High Short Interest Effect and Aggregate Volatility Risk

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Abstract

We propose a risk-based firm-type explanation on why stocks of firms with high relative short interest (RSI) have lower future returns. We argue that these firms have negative alphas because they are a hedge against expected aggregate volatility risk. Consistent with this argument, we show that these firms have high firm-specific uncertainty and option-like equity, and the aggregate volatility risk factor can largely explain the high RSI effect. The key mechanism is that high RSI firms have abundant growth options and, all else equal, growth options become less sensitive to the underlying asset value and more valuable as idiosyncratic volatility goes up. Idiosyncratic volatility usually increases together with aggregate volatility, i.e., in recessions.

1. Introduction

It is well established that stocks of firms with high relative short interest (henceforth RSI) have low future returns (e.g., Asquith, Pathak, and Ritter, 2005). In this paper, we call this pricing anomaly the high RSI effect. Theoretical models that try to explain the high RSI effect build on seminal work by Miller (1977) and Diamond and Verrecchia (1987). Miller (1977) argues that the presence of short sales constraints keeps pessimistic investors out of the market, which leads to overvaluation, and subsequent corrections result in low returns (see, e.g., Jones and Lamont (2002), Asquith et al. (2005), Boehme et al. (2006, 2009)). Diamond and Verrecchia (1987) propose that short sellers are more likely to be informed because short sales are more expensive than long transactions. Among others, Dechow et al. (2001) and Boehmer, Jones and Zhang (2008) argue that due to slow incorporation of the information short sellers have, highly shorted firms can have lower future returns.[1]

Both explanations for the high RSI effect, however, are not quite satisfactory for rational asset-pricing due to the assumption of some type of investors' irrationality. The Miller argument assumes that some optimists repeatedly fall prey to the winner's curse. Indeed, even if the short-sale constraints keep pessimists out of the market, the remaining optimists should not pay for the short-sale constrained stocks as much as they do since they should be aware of the bad historical performance of such stocks.[2] The informed short sellers argument suggests not only that short sellers short "bad" shares, but also that other investors fail to correctly process the information in short interest even after it is revealed to them. It is not surprising that heavily shorted firms underperform after they are shorted, but it is surprising, if one believes in investors' rationality, that heavily shorted firms continue to do poorly (several months into the future) even after everyone learns that they are heavily shorted.

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[1] This last sentence steps outside the Diamond and Verrecchia model because in their model prices are unbiased.

[2] Duffie et al. (2002) introduce bargaining power over lending fees and shows that, in a dynamic model and in the presence of irrational optimistic investors, some rational investors are willing to pay a very inflated price.

In this paper, we propose an alternative risk-based firm-type explanation on why high RSI firms have lower future returns. In contrast to the two theories above, this explanation does not require the assumption of investors' irrationality. It argues that high RSI firms have lower aggregate volatility risk, that is, they tend to outperform when expected aggregate volatility unexpectedly increases. The key reason is that high RSI firms turn out to be firms with high firm-specific uncertainty and option-like equity.[3]

Stocks of firms with high uncertainty and option-like equity are a good hedge against aggregate volatility risk. This is because when aggregate volatility increases in recessions, firm-specific uncertainty also elevates. Higher idiosyncratic volatility during periods of high aggregate volatility has two effects on option-like equity. First, all else equal, higher volatility means higher value of real options (see Grullon et al., 2012, for empirical evidence). Second, higher volatility at the level of the underlying asset makes the beta of option-like equity smaller (see Johnson, 2004, for a formal model) and that, in turn, leads to a smaller increase in expected return and smaller decrease in value in response to increasing aggregate volatility. So both effects lead to the conclusion that option-like firms behave as a hedge against aggregate volatility risk, and that the hedge will be naturally stronger for more volatile firms.

Abnormally good performance during periods of increasing aggregate volatility is a desirable feature. Campbell (1993) creates a model in which increasing aggregate volatility signals decreasing expected future consumption. For stocks whose value correlates positively with aggregate volatility news, investors require a lower risk premium because these stocks provide additional consumption precisely when investors have to cut their current consumption for consumption-smoothing motives. Chen's (2002) model adds precautionary savings motive and shows that the positive correlation of asset returns with aggregate volatility changes is

[3] Equity can be option-like either because equity is a claim on option-like assets (growth options) or because equity itself is an option on the assets due to existence of risky debt.

desirable, because such assets deliver additional consumption when investors have to consume less to boost precautionary savings. Ang, Hodrick, Xing, and Zhang (2006) confirm this prediction empirically and coin the term of aggregate volatility risk. They show that stocks with most positive sensitivity to aggregate volatility increases have abnormally low expected returns.

In this paper, we use both the previously established negative relation between firm-specific uncertainty and equity option-likeness and aggregate volatility risk to argue that high RSI firms have low expected returns because they are a hedge against aggregate volatility risk due to having higher firm-specific uncertainty and more option-like equity.

The negative relation between various measures of firm-specific uncertainty and equity option-likeness and aggregate volatility risk has been empirically confirmed in several prior studies. Barinov (2011) shows that growth firms and high idiosyncratic volatility firms have low aggregate volatility risk. Barinov (2013, 2014) demonstrates a similar relation between turnover and aggregate volatility risk and disagreement and aggregate volatility risk, respectively.

Our empirical analysis first examines whether high RSI firms have high uncertainty and option-like equity. We show that high RSI firms indeed possess higher levels of firm-specific uncertainty and more option-like equity than low RSI firms or firms in the whole Compustat sample. Since prior work has established that our measures of firm-specific uncertainty and equity option-likeness are negatively related to aggregate volatility risk, this evidence means that high RSI firms are also likely to have low aggregate volatility risk.

We start our tests of the aggregate volatility risk explanation of the high RSI effect with presenting anecdotal evidence from the most recent recession showing that high RSI firms experience much smaller losses than what is suggested by their market beta, implying that high RSI firms behave like a hedge against aggregate volatility risk. We then examine whether augmenting several benchmark asset pricing models with the aggregate volatility risk factor (FVIX factor) can explain the high RSI effect. We find that high RSI firms yield no negative alphas when controlling for FVIX. The main reason is that high RSI firms have strong and positive loadings on the FVIX factor that tracks changes in VIX, our measure of expected aggregate volatility. By construction, the FVIX factor earns positive returns when aggregate volatility increases. Therefore, positive FVIX betas of high RSI firms indicate that these firms outperform when aggregate volatility increases, and thereby behave as a hedge against aggregate volatility risk.

To strengthen our argument that high RSI firms are a hedge against aggregate volatility risk due to their high uncertainty and option-like equity, we propose several cross-sectional hypotheses: 1) high RSI firms earn negative alphas only when they have high uncertainty and option-like equity; 2) the difference in the alphas between high RSI firms with high and low uncertainty should shrink after FVIX is controlled for; and 3) FVIX betas of high RSI firms should increase in uncertainty and measures of equity option-likeness. While several existing mispricing stories may also explain the first prediction (about the alphas), the other two predictions (about the alphas controlling for FVIX and the FVIX betas) are new to the literature and enable us to discriminate between our argument and the existing mispricing explanations.

Consistent with these predictions, high RSI firms with low uncertainty/option-likeness have zero alphas while alphas of high RSI and high uncertainty/option-like firms are between -60 and -150 bp per month and highly significant.[4] Most importantly, we add two new findings. First, controlling for the FVIX factor shrinks significantly (by more than half and in many cases makes insignificant) the alphas of high RSI firms with high uncertainty or option-like equity and their difference from the alphas of high RSI firms with low uncertainty or non-option-like equity. Second, the FVIX betas of the high RSI firms with high uncertainty or high option-likeness are significantly more positive than those of the high RSI firms with low uncertainty or low option-

[4] Our benchmark model in the paper is the six-factor model that uses the three Fama-French (1993) factors, the momentum factor of Carhart (1997), the Pastor-Stambaugh (2003) liquidity factor, and the reversal factor.

likeness. The FVIX betas suggest that the negative alphas of high RSI firms with high uncertainty or option-like equity arise because these firms outperform during periods of increasing aggregate volatility. These new cross-sectional findings provide more convincing evidence on our risk-based firm-type explanation.

Controlling for the FVIX factor can also explain Asquith, Pathak and Ritter's (2005) finding of stronger high RSI effect among firms with low institutional ownership (henceforth IO). Asquith et al. (2005) interpret IO as a measure of potential supply of shares to short sellers, and attribute their finding to more binding short sale constraints. We show that this is related to the fact that institutions prefer to hold shares with lower uncertainty (e.g., Del Guercio, 1996), and that high RSI low IO firms have higher uncertainty and more positive FVIX betas.

To further strengthen the argument that the negative alphas of high RSI firms are due to the fact that these firms have positive FVIX betas, we also study the source of the relation between RSI and FVIX betas. Using multivariate Fama-MacBeth regressions, we come to the conclusion that short sellers inadvertently load on FVIX while targeting firms with high uncertainty[5] and option-like equity. The positive relation between FVIX and RSI is subsumed by the positive relation between RSI and uncertainty/equity option-likeness, and regressions of changes in RSI on changes in firm characteristics find that short sellers react to increases in firm-specific uncertainty and equity option-likeness by shorting more, but do not immediately react to changes in FVIX betas.

Our finding that high RSI firms perform relatively well when aggregate volatility increases does not necessarily indicate that these firms gain value when aggregate volatility increases. Since the market return and change in aggregate volatility are strongly negatively correlated (monthly correlation is -0.69), a positive FVIX beta does not imply that the asset gains

[5] To our knowledge, our paper is the first in the literature to document the positive relation between RSI and firm-specific uncertainty (suggesting that short sellers attempt to trade on the anomalies documented in Ang et al., 2006, and Diether et al., 2002).

value when aggregate volatility increases. Any asset with a positive market beta should lose when aggregate volatility increases, but an asset with a positive FVIX beta *loses less* than assets with similar betas. This is why high RSI firms are a hedge against aggregate volatility risk.

The main contribution of this paper is that we offer an alternative risk-based firm-type explanation for the high RSI effect. We show that a substantial part of the high RSI effect is explained by high RSI firms' ability to hedge against aggregate volatility risk. This explanation complements existing theories that focus on short sales constraints and informed short sellers. We show that, once aggregate volatility risk is controlled for, these two arguments play a significantly smaller role in explaining the high RSI effect.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 reports univariate results on high RSI firms. Section 4 examines high RSI firms in cross-section. Section 5 considers the conditional CAPM, and Section 6 studies the determinants of short interest. Section 7 performs robustness checks on the main finding, and Section 8 concludes.

2. Data Sources

The level of short interest in individual stocks is reported to the exchanges on the 15th calendar day of every month (if it is a business day).[6] RSI is outstanding short position divided by concurrent number of shares outstanding and available monthly between 1988 and 2010. Data on stock returns, price, share volume, shares outstanding are from CRSP.[7] All common domestic stocks listed on major exchanges are included.

[6] Exchanges report short interest twice per month since September 2007. To be consistent with short interest data from earlier period, we keep the data at the monthly frequency.

[7] We use monthly cum-dividend returns and complement them by the delisting returns from the CRSP events file. Following Shumway (1997) and Shumway and Warther (1999), we set delisting returns to -30% for NYSE and AMEX firms (exchcd codes equal to 1, 2, 11, or 22) and to -55% for NASDAQ firms (exchcd codes equal to 3 or 33) if CRSP reports missing or zero delisting returns and delisting is for performance reasons. Our results are robust to setting missing delisting returns to -100% or using no correction for the delisting bias.

