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Exploiting Option Information in the Equity Market

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ABSTRACT

Public option market information contains exploitable information for equity investors for an investable universe of liquid large-cap stocks. Strategies based on several option measures predict returns and alphas on the underlying stock. Transaction costs are an important factor given the high turnover of these strategies, but significant net alphas can be obtained when using a simple transaction cost reducing approach. These findings suggest that information diffuses from the option market into the underlying stock market.

Key words: stock selection, behavioral finance, alpha strategies, equity returns, option markets, stock markets, information spillover, asset pricing.
JEL: G11, G12

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1 Introduction

In this paper we examine whether public information contained in the option market predicts cross-sectional stock returns for a well-investable universe of highly liquid U.S. large-cap stocks and thus provides valuable, exploitable information for equity investors. Equity options have become an increasingly popular investment alternative over the past decades. They have asymmetric payoff characteristics and allow investors to take highly leveraged positions, making them important instruments for speculation or hedging. Options allow investors to take a view on the price development and risk of the underlying stocks. In fact, option prices reflect the expectations and worries investors have about future stock-price developments. Therefore, many practitioners view the equity option market as a primary source of information about the expected return, risk and sentiment of individual stocks and the equity market in general. The question is whether this public information also provides valuable information to investors. That is, can investors exploit this information?

Standard economic theory suggests not. In complete markets options are redundant securities and the public information they contain should already be reflected in the prices of other assets. Moreover, in efficient markets stock prices should adjust immediately to public information. However, empirical work and intuition suggest otherwise. Empirical studies generally find that options are non-redundant securities (see for example Buraschi and Jackwerth (2001)). Intuitively, the option market may lead the equity market if an investor with positive or negative information on a stock chooses to invest in the option market rather than in the stock itself. For example, Black (1975) argues that traders prefer to exploit private information by trading in the option market, because the option market provides reduced transaction costs, increased financial leverage and a lack of short selling constraints. If equity-market investors fail to trade on this information a lead-lag relationship will emerge between the option market and stock market. In fact, Hong and Stein (1999) argue that information diffuses gradually into and across markets, a finding empirically confirmed by Hong, Torous and Valkanov (2007)[1]. Similarly, Chakravarty, Gulen and Mayhew (2004) find that the equity option market contains information that is

[1] More specific, Hong, Torous and Valkanov (2007) find that information diffuses from several industry stock indices into the remainder of the stock market for up to two months.

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later on reflected in stock prices. These findings suggest that publicly available information contained in the option market affects future stock prices, causing stock return predictability.

Indeed, several recent studies propose option market measures that contain economically and statistically significant information for subsequent returns on the associated stocks. Xing, Zhang and Zhao (2010) employ the difference between the implied volatilities of out-of-the-money put and at-the-money call options, commonly referred to as the out-of-the-money volatility skew, a measure that reflects the (informed) worries investors have about negative price movements. They find that stocks with the largest skew underperform stocks with the smallest skew. Bali and Hovakimian (2009), and Goyal and Saretto (2009) utilize the difference between realized and implied volatilities, a measure that captures the volatility risk of a stock. They find that a strategy that buys stocks with the lowest realized versus implied volatility spread and shorts stocks with the highest spread produces significant positive returns. Bali and Hovakimian (2009) and Cremers and Weinbaum (2010) employ the spread between implied volatilities of at-the-money put versus call options, also known as the at-the-money volatility skew, which they argue captures the trading activity of informed investors or jump risk. Stocks with a low spread (i.e. stocks that have higher call than put implied volatilities) outperform stocks with a high spread. In addition, Cremers and Weinbaum (2010) employ the recent change in the spread between the implied volatilities of at-the-money put and call options, which might capture the change in informed trading, and find a negative relation with stock returns.

The aforementioned studies reveal strong predictive power of public option market information for stock returns between 1996 and 2005. However, all studies focus on a broad universe of stocks, which might not be exploitable for most practitioners due to their liquidity constraints and needs. In addition, they do not analyze the impact of transaction costs when evaluating the profitability. Moreover, some of the studies show a declining performance towards the end of their sample and omit the highly volatile period around the subprime crisis, a period in which many equity funds were closed. Given the relatively short sample period of the papers on this topic, these extra years are highly relevant. Hence, from a practitioner's perspective, the added value of these studies is yet unclear.

In this paper we examine whether the above four measures: i) out-of-the-money volatility skew, ii) realized versus implied volatility spread, iii) at-the-money volatility skew, and iv) the change in the at-the-money volatility skew, provide valuable information

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that is exploitable by equity investors. For this end, we (i) study these strategies on a well-investable universe of U.S. large caps, i.e. the stocks that are most interesting for practitioners due to their liquidity, (ii) extend the sample period to include the recent, volatile crisis period, (iii) examine the combined predictive power of the aforementioned variables in an integrated option information strategy (as from a practitioner's perspective it is important to know whether performance improves when combining the individual variables), and (iv) thoroughly analyze the impact of transaction costs. In addition, we examine the robustness of the strategy in different market conditions, as well as its interaction with information uncertainty.

Our findings are as follows. We find that publicly available information in the option market has been relevant for equity investors. Trading strategies based on the out-of-the-money volatility skew, realized versus implied volatility spread, at-the-money volatility skew, and the change in the at-the-money volatility skew all yield significant returns and alphas, using a well-investable universe of liquid large caps. Although some studies report that the predictive power decreases over time until 2004-2005, we also find significant returns in the recent crisis years, which can serve as out-of-sample evidence. Combining all four variables into a combined option information strategy yields even larger profit opportunities of 10% per year for the long-short portfolio, thereby strengthening the relevance of the publicly available information contained in option prices for equity investors. These results are robust over bull, bear, volatile and calm markets and are generally of similar magnitude for stocks with low or high information uncertainty. Furthermore, the documented anomalies are at least as strong when applied to the 100 largest U.S. stocks. Exploiting the option information measures requires an extremely high turnover. As a consequence, all profitability is estimated to be consumed by transaction costs on our investable universe. However, still more than half of the documented profitability persists for a strategy based on only the 100 largest stocks when we take simple steps to control the transaction costs of managing the portfolio. The net return is economically strong and statistically significant with a value of above 7% per year for the long-short portfolio. This leads us to conclude that the documented strategies are exploitable by practitioners.

In the remainder of this paper we will provide more detail on these results. Section 2 describes the option measures and our well-investable stock universe. Section 3 outlines the methodology. Section 4 reports the results of each of the four individual variables, the

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results of the combined option information strategy, its results over market conditions and information uncertainty portfolios, and the impact of transaction costs. Finally, Section 5 concludes.

2 Data and option market measures

This section describes first our data sample, followed by the option measures we employ, and the descriptive statistics of our sample and variables.

2.1 Sample

To examine the investability of the option information strategies, we limit our universe to the 1,250 largest stocks in the S&P/Citigroup U.S. Broad Market Index during the period between January 1996 and October 2009. This corresponds to a minimum market capitalization of approximately USD 1 billion in 2009, resulting in highly liquid stocks that can easily be traded at limited transaction costs. This requirement makes the stocks investable for many equity investors. Daily stock returns, including dividends and market capitalizations, are retrieved from FactSet Prices and accounting data from Compustat.

For the stocks in this universe we extract option data from OptionMetrics, which contains end-of-day bid and ask quotes, open interests and trading volumes for all equity options traded in the U.S. For individual equity options, which are American, OptionMetrics calculates implied volatilities and Greeks using a binominal-tree model based on the algorithm of Cox, Ross, and Rubinstein (1979). This algorithm copes with discrete dividend payments and the possibility of early exercise. We apply the following screens on all options to ensure that we select liquid and heavily traded options that we believe contain the most reliable information. We filter out options with zero volume or open interest. As most activity in options is concentrated in the short end, we select options with a remaining maturity of approximately one month by requiring a maturity between 10 and 40 trading days. We follow Xing *et al.* (2010) when separating options into at-the-money (ATM) and out-of-the-money (OTM). A put or call option is defined as ATM when the ratio of the strike price to the stock price is between 0.95 and 1.05 and a put option as OTM

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when the ratio is lower than 0.95, but higher than 0.80. When multiple options fall into the same group, we select options with moneyness closest to 1.00 (ATM) or 0.95 (OTM).[2]

2.2 Option measures

The first option market measure we employ is the OTM volatility skew, which is thought to reflect worries about negative price movements, for example due to an informational advantage (Xing *et al.* (2010)). For example, Gârleanu, Pedersen and Poteshman (2009) argue that companies for which investors have relatively pessimistic perceptions, investors would tend to buy put options either for protection against, or speculation on future stock price drops. This increase in the demand for put options leads to a higher price and implied volatility, yielding a steeper volatility smile. Stocks with a high volatility skew should therefore underperform stocks with a lower skew. Following Xing *et al.* (2010), we compute the OTM volatility skew as follows:

$$SKEW_{i,t}^{OTM} = IV_{i,t}^{OTMP} - IV_{i,t}^{ATMC} \quad (1)$$

where $IV_{i,t}^{OTMP}$ ($IV_{i,t}^{ATMC}$) denotes the implied volatility of the OTM put (ATM call) option on stock i in week t. We use the weekly average of the IV variables to reduce the effect of noise, while requiring at least two non-missing values during the past five days to compute the measure.

