Fundamental Analysis and Option Returns

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October 2011

Abstract

This paper investigates whether fundamental accounting signals can predict extreme stock price movements and whether such information is appropriately priced by the option market. We find that accounting signals exhibit incremental predictive information with respect to future option returns conditional on implied and historical stock volatility. A portfolio that exploits the information in these fundamental accounting signals earns economically and statistically significant returns.

We thank Cathy Schrand, Mark Trombley, and workshop participants at Cornell University, Yale University, The University of Texas at Dallas and University of Toronto for helpful comments and suggestions.

1. Introduction

Extensive work on fundamental analysis has examined the association between accounting data and future stock returns (e.g., Ou and Penman 1989; Bernard and Thomas 1990; Holthausen and Larcker 1992; Sloan 1996; Abarbanell and Bushee 1998; Piotroski 2000; Beneish et al. 2001). Typically, the motivation for this line of research is that accounting data is informative about a firm's expected future cash flows, but stock investors have not fully impounded this information into stock prices. This paper explores another dimension of fundamental analysis: we investigate the extent to which market participants can use accounting information to evaluate the volatility of a firm's operations and whether the option market appropriately prices this information.

Compared with prior work on fundamental analysis, our paper represents two innovations. First, we examine the role of fundamental analysis in the option market rather than in the stock market. These two markets have their own distinct features and clienteles. On one hand, the leveraged nature of option contracts attracts sophisticated investors that wish to fully exploit private information. On the other hand, several institutional features of the option market make it less efficient than the stock market. For example, an option contract based on a firm's stock typically has considerably lower trading volume than the stock itself (Battalio and Schultz 2006; Roll et al. 2010). Option markets also have relatively high transaction costs (e.g., bid–ask spreads) that may impede arbitrageurs from assuring that the option prices appropriately reflect all available information (Fleming et al. 1996; Pool et al. 2008). Second, and more importantly, we focus on the channel of volatility rather than the expected cash flow channel, which prior work on stock returns examines. Volatility plays a direct numerator effect in determining option prices, a distinct feature that differentiates the option market from the stock market. [1] Our research provides insight into the extent to which investors incorporate information from accounting signals that are related to fundamental volatility into option prices.

Following the finance literature on the volatility channel (e.g., Goyal and Saretto 2009), we focus on one specific derivative contract: an at-the-money straddle. A straddle contract arises from purchasing a call option and a put option (both of which have an exercise price close to the current stock price), resulting in a payoff that is a function of the absolute price movement in the underlying equity security. As the payoff from a straddle is unidirectional with respect to the nature of news, the fundamental information particularly relevant for a straddle differs from information relevant for the stock market.

We use two sets of fundamental signals: fundamental volatility based on the latest information released by the firm and fundamental volatility measured over a long time-series of fundamental signals. We synthesize our collection of fundamental signals into a single measure of the expected benefits that could accrue to an investor from holding a straddle position that matures in one month.[2] We document that our summary measure based on fundamental signals has incremental predictive ability with respect to future straddle option returns conditional on implied volatility and historical volatility. A hedge portfolio with a long position in high fundamental volatility options and a short position in low fundamental volatility options yields an average of 8.0% per month.[3] The results suggest that the option market does not fully

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[1] Prior work on fundamental analysis typically examines whether investors underreact or overreact to some fundamental information (e.g., Bernard and Thomas 1990; Sloan 1996). These papers suggest that stock returns are predictable because investors do not fully price this information into the numerator of stock prices (expected cash flows). In contrast, the numerator or payoff from owning a straddle is directly tied to the volatility of stock prices.

[2] Using a large sample, we aggregate our fundamental signals by estimating the historical association between our signals and the magnitude of equity price movements. We discuss the details of aggregating our fundamental signals in more detail in section 3.2.

[3] The hedge return estimates are conservative, as we only use earnings- and sales-based fundamental signals. A more comprehensive review of fundamental signals will almost surely increase the magnitude of hedge returns.

incorporate fundamental information into option prices. When fundamental volatility is high, implied volatility is too low temporarily, and vice versa. As a result, option returns become predictable ex ante.

Our study complements recent work by Goyal and Saretto (2009), which shows that the difference between historical and implied volatility predicts future straddle returns. Rather than examining market-based signals such as historical volatility, we focus on accounting-based fundamental signals and show their predictive power with respect to future option returns. We also provide evidence that incorporating our fundamental volatility signals into the historical volatility trading strategy increases significantly the hedge returns.[4]

Our work is also closely related to Beneish, Lee, and Tarpley (2001), who use multiple fundamental accounting characteristics to predict extreme price movements. The motivation for their analysis is the concern that models predicting future stock returns vary when return realizations are extreme. By partitioning on the basis of expected extreme performance in the first stage, the authors are better able to predict future stock returns in the second stage. In this sense, identifying extreme firms helps to improve return prediction models in the stock market. However, the ability to identify highly volatile firms is by itself particularly relevant for the option market, as that market directly prices volatility. In this paper, we apply Beneish et al.'s fundamental signals to the option market and examine whether these signals are useful in predicting option returns.

Our research contributes to existing literature in multiple ways. First, our work is the first study to use fundamental analysis to predict option returns. By examining the returns from

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[4] The hedge returns are above transaction costs even when we conservatively assume that investors buy options at the ask price and write options at the bid price. Goyal and Saretto (2009) find that after-cost profits to their strategy is much lower than the before-cost profits, and conclude that their strategy is "potentially profitable only to funds that can dedicate enough resources to its careful execution" (page 323).

various straddle positions, we provide direct insight into the extent to which fundamental volatility information is priced efficiently in the option market. Our results suggest that accounting-based fundamental signals are highly correlated with future straddle returns, suggesting that fundamental information is not efficiently impounded into option prices.[5]

Second, our research provides further insight into the extent to which fundamental analysis research in the stock market setting generalizes to other security markets. While existing research finds an association between accounting data and future stock returns and interprets these findings as evidence of under- or over-reaction of stock prices to accounting information, these results do not necessarily extrapolate to the option market. Our results on the volatility channel suggest that different mechanisms exist between stock and option markets. Our work also responds to the call by Richardson, Tuna, and Wysocki (2011) to explore the role of fundamental analysis in the pricing of credit derivatives. While we do not specifically explore credit derivatives, we provide insight in the use of accounting information to price option derivatives related to a firm's stock price.

Finally, examining the pricing of signals related to fundamental volatility in the option market can offer a better understanding of how market participants use accounting information over the insights gained by examining the pricing of these signals in the equity market. If the volatility related to fundamental signals is diversifiable, then theoretical models suggest that equity investors would not use these signals to determine expected returns. If fundamental volatility provides insight into the systematic component of volatility and thus is relevant for expected returns, empirical tests attempting to identify an association between these signals and

[5] Barth and So (2009) show that accounting variables are associated with both implied and realized volatility and interpret the difference between implied volatility from call options and realized volatility as risk premium. Risk is less of an issue in our setting, as we hold both call and put options in the straddle and are agnostic to the direction of stock price movement. The finance literature often argues that call options have higher risk whereas put options have lower risk (e.g., Coval and Shumway 2001). We further address the risk issue in Section 4.2.

realized stock returns would lack power due to the small variance of expected returns. These two concerns partially explain the mixed empirical evidence on the association between volatility proxies and realized returns (e.g., Fama and French 1992; Ang et al. 2006; Zhang 2006). Fortunately, these two concerns related to equity returns are mitigated for option returns, as the straddle return depends primarily on the magnitude of stock price movements, regardless of systematic or idiosyncratic volatility. Thus, by examining option returns we provide additional insight into whether investors efficiently use accounting information that is informative about volatility in the capital market.

The remainder of the paper is organized as follows. Section 2 provides a review of the literature on implied volatilities and fundamental analysis. Section 3 describes our variable measurement and empirical models. Section 4 presents our results. Section 5 provides sensitivity analyses, and section 6 concludes.

2. Prior literature and hypothesis development

2.1 Option returns

A growing body of research has examined option returns to make inferences related to expected returns and market efficiency.[6] Early work on option returns focused on the returns to option positions based on indexes (e.g., an S&P 100 index call option). For example, Coval and Shumway (2001) provide a theoretical and empirical analysis of the expected returns associated with option positions. They explain that owing to the leverage implicit in an option, call (put) options have higher (lower) expected returns than the underlying equity securities because these derivatives have higher (lower) exposure to risk. They confirm these predictions with empirical

[6] Alternatively, several papers have explored the rationality of option investors by examining the ability of implied volatility to predict future realized volatility. For example, Christensen and Prabhala (1998) find that implied volatility outperforms historical realized volatility as a predictor of future volatility.

analysis of S&P 100 index options. In addition, they observe that straddle positions that are insensitive to market risk (zero-beta straddles) have negative average returns, in contrast to the prediction from existing asset-pricing models that these securities should have an expected return equal to the risk-free rate, raising questions about the pricing of these securities.

More recently, researchers have explored the returns from options based on individual equity securities. For example, Goyal and Saretto (2009) find that the difference between implied and historical volatility can predict straddle option returns. They argue that implied volatility is incorrect when it deviates from historical volatility too much, as volatility tends to be quickly mean-reverting. As a result, straddle option returns tend to be positive when implied volatility is below historical volatility (implied volatility is too low) and negative when implied volatility is above historical volatility. While conventional wisdom holds that option investors are more sophisticated, the abnormal returns to the trading strategy in Goyal and Saretto (2009) raise questions as to how efficiently option prices incorporate publicly available information about volatility.

