

Option-Implied Volatility Measures and Stock Return Predictability

Xi Fu^{*}

Y. Eser Arisoy[†]

Mark B. Shackleton[‡]

Mehmet Umutlu[§]

Abstract

Using firm-level option and stock data, we examine the predictive ability of option-implied volatility measures proposed by previous studies and recommend the best measure using up-to-date data. Portfolio level analysis implies significant non-zero risk-adjusted returns on arbitrage portfolios formed on the call-put implied volatility spread, implied volatility skew, and realized-implied volatility spread. Firm-level cross-sectional regressions show that, the implied volatility skew has the most significant predictive power over various investment horizons. The predictive power persists before and after the 2008 Global Financial Crisis.

Key words: option-implied volatility; volatility skew; return predictability

JEL classification: G11; G12

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^{*} Corresponding author. Department of Economics, Finance and Accounting, University of Liverpool Management School, University of Liverpool, Chatham Street, Liverpool L69 7ZH, UK, Tel: +44(0)1517953000, Fax: +44(0)1517949827, Email: Xi.Fu@liverpool.ac.uk.

[†] ~~DRM Finance (CEREG),~~ Université Paris-Dauphine, [PSL Research University, DRM Finance, Place du Maréchal de Lattre de Tassigny, 75016775 Paris Cedex 16,](#) France, Tel: +33(0)144054360, Email: eser.arisoy@dauphine.fr.

[‡] Department of Accounting and Finance, Lancaster University Management School, Lancaster LA1 4YX, UK, Tel: +44(0)1524594131, Email: m.shackleton@lancaster.ac.uk.

[§] Department of International Trade and Finance, Yasar University, Bornova, 35100, Izmir, Turkey, Tel: +90(0)2324115195, Email: mehmet.umutlu@yasar.edu.tr.

1 Introduction

Options are forward-looking instruments and option-implied measures contain valuable information regarding investors' expectations about the return process of the underlying asset. Option-implied volatility has received particular attention due to the time-varying property of volatility which is a widely used parameter in asset pricing. It is well-documented that implied volatility extracted from option prices provides good forecasts of future volatility.¹ In a similar vein, recent studies examine the predictive ability of different option-implied volatility measures in the cross-section of stock returns. However, despite growing literature, there is no clear understanding of i) whether different option-implied volatility measures capture distinct information about the volatility curve, ii) which measures are important for investors in predicting stock returns, and iii) which measures would outperform in predicting stock returns in dynamically managed portfolios. By comparing the predictive ability of alternative option-implied volatility measures proposed in the literature, in the context of return predictability, this study highlights whether the proposed option-implied volatility measures are fundamentally different to each other and whether their predictive ability differs by investment horizon.²

The relationship between option-implied volatility and stock return predictability is of recent interest.³ For example, An, Ang, Bali and Cakici (2014) focus on the implied volatility of individual options and document the significant predictive power of implied volatility in

¹ See Christensen and Prabhala (1998), Szakmary, Ors, Kim and Davidson (2003), Poon and Granger (2005), Kang, Kim and Yoon (2010), Taylor, Yadav and Zhang (2010), Yu, Lui and Wang (2010), and Muzzioli (2011) for studies on the predictive ability of option-implied volatility on future volatility.

² The option-implied volatility measures used in this study are: the call-put implied volatility spread (*CPIV*), the implied volatility skew (*IVSKEW*), the "above-minus-below" (*AMB*), the "out-minus-at" of calls (*COMA*), the "out-minus-at" of puts (*POMA*), and the realized-implied volatility spread (*RVIV*). Details about these measures can be found in Section 2.2.

³ For example, Arisoy (2014) use returns on crash-neutral ATM straddles of the S&P 500 index as a proxy of the volatility risk, and returns on OTM puts of the S&P 500 index as a proxy of the jump risk, and find that the sensitivity of stock returns to innovations in aggregate volatility and market jump risk can explain the differences between returns on small and value stocks and returns on big and growth stocks. Doran, Peterson and Tarrant (2007) find supportive evidence that there is predictive information content within the volatility skew for short-term horizon.

predicting individual stock returns. More specifically, large increases in call (put) implied volatilities are followed by increases (decreases) in one-month ahead stock returns. Bali and Hovakimian (2009) investigate whether realized and implied volatilities can explain the cross-section of monthly stock returns and document that there is a positive relationship between the call-put implied volatility spread and one-month ahead stock returns. Cremers and Weinbaum (2010) focus on the predictive power of the call-put implied volatility spread and provide evidence that this measure predicts weekly returns to a greater extent for firms facing a more asymmetric informational environment.

Meanwhile, motivated by the empirically documented volatility skew for equity options, several studies examine the predictive power of information captured by options with different moneyness levels.⁴ For example, Xing, Zhang and Zhao (2010) examine the implied volatility skew, which is the difference between out-of-the-money put and at-the-money call implied volatilities, and find a significantly negative coefficient on the implied volatility skew in Fama-MacBeth cross-sectional regressions. Baltussen, Grient, Groot, Hennink and Zhou (2012) include four different implied volatility measures in their study: out-of-the-money volatility skew (i.e., implied volatility skew in Xing, Zhang and Zhao, 2010), realized versus implied volatility spread, at-the-money volatility skew (i.e., the difference between the at-the-money put and call implied volatilities), and weekly changes of at-the-money volatility skew. By analyzing weekly stock returns, they find negative relationships between weekly returns and four option-implied measures. In addition to two common factors used in previous studies (at-the-money call-put implied volatility spread and out-of-the-money implied volatility skew), Doran and Krieger (2010) construct three other measures based on implied volatility extracted from call and put options. These three measures are “above-minus-below”, “out-

⁴ The phenomenon that the implied volatility of equity options with low strike prices (such as deep out-of-the-money puts or deep in-the-money calls) is higher than that of equity options with high strike prices (such as deep in-the-money puts or deep out-of-the-money calls) is known as volatility skew (Hull, 2012). The volatility skew is widely observed for equity options (Bollen and Whaley, 2004; Bates, 2003; Gârleanu, Pedersen, and Poteshman, 2007; and Xing, Zhang and Zhao, 2010).

minus-at” of calls, and “out-minus-at” of puts.⁵ Results in their study show that differences between at-the-money call and put implied volatilities and those between out-of-the-money and at-the-money put implied volatilities both capture information about future equity returns.

From these studies, it is not clear whether separately constructed option-implied volatility measures in the literature capture fundamentally different information in predicting stock returns. In the presence of other volatility measures, some of these volatility measures may be redundant in predicting stock returns. Building on aforementioned studies, this paper compares the ability of the various option-implied volatility measures to predict one-week to three-month ahead returns. Addressing the question of which option-implied volatility measure(s) outperforms alternatives in predicting stock returns and whether their predictive ability persists over different investment horizons is crucial, having implications for portfolio managers and market participants. These groups can adjust their trading strategies and form portfolios based on option-implied volatility measure(s) that has the strongest predictive power and thus earn excess returns.

To compare the predictive power of option-implied volatility measures, we first form quintile portfolios sorted with respect to six option-implied volatility measures: the call-put implied volatility spread (*CPIV*), the implied volatility skew (*IVSKEW*), the “above-minus-below” (*AMB*), the “out-minus-at” of calls (*COMA*), the “out-minus-at” of puts (*POMA*), and the realized-implied volatility spread (*RVIV*). Then, we construct zero-cost arbitrage portfolios by taking a long position in portfolios with the highest implied volatility measure and a short position in portfolios with the lowest implied volatility measure. The arbitrage portfolio will have significantly non-zero return if there is a statistically significant

⁵ The “above-minus-below” is the difference between the mean implied volatility of in-the-money puts and out-of-the-money calls and the mean implied volatility of in-the-money calls and out-of-the-money puts. “Out-minus-at” of calls (puts) is the difference between the mean implied volatility of out-of-the-money calls (puts) and the mean implied volatility of at-the-money calls (puts).

relationship between stock returns and the corresponding option-implied volatility measure. However, portfolio level analysis might suffer from the aggregation effect due to omission of useful information in the cross-section because it does not control for the effects of other option-implied volatility measures and firm-specific effects simultaneously. Consequently, we further perform firm-level cross-sectional regressions to assess the predictive power of all six interlinked option-implied volatility measures.

Our study contributes to the literature in several aspects. First, this study compares the predictive ability of six different implied volatility measures. To the best of our knowledge, this is the most comprehensive study that compares the predictive power of option-implied volatility measures. Secondly, our study tests the predictive power of different option-implied volatility measures on stock returns over various investment horizons. This helps investors better understand the informational content captured by different option-implied volatility measures. Finally, the sample period, from 1996 until 2014, is longer than those used in previous studies. This enables us to analyze whether the predictive power of option-implied volatility measures documented previously is still significant in extended periods using recent data in the US markets.

The paper is organized as follows. Section 2 discusses the data and the methodology. Section 3 examines the relationship between expected stock returns and different option-implied volatility measures through portfolio level analysis and firm-level cross-sectional regressions. Section 4 discusses potential reasons for the predictive power of option-implied volatility measures through discussions on informed trading, skewness preference, constraints on short-sale, and delta hedging. Section 5 offers concluding remarks.

2 Data and Methodology

2.1 Data Sources

Our data come from several different sources. Financial statement data are downloaded from Compustat, monthly and daily stock return data are from CRSP, and option implied volatility data are from OptionMetrics. The factors in Fama-French (1993) three-factor model (i.e., *MKT*, *SMB*, and *HML*) are obtained from Kenneth French's online data library.⁶

To distinguish at-the-money options, we follow the criteria in Bali and Hovakimian (2009).⁷ That is, if the absolute value of the natural logarithm of the ratio of the stock price to the exercise price is smaller than 0.1, an option is denoted at-the-money. We denote options with the natural logarithm of the ratio of the stock price to the exercise price smaller than -0.1 as out-of-the-money call (in-the-money put) options. Options with the natural logarithm of the ratio of the stock price to the exercise price larger than 0.1 are denoted in-the-money call (out-of-the-money put) options. Then, we calculate the average implied volatilities for different kinds of options across all eligible options at the end of each calendar month. Our sample period starts from January 1996 and ends in December 2014 (i.e., 19 years).⁸

2.2 Option-Implied Volatility Measures

For equity options, it is normal to observe the existence of volatility skew (i.e., the volatility decreases as the strike price increases). As discussed in the previous section, empirical studies document that a different part of the volatility curve can capture relevant

⁶ Available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

⁷ Only stock data for ordinary common shares (CRSP share codes 10 and 11) are retained. Furthermore, closed-end funds, REITs (SIC codes 6720-6730 and 6798) and those companies whose shares were trading less than \$5 are excluded. For option data, we focus on the last trading day of each calendar month. We only retain stock options with days-to-maturity greater than 30 but less than 91 days. After deleting options with zero open interest or zero best bid prices and those with missing implied volatility, we further exclude options whose bid-ask spread exceeds 50% of the average of the bid and ask prices and options which are traded for less than \$0.25.

