Pricing of Firm Specific Jump Risk

Marius Ascheberg, Holger Kraft,
and Yildiray Yildirim*

Current version: October 23, 2012

Abstract

This paper studies the relationship between the cross section of stock returns and firm specific jump risk. Using option data, we estimate various option-based time-series. Sorting firms according to their firm specific jump risk, we find that this risk is priced for small stocks. Furthermore, we show that it is genuinely idiosyncratic, and not related to systematic volatility or systematic jump risk. We also find that firms have similar exposures to upward and downward jumps and both jumps are negatively priced, but the effect is more pronounce for downward jumps. Besides, it is documented that our results are closely linked to the idiosyncratic volatility (ivol) anomaly by Ang, Hodrick, Xing, and Zhang (2006). Therefore, if ivol proxies for an omitted factor, our results suggest that the exposure to idiosyncratic jump risk is related to this factor.

*Ascheberg, Marius.Ascheberg@hof.uni-frankfurt.de, Department of Finance, Goethe University Frankfurt; Kraft, holgerkraft@finance.uni-frankfurt.de, Department of Finance, Goethe University Frankfurt; Yildirim, yildiray@syr.edu, Whitman School of Management, Syracuse University. We thank Michael Brennan, Zhanhui Chen, Tilman Drerup, Ralitsa Petkova, Alexander Schmidt, Claudio Tebaldi, Ivo Welch, David Weinbaum and participants of the 2012 meeting of the German Finance Association for helpful comments and suggestions. Holger Kraft gratefully acknowledges financial support by German Research Foundation (DFG).

Pricing of Firm Specific Jump Risk

Current version: October 23, 2012

Abstract

This paper studies the relationship between the cross section of stock returns and firm specific jump risk. Using option data, we estimate various option-based time-series. Sorting firms according to their firm specific jump risk, we find that this risk is priced for small stocks. Furthermore, we show that it is genuinely idiosyncratic, and not related to systematic volatility or systematic jump risk. We also find that firms have similar exposures to upward and downward jumps and both jumps are negatively priced, but the effect is more pronounce for downward jumps. Besides, it is documented that our results are closely linked to the idiosyncratic volatility (ivol) anomaly by Ang, Hodrick, Xing, and Zhang (2006). Therefore, if ivol proxies for an omitted factor, our results suggest that the exposure to idiosyncratic jump risk is related to this factor.

Key words: Cross-section of stock returns, Idiosyncratic risk.

JEL Classification: G12, G14

1 Introduction

The question of which factors influence expected returns has been a key issue in finance over decades. Starting with the capital asset pricing model, several studies document additional priced factors that help to explain the cross-section of stock returns. These factors include size, book-to-market, short- term reversal, momentum, liquidity risk, disaster risk, volatility risk, and jump risk, among others. Classic asset pricing theory suggests that, in contrast to systematic risk, idiosyncratic risk does not carry a risk premium, since rational investors are able to diversify their portfolios. In recent empirical studies, the pricing of idiosyncratic risk has been documented, although there is no consensus on the direction in which idiosyncratic volatility influences the cross-section of equity returns. Most of these studies use historical return data and residuals of the Fama and French three-factor model. This is potentially problematic since risk measures derived from historical data might not be good predictors of future risk exposures.[1]

In this paper, we study the relationship between the cross section of stock returns and firm specific jump risk. We use a linear factor model to estimate individual stock return sensitivities with respect to returns of certain option strategies (written on a particular stock). Therefore, we are able to sort stocks based on individual measures of future risk exposures and form stock portfolios with similar exposures.[2] Natural candidates are sensitivities to returns on out-of-the-money (otm) call and put options which are written on the respective stock.[3] We find that individual jump risk (upward and downward jumps) carries a significantly negative risk premium for 40% of the companies in our sample (smaller firms). The effect is more pronounced for downward jumps.

Our methodology captures total risk of a stock. This includes exposures to systematic volatility and systematic jump risk. Later, we control for these risks in formation regressions and disentangle total jump risk from systematic volatility and systematic jump risk. It turns out that our results are robust to systematic risk exposures. This suggests that idiosyncratic (upward or downward) jump risk is negatively related to expected stock returns. We also document that the pricing of idiosyncratic jump risk is robust to short term reversals.

We also study the relation of our findings to the ivol anomaly. We document that both phenomena are closely related. In particular, our results show that a higher exposure to id-

[1] Fu (2009) addresses this issue and uses exponential GARCH models to estimate expected idiosyncratic volatilities.

[2] For S&P 500 index options, this method has already been applied by Ang, Chen, and Xing (2005) and Cremers, Halling, and Weinbaum (2010) to document the pricing of systematic volatility risk and systematic jump risk in the cross-section of US equity returns.

[3] Driessen and Maenhout (2006)and Cremers, Halling, and Weinbaum (2010) use returns on S&P 500 otm put options to proxy for systematic jump risk.

iosyncratic jump risk goes together with a higher ivol and that there are few stocks with high ivol and low exposure to idiosyncratic jump risk. Therefore, if ivol proxies for an omitted factor,[4] our findings suggest that the exposure to idiosyncratic jump risk is related to this factor. We also study the relation of idiosyncratic jump risk to cds spreads and consider sub-periods as well as different industries. On average, stocks with higher idiosyncratic jump risk have higher cds spreads. Besides, we find that idiosyncratic jump risk is not priced in the consumer or manufacturing industries. On the contrary, it is highly significant in the remaining industries (high tech, health, and others).

Our paper is related one strand of literature studies the effect of jump risk on expected stock returns. They conclude that market-neutral straddle returns are a good proxy for systematic volatility, while changes in VIX are insignificant. This is in contrast to Ang, Hodrick, Xing, and Zhang (2006) who find that VIX changes are a good proxy for volatility risk. These different results can be attributed to different research methodologies.[5] Cremers, Halling, and Weinbaum (2010) also find results suggesting that systematic jump risk is a priced risk factor, but much less significant (from a statistical and economic point of view) than systematic volatility risk. Our choice of proxies for individual jump risk is motivated by Cremers, Halling, and Weinbaum (2010). Their proxies for aggregate jump risk are derived from S&P 500 futures options: otm put option returns, market-neutral strangle[6] returns, and the difference between the implied volatilities of otm puts and at-the-money (atm) calls. Only the difference in implied volatilities of otm puts and atm calls gives significant results. In their work, the price of risk carries a negative sign, as expected from theory (see Yan (2011) [7]).