Following Goyal and Saretto (2009), several concurrent papers explore the cross-section of option returns.[7] Choy (2011) provides evidence that a firm's zero-beta straddle positions have more negative returns when retail investors account for a greater proportion of that firm's trading, a finding consistent with retail investor trades resulting in option prices where implied volatility is not a sufficient statistic for future realized volatility owing to behavioral biases. Other papers explore the determinants of put and call returns, but not straddle returns.[8] We add to

[7] Rather than examining the cross-section of individual option returns, Driessen, Maenhour, and Vilkov (2009) examine the importance of the correlation between the assets that compose an index by comparing the return from holding an index option position with the return from holding the individual options within that index.

[8] Boyer and Vorkink (2011) develop a measure of the ex-ante skewness associated with an option's return and find that this measure is negatively associated with both put and call option returns. Christoffersen, Goyenko, Jacobs, and Karoui (2011) provide evidence that illiquidity in the option market is positively associated with both put and call

this growing literature by examining whether option investors effectively incorporate accounting-based fundamental signals into option prices.

2.2 Accounting information, volatility, and option returns

A large literature in accounting examines the extent to which investors effectively interpret and price financial accounting information, although this literature has focused on the predictability of future earnings and future stock returns. A number of papers have suggested that accounting-based signals or fundamental analysis could generate abnormal returns (e.g., Bernard and Thomas 1990; Sloan 1996; Ou and Penman 1989; Holthausen and Larcker 1992; Abarbanell and Bushee 1998; Piotroski 2000).

On the volatility side, the literature shows that a firm's fundamental volatility determines (although does not fully explain) stock price volatility (Shiller 1981; Scheinkman and Xiong 2003; Paster and Veronesi 2003; Callen 2009). The high correlation between fundamental volatility and stock volatility creates the possibility for fundamental analysis to play a role in predicting stock volatility. While much of the literature on financial statement analysis has focused on the prediction of future earnings and future stock returns, research also examines whether accounting measures provide information about future uncertainty or the magnitude of future price movements. In direct relation to our study, Beneish et al. (2001) show that fundamental signals, such as earnings- or sales-based variables, can predict future extreme (either upward or downward) price movements after controlling for market-based signals.

Several recent accounting studies have also explored the link between accounting information and option markets with an emphasis on implied volatilities. Rogers, Van Buskirk, and Skinner (2009) find that the implied volatility values increase after managerial forecasts,

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option returns. However, illiquidity related to a firm's stock trading is negatively related to both put and call option expected returns.

particularly when the forecast conveys bad news. Dubinsky and Johannes (2006) find that the implied volatility imbedded in a firm's options tends to change when an earnings announcement occurs, suggesting that option investors understand the opportunity for a material jump in price at an earnings announcement. Barth and So (2009) explore whether accounting information is associated with the gap between implied volatility and the subsequent realized volatility during an earnings announcement window. They find that firms with losses or more volatile earnings are more likely to have implied volatilities that are higher than the subsequent realized volatilities at the earnings announcement and interpret the difference as a risk premium.[9] None of these papers examines the link between accounting signals and future option returns, especially after controlling for market-based signals used in the finance literature.

Building on the prior literature on accounting signals and future price volatility, this paper examines the role of fundamental signals in predicting option returns. The financial reporting system produces a rich set of fundamental variables that capture the uncertainty or volatility of a firm's operation. Historical stock volatility and implied volatility in option contracts may not fully reflect such underlying fundamental volatility, which manifests itself in the future. Similar to Goyal and Saretto (2009) who suggest that option investors under-react to historical volatility (i.e., ignoring the role of historical volatility in a mean reverting process), we posit that option implied volatility may temporarily deviate from fundamental volatility and, as a result, fundamental signals predict option returns. This leads to the central prediction of our paper: *historical fundamental signals predict option returns.*

[9] Pan (2002) suggests that investors price options with a risk premium to account for jumps in prices that could occur in the future (i.e., jump risk). This additional risk results in greater values for implied volatility values, which exceed the subsequent realized volatility. A premium related to uncertainty over future volatility may also explain partially the observed negative performance of a straddle position over time (Coval and Shumway 2001).

In tests of our hypothesis, two issues are important to address, both conceptually and empirically. First, we must show that fundamental signals convey incremental information about future option returns beyond what is captured in historical volatility, which the finance literature has shown to predict option returns. Historical volatility is a noisy measure of a firm's underlying volatility, leaving the room for fundamental volatility to play a role. Second, we must show that predictable option returns are not due to higher risk borne by option investors.

3. Research design and sample data

3.1 Measurement of individual fundamental signals

We use two sets of fundamental signals in our analysis of option returns. Our first set of signals includes fundamental volatility as reflected in sales and earnings released at an earnings announcement. These signals are drawn from work examining whether accounting signals can predict extreme stock price movements. Our second set of signals includes fundamental volatility measured over a long time-series of fundamental signals. To avoid the risk of data mining, we only consider sales- and earnings-based signals and rely on the signals identified by Beneish et al. (2001).[10]

Our first set of measures relates to short-term sales and earnings news. In evaluating return prediction models in the stock market, Beneish et al. (2001) find that information about sales growth (SGI, SLDY) and earnings performance (CHGEPS, LSY) is positively associated with the probability that a firm has extreme positive or negative price movements. Therefore, we include these four variables to capture the volatile nature of revenue and earnings streams.

[10] It is also worth noting that the sample used to analyze extreme stock returns in Beneish et al. (2001) ends in1997, while our analysis of option returns begins in 1996. As shown in Figure 2, our hedge results are robust to beginning our analysis in 1998.

Our second set of measures is meant to capture a firm's long-term fundamental volatility. In line with the sales- and earnings-based signals in our first set of measures, we measure fundamental volatility using the long-term volatility of its sales growth (STDEV_SGI) and the volatility of its changes in earnings (STDEV_CHGEPS). Both volatilities are calculated over the 6 years preceding quarter q (with a minimum of 15 observations required). The definitions for our fundamental signals are described below:

SGI	= $(Sales_q / Sales_{q-4})-1$
SLDY	= an indicator for cases where SGI is negative
CHGEPS	= $(IBQ_q - IBQ_{q-4})/MVE_{q-4}$, where IBQ_q =quarterly income before extraordinary items during quarter q and MVE_q=market value of equity at the end of quarter q
LSY	= an indicator if IBQ_q is negative during q, q-1, q-2, or q-3.
STDEV_SGI	= natural log of the standard deviation of SGI over the previous 6 years (minimum 15 observations).
STDEV_CHGEPS	= natural log of the standard deviation of CHGEPS over the previous 6 years (minimum 15 observations).

A timeline for the measurement of the fundamental signals is included in Panel A of Figure 1.

Our list of fundamental signals is by no means an exhaustive catalog of potentially useful metrics. Rather, our list is parsimonious and serves as the lower bound in predicting option returns. The prior literature extensively discusses both sales- and earnings-based signals, which are intuitively appealing since they represent the top and bottom lines of the income statement.

3.2 Fundamental signals and future stock price movements

Rather than examine the above signals individually, we combine them into a single measure that reflects the information they convey about the magnitude of stock price movements relevant to pricing a straddle position. As our analysis explores the returns an investor can earn from buying a straddle contract and holding it to maturity (one month), we examine how our signals relate to the absolute value of future monthly returns. We focus on the absolute value of returns during a month, because this value is equivalent to the value that could be realized at the end of the month from an at-the-money straddle the investor purchased at the beginning of the month.[11] The use of absolute return also directly follows the approach to identify extreme stock price performers in Beneish et al. (2001).

To identify the association between fundamental signals and the absolute value of subsequent returns, we match the fundamental signals calculated as of each quarterly earnings announcement date to the average absolute value of monthly returns in the three months following the month when a firm announces its earnings. To limit the weight on extreme realizations, we use the natural log of the average absolute value in our analysis and refer to this variable as SVAL. Next, as described below, we estimate the historical association between our fundamental signals and the subsequent price movements using the following equation:

$$SVAL_{q+1} = \theta_0 + \theta_1 SGI_q + \theta_2 SLDY_q + \theta_3 CHGEPS_q + \theta_4 LSY_q + \theta_5 STDEV\_SGI_q + \theta_6 STDEV\_CHGEPS_q + error \quad (1)$$

Where:

$SVAL_{q+1}$ = natural log of the average absolute monthly return over the three months following the month when the firm's earnings announcement occurs.

As noted above, the independent variables in equation (1) are from two groups: variables measured using data from the earnings announcement at time q (SGI, SLDY, CHGEPS, and LSY) and variables measured using a long series of historical data available before quarter q (STDEV_SGI, STDEV_CHGEPS). The dependent variable is measured over the three months following the month when earnings for quarter q are released.

Using the following process, we calculate rolling estimates of Equation (1) on the basis of data available when the firm reports its earnings. First, we divide all earnings announcements

[11] Importantly, the value that could be realized at the end of the month is distinct from the return on the straddle, as it does not incorporate the initial purchase price. Table 2 Panel C provides insight into this distinction, revealing a positive and highly significant association between future straddle returns and the magnitude of future stock price movements.

into groups based on the year and calendar quarter when the announcement occurred. For each calendar quarter, we estimate Equation (1) using a sample of historical data that are available at the beginning of that calendar quarter. We limit this sample to earnings announcements during the two years before the beginning of that calendar quarter. Next, we take coefficients for Equation (1) estimated using historical data and apply them to the current period's fundamental signals to obtain a predicted value (E[SVAL]). This empirical methodology is widely used on Wall Street to calculate alpha to proxy for future stock returns.

