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Analyst Disagreement and Aggregate Volatility Risk

Alexander Barinov*

Abstract

The paper explains why firms with high dispersion of analyst forecasts earn low future returns. These firms beat the capital asset pricing model in periods of increasing aggregate volatility and thereby provide a hedge against aggregate volatility risk. The aggregate volatility risk factor can explain the abnormal return differential between high- and low-disagreement firms. This return differential is higher for firms with abundant real options, and this fact can be explained by aggregate volatility risk. Aggregate volatility risk can also explain why the link between analyst disagreement and future returns is stronger for firms with high short-sale constraints.

I. Introduction

Diether, Malloy, and Scherbina (2002) establish the puzzling analyst disagreement effect: the negative cross-sectional relation between analyst forecast dispersion and future returns. This negative relation is puzzling since it appears that investors are paying a premium for bearing additional uncertainty about future earnings.

In this paper, I propose a risk-based explanation of the analyst disagreement effect. I hypothesize that investors tolerate the negative capital asset pricing model (CAPM) alphas of high-disagreement firms because these firms tend to beat the CAPM during periods of increasing aggregate volatility. The mechanism that partially saves high-disagreement firms from losses in volatile periods works through real options. First, analyst disagreement increases when aggregate volatility goes up (see Section III.A for empirical evidence). All else being equal, real options increase in value when disagreement about the value of the underlying asset increases (see Grullon, Lyandres, and Zhdanov (2012) for empirical evidence).

*Barinov, abarinov@terry.uga.edu, Terry College of Business, University of Georgia, 438 Brooks Hall, Athens, GA 30602. I thank Henk Berkman (the referee), Stephen Brown (the editor), and participants of the 2010 Mid-Atlantic Research Conference, the 2012 Financial Intermediation Research Society Conference, the 2010 Northern Financial Association Meetings, the 2010 Financial Management Association Meetings, the 2010 Southern Financial Association Meetings, and the 2010 Eastern Finance Association Meetings, as well as seminar participants at the University of Georgia for their comments and suggestions. All remaining errors are mine.

That makes their reaction to the increases of aggregate volatility in recessions less negative. This effect is naturally stronger for high-disagreement firms, since these firms witness a stronger absolute increase in disagreement when average disagreement and aggregate volatility go up.[1]

Second, higher disagreement during periods of high aggregate volatility implies that the value of real options becomes less sensitive to the value of the underlying asset and real options become less risky precisely when risks are high. This effect is also stronger for the firms with higher disagreement, and it implies that firms with high disagreement and abundant real options lose less in volatile periods due to a smaller increase in future discount rates.[2]

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 stocks that correlate positively with aggregate volatility news, because these stocks provide additional consumption precisely when investors have to cut their current consumption for consumption-smoothing 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 in response to higher aggregate volatility. Ang, Hodrick, Xing, and Zhang (2006) show empirically that stocks with the most positive sensitivity to aggregate volatility increases have abnormally low expected returns. My paper builds on this literature and shows that high-disagreement firms have low expected returns because they are a hedge against aggregate volatility risk.

The aggregate volatility risk explanation is broader than the conditional CAPM explanation that appears to be implied by the second channel linking disagreement and aggregate volatility risk. The conditional CAPM misses the fact that lower betas in recessions mean smaller losses in recessions, and during recessions, investors care about losses more than in expansions. Also, the first channel (higher disagreement in recessions makes real options do better than other assets of comparable risk) is completely outside of the conditional CAPM. Therefore, my explanation is a version of the intertemporal CAPM (ICAPM) and, as such, calls for the inclusion of the aggregate volatility risk factor rather than conditioning the market beta on volatility or any other variable(s) related to the business cycle.

The empirical tests of my hypothesis use the FVIX factor, a factor-mimicking portfolio that tracks daily changes in the VIX index. The VIX index measures the implied volatility of the options on the Standard & Poor's (S&P) 100 index, and therefore, it is a direct measure of the market expectation of aggregate

[1]The supporting empirical evidence is available from the author.

[2]The transformation of higher 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.

volatility. Ang et al. (2006) show that at the daily frequency, VIX has extremely high autocorrelation, and thus its change is a valid proxy for innovation in expected aggregate volatility, the variable of interest in the ICAPM context.

I find that the 2-factor ICAPM with the market factor and the FVIX factor explains 50%–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.

Consistent with my hypothesis, I also find that the analyst disagreement effect is stronger for firms with a higher market-to-book ratio and lower credit rating. This dependence of the analyst disagreement effect on real options measures is explained by the FVIX factor, confirming that the hedging power of high-disagreement firms against aggregate volatility risk increases with the value of the real options these firms have.

My evidence that the analyst disagreement effect increases with the market-to-book ratio and that 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 shown in 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.

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 causes a lower market beta of equity and lower expected return. Johnson uses cross-sectional regressions to show that the analyst disagreement effect increases with leverage and is absent for all-equity firms.

My paper extends Johnson (2004) in several important dimensions. First, I add the time-series dimension and show that the reduced market beta of real options because of higher disagreement comes during tough economic times, when lower risk and smaller losses are particularly welcome. Second, I find another interaction of disagreement and real options: Because, all else being equal, the value of an option increases in volatility, real options of high-disagreement firms offer partial protection against losses in times of high volatility and high 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 to a formal asset pricing test of the 2-factor ICAPM. Fourth, I generalize the idea in Johnson to all real options, including growth options.

II. Data

The sample period in the paper is from Jan. 1986 to Dec. 2010. Stocks with a 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 are excluded).

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The data on analyst forecasts are from the Institutional Brokers' Estimate System (IBES).

My proxy for expected aggregate volatility is an older version of the VIX index. It is calculated by the Chicago Board Options Exchange (CBOE) and measures the implied volatility of 1-month options on the S&P 100 index. I obtain values of the VIX index from CBOE data on Wharton Research Data Services (WRDS). Using the older version of the VIX provides a longer data series compared to newer CBOE indices. The availability of the VIX index determines my sample period of 1986–2010.

Following Ang et al. (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 daily changes in VIX on the daily excess returns to five quintiles sorted on the return sensitivity to changes in VIX. The sensitivity is the loading on the VIX change from the regression of daily stock returns in the past month on the market return and change in VIX. The fitted part of this regression less the constant is the FVIX factor. I cumulate returns at the monthly level to obtain the monthly returns to FVIX. All results in the paper are robust to changing the base assets from the VIX sensitivity quintiles to the 10 industry portfolios of Fama and French (1997) or to the six portfolios formed from two-by-three sorts on size and market-to-book ratio as in Fama and French (1993).

In Section V, I use two real options proxies: market-to-book ratio and credit rating. When I sort firms on market-to-book ratio at the end of the year, I use their value from the fiscal year ending no later than June of the sorting year. The quarterly sorts on credit rating use the credit rating lagged by two quarters.

In Section VI.B, I use two measures of short-sale constraints: residual institutional ownership (RI) and relative short interest (RSI). Following Nagel (2005), I drop all stocks below the 20th NYSE/AMEX size percentile in the tests with RI.[3] If the stock is listed on the Center for Research in Security Prices (CRSP) database but does not appear in the Thompson Financial 13F database, it is assumed to have zero institutional ownership.

Detailed definitions of all variables are in the Data Appendix.

III. Analyst Disagreement in the Time Series and Cross Section

A. 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 relation is necessary to make the prediction that high-analyst-disagreement firms are hedges against aggregate volatility risk: My theory proposes 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.

[3]NYSE stands for New York Stock Exchange; AMEX stands for American Stock Exchange.

Related evidence (see, e.g., Campbell, Lettau, Malkiel, and Xu (2001), Barinov (2011)) shows that the idiosyncratic volatility of the average firm is higher during recessions (as defined by the National Bureau of Economic Research (NBER)) and is strongly positively correlated with realized market volatility. In Table 1, I extend these results to analyst disagreement using expected aggregate volatility instead of realized volatility. The first measure of expected aggregate volatility is the VIX index, which is the implied volatility of 1-month options on the S&P 100 index. The second measure is the market volatility forecast from a threshold autoregressive conditional heteroskedasticity model (TARCH$(1,1)$).[4]

In the first rows of Panel A (average analyst disagreement) and Panel B (analyst disagreement of the median firm) of Table 1, I regress the logs of the respective variables on a 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 about 30% (t-statistics around 3), irrespective of whether one takes the contemporaneous value of the recession dummy or lags it by several months to account for stale forecasts. The dispersion of analyst forecasts for the median firm also increases significantly during recessions, by about 35% (t-statistics around 3).