Measuring uncertainty and equity option-likeness can be challenging because they are not directly observable. Our strategy is to adopt a number of proxies so that our results are not proxy-specific. Motivated by prior literature, we use three proxies for firm-level uncertainty: idiosyncratic volatility (Ang et al., 2006), analyst disagreement on earnings (Diether et al., 2002, Barinov, 2013), and share turnover (Harris and Raviv, 1993).

Idiosyncratic volatility is the standard deviation of the residuals from a Fama-French three factor model estimated for each firm-month using daily data. In the estimation, we require at least 15 daily returns. The returns to the three Fama-French factors and the risk-free rate are from Kenneth French's website at http://mba.tuck.dartmouth.edu/pages/faculty /ken.french/.[8]

Analyst disagreement is a common proxy for uncertainty. The more uncertainty a firm's earnings are, the more analysts tend to disagree with each other. 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. This measure excludes zero-mean forecasts and forecasts by only one analyst.

Share turnover also proxies for a firm's uncertainty. Harris and Raviv (1993) argue that investors trade more when they disagree about the asset value. Barinov (2014) shows empirically that turnover is strongly related to several volatility and uncertainty measures. Turnover is trading volume divided by shares outstanding. To make comparisons across exchanges more meaningful, we adjust NASDAQ's double counting following Gao and Ritter (2010).[9] Our analysis uses average monthly turnover in the previous year with at least 5 valid observations.

We adopt two common proxies for equity option-likeness. The first one, market-to-book ratio, is used extensively in the literature to proxy for a firm's growth opportunities (e.g., Fama and French, 1993, 1996, 2008). It is computed as the market value at the fiscal year end (CSHO

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[8] We thank Ken French for making the data available.

[9] NASDAQ volume is divided by 2 for the period from 1983 to January 2001, by 1.8 for the rest of 2001, by 1.6 for 2002-2003, and is unchanged after that. A firm is classified as a NASDAQ firm if its CRSP exchcd is 3.

times PRCC from the new Compustat files) divided by the book value of equity (CEQ plus TXDB from the new Compustat files).[10]

The second proxy is S&P credit rating that measures the real option created by the existence of risky debt (the firm's equity is a call option on its assets). The variable is SPLTICRM from the Adsprate Compustat file. Following the literature, we transform the credit rating into numerical format (1=AAA, 2=AA+, 3=AA, ... , 21=C, 22=D), with higher value indicating lower credit quality. As a firm gets closer to being bankrupt (i.e., the shareholders are more likely to exercise the option created by leverage), the firm's equity is more option-like.[11]

We also use Thompson Financial 13F database to obtain data on IO. IO is the sum of institutional holdings divided by shares outstanding from CRSP. If a stock is in CRSP, but not in Thompson Financial 13F database, it is assumed to have zero IO if the stock's capitalization is above the NYSE/AMEX 20th percentile, otherwise its IO is assumed to be missing. Following Nagel (2005), we also use residual IO from quarterly regression of Logit(IO) on log size and squared log size to eliminate the high correlation between size and IO.

3. Univariate analysis

3.1. High RSI and firm characteristics

The current literature on short selling is silent about aggregate volatility risk, yet, as we discuss in the introduction, investigating this potential risk is both theoretically and empirically

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[10] We also use sales growth (defined as (sales(t)-sales(t-1))/sales(t-1)), investment growth (defined as (capex(t)-capex(t-1))/capex(t-1))) and R&D-to-assets ratio to proxy for growth opportunities. Results are qualitatively similar.

[11] A firm's leverage can be an alternative measure of the equity option-likeness created by debt, but we choose credit rating because leverage is mechanically negatively correlated with market-to-book (the firm's market cap is both in the numerator of market-to-book and the denominator of leverage). In further tests, where we predict that the effect of RSI on future returns is stronger for firms with option-like equity (high market-to-book or high leverage), it is inevitable that either market-to-book or leverage will not generate the predicted results because of the mechanical negative link between them. For example, if the negative RSI effect on future returns is stronger for high market-to-book firms, it has to be also stronger for low leverage firms, because low leverage firms have much higher market-to-book than high leverage firms. The correlation between credit rating and market-to-book is weaker than the correlation between market-to-book and leverage. Hence, sorts on credit rating are more likely to create a test independent of the results of the sorts on market-to-book.

motivated (Campbell, 1993, Ang et al., 2006, Barinov, 2011, 2013). We argue that high RSI firms have low expected returns because they have lower aggregate volatility risk.

To establish the validity of this argument, we first check whether high RSI firms have high uncertainty and option-like equity. We perform this step here with the only intent of showing that high RSI firms tend to be of the type that is the least exposed to aggregate volatility risk. We discuss why short sellers may want to short these firms in Section 6.

We define high RSI based on both absolute cutoff percent and relative cross-sectional percentiles, as in Asquith et al. (2005). The first approach defines firms with RSI greater than 2.5% and 5% as high RSI firms. The second approach identifies firms based on their RSI relative to other firms. This is important because RSI has increased substantially over time. We sort all firms on RSI every month, and firms above the 90^{th} (95^{th}) percentiles are classified as high RSI firms.[12] Because short interest information is collected in the middle of a calendar month and published close to the end of that month, we form monthly short interest portfolios based on RSI from the previous month. This timing is important: in an efficient market, informed short sellers should be making profits before short interest is revealed to the public; but after short interest becomes publicly available, it should not predict abnormal returns.[13]

Table 1 compares the median characteristics of high RSI firms to the medians of low RSI firms (with RSI below the 90^{th} percentile) and firms in the Compustat universe.[14] We first check the uncertainty measures. The idiosyncratic volatility is reported in percent per day: for example, 0.027 for firms with RSI above the 90^{th} percentile means that, on average, these firms have idiosyncratic volatility of 2.7% per day. The analyst disagreement of 0.061 for the same firms

[12] We also use 10% and 99^{th} percentile and find similar results, but they are not reported due to small sample sizes.
[13] Section 7.3 shows that our results are robust to lagging RSI by one month to allow investors more time to process RSI information.
[14] Inferences are similar when low RSI is defined using alternative cut-offs (e.g. median RSI or RSI=2.5%).

means that the standard deviation of the EPS forecasts for these stocks is 6.1 cents for each dollar of EPS. These firms have 15.8% of shares outstanding changing hands each month.

Table 1 shows that high RSI firms indeed have significantly higher uncertainty than low RSI (Compustat) firms. For example, the median analyst disagreement for high RSI firms is 28-38% (15-25%) higher than for low RSI (Compustat) firms. Likewise, the turnover of a representative high RSI firm is more than twice higher than the turnover of the median low RSI firm or Compustat firm. The higher analyst disagreement and higher idiosyncratic volatility of high RSI firms stand out despite the fact that high RSI firms are two-thirds larger than low RSI (Compustat) firms. It is also interesting to note that in the high RSI sample all measures of uncertainty increase with RSI: uncertainty of firms in the 95^{th} percentile is higher than that of firms in the 90^{th} percentile, and the same is true for absolute cut-offs.

Similar patterns emerge with equity option-likeness. Specifically, high RSI firms have higher market-to-book (M/B) ratio and lower credit rating quality than low RSI firms or Compustat firms, which suggests that high RSI firms possess more option-like equity. High RSI firms have median M/B ratio of around 2.5, compared to the median M/B ratio of around 2 for low RSI firms and Compustat firms. High RSI sample have BB or BB- in general, worse than the credit rating of BBB+ (BBB) for the median low RSI (Compustat) firm.

Table 1 also compares average raw return of high RSI firms and other firms. The average monthly raw return of high RSI firms hovers around 50 bp, significantly different from the average return to all Compustat firms (around 90 bp) or to low RSI firms (around 120 bp). In untabulated results, we find that the average return of high RSI firms is statistically indistinguishable from the average risk-free rate (33 bp per month) in our sample period. It is striking that high RSI firms earn only slightly more than the risk-free rate, suggesting that they should be a hedge against an important risk.

Taken collectively, Table 1 shows that high RSI firms indeed have high uncertainty and more option-like equity. These features are associated with low expected returns because they are a hedge against aggregate volatility risk. The rest of the paper further explores this.

3.2. The aggregate volatility risk factor

We form the FVIX factor as the zero-investment portfolio that tracks daily changes in the VIX index. Daily changes in VIX are regressed on 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 factor-mimicking regression uses all available data from January 1986 to December 2010. The FVIX factor is the fitted part of the regression less the constant. To obtain the monthly values of FVIX, we compound its daily returns. All results in the paper are robust to using other base assets such as the 10 industry portfolios (from Fama and French, 1997) or the six size and book-to-market portfolios (from Fama and French, 1993).[15]

Panel A of Table 2 reports the average returns and alphas of the base assets for FVIX, the five volatility sensitivity quintiles. In order to be a good choice for base assets, the quintile portfolios need to have significant dispersion in volatility risk. The evidence in Panel A supports our choice. Similar to Ang et al. (2006), we find that firms with the most negative volatility sensitivity (highest volatility risk) earn by about 1% per month higher returns than firms with the most positive volatility sensitivity (lowest volatility risk). We also note that controlling for the

[15] Ang et al. (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 we find that the Ang et al. (2006) version of FVIX is significantly correlated with our version of FVIX and produces the betas of the same sign. 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.

asset-pricing factors (SMB, HML, Momentum, Liquidity, etc.) does not materially change the alpha differential between firms with positive and negative volatility sensitivity, suggesting that our volatility risk factor is unlikely to overlap with these known factors.

Panel B reports the coefficients from the factor-mimicking regression, which are also the weights of the quintile portfolios in FVIX. All coefficients but one are negative. This is expected because the change in VIX is strongly negatively correlated with the market, and one has to short almost all stocks, except for the ones with the most positive VIX sensitivity, to track the change in VIX. Panel B also shows that, expectedly, FVIX tend to short stocks with more negative volatility sensitivity more aggressively.

The factor-mimicking regression has rather high goodness-of-fit (R^2 of 49%). Consequently, the daily correlation between change in VIX and FVIX returns is 0.69, suggesting that FVIX is a good factor-mimicking portfolio.

Panel C reports the descriptive statistics of FVIX, its alpha and betas from a six-factor model (MKT, SMB, HML, Momentum, Liquidity, and Reversal).[16] The average return and the six-factor alpha of FVIX are strongly negative with the average FVIX return of -121 bp (t-stat= -3.4) and the six-factor alpha of FVIX of -50 bp per month (t -stat= -2.89). This should be the case. By construction, FVIX is a zero-investment portfolio that yields positive returns when expected aggregate volatility increases. Hence, holding FVIX means having an insurance against increases in aggregate volatility. Therefore, FVIX has to earn significantly negative return even after other sources of risk have been controlled for. Panel C also shows that FVIX is slightly left-skewed, highly volatile, and has little autocorrelation (since it mimics innovations). Consistent with Panel A, Panel C shows FVIX has no overlap with the other factors except for the market (strongly negative beta, consistent with similarly strong negative correlation of MKT and the

[16] This 6-factor model is our benchmark model in the paper. Results remain the same if we use other factor models like the Fama-French (1993) model, the Carhart (1997) model, or the Carhart model augmented with the Pastor-Stambaugh (2003) liquidity factor (5-factor model).

change in VIX) and SMB (FVIX has a small-stock tilt, consistent with our hypothesis that volatile firms have positive betas).

