Nagel (2005) suggests. Rather, this evidence is another piece of evidence in favor of aggregate volatility risk as the explanation of the analyst disagreement effect. The relation between the analyst disagreement effect and residual institutional ownership also sheds light on how institutional investors balance idiosyncratic risk and aggregate volatility risk.

6.2 Analyst Disagreement Effect and Short Sale Constraints

Boehme, Danielsen, and Sorescu (2006) use a portemanteau statistic based on relative short interest and the existence of options on the stock to proxy for the fees charged for a short sale. I do not have access to the relative short interest data and use instead the estimate of the probability to be on special from Ali and Trombley (2006). Being on special means that the borrower of the stock (the one who sells it short) has to pay the lender a higher fee than the risk-free rate the lender pays to the borrower for the use of the proceeds from the sale of the stock (the proceeds plus a 2% margin are left with the lender). Essentially, taking into account the foregone gains on the proceeds from the sale of the shorted stock, the shorting fee for the stock on special is higher than the risk-free rate.

Ali and Trombley (2006) use the estimates obtained by D'Avolio (2002), who regressed the being on special dummy (based on the real shorting fees in his eighteen-month sample) on several stock characteristic like cash flows, institutional ownership, size, and turnover (see equations (2) and (3)). Ali and Trombley (2006) find that this estimate of the probability to be on special behaves like a good proxy for short sale constraints in a long sample outside of the period D'Avolio (2002) looked at.

In Table 2, I find that the probability to be on special is strongly related to analyst disagreement and increases in more than two times as I go from the lowest disagreement quintile to the highest disagreement quintile. This strong relation implies that if one sorts on analyst disagreement in the subsample with high probability to be special (high short sale constraints), where disagreement is already high, the spread in disagreement and the resulting spread in returns will be larger than if one sorts on analyst disagreement in the subsample with low probability to be special, where disagreement is already low. If this

story is true, I expect that the aggregate volatility risk factor will explain why the analyst disagreement effect is stronger when short sale constraints are higher.

In Panel B of Table 6 I look at the analyst disagreement effect across probability to be on special quintiles. Sorting on analyst disagreement is performed separately within each probability to be on special quintile. All quintile breakpoints are from the sample of NYSE (exchcd=1) firms. The returns are equal-weighted.

I find that the analyst disagreement effect indeed increases from 20 bp per month, t-statistic 0.7, in the quintile with the lowest probability to be on special, to 52 bp per month, t-statistic 2.01, in the quintile with the highest probability[4]. The increase is statistically insignificant, but the fact that the analyst disagreement effect is significant only in the quintile with the highest probability to be on special (and marginally significant in the next quintile) suggest that the relation between the analyst disagreement effect and the probability to be on special we see in the point estimates is real.

The last row of Panel B shows quite strong relation between the probability to be on special and the exposure of the low minus high disagreement portfolio to aggregate volatility risk. The FVIX beta of the low minus high disagreement portfolio starts from -0.07, t-statistic -0.91, in the quintile with the lowest probability to be on special, and increases monotonically to -0.672, t-statistic -2.85, in the quintile with the highest probability to be on special, the difference being statistically significant with t-statistic -2.3. Also, the FVIX beta of the disagreement portfolio is significant only in the top two probability to be on special quintiles, which are the only ones where the analyst disagreement effect is visible.

Overall, I conclude that the relation between the analyst disagreement effect and the probability to be on special I observe in Panel B, as well as, most probably, the similar relation between the analyst disagreement effect and short sale constraints in Boehme, Danielsen, and Sorescu (2006) can be explained entirely by aggregate volatility risk and arises only because of the strong positive correlation between short sale constraints and analyst disagreement.

[4]The analyst disagreement effect is weak in all quintiles in Panel B because estimating the probability to be on special severely restricts the sample.

6.3 Analyst Disagreement Effect and Size

Diether, Malloy, and Scherbina (2002) and Sadka and Scherbina (2007) find that the analyst disagreement effect is stronger among small firms. They interpret this fact as the evidence that the analyst disagreement effect is mispricing that fails to be corrected because small firms are illiquid and relatively costly to trade.

Aggregate volatility risk can potentially contribute to explaining the relation between size and the analyst disagreement quintile, because size and analyst disagreement are negatively correlated (see Table 2), and sorting on disagreement in the smallest firms subsample would create a bigger spread in disagreement and aggregate volatility risk than sorting on disagreement in the largest firms subsample.

In Panel C of Table 6 I look at the analyst disagreement effect across the size quintiles. Sorting on analyst disagreement is performed separately within each size quintile. All quintile breakpoints are from the sample of NYSE (exchcd=1) firms. The returns are equal-weighted.

In the first row of Panel C I look at the equal-weighted CAPM alphas of the low minus high disagreement portfolio formed in different size quintiles. I find that the analyst disagreement effect varies from 56 bp per month, t-statistic 1.97, and 35 bp per month, t-statistic 1.36, in the largest and the second largest quintiles to 114 bp per month, t-statistic 5.16, in the smallest quintile. The difference between the smallest and the largest quintile is significant with t-statistic 2.57. This is consistent with the evidence in Diether, Malloy, and Scherbina (2002) and Sadka and Scherbina (2007) and their view that the analyst disagreement effect is mispricing that is not corrected because it exists primarily among illiquid firms.

In the last row of Panel C I find, quite surprisingly, that the FVIX betas of the disagreement portfolio are flat across the size quintiles, with the exception of the smallest size quintile, in which the FVIX beta of the disagreement portfolio is significantly smaller (not larger) than in other size quintiles. Consequentially, adding the FVIX factor to the CAPM makes the difference in the analyst disagreement effect between the smallest and the largest firms even more puzzling, primarily because the FVIX factor explains only a

small part of the analyst disagreement effect among the smallest firms, while in all other size quintiles the ICAPM alphas of the disagreement portfolio are very close to zero.

The bottom line from Panel C is that there is probably a part of the analyst disagreement effect related to liquidity and not to aggregate volatility risk. However, this liquidity part is restricted to the quintile of the smallest firms.

6.4 Analyst Disagreement Effect and Price Impact

Sadka and Scherbina (2007) show that the analyst disagreement discount is strong if the price impact measure from Sadka (2006) is high (indicating high trading costs) and non-existent if the Sadka (2006) price impact measure is low. They conclude that the analyst disagreement effect is mispricing that exists because of high trading costs.

The Sadka (2006) price impact measure uses intraday data and therefore is computationally intensive. I use a simpler measure of price impact suggested by Amihud (2002): the ratio of absolute return to dollar trading volume, averaged for each firm-year (only firms with at least 200 non-missing volume and return observations per year are included in the sample). In Panel D, I look at the analyst disagreement effect across the price impact quintiles. Sorting on analyst disagreement is performed separately within each price impact quintile. All quintile breakpoints are from the sample of NYSE (exchcd=1) firms. The returns are equal-weighted. Higher price impact means lower liquidity.

I find that the analyst disagreement effect is significant in all price impact quintiles, varying from 64 bp per month, t-statistic 2.27, in the lowest price impact quintile to 104 bp per month, t-statistic 4.72 in the highest price impact quintile. The difference is marginally significant with t-statistic 1.73.

Adding the FVIX factor reduces all alphas to almost zero, with t-statistics around 1. The only exception is the ICAPM alpha of the low minus high disagreement portfolio in the highest price impact quintile, which is only reduced to 76 bp, t-statistic 2.88. The FVIX betas of the disagreement portfolio are negative and highly significant in all price impact quintiles, but do not appear to depend on price impact.

Overall, Panel D supports my conclusion from Panel C that aggregate volatility cannot

explain the analyst disagreement effect for the most illiquid firms. However, the aggregate volatility factor is necessary and sufficient for explaining the analyst disagreement effect for the firms with less extreme illiquidity levels, for which the analyst disagreement effect is still sizeable and significant.

7 Analyst Disagreement Effect, Aggregate Volatility Exposure, and Conditional CAPM

The three previous sections argued that high disagreement firms earn negative CAPM alphas, because they beat the CAPM when expected aggregate volatility increases. This is especially true about high disagreement firms with valuable real options (as proxied for by market-to-book and credit rating), because in my story disagreement reduces the aggregate volatility risk of only real options, not all assets. This is also true about firms with high short sale constraints, because it turns out that the measures of short sale constraints are closely related to analyst disagreement.