TABLE 1

Analyst Disagreement, Aggregate Volatility, and the Business Cycle

Table 1 presents the regressions of the logarithm of the average (Panel A) and median (Panel B) analyst forecast dispersion on the NBER recession dummy (REC), VIX index, or the market volatility forecast from the TARCH$(1,1)$ model. The numbers on top of each panel are the number of months by which the independent variable is lagged. Detailed definitions of the variables are in the Data Appendix. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from Jan. 1986 to Dec. 2010. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Variable	−12	−9	−6	−3	0	3	6	9	12
Panel A. Average Analyst Disagreement									
REC	33.07	31.87	31.27	33.41	30.57	17.75	4.543	0.136	0.299
t-stat.	*2.89*	*3.13*	*3.03*	*3.23*	*3.38*	*2.73*	*0.54*	*0.01*	*0.04*
VIX	0.227	0.265	0.349	0.327	0.304	0.292	0.271	0.233	0.221
t-stat.	*3.90*	*4.40*	*4.54*	*4.32*	*4.53*	*4.85*	*4.80*	*3.68*	*3.39*
TARCH	0.239	0.321	0.433	0.447	0.442	0.441	0.400	0.352	0.342
t-stat.	*2.83*	*3.74*	*4.12*	*4.16*	*4.35*	*4.52*	*4.80*	*4.35*	*3.84*
REALIZED_VOL	0.185	0.196	0.247	0.224	0.217	0.171	0.154	0.145	0.160
t-stat.	*4.48*	*4.15*	*3.69*	*3.71*	*4.02*	*3.96*	*3.65*	*3.11*	*3.39*
Panel B. Median Analyst Disagreement									
REC	32.51	33.25	35.11	37.38	33.52	19.92	11.21	9.409	7.792
t-stat.	*2.28*	*2.75*	*2.92*	*3.16*	*3.55*	*2.93*	*1.36*	*1.10*	*1.11*
VIX	0.132	0.167	0.259	0.213	0.192	0.172	0.182	0.134	0.133
t-stat.	*1.97*	*2.26*	*2.67*	*2.22*	*2.45*	*2.68*	*3.18*	*2.29*	*2.33*
TARCH	0.153	0.240	0.349	0.357	0.340	0.342	0.338	0.290	0.265
t-stat.	*1.52*	*2.41*	*2.91*	*2.83*	*2.87*	*3.35*	*4.14*	*3.83*	*3.27*
REALIZED_VOL	0.134	0.143	0.199	0.162	0.155	0.112	0.100	0.078	0.093
t-stat.	*2.90*	*2.63*	*2.55*	*2.24*	*2.73*	*2.63*	*2.23*	*1.73*	*2.21*

[4]The TARCH$(1,1)$ model is a modification of the generalized autoregressive conditional heteroskedasticity model (GARCH$(1,1)$) that allows for the asymmetric volatility response to negative returns. See Glosten, Jagannathan, and Runkle (1993) for more details about TARCH models.

In the next rows, I regress the log of analyst forecast dispersion on the log of the VIX index values. Table 1 shows that a 1% increase in the VIX index triggers about a 0.3% increase in the average analyst forecast dispersion (t-statistics exceed 4). The increase in the median analyst forecast dispersion is about 0.2% per each 1% increase in VIX (t-statistics from 1.97 to 3.18).

The reaction of analyst disagreement to changes in the forecasted market volatility from the TARCH$(1, 1)$ model is smaller and hovers around 0.35%–0.45% for each 1% increase in forecasted volatility. The t-statistics for both the average and median are normally above 2.5. Similarly, the average/median analyst disagreement increases by 0.15%–0.25% when realized volatility increases by 1%. The smaller slopes are likely due to the fact that realized volatility fluctuates more than expected volatility, and in recessions, realized volatility is higher than in booms by 50%–60%.

In untabulated results, I find very similar evidence for average/median idiosyncratic volatility, and I confirm that the aggregate volatility measures I use above increase by 40%–60% during recessions. I conclude that analyst disagreement and idiosyncratic volatility strongly comove with aggregate volatility and, therefore, the necessary condition for my explanation of the value effect and the idiosyncratic volatility discount holds.

B. Descriptive Statistics across Analyst Disagreement Quintiles

In Table 2, I present descriptive statistics for analyst disagreement quintiles. I first sort all firms into disagreement quintiles using NYSE breakpoints. NYSE

TABLE 2

Descriptive Statistics

Table 2 presents median firm characteristics in each analyst disagreement quintile. The characteristics fall into three groups: real options (market-to-book ratio (MB), leverage (LEV), and credit rating (CRED)), liquidity (size and the Amihud (2002) price impact measure), and limits to arbitrage (institutional ownership (INST), residual institutional ownership (RI), and the relative short interest (RSI)). Detailed definitions of the variables are in the Data Appendix. The portfolio characteristics are measured on portfolio formation date. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from Jan. 1986 to Dec. 2010. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Variable	Low	DISP2	DISP3	DISP4	High	Low − High
MB	2.755	2.610	2.341	2.091	1.915	0.840
t-stat.	*67.0*	*47.2*	*39.0*	*34.1*	*28.6*	*20.2*
LEV	0.098	0.108	0.116	0.132	0.152	−0.055
t-stat.	*36.8*	*34.0*	*23.9*	*17.6*	*12.9*	*−4.65*
CRED	7.352	8.264	9.040	10.019	12.013	−4.662
t-stat.	*33.2*	*44.7*	*51.2*	*58.5*	*98.1*	*−25.8*
SIZE	825.7	865.0	656.0	491.6	334.9	490.8
t-stat.	*9.51*	*12.4*	*13.0*	*12.8*	*13.6*	*7.50*
ILLIQ	0.028	0.017	0.023	0.033	0.044	−0.016
t-stat.	*7.69*	*7.70*	*7.42*	*7.70*	*8.36*	*−6.70*
IVOL	0.016	0.017	0.018	0.020	0.024	−0.008
t-stat.	*31.2*	*31.0*	*32.2*	*32.8*	*31.8*	*−23.0*
INST	0.568	0.583	0.574	0.557	0.525	0.043
t-stat.	*25.2*	*27.0*	*27.1*	*26.1*	*21.8*	*8.29*
RI	1.495	1.475	1.496	1.513	1.539	−0.044
t-stat.	*10.7*	*10.5*	*10.6*	*11.0*	*12.5*	*−1.34*
RSI	0.015	0.017	0.019	0.021	0.025	−0.010
t-stat.	*6.90*	*6.84*	*6.92*	*6.96*	*7.07*	*−7.15*

firms are defined as 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 stocks with a price of \$5 or less on the date of portfolio formation. Then I compute the median of each firm characteristic (see detailed definitions in Data Appendix) in Table 2 separately for each quintile on the date when the quintile portfolio was formed. Quintile portfolios are rebalanced monthly.

In the first group of firm characteristics, I include market-to-book ratio, market leverage, and credit rating. I treat leverage and credit rating as two complementary indicators of how close to the money the real option created by leverage is. Default can be likely, because either the company has a lot of debt or its financial health is poor. I find that high-disagreement firms tend to be distressed firms with limited growth prospects. The credit rating variable confirms this: Its median increases monotonically from 7 (A−) in the lowest-disagreement quintile to 12 (BB) in the highest-disagreement quintile. This is consistent with the evidence in Avramov et al. (2009).

The second group of firm characteristics measures liquidity. I look at size (in billions of dollars) and the price impact measure of Amihud (2002), also known as the Amihud illiquidity ratio. The values of the Amihud measure in Table 2 represent the percentage change in stock price in response to trading \$1 million of the firm's stock in a day.

The relation between size and disagreement is clearly negative: Median size is at \$826 (\$335) million in the lowest- (highest-) disagreement quintile, suggesting that high-disagreement firms are relatively illiquid. This conclusion is supported by the Amihud (2002) price impact measure. For the median firm in the lowest- (highest-) disagreement quintile, pushing \$1 million through the market during a single day would move the price by about 2.8% (4.4%).

The third group of firm characteristics measures short-sale constraints. Here, I look at institutional ownership, RI (orthogonalized to size as in Nagel (2005), see eq. (A-1) in the Appendix), and RSI. As Asquith, Pathak, and Ritter (2005) argue, institutional ownership proxies for the supply of shares for shorting and RSI proxies for the demand for shorting. Short-sale-constrained firms should then have either low institutional ownership or high RSI or both.

I find that the variation in institutional ownership across disagreement quintiles is small: Institutions hold 52.5% of the median firm in the highest-disagreement quintile and 56.8% of the median firm in the lowest-disagreement quintile. The residual ownership is completely flat across the disagreement quintiles, suggesting that the variation in institutional ownership is driven primarily by size.