The second measure is the realized (historical) versus implied volatility spread, which is thought to capture the volatility risk of a stock; Bali and Hovakimian (2009) show that stocks with a higher spread between realized and implied volatility have higher volatility risk. Moreover, Bakshi and Kapadia (2003a, 2003b) show that the realized versus implied volatility spread bears a negative volatility risk premium. Stocks with a high realized versus implied volatility spread should therefore underperform. We measure the realized versus implied volatility spread by the difference between the realized volatility of the past 20 daily stock returns and the implied volatility:

$$RVIV_{i,t} = RV_{i,t} - IV_{i,t}^{ATM} \quad (2)$$

[2] We also replicated our analysis using 0.925 as the OTM boundary, which does not change our conclusions.

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where $RV_{i,t}$ is the realized volatility of stock i measured in week t and $IV_{i,t}^{ATM}$ is the average of the implied volatility of the ATM call and ATM put option on stock i in week t. As before, we employ a weekly average of the IV values to reduce the effect of noise. We require at least two non-missing values during the past five days to compute the measure.

The third measure is the ATM volatility skew, which relates to the trading activity of informed investors and jump premia. Bali and Hovakimian (2009) and Cremers and Weinbaum (2010) argue that more informed trading activity of pessimistic (optimistic) investors and lower (higher) positively priced jump risk lead to higher (lower) implied volatilities of ATM put as compared to ATM call options. Stocks with a high ATM volatility skew should therefore underperform. We take the difference between the implied volatilities of ATM put and call options as our ATM volatility skew measure:

$$SKEW_{i,t}^{ATM} = IV_{i,t}^{ATMP} - IV_{i,t}^{ATMC} \tag{3}$$

where $IV_{i,t}^{ATMP}$ denotes the implied volatility of the ATM put option on stock i in week t. As before, we take the weekly average of the IV variables to reduce the effect of noise, and we require at least two non-missing values during the past five days to compute the measure.

The fourth measure is the change in the ATM volatility skew, which is thought to reflect the change in informed trading. For example, Cremers and Weinbaum (2010) argue that an increase in the informed trading activity of pessimistic (optimistic) investors is likely to result in an increasing (decreasing) spread between the implied volatilities of ATM put and call options, which therefore should predict lower (higher) stock returns. Since we focus on a weekly frequency, we compute the change in the ATM volatility skew variable as the weekly change in the volatility spread between the ATM put and call options:[3]

$$\Delta SKEW_{i,t}^{ATM} = SKEW_{i,t}^{ATM} - SKEW_{i,t-1}^{ATM} \tag{4}$$

[3] One may argue that our measures are biased towards highly volatile stocks. Therefore, we additionally investigate a relative (instead of absolute) definition of these variables. This does not affect our conclusions reported in the following sections, albeit the results become slightly weaker.

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A remark seems to be in order here about the above option measures. We prefer to use a consistent methodology for all option measures. As a consequence, our definitions of the measures differ slightly from the ones employed by previous studies, due to the use of different option screens, the use of weekly averages to reduce the effect of noise, or our focus on weekly investment frequencies. For example, besides the use of different option screens in the studies, our measures for $RVIV$ and $SKEW^{ATM}$ differ from the measures proposed by Bali and Hovakimian (2009), who employ an average of all near-the-money call and put options at the end of a month. Similarly, our measures for $SKEW^{ATM}$ and $\Delta SKEW^{ATM}$ differ from the ones put forward by Cremers and Weinbaum (2010), who employ the open-interest weighted average difference between the implied volatilities of the call and put options across several option pairs with the same strike and maturity, and its daily change. These choices are however unlikely to be important, since our definitions capture the same economic ideas as the original measures proposed by the aforementioned studies.

2.3 Descriptive statistics

Panel A of Table 1 presents the coverage statistics of the option measures averaged for each week in our sample (Average), at the start of our sample (Start), and at the end of our sample (End).[4] The following points emerge. First, the coverage for the $SKEW^{OTM}$ is the lowest, with on average 619 out of the 1,250 stocks covered, as the availability of out-of-the-money option data is lower compared to at-the-money option data. Second, the coverage increases over our sample for all option measures. Third, the coverage is already substantial at the start of our sample period, witnessing coverage between 317 stocks (for $SKEW^{OTM}$) and 625 stocks (for $RVIV$). Fourth, when we investigate a strategy that combines the option variables, we require at least one option variable to be available, which leads to an average coverage of 901 stocks, starting with 690 stocks at the beginning and 1045 stocks at the end of our sample period.[5]

[Insert Table 1 about here]

[4] The Start and End figures are very much in line with the lowest and highest coverage percentiles.

[5] Note that the requirement of all four variables having data available would lead to a lower coverage of on average 546 stocks. This additional requirement however does not alter our conclusions. Results are available from the authors upon request.

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Panel B of Table 1 reports the descriptive statistics for the stocks and options included in our universe. Shown are the time-series averages of the cross-sectional means, standard deviations and quartiles. The first two rows of the table report the market capitalizations and book-to-market ratios of the companies included in our universe for which option information is available. As expected, the firms in our universe are large compared to the average firm listed on NYSE/AMEX/NASDAQ. The average (median) market capitalization equals USD 9.19 (USD 3.33) billion, compared to average (median) values of USD 2.19 (USD 0.17) billion for all stocks on NYSE/AMEX/NASDAQ and USD 7.53 (USD 2.13) billion for all stocks on the NYSE/AMEX/NASDAQ with information available in OptionMetrics over the same time period. The next rows describe our option measures. The $SKEW^{OTM}$ is 4.72% on average, the $RVIV$ is on average negative (-0.82%), the $SKEW^{ATM}$ is on average a positive 0.79% and the $\Delta SKEW^{ATM}$ is on average 0.00% per week. All these measures display substantial variability over the cross-section, witnessing average standard deviations between 2.08% ($SKEW^{ATM}$) and 10.67% ($RVIV$).

Panel C of Table 1 reports the average rank correlations between our four option price variables. All variables have low to moderate correlations with each other. Most notably, high values of $SKEW^{ATM}$ tend to coincide with high past week $\Delta SKEW^{ATM}$ witnessing their positive correlation of 53%. Similarly, $SKEW^{ATM}$ values tend to correlate with $SKEW^{OTM}$ values (43%), as also found recently by Doran and Krieger (2010).[6] These numbers indicate there might be some information overlap in the option variables, to which we will pay special care in the analyses reported in Section 4.2. The overlap, however, does not affect our conclusions concerning the exploitability of publicly available option market information by practitioners.

3 Methodology

To evaluate the information contained in option prices we employ the following procedure. Every Tuesday, we measure each variable given the latest close information

[6] Doran and Krieger (2010) note that $SKEW^{OTM}$ consists partly of the $SKEW^{ATM}$ and argue the use of $DKSKEW_{i,t}^{OTM} = IV_{i,t}^{OTMP} - IV_{i,t}^{ATMP}$ to capture crash worries. We have also investigated their measure, which does not affect subsequent conclusions about the relevance of publicly available option market information for equity investors. Section 4.2 discusses the results in more detail.

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from the option market.[7] Subsequently, we sort firms on each variable and form five quintile portfolios, from quintile 1 (Q1) to quintile 5 (Q5). Q1 (Q5) contains the stocks with the lowest (highest) variable value, for which we expect the highest (lowest) return. Of these portfolios we compute the equally-weighted return over the following week, since we have no micro or small caps in our sample (which are generally hard to invest in and which are therefore less interesting for practitioners), and since equally-weighted portfolios are generally better diversified on a sample of large cap stocks.[8] We stress however that the conclusions of our analyses do not change when we compute value-weighted returns, as reported in the Appendix.[9]

In our empirical analyses we include a one day lag between the strategy signals and portfolio construction. Therefore, stocks are bought at Wednesday close prices. This implementation lag allows for sufficient time to implement the portfolios, even for less technologically advanced investors, and avoids spurious findings caused by non-synchronous trading between options and stocks due to slightly different closing times of the exchanges (see Battalio and Schultz (2006)). We rebalance these portfolios every week, and calculate their returns in excess of the risk-free rate and their outperformance relative to the equally-weighted market portfolio. Moreover, we compute the performance of a long-short portfolio, computed as the return difference between the top (Q1) and bottom quintile (Q5).