Another strand of related literature studies the pricing of idiosyncratic risk. Chen and Petkova (2012) argue that if a factor is missing from the Fama-French three-factor model, then this factor (multiplied by a firm's loading on the factor) contaminates the residuals and can induce the ivol anomaly. They decompose the market variance into an average variance and an average correlation component. Subsequently, they provide evidence that portfolios constructed from ivol load differently on average variance, which has a negative price of risk. Notice that

[4]See, e.g., Wooldridge (2010), pp. 65ff., and Chen and Petkova (2012).

[5]Ang, Hodrick, Xing, and Zhang (2006) use monthly formation periods and investable portfolios (portfolios are constructed from previous' month's betas), while Cremers, Halling, and Weinbaum (2010) use monthly betas formed over a one-year window and run Fama-MacBeth regressions and portfolio sorts using contemporaneous betas. Cremers, Halling, and Weinbaum (2010) perform robustness checks and conclude that, in contrast to straddle positions, changes in VIX are not contemporaneously priced.

[6]A strangle is the combination of a call and a put with the same maturity. The strike of the call is higher than the strike of the put, creating a corridor in which the underlying does not change the payoff of the strangle. Market neutral strangles are created analog to the construction of a market-neutral straddle.

[7]Yan also decomposes the individual slope into a systematic and idiosyncratic component by regressing the individual slope on the slope of S&P 500 options and shows that the residuals (the idiosyncratic slope) drive the pricing relation. Our findings support these results.

average variance is not a traded factor. Therefore, Chen and Petkova (2012) also build a factor mimicking portfolio by regressing the non-traded factor on traded portfolio excess returns.[8]

The second major finding of Ang, Hodrick, Xing, and Zhang (2006) is that stocks with high idiosyncratic volatility relative to the Fama and French (1993) model have very low average returns in the following month. This is the so-called idiosyncratic volatility anomaly. It cannot be explained by size, book-to-market ratios, leverage, liquidity risk, volume, turnover, bid-ask spreads, coskewness risk, momentum or dispersion in analysts' forecasts. Bali and Cakici (2008) report that the ivol anomaly is strongly dependent on the research design and find evidence that idiosyncratic volatility has no significant effect in the cross-section. In particular, they cannot reproduce the ivol anomaly if stocks within portfolios are equal weighted (instead of value weighted as in Ang, Hodrick, Xing, and Zhang (2006)). Elkamhi, Lee, and Yao (2009) find that the ivol anomaly is intensified rather than reduced among stocks with active option trading and that options of these stocks exhibit a similar magnitude of mispricing. They conjecture that this finding is related to private information which is first revealed via option trading activity. By construction, our sample consists of stocks with active option trading and our results also suggest that information about future jumps is contained in options and stocks returns.

The remainder of the paper is structured as follows: Section 2 motivates as to why betas with respect to otm option returns are a reasonable proxy for firm specific jump risk. Section 3 summarizes how we merge the CRSP and OptionMetrics databases and subsequently use this data to construct returns of different option strategies on individual stocks. We also discuss the relation of these time series and the different kinds of risks. Section 4 explains how portfolios are constructed and reports various properties of these portfolios that are the main results of this paper. We find that jump risk is significantly priced and briefly discuss the relation to cds spreads. Section 5 performs robustness checks. In Section 6, we relate our finding to the ivol anomaly using double sorts. Section 7 concludes.

2 Betas as a Measure of Firm Specific Jump Risk

This section provides a motivation as to why betas with respect to otm option returns are a reasonable proxy for jump risk in a stock. For simplicity, we consider a jump-diffusion option pricing model (see, e.g., Merton (1976)) and argue that betas of stock returns on otm put and

[8] We have tried to replicate their results using a rolling window approach to avoid a look-ahead bias. However, for the resulting factor the pricing results do not hold anymore. Therefore, we do not relate our findings to their results.

call option returns are a measure of firm specific jump risk. The stock dynamics are given by

$$\mathrm{d}S_t = S_t \left[\mu \mathrm{d}t + \sigma \mathrm{d}W_t + L \mathrm{d}N_t \right],$$

where W_t is a Brownian motion, N_t is a Poisson process with constant intensity λ and L is a constant jump size. In this simple setup jump risk has two dimensions: size (L) and likelihood (λ). The beta of stock returns with respect to put or call returns reads

$$\beta_{\mathrm{Put}} = \frac{P}{S} \delta_{\mathrm{Put}}^{-1} \qquad \text{and} \qquad \beta_{\mathrm{Call}} = \frac{C}{S} \delta_{\mathrm{Call}}^{-1},$$

where P (C) is the option value and δ_{Put} (δ_{Call}) is the delta of the put (call) option. For illustration purposes, we use options that are 15% out of the money with a time to maturity of 100 actual days. Figure 1 depicts betas for different levels of the two jump risk dimensions. It can be seen that put betas are lower (higher in absolute value) if jump risk increases. Call betas are higher (also higher in absolute value) if jump risk increases. The spread between betas for varying jump risk is reasonably wide, such that we can expect our jump risk measure to be diverse across stocks.[9] In the following, we are going to regress stock returns on option returns to obtain betas. The advantage of using regressions is twofold: First, we do not have to fit an option pricing model to option data. It is well known that jump related parameters are hard to identify, especially if one uses relatively short time windows to capture the time variation of jump risk.[10] Second, we can control for factors that are priced in the cross-section of stock returns, but are harder to incorporate in a theoretical option pricing model (e.g. market, systematic volatility, systematic jump risk).

3 Data and Time Series Construction

This section describes how the dataset is constructed. We also explain how option data for individual stocks is used to calculate the relevant time series that proxy for jump risk.

3.1 Dataset

We start with the full OptionMetrics dataset. OptionMetrics is a comprehensive database providing historical prices, implied volatilities, and sensitivities for the entire US listed index

[9]Note that put and call betas are also affected if the diffusive volatility σ changes. We provide robustness checks in Subsection 5.6.

[10]Pan (2002) calibrates a model with stochastic volatility, jumps, dividends and stochastic short rate to 8 years of data on S&P 500 options. Despite the many observations, the jump related parameters are hard to identify.

and equity options markets. We use data from January 1996 to October 2010. The dataset contains both actual trades and quotes for which there are no trading volumes. We do not drop quotes with no trading volume, as this would significantly reduce the number of observations. We use several steps to ensure the quality of the quotes. All of the following option quotes are dropped:

1. **European options**. Our work relies on single-name equity options. In the US, these are usually of American type. The fraction of European options on US equity stocks is negligible, we thus restrict ourselves to American options.