For example, a firm reporting earnings during February of 1999 would be assigned to the first calendar quarter of 1999. For this quarter, we create a sample to estimate Equation (1) using data available before January 1, 1999. The sample would contain all firms that reported earnings after January 1, 1997 and before September 30, 1998. This date range ensures that three months of returns following the earnings announcement (needed to calculate the dependent variable in Equation (1)) are also observable before January 1, 1999. See Panel B of Figure 1 for a timeline of the measurement of Equation (1). The coefficients from this historical model would be applied to the signals available at the earnings announcement during February 1999, which would then be used to predict straddle returns in March, April, and May 1999. See Panel C of Figure 1 for a timeline of the matching of fundamental signals to straddle returns.

We begin our analysis of fundamental signals by estimating Equation (1) with all firms where we have sufficient Compustat data to calculate the fundamental signals and CRSP monthly return data to estimate the average absolute value of monthly returns in the three months following the earnings announcement. Before estimating Equation (1), we require the following sample selection criteria. We drop firm-quarters with earnings report dates that are more than 90 days after the end of the fiscal quarter. In addition, we drop firms with extremely low quarterly closing prices (less than \$1) and observations where the deflator of SGI or CHGEPS ($Sales_{q-4}$ and MVE_{q-4}, respectively) is less than \$1 million. We also require that each firm have non-missing Compustat data on the market value of equity and book value of equity at the end of quarter q. To limit the influence of outliers during the estimation period, the top and bottom 1% of the dependent and independent variables are winsorized in each sample before estimating Equation (1).

As we examine option returns that occur between January 1996 and September 2010, we estimate 60 versions of Equation (1) covering rolling windows from the fourth calendar quarter of 1995 through the third quarter of 2010.

Panel A of Table 1 presents the average of the descriptive statistics for the 60 subsamples. For example, across these 60 subsamples, the average mean and median for SVAL are -2.593 and -2.564 respectively. Panel B of Table 1 presents the average correlation matrix across the 60 samples to provide insight into the univariate associations between the signals. As expected, SVAL is positively correlated with all six components, pair-wise. By construction, SGI and SLDY are highly negatively correlated. Other pair-wise correlations are relatively low, with the magnitude below 0.40.

Panel C of Table 1 presents the distribution of coefficients from Equation (1) across the 60 samples. Consistent with univariate results in Panel B, the average and median coefficients on all of the fundamental signals are positive. In addition, variation occurs in the magnitude of the coefficient across signals, suggesting that equally weighting the signals may not be appropriate. However, we emphasize that we do not estimate Equation (1) to test whether these coefficients are positive. Instead, these coefficients are the first step (aggregating our fundamental signals into a single variable) in our analysis of option returns.

Panel D of Table 1 reports the association with the predictions from Equation (1) and the out-of-sample realizations of SVAL. Panel D illustrates that when firms are partitioned on the basis of E[SVAL] into high, medium, and low groups, the differences in the out-of-sample SVAL are highly significant. This finding suggests that fundamental signals are relevant for determining the ex ante value of a straddle position. Our subsequent tests explore the extent to which option markets incorporate these signals.

3.3 Option sample and descriptive statistics

While the analysis in Table 1 is based on all firms with sufficient Compustat and CRSP data, we restrict the remainder of our analysis to the subset of those firms with sufficient Optionmetrics data to calculate straddle returns. To measure straddle returns, we follow the method of Goyal and Seratto (2009) and use Optionmetrics data to calculate the returns to a straddle position in a particular stock. Specifically, we consider options that mature in the next month. From among these options with one month to maturity, we then select the contracts that are close to at-the-money, with moneyness (Mness) between 0.975 and 1.025.[12] Thus, for each stock and for each month in the sample, we select the call and the put contract that are close to at-the-month and expire the next month. After next-month expiration, we repeat the procedure and select a new pair of call and put contracts. As the straddle has both call and put contracts, the payoff to the straddle is determined purely by the deviation of stock price from its exercise price a month later. Whether stock price goes up or down is irrelevant, a concept in line with the volatility channel that we emphasize in the paper.

Matching our data on fundamental signals and historical volatility to Optionmetrics results in a sample of 84,488 firm-months composed of 52,549 firm-quarters (3,328 unique

[12] Our results are also robust to relaxing this constraint (including straddles that are either in-the-money or out-of-the-money).

firms). A comparison of the number of firm-months with the number of firm-quarters reveals that we typically are able to use the information from a given firm-quarter for between one and two straddle positions (84,488/52,549 = 1.61 monthly straddle contracts per firm-quarter) that are originated during the three months following the earnings announcement month. Thus, while we match the information available during an earnings announcement month to the subsequent three months, this match does not imply that all earnings announcements are matched to three straddle returns. The absence of a straddle return is largely attributable to the constraint that we require the straddle position to be roughly at-the-money.

Panel A of Table 2 presents descriptive statistics for firm-months with both fundamental signal data and straddle return data. The mean (median) straddle return SRET is -0.023 (-0.203), a result consistent with the prior literature and suggesting that straddle contracts on average lose money.

3.4 Measurement of unexpected information from fundamental signals

Ex ante, option investors may partially price the volatility information captured in fundamental signals. Therefore, E[SVAL] would be positively associated with implied volatility. To identify cases where the information from fundamental signals does not appear to be fully impounded into implied volatility, we adjust E[SVAL] relative to the level of implied volatility. We also remove the variation in E[SVAL] that relates to the gap between historical and implied volatility (DIFF_HVOL) to differentiate our analysis from the analysis of historical volatility in Goyal and Saretto (2009). In sum, we remove the variation in E[SVAL] that is due to implied volatility and historical volatility using the following model:

$$\text{E[SVAL]} = \gamma_0 + \gamma_1\text{IVOL} + \gamma_2\text{DIFF\_HVOL} + \text{error} \quad (2)$$

IVOL = natural log of implied volatility, where implied volatility is downloaded from Optionmetrics.

DIFF_HVOL = natural log of historical volatility minus natural log of implied volatility, where historical volatility is estimated using daily returns over the year preceding the month when the trading strategy is initiated. The standard deviation of daily returns is transformed in an annual standard deviation by multiplying it by the square root of 252.

Note that we measure the dependent and independent variables for Equation (2) contemporaneously.

Panel B of Table 2 presents descriptive statistics for the monthly regression estimates of Equation (2). As expected, fundamental volatility proxied by E[SVAL] is positively correlated with implied and historical volatilities. However, for the average month, R^2 from Equation (2) is 23%, suggesting that while E[SVAL] shares some common elements with historical and implied volatility, these market-based signals are not sufficient statistics for E[SVAL].

We label the residual value from Equation (2) as DIFF_FUND. A positive (negative) value of DIFF_FUND indicates that fundamental volatility is abnormally high (low) relative to other firms with comparable levels of implied and historical volatility.

Panel C of Table 2 reports the correlation matrix of the main variables of interest in this study. We observe that our main variable of interest, DIFF_FUND, has a positive association with both the magnitude of stock returns during the option contract (REAL_SVAL) and the returns that are earned from holding a straddle position (SRET) consistent with the main empirical prediction of the paper.[13] Panel C also presents correlations consistent with past research. As expected, there is a strong positive association between IVOL and HVOL, implying that while implied volatility may not efficiently capture all of the information in historical

[13] In addition to the univariate association between DIFF_FUND and REAL_SVAL, we also find that this association is robust to more detailed analysis. Specifically, we estimate a multivariate regression (with clustered standard errors based on firm and month) predicting REAL_SVAL using DIFF_FUND, HVOL, IVOL, and time fixed effects as independent variables. Using this specification, we find that DIFF_FUND has a positive and significant association with REAL_SVAL incremental to the other independent variables. We also observe that both HVOL and IVOL have a positive and significant association with REAL_SVAL.

volatility there is considerable overlap between these two signals. We also observe a positive association between DIFF_HVOL and SRET, consistent with the findings of Goyal and Saretto (2009).

4. Main results

4.1 Straddle hedge portfolios

In this section we formally investigate whether accounting information predicts future option returns. We first replicate the main result in Goyal and Sarreto (2009) using our sample. Column A of Table 3 presents the deciles of option returns as reported in Goyal and Sarreto (2009). Column B shows our replication results using our sample, which is limited to firms that have data on fundamental signals. Both columns also report hedge portfolios based on a comparison of the top and bottom deciles (HVOL_HEDGE1) and hedge returns based on a comparison of the top 30% with the bottom 30% (HVOL_HEDGE2). Overall, the performance of the hedge portfolios is fairly similar across these two samples (Column A: HEDGE1 = 22.7%; Column B: HEDGE1 = 20.1%)

We next present our main results based on the aggregate fundamental signal. Column C presents hedge portfolio analysis based on DIFF_FUND. We observe a positive association between DIFF_FUND and decile option returns. Straddle option returns fairly monotonically increase from -5.8% in D1 to 2.2% in D10, resulting a D10-D1 hedge return of 8.0% per month (t=5.36). The hedge portfolio based on the top and bottom 30% of observations (FUND_HEDGE2) yields an average monthly return of 5.6% (t=5.54). While the magnitude of hedge returns is lower than that based on historical volatility, monthly hedge returns based on fundamental volatility are nevertheless economically material. Note that reported hedge returns underestimate the power of fundamental analysis, as we only include earnings- and sales-based signals. A more comprehensive examination of fundamental signals will almost surely increase the magnitude of hedge returns.