When I turn to RSI, a clearer picture emerges, confirming that high-disagreement firms can indeed be short-sale constrained, as Diether et al. (2002) suggest. The RSI monotonically increases from a median of 1.5% in the lowest-disagreement quintile to a median of 2.5% in the highest-disagreement quintile. The difference is economically sizable, since for most firms, the RSI is very low. For example, 2.5% of outstanding shares being shorted would make the stock top 25% on RSI in most years.

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IV. Explaining the Analyst Disagreement Effect

A. Portfolio Sorts

My primary test of whether aggregate volatility risk can explain the analyst disagreement effect augments the CAPM and the Fama-French (1993) model with the aggregate volatility risk factor and verifies that the augmented models can explain the returns to 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.

In untabulated results, I look at the factor premium of FVIX to verify that FVIX is a valid ICAPM factor. The correlation between FVIX and the change in VIX is 0.698. Thus, FVIX appears to be a good factor-mimicking portfolio and a good hedge against aggregate volatility risk. Therefore, FVIX has to earn significantly negative returns, even after controlling for other sources of risk. Consistent with that, the raw return to FVIX is -1.21% per month (t-statistic $= -3.44$), and the CAPM alpha and the Fama-French (1993) alpha of FVIX are both -46 basis points (bp) per month (t-statistics of -3.86 and -3.26, respectively).

In Table 3, I examine the alphas and FVIX betas of the analyst disagreement quintiles. The first two rows confirm the evidence in Diether et al. (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 65 bp per month in equal-weighted returns and about 60 bp per month in value-weighted returns, all highly significant.

TABLE 3

Analyst Disagreement Effect and Aggregate Volatility Risk

Table 3 reports the alphas (in percents per month) and the FVIX betas for the analyst disagreement quintiles. The following models are used for measuring the alphas and betas: the CAPM, the Fama-French (1993) model, the 2-factor ICAPM with the market factor and the FVIX factor (ICAPM), and the Fama-French (1993) model augmented with FVIX (FF4). FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. The analyst disagreement quintiles are formed using last month's dispersion of analyst forecasts and are held for the following month. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from Jan. 1986 to Dec. 2010. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

	Panel A. Value-Weighted Returns						*Panel B. Equal-Weighted Returns*					
	Low	DISP2	DISP3	DISP4	High	Low – High	Low	DISP2	DISP3	DISP4	High	Low – High
α_{CAPM}	0.256	–0.056	0.039	0.124	–0.285	0.541	0.383	0.227	0.195	0.048	–0.281	0.665
t-stat.	*2.26*	*–0.90*	*0.56*	*1.24*	*–1.92*	*2.33*	*2.37*	*1.55*	*1.34*	*0.32*	*–1.49*	*3.44*
α_{FF}	0.260	–0.032	0.057	0.105	–0.352	0.612	0.281	0.126	0.098	–0.051	–0.387	0.667
t-stat.	*2.69*	*–0.47*	*0.79*	*1.12*	*–2.41*	*2.80*	*2.48*	*1.30*	*1.20*	*–0.68*	*–4.18*	*4.03*
α_{ICAPM}	–0.043	–0.199	0.014	0.216	0.094	–0.137	0.302	0.229	0.267	0.246	0.131	0.171
t-stat.	*–0.41*	*–2.94*	*0.21*	*1.88*	*0.68*	*–0.63*	*1.93*	*1.51*	*1.70*	*1.49*	*0.59*	*0.82*
β_{FVIX}	–0.649	–0.311	–0.053	0.200	0.822	–1.471	–0.176	0.004	0.155	0.429	0.896	–1.072
t-stat.	*–4.07*	*–4.30*	*–0.72*	*1.67*	*7.68*	*–6.05*	*–1.45*	*0.04*	*1.89*	*3.56*	*4.34*	*–3.91*
α_{FF4}	0.049	–0.165	0.016	0.140	–0.068	0.117	0.059	–0.032	–0.037	–0.099	–0.308	0.368
t-stat.	*0.56*	*–2.44*	*0.23*	*1.46*	*–0.52*	*0.61*	*0.54*	*–0.32*	*–0.45*	*–1.22*	*–3.07*	*2.26*
β_{FVIX}	–0.462	–0.292	–0.090	0.076	0.624	–1.087	–0.486	–0.347	–0.297	–0.105	0.172	–0.658
t-stat.	*–3.64*	*–4.15*	*–1.31*	*0.74*	*6.00*	*–5.18*	*–3.37*	*–3.21*	*–3.83*	*–1.77*	*2.08*	*–3.77*

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In the next two rows, I show that in the ICAPM with the market factor and FVIX factor, this return differential is completely wiped away in both value- and equal-weighted returns. The reason is the large spread in FVIX betas, which vary, for equal-weighted returns, from 0.896 (t-statistic $= 4.34$) in the highest-disagreement quintile, to -0.176 (t-statistic $= -1.45$) in the lowest-disagreement quintile. The positive FVIX betas of high-disagreement firms indicate that these firms react less negatively to aggregate volatility increases than what the CAPM predicts. Therefore, high-disagreement firms are less risky than what the CAPM says, which explains their negative CAPM alphas.

In the last two rows, I use the 4-factor model with the 3 Fama-French (1993) factors and the FVIX factor. The conclusions are very similar: Controlling for FVIX materially reduces the difference in alphas between low- and high-disagreement firms, and the 4-factor model reveals a significant exposure of low-analyst-disagreement firms to aggregate volatility risk and a significant hedging ability against aggregate volatility risk for high-disagreement firms.

Diether et al. (2002) find that momentum helps in explaining a part of the analyst disagreement effect. In untabulated results, I try using the momentum factor (from Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/)) and the Fama-French (1993) factors to explain the analyst disagreement effect.

I find that controlling for momentum does somewhat help to explain the analyst disagreement effect, reducing its magnitude from about 65 bp per month to around 50 bp per month, but the remaining 50 bp are still highly significant. I also use the momentum factor and FVIX together and find no overlap between the two. Adding the FVIX in a model with the momentum factor (e.g., the Carhart (1997) model) results in the same reduction in the alpha as adding FVIX to a similar model without the momentum factor (e.g., the Fama-French (1993) model). Adding the momentum factor to a model with FVIX does not change the FVIX betas.

B. Cross-Sectional Regressions

In Table 4, I take a different approach to verifying that aggregate volatility risk explains the analyst disagreement effect. I perform firm-level Fama-MacBeth (1973) regressions of raw returns on several firm characteristics (size, market-to-book ratio, and analyst disagreement), the market beta, and either the loading on the VIX change or the FVIX beta. I expect that analyst disagreement will lose significance and its slope will be materially reduced when I control for either the loading on the VIX change or the FVIX beta.

In column 1 of Table 4, I use analyst disagreement without controlling for aggregate volatility risk exposure. All the variables in Table 4, except for market beta, are transformed into ranks confined between 0 and 1. Therefore, the slopes are the return differentials (in percents per month) between firms with the lowest and highest value of the variable. The slope of the analyst disagreement variable estimates the analyst disagreement effect at 51.7 bp per month (t-statistic $= 2.17$), which is close to what I found in Table 3.

TABLE 4

Fama-MacBeth Regressions

Table 4 presents the results of firm-level Fama-MacBeth (1973) regressions run each month. The dependent variable is raw monthly return. The control variables are market beta (β_{MKT}), market capitalization, and market-to-book ratio. The main variables are analyst disagreement, the loading on VIX change (γ_{VIX}), and FVIX beta (β_{FVIX}). All independent variables, except market beta, are ranks with values between 0 and 1. All firm characteristics are from the previous calendar year. All betas are lagged by 1 month and come from firm-level regressions using data from the past 36 months. The loadings on VIX change and FVIX betas are from the 2-factor model with the market factor and the change in either VIX or FVIX. The *t*-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from Jan. 1986 to Dec. 2010.

	Panel A. Price > \$5			*Panel B. All Firms*		
Variable	1	2	3	4	5	6
β_{MKT}	0.070	0.035	0.108	0.132	0.041	0.142
t-stat.	*0.39*	*0.83*	*1.52*	*0.74*	*0.93*	*1.93*
SIZE	−0.136	−0.357	−0.371	−0.309	−0.887	−0.944
t-stat.	*−0.31*	*−0.82*	*−0.86*	*−0.69*	*−1.71*	*−1.93*
MB	−0.493	−0.211	−0.237	−0.517	−0.290	−0.288
t-stat.	*−1.22*	*−0.52*	*−0.59*	*−1.34*	*−0.68*	*−0.72*
DISP	−0.517	−0.209	−0.237	−0.574	−0.269	−0.278
t-stat.	*−2.17*	*−0.80*	*−0.92*	*−2.40*	*−0.94*	*−1.05*
β_{FVIX}		−0.983			−1.211	
t-stat.		*−2.41*			*−2.86*	
γ_{VIX}			−0.373			−0.584
t-stat.			*−2.33*			*−3.69*

In column 2 of Table 4, I add the FVIX beta. The loading on the FVIX beta implies a return differential of −98.3 bp per month (*t*-statistic = −2.41) between firms with the lowest and highest aggregate volatility risk. After I control for the FVIX beta, the analyst disagreement effect is reduced to −21 bp per month, statistically insignificant.