2. **Underlyings other than common stock.** We restrict the option underlyings to be common stocks, thus omitting mutual funds, exchange-traded funds, American depository shares/receipts and unspecified underlyings.

3. **Non-Standard Settlement**. Some option contracts involve non-standard settlement. OptionMetrics characterizes non-standard settlement as follows: *"The number of shares to be delivered may be different from 100 (fractional shares); additional securities and/or cash may be required; and the strike price and premium multipliers may be different than $100 per tick."*

4. **Bid or ask is zero, ask smaller than bid.** There are option quotes that have a bid or an ask quote equal to zero. In other cases, the ask is below the bid quote. Since these quotes are obviously erroneous or at least very illiquid, we drop them.

5. **High relative bid-ask spread.** We additionally remove quotes with a high relative bid-ask spread (above 40%). The relative bid-ask spread is defined as (ask − bid)/mid and used in multiple works on liquidity in option markets (see Cao and Wei (2010) and Christoffersen, Goyenko, Jacobs, and Karoui (2011)).

6. **No unique match to a historical CUSIP.** We exclude stocks for which the unique OptionMetrics identifier (secid) is matched to two different historical CUSIPs at the same time (using the OptionMetrics security names file). Otherwise, there would be problems when merging with CRSP data (see below).

7. **No underlying price quote.** We remove option quotes for days when there is no price quote of the underlying. A price quote is either a closing price or the average of the closing ask and the closing bid.

Table 1 reports the number of available option quotes as well as the numbers of dropped quotes (including the reasons for dropping them). We see that about half of the available quotes pass our filtering procedure. Table 2 summarizes the number of underlyings and options per underlying that are in our dataset (by year and for the whole period). In the first two years, 1996 and 1997, the number of stocks and the number of options on these stocks are significantly smaller than in the following years. The number of underlyings (1,256 in 1996 vs. 2,821 in 2010) as well as the number of options per underlying (105.74 in 1996 vs. 170.43 in 2010) increase over time, although this trend is not strictly monotone. On average, there are about 146 options traded on each stock during a year. Over the whole period, there are on average 844 options on each stock. There is considerably dispersion around this mean: On the one hand, there are stocks with more than 8,000 options and, on the other hand, there are few stocks that are the underlying of only one option.

Figure 2 depicts the moneyness and maturities of the call and put option quotes in our sample. We see that few options have maturities above 250 days and most of them are concentrated below 60 days. Below twenty days to maturity the quotes become sparse. This is because our filtering procedure excludes these quotes due to their high relative bid-ask spreads. We see that there are more quotes for in-the-money options (both put and call).

Finally, we merge OptionMetrics with stock data[11] from CRSP using the historical CUSIP.[12] We do this for two reasons: First, OptionMetrics does not provide delisting returns, which are needed to determine the return on constructed portfolios. Second, OptionMetrics data on underlying stocks is sometimes incomplete or wrong (e.g. the shares outstanding of stocks are zero). The resulting panel data contains information about price, return and shares outstanding from both databases. The two disagree in some cases. Table 3 summarizes these conflicts. To resolve them, we prefer CRSP over OptionMetrics data if CRSP data is available. For about 2.3% of the stock quotes, no corresponding CRSP quote can be found (i.e. there is no observation in CRSP for that historical CUSIP on this date). In these cases, we use the OptionMetrics data. Table 3 reports that significant conflicts only occur for the shares outstanding variable: In 57.5% of the cases where both databases provide quotes, CRSP and OptionMetrics agree

[11] We use daily CRSP returns to calculate betas and monthly CRSP returns to calculate portfolio returns. Not reported are results where we have calculated daily returns of monthly rebalanced portfolios. All results in this paper also hold for these daily returns. In most cases the results are more significant for daily returns.

[12] We merge CRSP and OptionMetrics by appending the CRSP return, price, shares outstanding and delisting return to OptionMetrics stock data. Since CRSP and OptionMetrics do not share a common unique identifier for underlying stocks, we have to resort to the historical CUSIP of a stock at a given date. In a first step, we merge the historical CUSIP from the OptionMetrics Security Names file to the OptionMetrics Security Price file. This is necessary because the underlying data from OptionMetrics only reports the last CUSIP (also called Header CUSIP) for an underlying. To match the data with CRSP, we then use the date and the historical CUSIP (the historical CUSIP is called ncusip in CRSP) of the stock at this date. This method ensures that complex mergers/splits/acquisitions remain intact in the way that OptionMetrics reflects them.

about the shares outstanding. In 40.9% of the cases the deviations are below 20%. Only in 1.6% of the cases the deviations are above 20%.

3.2 Construction of Proxies: Jump Risk

We are going to sort stocks according to their loadings on individual jump risk. Therefore, we use sensitivities of their returns on the returns of otm call and put options written on the corresponding stock. Later on, we provide evidence that our results still hold if we control for systematic volatility and systematic jump risk.

For each stock, we construct time series of otm put option returns in the following way: We distinguish by moneyness (80% to 98% and 50% to 90%) and time to maturity (10 to 150 days, 10 to 60 days, 60 to 150 days). This leads to six different time series. If the moneyness is between 80% and 98%, we call the corresponding time series *close* to atm. If it is between 50% and 90%, we call the corresponding time series *far* from atm. The time series with 10 to 60 actual days to maturity are referred to as *short term*, whereas the time series with 60 to 150 actual days to maturity are referred to as *long term*.[13] At a given day, for all quotes belonging to a certain time series we average ask and bid quotes across all options with the same strike and maturity.[14] From the resulting set of averaged ask and bid quotes, we select the most liquid one (smallest relative bid-ask spread (ask − bid)/mid). The return based on the mid prices is the value for the otm put return at this day.[15] Iterating over all days in the sample, we obtain six time series per stock. If at some day our cleaning procedure excludes all option quotes, we leave the put return missing at that day. By construction, we obtain proxies for different kinds of jumps: A short-term option position proxies for short-term jump risk, while a long-term position proxies for short-term and long-term risks. Furthermore, a far position captures big jumps, whereas a close position captures medium and big jumps.

In a similar manner, we construct six time series of otm call option returns for every stock. Close moneyness refers to a range from 102% to 120%, far moneyness ranges from 110% to 150%. Using call option quotes we can sort stocks based on their sensitivity to upward jump risk.