Subsequently, we control for market, size, value and momentum exposures by correcting the portfolio returns for the market return, the Fama and French (1992, 1993) size (SMB) and book-to-market (HML), and the Carhart (1997) momentum (UMD) factors (retrieved from Kenneth French's website). The resulting alpha, or estimated abnormal return, of portfolio j is the constant α_j in the regression

[7] Our results are not driven by the use of Tuesday close information to construct our variables. When we compute our results for other days of the week we obtain comparable results.

[8] Moreover, for investors who manage long-short portfolios or active portfolios against a benchmark, there is no need to take active positions in line with the market cap weight of stocks, as this would imply that the absolute risk-adjusted expected return on large-cap stocks is higher than on small-cap stocks.

[9] In unreported analyses we also adjust the raw variables for their industry medians to avoid unintended industry bets (e.g. caused by negative worries about entire industries). The performances (available upon request) are in general comparable to the ones reported in the current version, but sometimes at lower volatility.

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$$r_j = \alpha_j + \beta_j \cdot r_m + s_j \cdot SMB + h_j \cdot HML + u_j \cdot UMD + \varepsilon_j \quad (5)$$

where r_j is the excess return of portfolio j, r_m the excess return on the market portfolio and β_j, s_j, h_j and u_j the estimated factor exposures. In addition, we compute CAPM alphas by only including the excess market return in (5).[10]

Furthermore, we conduct Fama and MacBeth (1973) regressions to examine the predictive power of the variables while controlling for other return predicting variables. This procedure first estimates each week a cross-sectional regression of stock returns on predicting variables to obtain estimated effects (slope coefficients) of the tested variables. To ensure comparability across variables and limit the influence of outliers, we standardize each variable each week using the approach described in detail in the next paragraph. In the second stage, the slope coefficients are averaged over time and their t-statistics are calculated. We correct the t-statistics for heteroskedasticity and autocorrelation by applying Newey-West (1987) standard errors.

After studying the predictive power of each of the four individual variables, we test their joint profitability (before and after transaction costs), in an aggregate option information strategy. To this end, we transform the values of each individual variable into a cross-sectionally standardized score (z-score) that is comparable across variables. More specifically, the z-score of a variable is constructed by subtracting its cross-sectional median from the values of the variable and dividing by its median absolute deviation. We use the median and median absolute deviation instead of the mean and standard deviation to limit the influence of outliers. The effect of outliers is further reduced by winsorizing the z-scores at values of ±3. Subsequently, we obtain the combined z-score as the simple, naïve average of all variables[11] and rank the stocks into quintile portfolios following the same methodology we used for each individual variable.

[10] Moreover, we have also computed three factor alphas that correct for market, size and value exposures, and five factor alphas that correct for market, size, value, momentum and short-term reversal exposures. These results are omitted from the tables and main text for brevity, but the results are in line with the CAPM and four factor alphas. Results are available from the authors upon request.

[11] We require at least one option variable to be available for a stock to compute the average. In addition, when a stock has no coverage on a particular variable we assign a zero, neutral z-score to that variable.

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4 Results

This section presents our results on the relevance of public information contained in option prices. We first consider the portfolio sorts based on each variable in isolation, then we show the results of Fama and MacBeth (1973) cross-sectional firm-level regressions that control for other factors that may impact returns, followed by the results of a simple combined option information strategy. Next, we analyze the performance over different market conditions, and we examine the interaction between the combined option information strategy and information uncertainty. Finally, we examine the profitability of our option information strategy when incorporating transaction costs, to determine whether our findings are caused by non-exploitable return patterns.

4.1 Individual portfolios sorts

Table 2 reports the results of sorting each of our individual option variables in five portfolios and computing the subsequent weekly returns. For each variable we show the average annualized excess returns and Sharpe ratios for the quintiles. For both the long-short and quintile portfolios we additionally show the outperformances relative to the general equity market and information ratios as defined by the ratio of outperformance and the volatility of outperformance. Additionally, we present the alphas relative to the market model (CAPM alpha) and the four-factor model (4F alpha). The asterisks *, ** and *** indicate the significance of the outperformance and alphas at a 10%, 5% and 1% significance level respectively. Quintile 1 (Q1) contains the stocks which rank lowest on a measure, while quintile 5 (Q5) contains the stocks which rank highest on a measure. Hence, Q1 is composed of stocks with the lowest OTM volatility skew, the lowest realized versus implied volatility spread, the lowest ATM volatility skew and the lowest change in the ATM volatility skew, and therefore we expect Q1 to generate higher returns than Q5. Figure 1 shows the cumulative performance of the long-short portfolios through time.

[Insert Table 2 about here]

[Insert Figure 1 about here]

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Panel A of Table 2 reveals that stocks with the lowest (highest) $SKEW^{OTM}$, i.e. the lowest (highest) crash worries, typically experience the highest (lowest) returns. Quintile portfolio 1 generates on average 5.46% a year over the risk-free rate (3.23% over the market), decreasing to a negative -1.87% (-3.96%) for quintile portfolio 5. These outcomes result in a 7.48% return a year for the Q1-Q5 long-short portfolio. These results align with the results found by Xing *et al.* (2010) on a different universe between 1996 and 2005, and are highly economically and statistically significant. The resulting 4F alpha (CAPM alpha), or abnormal return, is 7.96% (7.49%). Hence, market beta, size, value and momentum effects cannot explain the observed return spread. Figure 1 shows that the performance is economically strong in the early years of our sample, weaker in the middle years of our sample, but economically strong again during the post Xing *et al.* (2010) sample period, thereby providing out-of-sample evidence of their idea on an investable universe.

As shown in Panel B of Table 2, stocks with the lowest (highest) *RVIV*, i.e. the lowest (highest) volatility risk, typically experience the highest (lowest) returns. Quintile portfolio 1 generates on average an excess return of 5.02% a year and an outperformance over the market of 1.06%. The returns decrease to an excess return of –2.36% and outperformance of -6.04% for quintile portfolio 5. These outcomes result in an economically and statistically significant return of 7.56% a year for the long-short portfolio, which is the highest of the four strategies investigated. The resulting 4F and CAPM alphas are a highly significant 7.06% and 9.13% respectively, indicating that market, size, value and momentum effects can only explain a small fraction of the observed return spread. Our findings confirm the ideas of Bali and Hovakimian (2009) on an investable universe that extends the sample beyond December 2004. The top line in Figure 1 shows that the performance is strongest during their sample period, but also positive in the subsequent years.[12]

Panel C of Table 2 reveals that stocks with the lowest (highest) $SKEW^{ATM}$, i.e. the least pessimistic informed trading or highest jump risk premia, generally experience the highest (lowest) returns. Quintile portfolio 1 generates on average 6.83% a year over the risk-free rate (2.81% over the market), decreasing to 0.42% (-3.37%) for quintile portfolio 5. These outcomes result in a highly economically and statistically significant return of 6.40% a year for the Q1-Q5 portfolio. As for the $SKEW^{OTM}$ and *RVIV* the returns on this portfolio

[12] Unlike the other variables, the result of this variable substantially improves when applying an industry adjustment, especially during the recent crisis years.

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cannot be explained by market, size, value and momentum exposures, witnessing a 4F alpha (CAPM alpha) of 7.96% (6.51%). These results extend the ideas of Bali and Hovakimian (2009) and Cremers and Weinbaum (2010) to a well-investable universe. However, Cremers and Weinbaum show that results deteriorate over the later part of their sample period. Figure 1 shows that the performance is economically strong in the earliest years of our sample, weak around the burst of the tech bubble, but economically strong again in the more recent years not considered by the Bali and Hovakimian and Cremers and Weinbaum studies.

Finally, Panel D of Table 2 contains the results of our fourth variable, the $\Delta SKEW^{ATM}$, which proxies the change in informed trading. We may expect an increase (decrease) in the informed trading activity of optimistic (pessimistic) investors to lead to higher subsequent returns. Indeed, we find that quintile portfolio 1 generates higher returns than quintile portfolio 5 (5.55% versus 0.11%). This results in an economically and statistically significant return of 5.45% a year for the Q1-Q5 long-short portfolio. As for the previous variables, the returns on this portfolio are not explained by market, size, value and momentum exposures, witnessing a 4F alpha (CAPM alpha) of 5.52% (5.69%). Figure 1 shows that the performance is flat in the early years of our sample, but steady and economically positive since 1999, including the post Cremers and Weinbaum (2010) sample period.

The results reported in this sub-section have shown that the option strategies deliver significant results when applied to an investable universe of large-cap stocks. Apart from $RVIV$, the strategies show a stable performance in the recent crisis period. Furthermore, Figure 1 shows that the return patterns of the four variables are quite different from each other, indicating potential diversification benefits when combined in one option strategy. A correlation analysis confirms this, as the correlations (not presented in tabular form) between the weekly Q1-Q5 quintile portfolio returns are low to moderate, ranging between -3% (between $RVIV$ and $SKEW^{OTM}$) and 44% (between $SKEW^{ATM}$ and $SKEW^{OTM}$).