3.3. High RSI stocks during the recent recession

Before conducting formal tests, we present some anecdotal evidence on high RSI firms from the most recent recession characterized by elevated aggregate volatility risk. Figure 1 shows the cumulative performance of the market (CumMKT), high RSI firms (CumHigh RSI), and the CAPM prediction of the performance of high RSI firms (CumMKT*Beta). All cumulative returns start at 1 on December 1, 2007.

The CAPM regression (untabulated) shows that the market beta of high RSI firms is 1.47. Hence, during the 18 recessionary months in the graph, when the market lost 35.6%, CAPM prediction suggests that high RSI firms should have lost much more, 49.75% (CumMKT*Beta). However, high RSI firms did not even lose as much as the market, despite their high beta. In fact, their cumulative returns (CumHigh RSI) stayed very close to the cumulative returns to the market (CumMKT), and by the end of the recession high RSI firms lost only 33.7%.

The discrepancy between the realized returns to high RSI firms and the CAPM prediction is summarized by the cumulative abnormal return line (CAR). Beyond showing that cumulative abnormal return to high RSI firms are around 30% (≈(1-0.337)/(1-0.4975)-1) by the end of the recession, the CAR line also shows that the difference between the actual performance of high RSI firms and the CAPM prediction of their performance starts around June 2008, when the true market decline began. In fact, during the ten months between June 2008 and March 2009 when almost all the market losses and high volatility episodes of the last recession happened, high RSI firms have negative abnormal return only once, and only slightly so. Even more, about 85% of the positive CAR to high RSI firms during the last recession (December 2007 – June 2009, 18 months) accrued during the ten months (June 2008 – March 2009) when all the action happened.

The performance of high RSI firms during the recent crisis makes us cautiously optimistic about the ability of FVIX to explain the high RSI effect. Even though high RSI firms witness losses comparable to the losses of the market, and therefore seem risky, their losses are not nearly as large as their market beta would suggest. Hence, while it is unlikely that FVIX will completely explain why high RSI firms earn close to the risk-free rate in the last two decades, it is also clear that the CAPM overestimates the negative alphas of high RSI firms by over-adjusting their returns for risk.

3.4. High RSI firms in the seven-factor model with FVIX

We start our formal asset pricing tests by first checking whether high RSI stocks generate negative alphas in our sample. This is confirmed by the data. Panel A of Table 3 shows that high RSI portfolio has equal-weighted CAPM alphas ranging from -67 to -102 bp per month, with t-statistics ranging from -2.74 to -3.73. Looking at alphas from alternative models in the next rows, we observe that the alphas are about 10 bp more negative in the Fama-French (1993) model (high RSI firms tend to be small, see Table 2, and should earn higher returns with Fama-French model), about 25 bp closer to zero in the Carhart (1997) model (high RSI firms tend to be recent losers), and do not change much after controlling for Pastor and Stambaugh (2003) liquidity risk factor (high RSI firms are no more illiquid than similarly small firms) and short-term reversal, ending up between -56 and -88 bp per month in our benchmark six-factor model (with MKT, SMB, HML, Momentum, Liquidity, Reversal). Overall, Panel A confirms that the high RSI effect persists in various known asset pricing models.

Our hypothesis is that high RSI firms have negative alphas because they outperform when aggregate volatility increases, a risk not considered in previous literature. Their ability to be a hedge against aggregate volatility risk comes from their high firm-specific uncertainty and option-like equity (recall Table 1). Given these firm features, we hypothesize that in the seven-factor model with the FVIX factor high RSI firms should load positively on FVIX, which should reduce their negative alphas.

We control for the FVIX factor in Panels B and C of Table 3. Panel B reports the alphas after adding FVIX to all five models (CAPM, Fama-French, Carhart, Carhart+Liquidity, and Carhart+Liquidity+Reversal). Adding FVIX reduces the alphas by 50 to 70 bp per month and makes them insignificant in all models. Also, the magnitude of the decline in the alphas does not seem to depend on what other factors we control for, confirming little overlap between FVIX and the other factors, as visible in Panel C of Table 2.

The success in explaining these alphas resides in the FVIX betas. The FVIX betas in Panel C of Table 3 are strongly positive in all cases, suggesting that high RSI firms outperform the prediction of all factor models in Panel A when aggregate volatility increases and therefore high RSI firms are hedges against aggregate volatility risk.[17]

4. High RSI effect in the cross-section

The previous section shows that high RSI firms have negative alphas because they are a hedge against aggregate volatility risk, due to their high firm-specific uncertainty and option-like equity. Existing research on the role of volatility risk in explaining anomalies (Barinov, 2011, 2013, 2014) shows that firms with high uncertainty and option-like equity (high analyst disagreement firms, high turnover firms, growth firms, etc.) are indeed hedges against aggregate volatility risk, which explains their negative alphas. The economic mechanism suggested in these papers is that, all else equal, the value of option-like firms reacts positively to increases in

[17] In unreported results, we repeat the tests in this section using value-weighted returns. We find that the high RSI effect is expectedly weaker, but still significant, in value-weighted returns (the alphas of high RSI are between -30 bp and -60 bp per month). We also find that the aggregate volatility risk explanation of high RSI effect is even stronger in value-weighted returns, since the FVIX betas of high RSI firms are larger, have higher t-statistics, and the alphas of high RSI firms controlling for FVIX are within a few basis points of zero.

volatility and their risk goes down as volatility goes up (the delta of an option decreases in volatility), causing even more positive price reaction to volatility increases.

The observations that high RSI firms have high uncertainty and option-likeness (Table 1) and FVIX explains the negative alphas of high RSI firms (Table 3) further lead to the prediction that the high RSI effect and, most importantly, its aggregate volatility risk explanation should be stronger for the firms with higher levels of uncertainty and/or more option-like equity. Grullon et al. (2012) find that higher volatility means higher value of real options. Johnson (2004) shows that higher volatility of the underlying asset makes the beta of option-like equity smaller, which in turn leads to a smaller increase in expected return and smaller decrease in value in response to increasing aggregate volatility. These effects suggest that in the cross-section of high RSI firms, the effect of functioning as a hedge against aggregate volatility risk should be stronger for the firms with higher levels of uncertainty and/or more option-like equity.

Extending our main hypothesis, we make the following cross sectional predictions:

- The six-factor alphas of high RSI firms with low uncertainty or non-option-like equity should be zero. The six-factor alphas of high RSI firms should significantly increase in uncertainty and equity option-likeness.
- Controlling for FVIX, the alphas of high RSI firms should be significantly reduced in all uncertainty and equity option-likeness groups and should not depend on either uncertainty measures or measures of equity option-likeness.
- FVIX betas of high RSI firms should significantly increase in uncertainty and equity option-likeness.

We note that although existing mispricing theories may also explain the six-factor alphas, the last two predictions are new to the literature and allow us to differentiate between our risk-based explanation and existing mispricing explanations.

We perform single sorts on the uncertainty and equity option-likeness measures in the high RSI sample. We refrain from performing double sorts of high RSI stocks on both uncertainty and equity option-likeness, because the high RSI subsample consists of only several hundred stocks, and any sensible double sorts (e.g., three-by-three, nine groups) produce underdiversified portfolios with the number of stocks in low double digits.

4.1. High RSI effect and uncertainty sorts

In this section, we examine high RSI effect sorted on proxies for uncertainty. Our basic sorting procedure is the same. Every month, we sort high RSI firms into terciles on one uncertainty measure at month t-1 and report their equal-weighted six-factor alphas, seven-factor alphas (the six factors plus FVIX), and FVIX betas in month t.[18]

Table 4 reports high RSI firms sorted on uncertainty measured with idiosyncratic volatility (Panel A), analyst disagreement (Panel B) and turnover (Panel C). The leftmost part of the table presents six-factor alphas. We observe that high RSI firms with low uncertainty have zero alphas except for turnover. At the same time, the alphas of high RSI firms with high uncertainty are highly significant and negative. These are largely consistent with the first prediction. The magnitudes of the alphas of high uncertainty high RSI stocks are large, but they are comparable with previous studies.

The remaining two sections of Table 4 present the test that discriminates between our story and the mispricing story in Miller (1977). The middle portion of the table reports the alphas controlling for FVIX and strongly supports our second prediction. Specifically, the six-factor

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[18] In unreported results, we repeat the tests in this and subsequent sections using value-weighted returns and reach the same conclusions. In value-weighted returns, the six-factor alphas of high RSI firms are uniformly smaller, though they still routinely top -50bp per month for high uncertainty firms, firms with option-like equity, and firms with low institutional ownership. The aggregate volatility risk explanation of the high RSI effect for high-uncertainty/option-like firms is even stronger in value-weighted returns, since value-weighted FVIX betas of high RSI firms are generally larger and more significant, and value-weighted seven-factor alphas of high RSI firms with high uncertainty/option-like equity are closer to zero.

model augmented with the FVIX factor reduces the alphas of high RSI firms with high idiosyncratic volatility by more than 100 bp per month and makes them insignificant. Similarly, alphas of high RSI firms with high disagreement are reduced by about eighty percent and are no longer significant. The same pattern is observed among high RSI firms with high turnover. Additionally, the alpha differentials between high uncertainty and low uncertainty among high RSI firms lose their significance once FVIX is controlled for.

The rightmost portion of Table 4 presents FVIX betas. The results support our last prediction that FVIX betas of high RSI firms should increase in uncertainty. Across all measures of uncertainty, larger FVIX betas are consistently observed as we go from low to high uncertainty, suggesting that the ability of high RSI firms to hedge against aggregate volatility increases with uncertainty.

Miller (1977) also predicts that the alphas of high RSI high disagreement stocks will be more negative than the alphas of high RSI stocks with low disagreement. But the evidence in the middle and right sections of the table is consistent with the aggregate volatility risk explanation of the high RSI effect, and not with mispricing explanation. First, by definition, the part of the alpha explained by covariance with an additional risk factor is not mispricing. Second, the mispricing theories of the high RSI effect make no prediction about the covariance of returns to high RSI firms and innovations to aggregate volatility. Indeed, it is hard to imagine why the absence of pessimistic traders in the market due to short-sale constraints (the Miller (1977) explanation of the high RSI effect) should make the returns covary more with changes in VIX.

4.2. High RSI effect and institutional ownership

Asquith, Pathak, and Ritter (2005) find that the high RSI effect is stronger for firms with low IO. Viewing short interest as demand from and IO as a potential supply of shares to short sellers, they argue that high RSI, low IO firms face more binding short sales constraints and therefore have more negative alphas. They ascribe this finding to Miller (1977) story: higher costs of short sale mean overpricing, and the costs of short sale are the highest if both demand (RSI) is high and supply (IO) is low. As will be shown next, this may not be the whole story and aggregate volatility risk also plays an important role.

In the left portion of Panel A of Table 5, we confirm the results in Asquith, Pathak, and Ritter (2005) for our sample period. We sort high RSI firms into terciles according to their IO in the previous quarter. The six-factor alphas for high RSI, low IO firms are large ranging from -88 bp to -106 bp per month, while the alphas for high RSI and high IO are much smaller.

Shleifer and Vishny (1997) show that institutions should prefer to hold stocks with low levels of volatility or uncertainty. Their argument is two-fold: first, portfolio managers feel underdiversified, because their personal wealth largely depends on the performance of the portfolio they manage, and they therefore want to avoid idiosyncratic volatility as much as possible. Second, higher idiosyncratic volatility means a higher probability that even the correct bets on mispriced stocks will have to be called off due to margin calls and cash outflows. Del Guercio (1996) and Falkenstein (1996) confirm empirically that IO is negatively related to idiosyncratic volatility.