4.2 Are fundamental-based option strategies risky?

To assess whether fundamental-based option strategies are risky, we conduct two sets of analysis. First, we examine the co-movement between hedge portfolio returns and common risk factors. The finance literature (e.g., Coval and Shumway 2001) suggests that theoretical asset pricing models, such as CAPM, also apply to options. The idea is that common state variables, such as consumption, capture all kinds of risks in the capital markets including the option market. Therefore, the expected return on an option should relate to the option's sensitivity to common risk factors. Empirically, prior studies (e.g., Goyal and Saretto 2009; Choy 2011; Boyer and Vorkink 2011) use common return factors to capture systematic risks. Following prior work, we use the four-factor model below to examine whether our fundamental trading strategy exposes investors to systematic risks.[14]

$$FUND\_HEDGE = \alpha + bMKT\_RF + sSMB + hHML + mUMD + error \qquad (3)$$

Where:

FUND_HEDGE	= the return to a hedge portfolio based on DIFF_FUND
MKT_RF	= the market return less the risk-free rate
SMB	= the size risk factor
HML	= the book-to-market risk factor
UMD	= the momentum risk factor

We note that our straddle contracts typically span two months (e.g., a straddle initiated on May 19 that expires on June 21) and do not all start on the same date. To address this concern,

[14] We also include the return to a straddle based on an S&P500 index option as another risk factor in Equation (3) and our inferences related to the portfolio alpha do not change.

we present results for two versions of Equation (3) using the factors for the initiation and the expiration months.

Panel A of Table 4 presents four models. In the first two columns the dependent variable is equal to FUND_HEDGE1, and in the third and fourth column the dependent variable is equal to FUND_HEDGE2. In all cases, abnormal returns (intercepts) and their associated t-statistics from the four-factor model are almost identical to raw returns reported in Column C of Table 3, regardless of which model is concerned. In addition, the coefficients on common risk factors are insignificantly different from zero in all cases except for HML_{t+1}. Overall, the results suggest that the hedge portfolio returns from our option strategies exhibit little co-movement with common risk factors.

Our second set of analysis is to examine the time series properties of our fundamental analysis portfolio. An alternative risk-based perspective suggests that portfolios with higher average returns must have inconsistent performance. In other words, investors may have positive returns over a long window, but the portfolio strategy exposes the investor to large negative outcomes. This concern particularly arises for option-based trading strategies where selling a straddle exposes the seller to potentially extreme negative outcomes. To address this concern, we examine the performance of our fundamental analysis portfolio over time, noting the overall frequency of negative returns and the performance by year.

Panel B of Table 4 provides further details on the distribution of monthly returns for both FUND_HEDGE1 and FUND_HEDGE2. In both cases, the fundamental analysis hedge portfolio delivers positive returns for more than 60% of months during the window. In addition, the returns to FUND_HEDGE2 contain noticeably fewer extreme outcomes (no observations with monthly returns below -30%).

Finally, Figure 2 plots the mean monthly returns to FUND_HEDGE1 and FUND_HEDGE2 by year. Both trading strategies are profitable in most years. FUND_HEDGE1 is positive in 12 of the 15 years, while FUND_HEDGE2 is positive in 14 of the 15 years. Even when the hedge portfolio returns are negative, in 1996, 2003 and 2010, the magnitude of these negative returns is relatively small.

In summary, we find fairly consistent and strong positive returns for the fundamental-based option strategy. Our evidence is unlikely to reflect an appropriate reward for a risky investment strategy (caused by the long positions being more risky than the short positions in the strategy).

4.3 Multivariate regression analysis

In addition to exploring hedge portfolio returns, we also examine the association between E[SVAL] and straddle returns through multiple regressions that allow for more control variables. We examine three sets of regression models:

$$\text{SRET} = a_0 + a_1\text{RANK\_DIFF\_FUND} + a_2\,\text{RANK\_DIFF\_HVOL} + \text{error} \quad \text{(4a)}$$
$$\text{SRET} = a_0 + a_1\text{RANK\_E[SVAL]} + a_2\text{RANK\_HVOL} + a_3\text{RANK\_IVOL} + \text{error} \quad \text{(4b)}$$
$$\text{SRET} = a_0 + \sum a_k\text{RANK\_SIGNAL}_{k,} + a_2\text{RANK\_HVOL} + a_3\text{RANK\_IVOL} + \text{error} \quad \text{(4c)}$$

where the prefix RANK_ represents the decile ranking of a variable scaled to be between zero and one.

The first model (Equation (4a)) includes the measures that were used to form the portfolios in Table 3. The second model (Equation (4b)) disaggregates the variables used to calculate DIFF_FUND and DIFF_HVOL (E[SVAL], HVAL, IVOL), including these measures in the regression as individual independent variables. The third model (Equation (4c)) further disaggregates E[SVAL] into the individual signals. Including the individual signals relaxes the constraint that the signals are aggregated in a manner consistent with Equation (1). All independent variables in Equations (4a), (4b) and (4c) are scaled decile ranks, implying that each coefficient represents the hedge return to a portfolio that exploits the variation in that measure (Abarbanell and Bushee, 1998).

Panel A of Table 5 presents estimates of Equation (4a). Column A (Column B) contains a univariate model where only RANK_DIFF_FUND (RANK_DIFF_HVOL) is included as an independent variable. Column C includes both measures together. The coefficient on RANK_DIFF_FUND is positive and significant in both Column A and Column C, indicating that information from fundamental signals is associated with straddle returns.

Panel B of Table 5 presents estimates of Equation (4b) where the root variables for each measure are included. As in Panel A, the fundamental signals measure, RANK_E[SVAL], has positive and significant coefficients in both a univariate specification (Column A) and a multivariate specification (Column C).

Panel C of Table 5 presents estimates of Equation (4c) that includes individual signals. The coefficients on the individual fundamental signals reveal that RANK_SGI and RANK_STDEV_CHGEPS have the greatest positive association with future straddle returns. In addition, when estimating Equation (4c), we also test the joint hypothesis that none of the signals is informative. The sum of the individual signals can also be interpreted as the hedge portfolio returns based on individual fundamental signals (Abarbanell and Bushee, 1998). As shown in Panel C, the sum of these coefficients is positive and significant in both the model that includes only the signals (Column (A)) and the model that also includes RANK_HVOL and RANK_IVOL as control variables (Column (B)).

5 Sensitivity analyses

5.1 Cross-sectional variations in option strategy returns

We examine cross-sectional variations in option strategy returns. Several firm characteristics might affect the profitability of implementing the fundamental-based option strategy. First, the observed returns from fundamental analysis may be larger among firms with higher transaction costs, where these costs may make exploiting the strategy too costly. We use two proxies for transaction costs: the closing bid–ask spread in the option market and the trading volume in the option market.[15] Second, the returns from fundamental analysis may be smaller among firms with better information environments. We use two proxies for information environment: firm size and analyst coverage. Third, the returns to fundamental analysis may be sensitive to whether an earnings announcement occurs during the window of time covered by the straddle contract.

We examine whether certain firm characteristics influence the association between straddle returns and our measure of fundamental volatility by including interaction terms into Equation (4a). This examination results in the following model:

$$\text{SRET} = a_0 + a_1\text{RANK\_DIFF\_FUND} + a_2\text{RANK\_DIFF\_HVOL} + a_3X + a_4X^*\text{RANK\_DIFF\_FUND} + a_5X^*\text{RANK\_DIFF\_HVOL} + \text{error} \quad (5)$$

Where:

X = ASK_BID, VOLUME, MVE, COVERAGE, or EA_DUM

ASK_BID = scaled decile rank of bid–ask spread for traded options, where the bid–ask spread is the difference between the highest closing bid and the lowest closing ask scaled by the mid-point of these two.

VOLUME = scaled decile rank of dollar volume of traded options, where dollar volume is option trade volume multiplied by the midpoint of the highest closing bid and the lowest closing ask prices.

MVE = scaled decile rank of market value of equity from the end of the most recent fiscal quarter

COVERAGE = scaled decile rank of the count of analysts covering the firm

EA_DUM = indicator that a straddle contract contain an earnings announcement.

[15] The closing bid–ask spread is positively correlated with average bid–ask spread. Therefore, we use the closing bid–ask spread as a partition variable rather than as a proxy for transaction cost. Average bid–ask spread data are not available.

Table 6 presents estimates of Equation (5). We begin our cross-sectional analysis by partitioning our sample on the basis of trading cost proxies. Column A indicates that the returns to a strategy based on historical volatility are significantly higher among firms where transacting in these stocks is more costly (i.e., a positive and significant coefficient on the interaction between ASK_BID and RANK_DIFF_HVOL, t = 2.61). These results are consistent with additional detail on the performance of the trading strategy documented by Goyal and Saretto (2009), which show that the returns to their trading strategy materially decrease when they consider transaction costs in the form of the bid–ask spread. However, the interaction between ASK_BID and RANK_DIFF_FUND is not significantly different from zero, indicating that future straddle returns from a fundamental-based trading strategy are not concentrated among sample firms with high transaction costs. In Column B, we examine VOLUME as another measure of transaction costs. We find no evidence that the results related to RANK_DIFF_FUND or RANK_DIFF_HVOL are concentrated in high- or low-volume options.

Next, in Columns C and D we present partitions based on information environment measures (firm size and analyst coverage). We observe that the association between RANK_DIFF_HVOL and SRET is significantly stronger among small firms and firms with less analyst coverage. However, we do not observe a significant interaction between either of the information environment proxies and RANK_DIFF_FUND, suggesting that the fundamental-based strategy works equally well between firms with a risk information environment and firms with a poor information environment.