The hitherto presented evidence is that in the ICAPM with the market factor and the aggregate volatility risk factor (the FVIX factor) these firms have positive FVIX betas. Because, by construction, the FVIX factor is strongly positively correlated with increases in expected aggregate volatility (proxied by the change in the VIX index), the positive FVIX betas imply less negative reaction to increases in expected aggregate volatility that what the CAPM predicts.

In this section, I corroborate the FVIX results by replacing FVIX with the change in VIX it mimics and showing that high disagreement firms, especially if they have abundant real options or tight short sale constraints, indeed beat the CAPM when expected aggregate volatility increases. I also fit the conditional CAPM to the arbitrage portfolios that measure the respective effects and show that in recessions high disagreement firms, especially if they have abundant real options or tight short sale constraints, tend to experience a decline in market risk exposure relative to low disagreement firms.

7.1 Analyst Disagreement Effect and Aggregate Volatility Exposure

In Table 7, I test the prediction that high disagreement firms react less negatively to aggregate volatility increases by using the daily changes in the VIX index, which measures expected aggregate volatility. I choose the daily frequency because at the daily horizon the VIX index is much closer to random walk than at the monthly horizon, and its changes are therefore much closer to innovations, which are of main interest in the ICAPM context. To make sure that the results are not driven by choosing the daily frequency, I also use daily return to FVIX and show that FVIX betas are similar at the daily frequency and at the monthly frequency.

I use several arbitrage portfolios to test my prediction. First, I look at the return differential between low and high disagreement stocks (Disp portfolio in Table 7). Then I look at the difference in this return differential between the extreme quintiles of the variables I looked at in Sections 5 and 6. I take the difference in difference such that my expectation is that its mean is positive, just like I did in the rightmost columns of Tables 5 and 6. For example, Disp MB portfolio in Table 7 measures the difference in the returns to the low minus high disagreement portfolio between growth and value stocks, and Disp Size portfolio looks at the same difference between the smallest and the largest stocks.

I fit four regressions to the returns of the arbitrage portfolios discussed above:

$$Ret = \alpha + \beta_{MKT} \cdot MKT + \beta^{CAPM}_{\Delta VIX} \cdot \Delta VIX \tag{4}$$

$$Ret = \alpha + \beta_{MKT} \cdot MKT + \beta^{CAPM}_{FVIX} \cdot FVIX \tag{5}$$

$$Ret = \alpha + \beta^{1f}_{\Delta VIX} \cdot \Delta VIX \tag{6}$$

$$Ret = \alpha + \beta^{1f}_{FVIX} \cdot FVIX \tag{7}$$

The variables of interest reported in Table 7 are $\beta_{\Delta VIX}$ and β_{FVIX}.

In Table 7, I look at equal-weighted returns in Panel A and value-weighted returns in Panel B. In the left part of each panel (Panel A1 and Panel B1) I look at the analyst disagreement effect and its relation to my measures of real options. In the right part of each panel (Panel A2 and Panel B2) I look at the alternative stories about the analyst disagreement discount and its relation to short sale constraints and liquidity measures.

The first column of each of the four panels reports the $\beta^{CAPM}_{\Delta VIX}$ from equation (4). If this slope is negative, the arbitrage portfolio in question underperforms the CAPM when aggregate volatility increases, which means that it exposes the investor to aggregate volatility risk. If aggregate volatility risk explains the analyst disagreement effect and its relation to all variables mentioned in Table 7, all $\beta^{CAPM}_{\Delta VIX}$ slopes should be negative.

I find significantly negative $\beta^{CAPM}_{\Delta VIX}$ for Disp, Disp MB, Disp RInst, and Disp Short, lending additional support to my earlier results that the analyst disagreement effect exists because high disagreement firms beat the CAPM when aggregate volatility increases, and low disagreement firms underperform the CAPM in these periods. This is especially true in the subsample of firms with high market-to-book, low institutional ownership, or high probability to be on special, which explains why the analyst disagreement effect is stronger for these firms. The conclusion I draw from $\beta^{CAPM}_{\Delta VIX}$ is strongly supported by β^{CAPM}_{FVIX} in the second column, as well as the previous results in Tables 5 and 6.

The magnitude of the slopes on the VIX changes seems to suggest that the impact of aggregate volatility on the arbitrage portfolios is moderate. For example, $\beta^{CAPM}_{\Delta VIX}$ of the Disp portfolio implies that this portfolio loses by 2.3 bp more than what the CAPM predicts for each one-point increase in VIX. Given that the VIX values are around 15 in expansions and can be over 40 in recessions[5], it implies that the Disp portfolio will underperform the CAPM by at most 70 bp as the economy goes all the way from expansion to recession. However, the regression of the market factor on the VIX change also yields a low, but highly significant coefficient of -0.13, implying that the market should drop by about 4% during recessions. I attribute the low coefficients to the fact that VIX can be a noisy estimate of the true expected aggregate volatility. This is supported by the evidence that β^{CAPM}_{FVIX} has much higher t-statistics than $\beta^{CAPM}_{\Delta VIX}$.

In contrast to the portfolios discussed above, Disp Lev, Disp Size, and Disp Illiq portfolios have significantly positive $\beta^{CAPM}_{\Delta VIX}$ and β^{CAPM}_{FVIX}, meaning that aggregate volatility risk cannot explain why the analyst disagreement effect is stronger for small and illiquid firms, or why it should be stronger for highly levered firms. This is consistent with the results I get in Tables 5 and 6 that use the FVIX factor in monthly regressions.

[5]VIX was 61.41 at the end of October 1987, going as high as 150.19 on October 19, 1987, and 61.38 at the end of October 1987, hitting 103.41 on October 10, 2008.

The evidence I have from Table 7 on the Disp Cred portfolio, which measures the difference in the analyst disagreement effect between the firms with the worst and the best credit rating, is mixed. $\beta^{CAPM}_{\Delta VIX}$ and β^{CAPM}_{FVIX} have different sign and are marginally significant in equal-weighted returns and insignificant in value-weighted returns. Hence, in Table 7 I can neither support nor refute the conclusion from Table 5 that the stronger analyst disagreement effect for the worst credit rating firms can be explained by aggregate volatility risk.

In the two rightmost columns of all panels of Table 7, I report the slopes from (6) and (7) - $\beta^{1f}_{\Delta VIX}$ and β^{1f}_{FVIX}. I do it to stress that my story about high disagreement firms being a hedge against aggregate volatility risk is conditional on market risk. For the Disp portfolio in Table 7, I find that controlling for the market factor, its $\beta^{CAPM}_{\Delta VIX}$ slope is significantly negative, but when returns to the Disp portfolio are regressed only on the change in VIX, $\beta^{1f}_{\Delta VIX}$ is significantly positive. In other words, buying low disagreement firms and shorting high disagreement firms does not result in a loss when aggregate volatility increases. However, the performance of this strategy during the periods of increasing aggregate volatility is below the CAPM prediction. The market beta of the Disp portfolio is -0.39, t-statistic -5.22, and since the correlation between the market factor and the change in VIX is -0.626, the Disp portfolio is expected to fare quite well during aggregate volatility increases, but it does not, averaging about 0.5% while aggregate volatility increases from normal to crisis levels.

Similar results apply to the Disp RInst and Disp Short portfolios, which have large and negative $\beta^{CAPM}_{\Delta VIX}$, but positive and significant $\beta^{1f}_{\Delta VIX}$. It means that when aggregate volatility increases, the Disp portfolio formed in the subsample of firms with high short sale constraints underperforms the CAPM by more than the Disp portfolio formed in the subsample of firms with low short sale constraints. But it happens only because the CAPM has much higher expectations about the performance of the former portfolio during aggregate volatility increases. Without controlling for exposure to the market movements, the Disp portfolio formed in the subsample of firms with high short sale constraints still beats the Disp portfolio formed in the subsample of firms with low short sale constraints when aggregate volatility increases, but it does not beat it by enough given the difference in their market betas.

Disp MB is the only portfolio for which $\beta^{CAPM}_{\Delta VIX}$ and $\beta^{1f}_{\Delta VIX}$ have the same sign. It means that during aggregate volatility increases the Disp portfolio in the growth quintile loses to the Disp portfolio in the value quintile both unconditionally and controlling for the market risk.