We also find that high RSI low IO firms indeed have higher idiosyncratic volatility and higher analyst disagreement (untabulated). The difference between low and high IO is substantial: the median analyst forecast dispersion of high RSI firms with low IO is three times higher than that of high RSI firms with high IO. This implies that sorting on IO among high RSI firms essentially sorts on uncertainty (in reverse order). Thus high RSI, low IO firms provide a good hedge against aggregate volatility risk, just as high RSI, high uncertainty firms do.

The middle portion of Panel A of Table 5 reports the alphas controlling for FVIX factor, which provides a discriminating test between our explanation and the short-sale constraint explanation in Asquith, et al. (2005). If IO is related to the RSI effect through the relation between IO and idiosyncratic volatility/disagreement and the consequent relation between IO and aggregate volatility risk, we should expect the dependence of the RSI effect on IO to weaken when FVIX is controlled for. This is observed in Panel A: the alphas of high RSI, low IO firms diminish to less than thirty percent of the six-factor alphas. The difference in the alphas between high RSI, low IO firms and high RSI, high IO firms also declines from about -80 bp per month to about -40 bp per month after controlling for FVIX factor.

The rightmost portion of Panel A reports the FVIX betas. We observe large and positive FVIX betas of high RSI, low IO firms. This is the key reason why the model with FVIX factor can explain the negative alphas. The large positive FVIX betas of high RSI, low IO firms indicate that these firms perform well when aggregate volatility increases, and therefore have much lower risk than what the six-factor model estimates.

One may be concerned that IO is highly correlated with size, and results in Panel A could be driven by size/liquidity effect. Although we control for size and liquidity with the 6-factor model, to further address this concern, we follow Nagel (2005) and compute residual IO, which is orthogonal to size. Panel B of Table 5 replaces IO with residual IO and presents nearly identical results. Controlling for FVIX materially reduces the alphas of high RSI firms with low residual IO. The FVIX betas start small and marginally significant for high RSI firms with high residual IO, and increase strongly and monotonically as residual IO decreases.

Taken together, these results offer an alternative explanation for the low returns of high RSI, low IO firms documented in Asquith, Pathak, and Ritter (2005). Compared to high RSI, high IO firms, firms with high RSI and low IO have more negative alphas because they have higher uncertainty and therefore lower aggregate volatility risk.

4.3. High RSI effect and option-like equity

We now test our predictions with respect to equity option-likeness. The first measure of equity option-likeness we consider is M/B ratio. M/B ratio is commonly used to proxy for a firm's growth options. The higher is the ratio, the more growth options the firm has. We also use the Standard & Poor's credit rating on a firm's long-term debt to proxy for equity option-likeness created by the existence of risky debt. Worse credit rating means higher probability of bankruptcy and higher probability of the forced or voluntary exercise of the call option on assets represented by equity. For firms with good credit rating, the probability of bankruptcy is fairly low, and the fact that their equity is a call option on the assets is relatively unimportant. But for firms with poor credit rating, the equity is more option-like.

In Panel A of Table 6, we sort high RSI firms into terciles on their M/B ratios from the previous year, and report equally-weighted portfolio alphas in the next month. The left part of Panel A shows that high RSI high M/B firms earn significantly negative six-factor alphas in the range of – 67 bp to -100 bp (t-statistics well above 3). Consistent with our first prediction, these alphas are significantly different from the alphas of high RSI low M/B firms (close to zero).

The main contribution of our research design lies in the seven-factor alphas and FVIX betas. Importantly, alphas of high RSI high M/B ratio firms, in the augmented model with FVIX, all shrink dramatically and turn insignificant. Moreover, these firms load more positively on the FVIX factor than the high RSI, low M/B firms. The difference in the FVIX betas is large and statistically significant, supporting our prediction that high RSI firms with high M/B ratio have more negative alphas because they outperform when aggregate volatility increases.

In Panel B of Table 6, we sort high RSI firms into terciles, those with good (BBB+ and above), medium, and bad (B+ and below) credit rating in the previous year. Consistent with the first prediction, high RSI firms with good rating have no negative alphas. In contrast, high RSI firms with bad rating have strong and negative alphas of -55 bp to -86 bp per month.

The seven-factor model with the FVIX factor reduces to zero the alphas of high RSI, bad credit rating firms. The explanation lie in the FVIX betas: the strongly positive FVIX betas of firms with high RSI and bad credit rating, versus the negative FVIX betas of firms with high RSI and good credit rating. The FVIX betas confirm that the difference in the six-factor alphas of the top and bottom portfolios can be attributed to the difference in equity option-likeness and the consequent difference in aggregate volatility risk between the two types of firms.

One may argue that negative alphas to firms with high M/B ratio or bad credit rating could be driven by overvaluation (Lakonishok et al., 1994, Avramov et al., 2009). Dechow et al. (2001) and Desai et al. (2006) show that short sellers use overvaluation proxies, such as M/B ratio, to choose stocks to short, and the use of these proxies generates more profits for short sellers. To the extent that short sellers trade on public signals such as M/B ratio and credit rating and other investors do not fully use the information in RSI, high RSI firms with either highest M/B ratio or bad credit rating will have the most negative alphas. The negative alphas observed in Table 6 could support the informed short sellers story.

However, the informed short sellers story cannot explain the fact that, after controlling for aggregate volatility risk, the alphas become slightly positive and insignificant. Since the return can be explained by a risk factor, it is, by definition, not mispricing, but rather a fair compensation for risk. Hence, the story of short sellers targeting overpriced growth or distressed firms is difficult to apply here. If the only reason heavily shorted firms with high M/B ratio or bad credit rating earn low expected returns is their loading on FVIX (and we cannot reject this hypothesis in the middle part of Table 6), then short sellers who short such firms are not really informed, as they do not receive any abnormal gains from shorting these firms, but only expected returns for bearing aggregate volatility risk as borne out by their positive FVIX betas.

5. High RSI effect in the Conditional CAPM

One traditional approach to measuring risk and changes in risk is the conditional CAPM. In the conditional CAPM, a stock with procyclical market beta (lower in recessions, higher in expansions) should have lower expected returns than what the static CAPM predicts. Barinov (2011) shows that, as both aggregate volatility and idiosyncratic volatility increase in recession, the value of growth options becomes less sensitive to the value of the underlying asset, and the growth options, therefore, become less risky when risks are high. This effect is more pronounced for more volatile firms and growth firms. Since high RSI firms possess high levels of uncertainty and option-like equity (see Table 1), these firms should have procyclical market betas. The betas of high RSI firms should be more procyclical if these firms have higher uncertainty or option-like equity.

To estimate the conditional CAPM, we employ four commonly used conditioning variables: the dividend yield, the default premium, the risk-free rate, and the term premium.[19] The conditional CAPM assumes that the market beta is a linear function of the four conditioning variables above.

Table 7 presents the difference in the market betas between recession and expansion for various high RSI portfolios. Recession is defined as the months when the expected market risk premium is above its average value, and expansion takes the rest of the sample. The expected market risk premium is the forecasted excess market return from regressing realized excess market returns on the previous month values of the four conditioning variables above.

Panel A shows that high RSI firms have procyclical market betas, consistent with the conditional CAPM explanation. The numbers are recession minus expansion beta differentials. A negative number means that the beta of the portfolio in question is lower in recession, that is, the

[19] We define the dividend yield, DIV, 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, is the yield spread between Moody's Baa and Aaa corporate bonds. The risk-free rate is the one-month Treasury bill rate, TB. The term spread, TERM, 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.

beta is procyclical and the portfolio is less risky than what the static CAPM estimates. Depending on the RSI cut-off, we find that in recessions the beta of high RSI firms decreases by 0.10-0.14 (t-statistics greater than 3).

Compared to other studies that use the conditional CAPM, the change in the beta of high RSI firms is large. For example, Petkova and Zhang (2005) find that the beta of the HML portfolio in 1963-2001 increases by only 0.05 from similarly defined expansion to recession. However, even this change is insufficient to explain the negative CAPM alphas of high RSI firms. Assuming that the maximum possible difference in the market risk premium between expansion and recession is 1% per month, the change of 0.14 in the market beta of high RSI firms suggests that the conditional CAPM can diminish the alphas of high RSI firms by at most 14 bp per month, as compared to the CAPM alphas between 67-102 bp per month (see Table 3). In untabulated results, we examine the alphas of high RSI firms in the conditional CAPM and find that the alphas indeed decline by only 10 bp from their CAPM values and remain highly significant. Hence, it is essential to add the FVIX factor to explain the performance of high RSI firms. Yet, the conditional CAPM produces betas that qualitatively support our conjecture that high RSI firms weather downturns better than what the static CAPM would suggest.

Panel B of Table 7 examines the arbitrage portfolios that buy high RSI, high uncertainty firms and short high RSI, low uncertainty firms. These portfolios earn negative CAPM alphas, because, as Table 4 shows, high RSI, high uncertainty firms have more negative alphas than high RSI, low uncertainty firms. Therefore, we expect that in the conditional CAPM these arbitrage portfolios have procyclical betas. The betas in Panel B come out extremely procyclical. Their decrease in recessions varies from close to 0.4 for turnover-based portfolios (long in high RSI high turnover, short in high RSI low turnover) to about 0.5 for idiosyncratic volatility based portfolios (long in high RSI high volatility firms, short in high RSI low volatility firms). Therefore, Panel B provides strong support for the conjecture that high RSI, high uncertainty firms weather downturns significantly better than high RSI, low uncertainty firms with similar average market betas.

In Panel C, we look at the change in betas for the portfolios long in high RSI firms with option-like equity (high M/B or bad credit rating) and short in high RSI firms with non-option-like equity (low M/B or good credit rating). We find that the betas of the portfolio that buys high RSI, bad credit rating or high M/B firms and shorts high RSI, good credit rating or low M/B firms are extremely procyclical (the betas drop by about 0.3 in recessions). The evidence in Panel C is largely consistent with our prediction that high RSI firms perform better in market downturns than what the static CAPM predicts only when these firms have option-like equity.

Panel D presents similar portfolios formed using IO. It turns out that the betas of high RSI, low IO firms decrease in recessions by a significantly greater amount than the betas of high RSI, high IO firms. The same conclusion holds if IO is replaced by residual IO. Hence, just as the FVIX betas suggest, during downturns high RSI, low IO firms perform better than high RSI, high IO firms with similar market betas from the static CAPM.

6. Why Short Sellers Short Firms with Positive FVIX Betas?

Our aggregate volatility risk explanation of the high RSI effect is based on two facts that are both empirically and theoretically motivated. First, we use the fact that short-sellers are targeting growth firms and distressed firms (see, e.g., Dechow et al., 2001). This is to be expected, since growth firms and distressed firms are known to have low future returns (see, e.g., Fama and French, 1993, Avramov et al., 2009) and are believed to be overpriced. Similarly, we hypothesize (and confirm in this section) that short sellers target high uncertainty firms, potentially for the same reasons.

Second, we use the fact that high uncertainty firms with option-like equity have positive FVIX betas (and hence, negative exposure to aggregate volatility risk). Barinov (2011, 2013) shows that this is the case and offers a theoretical explanation: when both aggregate volatility and firm-specific uncertainty increase during recessions, high-uncertainty, option-like firms perform relatively well, because, first, option value increases in volatility, holding everything else fixed, and, second, the beta of the option decreases in firm-specific uncertainty (see Johnson, 2004, for the formal proof of the latter statement).