In column 3 of Table 4, I replace FVIX beta by the loading on VIX change. The loading on VIX change also comes out significant, though its coefficient implies that sorting on volatility risk creates a smaller return differential of −37.3 bp (*t*-statistic = −2.33). The lower risk premium can be due to noise in VIX, which is eliminated by the factor-mimicking procedure. After controlling for the loading on the change in VIX, the analyst disagreement is reduced to −24 bp per month (*t*-statistic = −0.92).

In columns 4–6 of Table 4, I perform a robustness check on the results in columns 1–3 by including the stocks with prices below \$5 in the sample. I find that including these firms in the sample strengthens the results, if anything. The *t*-statistics and prices of risk increase both for the FVIX beta and the loading on VIX change, and aggregate volatility risk explains the same fraction of an initially larger and more significant analyst disagreement effect.

I conclude from Table 4 that controlling for aggregate volatility risk reduces the analyst disagreement effect by more than one-half and renders the remaining part insignificant. This conclusion supports very similar results shown in Table 3.

V. Analyst Disagreement Effect and Real Options

The main prediction of my theory 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 firms with abundant real options. Also, the difference in aggregate volatility risk exposure between high- and low-disagreement firms should be small for firms with few real options and increase significantly as one looks at firms that are more and more option-like.

In this section, I look at two measures of real options: market-to-book ratio (which measures growth options) and credit rating (which measures importance of the option created by risky debt and limited liability). While Johnson (2004) uses leverage to measure the importance of this real option, I look at credit rating instead for three reasons. First, market-to-book ratio and leverage are highly negatively correlated, much more so than market-to-book ratio and credit rating, both for mechanical reasons (market value of equity is in the numerator of market-to-book ratio and in the denominator of leverage) and because firms with low market-to-book ratio tend to choose higher levels of leverage. My theory, however, predicts that the analyst disagreement effect and the hedging power of high-disagreement firms will be higher for both high market-to-book ratio and high leverage firms, and these predictions work against each other.

Second, the importance 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.

Third, Avramov et al. (2009) show that the analyst disagreement effect exists only in the bottom two quintiles with the worst credit ratings and argue that the analyst disagreement effect arises because investors fail to fully acknowledge the expected future losses of distressed firms. It is of interest to see whether the findings of Avramov et al. (2009) can be explained by aggregate volatility risk, as my theory makes a similar prediction, but the explanation is different.

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

In Panel A of Table 5, I report the alphas and FVIX betas of the portfolio that buys firms in the lowest-disagreement quintile and shorts firms in the highest-disagreement quintile. This strategy is followed separately in each market-to-book quintile.

The first row of Panel A of Table 5 reports CAPM alphas. For value-weighted returns, they vary from 12.8 bp per month (t-statistic $= 0.37$) in the lowest market-to-book (value) quintile to 1.071% per month (t-statistic $= 3.38$) in the highest market-to-book (growth) quintile. In value-weighted returns, the analyst disagreement effect is small and insignificant outside of the top two growth quintiles. The equal-weighted returns in the right-hand part of Panel A and the Fama-French (1993) alphas in the fourth row show a similar picture.

When I look at the ICAPM alphas in the second row of Table 5, I no longer find any significant alphas in any market-to-book quintile both in equal- and value-weighted returns. The difference in the analyst disagreement effect between value and growth quintiles becomes very close to 0. In value-weighted (equal-weighted) returns, the difference declines from 94.3 bp per month, t-statistic of 2.37 (50.1 bp, t-statistic of 1.7), to 6.2 bp per month, t-statistic of 0.12 (-5 bp per month, t-statistic of -0.14). A similar picture holds in the alphas from the 4-factor model with the 3 Fama-French (1993) factors and FVIX in row 5.

TABLE 5

Analyst Disagreement Effect, Real Options, and Aggregate Volatility Risk

Table 5 presents the alphas (in percents per month) and the FVIX betas of the low-minus-high disagreement portfolio across quintiles of real options measures. The following models are used for measuring the alphas and betas: the CAPM, the 2-factor ICAPM with the market factor and the FVIX factor (ICAPM), the Fama-French (1993) model (FF), and the Fama-French (1993) model augmented with FVIX (FF4). The low-minus-high disagreement portfolio buys firms in the lowest-disagreement quintile and shorts firms in the highest-disagreement quintile. Each cell of the table presents the alpha or the FVIX beta of following this strategy within a market-to-book (credit rating) quintile. The low-minus-high disagreement portfolio is rebalanced monthly, the credit rating quintiles are rebalanced quarterly, and the market-to-book quintiles are rebalanced annually. FVIX is the factor-mimicking portfolio that tracks daily changes in VIX.

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

	Value-Weighted Returns						Equal-Weighted Returns					
	Value	MB2	MB3	MB4	Growth	Growth – Value	Value	MB2	MB3	MB4	Growth	Growth – Value
α_{CAPM}	0.128	0.384	0.074	0.634	1.071	0.943	0.331	0.589	0.613	0.838	0.832	0.501
t-stat.	*0.37*	*1.27*	*0.21*	*1.80*	*3.38*	*2.37*	*1.34*	*2.79*	*2.39*	*2.98*	*2.75*	*1.70*
α_{ICAPM}	0.025	0.206	–0.367	–0.063	0.088	0.062	0.144	0.264	0.312	0.197	0.094	–0.050
t-stat.	*0.07*	*0.70*	*–1.16*	*–0.19*	*0.26*	*0.12*	*0.51*	*1.24*	*1.23*	*0.65*	*0.26*	*–0.14*
β_{FVIX}	–0.223	–0.386	–0.956	–1.513	–2.134	–1.911	–0.406	–0.706	–0.654	–1.389	–1.601	–1.195
t-stat.	*–0.70*	*–1.47*	*–3.86*	*–3.85*	*–4.82*	*–4.28*	*–2.23*	*–3.28*	*–3.60*	*–3.35*	*–3.1*	*–2.64*
α_{FF}	0.186	0.477	0.025	0.606	0.940	0.754	0.391	0.619	0.604	0.760	0.723	0.332
t-stat.	*0.53*	*1.40*	*0.07*	*1.81*	*3.06*	*1.76*	*1.59*	*2.95*	*2.45*	*3.27*	*2.94*	*1.18*
α_{FF4}	0.030	0.306	–0.412	0.150	0.348	0.319	0.258	0.416	0.431	0.388	0.358	0.100
t-stat.	*0.08*	*0.94*	*–1.28*	*0.47*	*1.17*	*0.71*	*0.94*	*2.13*	*1.93*	*1.74*	*1.38*	*0.31*
β_{FVIX}	–0.343	–0.377	–0.961	–1.001	–1.299	–0.956	–0.291	–0.447	–0.381	–0.818	–0.801	–0.510
t-stat.	*–0.83*	*–1.47*	*–4.72*	*–2.93*	*–4.47*	*–2.20*	*–1.41*	*–2.24*	*–1.92*	*–3.95*	*–3.6*	*–2.18*

Panel B. Analyst Disagreement Effect and Credit Rating

	Value-Weighted Returns						Equal-Weighted Returns					
	Best	CRED2	CRED3	CRED4	Worst	Worst – Best	Best	CRED2	CRED3	CRED4	Worst	Worst – Best
α_{CAPM}	0.092	0.365	0.547	0.224	1.239	1.147	0.112	–0.064	0.400	0.223	1.204	1.092
t-stat.	*0.27*	*1.04*	*1.43*	*0.55*	*2.48*	*2.06*	*0.39*	*–0.19*	*1.31*	*0.71*	*2.89*	*2.47*
α_{ICAPM}	–0.064	0.226	0.102	–0.399	0.518	0.582	–0.196	–0.196	0.205	–0.038	0.533	0.729
t-stat.	*–0.18*	*0.59*	*0.29*	*–0.87*	*1.05*	*1.05*	*–0.61*	*–0.54*	*0.67*	*–0.11*	*1.19*	*1.47*
β_{FVIX}	–0.342	–0.306	–0.976	–1.373	–1.580	–1.238	–0.675	–0.288	–0.429	–0.574	–1.471	–0.797
t-stat.	*–1.09*	*–0.76*	*–2.43*	*–4.27*	*–4.30*	*–2.86*	*–2.29*	*–1.15*	*–1.75*	*–1.86*	*–7.33*	*–2.57*
α_{FF}	0.393	0.533	0.698	0.204	1.395	1.002	0.415	0.167	0.631	0.356	1.276	0.861
t-stat.	*1.18*	*1.47*	*1.71*	*0.48*	*3.08*	*1.88*	*1.61*	*0.56*	*2.03*	*1.05*	*3.05*	*1.99*
α_{FF4}	0.211	0.432	0.312	–0.262	0.477	0.267	0.147	0.224	0.500	0.183	0.684	0.537
t-stat.	*0.62*	*1.11*	*0.87*	*–0.56*	*0.98*	*0.49*	*0.54*	*0.71*	*1.77*	*0.52*	*1.52*	*1.14*
β_{FVIX}	–0.350	–0.212	–0.787	–1.211	–1.687	–1.337	–0.591	0.126	–0.290	–0.388	–1.308	–0.717
t-stat.	*–1.18*	*–0.55*	*–1.55*	*–3.44*	*–4.06*	*–3.12*	*–2.79*	*0.53*	*–0.79*	*–0.95*	*–5.57*	*–2.93*