7.2 Analyst Disagreement Effect and the Conditional CAPM

One of the predictions I make about high analyst disagreement firms is that their risk increases less than the risk of low disagreement firms as the economy goes into recession and aggregate volatility increases. I conclude that it is one of the reasons why, all else equal, high disagreement firms beat low disagreement firms when aggregate volatility increases, and therefore higher disagreement firms have lower aggregate volatility risk.

In this subsection, I test the prediction about risk changes directly, using the version of the conditional CAPM from Petkova and Zhang (2005). I predict that the conditional CAPM beta of the low minus high disagreement portfolio will increase in recessions, and this increase will be greater for the stocks with abundant real options or severe short sale constraints. I estimate the conditional CAPM beta by running the regression

$$Ret_{it} = \alpha_i + (\beta_{0i} + \beta_{1i} DIV_{t-1} + \beta_{2i} DEF_{t-1} + \beta_{3i} TB_{t-1} + \beta_{4i} TERM_{t-1}) \cdot (MKT_t - RF_t) + \epsilon_{it} \tag{8}$$

where DIV_t is dividend yield of the CRSP value-weighted index over the past twelve months, DEF_t is the default premium, defined as the difference in yields between Aaa and Baa corporate bonds, TB_t is the one-month Treasury bill rate, and $TERM_t$ is the term premium, defined as the yield differential between ten-year and one-year Treasury bonds. I define the conditional beta as

$$\beta_i = \beta_{0i} + \beta_{1i} \cdot DIV_{t-1} + \beta_{2i} \cdot DEF_{t-1} + \beta_{3i} \cdot TB_{t-1} + \beta_{4i} \cdot TERM_{t-1} \tag{9}$$

In Table 8, I report the values of the conditional beta from (9) in recessions and expansion, along with the difference between the two, for the eight arbitrage portfolios discussed in the previous section. I define recessions as the months when the expected market risk premium is above its in-sample median. The rest of the sample is labeled

expansion. I estimate the expected market risk premium from

$$MKT_t - RF_t = \gamma_0 + \gamma_1 \cdot DIV_{t-1} + \gamma_2 \cdot DEF_{t-1} + \gamma_3 \cdot TB_{t-1} + \gamma_4 \cdot TERM_{t-1} + \epsilon_t \quad (10)$$

I expect the conditional betas of all portfolios to increase in recessions (which would mean positive values in the Diff column in Table 8), if the risk shift is a potential explanation of the analyst disagreement effect and the dependence of the analyst disagreement effect on the variables I consider in Sections 5 and 6. In Table 8, I find that the beta differential is significantly positive for all portfolios except for Disp Lev, Disp Size, and Disp Illiq. It confirms my conclusion from Tables 5, 6, and 7 that the difference in performance in bad times and good times can explain the abnormal return differential between high and low disagreement firms, as well as the difference in the analyst disagreement effect between growth and value stocks, stocks with the highest and the lowest short sale constraints, and probably stocks with the worst and the best credit rating. Consistent with the evidence from Tables 5, 6, and 7 the risk shift is unlikely to explain why the analyst disagreement effect is stronger for small and illiquid firms, or why it should be stronger for highly levered firms.

The difference in the market beta between expansions and recessions for the portfolios in Table 8 is about 0.2. Because the variation in expected market risk premium across business cycle is at most 1% per month, the variation in the conditional beta can explain at most 20 bp of the analyst disagreement effect and its variation with the variables of interest, while the analyst disagreement effect and its variation usually exceed 50 bp per month. This is confirmed by the unreported alphas of the conditional CAPM. To put the performance of the conditional CAPM in the paper into context, Petkova and Zhang (2005) show that in their sample, the conditional CAPM can explain only 9 bp of the 50 bp abnormal return to HML. Hence, given the limited ability of the conditional CAPM to explain anomalies[6], the 20 bp improvement in the alphas is a significant success, showing that at least relative to other puzzles the risk shift between expansions and recessions for the Disp portfolio and related portfolios is sizeable.

[6]See Lewellen and Nagel (2006) for more critique of the conditional CAPM.

8 Conclusion

In this paper I show that the return differential between low and high disagreement firms can be explained by aggregate volatility risk. The same is true about the positive cross-sectional correlation of this return differential with market-to-book, credit rating (when high numerical values mean bad credit rating), and short sale constraints.

The story is that higher disagreement makes real options (growth options, the option created by leverage) respond less negatively to aggregate volatility increases. First, higher disagreement means that real options are less responsive to the value of the underlying asset. The main driving force behind this result is the well-known fact that the option delta decreases in volatility. Because disagreement does not change the systematic risk of the underlying asset, and the systematic risk of the option is, by Ito's lemma, the sensitivity of the option value to the value of the underlying asset times the systematic risk of the underlying asset, higher disagreement means lower systematic risk of real options. This link is especially helpful during recessions, when, as I show in Section 3, firm-level disagreement and aggregate volatility both increase. In these volatile periods, when the price of risk is high, the risk exposure of real options with high disagreement about the underlying asset declines. Hence, their expected return increases less and their value declines less because of that.

Second, real options with high disagreement about the underlying asset benefit more from the increase in disagreement that would benefit any option. It means that they will suffer less than the assets with comparable market risk when aggregate volatility and firm-level disagreement increase.

Campbell (1993) and Chen (2002) show that investors appreciate the stocks with the least negative correlation with aggregate volatility changes, because when expected aggregate volatility increases, investors have to cut their consumption and increase their savings for consumption-smoothing and precautionary savings motives. Ang, Hodrick, Xing, and Zhang (2006) show empirically that the firms with the least negative sensitivity to aggregate volatility increases have abnormally low expected returns.

I use the factor-mimicking portfolio that tracks daily innovations to expected aggregate

volatility as the aggregate volatility risk factor. I find that high disagreement firms load positively on this factor, which means that they beat the CAPM and the Fama-French model when aggregate volatility increases, and low disagreement firms load negatively on this factor. Controlling for aggregate volatility risk completely explains the analyst disagreement effect. I also corroborate my result that high disagreement firms beat expectations during hard times by replacing the aggregate volatility factor by the innovation in expected aggregate volatility it mimics and finding that the low minus high disagreement portfolio loads negatively on it. In the conditional CAPM, which I use as another way to support my main result, the market beta of the low minus high disagreement portfolio increases during recessions, exposing the investor to additional risk when the risk is the least welcome.

I also show that the analyst disagreement effect is stronger for firms with valuable real options (high market-to-book or bad credit rating), and this pattern can be explained by aggregate volatility risk, as predicted by my story. The aggregate volatility risk factor also explains why the analyst disagreement effect is stronger for the firms with higher probability to be on special or lower institutional ownership. The reason is that probability to be on special is strongly related to analyst disagreement, and double sorting on analyst disagreement and probability to be on special is very similar to sorting on analyst disagreement twice.

With institutional ownership, the story is more subtle. Institutional investors dislike both firm-specific uncertainty and aggregate volatility risk, but, according to my story, hedging against aggregate volatility risk is available only through holding high uncertainty (high disagreement) firms. In the subsample of low disagreement firms, institutional investors do not mind some more uncertainty and tend to hold the stocks with relatively high disagreement and relatively low levels of aggregate volatility risk. In the subsample of high disagreement firms, the reverse is true. Hence, low disagreement stocks with low institutional ownership have the highest level of aggregate volatility risk, and and high disagreement stocks with low institutional ownership have the lowest level of aggregate volatility risk, which explains why the return differential between low and high disagreement stocks is the widest among stocks with low institutional ownership.

I also use regressions with the innovations in expected aggregate volatility instead of the

aggregate volatility factor that mimics this innovation and confirm the above results that the abnormal losses of the low minus high disagreement strategy are higher if this strategy is pursued in the subsample of high market-to-book firms, or low credit rating firms, or low institutional ownership firms, or firms with high probability to be on special. The conditional CAPM also reports that in these subsamples the market beta of the low minus high disagreement portfolio increases more during the periods of high risk (recessions).

Sadka and Scherbina (2007) show that the analyst disagreement effect is stronger for smaller firms and more illiquid firms with higher price impact. They also find that the analyst disagreement effect becomes insignificant in about six months after portfolio formation, and conclude that the analyst disagreement effect is short-lived mispricing that takes time to correct because of illiquidity. I find that aggregate volatility risk cannot explain these patterns in the analyst disagreement effect. However, aggregate volatility risk can explain the analyst disagreement effect in all event-time periods and for all firms, except for the smallest firms quintile and the quintile with the highest price impact. I conclude that the analyst disagreement effect for small and illiquid firms can be partly mispricing, but the analyst disagreement effect also exists for many other more broad groups of firms, where aggregate volatility risk can handle it without the help of the mispricing-plus-liquidity story.