Summary statistics of otm put and call return time series are reported in Table 4. The average maturity for otm put and call positions is around 100 actual days. It slightly increases

[13]See Figure 2 for a histogram of available option quotes by moneyness and maturity.

[14]Since there are multiple issuers in the market, we have multiple quotes for options with the same strike and maturity.

[15]When calculating the return on an option position, we account for stock splits if they change the number of option contracts held.

to 107 actual days for the long-term position.[16] The average moneyness for close otm puts (short term and long term) is around 93%, for far otm puts it is around 85%. The average moneyness for close otm calls (short term and long term) is around 108%, for far otm puts it is around 117%. Also note that the average number of available stocks[17] is significantly lower for short-term options. Therefore, we do not report results for short-term otm put or short-term otm call positions. The results are in line with our finding for other maturities, albeit less significant.[18]

4 Portfolio Sorts

In this section, we explain how we form portfolios based on the sensitivities of stocks to their individual jump risks. We define the following daily returns at time t: The variable r_t^i denotes the return on the i-th stock, r_t^m the return on the market portfolio (CRSP value weighted), and r_t^f the Fama-French riskfree rate. Furthermore, c_t^i denotes the return of one of the option time series (otm put returns, otm call returns, etc). Each month (pre-formation period), we run the following regression to obtain a stock's beta β_c^i with respect to the option time series c_t^i:

$$r_t^i - r_t^f = \beta_0^i + \beta_m^i (r_t^m - r_t^f) + \beta_c^i c_t^i + \epsilon_t^i, \tag{1}$$

We do not include a stock if we have less than 14 observations. Following Bali, Cakici, Yan, and Zhang (2005) and Bali and Cakici (2008) we also disregard penny stocks (closing price at the end of the month is below five dollars).[19] However, our results are robust to this assumption.

In regression (1), we control for the impact of the market return r_t^m.[20] In the following month (post-formation period), we sort all stocks according to their betas with respect to the option time series from the previous month and form five portfolios ($j = 1, 2, 3, 4, 5$). The first portfolio consists of stocks with the smallest β_c^i, the fifth portfolio consists of stocks with the largest β_c^i. For all portfolios, we compute equally and value weighted monthly returns. As a result, we obtain monthly portfolio returns, $r_t^{\mathrm{PF},j}$, of monthly rebalanced portfolios. Additionally, we compute the returns of a difference portfolio ('five minus one') assuming that an investor is

[16] Therefore, we can conclude that long-term options are the most liquid ones with respect to their relative bid-ask spread.

[17] When we run the regression to obtain the beta of stock in a given month, we enforce a lower limit of 14 observations. If the limit is violated, we exclude the stock in the following month. This procedure makes sure that the betas are meaningful.

[18] Tables with results for short-term time series are available upon request.

[19] Note that this procedure is not forward-looking, since the estimates are used to form portfolios for the following month.

[20] Our results are robust to the inclusion of SMB and HML as additional factors in the formation regression.

long in the fifth portfolio ('large betas') and short in the first portfolio ('small betas'). By monthly re-balancing, we adjust for time-varying risk exposures β_c^i. We calculate the following portfolio characteristics:

- **Monthly excess returns of portfolios**. We calculate (arithmetic) mean, standard deviation, Sharpe ratio, skewness and kurtosis of monthly excess returns $r_t^{\mathrm{PF},j} - r_t^f$.

- **Alphas**. We use several factor models and report the portfolios alphas and their p-values. The factor models are the capital asset pricing model (Sharpe (1964), Lintner (1965), and Mossin (1966))

$$r_t^{\mathrm{PF}_i} - r_t^f = \alpha^{\mathrm{CAPM}} + \beta_m^{\mathrm{CAPM}}(r_t^m - r_t^f) + \epsilon_t^i, \tag{2}$$

  the Fama-French three-factor model (Fama and French (1992) and Fama and French (1993))

$$r_t^{\mathrm{PF}_i} - r_t^f = \alpha^{\mathrm{FF3}} + \beta_m^{\mathrm{FF3}}(r_t^m - r_t^f) + \beta_{\mathrm{SMB}}^{\mathrm{FF3}} r_t^{\mathrm{SMB}} + \beta_{\mathrm{HML}}^{\mathrm{FF3}} r_t^{\mathrm{HML}} + \epsilon_t^i, \tag{3}$$

  and the Carhart four-factor model (Carhart (1997))

$$r_t^{\mathrm{PF}_i} - r_t^f = \alpha^{\mathrm{C4}} + \beta_m^{\mathrm{C4}}(r_t^m - r_t^f) + \beta_{\mathrm{SMB}}^{\mathrm{C4}} r_t^{\mathrm{SMB}} + \beta_{\mathrm{HML}}^{\mathrm{C4}} r_t^{\mathrm{HML}} + \beta_{\mathrm{UMD}}^{\mathrm{C4}} r_t^{\mathrm{UMD}} + \epsilon_t^i. \tag{4}$$

  For every month in the sample, we run Newey and West (1987) regressions with one lag.[21] If the factor according to which the stocks are sorted is pricing relevant, we should see a monotone relationship in the alphas for the portfolios. This effect is significant, if the alpha of the long-short portfolio is significantly different from zero. Notice that we round the p-values up with a precision of 0.1%.

- **Average number of assets in portfolios**. The number of assets in the portfolios varies over time, since only assets with at least 14 days of data are included in the following month. Therefore, we also report the average number of assets in each portfolio.

- **Market Capitalizations of portfolios**. We report the relative initial market capitalizations of the portfolios (i.e. after the last day of the pre-formation period). The relative market capitalization is defined as the cumulative market capitalization of all stocks in a specific portfolio divided by the cumulative market capitalization of all stocks.

- **Pre-formation betas.** For every portfolio, we calculate the average pre-formation beta over the whole sample period. First we compute the average monthly pre-formation beta

[21] We use a one month lag because our betas are estimated in the previous month and portfolios are formed in the current month based on the previous months betas.

(equal or value weighted). Then we calculate the average sample pre-formation beta (equal weighted across months). Since portfolios are created using the pre-formation betas, the average betas will be monotonous across portfolios.

- **Post-formation betas.** Factor sensitivities of factor models vary over time. If they vary too quickly, sorting on pre-formation betas could be problematic. Therefore, we also calculate average sample post-formation betas to check whether the betas are sufficiently stable. Notice that stocks that are no longer traded in the post-formation period, do not contribute to the post-formation beta.