The FVIX betas in the third and sixth rows of Panel A of Table 5 also provide strong evidence that the relation between the analyst disagreement effect and market-to-book ratio is explained by aggregate volatility risk. For example, in value-weighted returns, the FVIX beta of the low-minus-high disagreement portfolio changes from -0.223 (t-statistic $= -0.7$) in the value quintile to -2.134 (t-statistic $= -4.82$) in the growth quintile, with the t-statistic for the difference of -4.28. Since negative FVIX betas mean underperformance during aggregate volatility increases, the values of FVIX betas reported above imply 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 ratio (more growth options).

To sum up, in this subsection I present two new pieces of evidence: that the strength of the analyst disagreement effect increases with market-to-book ratio, and that this increase can be explained by increasing exposure to aggregate volatility risk. Both pieces of evidence are consistent with my main hypothesis that the analyst disagreement effect arises because high analyst disagreement makes real options a hedge against aggregate volatility risk.

B. Analyst Disagreement Effect and Credit Rating

In Panel B 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, and D = 22), so the top credit rating quintile consists of the most distressed firms. The numbers in the table refer to the low-minus-high disagreement portfolio formed separately within each credit rating quintile.

In the first and fourth rows of Panel B of Table 5, I observe that the CAPM alphas and the Fama-French (1993) alphas do line up with my prediction that the analyst disagreement effect should be the strongest for firms with the worst credit ratings. For example, in equal-weighted CAPM alphas, the analyst disagreement effect starts at 11.2 bp per month (t-statistic $= 0.39$) 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 1.2% per month (t-statistic $=$ 2.89).

The pattern in the alphas in Panel B of Table 5 confirms similar results to those in Avramov et al. (2009). The discriminating test between their explanation (that investors systematically underestimate the expected losses of high-disagreement firms in the event of default) and my explanation (aggregate volatility risk) is to look at the FVIX betas, which I do in the third and sixth rows of Panel B.

Panel B of Table 5 shows that FVIX betas of the low-minus-high disagreement portfolio increase in absolute magnitude as one moves from the best credit rating firms to the worst credit rating firms. In value-weighted returns, the FVIX beta of the low-minus-high disagreement portfolio increases from -0.342 (t-statistic $= -1.09$) in the best credit rating quintile, to -1.58 (t-statistic $= -4.3$) in the worst credit rating quintile.

Equally important is the evidence in rows 2 and 5 of Table 5 (the ICAPM alphas and the 4-factor model alphas). Controlling for FVIX reduces the difference in the analyst disagreement effect between the best and worst credit rating firms by about one-half and makes it statistically insignificant, while also explaining the huge analyst disagreement effect for firms with the worst credit rating.

To sum up, FVIX betas strongly suggest that buying low- and shorting high-disagreement firms means unexpectedly large losses in the periods of increasing aggregate volatility, and these losses are significantly larger in the distressed firms subsample. Hence, the analyst disagreement effect is stronger for distressed firms because buying low- and shorting high-disagreement firms is riskier in this subsample, not because the credit rating effect subsumes the analyst disagreement effect, as Avramov et al. (2009) suggest.

C. Analyst Disagreement Effect and the Conditional CAPM

One of the predictions I make about high-analyst-disagreement firms with abundant real options is that their risk increases less than the risk of low-disagreement firms as the economy goes into recession and aggregate volatility increases. This is one of the reasons why, all else being equal, these firms beat the CAPM when aggregate volatility increases.

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 firms with abundant real options.

In columns 1–3 of Table 6, I estimate the conditional CAPM for three arbitrage portfolios. DISP is the portfolio that buys low-disagreement firms and shorts high-disagreement firms. DISP_MB (DISP_CRED) records the difference in the returns to the DISP strategy followed for growth and value firms (bad and good credit rating firms), as reported in the last column of Table 5.

I assume that the expected market risk premium and the market beta are linear functions of the lagged values of the default premium, the dividend yield of the market index, the 1-month T-bill rate, and the term premium. I then compare the estimated betas of the portfolios in expansions and recessions. 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 as expansion.

TABLE 6

The Analyst Disagreement Effect and the Conditional CAPM

Table 6 reports conditional CAPM betas across different states of the world, as well as the alphas (in percents per month) from the CAPM, the conditional CAPM (CCAPM), and the ICAPM with FVIX, for the three arbitrage portfolios that measure the analyst disagreement effect and its cross-sectional relation to measures of real options. DISP is the portfolio long in low-disagreement stocks and short in high-disagreement stocks. DISP_MB (DISP_CRED) is the return differential between the DISP portfolio formed in the highest market-to-book (worst credit rating) quintile and the DISP portfolio formed in the lowest market-to-book (best credit rating) quintile. Recession (REC) (Expansion (EXP)) 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, 1-month T-bill rate, and term premium. The *t*-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from Jan. 1986 to Dec. 2010. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Portfolio	β_{REC}	β_{EXP}	$\beta_{REC} - \beta_{EXP}$	α_{CAPM}	α_{CCAPM}	α_{ICAPM}
Panel A. Value-Weighted Returns						
DISP	−0.224	−0.581	0.357	0.541	0.320	−0.137
t-stat.	*−5.50*	*−11.6*	*5.55*	*2.33*	*1.45*	*−0.63*
DISP_MB	−0.113	−0.683	0.569	0.943	0.667	0.062
t-stat.	*−1.59*	*−6.79*	*4.62*	*2.37*	*1.57*	*0.12*
DISP_CRED	0.180	−0.218	0.398	1.147	0.953	0.582
t-stat.	*3.41*	*−3.61*	*5.01*	*2.06*	*1.72*	*1.05*
Panel B. Equal-Weighted Returns						
DISP	−0.205	−0.497	0.292	0.665	0.494	0.171
t-stat.	*−5.60*	*−12.6*	*5.39*	*3.44*	*2.65*	*0.82*
DISP_MB	−0.130	−0.546	0.416	0.501	0.290	−0.050
t-stat.	*−2.93*	*−9.11*	*5.48*	*1.70*	*0.93*	*−0.14*
DISP_CRED	0.156	−0.122	0.279	1.092	0.970	0.729
t-stat.	*3.47*	*−2.64*	*4.31*	*2.47*	*2.27*	*1.47*

Table 6 shows that, consistent with my hypotheses, for all portfolios the beta is significantly higher in recessions. The change in market beta between expansions and recessions is large for all portfolios and varies between 0.3 and 0.5 (as compared, e.g., with the similar change by about 0.1 for the HML portfolio in Petkova and Zhang (2005)).

In the last three columns of Table 6, I look at the alphas from the CAPM and the ICAPM with FVIX (repeated from Tables 3 and 5) and the alphas from the conditional CAPM. As expected (see Lewellen and Nagel (2006) for a general critique of the conditional CAPM), the time variation in the betas explains at most 20 bp–25 bp per month of the CAPM alphas that are generally 60 bp–100 bp per month. In some cases (see Panel A of Table 6), the conditional CAPM alphas are insignificant, but that is primarily due to their large standard errors. The ICAPM, on the other hand, does significantly better than the conditional CAPM in all cases, suggesting that the lower betas of high-disagreement firms in recessions are not the whole story, and the new factor, FVIX, is needed to explain the analyst disagreement effect.

VI. Alternative Explanations of the Analyst Disagreement Effect

A. Analyst Disagreement Effect and Downgrades

Avramov, Chordia, Jostova, and Philipov (2009), (2013) show that once one takes the 6 months before and after credit rating downgrades out of the sample, the analyst disagreement effect is no longer visible. Avramov et al. (2009), (2013) argue that if the analyst disagreement effect was risk, it would be strange to see the lower risk premium to high-disagreement firms realized during the few months around the downgrades. Avramov et al. (2009), (2013) suggest that the analyst disagreement effect arises because high-disagreement firms are more often downgraded than low-disagreement firms and investors cannot short firms that have recently been downgraded.