References

[1] Ali, Ashiq, and Mark A. Trombley, 2006, Short Sales Constraints and Momentum in Stock Returns, *Journal of Business Finance and Accounting*, v. 33, pp. 587-615

[2] Amihud, Yakov, 2002, Illiquidity and Stock Returns: Cross-Section and Time-Series Effects, *Journal of Financial Markets*, v. 5, pp. 31-56

[3] Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The Cross-Section of Volatility and Expected Returns, *Journal of Finance*, v. 61, pp. 259-299

[4] Avramov, Doron, Tarun Chordia, Gergana Jostova, and Alexander Philipov, 2009, Dispersion in Analysts' Earnings Forecasts and Credit Rating, *Journal of Financial Economics*, v. 91, pp. 83-101

[5] Barinov, Alexander, 2009, Aggregate Volatility Risk: Explaining the Small Growth Anomaly and the New Issues Puzzle, *Working Paper*, University of Georgia

[6] Boehme, Rodney D., Bartley R. Danielsen, and Sorin M. Sorescu, 2006, Short Sale Constraints, Differences of Opinion, and Overvaluation, *Journal of Financial and Quantitative Analysis*, v. 41, pp. 455-488

[7] Campbell, John Y., 1993, Intertemporal Asset Pricing without Consumption Data, *American Economic Review*, v. 83, pp. 487-512

[8] Campbell, John Y., Martin Lettau, Burton G. Malkiel, and Yexiao Xu, 2001, Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk, *Journal of Finance*, v. 56, pp. 1-43

[9] Chen, Joseph, 2002, Intertemporal CAPM and the Cross-Section of Stock Returns, *Working Paper*, University of Southern California

[10] D'Avolio, Gene, 2002, The Market for Borrowing Stock, *Journal of Financial Economics*, v. 66, pp. 271-306

[11] Diether, Karl, Christopher Malloy, and Anna Scherbina, 2002, Differences of Opinion and the Cross-Section of Returns, *Journal of Finance*, v. 57, pp. 2113-2141

[12] Fama, Eugene F., and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics*, v. 33, 3-56

[13] Fama, Eugene F., and Kenneth R. French, 1997, Industry Costs of Equity, *Journal of Financial Economics*, v. 43, pp. 153-193

[14] Glosten, Lawrence R., Ravi Jagannathan, and David E. Runkle, 1993, On the Relation between the Expected Value and the Volatility of the Nominal Return on Stocks, *Journal of Finance*, v. 48, pp. 1779-1801

[15] Grullon, Gustavo, Evgeny Lyandres, and Alexei Zhdanov, 2007, Real Options, Uncertainty, and Stock Returns, *Working Paper*, Rice University and University of Lausanne

[16] Johnson, Timothy C., 2004, Forecast Dispersion and the Cross-Section of Expected Returns, *Journal of Finance*, v. 59, pp. 1957-1978

[17] Lewellen, Jonathan, and Stefan Nagel, 2006, The Conditional CAPM Does Not Explain Asset Pricing Anomalies, *Journal of Financial Economics*, v. 82, pp. 289-314

[18] Miller, Edward M., 1977, Risk, Uncertainty, and Divergence of Opinion, *Journal of Finance*, v. 32, pp. 1151-1168

[19] Nagel, Stefan, 2004, Short Sales, Institutional Ownership, and the Cross-Section of Stock Returns, *Journal of Financial Economics*, v. 78, pp. 277-309

[20] Newey, Whitney, and Kenneth West, 1987, A Simple Positive Semi-Definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica*, v. 55, pp. 703-708

[21] Petkova, Ralitsa, and Lu Zhang, 2005, Is Value Riskier than Growth, *Journal of Financial Economics*, v. 78, pp. 187-202

[22] Sadka, Ronnie, 2006, Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk, *Journal of Financial Economics*, v. 80, pp. 309-349

[23] Sadka, Ronnie, and Anna Scherbina, 2007, Analyst Disagreement, Mispricing, and Liquidity, *Journal of Finance*, v. 62, pp. 2367-2403

[24] Shleifer, Andrei, and Robert W. Vishny, 1997, The Limits of Arbitrage, *Journal of Finance*, v. 52, pp. 35-55

Table 1. Analyst Disagreement, Aggregate Volatility, and the Business Cycle

The table presents the regressions of the logarithm of the average (Panel A) and median (Panel B) analyst forecast dispersion on the NBER recession dummy, VIX index, or the market volatility forecast from TARCH(1,1) model. The numbers on top of each panel is the number of months by which I lag the independent variable. Analyst forecast dispersion is the standard deviation of all outstanding earnings-per-share forecasts for the current fiscal year scaled by the absolute value of the average outstanding earnings forecast (zero-mean forecasts and forecasts by only one analyst excluded).

The NBER recession dummy is one for the months between NBER-announced peak and trough and zero otherwise. VIX index is from CBOE and measures the implied volatility of the one-month options on S&P 100. The TARCH(1,1) model (see Glosten, Jagannathan, and Runkle, 1993) is fitted to monthly returns to the CRSP value-weighted index:

$$Ret_t^{CRSP} = c + \epsilon_t, \quad \sigma_t^2 = c_0 + c_1\sigma_{t-1}^2 + c_2\epsilon_{t-1}^2 + c_3 \cdot I(\epsilon_{t-1} < 0)$$

The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006. The sample excludes the stocks with the price less than $5.

Panel A. Average Analyst Disagreement

	-12	**-9**	**-6**	**-3**	**0**	**3**	**6**	**9**	**12**
Rec	0.244	0.288	0.258	0.218	0.174	0.013	-0.109	-0.225	-0.247
t-stat	*2.10*	*2.50*	*2.23*	*2.17*	*1.81*	*0.11*	*-0.89*	*-1.86*	*-1.82*
VIX	0.179	0.209	0.268	0.251	0.271	0.252	0.260	0.262	0.247
t-stat	*2.35*	*2.90*	*4.04*	*3.34*	*3.38*	*2.94*	*2.99*	*2.62*	*2.57*
TARCH	0.020	0.082	0.133	0.157	0.158	0.142	0.133	0.111	0.068
t-stat	*0.23*	*1.02*	*1.76*	*2.19*	*2.28*	*1.94*	*1.65*	*1.26*	*0.70*

Panel B. Median Analyst Disagreement

	-12	**-9**	**-6**	**-3**	**0**	**3**	**6**	**9**	**12**
Rec	0.143	0.174	0.191	0.172	0.181	0.113	0.036	-0.016	-0.005
t-stat	*1.77*	*2.45*	*2.58*	*2.70*	*3.95*	*2.01*	*0.48*	*-0.22*	*-0.09*
VIX	0.034	0.051	0.124	0.085	0.104	0.089	0.126	0.111	0.124
t-stat	*0.42*	*0.66*	*1.64*	*0.92*	*1.13*	*0.96*	*1.44*	*1.16*	*1.33*
TARCH	0.057	0.074	0.109	0.123	0.110	0.097	0.101	0.100	0.076
t-stat	*0.98*	*1.33*	*2.09*	*2.24*	*1.87*	*1.62*	*1.64*	*1.58*	*1.17*

Table 2. Descriptive Statistics

The table presents median firm characteristics in each analyst disagreement quintile. The characteristics fall into three groups: real options (market-to-book, leverage, and credit rating), liquidity (size and the Amihud (2002) price impact measure), and limits to arbitrage (institutional ownership, residual institutional ownership, and the Ali and Trombley (2006) probability to be on special).

Analyst disagreement is measured as the standard deviation of all outstanding earnings-per-share forecasts for the current fiscal year scaled by the absolute value of the average outstanding earnings forecast (zero-mean forecasts and forecasts by only one analyst excluded).

Market-to-book is defined as market value of equity (Compustat item #25 times Compustat item #199) divided by book equity (Compustat item #60) plus deferred taxes (Compustat item #74). Leverage is long-term debt (Compustat item #9) plus short-term debt (Compustat item #34) divided by market value of equity (Compustat item #25 times Compustat item #199). Cred is the S&P credit rating (item #280 from the Compustat annual file). The numeric S&P rating is increasing in credit risk: 1=AAA, 2=AA+, 3=AA, ..., 21=C, 22=D. Higher credit rating therefore means higher risk of default.