⁸ The first observation of the implied volatility is available at the end of January, 1996. So the return observation starts from February, 1996. The last observation of monthly stock returns is the return in December, 2014. Since this study uses three-month holding period return, the last observation for three-month return should be the return during the period from October, 2014 to December, 2014, whereas the last observation for each volatility measure is constructed at the end of September 2014. So the sample consists of 225 monthly observations. The sample size is discussed in detail in section 3.1.

information about future stock returns (Bali and Hovakimian, 2009; Baltussen et al., 2012; Cremers and Weinbaum, 2010; Xing, Zhang and Zhao, 2010; Doran and Krieger, 2010; etc.). In following subsections, we discuss how different option-implied volatility measures reflect investors' expectations about future market conditions.

2.2.1 Call-Put Implied Volatility Spread

Drawing upon the method documented in Bali and Hovakimian (2009), $CPIV$ is constructed as follows:

$$CPIV = IV_{ATM,call} - IV_{ATM,put} \quad (1)$$

where $CPIV$ is the call-put implied volatility spread, $IV_{ATM,call}$ is the average of implied volatilities extracted from all at-the-money call options, and $IV_{ATM,put}$ is the average of implied volatilities extracted from all at-the-money put options available on the last trading day in each calendar month.

If investors expect decreases in underlying asset prices in the near future, they will choose to buy put options and sell call options. In this case, prices of put options will increase while prices of call options will decrease, suggesting higher implied volatilities for put options and lower implied volatilities for call options. A more negative $CPIV$ predicts decreases in underlying asset prices (i.e., more negative returns) and vice versa. Thus, it is expected that future asset returns should be positively correlated with $CPIV$.

2.2.2 Implied Volatility Skew

To construct $IVSKEW$ proposed by Xing, Zhang and Zhao (2010), we calculate the difference between the average of implied volatilities extracted from out-of-the-money put options and the average of implied volatilities extracted from at-the-money call options:

$$IVSKEW = IV_{OTM,put} - IV_{ATM,call} \quad (2)$$

where $IVSKEW$ is the implied volatility skew, $IV_{OTM,put}$ is the average of implied volatilities extracted from out-of-the-money put options at the end of each calendar month.

If investors expect that there will be a downward movement in underlying asset price, they will choose to buy out-of-the-money put options. An increase in the demand for out-of-the-money put options further leads to increases in their prices, and thus in their implied volatilities. In this case, the spread between out-of-the-money put implied volatilities and at-the-money call implied volatilities will become larger. $IVSKEW$ reflects investor's concern about future downward movements in underlying asset prices. A higher $IVSKEW$ indicates a higher probability of large negative jumps in underlying asset prices. So, $IVSKEW$ is expected to be negatively related to future returns on underlying assets.

2.2.3 Above-Minus-Below

AMB represents the difference between average implied volatility of options whose strike prices are above current underlying price and average implied volatility of options whose strike prices are below current underlying price. Following Doran and Krieger (2010), this study defines AMB as:

$$AMB = \frac{(IV_{ITM,put} + IV_{OTM,call}) - (IV_{ITM,call} + IV_{OTM,put})}{2} \quad (3)$$

where $IV_{ITM,put}$, $IV_{OTM,call}$, $IV_{ITM,call}$, and $IV_{OTM,put}$ are mean implied volatilities of all in-the-money put options, all out-of-the-money call options, all in-the-money call options, and all out-of-the-money put options, respectively.

The variable AMB captures the difference between the average implied volatilities of low-strike-price options and the average implied volatilities of high-strike-price options. Thus, AMB captures the volatility curve asymmetry by investigating both of its tails. More (less) negative values of AMB are indications of more trading of pessimistic (optimistic) investors and thus lower (higher) future stock returns are expected.

2.2.4 Out-Minus-At

Doran and Krieger (2010) also introduce two other measures, which capture the difference between out-of-the-money and at-the-money implied volatilities of call/put options.

$$COMA = IV_{OTM,call} - IV_{ATM,call} \quad (4)$$

$$POMA = IV_{OTM,put} - IV_{ATM,put} \quad (5)$$

All measures in these two equations have the same meanings as in the previous equations (1) – (3).

In contrast to *AMB*, *COMA* (*POMA*) use only out-of-the-money and at-the-money call (put) options to capture the volatility curve asymmetry. In the option market, it is observed that out-of-the-money and at-the-money call and put options are the most liquid and heavily traded whereas in-the-money options are not traded much (Bates, 2000). It is also reported that bullish traders generally buy out-of-the-money calls while bearish traders buy out-of-the-money puts (Gemmill, 1996). To follow a trading strategy based on volatility curve asymmetry, it is more convenient to construct a measure using the most liquid options for which data availability is not a concern. Positive *COMA* is associated with bullish expectations, indicating an increase in the trading of optimistic investors. However, a positive *POMA* reflects the overpricing of out-of-the-money puts relative to at-the-money puts due to increased demand for out-of-the-money puts that provide hedging against negative jump risk.

2.2.5 Realized-Implied Volatility Spread

In the spirit of Bali and Hovakimian (2009), we calculate realized volatility (*RV*), which is the annualized standard deviation of daily returns over the previous month, and then construct a realized-implied volatility spread, *RVIV*, as follows:

$$RVIV = RV - IV_{ATM} \quad (6)$$

where IV_{ATM} is the average implied volatility of at-the-money call and put options.

The variable *RVIV* is related to volatility risk, which has been widely tested in empirical papers. When testing the volatility risk premium, previous articles focus on the difference between realized volatility and implied volatility (proxied by a variance swap rate). However, rather than using a variance swap rate (which is calculated by using options with different moneyness levels), we focus on at-the-money implied volatility (a standard deviation measure).

2.2.6 Discussion on Option-Implied Volatility Measures

To better show that various option-implied volatility measures capture different information about the volatility curve, Exhibit 1 plots call and put implied volatilities of Adobe System Inc. on December 29, 2000. Options included in this Exhibit have an expiration date of February 17, 2001 (i.e., two months ahead).

[Insert Exhibit 1 here]

From this exhibit, it is clear that *CPIV* captures the middle of the volatility curve, which reflects small deviations from put-call parity. *IVSKEW* reflects the left of the put volatility curve and the middle of the call volatility curve. The *AMB* measure captures the tails of the volatility curve. *COMA* captures the right side and middle of the volatility curve for call options, while *POMA* captures the left side and middle of the volatility curve for put options.

From call and put options with the same strike price and time-to-expiration, it is easy to observe small deviations from put-call parity. That is, small differences between paired call and put implied volatilities are apparent. However, these deviations do not necessarily indicate arbitrage opportunities (discussed in Section 4.5). Furthermore, measures *IVSKEW*, *AMB*, *COMA* and *POMA* provide some indications about the shape of the implied volatility curve. Lower *AMB* and *COMA* indicate more negatively skewed implied volatility curves.

Lower *POMA* and *IVSKEW* indicate less negatively skewed implied volatility curves.⁹ Thus, we expect to observe a positive relationship between *AMB* or *COMA* and stock returns, but a negative relationship between *IVSKEW* or *POMA* and stock returns.

Overall, *CPIV*, *IVSKEW*, *AMB*, *COMA* and *POMA* capture different parts of the volatility curve. Therefore it is interesting to test whether these measures (i.e., different parts of the volatility curve) have different predictive ability for asset returns. Taken together, all five option-implied volatility measures capture much of the information contained in the cross-section of implied volatilities (Doran and Krieger, 2010). However, some of them are interdependent, e.g., $IVSKEW = POMA - CPIV$. So, these three measures cannot be included in the same model because of the multi-collinearity problem. In addition to these measures, we further include another volatility measure used in Bali and Hovakimian (2009), *RVIV*.

2.3 Firm Specific Variables

In order to see whether option-implied volatility measures can predict stock returns after controlling for known firm-specific effects, we also include several firm-level control variables. To control for the size effect documented by Banz (1981), we use the natural logarithm of a company's market capitalization (in thousands of USD) on the last trading day of each month. Following Fama and French (1992), we use the book-to-market ratio as another firm-level control variable. Jegadeesh and Titman (1993) document the existence of a momentum effect (i.e., past winners, on average, outperform past losers in short future periods). We use past one-month returns to capture the momentum effect. Stock trading volumes are included as another variable (measured in hundred millions of shares traded in the previous month). The market beta reflects the historical systematic risk and is calculated by using daily returns available in the previous month using the standard CAPM

⁹ Compared to *POMA*, *IVSKEW* uses at-the-money call options, which are more liquid than at-the-money put options and are seen as the investors' consensus on the firm's uncertainty (Xing, Zhang, and Zhao, 2010).

framework.¹⁰ The bid-ask spread is used to control for liquidity risk. It is defined as the mean daily percentage bid-ask spread over the previous month where the percentage bid-ask spread is the difference between ask and bid prices scaled by the mean of the bid and ask prices (Bali and Hovakimian, 2009). Finally, we also control for option trading volume (measured in millions of options traded in the previous month), which is documented to contain information about future stock prices.¹¹

3 Results

3.1 Descriptive Results

Exhibit 2 presents some descriptive statistics, such as mean, standard deviation, minimum, 5th percentile, 25th percentile, median, 75th percentile, 95th percentile and maximum of each volatility measure, sample size available for each measure, as well as pairwise correlations.¹²

[Insert Exhibit 2 here]

On the basis of all available observations on the last trading day of each month during the sample period, Panel A of Exhibit 2 reports descriptive statistics for option-implied volatility measures. Therefore, the sample size varies for each measure. It is observed that *CPIV*, *AMB*, *COMA* and *RVIV* have negative means, while those for *IVSKEW* and *POMA* are positive. The last column of Panel A shows that, the sample size for *CPIV* is largest (i.e., 230,884), whereas the sample size for *AMB* is smallest (i.e., 66,104). *CPIV* is constructed by using near-the-money call and put options while *AMB* is constructed by using deep out-of-the-money and in-the-money call and put options. It is expected that more

¹⁰ It is required that stocks should have more than 15 daily observations in the previous month for beta calculation.