The explanations of the analyst disagreement effect suggested in this paper and in the work of Avramov et al. (2009), (2013) are not mutually exclusive. For example, Avramov et al. (2013) find that the frequency of downgrades is weakly related to the business cycle. Hence, it is unlikely that FVIX is picking up the impact of downgrades. However, it is useful to consider the relative importance of the two explanations.

In Panel A of Table 7, I repeat the Avramov et al. (2009) analysis by excluding from the sample the 6 months before and after a downgrade. The CAPM alphas show that the analyst disagreement effect disappears when downgrades are excluded. However, the association between analyst disagreement and the FVIX betas, which is the main focus of my paper, does not depend on whether the downgrades are in the sample.

While it may seem that FVIX has nothing to explain once downgrades are excluded, this impression is incorrect from the equilibrium perspective. As Avramov et al. (2009) acknowledge, dropping future downgrades from the sample introduces a strong selection bias in the returns to portfolios sorted on analyst

TABLE 7

The Analyst Disagreement Effect and Downgrades

Table 7 reports the CAPM alphas and the ICAPM alphas (in percents per month), as well as the FVIX betas of the analyst disagreement quintiles with some months around portfolio formation (named in the panel headers) omitted from the sample. Time t is the portfolio formation month, time $t-6$ is 6 months prior to portfolio formation, etc. I use the monthly credit rating data from S&P and define a month with a downgrade as a month in which the credit rating becomes worse than in the previous month. Panel A, for example, excludes from the sample all stocks that had at least one downgrade month any time between 6 months prior to the portfolio formation and 6 months after portfolio formation.

	Low	DISP2	DISP3	DISP4	High	Low – High	Low	DISP2	DISP3	DISP4	High	Low – High
	Panel A. No Downgrades in $t-6$ to $t+6$						*Panel B. No Downgrades in $t-6$ to t*					
α_{CAPM}	0.473	0.181	0.399	0.538	0.394	0.079	0.411	0.097	0.252	0.333	0.037	0.374
t-stat.	*2.97*	*1.04*	*2.36*	*2.53*	*1.70*	*0.36*	*2.56*	*0.58*	*1.56*	*1.64*	*0.16*	*1.65*
α_{ICAPM}	0.282	0.123	0.413	0.597	0.587	−0.305	0.227	0.040	0.269	0.410	0.250	−0.023
t-stat.	*1.92*	*0.67*	*2.44*	*2.69*	*2.49*	*−1.31*	*1.51*	*0.22*	*1.65*	*1.93*	*1.04*	*−0.10*
β_{FVIX}	−0.421	−0.126	0.031	0.131	0.426	−0.846	−0.405	−0.126	0.037	0.170	0.468	−0.873
t-stat.	*−2.02*	*−0.78*	*0.19*	*0.74*	*2.42*	*−3.44*	*−1.96*	*−0.74*	*0.23*	*0.94*	*2.47*	*−4.08*
	Panel C. Only Downgrades in $t-6$ to t						*Panel D. No Downgrades in $t+1$ to $t+6$*					
α_{CAPM}	0.323	−0.032	−0.430	−0.820	−0.290	0.672	0.470	0.183	0.397	0.538	0.434	0.036
t-stat.	*0.59*	*−0.08*	*−1.08*	*−1.92*	*−0.73*	*1.28*	*2.93*	*1.05*	*2.33*	*2.53*	*1.80*	*0.16*
α_{ICAPM}	0.078	−0.318	−0.350	−0.517	−0.007	0.094	0.272	0.114	0.414	0.611	0.638	−0.366
t-stat.	*0.12*	*−0.79*	*−0.83*	*−1.37*	*−0.02*	*0.16*	*1.83*	*0.62*	*2.39*	*2.78*	*2.57*	*−1.51*
β_{FVIX}	−0.476	−0.593	0.178	0.671	0.622	−1.124	−0.437	−0.152	0.039	0.161	0.448	−0.885
t-stat.	*−0.70*	*−1.69*	*0.67*	*1.96*	*2.03*	*−2.20*	*−2.07*	*−0.92*	*0.24*	*0.92*	*2.32*	*−3.41*

disagreement. This selection bias is naturally stronger for high-disagreement firms that are more likely to be downgraded.[5]

In Panel B of Table 7, I eliminate only past, but not future, downgrades from the sample. I observe that the analyst disagreement effect reemerges at 37 bp per month (t-statistic $= 1.65$) in the CAPM alphas and 50 bp per month (t-statistic $= 2.56$) in the Fama-French (1993) alphas (not tabulated). The weaker analyst disagreement effect for firms with no downgrades is expected according to my theory, since, as Avramov et al. (2013) show, downgrades are less common for firms with a good credit rating, and Panel B of Table 5 shows that the analyst disagreement effect is weaker for these firms. Yet, the analyst disagreement effect is still visible in the sample with no past downgrades and no selection bias, and FVIX is needed to explain it.

In Panel C of Table 7, I test the hypothesis of Avramov et al. (2009) that the analyst disagreement effect arises because stock prices of high-disagreement firms are slow to react to downgrades. I look at the analyst disagreement effect in the subsample of firms that have experienced a downgrade in the past 6 months. I do not find a significant analyst disagreement effect in this subsample, though that may be partly due to the small number of firms in each portfolio: The analyst disagreement effect stands at 67 bp per month (t-statistic $= 1.28$).

When I control for FVIX, the point estimate of the analyst disagreement effect for downgraded firms is reduced to only 9 bp per month, and I also discover that the FVIX betas of the disagreement quintiles increase significantly and almost

[5]Avramov et al. (2013) find that each month, 13 firms with high analyst disagreement are downgraded, versus 9 downgrades per month for firms with low disagreement.

monotonically with disagreement. This is to be expected: According to my theory, the analyst disagreement effect should be stronger for distressed firms, because their equity is more option-like, and option-like equity is a better hedge against aggregate volatility risk.

The absence of analyst disagreement effect in the ICAPM alphas, even in the subsample of recently downgraded firms, seems inconsistent with the hypothesis of slow price adjustment from Avramov et al. (2009). Panel C of Table 7 suggests that after one controls for risk properly, the price reaction of high-disagreement firms to downgrades does not appear slow anymore.

Avramov et al. (2009) also point out that it is strange that the entire analyst disagreement effect is realized around the few months of future downgrades. According to Avramov et al. (2009), it would be more natural to expect that if high-disagreement firms are less risky than low-disagreement firms, high-disagreement firms will have lower returns most of the time.

The validity of this argument hinges on whether the risk of high- and low-disagreement firms is the same in periods with no future downgrades. If it is, then it is indeed strange that the low risk premium of high-disagreement firms is concentrated around future downgrades. However, if the risk of high-disagreement firms is low outside of periods with future downgrades, then the fact that high- and low-disagreement firms earn similar returns indicates that high-disagreement firms earn positive "abnormal returns" when future downgrades do not happen, as compensation for the large negative "abnormal returns" when future downgrades do happen.[6]

The discriminating test is to look at the subsample with future downgrades excluded and test whether analyst disagreement is still related to aggregate volatility risk. This is done in Panel A of Table 7, where both past and future downgrades are excluded. I find that high-disagreement firms do have less risk (and more positive FVIX betas) even outside of the downgrade months. In Panel D, I repeat this test with only future downgrades excluded and past downgrades left in the sample and observe similar results.

I conclude that the low risk of high-disagreement firms is not concentrated around future downgrades. The low risk is still present if the future downgrades are dropped from the sample. The seeming concentration of the analyst disagreement effect around future downgrades is then all look-ahead bias, not some unusual behavior of the risk premium.

B. Analyst Disagreement Effect and Short-Sale Constraints

The first explanations of the analyst disagreement effect rely on the mispricing theory of Miller (1977). Miller argues that if short-sale constraints exist, higher disagreement leads to overpricing and lower future returns, because pessimistic investors have to stay out of the market (they cannot sell short), and the stock price in the market reflects the overoptimistic average valuation of the remaining investors. The overoptimism of the remaining investors is higher when investors disagree more.

[6]Keep in mind that one is talking about future downgrades; hence, the "abnormal return" is not a return to a trading strategy, but rather just a residual of an asset pricing model.

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Existing empirical studies confirm that the analyst disagreement effect is stronger when short-sale constraints are more restrictive. Nagel (2005) finds that the analyst disagreement effect is stronger for firms with low institutional ownership (a proxy for the supply of shares for shorting). Boehme, Danielsen, and Sorescu (2006) find that the analyst disagreement effect is significantly stronger if the expected shorting fee (a function of RSI) is high.