Size is shares outstanding times price from the CRSP monthly returns file. The Amihud (2002) Illiquidity measure (Illiq) is the average ratio of absolute return to dollar volume. The ratio is computed daily and averaged within each firm-year (firms with less than 200 valid return observations in a year and the stock price of less than $5 at the end of the previous year are excluded).

Inst is institutional ownership, the sum of institutional holdings from Thompson Financial 13F database, divided by the shares outstanding from CRSP (if the stock is on CRSP, but not on Thompson Financial 13F database, it is assumed to have zero institutional ownership; if the stock capitalization is below the 20th NYSE/AMEX percentile, its institutional ownership is assumed to be missing). RInst is residual institutional ownership, defined as the residual from the logistic regression (1) of institutional ownership on log size and its square. Short is the probability to be on special (i.e., have high costs of shorting), defined in (2) and (3).

The portfolio characteristics are measured on the portfolio formation date. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006. The sample excludes the stocks with the price less than $5 on the portfolio formation date.

	Low	**Disp2**	**Disp3**	**Disp4**	**High**	**L-H**
MB	2.716	2.558	2.283	2.032	1.867	0.849
t-stat	*71.0*	*47.2*	*40.4*	*35.5*	*30.6*	*21.6*
Lev	0.098	0.113	0.127	0.149	0.175	-0.077
t-stat	*40.5*	*39.0*	*27.9*	*21.9*	*15.8*	*-6.88*
Cred	7.010	7.815	8.542	9.595	11.798	-4.788
t-stat	*30.4*	*47.1*	*57.1*	*68.4*	*119.6*	*-23.0*
Size	0.614	0.736	0.571	0.432	0.294	0.320
t-stat	*11.1*	*12.5*	*12.8*	*12.3*	*13.2*	*9.06*
Illiq	0.032	0.019	0.025	0.035	0.044	-0.013
t-stat	*9.74*	*9.33*	*8.87*	*9.35*	*9.93*	*-5.92*
Inst	0.519	0.536	0.527	0.513	0.474	0.045
t-stat	*29.9*	*32.6*	*32.5*	*30.4*	*24.8*	*8.05*
RInst	1.691	1.667	1.693	1.719	1.722	-0.030
t-stat	*15.3*	*14.5*	*14.9*	*16.0*	*18.7*	*-1.02*
Short	0.037	0.039	0.048	0.059	0.077	-0.040
t-stat	*26.3*	*24.6*	*28.3*	*30.1*	*33.4*	*-25.3*

Table 3. Analyst Disagreement Effect and Aggregate Volatility Risk

The table reports the alphas and the FVIX betas, as well as raw returns, for the analyst disagreement quintiles. The following models are used for measuring the alphas and betas: the CAPM, the Fama-French model, the two-factor ICAPM with the market factor and the FVIX factor (ICAPM), and the Fama-French model augmented with FVIX (FF4). FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX. FVIX is the fitted value less the constant from the regression of daily changes in the VIX index on the daily excess returns to the 2-by-3 sorts on size and book-to-market. The returns of the FVIX factor are cumulated to the monthly level. Panel A looks at equal-weighted returns, and Panel B looks at equal-weighted returns. 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 average outstanding earnings forecast (zero-mean forecasts and forecasts by only one analyst excluded). The analyst disagreement quintiles are formed using the last month dispersion of analyst forecasts and are held for the following month. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006. The sample excludes the stocks with the price less than $5 on the portfolio formation date.

	Panel A. Equal-Weighted Returns							**Panel B. Value-Weighted Returns**					
	Low	**Disp2**	**Disp3**	**Disp4**	**High**	**L-H**		**Low**	**Disp2**	**Disp3**	**Disp4**	**High**	**L-H**
Raw	1.432	1.261	1.262	1.159	0.921	0.511	**Raw**	1.213	0.946	1.110	1.201	0.960	0.254
t-stat	*5.11*	*4.34*	*4.01*	*3.28*	*2.21*	*2.02*	**t-stat**	*4.97*	*3.44*	*3.91*	*3.83*	*2.54*	*0.85*
$\boldsymbol{\alpha}_{CAPM}$	0.454	0.245	0.196	0.012	-0.311	0.765	$\boldsymbol{\alpha}_{CAPM}$	0.298	-0.068	0.023	0.098	-0.241	0.539
t-stat	*2.45*	*1.44*	*1.20*	*0.07*	*-1.49*	*3.53*	**t-stat**	*2.15*	*-1.00*	*0.30*	*0.93*	*-1.54*	*2.03*
$\boldsymbol{\alpha}_{FF}$	0.272	0.083	0.059	-0.112	-0.392	0.665	$\boldsymbol{\alpha}_{FF}$	0.256	-0.045	0.050	0.047	-0.277	0.532
t-stat	*2.03*	*0.70*	*0.63*	*-1.41*	*-3.79*	*3.37*	**t-stat**	*2.21*	*-0.58*	*0.60*	*0.45*	*-1.77*	*2.20*
$\boldsymbol{\alpha}_{ICAPM}$	0.341	0.190	0.230	0.137	0.003	0.338	$\boldsymbol{\alpha}_{ICAPM}$	0.038	-0.125	0.048	0.149	-0.042	0.081
t-stat	*2.10*	*1.19*	*1.36*	*0.76*	*0.01*	*1.49*	**t-stat**	*0.30*	*-1.55*	*0.56*	*1.12*	*-0.25*	*0.30*
$\boldsymbol{\beta}_{FVIX}$	-0.201	-0.096	0.060	0.222	0.557	-0.758	$\boldsymbol{\beta}_{FVIX}$	-0.461	-0.100	0.044	0.091	0.352	-0.813
t-stat	*-2.32*	*-1.38*	*0.88*	*2.35*	*3.81*	*-4.97*	**t-stat**	*-4.92*	*-1.30*	*0.72*	*0.91*	*4.27*	*-5.03*
$\boldsymbol{\alpha}_{FF4}$	0.066	-0.084	-0.058	-0.160	-0.335	0.402	$\boldsymbol{\alpha}_{FF}$	0.038	-0.122	0.043	0.103	-0.095	0.133
t-stat	*0.61*	*-0.87*	*-0.67*	*-2.11*	*-3.34*	*2.40*	**t-stat**	*0.37*	*-1.80*	*0.53*	*0.99*	*-0.67*	*0.64*
$\boldsymbol{\beta}_{FVIX}$	-1.603	-1.302	-0.910	-0.376	0.443	-2.046	$\boldsymbol{\beta}_{FVIX}$	-1.691	-0.596	-0.055	0.436	1.413	-3.104
t-stat	*-9.28*	*-7.99*	*-4.47*	*-2.39*	*2.76*	*-8.47*	**t-stat**	*-10.19*	*-3.83*	*-0.37*	*2.04*	*6.07*	*-9.51*