4.1 Portfolios based on Jump Risk Proxies

We first report the results for put option sensitivities. For equally weighted portfolios we find strong relationships between the betas of the different put time series and factor model alphas.[22] Table 5 summarizes the monthly mean returns of the monthly rebalanced portfolios using equal weights. Note that all values except Kurtosis are expressed in percentages. For the first three portfolios ('low betas'), the average monthly excess returns strongly increase with the beta loadings. The last three portfolios ('high betas') have very similar, but slightly decreasing returns. Since the standard deviations strongly decrease, the Sharpe ratios increase in a very pronounced way. Furthermore, skewness strongly decreases with the beta loading, whereas kurtosis increases.

Table 6 reports the alphas with respect to different factor models and their significances. Note that all values are expressed in percentages. For the CAPM and and the Fama-French model, we find monotonously increasing alphas: Portfolios with higher betas have higher alphas. Only for the Carhart model, there are small deviations for the close and far time series. Notice that the alphas are properly ordered for the corresponding long-term time series, though. For the Fama-French and the Carhart model, the alphas of the first portfolios are negatively significant.[23] Additionally, with one exception where the p-value is only 7%, the difference portfolios ('five minus one') have significantly positive alphas at the 5% level.

To identify the risk-premium, we consider the pre- and post-formation betas reported in Table 6. All otm put time series have negative betas, since put and stock prices are negatively

[22] We do not find this relationship for value weighted portfolios and thus do not report the corresponding results.

[23] The reason why CAPM alphas are not as significant as Fama-French alphas will be clear later. We will document a strong relationship between size and the pricing of idiosyncratic jump risk. The stocks that exhibit negative alphas due to idiosyncratic jump risk are usually small- to mid-caps. Small firms exhibit positive risk premia due to their size, but the idiosyncratic jump risk has a negative risk premium (see below). These contrarian influences cannot be separated in the CAPM. The Fama-French three-factor model controls for the size effect and is thus better suited to study the pricing of idiosyncratic jump risk.

related. On average, the betas of the first portfolios are about -0.30 in the pre-formation period, whereas the betas of the fifth portfolios are -0.08. In the post-formation period, we obtain -0.26 and -0.11. This documents that the portfolios are also significantly diverse with respect to their exposures to idiosyncratic jump risk in the post-formation period. The stocks in the first portfolio are most sensitive to idiosyncratic jump risk (measured by the absolute value of beta). The stocks in the fifth portfolio are least sensitive. This suggests that the risk-premium on idiosyncratic jump risk is negative. Next, we consider the average market capitalization of stocks in the portfolios. The market cap of stocks with higher exposure to idiosyncratic jump risk are smaller. There are two possible explanations: Our results could be driven by size and not by idiosyncratic jump risk exposure or idiosyncratic jump risk could not be significantly priced for large firms.

We will come back to this question in Section 5.3 where we double sort on market capitalization and the idiosyncratic jump risk exposure. Notice that the relative market caps of the portfolios are similar to the market caps of portfolios sorted on ivol. We will relate our results to the ivol anomaly in Section 6.

Now, we report results for portfolios based on otm call sensitivities. As for otm put returns, we only have significant results for equal weighted portfolios. Table 7 summarizes the results for monthly mean returns on monthly rebalanced portfolios. We do not find monotone relations in mean returns. Nevertheless, the returns on the fourth and fifth portfolios are the smallest. Standard deviation and skewness increase monotonically. With few exceptions kurtosis decreases. The fourth and fifth portfolio have the lowest Sharpe ratios, while the first portfolio has the highest Sharpe ratio.

Table 8 reports the alphas of the different factor models and their significances. In contrast to portfolios sorted on otm put sensitivities, there is not a clear monotone relationship for all alphas. For close otm call positions, the alphas decrease from the third portfolio to the fifth portfolio. For far out-of-the-money call positions, the alphas decrease monotonically over all portfolios. The Fama-French alphas of the difference portfolios are significant at the 1% level for all time series except for returns based on call options close to atm that significant at the 5% level. Portfolio five has the most significantly negative alphas in the Fama-French three-factor and Carhart four-factor models. These alphas are more significant than those of the difference portfolio.

Lastly, Table 8 also reports the pre- and post-formation betas and the market capitalizations of the constructed portfolios. Again the portfolios have sufficiently diverse betas in the post-formation period. All betas are positive and the biggest for the fifth portfolio in which the exposure to idiosyncratic upward jump risk is the highest. This suggests that the risk premium on idiosyncratic upward jump risk is negative. Besides, stocks with a higher sensitivity to upward jump risk have smaller market capitalization.

4.2 Overlap in OTM Put and OTM Call Sensitivity based Portfolios

Both risk premia for idiosyncratic jump risk are negative. Besides, the market capitalization decreases with higher jump risk exposure. To see whether there is a similarity between portfolios based on sensitivities to otm put returns and portfolios based on sensitivities to otm call returns, we determine the overlap between these portfolios. For all portfolios based on put returns, we calculate the average portfolio number based on call returns and vice versa. The results are reported in Table 9. We see that there is a lot of overlap for all time series. Stocks with low put betas (high downward jump sensitivity) are in general in a portfolio with high call betas (high upward jump sensitivity) and vice versa. For 50% of the firms, the portfolio numbers are the exact complements (e.g. portfolio one for puts and portfolio five for calls).

4.3 CDS Spreads

Now, we briefly discuss how exposure to idiosyncratic jump risk is related to the size of cds spreads. We use cds data from Markit to determine five year credit spreads. The sample ranges from 2001 to 2010 and involves more than 700 firms. We calculate monthly returns on monthly rebalanced portfolios based on put and call sensitivities from (1) as before. The sample is not restricted to firms for which we have cds quotes, but we calculate the average cds quote of firms in a portfolio using the quotes available. Table 10 reports the average five year cds spreads of each portfolio. We use the latest cds quotes from the pre-formation periods, but the results are similar for post-formation quotes. Stocks in portfolios with higher idiosyncratic jump risk have less cds quotes available, since these are smaller companies. Firms in portfolios with higher idiosyncratic jump risk (low returns and alphas) have a higher cds spread (credit risk) than firms with less idiosyncratic jump risk. This relation is monotone across all portfolios. A firm in the portfolio with the highest jump risk has an average five year cds spread of at least 5.0%. This indicates that our idiosyncratic jump measures proxy for default risk.