In this section, I use the FVIX factor to explain the link between the analyst disagreement effect and short-sale constraints. My theory does not imply that in the 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.

In Panel A of Table 8, I look at the equal-weighted alphas and FVIX betas of the low-minus-high disagreement portfolio across the RI quintiles. The results are similar to Nagel (2005), who 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 quintiles is economically large but marginally significant.

In the subsequent rows of Panel A of Table 8, I show that the relation between the analyst disagreement effect and institutional ownership is due to aggregate volatility risk. For example, if one turns to the ICAPM in rows 2 and 3, the FVIX beta of the low-minus-high disagreement portfolio is -1.275 (t-statistic $= -3.05$) in the lowest institutional ownership quintile and -0.765 (t-statistic $= -3.82$) in the highest institutional ownership quintile. The difference in the FVIX betas shows that buying low- and shorting high-disagreement firms exposes the

TABLE 8

Analyst Disagreement Effect and Limits to Arbitrage

Table 8 presents the alphas (in percents per month) and FVIX betas of the low-minus-high disagreement portfolio across limits to arbitrage quintiles. The following models are used for measuring the alphas and betas: the CAPM, the 2-factor ICAPM with the market factor and the FVIX factor (ICAPM), the Fama-French (1993) model (FF), and the Fama-French (1993) model augmented with FVIX (FF4). The low-minus-high disagreement portfolio buys firms in the lowest-disagreement quintile and shorts firms in the highest-disagreement quintile. The low-minus-high disagreement portfolio is rebalanced monthly, the quintile portfolios formed on residual institutional ownership (RI) are rebalanced quarterly, and the quintile portfolios formed on relative short interest (RSI) are rebalanced monthly. The *t*-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from Jan. 1986 to Dec. 2010. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

	Panel A. Analyst Disagreement Effect and RI						*Panel B. Analyst Disagreement Effect and RSI*					
	Low	RI2	RI3	RI4	High	Low – High	Low	RSI2	RSI3	RSI4	High	High – Low
α_{CAPM}	0.731	0.450	0.299	0.358	0.150	0.581	0.633	0.356	0.512	0.359	0.503	–0.130
t-stat.	*2.76*	*1.73*	*1.19*	*1.81*	*0.66*	*2.29*	*3.36*	*1.76*	*2.13*	*1.42*	*1.87*	*–0.48*
α_{ICAPM}	0.143	–0.079	–0.200	–0.045	–0.203	0.346	0.311	–0.077	0.014	–0.227	0.047	–0.264
t-stat.	*0.56*	*–0.28*	*–0.75*	*–0.22*	*–0.78*	*1.53*	*1.60*	*–0.40*	*0.05*	*–0.75*	*0.14*	*–0.83*
β_{FVIX}	–1.275	–1.149	–1.083	–0.876	–0.765	–0.510	–0.677	–0.909	–1.047	–1.232	–0.959	–0.282
t-stat.	*–3.05*	*–3.53*	*–3.90*	*–4.61*	*–3.82*	*–1.84*	*–5.22*	*–3.52*	*–3.02*	*–4.02*	*–2.51*	*–0.93*
α_{FF}	0.634	0.424	0.309	0.418	0.243	0.390	0.707	0.434	0.585	0.418	0.536	–0.171
t-stat.	*2.92*	*1.84*	*1.39*	*2.28*	*1.18*	*1.89*	*3.86*	*2.55*	*2.80*	*2.03*	*2.03*	*–0.61*
α_{FF4}	0.299	0.117	0.022	0.161	0.088	0.210	0.499	0.160	0.347	0.085	0.263	–0.236
t-stat.	*1.45*	*0.53*	*0.10*	*0.86*	*0.40*	*1.02*	*2.81*	*1.02*	*1.60*	*0.41*	*0.99*	*–0.79*
β_{FVIX}	–0.736	–0.674	–0.630	–0.565	–0.341	–0.395	–0.429	–0.565	–0.491	–0.687	–0.562	–0.134
t-stat.	*–2.60*	*–2.85*	*–3.12*	*–2.82*	*–2.62*	*–1.89*	*–3.98*	*–2.40*	*–2.50*	*–4.52*	*–1.89*	*–0.54*

investor to significantly higher aggregate volatility risk if this strategy is followed for stocks with low institutional ownership.

Also, after I control for FVIX, the alphas of the low-minus-high disagreement portfolio vary less with institutional ownership (the respective difference in the alphas from the 4-factor model is only 21 bp per month, t-statistic of 1.02). Moreover, the large alpha of the low-minus-high disagreement portfolio in the lowest institutional ownership quintile, which is the ultimate evidence of the analyst disagreement effect being mispricing in Nagel (2005), changes from 73 bp per month (t-statistic $= 2.76$) in the CAPM to 14 bp per month (t-statistic $= 0.56$) in the ICAPM.

In Panel B of Table 8, I find no evidence that the analyst disagreement effect depends on RSI. The analyst disagreement effect seems to be strong and mostly significant in all RSI quintiles, and the alphas of the low-minus-high disagreement portfolio are slightly lower, not higher, for firms with high RSI. Likewise, I observe no difference in the FVIX betas of the low-minus-high disagreement portfolio between firms with high and low RSI.

Boehme et al. (2006) use somewhat different measures of short-sale constraints and analyst disagreement. They estimate the shorting fee to be a nonlinear function of residual short interest and the dummy for the availability of the option on the stock. They also estimate analyst disagreement as a nonlinear function of idiosyncratic volatility and turnover. In untabulated results, I also do not find any association between the measure of shorting cost from Boehme et al. and the analyst disagreement effect redefined using their measure. I conclude that their results are sample-specific and that they largely disappear once I include another 8 years of data (the sample in Boehme et al. ends in 2002).

C. Analyst Disagreement Effect and Liquidity

Sadka and Scherbina (2007) take a different approach in showing that the analyst disagreement effect is mispricing. They argue that the mispricing is not corrected because of high trading costs. Sadka and Scherbina show that the analyst disagreement discount is strong if the price impact measure from Sadka (2006) is high, indicating high trading costs. In the same vein, Diether et al. (2002) show that the analyst disagreement effect is stronger for small stocks.

In Panels A and B of Table 9, I look at the analyst disagreement effect across size and price impact quintiles, respectively. Since 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.

When I look at the CAPM and the ICAPM alphas, I find no evidence that the analyst disagreement effect is stronger for illiquid firms in my sample period (1986–2010). The CAPM alphas of the low-minus-high disagreement portfolio are significant in all size/price impact quintiles. The alphas tend to be relatively flat except for the most illiquid quintile, where they increase by around 30 bp per month, but the increase is statistically insignificant.

The ICAPM alphas and the 4-factor (3 Fama-French (1993) factors plus FVIX) alphas offer some evidence that the analyst disagreement effect may

TABLE 9

Analyst Disagreement Effect and Liquidity

Table 9 presents the alphas (in percents per month) and FVIX betas of the low-minus-high disagreement portfolio across liquidity quintiles. The following models are used for measuring the alphas and betas: the CAPM, the 2-factor ICAPM with the market factor and the FVIX factor (ICAPM), the Fama-French (1993) model (FF), and the Fama-French (1993) model augmented with FVIX (FF4). FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX. The low-minus-high disagreement portfolio buys firms in the lowest-disagreement quintile and shorts firms in the highest-disagreement quintile. The low-minus-high disagreement portfolio is rebalanced monthly, the size quintiles and the Amihud (2002) illiquidity quintiles are rebalanced yearly. The *t*-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from Jan. 1986 to Dec. 2010. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