Table 4. Analyst Disagreement and Aggregate Volatility Risk in Event Time

The table reports the alphas and the FVIX betas, as well as raw returns, for the low minus high disagreement portfolios, formed using the data on analyst forecast dispersion lagged by the number of months shown in the first row (one to twelve). For example, in column five I use analyst forecast dispersion measured five months ago to form analyst disagreement quintile and define the low minus high disagreement portfolio as the return differential between the lowest and the highest disagreement quintiles. 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 average outstanding earnings forecast (zero-mean forecasts and forecasts by only one analyst excluded). The following models are used for measuring the alphas and betas: the CAPM, the Fama-French model, the two-factor ICAPM with the market factor and the FVIX factor (ICAPM), and the Fama-French model augmented with FVIX (FF4). The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006. The sample excludes the stocks with the price less than $5 on the portfolio formation date.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**1-12**
Raw	0.511	0.373	0.352	0.373	0.262	0.117	0.169	0.071	0.112	0.078	0.093	-0.009	0.520
t-stat	*2.02*	*1.46*	*1.39*	*1.48*	*1.02*	*0.47*	*0.66*	*0.28*	*0.45*	*0.32*	*0.39*	*-0.04*	*5.73*
$\boldsymbol{\alpha}_{CAPM}$	0.765	0.628	0.610	0.630	0.529	0.392	0.445	0.338	0.373	0.342	0.341	0.232	0.533
t-stat	*3.53*	*2.84*	*2.75*	*2.83*	*2.35*	*1.83*	*2.03*	*1.61*	*1.76*	*1.63*	*1.65*	*1.15*	*5.87*
$\boldsymbol{\alpha}_{FF}$	0.665	0.513	0.507	0.532	0.424	0.264	0.322	0.216	0.280	0.251	0.280	0.160	0.505
t-stat	*3.37*	*2.50*	*2.47*	*2.56*	*2.21*	*1.41*	*1.71*	*1.21*	*1.51*	*1.41*	*1.60*	*0.87*	*5.66*
$\boldsymbol{\alpha}_{ICAPM}$	0.338	0.178	0.186	0.216	0.104	-0.047	0.029	-0.075	-0.019	-0.042	-0.007	-0.102	0.439
t-stat	*1.49*	*0.74*	*0.83*	*0.95*	*0.48*	*-0.22*	*0.13*	*-0.36*	*-0.09*	*-0.22*	*-0.03*	*-0.49*	*4.60*
$\boldsymbol{\beta}_{FVIX}$	-0.758	-0.798	-0.752	-0.734	-0.753	-0.779	-0.738	-0.732	-0.694	-0.681	-0.617	-0.592	-0.166
t-stat	*-4.97*	*-4.91*	*-5.28*	*-5.15*	*-5.61*	*-6.15*	*-5.92*	*-5.88*	*-5.79*	*-6.09*	*-5.50*	*-6.00*	*-1.39*
$\boldsymbol{\alpha}_{FF4}$	0.402	0.253	0.250	0.274	0.152	0.012	0.081	-0.022	0.020	-0.011	0.044	-0.053	0.454
t-stat	*2.40*	*1.48*	*1.49*	*1.59*	*0.98*	*0.08*	*0.48*	*-0.14*	*0.13*	*-0.08*	*0.29*	*-0.32*	*4.74*
$\boldsymbol{\beta}_{FVIX}$	-2.046	-2.022	-1.996	-2.010	-2.120	-1.960	-1.872	-1.853	-2.024	-2.037	-1.838	-1.654	-0.392
t-stat	*-8.47*	*-8.18*	*-8.39*	*-7.91*	*-8.13*	*-7.24*	*-5.95*	*-6.22*	*-7.50*	*-7.39*	*-6.14*	*-5.47*	*-1.42*

Table 5. Analyst Disagreement Effect, Real Options, and Aggregate Volatility Risk

The table presents the CAPM and ICAPM alphas and the FVIX betas of the low minus high disagreement portfolio across quintiles of real options measures. The ICAPM is the two-factor model with the market factor and the FVIX factor. FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX. FVIX is the fitted value less the constant from the regression of daily changes in the VIX index on the daily excess returns to the 2-by-3 sorts on size and book-to-market. The returns of the FVIX factor are cumulated to the monthly level.

Panel A looks at the sorts on market-to-book, Panel B performs the sorts on market leverage, and Panel C deals with the sorts on credit rating. The left part of each panel uses equal-weighted returns, and the right part uses value-weighted returns. The low minus high disagreement portfolio buys the firms in the lowest disagreement quintile and shorts the firms in the highest disagreement quintile. Each cell of the table presents the characteristics of following this strategy within a market-to-book (leverage, credit rating) quintile. The low minus high disagreement portfolio is rebalanced monthly, the other quintiles are rebalanced annually.

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 average outstanding earnings forecast (zero-mean forecasts and forecasts by only one analyst excluded). Market-to-book is defined as market value of equity (Compustat item #25 times Compustat item #199) divided by book equity (Compustat item #60) plus deferred taxes (Compustat item #74). Leverage is long-term debt (Compustat item #9) plus short-term debt (Compustat item #34) divided by market value of equity (Compustat item #25 times Compustat item #199). Cred is the S&P credit rating (item #280 from the Compustat annual file). The numeric S&P rating is increasing in credit risk: 1=AAA, 2=AA+, 3=AA, ... , 21=C, 22=D. Higher credit rating therefore means higher risk of default.

The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006. The sample excludes the stocks with the price less than $5 on the portfolio formation date.

Panel A. Analyst Disagreement Effect and Market-to-Book

	Equal-Weighted Returns							Value-Weighted Returns					
	Value	**MB2**	**MB3**	**MB4**	**Growth**	**G-V**		**Value**	**MB2**	**MB3**	**MB4**	**Growth**	**G-V**
α_{CAPM}	0.455	0.542	0.473	0.826	0.802	0.347	α_{CAPM}	0.238	0.284	0.136	0.249	1.275	1.037
t-stat	*2.08*	*2.51*	*2.15*	*3.04*	*2.49*	*1.17*	**t-stat**	*0.78*	*0.84*	*0.49*	*0.73*	*3.43*	*2.25*
α_{ICAPM}	0.278	0.325	0.100	0.342	0.147	-0.131	α_{ICAPM}	0.350	0.204	-0.076	-0.289	0.546	0.196
t-stat	*1.17*	*1.41*	*0.39*	*1.04*	*0.46*	*-0.46*	**t-stat**	*1.15*	*0.60*	*-0.26*	*-0.75*	*1.39*	*0.41*
β_{FVIX}	-0.314	-0.384	-0.660	-0.857	-1.161	-0.847	β_{FVIX}	0.199	-0.141	-0.376	-0.954	-1.290	-1.490
t-stat	*-2.07*	*-3.69*	*-3.61*	*-2.96*	*-6.34*	*-6.12*	**t-stat**	*1.51*	*-1.06*	*-2.44*	*-4.01*	*-5.98*	*-5.68*

Panel B. Analyst Disagreement Effect and Leverage

	Equal-Weighted Returns							Value-Weighted Returns					
	Low	**Lev2**	**Lev3**	**Lev4**	**High**	**H-L**		**Low**	**Lev2**	**Lev3**	**Lev4**	**High**	**H-L**
α_{CAPM}	0.569	0.580	0.359	0.504	0.612	0.042	α_{CAPM}	0.631	0.663	0.284	0.204	0.508	-0.122
t-stat	*2.51*	*2.37*	*1.40*	*2.45*	*2.55*	*0.19*	**t-stat**	*2.04*	*1.82*	*0.84*	*0.61*	*1.63*	*-0.33*
α_{ICAPM}	0.101	0.157	0.139	0.410	0.405	0.304	α_{ICAPM}	-0.077	0.165	0.106	-0.061	0.418	0.495
t-stat	*0.39*	*0.52*	*0.51*	*1.97*	*1.69*	*1.15*	**t-stat**	*-0.23*	*0.42*	*0.31*	*-0.18*	*1.32*	*1.46*
β_{FVIX}	-0.829	-0.749	-0.390	-0.166	-0.365	0.464	β_{FVIX}	-1.254	-0.881	-0.315	-0.469	-0.160	1.094
t-stat	*-3.36*	*-3.49*	*-4.01*	*-1.97*	*-5.15*	*1.94*	**t-stat**	*-6.82*	*-3.73*	*-2.50*	*-2.67*	*-0.67*	*4.73*

Panel C. Analyst Disagreement Effect and Credit Rating

	Equal-Weighted Returns							Value-Weighted Returns					
	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**W-B**		**Best**	**Cred2**	**Cred3**	**Cred4**	**Worst**	**W-B**
α_{CAPM}	0.197	-0.066	-0.069	0.548	1.134	0.938	α_{CAPM}	0.353	0.192	0.328	0.479	0.327	-0.026
t-stat	*0.82*	*-0.26*	*-0.24*	*1.55*	*2.27*	*1.95*	**t-stat**	*1.33*	*0.63*	*0.78*	*0.86*	*0.57*	*-0.04*
α_{ICAPM}	0.249	-0.045	-0.048	0.472	0.826	0.577	α_{ICAPM}	0.213	0.004	0.142	0.481	0.274	0.061
t-stat	*1.01*	*-0.16*	*-0.15*	*1.24*	*1.55*	*1.17*	**t-stat**	*0.76*	*0.01*	*0.31*	*0.86*	*0.45*	*0.09*
β_{FVIX}	0.093	0.038	0.038	-0.134	-0.547	-0.639	β_{FVIX}	-0.249	-0.334	-0.330	0.005	-0.095	0.153
t-stat	*0.87*	*0.36*	*0.34*	*-0.79*	*-2.72*	*-3.19*	**t-stat**	*-1.75*	*-2.02*	*-1.94*	*0.02*	*-0.35*	*0.47*

Table 6. Aggregate Volatility Risk and the Alternative Explanations of the Analyst Disagreement Effect

The table presents the CAPM and ICAPM alphas and the FVIX betas of the low minus high disagreement portfolio across quintile sorts on limits to arbitrage and liquidity measures. The ICAPM is the two-factor model with the market factor and the FVIX factor. FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX. FVIX is the fitted value less the constant from the regression of daily changes in the VIX index on the daily excess returns to the 2-by-3 sorts on size and book-to-market. The returns of the FVIX factor are cumulated to the monthly level.