4.2 Firm-level regressions

The above results reveal that forming portfolios based on each of the four option price variables would have generated significant profits. To control for heretofore unincluded variables that may impact returns, and to test for the option price variables' joint significance we continue our analysis with Fama and MacBeth (1973) regressions.

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[Insert Table 3 about here]

Table 3 reports the results in terms of estimated standardized coefficients and their significance. All coefficients are annualized by multiplying them with 52, so that the values represent the annualized return changes caused by a one standard deviation shock in the underlying variables. For the sake of brevity, we largely focus on models 6-10, which include the control variables logarithm of the market capitalization (ME), book-to-market (BM), 9 minus 1 month momentum (MoM), market beta (Beta) and short-term reversal (STR) (although the same picture emerges from models 1-5). We first consider the firm-level regressions using each variable in isolation. The results confirm our earlier portfolio results. Models 6-9 show that in isolation, each option variable displays statistically significant negative predictive power for subsequent weekly stock returns after correcting for control variables. In economic terms the coefficients also imply strong predictive power, with a three-standard deviation change in the variables (roughly comparable to the difference between the top minus bottom portfolio) resulting in a 4.11% to 5.64% change in annualized returns. Moreover, the regression results also reveal that the option strategies are substantially different from the other well-known stock selection strategies: momentum, reversal, beta, size and value. This may not come as a full surprise, given that the motivation of the option variables we study (i.e., volatility risk, jump risk, and informed trading) differ fundamentally from the motivation of these traditional stock-selection strategies (i.e., herding, under- and overreaction, (distress) risk and under- or overvaluation).

Next, we consider the effect of all option price variables jointly. Model 5 of Table 3 reveals that all option variables jointly contain predictive information for stock returns, witnessing a significant R^2 of 2.6%. Similarly, the R^2 of model 10 (which includes all control variables) is 13.7%, compared to R^2's of 11.8% to 12.3% for models 6-9, where only a single option measure is considered. The individual variables $RVIV$, $SKEW^{ATM}$ and $\Delta SKEW^{ATM}$ remain significant and of roughly similar magnitude as in models 6-9. By contrast, the coefficient of $SKEW^{OTM}$ becomes insignificant and positive. This result may be caused by the correlation between the $SKEW^{ATM}$ and $SKEW^{OTM}$ measures. In fact, Doran and Krieger (2010) note that the $SKEW^{OTM}$ of Xing *et al.* (2010) consists partly of the $SKEW^{ATM}$ and

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argue for using $DKSKEW_{i,t}^{OTM} = IV_{i,t}^{OTMP} - IV_{i,t}^{ATMP} = SKEW_{i,t}^{OTM} - SKEW_{i,t}^{ATM}$ instead to capture worries about negative price movements. Interestingly, their findings reveal that higher values of the latter measure result in higher instead of lower returns.

To examine this effect in more detail, we rerun the individual portfolio sort and Fama-McBeth regressions using $DKSKEW^{OTM}$, which has a correlation of 75% with $SKEW^{OTM}$. The unreported results from these analyses are qualitatively similar as those reported in Table 3. Additionally, we do not confirm the positive relation between values of the $DKSKEW^{OTM}$ and subsequent returns, as documented by Doran and Krieger (2010). In fact, we find a negative (but still insignificant) coefficient in both the univariate as well as multivariate Fama-McBeth regressions, and an insignificant long-short return (4F alpha) of -2.65% (-2.04%) using a portfolio sort.

To conclude, the Fama-McBeth regressions confirm our statement that information contained in publicly available option prices predicts returns on the underlying stocks, even after controlling for a set of other return predicting variables.

4.3 Combined option information strategy

The above results reveal predictive power of the option variables for stock returns over the subsequent week. From an investor's perspective, the joint value of the option market information variables is especially interesting. Therefore, we aggregate the option variables into a simple combined option information strategy, using the procedure outlined in Section 3.

[Insert Table 4 about here]

Even though not all option variables are individually significant in the multivariate Fama-McBeth regressions, we choose to combine all of our four option variables, since all variables have revealed substantial predictive power in the individual portfolio sorts and their strategy returns are not highly correlated.[13] Table 4 contains the results. Sorting stocks based on the combined option information measure leads to large spreads in

[13] We endorse the view that a model with higher in-sample risk-return characteristics may be found. However, to avoid any in-sample optimization we leave this up to the user.

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subsequent weekly returns, larger than observed for each individual option market variable. Quintile portfolio 1 generates on average 8.09% a year over the risk-free rate (4.37% over the market), monotonically decreasing to a negative -1.64% (-5.03%) for quintile portfolio 5. These outcomes result in a highly economically and statistically significant return of 9.90% a year for the Q1-Q5 long-short portfolio with an information ratio of 1.13. The 4F and CAPM alphas reveal similar results, with values of 10.06% and 10.09% respectively. Figure 2 shows the cumulative performance of the long-short portfolio over time. Apart from a drawdown in 2009, the strategy delivers a strong, increasing stable outperformance, also in the recent, previously out-of-sample crisis years.[14]

[Insert Figure 2 about here]

4.4 Robustness Analyses

The above results have shown that the long-short portfolio based on the combined option information strategy yields economically and statistically significant returns. We will further analyze the robustness of these findings by examining the portfolio performance over different market conditions, and by investigating the interaction of the combined strategy with various measures of information uncertainty.

4.4.1 Performance in different market conditions

To examine the stability of the combined option strategy's performance in different market conditions, we split our sample into (i) bull and bear markets based on positive and negative monthly market returns, and (ii) volatile and calm markets based on the VIX being above or below its median value. Table 5 reports the results. The performance of the strategy is strong in both bull and bear markets (although even higher in bear markets) witnessing top minus bottom returns (4F alphas) of 11.94% (11.82%) in bear versus 8.57% (9.34%) in bull markets. The results are also stable across volatility regimes, with the strongest performance in volatile markets. The top minus bottom returns (4F alphas) are 11.34% (10.67%) in volatile markets versus 8.36% (6.19%) in calm markets. These results

[14] In addition, we may wonder if the performance of the combined option information strategy improves if we consider the stocks with stronger signals, for example by employing decile instead of quintile portfolios. We report these results in the Appendix, which indeed, reveal slightly stronger results in terms of outperformance and alpha as compared to the quintile results.

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confirm that the strategy is not only working over the whole sample, but also in different sub-samples and market environments.

[Insert Table 5 about here]

4.4.2 The impact of information uncertainty

Next, we analyze how the profitability of the combined option information strategy interacts with information uncertainty. In a recent paper, Zhang (2006) argues and finds that behavioral biases exacerbate if information uncertainty is higher, and that, as a consequence, momentum profits are stronger among stocks surrounded with high information uncertainty than among low uncertainty stocks. Information uncertainty may also be an amplifier of the combined option information strategy. Part of its predictive effect may be due to the signaling of private information, and the advantage of private information may be affected by the uncertainty regarding the usefulness and value of information.

[Insert Table 6 about here]

To investigate whether the results of our combined option information strategy are indeed affected by information uncertainty, we perform the following analysis. We rank the stocks with option information available in five quintiles based on three measures for information uncertainty: market capitalization, past 52-weeks volatility, and the number of analysts covering the stock. Within each of these groups, we sort the stocks on our combined option signal and examine the performance of a long-short quintile portfolio. The results are presented in Table 6. Lower market capitalization, higher volatility and a lower number of analysts covering a stock indicates higher information uncertainty. The combined option information strategy yields a significant outperformance and 4F alpha for all long-short portfolios for all three information uncertainty measures. In addition, the last column of Table 6 reveals that the profitability of the combined option information strategy is not significantly stronger for high versus low information uncertainty portfolios. For example, the long-short combined option information strategy has an outperformance (4F

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alpha) of 13.87% (14.62%) for the quintile of smallest stocks in our sample, versus 12.85% (13.05%) for the quintile of largest stocks in our sample. These results reveal that information uncertainty does not amplify the profitability of the combined option variables.

4.5 The impact of transaction costs

The above analyses reveal that public option market information contains valuable information for equity investors. From an investor's perspective, it is important to know whether this conclusion also holds after accounting for transaction costs. In fact, several recent studies show that many anomalies are not profitable after transaction costs (see for example Lesmond, Schill and Zhou (2004), and Avramov, Chordia and Goyal (2006)). Therefore, we next examine the net profitability of our combined option information strategy.