¹¹ Pan and Poteshman (2006) find strong evidence that option trading volume contains information about future stock prices. Doran, Perterson, and Tarrant (2007) incorporate option trading volume when analyzing whether the shape of implied volatility skew can predict the probability of a market crash or spike.

¹² The option-implied volatility measures in Exhibit 2 are reported in decimals, not in percentages. The full sample presented in Panel A consists of 4,999 US firms, and the intersection sample in Panel B consists of 3,317 US firms.

near-the-money options are available than deep out-of-the-money and in-the-money options. So the larger sample size for *CPIV* and the much smaller sample size for *AMB* are reasonable.

Panel B of Exhibit 2 reports the descriptive statistics of the intersection sample which consists of stocks with all option-implied volatility measures available. The intersection sample has 62,562 stock-month observations.¹³ *CPIV*, *AMB*, *COMA* and *RVIV* have negative means, whereas *IVSKEW* and *POMA* have positive means. The negative sample mean of *CPIV* shows that put options on individual companies tend to have higher average implied volatility than calls. Individual firms tend to have negative implied volatility skew as seen by the positive sample means of *POMA* and *IVSKEW* and negative sample means of *AMB* and *COMA*. These results support the view that, on average, implied volatility curve is asymmetric for individual equities as observed in Exhibit 1.

As discussed in Section 2.2, *IVSKEW* is the difference between *POMA* and *CPIV*. On average, 15.98 percent of the value of the negative skew stems from the difference between at-the-money implied volatility of puts and at-the-money implied volatility of calls, and the other 84.02 percent can be due to the difference between out-of-the-money implied volatility and at-the-money implied volatility of puts. Given the positive relationship between stock returns and *CPIV* and the negative relationship between stocks returns and *IVSKEW* documented in previous studies (Bali and Hovakimian, 2009; Cremers and Weinbaum, 2010; Doran and Krieger, 2010; and Xing, Zhang, and Zhao, 2010), we infer whether or not *POMA* (which represents the left-hand side of the put implied volatility curve) plays a significant role in predicting stock returns. If there is no empirical evidence in favor of significant predictive ability for *POMA*, the predictive power of *IVSKEW* should be driven by the

¹³ The intersection sample in Doran and Krieger (2010) consists of 62,076 company months during the period from January 1996 to September 2008. Thus, the size of our intersection sample during the same period is smaller than that of Doran and Krieger (2010). This can be due to the different moneyness criteria and more control variables used in this study.

difference between at-the-money put implied volatilities and the at-the-money call implied volatilities.

Panel C of Exhibit 2 presents pairwise correlations; there are four high average correlations. The correlation between *CPIV* and *IVSKEW* is -0.6580, the correlation between *IVSKEW* and *POMA* is 0.7333, the correlation between *AMB* and *COMA* is 0.6678, and the correlation between *AMB* and *POMA* is -0.6842. Other pairwise correlations are relatively low. These high correlations indicate that there might be some information overlap in option-implied measures. By trying to avoid overlap, this study takes into account potential multicollinearity problem when conducting multivariate firm-level cross-sectional regressions.

3.2 Portfolio Level Analysis

In order to examine the relationship between quintile portfolio returns and each volatility measure, we construct quintile portfolios, and further form a “5-1” arbitrage portfolio within the full sample by holding a long position on the quintile portfolio with the highest volatility measure and a short position on the quintile portfolio with the lowest volatility measure. Then, we test the null hypothesis that the “5-1” arbitrage portfolio has a mean return equal to zero. If the average return on the “5-1” arbitrage portfolio is significantly positive (negative), there is a positive (negative) relationship between the volatility measure and portfolio returns. Results for portfolio level analysis are presented in Exhibit 3.

[Insert Exhibit 3 here]

We first examine the effect of *CPIV* on subsequent one-month portfolio returns. For both equally-weighted and value-weighted portfolios, returns increase monotonically from portfolios with the lowest *CPIV* to portfolios with the highest *CPIV*. The mean return on the equally-weighted “5-1” arbitrage portfolio is 1.12% per month (with a p-value close to 0), and the mean return on the value-weighted “5-1” arbitrage portfolio is 0.97% per month (with

a p-value of 0.0002). Significant positive mean returns on “5-1” arbitrage portfolios indicate a positive relationship between *CPIV* and portfolio returns. We also control for Fama-French risk factors to examine whether there are risk-adjusted return differences for arbitrage portfolios. Results are consistent with those obtained for raw return differences. Jensen’s alpha with respect to Fama-French three-factor model is 1.16% per month (with a p-value close to 0) for equally-weighted “5-1” arbitrage portfolios and it is 1.10% per month (with a p-value of 0.0001) for value-weighted “5-1” arbitrage portfolios. These results for *CPIV* are comparable with the results in Bali and Hovakimian (2009). Bali and Hovakimian (2009) document that the equally-weighted (value-weighted) raw return on the arbitrage portfolio is, on average, 1.425% (1.045%) per month with a t-statistic of 7.9 (4.2) and the equally-weighted (value-weighted) Jensen’s alpha on the arbitrage portfolio is 1.486% (1.140%) with a t-statistic of 8.6 (4.5).

Next, we focus on the effect of *IVSKEW*. The results in Exhibit 3 show a monotonic decreasing pattern in equally- and value-weighted portfolio returns. Portfolios with lower *IVSKEW* outperform those with higher *IVSKEW*. Average monthly returns on “5-1” equally-weighted and value-weighted arbitrage portfolios are always negative and statistically significant at a 5% level (-0.86% with a p-value close to 0 and -0.64% with a p-value of 0.0133, respectively). The negative relationship between *IVSKEW* and portfolio return is still significant after controlling for market excess returns (*MKT*), size (*SMB*) and book-to-market ratio (*HML*).

Exhibit 3 shows weak evidence for a negative relationship between *AMB* and portfolio returns. For equally-weighted “5-1” arbitrage portfolio, Jensen’s alpha with respect to Fama-French three-factor model is -0.44% per month, which is marginally significant at a 10% level.

Exhibit 3 also presents quintile portfolio level analysis results for two “out-minus-at” measures. For both *COMA* and *POMA*, there is no evidence ~~on~~of ~~the~~a relationship between these two measures and one-month ahead asset returns (the average monthly return and Jensen’s alpha with respect to Fama-French three-factor models on each “5-1” arbitrage portfolio are not significantly non-zero).

Finally, results in Exhibit 3 confirm a negative relationship between *RVIV* and one-month ahead portfolio returns. Both the average return and the Jensen’s alpha decrease monotonically from the portfolio with the lowest *RVIV* to that with the highest *RVIV*. Such a negative relationship is always significant at a 5% level no matter whether the return is risk-adjusted or not. For example, Jensen’s alpha for an equally-weighted “5-1” arbitrage portfolio is -0.57% per month with a p-value of 0.0007 and that for value-weighted “5-1” arbitrage portfolio is -0.64% per month with a p-value of 0.0039. These results are broadly comparable to results in Bali and Hovakimian (2009). They document that Jensen’s alpha for the arbitrage portfolio constructed on *RVIV* is -0.587% with a significant t-statistic of -2.5 when using the equally-weighted scheme, and -0.642% with a significant t-statistic of -2.2 when using the value-weighted scheme.

To summarize, results in Exhibit 3 confirm that *CPIV* is positively related to one-month ahead portfolio returns, whereas *IVSKEW* and *RVIV* are negatively related. Exhibit 3 also provides weak evidence about the negative relationship between *AMB* and portfolio returns. However, through portfolio level analysis, *COMA* and *POMA* do not have significant power to explain one-month ahead portfolio returns.

Although portfolio level analysis helps determine potential candidates among several option-implied volatility measures in predicting future returns, it does not allow us to control for firm-specific effects. Some other firm-specific effects may also play a role in explaining

stock returns. To address this issue, we perform firm-level cross-sectional regressions in the following subsection.

3.3 Firm-Level Cross-Sectional Regression Results

This subsection provides results from firm-level cross-sectional regressions with firm-specific control variables (i.e., size, book-to-market ratio, previous one-month return, stock trading volume, historical beta, bid-ask spread, and option trading volume). In the first step of the firm-level cross-sectional regressions, at the end of each calendar month, stock returns of different firms are regressed on explanatory variables (e.g., option-implied volatility measures and control variables) cross-sectionally. Thus, during the full sample period, there are 225 estimations for the coefficient on each explanatory variable. In the second step, we test whether the coefficient on each explanatory variable has non-zero time-series mean. First cross-sectional regressions focus on the predictive power of each of several option-implied volatility measures, *CPIV* , *IVSKEW* , *AMB* , *COMA* , *POMA* and *RVIV* . Then, various volatility measures are included in the same model in order to compare the predictive power of each measure. Such an analysis sheds light on which volatility measure is the most useful in predicting individual stock returns.

Furthermore, we test the predictive ability of different option-implied volatility measures at various investment horizons from one week to three months. Results for one-week and two-week horizons and results for two-month and three-month horizons are similar. Therefore, we only report the results for one-week, one-month and three-month investment horizons to save space.¹⁴ Finally, we perform subperiod analysis and compare results before and after the 2008 Global Financial Crisis.

¹⁴ Results for two-week and two-month investment horizons are available upon request.

3.3.1 The Full Period Analysis

First, we examine the predictive power of each volatility measure covering the full sample period. Then, we test how each volatility measure performs when competing with others through multivariate regressions. Exhibit 4 shows results for the one-week investment horizon.