	Panel A. Analyst Disagreement Effect and Size						*Panel B. Analyst Disagreement Effect and Price Impact*					
	Small	SIZE2	SIZE3	SIZE4	Big	Small – Big	Low	ILLIQ2	ILLIQ3	ILLIQ4	High	High – Low
α_{CAPM}	0.942	0.590	0.461	0.354	0.593	0.349	0.615	0.459	0.441	0.508	0.900	0.285
t-stat.	*4.62*	*2.80*	*1.90*	*1.62*	*2.42*	*1.62*	*2.45*	*2.08*	*1.92*	*2.37*	*4.75*	*1.29*
α_{ICAPM}	0.564	0.215	–0.019	–0.235	0.012	0.552	0.053	0.048	–0.053	0.115	0.525	0.471
t-stat.	*2.43*	*0.94*	*–0.07*	*–1.03*	*0.05*	*2.42*	*0.22*	*0.20*	*–0.19*	*0.50*	*2.37*	*1.80*
β_{FVIX}	–0.821	–0.813	–1.043	–1.279	–1.261	0.440	–1.219	–0.891	–1.073	–0.853	–0.815	0.404
t-stat.	*–4.34*	*–2.50*	*–3.19*	*–3.43*	*–5.42*	*2.71*	*–4.88*	*–3.36*	*–3.37*	*–3.20*	*–4.12*	*1.74*
α_{FF}	0.954	0.554	0.448	0.357	0.606	0.349	0.643	0.503	0.463	0.518	0.906	0.264
t-stat.	*4.91*	*2.97*	*2.02*	*1.70*	*2.64*	*1.63*	*2.68*	*2.54*	*2.23*	*2.81*	*4.96*	*1.15*
α_{FF4}	0.710	0.349	0.138	–0.075	0.139	0.571	0.205	0.258	0.175	0.295	0.670	0.464
t-stat.	*3.65*	*1.87*	*0.62*	*–0.36*	*0.66*	*2.71*	*0.85*	*1.30*	*0.76*	*1.55*	*3.70*	*1.87*
β_{FVIX}	–0.536	–0.450	–0.680	–0.947	–1.026	0.489	–0.961	–0.539	–0.632	–0.490	–0.520	0.441
t-stat.	*–4.15*	*–2.12*	*–2.84*	*–2.88*	*–4.63*	*2.97*	*–3.84*	*–2.15*	*–2.67*	*–2.41*	*–5.43*	*2.27*

partially be mispricing that persists because of illiquidity. The ICAPM alphas and the 4-factor alphas of the low-minus-high disagreement portfolio are insignificant and very close to 0 in all quintiles except for the most illiquid one. In the smallest quintile and the quintile with the highest price impact, the ICAPM alphas and the 4-factor alphas exceed 50 bp per month and are statistically significant, along with the difference in the alphas between the most illiquid and most liquid quintiles.

The FVIX betas of the low-minus-high portfolio, however, appear more negative in the most liquid quintile, which suggests that, on the one hand, FVIX cannot explain the relation between the analyst disagreement effect and liquidity (if any) and, on the other hand, that FVIX is unlikely to pick up any liquidity-related effects.

The difference between the patterns in the CAPM alphas in Table 8 and in Diether et al. (2002) and Sadka and Scherbina (2007) is primarily due to the different sample periods. I find that in the last 4 years of my sample (2007–2010) the cross-sectional relation between liquidity and the analyst disagreement effect is either positive (the analyst disagreement effect is stronger for liquid firms) or nonexistent. In particular, in 2008, the low-minus-high disagreement portfolio, formed in the most liquid quintile, outperformed the similar portfolio, formed in the most illiquid quintile, by a total of 24%. Omitting the last 4 years of the sample allows me to match quite closely the results in Diether et al. and Sadka and Scherbina.

The fact that in 2008, buying low-disagreement illiquid firms and shorting high-disagreement illiquid firms resulted in relatively poor performance, points toward an alternative explanation of the analyst disagreement effect and of why it is stronger for illiquid firms. This potential explanation is liquidity risk.

Sadka and Scherbina (2007) find some suggestive evidence of this by showing in their Table 8 that the low-minus-high disagreement portfolio tends to lose money when aggregate liquidity decreases.

In untabulated results, I use several liquidity factors on the analyst disagreement quintiles and find that controlling for liquidity risk does not make the analyst disagreement effect smaller and that the liquidity betas seem to be largely unrelated to analyst disagreement. I also find that controlling for liquidity risk does not impact the FVIX betas, suggesting a low degree of overlap between FVIX and liquidity risk. I conclude that there is no overlap between FVIX and either liquidity or liquidity risk, and that liquidity risk does not help to explain the analyst disagreement effect.

VII. Conclusion

In this paper, I show that the analyst disagreement effect can be explained by aggregate volatility risk. I use a 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 (1993) 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.

The explanation is that higher disagreement makes real options (growth options, the option created by risky debt) respond less negatively to aggregate volatility increases. First, higher disagreement means that real options are less responsive to the value of the underlying asset and therefore less risky. The main driving force behind this result is the well-known fact that the option delta decreases in volatility. This link between disagreement and systematic risk is helpful during recessions, when, as I show in Section III.A, firm-level disagreement and aggregate volatility both increase. In recessions, the risk exposure of firms with high disagreement and abundant real options declines. Hence, their expected return increases less and their value drops less.

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

Consistent with this explanation, I show that the analyst disagreement effect is stronger for firms with high market-to-book ratio or bad credit rating, and this pattern can be explained by aggregate volatility risk. The aggregate volatility risk factor also explains why the analyst disagreement effect is stronger for firms with lower institutional ownership, suggesting a possible risk-based explanation behind the evidence usually interpreted in favor of the mispricing theories of the analyst disagreement effect.

Sadka and Scherbina (2007) show that the analyst disagreement effect is stronger for smaller firms and more illiquid firms with higher price impact. I find that these patterns are not robust to including 4 more years of data (2007–2010) and are not related to aggregate volatility risk. I also find that liquidity factors

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cannot explain the analyst disagreement effect or its relation to market-to-book ratio, credit rating, or short-sale constraints.

Avramov et al. (2009), (2013) find that the analyst disagreement effect disappears if one excludes past and future downgrades that occur 6 months before or after portfolio formation. Avramov et al. (2009), (2013) conclude that the analyst disagreement effect arises because of the difficulty of shorting and the consequent overpricing of high-disagreement firms that have just been downgraded.

I find that the cross-sectional relation between disagreement and FVIX betas is robust to excluding past and future downgrades from the sample, rejecting the hypothesis of Avramov et al. (2009), (2013) that the low risk of high-disagreement firms is concentrated around downgrades. I also find that FVIX can explain the alphas of high-disagreement firms that have just been downgraded and that the analyst disagreement effect remains sizeable when I exclude only past downgrades, but not future downgrades.

Appendix. Data

CRED (credit rating): Standard & Poor's rating (SPLTICRM variable in the Compustat quarterly file). The credit rating is coded as 1 = AAA, 2 = AA+, 3 = AA, . . . , 21 = C, 22 = D.

DISP (analyst forecast dispersion): the standard deviation of all outstanding earnings-per-share forecasts for the current fiscal year scaled by the absolute value of the outstanding earnings forecast (zero-mean forecasts and forecasts by only one analyst are excluded). Earnings forecasts are from the IBES Summary file.

ILLIQ (Amihud illiquidity measure): the average ratio of absolute return to dollar volume, both from CRSP. The ratio is computed daily and averaged within each firm-year (firms with less than 200 valid return observations in a year and a stock price of less than $5 at the end of the previous year are excluded).

IVOL (idiosyncratic volatility): the standard deviation of residuals from the Fama-French (1993) model, fitted to the daily data for each month (at least 15 valid observations are required). Average IVOL is averaged for all firms within each month.

LEV (leverage): long-term debt (DLTT) plus short-term debt (DLC) divided by equity value, all items from Compustat annual.

MB (market-to-book): equity value (share price, PRCC, times number of shares outstanding, CSHO) divided by book equity (CEQ) plus deferred taxes (TXDB), all items from Compustat annual files.

NBER (the NBER recession dummy): 1 for the months between NBER-announced peak and trough periods, and 0 otherwise.

REALIZED_VOL (realized market volatility): the square root of the average squared daily return to the market portfolio (CRSP value-weighted index) within each given month.

RI (residual institutional ownership): the residual (ϵ) from the logistic regression of institutional ownership on log(SIZE) and its square:

$$\log\left(\frac{\text{INST}}{1-\text{INST}}\right) = \gamma_0 + \gamma_1 \log(\text{SIZE}) + \gamma_2 \log^2(\text{SIZE}) + \epsilon. \tag{A-1}$$

Institutional ownership is the sum of institutional holdings from Thompson Financial 13F database, divided by the shares outstanding from CRSP. All stocks below the 20th NYSE/AMEX size percentile are dropped. If the stock is not dropped, appears on CRSP, but not on Thompson Financial 13F, it is assumed to have zero institutional ownership.

RSI (residual short interest): outstanding shorts reported by NYSE and NASDAQ divided by the number of shares outstanding. The data are monthly and reported on the 15th calendar day of each month.

SIZE (market capitalization): shares outstanding times price, both from the CRSP monthly returns file.

TARCH (expected market volatility): from the TARCH$(1, 1)$ model (see Glosten et al. (1993)) fitted to monthly returns to the CRSP value-weighted index:

$$\begin{aligned} \text{RET}_t^{\text{CRSP}} &= \gamma_0 + \gamma_1 \text{RET}_{t-1}^{\text{CRSP}} + \epsilon_t, \\ \sigma_t^2 &= c_0 + c_1\sigma_{t-1}^2 + c_2\epsilon_{t-1}^2 + c_3 I(\epsilon_{t-1} < 0). \end{aligned} \tag{A-2}$$

The regression is estimated for the full sample. I take the square root out of the volatility forecast to be consistent with my measure of idiosyncratic volatility.

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