To this end, we need an estimate of the transaction costs per individual stock. Commonly, researchers and practitioners employ the model of Keim and Madhavan (1997). These authors regress total transaction costs (including commissions paid and an estimate of price impact) for trading NYSE-AMEX stocks during 1991 to 1993 on several characteristics of the trade and the traded stock. However, as pointed out by De Groot, Huij, and Zhou (2012), the transaction cost estimates resulting from the Keim and Madhavan model should be interpreted with caution when applied to the most recent decades. The reason is that Keim and Madhavan (1997) estimate their model over all stocks using data between 1991 and 1993, while market microstructures and transaction costs have substantially altered since. In fact, De Groot *et al.* find that the Keim and Madhavan model systematically yields negative cost estimates for a large group of liquid stocks over our sample period. For example, the median single-tip transaction cost estimates of the Keim and Madhavan (1997) model for the S&P500 stocks are -9 basis points over our sample period, substantially *lower* than the 9bp based on estimates of De Groot *et al.* This implies that we would clearly *underestimate* transaction costs (and hence overestimate the net return) when applying the Keim and Madhavan transaction cost estimates to our universe. Furthermore, during our sample period, the transaction cost estimates of De Groot *et al.* declined for the S&P500 universe from median single-trip transaction costs of approximately 12bp in 1996 to a low of 6.5bp in 2008, indicating the general increase in liquidity over time.

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Therefore, we follow the procedure proposed by De Groot *et al.* to estimate each stock's transaction costs. They propose to estimate transaction costs by ranking a stock based on its dollar volume in a given quarter, and applying the transaction cost estimates for the matching quarterly dollar volume sorted decile portfolio of S&P1500 or S&P500 stocks, as presented in their Table 1, Panel B and Table 2, Panel B, respectively. These estimates are obtained from Nomura Securities, one of the major brokers in the cash equity market, and include both estimates of commissions and the price impact of trades. The assumed trade size for these estimates is one million USD per stock by the end of 2009, deflated back in time with 10% per annum. Consequently, the estimates are valid for a sizable strategy.[15]

[Insert Table 7 about here]

Table 7 presents the results when incorporating transaction costs. The first column of Table 7 provides the results of the long-short combined option information strategy applied to our investable universe consisting of the largest 1,250 U.S. stocks. Clearly, transaction costs can have a dramatic impact on the profitability of the combined option information strategy, due to a high turnover of 150% single-counted per week (compared to a maximum possible turnover of 200% per week). As a result, the outperformance drops from a positive 9.90% per year to a negative -9.88%, suggesting that the strategy is not exploitable.

Since the turnover of the combined option information strategy is very high, we may wonder what happens if we only focus on stocks with the lowest transaction costs. Therefore, we next repeat the same exercise on the extremely liquid universe of the 100 largest stocks in terms of market capitalization, generally the stocks with the highest liquidity and lowest transaction costs. For this universe, De Groot *et al.* employ average single-trip transaction costs of approximately 7bp over our sample period, versus 13bp for the S&P1500 stocks. The second column of Table 7 shows that the gross outperformance increases from 9.90% to 13.57% per year when applied to these 100 largest stocks. Hence,

[15] For example, a strategy that invests an equal amount in each of the 20% most or least attractively ranked stocks in our universe (the largest 1,250 U.S. stocks) would be able to employ a capital of 250 million by the end of 2009 at these transaction costs.

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the gross profitability of the combined option information strategy does not decrease for the largest and generally most liquid and most followed stocks. At the same time turnover remains similar, and as a consequence, the impact of transaction costs substantially reduces from 19.78% to 11.18%, leading to a positive net outperformance of 2.39% a year. Although still sizable in economic terms, this number is not statistically significant.

Still, the above analysis deals relatively naively with transaction costs. In fact, portfolio optimization theory prescribes to efficiently trade-off the decay in predictive power versus reduction in transaction costs, in order to maximize expected net risk-adjusted performance. We apply this principle by using a simple turnover reducing portfolio construction approach to the above two universes. More specifically, at the beginning of our sample period we form a long-short portfolio based on the option strategy signal. Once included in the long (short) portfolio, a stock is held until the day that it is ranked as the most unattractive (attractive), that is, it has fallen to the bottom (for long positions) or top (for short positions) quintile. On the day a stock falls out of the portfolio, it is replaced by the most attractive (for long positions) or least attractive (for short positions) ranked stock not yet included in the portfolio. Hence, trades only occur the moment that a stock migrates from the most (least) attractive 20% stocks to the least (most) attractive 20% stocks. This not only limits the turnover of the portfolio to stocks that are expected to move strongly into the adverse direction, but also ensures that the number of stocks in the portfolio is equal to the long-short portfolio in the previous analysis.

The results of such a dynamic portfolio are presented in the last two columns of Table 7. We first examine this approach in our investable universe of 1,250 U.S. large-cap stocks. Gross outperformance deteriorates marginally, as the performance for the 1,250 largest stocks is 9.84% annually (9.90% for the static long-short portfolio). However, turnover decreases by more than one-third from 150% to 97%, leading to a substantial reduction in transaction costs from 19.78% to 14.02%. Still, the net outperformance of the strategy is negative (-4.18%). Next, we repeat the same exercise on the extremely liquid universe of the 100 largest stocks (see column 4 of Table 7). Again, gross outperformance deteriorates marginally, from 13.57% previously to 12.95%. Simultaneously, the impact of transaction costs reduces to a relatively small 5.34%, which leads to an economically and statistically significant outperformance of 7.61% per year and a 4F alpha of 7.53%. Hence,

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significant outperformance remains when accounting for transaction costs by means of a turnover reducing approach on a low transaction cost universe.[16]

In the above analysis we investigate a long-short strategy, and hence may also face shorting costs. The net returns of the above long-short strategy are large enough to cover realistic shorting costs of 50bp to 100bp. As a comparison, D'Avolio (2002) estimates the shorting costs to average 60bp for a much broader universe. In addition, an investor can reduce, or even avoid shorting costs, by taking active positions based on the combined option information strategy against a certain benchmark index, as commonly done by many institutional equity managers.

To summarize, although the gross return of the combined option information strategy is high, its turnover is also substantial. As a consequence, the impact of transaction costs can substantially diminish its net profitability. However, large significant net returns can be obtained when avoiding stocks that have high transaction costs and employing turnover reducing portfolio construction rules. This leads us to conclude that publicly available information contained in option prices can be profitably exploited by investors.

5 Conclusion

We show that publicly available information extracted from traded equity options contains valuable information for future stock returns. Trading strategies based on worries about negative price movements (i.e. out-of-the-money volatility skew), volatility risk (i.e. realized versus implied volatility spread), informed trading and jump risk (i.e. at-the-money volatility skew), and the change in informed trading (i.e. change in the at-the-money volatility skew) yield significant returns and alphas. The performances remain significant after correcting for market, size, value, momentum, reversal and other return predicting factors. Hence, we find that the option information strategies are substantially different from other well-known stock selection strategies. These findings extend the results of

[16] We may wonder how sensitive these results are to our particular choice of rebalancing rules. Comfortably, when we sell (buy) a long (short) position when a stock has fallen to the bottom (top) 50%, 60% or 70% percentile (instead of the 80% percentile), we also find a substantial reduction in turnover to 142%, 118% and 95% respectively, and significant, positive net outperformance (4F alpha) of 11.12% (11.62%), 9.44% (10.47%), and 9.18% (9.14%) respectively when applied to the largest 100 stocks.

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earlier studies to a well-investable universe of liquid U.S. large caps, a universe highly relevant for equity investors. Moreover, a combined option information strategy shows even stronger results with an annualized performance of around 10%, thereby strengthening the relevance of the publicly available information contained in option prices for equity investors. Although several studies report that the predictive power of option market variables decreases over time, we find significant returns also in recent out-of-sample years. These results are robust over bull, bear, volatile and calm markets and are generally of similar magnitude for stocks with low or high information uncertainty. In addition, the documented anomalies are at least as strong when applied to the 100 largest stocks. We further find that the profitability of the combined option information strategy can be dramatically reduced by transaction costs, since exploiting the option information measures requires extremely high turnover. However, the strategy remains profitable when focusing on a low transaction cost universe and employing simple procedures to reduce transaction costs, as annual net returns above 7% can be achieved. This suggests that information diffuses gradually from the equity option market into the underlying stock market.