The question that remains is why short sellers end up targeting firms with positive FVIX betas, as the analysis in the previous sections shows. Do they act on the (possibly erroneous) belief that option-like firms with high uncertainty are overpriced and inadvertently load on FVIX when targeting such firms? Or do they consciously choose to short firms with positive FVIX betas, thereby exposing themselves to aggregate volatility risk, in an effort to increase the expected return to the short position? Both explanations seem plausible. The tests in this section aim to differentiate between these two explanations.

Panel A of Table 8 performs Fama-MacBeth regressions (in logs) of RSI on characteristics that has been previously shown to be related to short interest, plus FVIX beta and firm-specific uncertainty measures.[20] All firm characteristics, including the FVIX beta, are measured one period prior to RSI and are therefore known to short sellers.

The first three variables suggest that short sellers are cost-conscious: they tend to short stocks of larger firms, firms with higher stock price and higher IO. The next three variables show that short-sellers tend to short losers, target firms with high market betas, and do not take into account the short-term reversal of Jegadeesh (1990) in their trades.

Column 1 of Panel A shows that, consistent with our previous analysis, short sellers target firms with positive FVIX betas. However, the coefficient becomes weaker as we control for measures of firm-specific uncertainty (idiosyncratic volatility, analyst disagreement, and

[20] We also experiment with a probit regression of the dummy for high RSI firms on the firm characteristics from Table 8. The results are very similar, suggesting that the relation between short interest and the firm characteristics stays qualitatively the same even for the firms with extremely high RSI.

turnover) and measures of equity option-likeness (M/B ratio and credit rating). In Columns 5-8, the slope on FVIX beta flips its sign and becomes significantly negative (except for Column 6), which suggests that controlling for firm-specific uncertainty and equity option-likeness, short sellers target firms with negative FVIX betas, not positive FVIX betas.[21]

The evidence in Panel A seems more consistent with the idea that short sellers inadvertently load on FVIX while targeting allegedly overpriced stocks with high uncertainty and option-like equity.[22] They make no strong effort to target stocks with positive FVIX betas outside of this group, and they do not lean towards stocks with more positive FVIX betas in this group either.[23] The result that the positive relation between FVIX betas and RSI is subsumed by measures of firm-specific uncertainty and equity option-likeness is also consistent with evidence in Section 4 that the high RSI effect exists only if firm-specific uncertainty is high or equity is option-like.

In unreported regression of changes in RSI on changes in the explanatory variables, we find that while RSI does respond positively to increases in firm-specific uncertainty and equity option-likeness, there is no apparent relation between changes in RSI and changes in FVIX betas. This evidence suggests again that short sellers do not target firms with positive FVIX betas. Rather, the tendency of high RSI firms to have positive FVIX betas is a by-product of their effort to short firms with high uncertainty and option-like equity.

Short sellers' decision to target firms with high uncertainty and option-like equity is not necessarily ill-informed. First, we do not observe the precise shorting date, and cannot exclude the possibility that informed short sellers make significant profits between the shorting date and

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[21] While controlling for all measures of firm-specific uncertainty and equity option-likeness materially reduces the initially positive link between FVIX beta and short interest, turnover and credit rating seem to be of particular importance.

[22] The evidence that short sellers target high-uncertainty firms is, to our knowledge, new to the literature.

[23] The latter conclusion is further confirmed by unreported regressions that use interaction variables for FVIX betas, on the one hand, and measures of firm-specific uncertainty and equity option-likeness on the other.

the date when short interest is revealed to the public, as should be the case in a (semi-strongly) efficient market.

Second, the evidence in Section 4 shows that while in many cases we cannot reject the hypothesis that, after short interest becomes publicly available, heavily shorted firms with high uncertainty and option-like equity are fairly priced (i.e., their alphas are insignificantly negative), some alphas of these firms are still negative and economically large. Hence, even after controlling for FVIX, there is no obvious evidence that short sellers hurt their trading profit by shorting firms with high uncertainty and option-like equity, and it is quite possible that our tests just lack power to elicit the profitability of their strategies. So the main point is not that heavily shorted firms do not underperform at all (though the majority of our results are consistent with this view), but that the apparent underperformance is substantially reduced after controlling for aggregate volatility risk.

Alternatively, short sellers' ability to time market or volatility could play a role in explaining the lack of evidence that controlling for other determinants of short interest, short sellers target firms with positive FVIX betas. If short sellers are able to predict the movements of market volatility, they may positively (negatively) load on FVIX before volatility increases (decreases), and overall in the whole sample the relation between short interest and FVIX betas will be weak and can have either sign.[24]

Panels B and C of Table 8 test this hypothesis by regressing the time series of the select coefficients from the Fama-MacBeth regression in Column 8 of Panel A on the next-month returns to the market and FVIX. Panel B (C) performs these regressions using the market return and FVIX return separately (simultaneously).

[24] We do not have strong priors on whether short sellers time the market or not. While short sellers are widely believed to be informed, they are usually believed to be informed about individual stocks, and not necessarily about the whole market.

We find no evidence that short sellers are able to time the market volatility and load more on FVIX just before FVIX posts positive returns or just before the market loses (which is often synonymous to increased volatility). In fact, it seems like short sellers have weak tendency to load more on FVIX just before the market goes up (and hence, FVIX loses due to its negative market beta). Likewise, it does not seem that the decision of short sellers to target firms with high uncertainty and option-like equity is driven by market timing or volatility timing, or that short sellers time the market or market volatility while deciding on what the market beta of shorted stocks has to be (see the last column of Panels B and C). We conclude that the lack of evidence that, controlling for other determinants of short interest, short sellers target firms with positive FVIX betas is not due to their market/volatility timing effort, because short sellers do not seem to be timing either market or volatility. The latter result that short sellers do not time either market or volatility and accept the consequences that they inadvertently load on some risk factors while choosing the stocks to short, is, to our knowledge, new to the literature.

7. Robustness Checks

7.1. Alternative versions of FVIX

For robustness, we also construct alternative FVIX including six size and book-to-market portfolios from Fama-French (1993) (FVIX6) and 10 industry portfolios from Fama-French (1997) (FVIXIND). The correlations among the main version of FVIX used in the paper and these two alternative methods are 0.98, 0.98, and 0.97 respectively. All versions of FVIX have similar characteristic: high negative average returns, slightly left-skewed, and highly volatile.

We repeat our main analysis with alternative FVIX. The results show that our main findings are fairly robust to the alternative FVIX construction methods. For example, alphas of high RSI (RSI>2.5%) firms are reduced significantly to -11 bp (-5 bp) and are not significant anymore when FVIX6 (FIVXIND) is added to the 6-factor model, and FVIX6 (FIVXIND) beta is highly significant. We also obtain similar results when we examine the cross-section of high RSI firms. High RSI firms with high firm-specific uncertainty and more option-like equity do not yield significant alphas when each version of FVIX is controlled for. We find that the alphas do not differ a lot as we switch between different FVIX definitions, and FVIX betas remain significant and similar in magnitude. Overall, there is, expectedly, a slight advantage to our main version of FVIX due to the fact that its base assets provide a better dispersion in volatility risk, but the other versions of FVIX work almost as well and deliver qualitatively similar results.

We also consider a tradable version of FVIX (FVIXT) that uses only the information available to investors in running the factor-mimicking regression (the rest of the paper uses the full-sample factor-mimicking regression, as is customary in the literature since Breeden et al., 1989). The expanding-window factor-mimicking regression we use to create FVIXT makes a conservative assumption that investors did not know what expected volatility was equal to and how to hedge against it before VIX was introduced.

We find that the factor risk premium of FVIXT is even greater than that of FVIX. When FVIXT is used to explain the alphas of high RSI firms and the difference in the alphas of high RSI firms between the subsamples described in Tables 4-6, we find that in the vast majority of cases the alphas from the seven-factor model with FVIXT and the seven-factor model with the usual FVIX differ by at most 10 bp per month. We also find that FVIXT betas of all portfolios we consider are still statistically significant, though numerically somewhat smaller than FVIX betas due to the higher factor risk premium of FVIXT. We thus conclude that our main results do not change when FVIX is replaced by fully tradable FVIXT.

7.2. Replacing FVIX with the change in VIX

In previous sections, we present evidence that high RSI firms have positive FVIX betas. Because, by construction, the FVIX factor is strongly positively correlated with increases in expected aggregate volatility (as proxied for by the change in the VIX index), the positive FVIX betas imply that the reaction of high RSI stocks to increases in expected aggregate volatility is less negative than what the traditional asset pricing models predict.

In this subsection, we present more direct evidence that high RSI firms indeed outperform when aggregate volatility increases. We replace the FVIX factor with the VIX change and test if high RSI firms have positive loadings on the VIX change, and if the loadings become more positive for high FVIX firms with high uncertainty and option-like equity.

In unreported results, we regress returns to high RSI firms and the difference in the returns of high RSI firms between the subsamples described in Tables 4-6on the six factors and the change in VIX. We perform the regressions at the daily frequency, because at the daily frequency the change in VIX is closer to innovation in VIX.

We find that the change in VIX is positive and significant in all regressions. The magnitude of its slopes suggests that when VIX increases, high RSI firms witness losses that are 50% lower than those predicted by the six-factor model. Likewise, the slopes on the VIX change imply that the arbitrage portfolios that buy high RSI firms with high M/B (bad credit rating, low IO, high volatility) and short high RSI firms with low M/B (good credit rating, high IO, low volatility) tend to witness gains comparable in the magnitude to the losses predicted by the six-factor model when VIX increases.

7.3. High RSI Effect in Event-Time

Previous studies document that the high RSI effect is relatively short-lived and lasts from 2 to 12 months (Asquith et al. 2005). In unreported results, we also study the performance of high RSI firms in event-time and check whether FVIX betas exhibit a similar pattern. If the high RSI effect indeed lasts at most 12 months, we expect FVIX betas of high RSI firms to also decline fast in event time, though they might stay significant longer than alphas, because risk is likely to be persistent.

We examine the alphas of high RSI firms several months after the portfolio formation. With the six-factor model, the high RSI effect remains visible for up to 24 months, but the larger part of it dissipates in 18 months. FVIX betas exhibit a very similar, though somewhat muted pattern. They are close to being flat within the first year after portfolio formation, decline significantly in the second year, but still remain visible even after two years. We thus conclude that the event time behavior of the high RSI effect is largely consistent with FVIX being the explanation for at least a significant part of the high RSI effect.

Additionally, since short interest data are released to the public about 10 days prior to the end of a calendar month, to further ensure that investors have enough time to process such information, we also form RSI portfolios by skipping a month and repeat our main analysis.

We find that high RSI firms still exhibit significant negative six-factor alphas (-49 bp to -87 bp per month), suggesting the robustness of the high RSI effect. Also the decline in (the absolute magnitude of) the alphas after skipping a month is minuscule, suggesting that potential lack of information about RSI in the first month has minimal impact on our results. When we include FVIX factor to the six-factor model, the alphas of high RSI firms are reduced dramatically and no longer significant. Furthermore, these high RSI firms load positively on FVIX factor and their FVIX betas barely change when skipping a month, suggesting that the explanatory power of FVIX is robust to potential portfolio forming timing issue.