Finally, Column E examines whether the presence of an earnings announcement by the firm underlying the option during the straddle contract affects the straddle return. Consistent with Goyal and Saretto (2009), we observe that the association between RANK_DIFF_HVOL and future straddle returns is not sensitive to the presence of earnings announcements. However, we observe that the association between RANK_DIFF_FUND and future straddle returns is significantly weaker when an earnings announcement occurs during the straddle window. This evidence is consistent with investors anticipating the likelihood of large changes in stock price related to fundamental uncertainty when an earnings announcement occurs and incorporating that information into prices, but not anticipating that fundamental news reaches the market during months when no earnings announcement occurs. Thus, consistent with recent evidence that news on earnings announcements constitutes a relatively small fraction of annual news (Ball and Shivakumar, 2008), we observe that fundamental signals are particularly useful in predicting price movements on non-earnings announcement months.

5.2 The time-series pattern of implied volatility around the portfolio formation date

We have motivated our analysis from the fundamental volatility perspective. That is, our fundamental signals capture fundamental volatility and implied volatility may deviate from the true underlying volatility. In portfolios sorted by our fundamental score, implied volatility is too low relative to fundamental volatility for D10 options and too high for D1 options. If this story holds, a natural prediction is that implied volatility should increase for D10 options and decline for D1 options after the portfolio formation date, given that implied volatility should converge to the true underlying volatility over time.

In Figure 3, we plot the time-series pattern of implied volatility of D1 and D10 options. We consider a range of 12 months before and 12 months after the portfolio formation date (t=0). The results are striking. For D1 options, implied volatility is higher at time zero than in previous months. After time zero, implied volatility increases to the level seen in the previous months. In contrast, for D10 options implied volatility is much lower at time zero than in adjacent months, resulting a clean "V" shape of implied volatility. The results are consistent with the story that implied volatility temporally deviates from fundamental volatility, resulting predictable option returns.

5.3 Additional fundamental signals

So far, we only use earnings- and sales-based fundamental signals. Given the richness of fundamental signals in the financial reporting system, it is certainly possible that other fundamental signals may add value to our fundamental-based option trading strategy. In absence of a good theory or story, an empirical investigation of different signals runs the risk of data mining. With that caveat in mind, we conduct additional analyses and find that accruals, capital expenditure, and external financing tend to improve the option trading strategy.[16] To incorporate these additional signals into our analysis, we re-estimate into Equation (4c) with these additional independent variables (results not tabulated). We find that the coefficient on RANK_CAPEX is positive and significant (t=2.28). While the coefficients on RANK_ACC and RANK_XFIN are both positive, but neither is significant (t=1.41 and 1.31, respectively). The sum of all of the fundamental signal coefficients increases from 15.0% to 22.6% and its corresponding t-statistic from 4.56 to 4.73. This additional analysis indicates that including additional signals appears to further improve the trading strategy returns.

5.4 Combining the historical volatility and fundamental signals trading strategies

We show that fundamental signals contain information about future volatility incremental to what captured in historical volatility. From the investment perspective, a natural approach is to

[16] Capital expenditures (CAPEX), Accruals (ACC) and External financing (XFIN) are calculated using annual data and matched to earnings announcement dates that are at least four months after the fiscal year end. CAPEX is defined as capital expenditures divided by average assets. ACC is defined as Income from continuing operations minus cash flow from operations divided by average assets. XFIN is defined based on cash flow data as in Bradshaw, Richardson, and Sloan (2006).

combine these two types of signals. While there are many ways to combine fundamental signals with historical volatility, we adopt the following trading strategy. We begin with the deciles of DIFF_HVOL, where the D1 and D10 are the short and long positions in Goyal and Saretto (2009). Next, we further sort the observations in the D1 and D10 into three groups each based on DIFF_FUND. Finally, to calculate the hedge return from using both signals (HEDGE1_BOTH), we pick D1 with the lowest fundamental score as our short position (SHORT1_BOTH) and D10 with the highest fundamental score as our long position (LONG1_BOTH). We also report hedge returns from the firms that are in the top and bottom deciles of DIFF_HVOL, but do not have values of DIFF_FUND that would result in them being in the combined strategy (i.e., observations in D1 (D10) of DIFF_HVOL where DIFF_FUND is not in the bottom (top) thirty three percentiles).

Panel A of Table 7 shows that the volatility-fundamental strategy yields much higher returns (HEDGE1_BOTH) than the one based on only historical volatility (28.3% vs. 20.1%). We also observe that the returns to the strategy that uses the observations where the historical volatility and fundamental signals do not agree (HEDGE1_NOT_BOTH) are lower and less significant (Average return=16.7%)

5.5 Transaction costs

In the main analysis, we compute option returns using the mid-point of closing bid and ask prices. It is possible that investors cannot trade options at that price, even though Mayhew (2002) and De Fontnouvelle, Fisher, and Harris (2003) show that the typical ratio of the effective spread to the quoted spread is less than 0.5. As a robustness check, we examine option returns under two conservative assumptions. First, investors buy options at the ask price and write options at the bid price. Second, we use the closing bid-ask spread to proxy for the average bid-ask spread. As option prices tend to be more volatile towards the closing, closing bid-ask spread tends to be larger than the average bid-ask spread.

Panel B of Table 7 results suggest that the D10-D1 hedge return of the fundamental-based strategy drops from 8.0% (t=5.36) in Table 3 to -9.3% (t=-5.90). The hedge return of the fundamental plus volatility strategy drops from 28.3% in section 5.3 to 7.5% (t=2.35) per month. Therefore, given a very conservative assumption of transaction costs, the fundamental trading strategy alone does not yield any positive abnormal returns. However, when combined with historical volatility, the strategy still achieves a sizable hedge return. The importance of combining these strategies can also be seen from examining the after transaction costs returns of the strategy where the historical volatility and fundamental signals do not agree (HEDGE1_NOT_BOTH), which are not significantly different from zero after transaction costs (Average return=-2.5 %, t=-1.04).

5.6 Call and put option returns

The results so far are based on straddle returns. It is interesting to see whether call or put options drive the straddle returns. In untabulated analysis, we find that returns to the long position are driven by call options, whereas returns to the short position are driven by put options. The average return on call options in the top (bottom) deciles of DIFF_FUND are 17.4% (4.2%), while the average return on put options in the top (bottom) deciles of DIFF_FUND are -10.6% (-16.9%).[17] The asymmetric results between calls and puts are at least partially driven by the fact that the market return tends to be positive in the sample period. When the market goes up, call options are more likely to be in the money than put options, contributing more to the

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[17] The return on the straddle is not equal to the sum of the put and all returns as these two returns are weighted by the cost of the option purchased to form the straddle.

long position. By the same token, shorting puts tend to make more money than shorting calls when the market goes up.

6. Conclusion

In this paper, we examine the extent to which accounting information is useful in evaluating the volatility of a firm's operations and whether this information is appropriately priced by the option market. We find evidence that information about a firm's fundamental volatility is useful for predicting the cross-section of straddle returns. Hedge portfolios with long and short straddle contract positions based on accounting signals earn statistically and economically significant returns. We also show that the fundamental-based strategy is additive to the historical volatility-based strategy. Cross-sectionally, transaction costs are less of an issue for the fundamental-based strategy than for the historical volatility-based strategy. Our evidence provides insight into a new dimension of fundamental analysis—using accounting signals to evaluate fundamental volatility and examining whether such information is priced in the option market. Our evidence complements prior fundamental analysis research on equity returns, which focused on fundamental signals to predict future operating performance and stock returns.

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Appendix A – Variable definitions

Variable	Definition
SGI	= $(Sales_q / Sales_{q-4}) - 1$.
SLDY	= an indicator for cases where SGI is negative.
CHGEPS	= (IBQ(q) – IBQ(q-4))/MVE(q-4), where IBQ(q) = quarterly income before extraordinary items during quarter q and MVE(q) = market value of equity at the end of quarter q.
LSY	= an indicator if IBQ(q) is negative during q, q-1, q-2, or q-3.
STDEV_SGI	= natural log of the standard deviation of SGI over the previous 6 years (minimum of 15 observations).
STDEV_CHGEPS	= natural log of the standard deviation of CHGEPS over the previous 6 years (minimum of 15 observations).
SVAL	= natural log of the average absolute monthly return over the three months following the month when the firm's earnings announcement occurs.
E[SVAL]	= predicted SVAL based on coefficients from Equation (1) estimated over the prior two years using only data available prior to the firm's earnings announcement.
SRET	= monthly return to a straddle position initiated in firm i at time t.
HVOL	= natural log of historical volatility, where historical volatility is estimated using daily returns over the year preceding the month when the trading strategy is initiated. The standard deviation of daily returns is transformed in an annual standard deviation by multiplying it by the square root of 252.
IVOL	= natural log of implied volatility where implied volatility is downloaded from Optionmetrics.
DIFF_HVOL	= HVOL – IVOL
REAL_SVAL	= natural log of the absolute value of the buy and hold return over the straddle position window.
DIFF_FUND	= Residual value from Equation (3), which is a regression of E[SVAL] on IVOL and HVOL that is estimated monthly.
ASK_BID	= scaled decile rank of bid–ask spread for traded options, where the bid–ask spread is the difference between the highest closing bid and the lowest closing ask scaled by the mid-point of these two.
VOLUME	= scaled decile rank of volume of traded options, where dollar volume is option trade volume multiplied by the midpoint of the highest closing bid and the lowest closing ask prices.
MVE	= scaled decile rank of market value of equity from the end of the

		most recent fiscal quarter.
COVERAGE	=	scaled decile rank of the count of analysts covering the firm.
EA_DUM	=	indicator that a given straddle contract contain an earnings announcement.