We have documented that the four option variables have been a strong predictor of individual stock returns that seems of relevance for practitioners. Interestingly, the option information strategies differ substantially from other well-known stock-selection strategies, like momentum and value, strategies commonly applied by practitioners. Finally, we may raise the question if one can expect these effects to persist going forward? Although time has to ultimately answer this question, several points may be worth considering here. First, we provide out-of-sample evidence on the predictive power of the four option variables, suggesting that their profitability is unlikely to be caused by data mining. Second, the explanations of the anomalies (proposed by the original studies) are volatility and jump risk compensation, and information trading. Although these risks may materialize at some points, their premia tend to be structural components of the economic system. The latter may also be argued for the presence of private information. If some investors indeed will possess private information in the future, the question becomes if and when they would be willing to express their views in the option market (such that price discovery will take place in that market). The model of Easley, O'Hara and Srinivas (1998), which provides a theoretical framework for understanding where informed investors will trade, may be useful here. In their model, informed traders who want to maximize profits, choose to trade in the option market if the leverage or liquidity in the options is high, if the liquidity in the

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stock is low, or if there are already many informed investors in the stock market. This suggests that the option prices that will continue to signal private information are the ones that have high leverage or liquidity and of which the stock has low liquidity or a large informed investor base. Third, these anomalies may have been less well-known compared to for example value and momentum strategies, but their documentation may promote a greater awareness. This may result in the entrance of new investors in these anomalies, which could potentially decrease their profitability.

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Table 1: Descriptive statistics

The table shows coverage, summary statistics and rank correlations for our universe of U.S. large-cap stocks for the period January 1996 to October 2009. Data are obtained from FactSet and Compustat (for stocks) and OptionMetrics (for options). Panel A shows the number of stocks in our universe (of 1,250 stocks) with coverage for each of the variables, averaged over time and at the start and end of the sample period. The last column shows the number of stocks with at least one option variable available. Panel B contains summary statistics. Shown are the mean, cross-sectional standard deviation, 25% percentile, the median, and 75% percentile of the market capitalization (ME), book-to-market (BM), and the four variables, the OTM skew ($SKEW^{OTM}$), the volatility spread ($RVIV$) (the difference between the realized volatility and implied volatility of ATM call options), the ATM skew ($SKEW^{ATM}$), and the weekly change in the ATM skew ($\Delta SKEW^{ATM}$). Panel C contains Spearman's rank correlations between the four variables we employ. We first calculate the summary statistics or rank correlations over the cross-section and then average the resulting numbers over the time-series.

Panel A:	**Stock coverage**				
Time period	$SKEW^{OTM}$	$RVIV$	$SKEW^{ATM}$	$\Delta SKEW^{ATM}$	All
Average	619	842	795	708	901
Start	317	625	494	387	690
End	865	1012	999	924	1045

Panel B:	**Summary statistics**				
Characteristic	**Mean**	**Stdev**	**25%**	**50%**	**75%**
ME ($ bln)	9.19	16.80	1.62	3.33	8.66
BM	0.37	0.24	0.20	0.33	0.50
$SKEW^{OTM}$ (%)	4.72	3.47	2.50	4.23	6.41
$RVIV$ (%)	-0.82	10.67	-7.54	-1.84	4.56
$SKEW^{ATM}$ (%)	0.79	2.08	-0.31	0.62	1.74
$\Delta SKEW^{ATM}$ (%)	0.00	2.15	-1.12	0.00	1.12

Panel C:	**Rank correlations**			
Variable	$SKEW^{OTM}$	$RVIV$	$SKEW^{ATM}$	$\Delta SKEW^{ATM}$
$SKEW^{OTM}$	100%			
$RVIV$	2%	100%		
$SKEW^{ATM}$	43%	1%	100%	
$\Delta SKEW^{ATM}$	21%	1%	53%	100%

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Table 2: Portfolio returns of individual option market variables

This table shows the portfolio returns of the four option variables for our universe of U.S. large-cap stocks. We show the results of the quintile portfolios (Q1 to Q5) and the long-short portfolio (Q1-Q5) that are constructed by sorting in increasing order on $SKEW^{OTM}$ (Panel A), *RVIV* (Panel B), $SKEW^{ATM}$ (Panel C), and $\Delta SKEW^{ATM}$ (Panel D). The equally-weighted portfolios are constructed using Tuesday close information, implemented with a one-day lag and held for one week. We report the geometric excess return, Sharpe ratio, outperformance, and information ratio of these portfolios on an annual basis. In addition, we estimate the CAPM and four-factor (4F) alphas of the quintile portfolios and report the alphas on an annual basis. The sample period is January 1996 to October 2009. Asterisks *, ** and *** indicate significance at 10%, 5% and 1% respectively.

Panel A:			$SKEW^{OTM}$			
Statistic	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q1-Q5**
Excess Return (%)	5.46	4.18	2.36	0.34	-1.87	
Sharpe Ratio	0.21	0.18	0.10	0.01	-0.08	
Outperformance (%)	3.23**	1.97*	0.18	-1.79*	-3.96**	7.48***
Information Ratio	0.58	0.45	0.05	-0.44	-0.67	0.76
CAPM Alpha (%)	3.38	2.08	0.23	-1.71	-3.86*	7.49***
4F Alpha (%)	2.87*	1.40	-0.01	-2.13	-4.73***	7.96***
Panel B:			*RVIV*			
Statistic	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q1-Q5**
Excess Return (%)	5.02	6.56	5.79	3.69	-2.36	
Sharpe Ratio	0.22	0.32	0.27	0.16	-0.08	
Outperformance (%)	1.06	2.54*	1.81	-0.22	-6.04**	7.56*
Information Ratio	0.16	0.47	0.38	-0.05	-0.54	0.49
CAPM Alpha (%)	2.96	4.47***	3.68***	1.57	-4.13	9.13***
4F Alpha (%)	2.02	3.12**	2.52**	0.89	-3.10	7.06**
Panel C:			$SKEW^{ATM}$			
Statistic	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q1-Q5**
Excess Return (%)	6.83	6.97	3.52	1.62	0.42	
Sharpe Ratio	0.28	0.31	0.16	0.07	0.02	
Outperformance (%)	2.81**	2.95***	-0.38	-2.21**	-3.37***	6.40***
Information Ratio	0.61	0.82	-0.11	-0.67	-0.73	0.91
CAPM Alpha (%)	4.63***	4.70***	1.37	-0.48	-1.58	6.51***
4F Alpha (%)	4.93***	4.25***	0.59	-1.47	-2.66	7.96***

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Panel D:	$\Delta SKEW^{ATM}$					
Statistic	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q1-Q5**
Excess Return (%)	5.55	4.92	4.16	4.05	0.11	
Sharpe Ratio	0.22	0.22	0.19	0.18	0.00	
Outperformance (%)	1.67	1.06	0.32	0.22	-3.58***	5.45***
Information Ratio	0.35	0.28	0.08	0.06	-0.74	0.78
CAPM Alpha (%)	3.37*	2.81*	2.05	1.91	-2.08	5.69***
4F Alpha (%)	3.00*	2.21	1.10	1.36	-2.25	5.52***

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Table 3: Firm-level regressions

This table shows the results of cross-sectional regressions of weekly excess returns using the Fama-MacBeth (1973) methodology that controls for firm characteristics based on our universe of U.S. large-cap stocks from January 1996 to October 2009. We examine the predictability of the $SKEW^{OTM}$, $RVIV$, $SKEW^{ATM}$ and $\Delta SKEW^{ATM}$ while controlling for the logarithm of the market capitalization (ME), book-to-market (BM), 9 minus 1 month momentum (MoM), market beta (Beta) and short-term reversal (STR). Raw signals are first transformed into standardized z-scores. The estimated coefficients are multiplied by 52 to represent the annualized return effects caused by a one standard deviation increase in the variable. We report the average estimated coefficients, R-squared (R^2), and the average number of cross-sectional stock observations of each model. Asterisks *, ** and *** indicate significance at 10%, 5% and 1% respectively, based on Newey-West (1987) adjusted standard errors.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	9.15	10.53*	10.43*	10.19*	9.99*	9.50*	11.13**	11.43**	11.27**	9.90*
$SKEW^{OTM}$	-1.93***				-0.58	-1.37***				0.19
$RVIV$		-1.93*			-2.60**		-1.68***			-2.06***
$SKEW^{ATM}$			-1.74***		-0.87			-1.88***		-1.41**
$\Delta SKEW^{ATM}$				-1.45***	-1.25**				-1.40***	-1.07**
log(ME)						-0.08	-0.68	-0.98	-0.99	-0.55
BM						0.88	0.92	0.94	0.96	0.74
MoM						1.47	1.39	1.52	1.39	1.38
Beta						-2.29	-1.96	-2.38	-2.26	-1.76
STR						-3.63***	-3.30***	-3.42***	-3.82***	-3.33***
R^2	0.5%	1.1%	0.2%	0.3%	2.6%	12.3%	12.0%	11.8%	12.1%	13.7%
N	619	842	795	708	546	607	825	780	697	536

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Table 4: Portfolio returns of the combined option information strategy

This table shows the portfolio returns of the option information strategy based on $SKEW^{OTM}$, $RVIV$, $SKEW^{ATM}$ and $\Delta SKEW^{ATM}$ for our universe of U.S. large-cap stocks. We show the results of the quintile portfolios (Q1 to Q5) and the long-short portfolio (Q1-Q5). Individual variables are standardized using a cross-sectional z-score. The stocks are then sorted in increasing order into portfolios based on the average of the four individual z-scores. The portfolios are constructed using Tuesday close information, implemented with a one-day lag and held for one week. We report the equally-weighted geometric excess return, Sharpe ratio, outperformance and information ratio of these portfolios on an annual basis. In addition, we estimate the CAPM and four-factor (4F) alphas of the quintile portfolios and report the alphas on an annual basis. The sample period is January 1996 to October 2009. Asterisks *, ** and *** indicate significance at 10%, 5% and 1% respectively.