7.4 Low RSI effect

Prior research (Boehmer et al., 2008) also suggests a low RSI effect of positive alpha of low RSI firms. While studying the low RSI effect is beyond the scope of the paper, it is interesting to see whether FVIX can help explaining it. We find, somewhat contrary to our expectations, that low RSI firms (bottom RSI quintile) are even more volatile than high RSI firms, despite having lower M/B ratio and similar credit rating as high RSI firms.

We thus do not expect that low RSI firms have significantly negative FVIX beta that would explain their positive alpha. This is confirmed in the data. In equal-weighted portfolios dominated by small volatile firms, the low RSI effect exists, but the FVIX beta of low RSI firms is still positive, though smaller than the FVIX beta of high RSI firms. In value-weighted portfolios, we do find a significantly negative FVIX beta of low RSI firms, but it is not quite helpful either because of the lack of the low RSI effect in value-weighted returns.

We also check different sample construction methods (e.g. CRSP vs. NYSE breakpoints, $5/share filter) and different weighting schemes (value-weighing vs. equal-weighting), and find that low RSI firms do not deliver positive alphas consistently. They produce significant alphas with equal-weighted method, suggesting that the returns are mainly driven by small stocks. In value-weighted returns, the alphas of low RSI firms are drastically reduced after excluding stocks priced below $5 or when one switches from CRSP breakpoints to NYSE breakpoints. The high RSI effect, in sharp contrast, is very robust to these changes in research design.

8. Conclusion

The existing short selling literature has focused on short sales constraints or asymmetric information between short sellers and other traders to explain why high RSI stocks have negative future abnormal returns. Motivated by the aggregate volatility risk literature, this study offers an alternative risk-based firm-type explanation with an aggregate volatility risk factor.

The main difference between the existing explanations of the low returns to high RSI stocks and our explanation is that the existing explanations have to assume investors' irrationality, while our explanation points out the low risk of high RSI stocks. This is not only a methodological difference. If the low returns to high RSI firms are due to investors' irrationality, a rational investor has to short or at least ignore such stocks. We question this investment recommendation: our analysis shows that, controlling for aggregate volatility risk, there are little significant abnormal gains to be earned from shorting or ignoring high RSI firms.

We show that high RSI firms outperform when expected aggregate volatility increases. The main reason is that high RSI firms have high levels of firm-specific uncertainty and option-like equity. Firm-specific uncertainty tends to increase when aggregate volatility increases. This increase in uncertainty makes option-like equity less sensitive to the value of the underlying asset and, all else equal, less risky and more valuable. Also, all else equal, higher uncertainty means higher value of option-like equity due to options' convexity in the value of the underlying asset.

We find that the alphas of high RSI firms drop to a few bp and become insignificant after controlling for the FVIX factor. The loadings of high RSI firms on the FVIX factor strongly support our prediction that high RSI firms outperform when aggregate volatility increases.

Consistent with our hypothesis that high RSI firms have negative alphas because of their high uncertainty and option-like equity, we document that high RSI firms earn negative alphas only if these firms have high uncertainty or option-like equity. While several mispricing stories in the literature offer a similar prediction, we come up with further cross-sectional predictions that differentiate our explanation from the rest of the literature. We predict and find that the negative alphas of high RSI firms with high uncertainty or option-like equity decline substantially, and in many cases, disappear in the models augmented with the FVIX factor. The loadings on FVIX also show, as predicted, that the ability to outperform in the periods of increasing aggregate volatility is confined to the high RSI firms with substantial uncertainty or option-like equity.

We also show that high RSI firms with low IO have higher uncertainty measures and therefore outperform when aggregate volatility increases than high RSI firms with high IO. We thus provide a complementary story to explain the result in Asquith, Pathak, and Ritter (2005) that high RSI, low IO firms have the most negative alphas.

Further supporting the aggregate volatility risk explanation, high RSI firms have procyclical (i.e., lower in recessions) market betas, and this procyclicality is strongest among high RSI firms with high uncertainty and option-like equity. Also, we show high RSI firms load positively on the VIX change, and that the loadings on the VIX change are significantly higher for the high RSI firms with high uncertainty and option-like equity.

We also analyze the motives that make short sellers short firms with positive FVIX betas. Our tests suggest that short sellers do not directly target firms with positive FVIX betas, whether in an effort to increase the expected return of the short position or in an effort to time changes in aggregate volatility. Rather, short sellers just inadvertently load on the FVIX factor while trying to short the firms that they perceive as overpriced (high uncertainty firms, growth firms, and distressed firms). While in many cases, after controlling for aggregate volatility risk, we cannot reject the hypothesis such firms, even if targeted by short sellers, are not overpriced, in some cases alphas are economically large, implying that the short sellers do not harm themselves by shorting these firms, even if the shorting comes together with loading up on the FVIX factor.

Our analysis points out that once aggregate volatility risk is controlled for, the evidence in favor of mispricing driven by either short sales constraints or information asymmetry becomes minimal. Overall, we conclude that most of the high RSI effect is not mispricing and can be explained by low aggregate volatility risk of heavily shorted firms.

Our results also speak to the ongoing world-wide regulatory actions that restrict short sellers in various forms. The finding that heavily shorted firms earn low future returns primarily because they have lower aggregate volatility risk should help ease the concern that many practitioners, regulators, and public commentators have about potential destabilizing effects of short selling.

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Table 1. Summary statistics

This table compares median stock characteristics of high RSI stocks to the median stock characteristics of low RSI stocks and the Compustat universe. Size is monthly market capitalization. IVol refers to idiosyncratic volatility and is the standard deviation of the Fama-French model residuals. The Fama-French model is fitted to daily returns in each firm-month. Dispersion is the standard deviation of earnings forecasts divided by the average forecast. Turnover is average monthly share turnover over the past year. M/B is market-to-book ratio. Credit rating is a firm's S&P credit rating score. The comparison on returns is between average monthly raw returns. High RSI is defined as short interest that is above 2.5%, 5%, 90th percentile, and 95th percentile, respectively. Low RSI is defined as below 90th percentile. The sample period is from 1988 to 2010.

		high RSI-low RSI	high RSI - compustat universe		high RSI-low RSI	high RSI - compustat universe		high RSI-low RSI	high RSI - compustat universe		high RSI-low RSI	high RSI - compustat universe
high RSI=	**>2.5%**	**>2.5%**	**>2.5%**	**>5%**	**>5%**	**>5%**	**>90%ile**	**>90%ile**	**>90%ile**	**>95%ile**	**>95%ile**	**>95%ile**
IVol	0.026	0.000	0.003	0.026	0.001	0.003	0.027	0.001	0.004	0.027	0.002	0.004
t-stat		*0.81*	*6.22*		*1.99*	*6.78*		*2.52*	*7.75*		*3.87*	*9.62*
Dispersion	0.056	0.014	0.006	0.062	0.020	0.012	0.061	0.018	0.011	0.066	0.023	0.016
t-stat		*5.11*	*2.21*		*5.54*	*3.29*		*9.15*	*5.20*		*7.77*	*5.00*
Turnover	0.123	0.666	0.062	0.144	0.088	0.084	0.158	0.102	0.097	0.179	0.123	0.118
t-stat		*14.0*	*16.6*		*12.7*	*14.3*		*7.20*	*7.53*		*7.36*	*7.65*
M/B	2.440	0.569	0.542	2.574	0.702	0.675	2.547	0.676	0.648	2.639	0.765	0.738
t-stat		*8.53*	*8.32*		*10.5*	*10.3*		*11.4*	*11.8*		*13.4*	*13.7*
Rating	11.97	2.86	2.63	12.65	3.54	3.31	12.61	3.49	3.27	12.95	3.83	3.61
t-stat		*8.9*	*11.9*		*12.4*	*18.3*		*16.9*	*29.8*		*16.0*	*26.8*
Return(%)	0.623	-0.595	-0.514	0.485	-0.734	-0.652	0.462	-0.756	-0.675	0.430	-0.789	-0.707
t-stat	*1.60*	*-4.89*	*-4.33*	*1.24*	*-5.07*	*-5.19*	*1.13*	*-5.27*	*-5.27*	*1.08*	*-5.21*	*-5.02*
Size	0.469	0.332	0.329	0.473	0.336	0.333	0.458	0.321	0.319	0.433	0.295	0.293
t-stat		*10.5*	*12.1*		*10.4*	*12.0*		*10.7*	*12.4*		*11.5*	*13.5*

Table 2. Summary statistics of FVIX

This table reports summary statistics of FVIX. Panel A reports returns on base quintile assets. Panel B reports weights on the based assets. Panel C presents descriptive statistics of FVIX, its alpha and betas from a six-factor model (MKT, SMB, HML, Momentum, Liquidity, and Reversal).

Panel A. Returns on base quintile assets

Alphas	Neg	VIX2	VIX3	VIX4	Pos	Neg-Pos
Raw	1.22	0.97	0.93	0.87	0.38	0.84
t-stat	*3.64*	*3.80*	*3.47*	*2.86*	*0.94*	*4.01*
CAPM	0.25	0.12	0.07	-0.04	-0.70	0.95
t-stat	*1.84*	*1.65*	*0.88*	*-0.69*	*-4.54*	*4.28*
Fama-French	0.29	0.12	0.05	-0.06	-0.65	0.94
t-stat	*2.11*	*1.58*	*0.74*	*-0.98*	*-4.29*	*3.87*
Carhart	0.38	0.11	0.02	-0.09	-0.59	0.98
t-stat	*2.60*	*1.29*	*0.31*	*-1.24*	*-3.50*	*3.50*
Carhart+PSLiq	0.42	0.15	0.01	-0.11	-0.58	1.01
t-stat	*2.78*	*1.69*	*0.09*	*-1.57*	*-3.66*	*3.71*
Carhart+PSLiq +Reversal	0.41	0.15	0.00	-0.11	-0.58	0.99
t-stat	*2.68*	*1.68*	*-0.01*	*-1.52*	*-3.54*	*3.54*

Panel B. Weights on the base assets

	Neg	VIX2	VIX3	VIX4	Pos	Const
Weights	-0.04	-0.67	-0.27	-0.74	0.20	0.05
t-stat	*-0.64*	*-4.28*	*-2.11*	*-1.64*	*1.23*	*2.49*

Panel C. Summary Statistics

		Mean	Median	Std	AC(1)		
FVIX		-1.21	-2.07	6.02	0.02		
	Alpha	**MKT**	**SMB**	**HML**	**Mom**	**PSLiq**	**Rev**
FVIX	-0.50	-1.36	0.21	-0.03	-0.01	0.04	0.01
t-stat	*-2.89*	*-24.10*	*5.10*	*-0.40*	*-0.31*	*1.32*	*0.15*

Table 3. Uivariate results

This table reports equally-weighted alphas from various models, alphas from FVIX+other factors and FVIX betas of high RSI stocks. Carhart model adds the momentum factor to the three Fama-French factors. PSLiq refers to Pastor and Stambaugh liquidity factor. Reversal refers to the reversal factor. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from 1988 to 2010.