[Insert Exhibit 4 here]

Models I to VI focus on the predictive power of each option-implied volatility measure individually. Model I indicates that stocks with higher *CPIV* outperform those with lower *CPIV* in the following one-week period. Such a positive relationship between *CPIV* and stock returns is significant at a 1% level. Model II investigates how *IVSKEW* correlates with one-week ahead stock returns. The statistically significant and negative coefficient on *IVSKEW* confirms a negative relationship between stock returns and *IVSKEW*. Model III provides evidence in favor of a marginally significant predictive ability of *AMB*. Inconsistent with our expectations, empirical results show that *AMB* is negatively related to one-week ahead stock returns. For the one-week investment horizon, we do not find any evidence about the significant impact of *COMA*, *POMA* or *RVIV* on stock returns.

The remaining four models in Exhibit 4 (Models VII to X) investigate which option-implied volatility measures have stronger predictive power when competing with other measures. Models VIII and X indicate that among six option-implied volatility measures, *IVSKEW* has significant predictive power.¹⁵ Furthermore, Models VII and IX indicate that both *CPIV* and *POMA* play important roles in explaining the significant predictive power of *IVSKEW*. That is, both at-the-money call and put options and out-of-the-money put options capture relevant information about return prediction.

¹⁵ If *IVSKEW* and *CPIV / POMA* are included in the same multi-variate regression model, *IVSKEW* still gains significant predictive ability whereas the predictive power of *CPIV / POMA* disappears.

The multicollinearity issue may affect the significant coefficient on *AMB*. In these three models, the relationship between *AMB* and one-week ahead stock returns becomes stronger compared to what is shown in Model III of Exhibit 4. As discussed in subsections 2.2.3 and 2.2.6, *AMB* measures the volatility curve asymmetries. Compared with three other measures (*IVSKEW*, *COMA* and *POMA*) that reflect the shape of implied volatility curve, *AMB* is constructed using both in-the-money and out-of-the-money options. In-the-money options may not capture information as we expect due to infrequent trading activity.

Finally, over the one-week horizon, *RVIV* has marginally significant power in predicting future stock returns when competing with other option-implied volatility measures. This is consistent with the finding of portfolio level analysis discussed in Section 3.2.

In order to examine [whether](#) the predictive power of different option-implied volatility measures persists over longer periods, we investigate how different measures perform in predicting one-month ahead stock returns. Exhibit 5 presents corresponding results.

[Insert Exhibit 5 here]

Models I and II indicate that the predictive power of *CPIV* or *IVSKEW* persists over a longer investment horizon. Model V of Exhibit 5 indicates that a higher *POMA* predicts lower one-month ahead stock return. Such a negative relationship is significant at the 5% level. Then, Models VIII to X indicate that, when competing with other option-implied volatility measures, *IVSKEW* has additional significant predictive power. The significant and negative slope on *IVSKEW* is driven by deviations from put-call parity and volatility curve asymmetry. As shown in Models VII and IX, even though both *CPIV* and *POMA* have significant slopes, the predictive power of *CPIV* is more significant. Compared to results in Exhibit 4, *RVIV* loses its predictive power for the one-month horizon.

Finally, we test the predictability of different option-implied volatility measures over the three-month horizon.

[Insert Exhibit 6 here]

As shown in Exhibit 6, regressions models focusing on each individual option-implied volatility measure (Models I to VI) further confirm the predictive power of *CPIV* , *IVSKEW* , and *POMA* on stock returns. In the remaining four models (Models VII to X), it is obvious that the predictability of *IVSKEW* stems from information captured by both *CPIV* and *POMA* . Meanwhile, out-of-the-money call implied skew becomes important in return prediction, since *COMA* has a marginally significant and positive slope in cross-sectional regressions (Models VII and IX).

Results in Exhibits 4 to 6 imply an asymmetric effect of the volatility risk. As can be inferred from Exhibit 1, *COMA* reflects information on the right and middle part of the volatility curve, and *IVSKEW* and *POMA* reflect information on the left and middle part of the volatility curve. The right part of the implied volatility curve captures positive information (investors with bullish expectations choose to trade out-of-the-money call options)~~right part of the implied volatility curve actually captures negative information (investors choose to trade out-of-the-money put options to be protected from large negative jumps)~~, while the left part of the implied volatility curve actually captures negative information (investors choose to trade out-of-the-money put options to be protected from large negative jumps)~~left part of the implied volatility curve captures positive information (investors with bullish expectations choose to trade out-of-the-money call options)~~. Results for multivariate regressions reflect that investors may treat these two kinds of information differently. For shorter investment horizons, investors are more sensitive to negative information captured by out-of-the-money put options, and such kind of information predicts future stock returns. For longer horizons, there is more uncertainty about future market conditions, and there is a higher chance that out-of-the-money call options come in-the-money at maturity. Information captured by out-of-the-money call options becomes

increasingly important as investment horizons extend. Thus, *COMA* predicts stock returns over longer horizon. Even though both *COMA* and *POMA* capture the shape of the implied volatility curve, these two measures do not predict stock returns in the same way.

From results discussed in this subsection, it is inferred that, among all six option-implied volatility measures, *IVSKEW* has the most significant power in predicting future stock returns.¹⁶ For the one-week investment horizon, the significant effect of *IVSKEW* is affected by deviations from put-call parity and the left part of implied volatility curve. For one-month and three-month horizons, the predictive power of *POMA* becomes weaker. For longer investment horizon, like three-month, positive news is important for investors since they are more optimistic about the long-term performance of the market. Thus, *COMA* gains a significant coefficient in cross-sectional regressions.

3.3.2 The Subperiod Analysis

Our sample period is from 1996 to 2014, and it covers the financial crisis. It is interesting to examine whether information captured by different kinds of options is perceived in the same way before and after the recent financial crisis. In this subsection, firm-level cross-sectional regressions are conducted for two sub periods: before and after September 2008. Exhibits 7 and 8 show how option-implied volatility measures perform in predicting one-week ahead stock returns before and after the crisis, respectively.

[Insert Exhibits 7 & 8 here]

Compared to results presented in Exhibit 4, similar results can be found in Exhibits 7 and 8. That is, *IVSKEW* is important in predicting one-week ahead stock returns in both sub periods. The role played by *CPIV* or *POMA* seems to change during two subperiods.

¹⁶ In addition to firm-level cross-sectional regressions, this study also performs pooled regressions for the sample, which involves both time-series and cross-sectional data. Results for pooled regressions confirm the importance of *CPIV* and *IVSKEW* in predicting future stock returns over various horizons from one-week to three-month. A higher *CPIV* predicts a higher future stock return, whereas a higher *IVSKEW* predicts a lower future stock return. Furthermore, controlling for time fixed effects does not affect the significance of the predictive power of *CPIV* and *IVSKEW*. More detailed results are available upon requests.

CPIV has predictive power before the crisis, but its predictive ability does not persist after the crisis. However, for *POMA*, the predictability over the one-week horizon becomes stronger after the crisis. After the crisis, investors would be more sensitive to negative shocks (i.e., crashes) captured by the left part of the put implied volatility curve. Thus, for the one-week investment horizon, potential negative jumps captured by *IVSKEW* would contain relevant information about stock return prediction. No matter which sample period is investigated, the predictability of *IVSKEW* at the one-week horizon is stronger than any other measures used in this study.

4. Discussion

Results of empirical tests presented above provide useful insights about how option-implied volatility measures perform in predicting future stock returns. From Exhibit 1, it is clear that different option-implied volatility measures capture different portions of the implied volatility curve. Thus, different volatility measures perform differently in predicting stock returns. This section discusses why some measures (especially *IVSKEW* and *CPIV*) dominate others in predicting future stock returns.

4.1 Informed Trading

The volatility curve asymmetry could be due to investors' trading in option markets (Bollen and Whaley, 2004). When the demand for a particular option contract is strong, due to arbitrage limits, competitive risk-averse option market makers are not able to hedge their positions perfectly and they require a premium for taking this risk. As a result, the demand for an option drives up its price. In this type of equilibrium, one would expect a positive relation between option expensiveness which can be measured by implied volatility and end-user demand. Investors with positive (negative) expectations about the future market conditions will increase their demand for call (put) options and/or reduce their demand for

puts (calls), implying an increase in call (put) implied volatility and/or a decrease in put (call) implied volatility.

By using a VAR-bivariate-GARCH model, Bali and Hovakimian (2009) provide evidence supporting a significant volatility spillover effect where information propagates from individual equity options to individual stocks. Due to this spillover effect, option-implied information could contain useful information about stock return prediction.

From the previous literature, if investors choose to trade in option markets first, their trading activities will generate volatility curve asymmetry. The volatility curve asymmetry captures relevant information in predicting future stock returns due to spillover effect from option markets to stock markets.

Previous literature discusses potential reasons which drive trading activities in option markets. Bali and Hovakimian (2009) claim that informed investors, who know that stock prices will change but are not sure about the direction, choose to trade in the options market. This could be due to the fact that options provide leverage for investors; investors get much higher profits from trading options than those from trading underlying stocks. Also, trading options provide insurance for undesirable changes in underlying asset prices.

Cremers and Weinbaum (2010) show that deviations from put-call parity are more likely to occur in stocks with high probability of informed trading (PIN), supporting the view that *CPIV* contains information about future prices of underlying stocks. Furthermore, deviations from put-call parity tend to predict returns to a greater extent in firms that face a more asymmetric information environment.

Consistently, Xing, Zhang and Zhao (2010) find that the predictive power of the implied volatility skew is driven by informed trading. That is, informed traders act in the options market and that the stock market is slow to incorporate information from the options market.

Furthermore, information captured by the implied volatility skew is closely related to firm fundamentals, which can predict subsequent underlying asset returns.

Lin and Lu (2015) document that insider traders choose to trade in option markets first. The predictive power of option implied volatilities on stock returns becomes stronger around analyst-related events. This finding supports the [fact-argument](#) that the predictability of option-implied volatilities is driven by insiders' information on upcoming analyst-related news.

Overall, option-implied information captures relevant information about future movements in underlying asset prices due to the spillover effect of informed trading from option markets to stock markets.

4.2 Skewness Preference

Investors' preference [to-over](#) skewness also helps explain the relationship between option-implied volatility measures and future stock returns. Bakshi, Kapadia and Madan (2003) show that a more negative risk-neutral skewness is equivalent to a steeper slope of implied volatility curve, everything else being equal. This indicates a negative relationship between $IVSKEW / POMA$ and risk-neutral skewness and a positive relationship between $AMB / COMA$ and risk neutral skewness. The negative relationship between $IVSKEW$ ($POMA$) and future stock returns shown in previous analysis indicates a negative skewness preference. However, the negative relationship between AMB and future stock returns shows conflicting findings: a positive skewness preference.