5 Robustness

5.1 Controlling for Systematic Volatility

Ang, Hodrick, Xing, and Zhang (2006) document that systematic volatility is a priced factor in the cross-section of stock returns. Apparently, otm put returns on individual stocks are also affected by the exposure of the underlying stock to systematic volatility risk. To control for this exposure, we first establish a proxy for systematic volatility risk that is significantly priced in our sample. Then we include the corresponding factor in the formation regression (1) to control for systematic volatility exposure.

A Proxy for Systematic Volatility Risk To proxy for systematic volatility risk, Ang, Hodrick, Xing, and Zhang (2006) use daily changes in the VIX. They also use returns on market-neutral atm straddle positions calculated from option data on the S&P 500 index. In this section, we test which of these proxies is more significantly priced in our sample. We then use this proxy in robustness checks.

An atm straddle consists of a long position in an atm call and a long position in an atm put. A straddle position becomes more valuable if the market moves far away from its current level. Therefore, a straddle price increases with volatility.[24] We construct market-neutral atm straddle returns following Coval and Shumway (2001). Let C_t and P_t denote the mid price of the call and put option on day t and S_t the S&P 500 level on day t. Besides, Δ_t^C and Δ_t^P denote the Cox-Ingersoll-Ross binomial tree implied deltas of the call and the put as reported in OptionMetrics. We first calculate the option sensitivity with respect to the stock return via $s_{t-1}^C = \Delta_{t-1}^C r_t^S S_{t-1}/C_{t-1}$ with where $r_t^S = (S_t - S_{t-1})/S_{t-1}$. We then compute the market-neutral atm straddle return using $r_t^{\text{atm}} = \theta r_t^C + (1-\theta) r_t^P$ with $\theta = -s_{t-1}^P/(s_{t-1}^C - s_{t-1}^P)$ and $r_t^C = (C_t - C_{t-1})/C_{t-1}$.

In the next step, we run monthly formation regressions

$$r_t^i - r_t^f = \beta_0^i + \beta_m^i (r_t^m - r_t^f) + \beta_{\text{sys vol}}^i v_t + \epsilon_t^i \tag{5}$$

with daily returns for stocks that, in the particular month, have at least 14 returns in our sample. The systematic volatility proxy, v_t, is either the change in VIX or the return on a

[24] We construct at-the-money straddle returns for a given day by first creating all call and put pairs with the same strike and maturity, which are quoted on the previous day and the given day. We restrict the feasible options to have a maturity between 10 and 150 (actual) days and a moneyness between 95% and 105%. We then select the pair which is closest to a moneyness of one. Finally, the at-the-money straddle return is obtained using the mid-prices of the options, adjusted for splits.

market-neutral atm straddle. We construct five portfolios based on sensitivities to aggregate volatility, $\beta_{\text{sys vol}}$, in the previous month and calculate monthly returns on monthly rebalanced portfolios. This is similar to the procedure for the individual time series.

Table 11 summarizes the mean monthly returns and alphas with respect to the factor models of all systematic volatility proxies. Changes in VIX do not significantly drive the returns in equal weighted portfolios. For value weighted portfolios the results are statistically not significant. In contrast, returns on market-neutral atm straddles are a good proxy for systematic volatility risk in equal and value weighted portfolios. The equal weighted difference portfolios are significant at the 5% level in every factor model. For value weighted portfolios, the results are significant at the 1% level.[25]

Consistent with Ang, Hodrick, Xing, and Zhang (2006), we find that stocks with high sensitivities to innovations in systematic volatility have low average returns. In the following, we use market-neutral atm straddle returns as proxy for systematic volatility exposure.

Alternative Formation Regression Instead of (1), we now run the formation regression

$$r_t^i - r_t^f = \beta_0^i + \beta_m^i (r_t^m - r_t^f) + \beta_{\text{sys vol}}^i v_t + \beta_c^i c_t^i + \epsilon_t^i \tag{6}$$

to obtain betas β_c^i for each month. As systematic volatility proxy v_t we use returns of market-neutral atm straddles on the S&P 500. The other steps of the portfolio construction are identical to the steps described in Section 4.

Table 12 reports the mean returns, alphas, their significances, pre-formation betas, and post-formation betas for portfolios based on otm put return sensitivities. The differences to the previous results in Table 6 are marginal . The same is true for portfolios based on otm call return sensitivities.

5.2 Controlling for Systematic Jump Risk

Similar to systematic volatility risk, we wish to check whether systematic jump exposures (market disaster risk) drive our result. Cremers, Halling, and Weinbaum (2010) use different time series derived from S&P 500 options to proxy for innovations in systematic jump risk. They provide empirical evidence that systematic jump risk is priced, albeit statistically and economically less significant than systematic volatility risk.

[25] We also run the short-term and long-term versions of market-neutral atm straddles. For short-term options, the significance is slightly less. When using long-term options, the equal weighted portfolios show no significant pricing relation and the alphas of value weighted portfolios have a smaller significance of at least 86%.

To control for this, we first establish a proxy for systematic jump risk that is significantly priced in our sample. After that we include the corresponding factor in the formation regression (6) to control for systematic volatility and systematic jump risk exposure.

A Proxy for Systematic Jump Risk There are multiple possible proxies for systematic jump risk: otm put returns (all combinations of moneyness and maturity), market-neutral strangle returns, daily changes in the downward smile (difference between 95% implied volatility and atm implied volatility, with 30 actual days to maturity). All these proxies are also used by Cremers, Halling, and Weinbaum (2010). We run the following formation regression

$$r_t^i - r_t^f = \beta_0^i + \beta_m^i (r_t^m - r_t^f) + \beta_{\text{sys vol}}^i v_t + \beta_{\text{sys jump}}^i j_t + \epsilon_t^i, \tag{7}$$

where j_t is one of the jump proxies. Note that we also include market-neutral atm straddle returns as systematic volatility proxy v_t. We find a significant pricing impact for otm put returns and changes in the downward smile. Table 13 summarizes the results. The alphas of the difference portfolios are significant at least at the 10% level for put sensitivities. The significances are at least 5% for the changes in downward smile.[26] These results document a negative risk premium on systematic jump risk and thus agree with Cremers, Halling, and Weinbaum (2010). In the following, we use changes in the downward smile as a proxy for systematic jump risk.