Figure 1 - Timeline

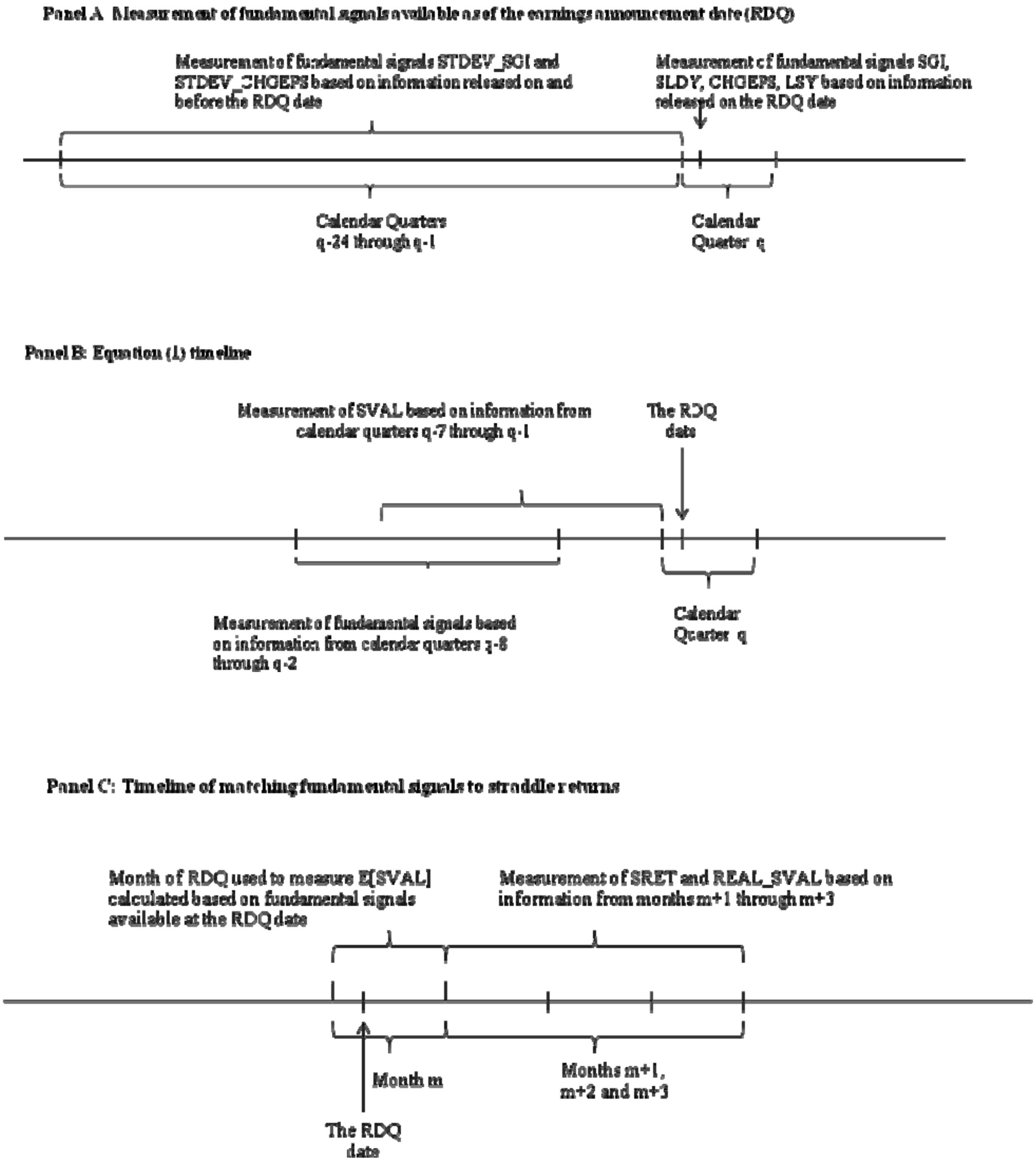
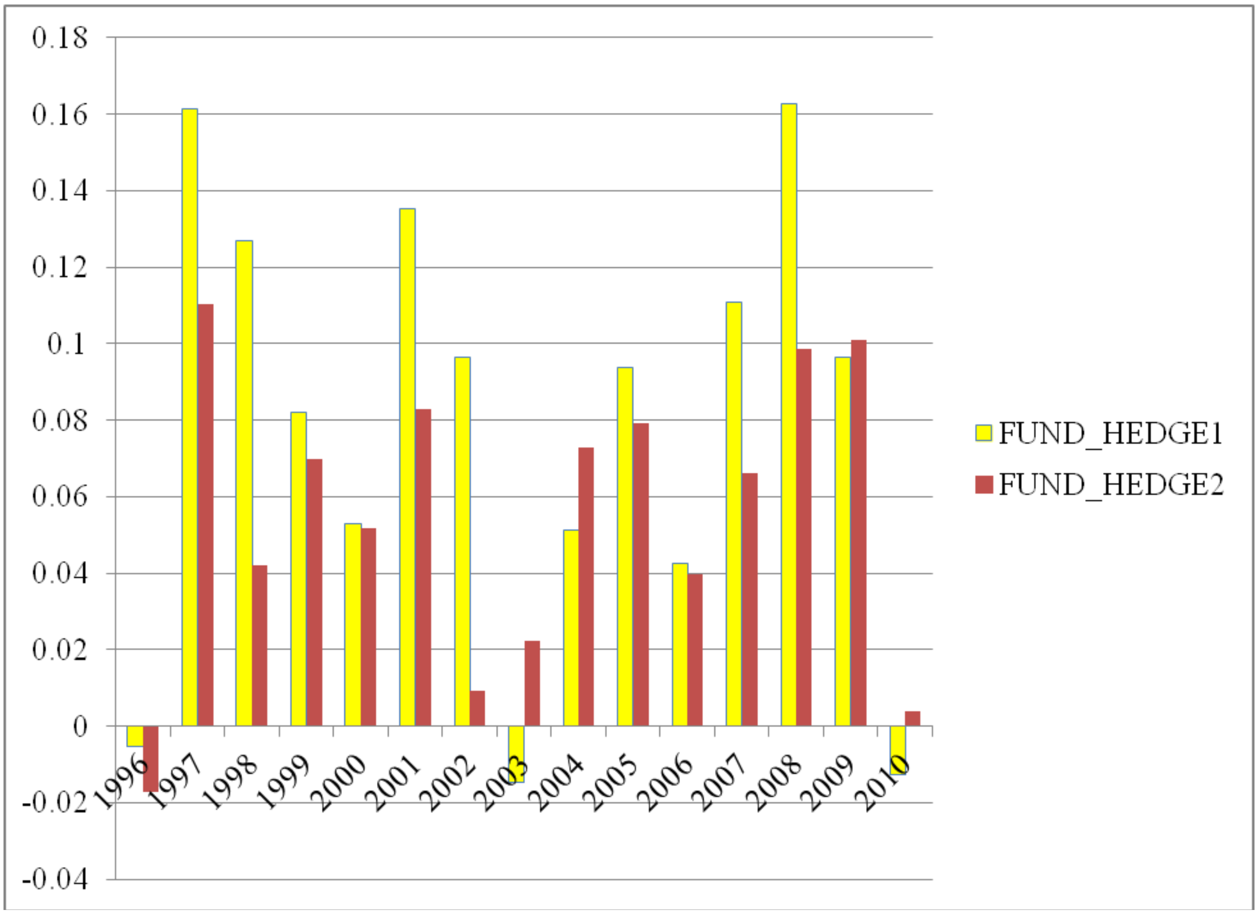
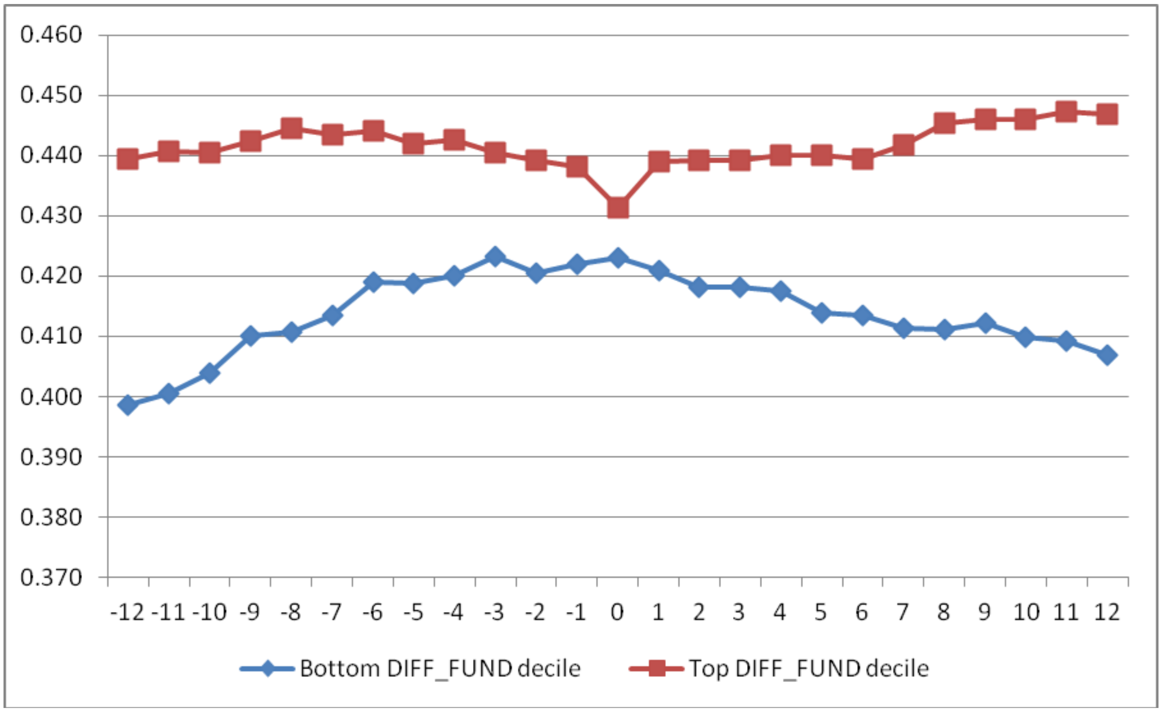


Figure 2 Average monthly returns to fundamental-based hedge portfolios over time



This figure provides the average monthly return to the hedge portfolio over time. Each month, we sort straddle options into ten deciles based on our fundamental score (DIFF_FUND). FUND_HEDGE1 (FUND_HEDGE2) is a hedge portfolio based on the top and bottom decile (three deciles) of DIFF_FUND.