high RSI=	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**
Panel A. Alphas				
CAPM	-0.67	-0.84	-0.85	-1.02
t-stat	*-2.74*	*-3.17*	*-3.35*	*-3.73*
Fama-French	-0.77	-0.95	-0.98	-1.16
t-stat	*-5.43*	*-5.86*	*-6.70*	*-6.76*
Carhart	-0.53	-0.68	-0.69	-0.85
t-stat	*-3.98*	*-4.57*	*-4.68*	*-5.12*
Carhart+PSLiq	-0.53	-0.68	-0.68	-0.84
t-stat	*-4.08*	*-4.72*	*-4.76*	*-5.27*
Carhart+PSLiq +Reversal	-0.56	-0.72	-0.72	-0.88
t-stat	*-4.28*	*-4.95*	*-5.08*	*-5.35*
Panel B. Alphas w/ FVIX				
CAPM	-0.24	-0.37	-0.38	-0.52
t-stat	*-0.88*	*-1.23*	*-1.28*	*-1.61*
Fama-French	-0.20	-0.32	-0.34	-0.47
t-stat	*-0.72*	*-1.05*	*-1.15*	*-1.45*
Carhart	0.01	-0.08	-0.08	-0.20
t-stat	*0.05*	*-0.26*	*-0.24*	*-0.57*
Carhart+PSLiq	0.07	-0.02	0.00	-0.12
t-stat	*0.26*	*-0.07*	*-0.01*	*-0.36*
Carhart+PSLiq +Reversal	0.03	-0.07	-0.05	-0.18
t-stat	*0.09*	*-0.23*	*-0.17*	*-0.51*
Panel C. FVIX Betas				
CAPM	0.89	0.99	1.00	1.06
t-stat	*2.98*	*2.91*	*3.24*	*2.90*
Fama-French	0.82	0.90	0.94	0.99
t-stat	*3.22*	*3.23*	*3.44*	*3.16*
Carhart	0.81	0.90	0.94	0.98
t-stat	*3.08*	*3.05*	*3.28*	*2.95*
Carhart+PSLiq	0.83	0.91	0.96	1.00
t-stat	*3.30*	*3.25*	*3.55*	*3.16*
Carhart+PSLiq +Reversal	0.81	0.89	0.94	0.98
t-stat	*2.87*	*2.82*	*3.07*	*2.75*

Table 4. High RSI and firm-specific uncertainty

This table reports equally-weighted six-factor alphas, FVIX + six factor alphas and FVIX betas of high RSI stocks sorted on idiosyncratic volatility (Panel A), analyst dispersion (Panel B), and turnover (Panel C). The six-factor model includes MKT, SMB, HML, Momentum, Liquidity, and Reversal factors. IVol refers to idiosyncratic volatility and is the standard deviation of the Fama-French model residuals. The Fama-French model is fitted to daily returns in each firm-month. Dispersion is the standard deviation of earnings forecasts divided by the average forecast. Turnover is average monthly share turnover over the past year. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from 1988 to 2010.

	Alphas				Alphas w/ FVIX				FVIX betas			
high RSI=	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**
Panel A. High RSI and Idiosyncratic Volatility												
Low	-0.02	-0.12	-0.15	-0.18	0.04	0.09	0.06	0.18	-0.05	0.16	0.19	0.44
t-stat	*-0.18*	*-0.79*	*-1.19*	*-1.35*	*0.28*	*0.41*	*0.30*	*0.73*	*-0.60*	*1.33*	*1.82*	*3.07*
Medium	-0.32	-0.44	-0.49	-0.62	0.22	0.18	0.09	0.02	0.70	0.82	0.78	0.83
t-stat	*-2.42*	*-3.03*	*-3.53*	*-3.29*	*0.78*	*0.57*	*0.30*	*0.05*	*2.69*	*2.66*	*2.73*	*2.28*
High	-1.16	-1.47	-1.26	-1.56	-0.05	-0.38	-0.09	-0.44	1.69	1.65	1.78	1.66
t-stat	*-4.00*	*-4.67*	*-4.12*	*-4.49*	*-0.10*	*-0.77*	*-0.17*	*-0.80*	*3.15*	*2.94*	*3.05*	*2.66*
H-L	-1.13	-1.36	-1.11	-1.37	-0.09	-0.47	-0.15	-0.62	1.74	1.49	1.59	1.22
t-stat	*-3.42*	*-3.82*	*-3.32*	*-3.64*	*-0.21*	*-1.17*	*-0.35*	*-1.44*	*3.41*	*3.10*	*2.88*	*2.26*
Panel B. High RSI and Analyst Disagreement												
Low	-0.12	-0.22	-0.25	-0.32	0.07	0.04	0.05	0.03	0.15	0.24	0.34	0.41
t-stat	*-0.88*	*-1.17*	*-1.60*	*-1.61*	*0.35*	*0.15*	*0.19*	*0.10*	*1.26*	*1.46*	*2.33*	*2.10*
Medium	-0.08	-0.34	-0.24	-0.47	0.37	0.20	0.29	0.16	0.56	0.70	0.70	0.85
t-stat	*-0.52*	*-1.96*	*-1.54*	*-2.69*	*1.43*	*0.65*	*1.02*	*0.45*	*2.45*	*2.40*	*2.66*	*2.32*
High	-0.65	-0.81	-0.76	-0.91	0.15	0.00	0.04	-0.14	1.18	1.20	1.18	1.11
t-stat	*-3.19*	*-3.52*	*-3.24*	*-3.10*	*0.41*	*0.00*	*0.10*	*-0.32*	*3.25*	*3.41*	*3.29*	*2.76*
H-L	-0.52	-0.60	-0.51	-0.59	0.09	-0.04	-0.01	-0.17	1.04	0.97	0.84	0.71
t-stat	*-2.11*	*-1.95*	*-1.72*	*-1.70*	*0.28*	*-0.12*	*-0.02*	*-0.45*	*3.41*	*3.70*	*2.82*	*2.37*
Panel C. High RSI and Turnover												
Low	-0.32	-0.38	-0.44	-0.51	0.07	0.07	0.06	0.03	0.46	0.53	0.63	0.68
t-stat	*-2.04*	*-2.17*	*-2.26*	*-2.34*	*0.26*	*0.23*	*0.16*	*0.07*	*1.95*	*2.09*	*2.37*	*2.10*
Medium	-0.55	-0.77	-0.70	-0.94	0.01	-0.13	-0.05	-0.20	0.76	0.87	0.90	1.02
t-stat	*-3.88*	*-5.04*	*-5.39*	*-5.71*	*0.04*	*-0.38*	*-0.17*	*-0.53*	*2.74*	*2.59*	*2.93*	*2.71*
High	-0.71	-0.94	-0.92	-1.15	0.06	-0.11	-0.10	-0.31	1.16	1.25	1.23	1.23
t-stat	*-3.74*	*-4.33*	*-4.39*	*-4.76*	*0.18*	*-0.31*	*-0.29*	*-0.83*	*3.39*	*3.29*	*3.48*	*3.17*
H-L	-0.40	-0.56	-0.48	-0.64	-0.02	-0.18	-0.16	-0.34	0.70	0.71	0.60	0.56
t-stat	*-1.89*	*-2.27*	*-2.09*	*-2.66*	*-0.08*	*-0.72*	*-0.69*	*-1.38*	*4.49*	*3.58*	*3.49*	*3.98*

Table 5. High RSI and institutional ownership

This table reports equally-weighted six-factor alphas, FVIX + six factor alphas and FVIX betas of high RSI stocks sorted on institutional ownership (IO) (Panel A) and residual IO (Panel B). The six-factor model includes MKT, SMB, HML, Momentum, Liquidity, and Reversal factors. IO is defined as shares owned by institutions as a percent of total shares outstanding. Residual IO is the residual from the logistic regression of IO on log size and its square. The regression is fitted to all firms within each separate quarter. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from 1988 to 2010.

	Alphas				**Alphas w/ FVIX**				**FVIX betas**			
high RSI=	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**
Panel A. High RSI and IO												
Low	-0.88	-1.02	-0.97	-1.06	-0.20	-0.32	-0.18	-0.24	0.98	0.99	1.18	1.16
t-stat	*-4.79*	*-4.73*	*-4.35*	*-4.12*	*-0.65*	*-0.94*	*-0.52*	*-0.60*	*2.70*	*2.48*	*2.83*	*2.40*
Medium	-0.37	-0.55	-0.56	-0.73	0.21	0.12	0.08	-0.04	0.80	0.95	0.90	0.98
t-stat	*-3.07*	*-3.77*	*-4.28*	*-4.44*	*0.84*	*0.40*	*0.29*	*-0.12*	*2.94*	*3.07*	*3.16*	*2.88*
High	-0.16	-0.22	-0.32	-0.46	0.15	0.13	0.02	-0.08	0.33	0.39	0.48	0.72
t-stat	*-1.06*	*-1.24*	*-1.92*	*-2.12*	*0.62*	*0.45*	*0.06*	*-0.22*	*2.28*	*2.16*	*2.42*	*2.90*
L-H	*-0.72*	*-0.80*	*-0.72*	*-0.78*	*-0.35*	*-0.45*	*-0.30*	*-0.43*	*0.65*	*0.60*	*1.29*	*0.95*
t-stat	*-3.20*	*-2.89*	*-2.58*	*-2.35*	*-1.69*	*-1.70*	*-1.19*	*-1.27*	*2.37*	*2.27*	*5.23*	*3.34*
Panel B. High RSI and Residual IO												
Low	-0.86	-1.02	-0.96	-0.99	-0.26	-0.37	-0.21	-0.21	0.86	0.92	1.13	1.11
t-stat	*-4.89*	*-5.03*	*-4.76*	*-3.98*	*-0.99*	*-1.22*	*-0.70*	*-0.59*	*2.50*	*2.44*	*3.05*	*2.47*
Medium	-0.40	-0.53	-0.53	-0.63	0.19	0.14	0.10	0.09	0.82	0.94	0.88	1.02
t-stat	*-3.29*	*-3.48*	*-3.48*	*-3.71*	*0.72*	*0.45*	*0.34*	*0.25*	*3.02*	*2.95*	*2.83*	*2.81*
High	-0.14	-0.24	-0.31	-0.59	0.23	0.17	0.08	-0.15	0.42	0.47	0.46	0.51
t-stat	*-0.96*	*-1.37*	*-1.91*	*-2.81*	*0.88*	*0.55*	*0.29*	*-0.42*	*2.68*	*2.47*	*2.72*	*2.36*
L-H	*-0.72*	*-0.78*	*-0.65*	*-0.41*	*-0.49*	*-0.53*	*-0.30*	*-0.07*	*0.44*	*0.46*	*0.67*	*0.59*
t-stat	*-3.33*	*-3.08*	*-2.50*	*-1.37*	*-2.68*	*-2.46*	*-1.41*	*-0.24*	*1.86*	*1.92*	*2.40*	*2.00*

Table 6. High RSI and real options

This table reports equally-weighted six-factor alphas, FVIX + six factor alphas and FVIX betas of high RSI stocks sorted on market-to-book (Panel A) and credit rating (Panel B). The six-factor model includes MKT, SMB, HML, Momentum, Liquidity, and Reversal factors. Credit rating is a firm's S&P credit rating score. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from 1988 to 2010.