Existing literature also documents mixed results about skewness preference. Bali, Cakici and Whitelaw (2011), Bali and Murray (2013), and Conrad, Dittmar and Ghysels (2013) find a positive skewness preference, whereas Rehman and Vilkov (2012), Stilger, Kostakis and Poon (2015), and Xing, Zhang and Zhao (2010) document a negative skewness preference.

Due to mixed findings about skewness preference in previous literature, Lazos, Coakley and Liu (2015) investigate how heterogeneous expectations affect skewness preference. Their empirical analysis shows that when investors are pessimistic (optimistic), their overconfidence produces an undervaluation (overvaluation) which explains their negative skewness preference. The overconfidence of neutral investors who exhibit either pessimism or optimism leads to overvaluation of assets, indicating a positive skewness preference. Thus, investors with heterogeneous expectations may have different preference ~~to~~ over skewness.

Variables *IVSKEW* and *POMA* capture pessimistic fears. The negative relationship between *IVSKEW* / *POMA* and stock returns are consistent with the negative skewness preference of pessimistic investors. The variable *AMB* captures neutral expectations (pessimistic expectations in the left tail and optimistic expectations in the right tail). Due to the positive relationship between *AMB* and risk neutral skewness, a negative relationship between *AMB* and stock returns indicates that investors are willing to accept lower returns in order to pursue higher skewness. This is consistent with the positive skewness preference of neutral investors.

4.3 Put-Call Parity

Next, we focus on why call-put implied volatility spreads (capturing deviation from put-call parity) predict future stock returns. Put-call parity indicates a relationship between prices of call and put options with the same expiration date and strike price.

$$P_t + S_t - D_t = C_t + Ke^{-r(T-t)} \quad (7)$$

where t as the current time, T as the time of expiration, S_t as the price of the underlying asset, K as the strike price, r as the continuous risk-free rate, and D_t as the present value of dividends paid on the underlying asset before expiration, and C_t and P_t are prices of call and put options. It is expected that equation (7) holds in perfect markets. Due to the existence of

market frictions, following Finucane (1991), the put-call parity after controlling option bid-ask spread could be written as:

$$P_t^a - C_t^b - Ke^{-r(T-t)} + S_t - D_t \geq 0 \quad (8)$$

$$C_t^a - P_t^b + K - S_t + D_t \geq 0 \quad (9)$$

where P_t^b , C_t^b , P_t^a and C_t^a are the put and call bid and ask prices. Defining δ_t^C and δ_t^P as the bid-ask spreads of the call and put options,

$$C_t^a = C_t^b + \delta_t^C \quad (10)$$

$$P_t^b = P_t^a - \delta_t^P \quad (11)$$

and substituting (10) and (11) into (9) yields the second condition in terms of C_t^b and P_t^a :

$$C_t^b - P_t^a + K - S_t + D_t + (\delta_t^C + \delta_t^P) \geq 0 \quad (12)$$

Defining

$$E_t \equiv C_t^b - P_t^a + Ke^{-r(T-t)} - S_t + D_t \quad (13)$$

and substituting into (8) and (12) yields the frictionless market bounds for the measure E_t

$$K(e^{-r(T-t)} - 1) - \delta_t^C - \delta_t^P \leq E_t \leq 0 \quad (14)$$

E_t , which may be interpreted as a measure of deviation from put-call parity, is used as the basic measure of relative put and call prices. Higher values of E_t mean that calls are priced high relative to puts, and lower values imply relatively high put prices.

By calculating E_t for each individual asset, we are able to distinguish stocks with no violation of equation (14) and we would expect that put-call parity holds by [distinction definition](#) for these stocks. For these stocks, we test whether *CPIV* captures important information about future stock returns. For stocks with no deviation from put-call parity

under the control of option bid-ask spread from equation (14), results show that *CPIV* is still significantly and positively related to future stock returns.¹⁷

The upper and lower bounds used in equation (14) fail to reflect other frictions, such as constraints on short sale. That is, for stocks with no deviation from put-call parity after controlling for option bid-ask spread, *CPIV* still has significant predictive power. This may indicate that the market is not frictionless and option-implied volatility measures capture other relevant information, such as constraints on short sale, which are discussed in the next subsection.

4.4 Short Sale Constraints

In stock markets, following a buy-and-hold strategy generates profits if stock price increases. On the other hand, to avoid potential loss due to a decrease in a stock price in the future, pessimistic investors holding the stock choose to sell it. Pessimistic investors who do not hold the stock are able to make profits only by short selling the stock.

In order to short sell a stock, borrowers have to find lenders who hold the stock and are willing to lend the stock to others. After posting a collateral as required, borrowers can borrow the stock from lenders and sell it at the market price. If the stock price decreases, borrowers will repurchase the same shares back but at a lower price. Then, borrowers return the stock back to lenders and get the collateral back together with the rebate rate.¹⁸ During such a process, lenders will charge borrowers a fee (i.e., the repo rate for individual stocks).

¹⁷ The results for portfolio level analysis on *CPIV* among stocks with no deviation from put-call parity as shown in equation (14) show that the average return on the equally-weighted “5-1” long-short portfolio constructed on *CPIV* is 0.88% per month (with a p-value close to 0), and the average return on the value-weighted “5-1” long-short portfolio is 0.71% per month (with a p-value of 0.0012). More details are available upon request.

¹⁸ In order to short sell an asset, borrowers have to put up a collateral to lenders. After borrowers return the asset back to lenders, lenders need to give the collateral back and also pay rebate rates (e.g., the portion of interest or dividends of shares earned from the collateral) to borrowers. Thus, the rebate rate is a proxy for the difficulty of short selling from the stock lending market. If short selling is difficult, the rebate rate will be lower and can even become negative.

Thus, from short sale, profits for borrowers are always less than the magnitude of decrease in stock price.

In stock markets, constraints on short sale exist (e.g. difficulty in borrowing shares, fee paid to the lender, fee paid to the broker, etc.). Studies claim that short sale constraints predict future stock returns (e.g., Figlewski, 1981; Ofek, Richardson and Whitelaw, 2004; Cohen, Diether and Malloy, 2007).

Under the condition of no arbitrage, the put-call parity holds if there is no friction in the market. By rearranging Equation (7), we can get:

$$S_t = C_t - P_t + Ke^{-r(T-t)} + D_t \quad (15)$$

If the stock market price is different from the price implied in Equation (15), stock market price and implied price will converge to the same level due to investors' arbitrage activities. However, due to the existence of constraints on short sale and the repo rate, when stock market prices are higher than implied prices, there does not exist an arbitrage which leads to the convergence of two values (Lamont and Thaler, 2003; Ofek and Richardson, 2003; and Ofek, Richardson and Whitelaw, 2004).

In the presence of short sale constraints, through trading call and put options, option markets provide investors the chance to short stocks that they may not be able to borrow and sell in stock markets (Figlewski and Webb, 1993), and put options become relatively expensive compared with their corresponding calls. Figlewski and Webb (1993) document that the difference between put and call implied volatilities is closely correlated with short interest, a proxy for constraints on short sale.¹⁹ Ofek, Richardson and Whitelaw (2004) provide supportive evidence that, for stocks that are difficult or expensive to short, a deviation from put-call parity is more likely to be observed. Thus, deviation from put-call

¹⁹ A stock's short interest refers to the total number of shares that have been sold short and not yet covered (repurchased) as of a point in time.

parity may reflect difficulty in short selling stocks and may contain useful information about stock return prediction.

By using the rebate rate as a proxy, Cremers and Weinbaum (2010) fail to find evidence that predictability of option-implied information is driven by stocks that are hard to short. However, such a finding could be affected by the data limitation, since they use private data only covering two-year period from October 2003 to December 2005.

Thus, due to the constraints on short-sale, frictions exist for short sellers due to the repo rate paid by borrowers to lenders. This further indicates that put-call parity may not hold in presence of such frictions. The call-put implied volatility spread, *CPIV*, may capture the unobserved repo rate of individual stocks and reflect how difficult it is to short sell the underlying stock. So, constraints on short sale could be a potential reason for the predictive ability of option-implied volatility measures.²⁰

4.5 Delta-Hedge Trading Strategy

Doran and Krieger (2010) propose that the predictive power of option-implied volatility measures on stock returns could be due to trading activities of delta-hedge traders. For example, if *CPIV* increases, in order to be delta-neutral, option traders need to purchase the underlying stock to hedge the increase in delta. The purchase of the underlying stock will drive up future stock prices and further lead to a positive future stock return.

Thus, in addition to skewness preference and constraints on short sale, delta rebalancing is another potential reason for the predictability of option-implied volatility measures on stock returns.

²⁰ As claimed by Adrian, Begalle, Copeland and Martin (2012), repo rates are hard to collect. Thus, repo rates have not been used in this study.

5. Conclusion

This study focuses on the relationship between option-implied volatility measures and future stock returns and results can be summarized as follows. First, a portfolio level analysis implies a positive relationship between *CPIV* and one-month ahead portfolio returns and a negative relationship between *IVSKEW* and *RVIV* and future one-month portfolio returns.

Firm-level cross-sectional regressions indicate that, over different investment horizons (from one-week to three-month), *IVSKEW* has the most important predictive information. Both deviations from put-call parity and put implied volatility curve capture useful information in return prediction over various horizons. However, the predictive power of the put implied volatility curve becomes weaker for one-month and three-month horizons.

In addition, we confirm the asymmetric effect of volatility risk. Out-of-the-money call and put options capture fundamentally different information about future stock returns. Our results imply that investors care about and overweigh negative future return shocks, especially over short horizons. Additionally, over longer horizons (three-month), investors take positive expectations into consideration as well.

Finally, the subsample analysis confirms that the strong predictive ability of *IVSKEW* over one-week horizon persists before and after the recent crisis. The driver of the effect of *IVSKEW* on one-week ahead stock returns changes during the full sample period. Before the financial crisis, the main driver is a deviation from put-call parity. However, after the crisis, *POMA* is more important in predicting one-week ahead stock returns, suggesting that investors are more sensitive to negative shocks captured by out-of-the-money put options.