Statistic	Q1	Q2	Q3	Q4	Q5	Q1-Q5
Excess Return (%)	8.09	6.17	3.18	1.85	-1.64	
Sharpe Ratio	0.34	0.29	0.15	0.08	-0.06	
Outperformance (%)	4.37***	2.52**	-0.38	-1.66*	-5.03***	9.90***
Information Ratio	0.92	0.64	-0.11	-0.49	-0.86	1.13
CAPM Alpha (%)	5.79***	4.01***	1.10	-0.24	-3.71*	10.09***
4F Alpha (%)	5.38***	2.78**	0.20	-0.90	-4.03**	10.06***

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Table 5: Performance in different market conditions

This table shows the performance of the long-short portfolio of the combined option information strategy for our universe of U.S. large-cap stocks over bull (positive monthly return) and bear (negative monthly return) markets, as well as volatile (VIX above sample median) and calm (VIX below sample median) markets. The equally-weighted portfolios are constructed using Tuesday close information, implemented with a one-day lag and held for one week. We report the geometric outperformance and information ratio of these portfolios on an annual basis. In addition, we estimate the CAPM and four-factor (4F) alphas of the portfolio and report the alphas on an annual basis. The sample period is January 1996 to October 2009. Asterisks *, ** and *** indicate significance at 10%, 5% and 1% respectively.

Statistic	Bull	Bear	Volatile	Calm
Outperformance (%)	8.57***	11.94***	11.34***	8.36***
Information Ratio	1.20	1.32	1.15	1.57
CAPM Alpha (%)	8.81***	11.25***	10.33***	6.20***
4F Alpha (%)	9.34***	11.82***	10.67***	6.19***

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Table 6: Double sorts on information uncertainty measures

This table shows the performance of our combined option signal within different segments of the market, based on a conditional double sort. First, we construct five groups based on market capitalization, past 52 week volatility or the number of analysts. Second, within each group, we sort the stocks on our combined option signal and calculate the returns of a long-short quintile portfolio. These equally-weighted portfolios are constructed using Tuesday close information, implemented with a one-day lag and held for one week. We report the geometric outperformance, information ratio, CAPM alpha and 4F alpha of these portfolios on an annual basis. In the last column we report the same statistics when we compare the long-short portfolio returns between the high and low groups based on market capitalization, volatility or analyst coverage. The sample period is January 1996 to October 2009. Asterisks *, ** and *** indicate significance at 10%, 5% and 1% respectively.

Panel A:			**Market capitalization**			
Statistic	**Low**	**2nd**	**3rd**	**4th**	**High**	**HML**
Outperformance (%)	13.87***	8.10**	9.96***	8.27***	12.85***	-0.87
Information Ratio	0.93	0.56	0.72	0.65	1.00	-0.06
CAPM alpha (%)	14.22***	8.97***	10.55***	9.03***	13.01***	0.49
4F alpha (%)	14.62***	10.48***	9.78***	8.83***	13.05***	0.21
Panel B:			**Volatility**			
Statistic	**Low**	**2nd**	**3rd**	**4th**	**High**	**HML**
Outperformance (%)	4.83***	5.78***	11.41***	13.44***	10.90**	5.76
Information Ratio	0.71	0.65	1.08	0.99	0.59	0.32
CAPM alpha (%)	5.03***	5.91***	11.51***	13.23***	12.05**	7.06
4F alpha (%)	4.96***	6.07***	11.67***	14.98***	11.00**	6.09
Panel C:			**Number of analysts**			
Statistic	**Low**	**2nd**	**3rd**	**4th**	**High**	**HML**
Outperformance (%)	12.11***	10.29***	12.01***	7.13*	11.66***	-0.41
Information Ratio	0.82	0.72	0.91	0.51	0.78	-0.02
CAPM alpha (%)	12.79***	10.81***	12.57***	8.61***	12.08***	1.49
4F alpha (%)	14.6***	9.25***	12.85***	7.63**	11.64***	-0.81

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Table 7: Gross and net performance of strategies based on the option information

This table presents the gross and net outperformance of the long-short portfolio based on the combined option strategies within the universe of the 1,250 and 100 largest U.S. stocks. The portfolios are equally-weighted, constructed using Tuesday close information and implemented with a one day lag. The static portfolios only contain stocks which are ranked among the top (bottom) 20% of the universe and are rebalanced every week. The dynamic portfolios are constructed using an approach that does not directly sell (buy back) stocks that are no longer in the top (bottom) quintile, but waits until the day that these stocks are ranked among the bottom (top) 20% of stocks. Reported are the annualized geometric (net) outperformance, (net) information ratio, weekly single-counted turnover (TO) and the average holding period (HP) in days. In addition, we present the annualized net CAPM and four-factor (4F) alphas of the long-short portfolios. Transaction cost estimates used for calculating net outperformance are based on Panel B of Table 1 and 2 presented in De Groot, Huij and Zhou (2012). The sample period is January 1996 to October 2009. Asterisks *, ** and *** indicate significance at 10%, 5% and 1% respectively.

	Static Portfolios		**Dynamic Portfolios**	
Statistic	1,250 Large	100 Large	1,250 Large	100 Large
Outperformance (%)	9.90***	13.57***	9.84***	12.95***
Information Ratio	1.13	0.95	1.07	0.92
TO (%)	150	150	97	70
HP (days)	6.7	6.7	10.3	14.3
Net Outperformance (%)	-9.88	2.39	-4.18	7.61**
Net Information Ratio	-1.09	0.17	-0.45	0.54
Net CAPM Alpha (%)	-9.69	3.48	-3.53	8.53***
Net 4F Alpha (%)	-9.87	3.08	-4.00	7.53***

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Figure 1: Cumulative performance of individual option market variables

This figure shows the cumulative (out)performance of the long-short strategy based on $SKEW^{OTM}$, $RVIV$, $SKEW^{ATM}$ or $\Delta SKEW^{ATM}$ for our universe of U.S. large-cap stocks. Our sample runs from January 1996 to October 2009. The equally-weighted portfolios are implemented with a one-day lag and held for one week.