	Alphas				Alphas w/ FVIX				FVIX betas			
high RSI=	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**
Panel A. high RSI and Market-to-Book												
Low	0.17	0.09	0.06	-0.32	0.75	0.76	0.69	0.29	0.79	0.93	0.87	0.80
t-stat	*0.81*	*0.43*	*0.23*	*-1.36*	*2.11*	*2.00*	*1.76*	*0.77*	*3.00*	*3.36*	*3.28*	*2.67*
Medium	-0.30	-0.41	-0.57	-0.53	0.22	0.23	0.04	0.18	0.70	0.91	0.85	1.01
t-stat	*-2.03*	*-2.24*	*-3.60*	*-2.48*	*0.84*	*0.72*	*0.14*	*0.51*	*3.13*	*3.04*	*3.18*	*3.01*
High	-0.67	-1.00	-0.73	-0.92	0.15	-0.21	0.08	-0.12	1.24	1.18	1.25	1.20
t-stat	*-3.40*	*-4.61*	*-3.25*	*-3.33*	*0.45*	*-0.64*	*0.25*	*-0.34*	*3.65*	*3.38*	*3.36*	*3.33*
H-L	-0.84	-1.09	-0.79	-0.60	-0.60	-0.97	-0.61	-0.42	0.45	0.24	0.38	0.40
t-stat	*-3.04*	*-3.72*	*-2.45*	*-1.62*	*-2.10*	*-3.11*	*-1.85*	*-1.08*	*3.16*	*1.48*	*2.22*	*2.34*
Panel B. High RSI and Credit Rating												
Low (Good)	-0.08	-0.08	-0.33	-0.42	-0.22	-0.19	-0.37	-0.37	-0.34	-0.36	-0.23	-0.12
t-stat	*-0.56*	*-0.32*	*-1.33*	*-1.28*	*-1.65*	*-0.85*	*-1.39*	*-0.99*	*-5.56*	*-2.94*	*-1.69*	*-0.61*
Medium	0.08	-0.03	-0.11	-0.33	0.29	0.46	0.36	0.14	0.18	0.61	0.60	0.54
t-stat	*0.44*	*-0.13*	*-0.58*	*-1.14*	*1.26*	*1.41*	*1.24*	*0.39*	*1.22*	*2.91*	*2.71*	*1.83*
High (Bad)	-0.55	-0.63	-0.67	-0.86	0.27	0.21	0.19	0.08	1.24	1.30	1.32	1.45
t-stat	*-2.87*	*-2.76*	*-2.78*	*-2.40*	*0.77*	*0.58*	*0.50*	*0.17*	*3.19*	*3.44*	*3.26*	*2.78*
H-L	-0.47	-0.55	-0.33	-0.44	0.49	0.41	0.56	0.45	1.58	1.66	1.54	1.57
t-stat	*-1.83*	*-1.51*	*-0.95*	*-0.86*	*1.44*	*1.07*	*1.39*	*0.83*	*4.04*	*4.45*	*3.88*	*3.21*

Table 7. Conditional CAPM

The table presents the difference in market betas between recession and expansion for various portfolios. The beta is a linear function of the four conditioning variables - the dividend yield, the default premium, the risk-free rate, and the term premium. Recession is defined as the months when the expected market risk premium is above its average value, and expansion takes the rest of the sample. The expected market risk premium is the forecasted excess market return from the regression of realized excess market returns on the previous month values of the four conditioning variables. Panel A includes the high RSI portfolio (Table 2). Panel B includes the arbitrage portfolios buying high RSI stocks with high value of idiosyncratic volatility, dispersion, or turnover, and shorting the high RSI stocks with low value of idiosyncratic volatility, dispersion, or turnover. Panel C includes the arbitrage portfolios buying high RSI stocks with high value of M/B, bad credit rating, and shorting high RSI stocks with low value of M/B, or good credit rating. Panel D reports the arbitrage portfolios buying high RSI firms with low value of IO or residual IO and shorting high RSI firms with high value of IO or residual IO. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation.

high RSI=	**>2.5%**	**>5%**	**>90% ile**	**>95% ile**
Panel A. High RSI portfolio				
high RSI	-0.13	-0.14	-0.14	-0.10
t-stat	*-7.26*	*-6.03*	*-6.09*	*-3.26*
Panel B. High RSI and firm specifc uncertainty				
Idiosyncratic volatility	-0.50	-0.44	-0.46	-0.55
t-stat	*-8.18*	*-5.28*	*-7.65*	*-7.73*
Dispersion	-0.24	-0.36	-0.33	-0.40
t-stat	*-3.69*	*-3.58*	*-3.79*	*-4.83*
Turnover	-0.39	-0.38	-0.34	-0.28
t-stat	*-6.68*	*-4.98*	*-5.11*	*-4.93*
Panel C. High RSI and real option				
M/B	-0.34	-0.20	-0.23	-0.37
t-stat	*-3.93*	*-2.22*	*-2.75*	*-4.52*
Credit Rating	-0.32	-0.17	-0.27	0.01
t-stat	*-5.62*	*-3.15*	*-4.08*	*0.19*
Panel D. High RSI and IO				
IO	-0.31	-0.32	-0.29	-0.21
t-stat	*-7.32*	*-6.77*	*-3.78*	*-2.37*
Residual IO	-0.24	-0.41	-0.28	-0.20
t-stat	*-6.09*	*-7.89*	*-5.23*	*-5.11*

Table 8.Why Short Sellers Short Firms with Positive FVIX Betas?

Panel A reports Fama-MacBeth regression of log (RSI) on FVIX and measures of uncertainty and option-likeness controlling for price, size, IO, market beta, momentum and return reversal. Panel B (C) regresses coefficients from Model 8 in Panel A on next-month returns to the market and FVIX, seperately (simultaneously). Price is log of stock price. Size is log of monthly market capitalization. IO is log of shares owned by institutions as a percent of total shares outstanding. Market Beta is beta from CAPM model. Momentum is the return between month t-12 and t-2. Reversal is the past month return. FVIX is FVIX beta. M/B is log of market-to-book ratio. IVol refers to log of the standard deviation of the Fama-French model residuals. The Fama-French model is fitted to daily returns in each firm-month. Dispersion is log of the standard deviation of earnings forecasts divided by the average forecast. Turnover is log of average monthly share turnover over the past year. Rating is a firm's S&P credit rating.

Panel A: Fama-MacBeth regression

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Price	-11.64	15.24	23.47	25.05	14.62	37.68	24.71	20.44
t-stat	*-4.91*	*6.68*	*10.4*	*13.9*	*11.7*	*13.6*	*17.9*	*11.7*
Size	33.09	17.10	20.38	1.706	1.214	9.424	-2.909	-8.447
t-stat	*10.1*	*6.29*	*7.29*	*0.63*	*0.48*	*6.80*	*-1.15*	*-5.49*
IO	8.153	6.823	12.30	63.16	1.383	7.896	10.51	12.66
t-stat	*3.60*	*2.99*	*4.38*	*19.0*	*1.90*	*3.27*	*4.40*	*4.62*
Market Beta	65.31	57.36	52.96	46.53	11.54	39.43	12.50	10.29
t-stat	*15.8*	*14.6*	*13.7*	*12.9*	*7.21*	*12.1*	*6.16*	*4.97*
Momentum	-0.119	-4.590	-7.956	-0.366	-25.15	-22.11	-22.04	-19.11
t-stat	*-0.05*	*-1.98*	*-3.32*	*-0.15*	*-13.7*	*-7.15*	*-11.7*	*-7.45*
Reversal	-0.298	-0.262	-0.183	-0.175	-0.011	-0.107	0.011	0.111
t-stat	*-6.62*	*-6.58*	*-5.24*	*-4.74*	*-0.41*	*-2.10*	*0.36*	*2.32*
FVIX	2.012	1.432	0.863	1.006	-0.889	-0.231	-1.125	-1.045
t-stat	*3.89*	*4.16*	*2.71*	*2.28*	*-2.87*	*-0.40*	*-3.91*	*-2.69*
M/B		29.57	26.74	31.79	22.91	5.039	20.95	12.17
t-stat		*18.5*	*18.6*	*16.4*	*15.2*	*3.62*	*14.4*	*8.27*
IVol			46.90				4.110	2.919
t-stat			*20.8*				*4.05*	*1.88*
Dispersion				19.29			11.22	4.527
t-stat				*13.3*			*11.3*	*8.63*
Turnover					106.95		94.64	82.53
t-stat					*74.9*		*56.4*	*47.7*
Rating						16.88		5.379
t-stat						*44.7*		*15.9*
AdjRsq	18.42	17.24	19.90	22.42	45.65	19.86	42.62	43.00

Panel B: Regress coefficients from Model 8 in Panel A on next-month market return and FVIX, seperately

Coef=	FVIX	M/B	IVol	Dispersion	Turnover	Rating	Market Beta
MKT	0.112	0.147	0.086	-0.037	-0.281	0.026	0.395
t-stat	*2.04*	*0.90*	*0.33*	*-0.42*	*-1.43*	*0.87*	*1.26*
FVIX	-0.079	-0.081	-0.099	0.032	0.226	-0.017	-0.288
t-stat	*-0.68*	*-2.12*	*-0.51*	*0.48*	*1.65*	*-0.83*	*-1.34*

Panel C: Regress coefficients from Model 8 in Panel A on next-month market return and FVIX.

Coef=	FVIX	M/B	IVol	Dispersion	Turnover	Rating	Market Beta
MKT	0.180	0.264	0.322	-0.115	-0.562	0.057	0.634
t-stat	*2.36*	*1.17*	*0.93*	*-0.90*	*-1.59*	*1.08*	*1.50*
FVIX	0.359	-0.021	-0.533	0.087	0.371	0.016	-0.106
t-stat	*1.00*	*-0.12*	*-0.71*	*0.43*	*0.55*	*0.18*	*-0.15*

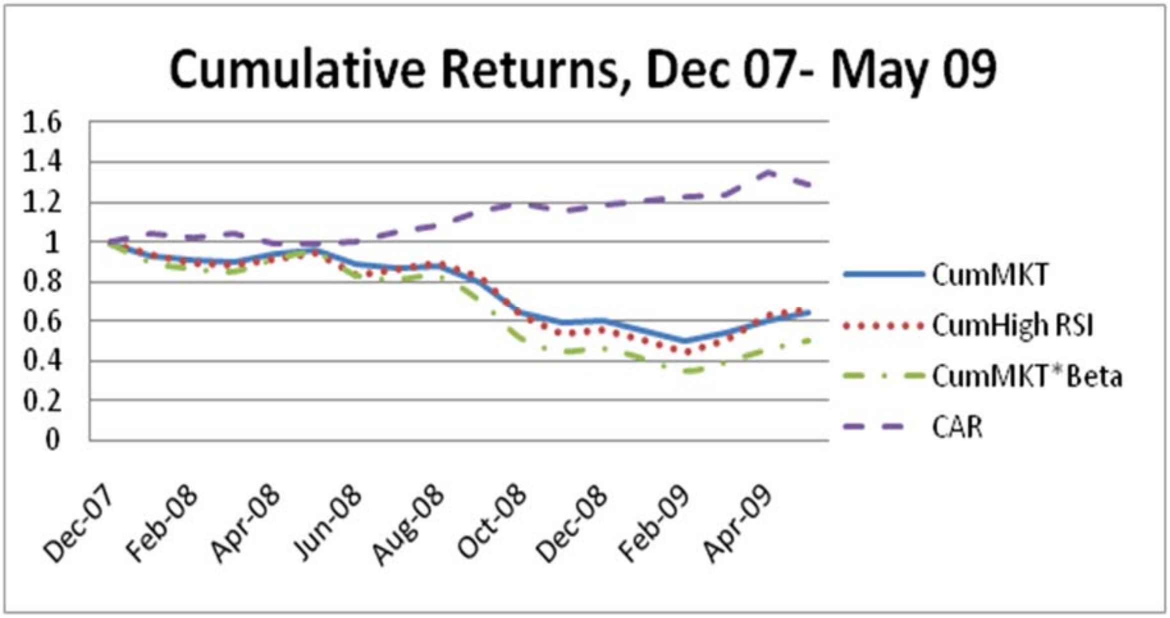

Figure 1. Cumulative returns in recent recession