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Exhibit 1: Volatility Curve Asymmetry and Implied Volatility Measures

Notes: This exhibit plots implied volatility extracted from each call and put options on Adobe Systems Inc on December 29, 2000. To get this exhibit, only options with expiration date of February 17, 2001 are retained. The closing price for Adobe Systems Inc on December 29, 2000 is 58.1875.

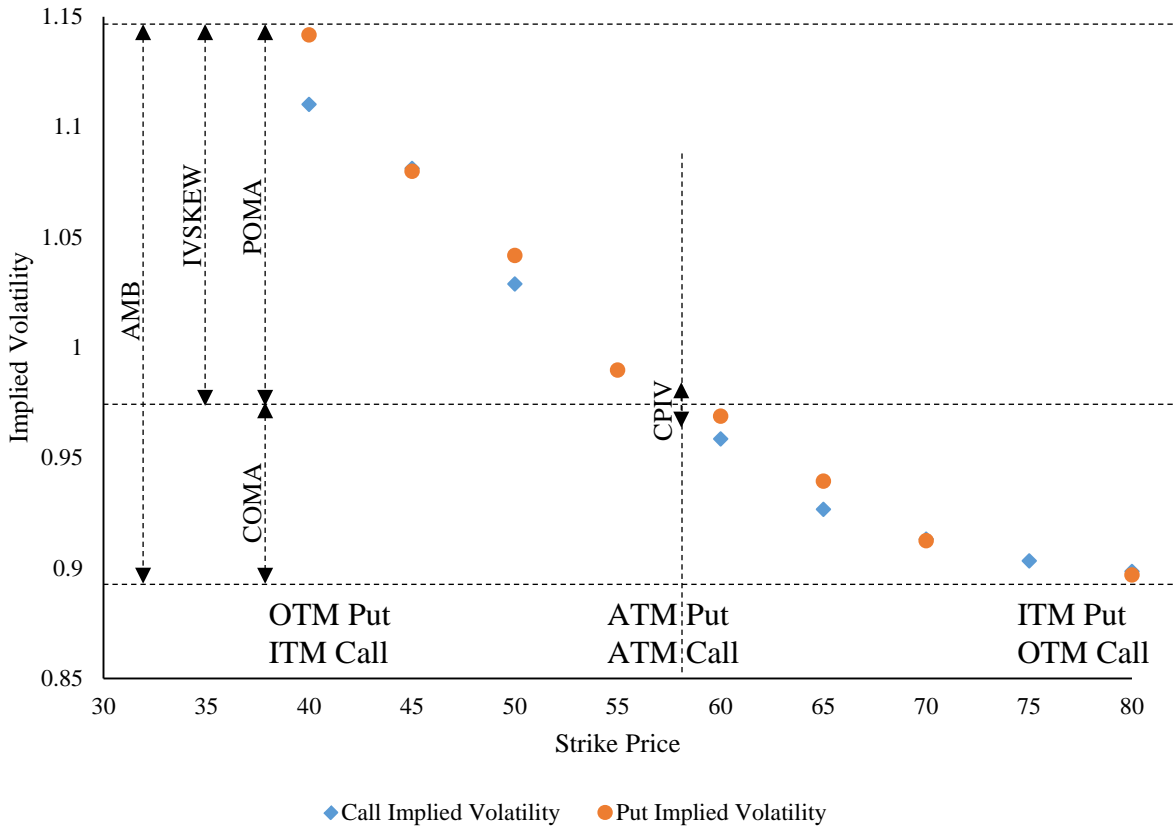


Exhibit 2: Summary Statistics

Notes: Descriptive statistics presented in Exhibit 2 are calculated based on option-implied volatility measures and firm-specific variables at the end of each calendar month from January 1996 to October 2014.

<i>Panel A: Full Sample</i>										
	Mean	Std	Min	5 th Pct	25 th Pct	Median	75 th Pct	95 th Pct	Max	Sample Size
<i>CPIV</i>	-0.0072	0.0479	-2.4244	-0.0664	-0.0187	-0.0046	0.0085	0.0459	1.3637	230884
<i>IVSKEW</i>	0.0631	0.0655	-1.0576	-0.0047	0.0319	0.0534	0.0809	0.1594	2.0332	121205
<i>AMB</i>	-0.0810	0.0934	-1.0599	-0.2385	-0.1262	-0.0727	-0.0281	0.0466	0.6575	66104
<i>COMA</i>	-0.0199	0.0434	-1.3960	-0.0742	-0.0366	-0.0196	-0.0034	0.0317	2.5235	109321
<i>POMA</i>	0.0526	0.0482	-0.8965	-0.0033	0.0271	0.0463	0.0693	0.1287	2.0444	116557
<i>RVIV</i>	-0.0188	0.1848	-3.2866	-0.2291	-0.1021	-0.0390	0.0349	0.2598	21.0411	285144

<i>Panel B: Intersection Sample (Sample Size=62562)</i>										
	Mean	Std	Min	5 th Pct	25 th Pct	Median	75 th Pct	95 th Pct	Max	
<i>CPIV</i>	-0.0108	0.0457	-1.0291	-0.0715	-0.0175	-0.0048	0.0053	0.0311	0.6255	
<i>IVSKEW</i>	0.0676	0.0671	-0.5534	-0.0046	0.0328	0.0561	0.0877	0.1758	1.5713	
<i>AMB</i>	-0.0828	0.0929	-1.0599	-0.2404	-0.1275	-0.0741	-0.0297	0.0435	0.6510	
<i>COMA</i>	-0.0245	0.0341	-0.5434	-0.0771	-0.0393	-0.0225	-0.0074	0.0212	0.6904	
<i>POMA</i>	0.0568	0.0506	-0.2255	-0.0027	0.0282	0.0488	0.0747	0.1414	1.0365	
<i>RVIV</i>	-0.0031	0.2265	-2.0835	-0.2477	-0.1063	-0.0323	0.0652	0.3399	9.2399	

(Continued)

	<i>CPIV</i>	<i>IVSKEW</i>	<i>AMB</i>	<i>COMA</i>	<i>POMA</i>	<i>RVIV</i>
<i>IVSKEW</i>	-0.6580					
<i>AMB</i>	-0.3010	-0.3107				
<i>COMA</i>	-0.1921	-0.2972	0.6678			
<i>POMA</i>	0.0295	0.7333	-0.6842	-0.5679		
<i>RVIV</i>	0.0031	0.0701	-0.0275	-0.0220	0.0958	
<i>ln(size)</i>	0.1151	0.0202	-0.1409	-0.0651	0.1307	0.0525
<i>B / M Ratio</i>	-0.0041	0.1467	-0.1365	-0.1558	0.1910	0.0642
<i>Momentum</i>	-0.0274	0.0026	-0.0323	0.0339	-0.0212	0.1483
<i>Stock Volume</i>	0.0212	0.1027	-0.1180	-0.1016	0.1554	0.1023
<i>Market Beta</i>	0.0047	0.0451	-0.0576	-0.0716	0.0641	0.2506
<i>Bid – Ask Spread</i>	-0.0231	-0.0839	0.1720	0.1335	-0.1322	0.0419
<i>Option Volume</i>	0.0058	0.0722	-0.0660	-0.0146	0.1011	0.0430

Exhibit 3: Portfolio Level Analysis on Option-Implied Volatility Measures

Notes: Quintile portfolios are constructed every month by sorting stocks on each option-implied volatility measure at the end of the previous month. Call-put implied volatility spread (*CPIV*) is ~~the difference between~~ the average implied volatility of at-the-money calls ~~and minus~~ the average implied volatility of at-the-money puts. Implied volatility skew (*IVSKEW*) is ~~the difference between~~ the average implied volatility of out-of-the-money puts ~~and minus~~ the average implied volatility of at-the-money calls. “Above-minus-below” (*AMB*) is ~~the difference between~~ the average implied volatility of options whose strike prices are above the current underlying price ~~and minus~~ the ~~mean-average~~ implied volatility of options whose strike prices are below the current underlying price. “Out-minus-at” of calls (*COMA*) is ~~the difference between~~ the average implied volatility of out-of-the-money calls ~~and minus~~ the average implied volatility of at-the-money calls. “Out-minus-at” of puts (*POMA*) is ~~the difference between~~ the average implied volatility of out-of-the-money puts ~~and minus~~ the average implied volatility of at-the-money puts. Realized-implied volatility spread (*RVIV*) is ~~the difference between~~ the realized volatility (i.e. the annualized standard deviation of daily returns over the previous month) ~~and minus~~ the average of at-the-money call and put implied volatilities. Quintile 1 (5) denotes the portfolio of stocks with the lowest (highest) option-implied volatility measure. The Jensen’s alphas are reported in rows labeled “Alpha”. The column “5-1” refers to the arbitrage portfolio with a long position in portfolio 5 and a short position in portfolio 1. The row “Return” documents data about raw returns on portfolios, and the row “Alpha” shows data about Jensen’s alpha with respect to Fama-French three factor model. P-values reported in Exhibit 3 are calculated using Newey-West method to control for serial correlation. Hereafter, *, **, and *** denote for significance at 10%, 5% and 1% level, respectively.