Figure 3 The time series pattern of implied volatility around the portfolio formation date



This figure provides the average implied volatility for the top and bottom DIFF_FUND deciles from 12 months before the portfolio formation date to 12 months after.

Table 1
The association between fundamental signals and future stock return volatility

Panel A: Average distributions of dependent and independent variables from Equation (1)

Variable	Mean	STDEV	Q1	Median	Q3
SVAL	-2.593	0.714	-3.050	-2.564	-2.098
SGI	0.126	0.320	-0.025	0.078	0.211
SLDY	0.300	0.449	0.000	0.033	0.733
CHGEPS	0.003	0.048	-0.006	0.002	0.009
LSY	0.382	0.484	0.000	0.017	1.000
STDEV_SGI	-1.535	0.930	-2.169	-1.622	-1.042
STDEV_CHGEPS	-3.773	1.326	-4.705	-3.853	-2.919

Panel B: Correlation matrix (Pearson upper triangle, Spearman lower triangle)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) SVAL	1.000	0.040	0.060	0.010	0.260	0.240	0.290
(2) SGI	0.020	1.000	-0.560	0.180	-0.090	0.180	0.010
(3) SLDY	0.060	-0.780	1.000	-0.140	0.230	0.070	0.120
(4) CHGEPS	0.010	0.370	-0.300	1.000	-0.080	0.030	0.080
(5) LSY	0.260	-0.180	0.230	-0.160	1.000	0.270	0.360
(6) STDEV_SGI	0.250	0.100	0.070	0.030	0.270	1.000	0.400
(7) STDEV_CHGEPS	0.310	-0.050	0.130	0.060	0.380	0.430	1.000

Panel C: Estimated parameters from60rolling models predicting SVAL

$$SVAL= \theta_0 +\theta_1 SGI + \theta_2 SLDY + \theta_3 CHGEPS + \theta_4 LSY + \theta_5 STDEV\_SGI + \theta_6 STDEV\_CHGEPS + error \quad (1)$$

Variable	Mean	STDEV	Q1	Median	Q3
Intercept	-2.210	0.139	-2.288	-2.203	-2.114
Coefficient on SGI	0.104	0.061	0.065	0.117	0.147
Coefficient on SLDY	0.034	0.056	-0.011	0.030	0.073
Coefficient on CHGEPS	0.028	0.574	-0.029	0.173	0.325
Coefficient on LSY	0.234	0.055	0.190	0.224	0.291
Coefficient on STDEV_SGI	0.085	0.029	0.071	0.082	0.107
Coefficient on STDEV_CHGEPS	0.097	0.020	0.079	0.102	0.113
R^2 over estimation period	0.130	0.021	0.111	0.126	0.151
Number of Observations	22,117	2,374	19,796	22,725	23,894

Panel D: Out-of-sample analysis association between future SVAL and E[SVAL]

	Groups based on E[SVAL]			
	Low N=65,246	Medium N=65,291	High N=65,263	High vs. Low Test statistic
Mean SVAL	-2.858	-2.592	-2.274	147.87
Median SVAL	-2.825	-2.556	-2.239	141.30

Table 1 provides descriptive statistics on the variables used to estimate the association between accounting signals and the magnitude of future stock price movements (Equation (1)), the estimated coefficients, and the out-of-sample properties of the predicted values. SVAL is natural log of the average absolute month returns over three months following the month of earnings announcement. E(SVAL) is predicted SVAL based on Equation (1). SGI is sales growth. SLDY is an indicator for cases where SGI is negative. CHGEPS is earnings surprises. LSY is an indicator for negative earnings. STDEV_SGI is the standard deviation of SGI. STDEV_CHGEPS is the standard deviation of CHGEPS. Please see Appendix for detailed variable definitions. Equation (1) is estimated using 60 rolling window samples composed of firms with sufficient Compustat and CRSP data to calculate the dependent and independent variables in Equation (1). The top and bottom 1% of all variables in Panel A are winsorized in each estimation sample. Panel A presents descriptive statistics for the variables used to estimate Equation (1). Panel B presents the univariate correlations between the variables used to estimate Equation (1). Both Panels A and B reflect average values that are averaged across the 60 samples that are used to estimate Equation (1). Panel C presents descriptive statistics on the coefficient estimates of Equation (1) across the different estimation samples. Panel D presents evidence on the association between out-of-sample predicted values and realized return movements. In Panel D the test statistic for a High vs. Low difference in means (medians) is a t-statistic (Wilcoxon Z-statistic).

Table 2
Descriptive statistics

Panel A: Descriptive statistics

Variable	Mean	STDEV	Q1	Median	Q3
SRET	-0.023	0.820	-0.627	-0.203	0.375
IVOL	-0.996	0.440	-1.300	-1.004	-0.701
HVOL	-0.968	0.464	-1.301	-0.981	-0.653
DIFF_HVOL	0.026	0.264	-0.138	0.010	0.167
E[SVAL]	-2.684	0.330	-2.929	-2.700	-2.460
REAL_SVAL	-2.960	1.292	-3.559	-2.758	-2.137

Panel B: Models to estimate abnormal levels of E[SVAL]

$$E[SVAL] = \gamma_0 + \gamma_1 IVOL + \gamma_2 DIFF\_HVOL + error \quad (2)$$

Independent variable	Coefficient (t-stat)
Intercept	-2.362 (-79.74)
IVOL	0.319 (11.23)
DIFF_HVOL	0.201 (3.60)
R^2	0.230
N (per monthly regression)	477

Panel C: Correlation matrix (Pearson upper triangle, Spearman lower triangle)

Variable	(1)	(2)	(3)	(4)	(5)	(6)
(1) SRET	1.000	-0.011	-0.009	0.003	0.028	0.599
(2) IVOL	-0.013	1.000	0.824	-0.202	0.000	0.324
(3) HVOL	-0.009	0.827	1.000	0.382	0.005	0.266
(4) DIFF_HVOL	0.010	-0.171	0.359	1.000	0.000	-0.063
(5) DIFF_FUND	0.023	0.015	0.021	-0.001	1.000	0.012
(6) REAL_SVAL	0.768	0.386	0.325	-0.062	0.026	1.000

Table 2 presents descriptive statistics on the 84,488 firm-months in our main sample. SRET is straddle option returns. IVOL is implied volatility. HVOL is historical volatility. DIFF_HVOL is the difference between HVOL and IVOL. E(VAL) is predicted absolute value of monthly price movement over three months following the month of earnings announcement. E[SVAL] is the predicted value from Equation (1), using coefficients estimated from historical data. DIFF_FUND is calculated as the residual from Equation (2) that is estimated monthly. REAL_SVAL is the natural log of the absolute value of equity returns during the straddle window. Panel A presents univariate descriptive statistics. Panel B presents average coefficient and average t-statistic from the monthly regressions to estimate Equation (2). Panel C presents univariate correlations between the main variables used in this study. The top and bottom 1% of all variables (except SRET) are winsorized each month. Please see Appendix for detailed variable definitions.

Table 3
Portfolio analysis

Deciles	(A) Portfolio Returns reported in Table 3 of Goyal and Saretto (2009)	(B) Replication of Goyal and Saretto (2009) based on sample firms (DIFF_HVOL)	(C) Portfolios based on fundamental signals (DIFF_FUND)
D1	-0.128	-0.128	-0.058
D2	-0.078	-0.057	-0.042
D3	-0.057	-0.045	-0.043
D4	-0.033	-0.039	-0.032
D5	-0.018	-0.018	-0.017
D6	-0.010	0.004	-0.023
D7	-0.002	-0.014	-0.022
D8	0.007	-0.004	-0.003
D9	0.027	0.017	0.008
D10	0.099	0.074	0.022
HEDGE1 (D10-D1)	0.227	0.201 (9.63)	0.080 (5.36)
HEDGE2 (Top three – Bottom three)	0.132	0.105 (8.39)	0.056 (5.54)

Table 3 presents evidence on the performance of hedge returns arising from to straddle positions. For comparison to prior work, Column (A) presents statistics of the DIFF_HVOL strategy from Goyal and Saretto (2009). Column (B) replicates Goyal and Saretto's results using our sample data. Column (C) presents portfolio results based on the fundamental score DIFF_FUND. IVOL is implied volatility. HVOL is historical volatility. DIFF_HVOL is the difference between HVOL and IVOL. DIFF_FUND is the residual fundamental score after controlling for IVOL and HVOL (Equation (2)). More positive (negative) values of DIFF_FUND indicate observations where the expected price movement based on fundamental signals is larger (smaller) than would be predicted based on historical or implied volatility. HEDGE1 (HEDGE2) is a hedge portfolio based on the top and bottom decile (three deciles). All other variables are defined in Appendix A.