Alternative Formation Regression Instead of (1), we now run the alternative formation regression

$$r_t^i - r_t^f = \beta_0^i + \beta_m^i (r_t^m - r_t^f) + \beta_{\text{sys vol}}^i v_t + \beta_{\text{sys jump}}^i j_t + \beta_c^i c_t^i + \epsilon_t^i \tag{8}$$

to obtain the monthly betas β_c^i. As a systematic volatility proxy v_t, we include the return of market-neutral atm straddles on the S&P 500. As a systematic jump risk proxy j_t, we use the changes in the downward smile calculated from S&P 500 option data. The further steps of the portfolio construction are identical to the steps outlined in Section 4.

Table 14 reports the mean returns, alphas, their significances, pre-formation betas, and post-formation betas for portfolios based on otm put return sensitivities using changes in downward smile from S&P 500 options as systematic jump risk proxy. The differences to the results reported in Table 6 are marginal. However, the significances of the results slightly improve,

[26]Note that the significance increases to 1% in value weighted portfolios. We also test the upward smile as a proxy for systematic jump risk. We find pricing evidence, albeit less significant as for the downward smile.

especially for the alphas of the Carhart model. Not reported are the results for idiosyncratic otm call returns since they are similar.

5.3 Controlling for Size

Section 4.1 identifies a monotone and significant relationship between alphas for equal weighted portfolios that are constructed from otm put or otm call sensitivities. This relation still holds when we control for systematic volatility exposure and systematic jump risk exposure. However, the relationship does not exist for value weighted portfolios. One possible explanation could be that our effect is simply the size effect. This is unlikely though since the size effect implies higher returns for small stocks, which is in contrast to our findings in Table 6. Instead, if big stocks have no premium on idiosyncratic jump risk, this would explain why we cannot show a monotone increase in alphas using value weighted portfolios. To address this, we double sort based on market capitalization and the firm specific sensitivity β_c^i.

To obtain the stock sensitivity β_c^i, we we run the monthly regression (8) where we control for systematic volatility and systematic jump risk exposures. In the following month, we double sort all stocks: First, we sort based on market capitalization of the last day of the pre-formation period to obtain five portfolios (first portfolio contains small stocks, fifth portfolio contains big stocks). Within these portfolios, we sort the stocks based on their sensitivities β_c^i of the previous month and form five sub-portfolios. This procedure yields 25 double sorted portfolios, all consisting of roughly the same number of firms. We then calculate equal and value weighted monthly returns of these portfolios. Using these returns, we run the factor model regressions (2), (3) and (4) to calculate alphas and their significances. Besides, we compute the average pre-formation betas of the portfolios (value or equal weighted in the cross section, equal weighted across months).

Table 15 reports the alphas of portfolios sorted on market capitalizations and sensitivities to otm put returns. For small stocks (market cap portfolios one and two), the alphas increase monotonically from the first to the fifth sub-portfolio. Besides, the alphas of the difference portfolios are significant at the 5% level. For bigger stocks this relation disappears, both for equal and value weighted portfolios. These results explain why we did not find a relation for value weighted portfolios in Section 4.1 where we did not sort on market capitalization.

Table 16 reports the pre-formation betas β_c^i for all 25 sub-portfolios based on otm puts. On average, smaller stocks have smaller betas (higher absolute sensitivities). But there are also some stocks with high market capitalization that also exhibit small betas. For single sorts on β_c^i, these stocks would be in more sensitive portfolios, although they do not carry a risk premium on idiosyncratic jump risk. With weights proportional to market capitalization, these stocks have a significant effect on the corresponding portfolio returns. Consequently, we were only able to document a monotone pricing relation for equal weighted portfolios, but not for value weighted portfolios. In the light of these results, it is clear that there is a negative risk premium on idiosyncratic downward jump risk for small caps.[27]

5.4 Controlling for Short-Term Reversal

Huang, Liu, Ree, and Zhang (2010) argue that the ivol anomaly is strongly related to short-term reversal effects. We control for this by using dependent double sorts, first forming five portfolios based on the returns of the previous month and then forming five sub-portfolios by sorting on betas derived from our time series. In three out of five portfolios, our effect is still significantly present (at the 5% level).[28]

5.5 Alternative Formation Period Lengths

Previously, we have used a formation period of one month to obtain our idiosyncratic jump risk measure β_c^i applying regressions (1), (6) or (8). The respective regressions involve at least 14 observations, otherwise the estimate is set to missing. One may argue that the estimated betas are volatile due to the short time period. In the following, we use the past two and three months to estimate betas (with a minimum of 14 observations in each month). The results for monthly rebalanced portfolios are reported in Table 17. The findings for put betas are very similar. If anything, the magnitude and significance improves slightly. The alphas of the call beta portfolios are significant at the 1% level, which is an improvement to the one month formation period. The betas are as stable over time as before.

5.6 Controlling for Implied Volatility

As discussed in Section 2, the betas of stock returns with respect to otm put returns are not only affected by jump risk. In a jump-diffusion model, the betas also change if the diffusive volatility σ changes. To control for these effects, we include the daily changes of atm implied volatilities (with 30 actual days to maturity) in the formation regression:

$$r_t^i - r_t^f = \beta_0^i + \beta_m^i(r_t^m - r_t^f) + \beta_{\text{sys vol}}^i v_t + \beta_{\text{sys jump}}^i j_t + \beta_{\text{imp vol}}^i \Delta\sigma_t^i + \beta_c^i c_t^i + \epsilon_t^i, \tag{9}$$

[27]The same is true for portfolios sorted on otm call return sensitivities, albeit only for long-term options.

[28]Tables are available upon request.

where $\Delta\sigma_t^i = \sigma_t^i - \sigma_{t-1}^i$ is the time t daily difference in the firm specific implied volatility. Table 18 reports the results for monthly rebalanced portfolios. The magnitude and significance of the difference portfolio alpha is slightly reduced for put beta based portfolios, while call beta based portfolios are hardly affected by the additional proxy in the formation regression. The slight decrease is reasonable since implied volatilities are only an imperfect proxy for diffusive volatility. To summarize, the estimation of firm specific jump risk via put and call betas is hardly affected by implied volatility changes.