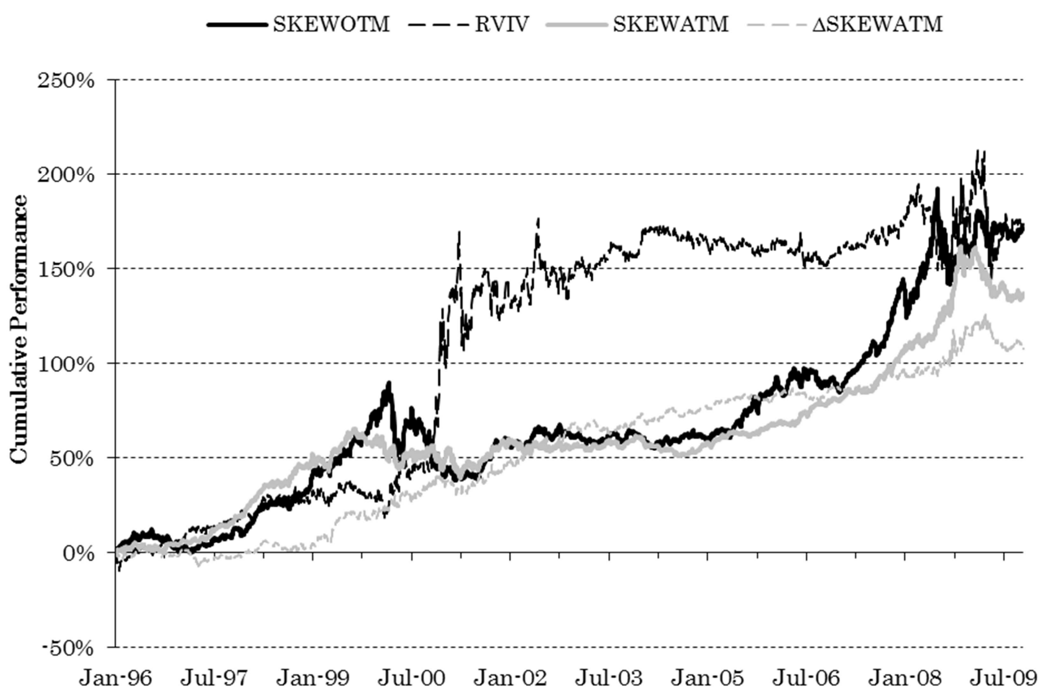

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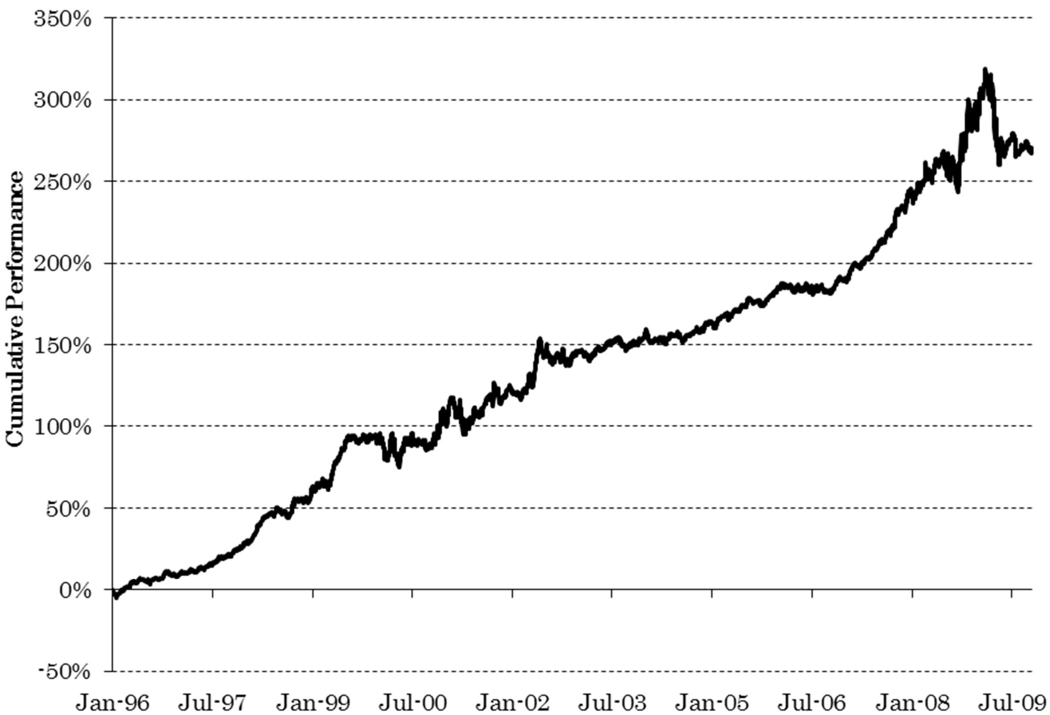
Figure 2: Cumulative performance of the combined option information strategy

This figure shows the cumulative (out)performance of the long-short combined option information strategy for our universe of U.S. large-cap stocks. Our sample runs from January 1996 to October 2009. The equally-weighted portfolio is implemented with a one-day lag and held for one week.



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Appendix

Table A1: Value-weighted portfolio returns of individual and combined option market variables

This table shows the portfolio returns of the individual and combined option variables for our universe of 1,250 U.S. large-cap stocks. We show the results of the quintile portfolios (Q1 to Q5) and the long-short portfolio (Q1-Q5) that are constructed by sorting in increasing order on $SKEW^{OTM}$ (Panel A), *RVIV* (Panel B), $SKEW^{ATM}$ (Panel C), $\Delta SKEW^{ATM}$ (Panel D) and four combined option variables (Panel E). The value-weighted portfolios are constructed using Tuesday close information, implemented with a one-day lag and held for one week. We report the geometric excess return, Sharpe ratio, outperformance, and information ratio of these portfolios on an annual basis. In addition, we estimate the CAPM and four-factor (4F) alphas of the quintile portfolios and report the alphas on an annual basis. The sample period is January 1996 to October 2009. Asterisks *, ** and *** indicate significance at 10%, 5% and 1% respectively.

Panel A:			$SKEW^{OTM}$			
Statistic	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q1-Q5**
Excess Return (%)	7.82	3.72	0.21	1.44	-2.84	
Sharpe Ratio	0.33	0.17	0.01	0.06	-0.11	
Outperformance (%)	5.75***	1.72	-1.72	-0.52	-4.71*	10.98***
Information Ratio	0.65	0.28	-0.34	-0.09	-0.48	0.75
CAPM Alpha (%)	5.25***	1.39	-2.16	-0.85	-5.12***	11.24***
4F Alpha (%)	5.25***	1.54	-1.85	-0.09	-5.04***	11.28***
Panel B:			*RVIV*			
Statistic	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q1-Q5**
Excess Return (%)	7.89	5.78	2.32	1.38	-3.18	
Sharpe Ratio	0.34	0.29	0.12	0.06	-0.11	
Outperformance (%)	5.22*	3.15*	-0.22	-1.15	-5.59	11.45**
Information Ratio	0.51	0.49	-0.04	-0.21	-0.41	0.60
CAPM Alpha (%)	5.45**	3.33**	0.12	-0.98	-5.38**	12.87***
4F Alpha (%)	4.95*	2.84	0.17	-0.39	-3.20	10.18**
Panel C:			$SKEW^{ATM}$			
Statistic	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q1-Q5**
Excess Return (%)	5.8	4.64	0.34	0.13	0.28	
Sharpe Ratio	0.24	0.22	0.02	0.01	0.01	
Outperformance (%)	3.17	2.04	-2.16*	-2.36	-2.22	5.51*
Information Ratio	0.39	0.41	-0.45	-0.43	-0.24	0.45
CAPM Alpha (%)	3.40	2.19	-2.01	-2.20	-1.93	6.48*
4F Alpha (%)	4.91***	2.85**	-1.71	-2.61	-3.22	9.58***

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Panel D:	$\Delta SKEW^{ATM}$					
Statistic	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q1-Q5**
Excess Return (%)	3.44	3.06	2.57	1.80	-2.76	
Sharpe Ratio	0.14	0.14	0.12	0.08	-0.11	
Outperformance (%)	1.13	0.76	0.28	-0.47	-4.94**	6.39**
Information Ratio	0.14	0.14	0.06	-0.09	-0.58	0.56
CAPM Alpha (%)	1.11	0.72	0.20	-0.57	-5.19***	7.17***
4F Alpha (%)	1.62	1.53	0.15	-0.51	-5.44***	8.06***
Panel E:	**Combined Option Information**					
Statistic	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q1-Q5**
Excess Return (%)	8.45	6.37	1.51	-0.44	-3.79	
Sharpe Ratio	0.37	0.31	0.07	-0.02	-0.14	
Outperformance (%)	5.83***	3.80***	-0.94	-2.85*	-6.12**	12.73***
Information Ratio	0.78	0.68	-0.19	-0.51	-0.59	0.90
CAPM Alpha (%)	5.91***	3.85***	-0.81	-2.80*	-6.17***	13.50***
4F Alpha (%)	6.69***	3.37***	-0.60	-2.04	-5.79***	14.10***

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Table A2: Decile portfolio returns of combined option information strategy

This table shows the portfolio returns of the combined option variables for our universe of 1,250 U.S. large-cap stocks. We show the results of the decile portfolios (D1 to D10) and the long-short portfolio (D1-D10) that are constructed by sorting in increasing order on the combined option variables. The equally-weighted portfolios are constructed using Tuesday close information, implemented with a one-day lag and held for one week. We report the geometric excess return, Sharpe ratio, outperformance, and information ratio of these portfolios on an annual basis. In addition, we estimate the CAPM and four-factor (4F) alphas of the quintile portfolios and report the alphas on an annual basis. The sample period is January 1996 to October 2009. Asterisks *, ** and *** indicate significance at 10%, 5% and 1% respectively.

	Combined Option Information										
Statistic	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**	**D1-D10**
Excess Return (%)	7.92	8.10	7.34	4.92	1.84	4.45	1.82	1.76	0.82	-4.24	
Sharpe Ratio	0.31	0.35	0.33	0.23	0.08	0.20	0.08	0.07	0.03	-0.15	
Outperformance (%)	4.20**	4.37***	3.64***	1.30	-1.67	0.85	-1.69	-1.75	-2.66*	-7.53***	12.69***
Information Ratio	0.61	0.80	0.69	0.27	-0.36	0.18	-0.36	-0.37	-0.47	-0.88	1.13
CAPM Alpha (%)	5.31**	5.37***	4.72***	2.42	-0.63	1.94	-0.66	-0.68	-1.51	-6.57***	12.98***
4F Alpha (%)	5.21***	4.64***	3.57**	1.12	-1.65	1.15	-1.53	-1.15	-1.95	-6.77***	13.20***

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