Panel A looks at the sorts on residual institutional ownership, Panel B performs the sorts on probability to be on special, and Panels C and D deal with the sorts on size and price impact (Amihud (2002) illiquidity measure), respectively. The low minus high disagreement portfolio buys the firms in the lowest disagreement quintile and shorts the firms in the highest disagreement quintile. Each cell of the table presents the characteristics of following this strategy within a price impact (size, etc.) quintile. The low minus high disagreement portfolio is rebalanced monthly, the size quintiles are rebalanced monthly, quintile portfolios formed on residual institutional ownership and probability to be on special are rebalanced quarterly, the Amihud (2002) illiquidity quintiles are rebalanced yearly.

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 average outstanding earnings forecast (zero-mean forecasts and forecasts by only one analyst excluded). Size is shares outstanding times price from the CRSP monthly returns file. The Amihud (2002) Illiquidity measure (Illiq) is the average ratio of absolute return to dollar volume. The ratio is computed daily and averaged within each firm-year (firms with less than 200 valid return observations in a year and the stock price of less than $5 at the end of the previous year are excluded). RInst is residual institutional ownership, defined as the residual from the logistic regression (1) of institutional ownership on log size and its square. Institutional ownership is the sum of institutional holdings from Thompson Financial 13F database, divided by the shares outstanding from CRSP (if the stock is on CRSP, but not on Thompson Financial 13F database, it is assumed to have zero institutional ownership; if the stock capitalization is below the 20th NYSE/AMEX percentile, its institutional ownership is assumed to be missing). Short is the probability to be on special (i.e., have high costs of shorting), defined in (2) and (3).

The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006. The sample excludes the stocks with the price less than $5 on the portfolio formation date.

Panel A. Analyst Disagreement Effect and Residual Institutional Ownership

	Low	RInst2	RInst3	RInst4	High	L-H
α_{CAPM}	1.096	0.643	0.547	0.595	0.631	0.465
t-stat	*3.61*	*2.51*	*2.31*	*2.88*	*2.68*	*1.83*
α_{ICAPM}	0.458	0.159	0.150	0.327	0.437	0.020
t-stat	*1.88*	*0.54*	*0.59*	*1.39*	*1.67*	*0.10*
β_{FVIX}	-1.131	-0.858	-0.703	-0.475	-0.343	-0.788
t-stat	*-7.91*	*-4.27*	*-5.48*	*-3.92*	*-2.10*	*-8.17*

Panel B. Analyst Disagreement Effect and Probability to Be on Special

	Low	Short2	Short3	Short4	High	H-L
α_{CAPM}	0.202	0.474	0.354	0.479	0.521	0.329
t-stat	*0.70*	*1.80*	*1.36*	*1.86*	*2.01*	*0.95*
α_{ICAPM}	0.163	0.469	0.244	0.158	0.141	-0.009
t-stat	*0.56*	*1.68*	*0.82*	*0.57*	*0.43*	*-0.02*
β_{FVIX}	-0.070	-0.009	-0.195	-0.568	-0.672	-0.602
t-stat	*-0.91*	*-0.09*	*-1.30*	*-2.85*	*-2.85*	*-2.30*

Panel C. Analyst Disagreement Effect and Size

	Small	Size2	Size3	Size4	Big	S-B
α_{CAPM}	1.136	0.778	0.590	0.351	0.557	0.578
t-stat	*5.16*	*2.85*	*2.21*	*1.36*	*1.97*	*2.57*
α_{ICAPM}	0.828	0.292	0.181	-0.109	0.113	0.715
t-stat	*3.20*	*1.02*	*0.66*	*-0.37*	*0.45*	*3.37*
β_{FVIX}	-0.545	-0.860	-0.725	-0.816	-0.788	0.242
t-stat	*-3.38*	*-5.32*	*-3.12*	*-4.00*	*-4.70*	*2.28*

Panel D. Analyst Disagreement Effect and Price Impact

	Low	Illiq2	Illiq3	Illiq4	High	H-L
α_{CAPM}	0.636	0.507	0.545	0.635	1.042	0.406
t-stat	*2.27*	*2.14*	*2.26*	*2.68*	*4.72*	*1.73*
α_{ICAPM}	0.282	0.170	0.154	0.299	0.762	0.480
t-stat	*1.00*	*0.67*	*0.53*	*1.15*	*2.88*	*1.69*
β_{FVIX}	-0.628	-0.598	-0.693	-0.596	-0.497	0.131
t-stat	*-5.83*	*-5.02*	*-3.57*	*-3.63*	*-2.88*	*0.71*

Table 7. The Analyst Disagreement Effect and the Exposure to Aggregate Volatility Changes

The table reports the sensitivity to aggregate volatility changes of the anomalous arbitrage portfolios. The sensitivity is measured by estimating the following regressions:

$$Ret = \alpha + \beta_{MKT} \cdot MKT + \boldsymbol{\beta^{CAPM}_{\Delta VIX}} \cdot \Delta VIX \tag{11}$$

$$Ret = \alpha + \beta_{MKT} \cdot MKT + \boldsymbol{\beta^{CAPM}_{FVIX}} \cdot FVIX \tag{12}$$

$$Ret = \alpha + \boldsymbol{\beta^{1f}_{\Delta VIX}} \cdot \Delta VIX \tag{13}$$

$$Ret = \alpha + \boldsymbol{\beta^{1f}_{FVIX}} \cdot FVIX \tag{14}$$

Disp is the portfolio long in low disagreement stocks and short in high disagreement stocks. Other portfolios measure the difference in the Disp portfolio returns between the highest and the lowest quintiles of the variables mentioned in their name (for example, Disp Lev is the return differential between the Disp portfolio formed in the highest leverage quintile and the Disp portfolio formed in the lowest leverage quintile). The detailed description of the variables is in the header of Table 2. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006. The sample excludes the stocks with the price less than $5 on the portfolio formation date.

Panel A. Equal-Weighted Returns

A1. Analyst Disagreement and Real Options

	$\beta^{CAPM}_{\Delta VIX}$	β^{CAPM}_{FVIX}	$\beta^{1f}_{\Delta VIX}$	β^{1f}_{FVIX}
Disp	-0.013	-0.500	0.019	0.152
t-stat	*-3.24*	*-9.72*	*4.77*	*8.44*
Disp MB	-0.034	-0.896	-0.011	-0.014
t-stat	*-5.42*	*-12.4*	*-1.97*	*-0.54*
Disp Lev	0.013	0.504	0.001	0.011
t-stat	*2.40*	*9.33*	*0.28*	*0.65*
Disp Cred	0.036	-0.239	0.055	0.129
t-stat	*2.10*	*-1.88*	*3.03*	*2.34*

A2. Alternative Explanations

	$\beta^{CAPM}_{\Delta VIX}$	β^{CAPM}_{FVIX}	$\beta^{1f}_{\Delta VIX}$	β^{1f}_{FVIX}
Disp Illiq	0.030	0.525	0.009	-0.049
t-stat	*2.91*	*6.57*	*1.14*	*-1.42*
Disp Size	0.026	0.550	0.022	0.091
t-stat	*4.17*	*7.86*	*4.26*	*3.90*
Disp RInst	-0.020	-0.713	0.019	0.166
t-stat	*-1.90*	*-12.5*	*1.52*	*7.79*
Disp Short	-0.073	-0.224	0.038	0.787
t-stat	*-5.09*	*-2.89*	*3.76*	*10.4*