Panel A: Equally-Weighted Portfolios								
		1	2	3	4	5	5-1	p-value
<i>CPIV</i>	<i>Return</i>	0.0042	0.0078	0.0096	0.0110	0.0154	0.0112***	0.0000
	<i>Alpha</i>	-0.0068	-0.0021	0.0000	0.0014	0.0048	0.0116***	0.0000
<i>IVSKEW</i>	<i>Return</i>	0.0110	0.0094	0.0083	0.0064	0.0024	-0.0086***	0.0000
	<i>Alpha</i>	0.0011	-0.0004	-0.0015	-0.0037	-0.0089	-0.0099***	0.0000
<i>AMB</i>	<i>Return</i>	0.0082	0.0105	0.0081	0.0079	0.0042	-0.0040	0.1245
	<i>Alpha</i>	-0.0025	-0.0004	-0.0025	-0.0027	-0.0069	-0.0044*	0.0666
<i>COMA</i>	<i>Return</i>	0.0083	0.0104	0.0109	0.0092	0.0081	-0.0003	0.8956
	<i>Alpha</i>	-0.0032	0.0000	0.0005	-0.0012	-0.0027	0.0006	0.7764
<i>POMA</i>	<i>Return</i>	0.0061	0.0092	0.0086	0.0099	0.0061	0.0001	0.9784
	<i>Alpha</i>	-0.0042	-0.0005	-0.0013	-0.0002	-0.0048	-0.0006	0.7300
<i>RVIV</i>	<i>Return</i>	0.0124	0.0107	0.0090	0.0090	0.0075	-0.0048***	0.0039
	<i>Alpha</i>	0.0020	0.0010	-0.0007	-0.0010	-0.0037	-0.0057***	0.0007

Panel B: Value-Weighted Portfolios								
		1	2	3	4	5	5-1	p-value
<i>CPIV</i>	<i>Return</i>	0.0037	0.0063	0.0093	0.0098	0.0134	0.0097***	0.0002
	<i>Alpha</i>	-0.0057	-0.0017	0.0018	0.0023	0.0054	0.0110***	0.0001
<i>IVSKEW</i>	<i>Return</i>	0.0125	0.0113	0.0088	0.0066	0.0060	-0.0064**	0.0133
	<i>Alpha</i>	0.0048	0.0038	0.0016	-0.0010	-0.0033	-0.0082***	0.0008
<i>AMB</i>	<i>Return</i>	0.0087	0.0122	0.0071	0.0130	0.0038	-0.0048	0.2925
	<i>Alpha</i>	0.0001	0.0037	-0.0013	0.0045	-0.0055	-0.0056	0.1753
<i>COMA</i>	<i>Return</i>	0.0086	0.0115	0.0102	0.0086	0.0056	-0.0030	0.4058
	<i>Alpha</i>	-0.0012	0.0030	0.0020	0.0004	-0.0030	-0.0019	0.5934
<i>POMA</i>	<i>Return</i>	0.0084	0.0094	0.0083	0.0099	0.0085	0.0001	0.9802
	<i>Alpha</i>	0.0005	0.0016	0.0007	0.0022	0.0000	-0.0005	0.8382
<i>RVIV</i>	<i>Return</i>	0.0121	0.0110	0.0089	0.0070	0.0062	-0.0059**	0.0138
	<i>Alpha</i>	0.0034	0.0034	0.0016	-0.0007	-0.0030	-0.0064***	0.0039

Exhibit 4: Firm-Level Cross-Sectional Regression Results Over One-Week

Notes: Exhibit 4 presents the firm-level cross-sectional regression results for the intersection sample during the full sample period. The dependent variables are one-week returns on individual stocks after factor construction at the end of each calendar month. P-values are calculated using Newey-West method.

	I	II	III	IV	V	VI	VII	VIII	IX	X
Intercept	0.0049	0.0042	0.0048	0.0041	0.0042	0.0016	0.0031	0.0027	0.0032	0.0028
P-value	0.6350	0.6850	0.6471	0.6947	0.6838	0.8735	0.7555	0.7852	0.7458	0.7762
<i>CPIV</i>	0.0705***						0.0625***		0.0736***	
P-value	0.0000						0.0002		0.0000	
<i>IVSKEW</i>		-0.0418***						-0.0546***		-0.0459***
P-value		0.0000						0.0000		0.0000
<i>AMB</i>			-0.0147**				-0.0252**	-0.0296***		
P-value			0.0281				0.0116	0.0003		
<i>COMA</i>				-0.0158			0.0218	0.0295	-0.0013	-0.0122
P-value				0.4207			0.3509	0.1908	0.9538	0.5431
<i>POMA</i>					-0.0179		-0.0532***		-0.0330***	
P-value					0.1449		0.0002		0.0057	
<i>RVIV</i>						-0.0052	-0.0067**	-0.0065**	-0.0067**	-0.0063**
P-value						0.1141	0.0413	0.0448	0.0395	0.0509
<i>Size</i>	0.0001	0.0003	0.0000	0.0001	0.0002	0.0003	0.0002	0.0002	0.0002	0.0003
P-value	0.8164	0.6452	0.9538	0.8410	0.7662	0.6583	0.7254	0.7090	0.6838	0.6418
<i>B/M Ratio</i>	-0.0037	-0.0034	-0.0032	-0.0032	-0.0031	-0.0032	-0.0034	-0.0033	-0.0034	-0.0032
P-value	0.1154	0.1378	0.1672	0.1753	0.1853	0.1633	0.1700	0.1723	0.1689	0.1807
<i>Pre 1M Return</i>	-0.0015	-0.0014	-0.0018	-0.0016	-0.0012	-0.0017	0.0001	-0.0004	0.0004	0.0000
P-value	0.7366	0.7426	0.6889	0.7071	0.7812	0.6898	0.9817	0.9314	0.9181	0.9907
<i>Stock Volume</i>	-0.0005	-0.0005	0.0003	0.0001	0.0000	0.0006	0.0006	0.0008	0.0006	0.0007
P-value	0.6457	0.6271	0.8167	0.9084	0.9916	0.5323	0.5375	0.4605	0.5985	0.5206
<i>Market Beta</i>	-0.0004	-0.0003	-0.0004	-0.0005	-0.0003	0.0001	0.0000	-0.0001	-0.0001	-0.0001
P-value	0.7411	0.8135	0.7027	0.6429	0.8074	0.9141	0.9783	0.9634	0.9675	0.9634
<i>Bid-ask Spread</i>	-0.0158*	-0.0146	-0.0200**	-0.0202**	-0.0202**	-0.0206**	-0.0147*	-0.0131	-0.0147*	-0.0140
P-value	0.0784	0.1104	0.0133	0.0157	0.0138	0.0126	0.0906	0.1359	0.0979	0.1185
<i>Option Volume</i>	-0.0006	0.0000	-0.0029	-0.0025	-0.0022	-0.0039	-0.0033	-0.0032	-0.0032	-0.0028
P-value	0.8352	0.9924	0.3727	0.3990	0.4582	0.1951	0.2252	0.2688	0.2327	0.3131

Exhibit 5: Firm-Level Cross-Sectional Regression Results Over One-Month

Notes: Exhibit 5 presents the firm-level cross-sectional regression results for the intersection sample during the full sample period. The dependent variables are one-month returns on individual stocks after factor construction at the end of each calendar month. P-values are calculated using Newey-West method.

	I	II	III	IV	V	VI	VII	VIII	IX	X
Intercept	0.0211	0.0190	0.0206	0.0189	0.0188	0.0186	0.0194	0.0183	0.0179	0.0175
P-value	0.2412	0.2987	0.2570	0.3031	0.3096	0.2991	0.2836	0.3037	0.3210	0.3252
<i>CPIV</i>	0.1062***						0.1148***		0.1151***	
P-value	0.0005						0.0002		0.0000	
<i>IVSKEW</i>		-0.0795***						-0.0897***		-0.0848***
P-value		0.0000						0.0000		0.0000
<i>AMB</i>			-0.0005				-0.0094	-0.0233*		
P-value			0.9696				0.6059	0.0815		
<i>COMA</i>				0.0055			0.0232	0.0248	0.0163	-0.0083
P-value				0.8958			0.6207	0.5967	0.6939	0.8349
<i>POMA</i>					-0.0540**		-0.0596*		-0.0572**	
P-value					0.0378		0.0574		0.0200	
<i>RVIV</i>						0.0040	0.0007	0.0007	0.0001	0.0005
P-value						0.5237	0.9099	0.9113	0.9826	0.9349
<i>Size</i>	-0.0003	0.0001	-0.0003	-0.0001	0.0000	-0.0001	0.0000	0.0000	0.0000	0.0001
P-value	0.7944	0.9566	0.7899	0.8967	0.9765	0.8837	0.9634	0.9786	0.9668	0.9151
<i>B/M Ratio</i>	-0.0165***	-0.0158***	-0.0159***	-0.0155***	-0.0154***	-0.0160***	-0.0157***	-0.0155***	-0.0153***	-0.0153***
P-value	0.0034	0.0053	0.0047	0.0058	0.0057	0.0043	0.0053	0.0066	0.0062	0.0067
<i>Pre 1M Return</i>	0.0000	0.0000	-0.0006	-0.0009	-0.0003	0.0001	0.0027	0.0013	0.0022	0.0019
P-value	0.9999	0.9988	0.9415	0.9112	0.9744	0.9872	0.7538	0.8773	0.8035	0.8294
<i>Stock Volume</i>	-0.0034	-0.0035	-0.0027	-0.0032	-0.0030	-0.0026	-0.0035*	-0.0032*	-0.0033*	-0.0030
P-value	0.1126	0.1014	0.2104	0.1350	0.1650	0.2366	0.0680	0.0976	0.0962	0.1306
<i>Market Beta</i>	0.0003	0.0008	0.0006	0.0005	0.0009	0.0010	0.0011	0.0011	0.0012	0.0012
P-value	0.8864	0.6793	0.7657	0.8117	0.6408	0.6296	0.6060	0.5962	0.5587	0.5599
<i>Bid-ask Spread</i>	-0.0150	-0.0163	-0.0295*	-0.0298*	-0.0314**	-0.0287*	-0.0140	-0.0130	-0.0132	-0.0139
P-value	0.3443	0.2751	0.0566	0.0592	0.0489	0.0549	0.3718	0.3739	0.3894	0.3442
<i>Option Volume</i>	0.0046	0.0057	0.0018	0.0031	0.0038	0.0011	0.0042	0.0035	0.0033	0.0034
P-value	0.5283	0.4125	0.8016	0.6692	0.5923	0.8760	0.5240	0.5963	0.6116	0.6039

Exhibit 6: Firm-Level Cross-Sectional Regression Results Over Three-Month

Notes: Exhibit 6 presents the firm-level cross-sectional regression results for the intersection sample during the full sample period. The dependent variables are one-quarter returns on individual stocks after factor construction at the end of each calendar month. P-values are calculated using Newey-West method.