Table 4
Evaluation of monthly returns from fundamental analysis portfolios

Panel A: Returns to fundamental analysis portfolios and risk factors

$$FUND\_HEDGE = \alpha + bMKT\_RF + sSMB + hHML + mUMD + error \quad (3)$$

	FUND_HEDGE1		FUND_HEDGE2	
Independent variables	Risk data In month t	Risk data In month t+1	Risk data In month t	Risk data In month t+1
Intercept	0.086 (5.38)	0.084 (5.35)	0.058 (5.40)	0.054 (5.06)
MKT_RF	-0.103 (-0.28)	-0.416 (-1.16)	0.228 (0.93)	0.076 (0.31)
SMB	-0.036 (-0.08)	-0.286 (-0.66)	0.146 (0.49)	0.034 (0.12)
HML	-0.276 (-0.58)	0.522 (1.11)	-0.063 (-0.19)	0.785 (2.46)
UMD	-0.032 (-0.11)	-0.027 (-0.10)	-0.114 (-0.60)	0.154 (0.82)
R^2	0.002	0.034	0.016	0.040

Panel B: Distribution of FUND_HEDGE returns

	FUND_HEDGE1	FUND_HEDGE2
Percent of months with returns less than 0%	37.9%	36.7%
Percent of months with returns less than -10%	16.4%	10.7%
Percent of months with returns less than -20%	6.8%	1.7%
Percent of months with returns less than -30%	2.3%	0.0%
Percent of months with returns less than -40%	1.1%	0.0%
Percent of months with returns less than -50%	0.0%	0.0%

Table 4 presents an examination of whether a fundamental-based trading strategy exposes option investors to systematic risks. Panel A presents evidence on the association between hedge returns and common risk factors, where the intercept (or alpha) measures abnormal performance. The monthly risk factors (MKT_RF, SMB, HML, and UMD) in Equation (4) are obtained from Ken French's website. T-statistics are in parenthesis. Panel B examines the frequency and magnitude of negative returns to this hedge portfolio strategy. DIFF_FUND is the residual fundamental score after controlling for IVOL and HVOL (Equation (2)). FUND_HEDGE1 (FUND_HEDGE2) is a hedge portfolio based on the top and bottom decile (three deciles) of DIFF_FUND. All other variables are defined in Appendix A.

Table 5
Regressions predicting the cross-section of straddle returns

SRET $= a_0 + a_1$RANK_DIFF_FUND $+ a_2$ RANK_DIFF_HVOL + error (4a)
SRET $= a_0 + a_1$RANK_E[SVAL] $+ a_2$RANK_HVOL $+ a_3$RANK_IVOL + error (4b)
SRET $= a_0 + \sum a_k$RANK_SIGNAL$_{k,}$ $+ a_2$RANK_HVOL $+ a_3$RANK_IVOL + error (4c)

Panel A: Estimates of equation (4a)

Independent variables	A	B	C
Intercept	-0.060 (-2.92)	-0.093 (-5.84)	-0.129 (-7.92)
RANK_DIFF_FUND	0.078 (5.68)		0.072 (5.73)
RANK_DIFF_HVOL		0.143 (8.84)	0.145 (8.96)
R^2	0.006	0.009	0.014
N (per monthly regression)	477	477	477

Panel B: Estimates of equation (4b)

Independent variables	A	B	C
Intercept	-0.056 (-3.00)	-0.033 (-1.31)	0.054 (2.18)
RANK_E[SVAL]	0.070 (5.62)		0.083 (6.13)
RANK_HVOL		0.271 (9.03)	0.249 (8.14)
RANK_IVOL		-0.248 (-7.12)	-0.266 (-7.61)
R^2	0.005	0.020	0.025
N (per monthly regression)	477	477	477

Panel C: Estimates of equation (4c)

Independent variables	A	B
Intercept	-0.083 (-3.56)	-0.078 (-3.02)
RANK_SGI	0.044 (2.52)	0.043 (2.46)
SLDY	0.014 (1.12)	0.013 (1.01)
RANK_CHGEPS	-0.011 (-0.90)	-0.005 (-0.44)
LSY	0.015 (1.71)	0.018 (2.18)
RANK_STDEV_SGI	0.024 (1.74)	0.026 (1.82)
RANK_STDEV_CHGEPS	0.047 (3.57)	0.055 (5.03)
RANK_HVOL		0.245 (8.03)
RANK_IVOL		-0.270 (-7.69)
R^2	0.025	0.045
N (per monthly regression)	477	477
Sum of coefficients on fundamental signals	0.133 (4.40)	0.150 (4.56)

Table 5 presents multivariate regression analysis of the association between fundamental signals and straddle returns. Panel A presents regression models that include measures that are adjusted relative to implied volatility (DIFF_HVOL, DIFF_FUND). Panel B presents regression models that contain signals of volatility (RANK_HVOL and RANK_E[SVAL]) and implied volatility (RANK_IVOL). Panel C presents evidence on the association between individual fundamental signals (components of E[SVAL]) and straddle returns. All independent variables are transformed into scaled decile ranks except SLDY and LSY, which are indicator variables. The t-statistics in this table are based on Fama-MacBeth regressions. All other variables are defined in Appendix A.

Table 6
Cross-sectional variation in fundamental analysis portfolios

$$SRET = a_0 + a_1RANK\_DIFF\_FUND + a_2RANK\_DIFF\_HVOL + a_3X + a_4X*RANK\_DIFF\_FUND + a_5X*RANK\_DIFF\_HVOL + error \quad (5)$$

Independent variables	(A) X=ASK_BID	(B) X=VOLUME	(C) X=MVE	(D) X=COVERAGE	(E) X=EA_DUM
Intercept	-0.094 (-4.46)	-0.122 (-5.61)	-0.124 (-6.53)	-0.150 (-7.85)	-0.180 (9.46)
RANK_DIFF_FUND	0.062 (3.04)	0.044 (2.36)	0.043 (2.26)	0.085 (4.82)	0.100 (6.54)
RANK_DIFF_HVOL	0.090 (3.36)	0.156 (7.47)	0.190 (8.66)	0.198 (9.20)	0.156 (9.09)
X	-0.063 (-2.37)	-0.004 (-0.18)	-0.006 (-0.25)	0.048 (2.30)	0.123 (5.08)
X*RANK_DIFF_FUND	0.016 (0.52)	0.049 (1.55)	0.049 (1.60)	-0.036 (-1.33)	-0.073 (-2.24)
X*RANK_DIFF_HVOL	0.095 (2.61)	-0.035 (-1.04)	-0.085 (-2.50)	-0.110 (-3.32)	0.027 (0.81)
R^2	0.027	0.026	0.028	0.025	0.027
N (per monthly regression)	477	477	477	477	477

Table 6 presents an examination of the cross-sectional variation in the association between fundamental signals (RANK_E[SVAL]) and straddle returns. Each column reports a separate regression model where the sample is partitioned based on a given firm characteristic (X) and the coefficients in the model are allowed to vary with the firm characteristic through a main effect and interaction terms. Each column presents the average coefficient and the absolute value of the corresponding Fama-MacBeth t-statistic below in parenthesis. All other variables are defined in Appendix A.

Table 7
Combinations of trading strategies and the role of transaction costs

Panel A: Hedge Returns before transaction costs from individual and combined trading strategies

Variable	Average return before transaction cost	t-statistic
HVOL_HEDGE1	0.201	9.63
FUND_HEDGE1	0.080	5.36
HEDGE1_BOTH	0.283	9.49
HEDGE1_NOT_BOTH	0.167	7.37

Panel B: Hedge Returns after transaction costs from individual and combined trading strategies

Variable	Average return after transaction cost	t-statistic
HVOL_HEDGE1	0.005	0.21
FUND_HEDGE1	-0.093	-5.90
HEDGE1_BOTH	0.075	2.35
HEDGE1_NOT_BOTH	-0.025	-1.04

Table 7 presents an examination of the returns from trading strategies that combine both the DIFF_HVOL and DIFF_FUND signals and the role of transaction costs. HVOL_HEDGE1 (FUND_HEDGE1) is the return to a hedge portfolio that purchases straddles when DIFF_HVOL (DIFF_FUND) is in the top decile and sells straddles that are in the bottom decile of DIFF_HVOL (DIFF_FUND). BOTH_HEDGE1 is calculated as LONG1_BOTH – SHORT1_BOTH, where LONG1_BOTH (SHORT1_BOTH) is the return on stocks that are in the top (bottom) decile of DIFF_HVOL and also the top (bottom) 33 percent of DIFF_FUND conditional on the decile of DIFF_HVOL. HEDGE1_NOT_BOTH is calculated as LONG1_NOT_BOTH – SHORT1_NOT_BOTH, where LONG1_NOT_BOTH (SHORT1_NOT_BOTH) is the return on stocks that are in the top (bottom) decile of DIFF_HVOL and also the bottom (top) 67 percent of DIFF_FUND conditional on the decile of DIFF_HVOL. Panel A presents the returns before transaction costs. Panel B presents the returns after transaction costs. Transaction costs are incorporated into the straddle returns by assuming that long positions are acquired by purchasing the straddle at the ask price and short positions are acquired by selling straddle contracts at the bid price.