Panel B. Value-Weighted Returns

B1. Analyst Disagreement and Real Options

	$\beta^{CAPM}_{\Delta VIX}$	β^{CAPM}_{FVIX}	$\beta^{1f}_{\Delta VIX}$	β^{1f}_{FVIX}
Disp	-0.023	-0.909	0.010	0.077
t-stat	*-3.42*	*-10.7*	*1.55*	*2.77*
Disp MB	-0.059	-1.912	-0.023	-0.112
t-stat	*-4.49*	*-14.0*	*-2.27*	*-2.45*
Disp Lev	0.063	0.956	0.022	-0.098
t-stat	*3.38*	*8.14*	*1.41*	*-1.70*
Disp Cred	0.012	-0.124	0.042	0.223
t-stat	*0.77*	*-0.68*	*2.73*	*4.77*

B2. Alternative Explanations

	$\beta^{CAPM}_{\Delta VIX}$	β^{CAPM}_{FVIX}	$\beta^{1f}_{\Delta VIX}$	β^{1f}_{FVIX}
Disp Illiq	-0.005	0.119	-0.003	0.033
t-stat	*-0.47*	*1.18*	*-0.35*	*1.23*
Disp Size	0.012	0.449	0.017	0.136
t-stat	*1.41*	*5.66*	*2.37*	*5.98*
Disp RInst	-0.035	-0.673	-0.001	0.114
t-stat	*-4.27*	*-8.01*	*-0.13*	*4.10*
Disp Short	-0.079	0.101	0.039	0.884
t-stat	*-4.38*	*0.71*	*2.80*	*10.7*

Table 8. The Analyst Disagreement Effect and the Conditional CAPM

The table reports conditional CAPM betas across different states of the world for the eight arbitrage portfolios that measure the analyst disagreement effect and its cross-sectional relation to several variables. Disp is the portfolio long in low disagreement stocks and short in high disagreement stocks. Other portfolios measure the difference in the Disp portfolio returns between the highest and the lowest quintiles of the variables mentioned in their name (for example, Disp Lev is the return differential between the Disp portfolio formed in the highest leverage quintile and the Disp portfolio formed in the lowest leverage quintile). The detailed description of the variables is in the header of Table 2. Recession (Expansion) is defined as the period when the expected market risk premium is higher (lower) than its in-sample median. The expected risk premiums and the conditional betas are assumed to be linear functions of dividend yield, default spread, one-month Treasury bill rate, and term premium. Panel A presents the results with equal-weighted returns, and Panel B looks at value-weighted returns. The standard errors reported use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from August 1963 to December 2006. The sample excludes the stocks with the price less than $5 on the portfolio formation date.

Panel A. Equal-Weighted Returns

	Rec	**Exp**	**Diff**		**Rec**	**Exp**	**Diff**
Disp	-0.193	-0.421	0.229	**Disp Illiq**	0.061	0.301	-0.240
t-stat	*-3.76*	*-6.57*	*3.01*	**t-stat**	*2.93*	*8.80*	*-6.23*
Disp MB	-0.187	-0.416	0.230	**Disp Size**	-0.086	0.034	-0.120
t-stat	*-5.60*	*-9.23*	*4.33*	**t-stat**	*-3.77*	*1.08*	*-3.30*
Disp Lev	0.117	0.207	-0.090	**Disp RInst**	-0.179	-0.367	0.188
t-stat	*18.81*	*23.52*	*-8.44*	**t-stat**	*-6.38*	*-7.69*	*3.58*
Disp Cred	0.157	-0.225	0.382	**Disp Short**	0.034	-0.161	0.194
t-stat	*5.40*	*-6.09*	*8.29*	**t-stat**	*1.44*	*-5.88*	*5.77*

Panel B. Value-Weighted Returns

	Rec	**Exp**	**Diff**		**Rec**	**Exp**	**Diff**
Disp	-0.173	-0.455	0.282	**Disp Illiq**	-0.040	0.071	-0.111
t-stat	*-2.95*	*-5.55*	*3.00*	**t-stat**	*-2.36*	*2.99*	*-4.06*
Disp MB	-0.303	-0.635	0.331	**Disp Size**	-0.097	-0.050	-0.047
t-stat	*-5.08*	*-7.53*	*3.40*	**t-stat**	*-3.85*	*-1.57*	*-1.23*
Disp Lev	-0.054	0.412	-0.466	**Disp RInst**	-0.039	-0.211	0.173
t-stat	*-1.59*	*6.79*	*-6.89*	**t-stat**	*-2.79*	*-13.69*	*8.45*
Disp Cred	-0.143	-0.228	0.085	**Disp Short**	-0.013	-0.068	0.055
t-stat	*-7.26*	*-9.70*	*2.98*	**t-stat**	*-0.43*	*-2.09*	*1.40*

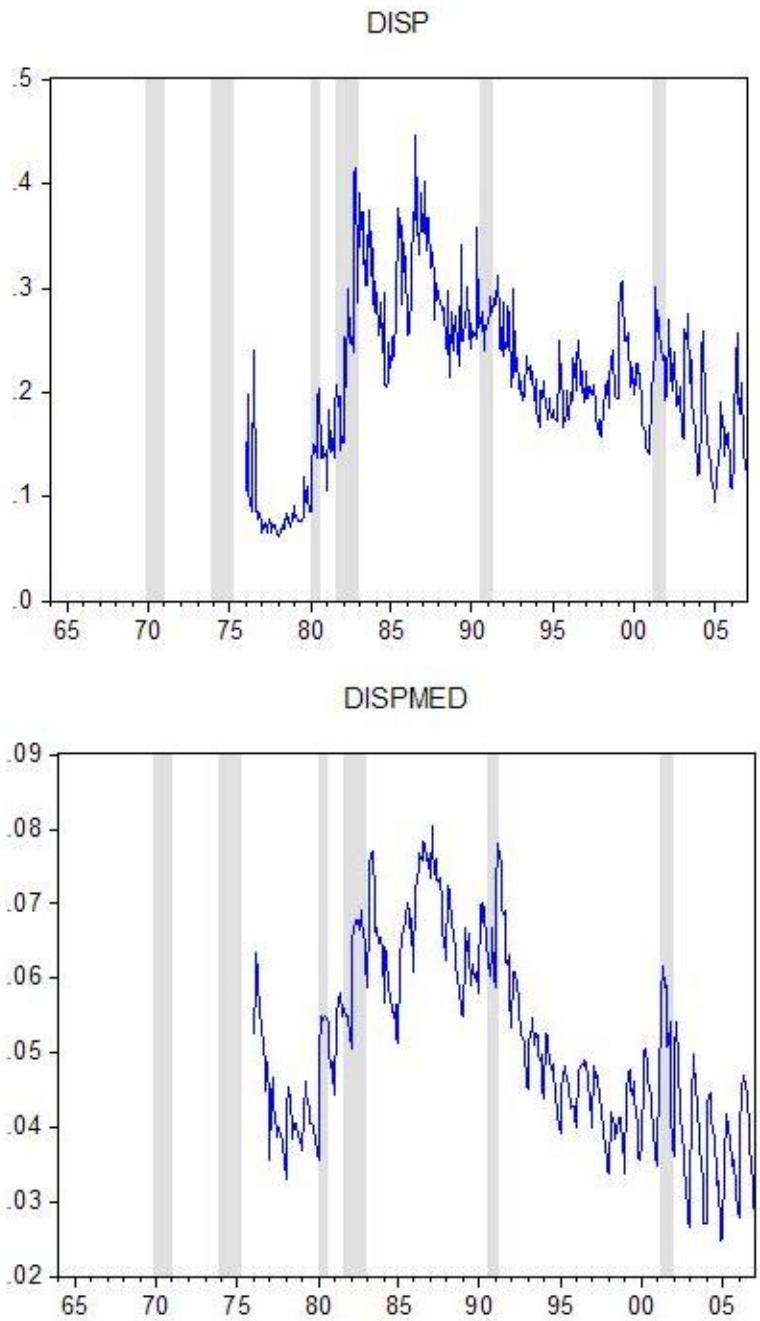

Figure 1. Average and Median Analyst Disagreement
The figure shows monthly market-wide averages (Disp) and medians (DispMed) of firm-level analyst forecast dispersion. Analyst forecast dispersion is the standard deviation of all outstanding earnings-per-share forecasts for the current fiscal year scaled by the absolute value of the average outstanding earnings forecast (zero-mean forecasts and forecasts by only one analyst excluded). The shaded areas are NBER recessions.