	I	II	III	IV	V	VI	VII	VIII	IX	X
Intercept	0.0378	0.0385	0.0380	0.0370	0.0374	0.0379	0.0375	0.0373	0.0369	0.0372
P-value	0.4606	0.4553	0.4647	0.4762	0.4769	0.4640	0.4667	0.4663	0.4747	0.4669
<i>CPIV</i>	0.1301**						0.1719***		0.1681***	
P-value	0.0146						0.0009		0.0011	
<i>IVSKEW</i>		-0.1541***						-0.1565***		-0.1590***
P-value		0.0001						0.0000		0.0000
<i>AMB</i>			0.0085				-0.0249	-0.0312		
P-value			0.7334				0.3785	0.1944		
<i>COMA</i>				0.1060			0.1459*	0.1298	0.1281*	0.0903
P-value				0.1555			0.0754	0.1106	0.0946	0.2186
<i>POMA</i>					-0.1070*		-0.1226**		-0.1156**	
P-value					0.0655		0.0537		0.0321	
<i>RVIV</i>						0.0140	0.0026	0.0026	0.0026	0.0031
P-value						0.1767	0.7749	0.7758	0.7798	0.7424
<i>Size</i>	0.0003	0.0007	0.0003	0.0004	0.0006	0.0003	0.0006	0.0007	0.0007	0.0007
P-value	0.9298	0.8187	0.9277	0.8878	0.8499	0.9179	0.8431	0.8234	0.8217	0.7989
<i>B/M Ratio</i>	-0.0527***	-0.0531***	-0.0518***	-0.0520***	-0.0523***	-0.0515***	-0.0529***	-0.0530***	-0.0534***	-0.0531***
P-value	0.0003	0.0002	0.0004	0.0004	0.0003	0.0004	0.0003	0.0003	0.0002	0.0003
<i>Pre 1M Return</i>	-0.0008	0.0018	-0.0018	-0.0029	0.0000	-0.0018	0.0064	0.0045	0.0060	0.0042
P-value	0.9627	0.9139	0.9109	0.8568	0.9988	0.9125	0.7023	0.7929	0.7245	0.8036
<i>Stock Volume</i>	-0.0041	-0.0046	-0.0038	-0.0043	-0.0044	-0.0055	-0.0054	-0.0055	-0.0054	-0.0054
P-value	0.3731	0.3084	0.3987	0.3518	0.3293	0.1860	0.2013	0.1891	0.2087	0.2049
<i>Market Beta</i>	0.0041	0.0050	0.0050	0.0051	0.0053	0.0055	0.0061	0.0063	0.0061	0.0064
P-value	0.3465	0.2565	0.2544	0.2409	0.2328	0.2300	0.1890	0.1757	0.1861	0.1672
<i>Bid-ask Spread</i>	-0.0620*	-0.0686**	-0.0979***	-0.0999***	-0.1058***	-0.1019***	-0.0585*	-0.0587*	-0.0589*	-0.0606*
P-value	0.0612	0.0446	0.0065	0.0057	0.0041	0.0050	0.0778	0.0774	0.0758	0.0706
<i>Option Volume</i>	0.0242*	0.0245**	0.0218	0.0239*	0.0238*	0.0261**	0.0250**	0.0246**	0.0250**	0.0256**
P-value	0.0587	0.0442	0.1030	0.0835	0.0624	0.0428	0.0434	0.0469	0.0334	0.0317

Exhibit 7: Firm-Level Cross-Sectional Regression Results Over One-Week before the Crisis

Notes: Exhibit 7 presents the firm-level cross-sectional regression results for the intersection sample during the period before September 2008. The dependent variables are one-week returns on individual stocks after factor construction at the end of each calendar month. P-values are calculated using Newey-West method.

	I	II	III	IV	V	VI	VII	VIII	IX	X
Intercept	0.0074	0.0066	0.0051	0.0047	0.0036	0.0030	0.0065	0.0058	0.0059	0.0057
P-value	0.5760	0.6177	0.7050	0.7279	0.7846	0.8180	0.6171	0.6586	0.6473	0.6601
<i>CPIV</i>	0.0862***						0.0837***		0.0939***	
P-value	0.0000						0.0001		0.0000	
<i>IVSKEW</i>		-0.0450***						-0.0628***		-0.0498***
P-value		0.0000						0.0000		0.0000
<i>AMB</i>			-0.0157*				-0.0272*	-0.0378***		
P-value			0.0848				0.0541	0.0008		
<i>COMA</i>				-0.0101			0.0469*	0.0466*	0.0227	-0.0032
P-value				0.6539			0.0764	0.0781	0.3358	0.8921
<i>POMA</i>					-0.0155		-0.0453**		-0.0246*	
P-value					0.3135		0.0184		0.0975	
<i>RVIV</i>						-0.0062	-0.0082**	-0.0078**	-0.0079**	-0.0073*
P-value						0.1295	0.0401	0.0497	0.0447	0.0657
<i>Size</i>	0.0001	0.0002	0.0001	0.0002	0.0003	0.0003	0.0001	0.0001	0.0002	0.0002
P-value	0.8971	0.7619	0.8893	0.8013	0.7098	0.7382	0.9028	0.8591	0.8267	0.7878
<i>B/M Ratio</i>	-0.0068**	-0.0064**	-0.0059*	-0.0059*	-0.0057*	-0.0060*	-0.0061*	-0.0060*	-0.0061*	-0.0059*
P-value	0.0354	0.0458	0.0659	0.0736	0.0772	0.0587	0.0745	0.0753	0.0748	0.0733
<i>Pre 1M Return</i>	-0.0027	-0.0030	-0.0029	-0.0028	-0.0026	-0.0018	0.0006	-0.0001	0.0008	0.0002
P-value	0.6359	0.5910	0.6131	0.6208	0.6466	0.7423	0.9086	0.9819	0.8880	0.9685
<i>Stock Volume</i>	-0.0007	-0.0007	0.0004	0.0001	0.0000	0.0010	0.0010	0.0012	0.0009	0.0011
P-value	0.6713	0.6747	0.8244	0.9317	0.9903	0.5177	0.4911	0.4208	0.5471	0.4681
<i>Market Beta</i>	0.0000	0.0002	0.0000	0.0000	0.0002	0.0005	0.0006	0.0005	0.0006	0.0005
P-value	0.9823	0.8920	0.9781	0.9882	0.8903	0.7433	0.7099	0.7276	0.7260	0.7366
<i>Bid-ask Spread</i>	-0.0080	-0.0078	-0.0084	-0.0082	-0.0077	-0.0083	-0.0071	-0.0067	-0.0063	-0.0070
P-value	0.2786	0.3113	0.2525	0.2623	0.2851	0.2374	0.3195	0.3584	0.3730	0.3411
<i>Option Volume</i>	-0.0017	-0.0009	-0.0050	-0.0043	-0.0041	-0.0064	-0.0058	-0.0055	-0.0057	-0.0050
P-value	0.6965	0.8393	0.2973	0.3184	0.3527	0.1426	0.1422	0.1841	0.1428	0.2118

Exhibit 8: Firm-Level Cross-Sectional Regression Results Over One-Week after the Crisis

Notes: Exhibit 8 presents the firm-level cross-sectional regression results for the intersection sample during the period after September 2008. The dependent variables are one-week returns on individual stocks after factor construction at the end of each calendar month. P-values are calculated using Newey-West method.

	I	II	III	IV	V	VI	VII	VIII	IX	X
<i>Intercept</i>	-0.0003	-0.0008	0.0041	0.0029	0.0054	-0.0013	-0.0040	-0.0036	-0.0023	-0.0031
P-value	0.9845	0.9583	0.7984	0.8580	0.7382	0.9355	0.7948	0.8107	0.8801	0.8377
<i>CPIV</i>	0.0378**						0.0184		0.0314	
P-value	0.0344						0.3492		0.1203	
<i>IVSKEW</i>		-0.0353**						-0.0375**		-0.0378**
P-value		0.0319						0.0191		0.0182
<i>AMB</i>			-0.0126				-0.0211**	-0.0126		
P-value			0.1168				0.0228	0.1380		
<i>COMA</i>				-0.0278			-0.0305	-0.0061	-0.0511	-0.0308
P-value				0.4616			0.4762	0.8817	0.2205	0.4064
<i>POMA</i>					-0.0229		-0.0697***		-0.0503***	
P-value					0.2589		0.0005		0.0072	
<i>RVIV</i>						-0.0032	-0.0037	-0.0039	-0.0041	-0.0042
P-value						0.5993	0.5523	0.5175	0.5031	0.4789
<i>Size</i>	0.0002	0.0004	-0.0001	0.0000	-0.0001	0.0003	0.0004	0.0004	0.0004	0.0004
P-value	0.8038	0.6873	0.8891	0.9614	0.9470	0.7602	0.5993	0.6398	0.6519	0.6296
<i>B/M Ratio</i>	0.0027	0.0027	0.0024	0.0024	0.0024	0.0026	0.0023	0.0023	0.0023	0.0025
P-value	0.1211	0.1321	0.1615	0.1752	0.1646	0.1517	0.2022	0.2149	0.2016	0.1693
<i>Pre 1M Return</i>	0.0011	0.0020	0.0006	0.0008	0.0017	-0.0015	-0.0010	-0.0009	-0.0003	-0.0003
P-value	0.8665	0.7564	0.9236	0.8995	0.7881	0.8218	0.8645	0.8880	0.9630	0.9607
<i>Stock Volume</i>	-0.0001	-0.0002	0.0000	0.0001	0.0000	0.0000	-0.0002	-0.0002	-0.0002	-0.0002
P-value	0.7944	0.6501	0.9356	0.8517	0.9925	0.9555	0.7243	0.7551	0.6951	0.6858
<i>Market Beta</i>	-0.0012	-0.0012	-0.0014	-0.0016	-0.0013	-0.0006	-0.0013	-0.0013	-0.0013	-0.0013
P-value	0.6011	0.6260	0.5742	0.5350	0.6321	0.8287	0.6997	0.6988	0.7015	0.7037
<i>Bid-ask Spread</i>	-0.0319	-0.0286	-0.0440**	-0.0450**	-0.0462**	-0.0462**	-0.0307	-0.0265	-0.0322	-0.0285
P-value	0.1646	0.2167	0.0208	0.0247	0.0180	0.0211	0.1718	0.2457	0.1617	0.2195
<i>Option Volume</i>	0.0017*	0.0020*	0.0014*	0.0013	0.0016	0.0013*	0.0019*	0.0017*	0.0020*	0.0018*
P-value	0.0516	0.0716	0.0946	0.1066	0.1032	0.0846	0.0629	0.0869	0.0572	0.0792