5.7 Other Proxies for Risk

In addition to otm put and call returns, we also construct a return series on a joint position consisting of a long position in a close otm put and a short position in a far otm put. The results are comparable to the results for otm put options, but less significant. We also construct different time series from option implied volatilities that can possibly proxy for jump risks. Cremers, Halling, and Weinbaum (2010) use the difference in the implied volatility of an 95%-moneyness put and an at-the-money call. Analogously, we use the following smile time series: $\mathrm{IV}(1.1, 30) - \mathrm{IV}(0.9, 30)$, $\mathrm{IV}(1.2, 30) - \mathrm{IV}(1.0, 30)$, $\mathrm{IV}(1.0, 30) - \mathrm{IV}(0.8, 30)$, $\mathrm{IV}(1.1, 90) - \mathrm{IV}(0.9, 90)$, $\mathrm{IV}(1.2, 90) - \mathrm{IV}(1.0, 90)$, and $\mathrm{IV}(1.0, 90) - \mathrm{IV}(0.8, 90)$, where $IV(m, d)$ is the Cox-Ingersoll-Ross binomial tree implied volatility for an option with moneyness m and a maturity of d actual days. Yan (2011) shows in a simplified model that jump risk can be proxied by the slope of the implied volatility surface. These time series are very persistent through time (they have high auto-correlation). To proxy for innovations in jump risk, we use first differences.[29] We obtain $\mathrm{IV}(m, d)$ by linearly interpolating between option quotes.[30] We do not find any significant results. In the light of Dennis, Mayhew, and Stivers (2006), this is not surprising. These authors show that the correlation between individual stock returns and individual implied volatility is close to zero.[31]

5.8 Splitting the Sample: Subperiods and Industries

We split our sample into three subperiods of about the same length: January 1996 to December 2000, January 2001 to December 2005, Januar 2006 to October 2010. In each period we build monthly rebalanced portfolios for each time-series as described in Section 4.[32] The

[29]This is analogue to Ang, Hodrick, Xing, and Zhang (2006), who use daily changes in VIX to proxy for changes in systematic volatility

[30]We do not use the OptionMetrics standardized options dataset.

[31]Tables with results for the time series from Section 5.7 are available upon request.

[32]We only report results for portfolios based on betas calculated from formation regression (8). This formation regression controls for market return, market volatility risk, and market jump risk. Our findings are similar if

monthly alphas in the five portfolios are monotonous as before (increasing for put time series and decreasing for call time series) with the lowest alphas in the portfolios with the highest idiosyncratic jump risk. However, the magnitudes of the variation and the significances vary from period to period. Table 19 reports the returns and alphas of the difference portfolio in each subperiod. We document that the magnitude and significance of the abnormal returns is very small in the first period. The alphas vary in sign between different factor models and they are not significant. During the boom years from 2001 to 2005, the magnitude and significance increases strongly. The alphas are positive for all factor models and the significance improves. In the recent period, our effect is the strongest. The magnitude of the alphas is the highest and the significance is at least at 2% for Fama-French three-factor model alphas and 1% for Carhart four-factor model alphas. Second, we split the sample into five subindustries: consumer, manufacturing, high tech, health, and others[33]. Table 20 reports the returns and alphas of the difference portfolio in each subindustry. There are only small and insignificant alphas in the consumer and manufacturing industry. For the high tech industry, we find monthly abnormal Fama-French returns of 0.74% that are significant at the 5% level. For health and other industries, there is a very significant pricing effect (at least 5% level) with the highest magnitude of alphas (at least 1.1%).

6 The Fama-French Three-Factor Idiosyncratic Volatility Anomaly

Ang, Hodrick, Xing, and Zhang (2006) document that stocks with high idiosyncratic volatilities exhibit lower returns. In this section, we study whether our results are related to this so-called ivol anomaly. First, we show that the ivol anomaly is also present in our sample. Then we relate our findings on the pricing of idiosyncratic jump risk to the pricing of the idiosyncratic volatility using double sorts.

we use the formation regression (1) or (6).

[33]These are the five industry categories from Kenneth French. The corresponding SIC codes can be downloaded from his website. Consumer includes consumer durables, non-durables, wholesale, retail, and some services (laundries, repair shops). Manufacturing includes manufacturing, energy, and utilities. High tech includes business equipment, telephone and television transmission. Health includes health care, medical equipment, and drugs. Others include mines, construction, building maintenance, transport, hotels, bus service, entertainment, and finance.

6.1 Ivol Anomaly in Our Sample

For each month, we run regression (3) for each stock with at least 14 return observations and a price of at least five dollar at the last trading day of the month. This allows us to calculate the corresponding root mean squared error (ivol). In the following month, we sort all stocks based on their ivols and form five portfolios. The first portfolio contains stocks with the lowest ivols and the fifth portfolio contains stocks with the highest ivols. Then we compute equal and value weighted monthly portfolio returns $r_t^{\mathrm{PF},j}$ of these monthly rebalanced portfolios. Additionally, we construct a difference portfolio ('five minus one') that involves a long position in stocks with the highest ivols and a short position in stocks with the lowest ivols.

We study two samples: First, we consider our full sample, i.e. stocks that are in OptionMetrics and that can be merged to CRSP. Second, we only include observations for which we can calculate a beta with respect to otm put close returns. Tables 21 and 22 summarize the average monthly returns, factor model alphas, and the pre- and post-formation ivols of these portfolios (see Section 4 for details on how these quantities are calculated). For the full sample, we find that the ivol anomaly is only present for the value weighted difference portfolios with significance levels of 5% (Fama-French and Cahart). There is no ivol anomaly for equal weighted portfolios. For the restricted sample, we document ivol anomalies for both equal and value weighted portfolios with significance levels of 1% and 5%, respectively. The different signifcances of the ivol anomaly in both samples is in line with Bali and Cakici (2008), who argue that the ivol pricing is dependent on sample cross-section and portfolio weighting.

6.2 Relation to Ivol Anomaly

To study the relation of our findings to the ivol anomaly,[34] we now double sort our sample: First, we create five portfolios based on the previous month's ivols with respect to the Fama-French model (3). All these portfolios are then sorted into five sub-portfolios based on sensitivities to option position returns (from (8)) in the previous month. This leads to 25 monthly return time series of monthly rebalanced portfolios. Table 23 reports the corresponding results for equal weighted, monthly rebalanced portfolios first sorted on ivol, second on β_c^i. There is no significant pricing based on put sensitivities in four out of five ivol portfolios. For the highest ivol, the difference portfolio with respect to put sensitivities has economically significant abnormal returns of 0.751% and 0.880% that are borderline significant at the 10% level. This weak significance can be attributed to the short time series and to the double sorting procedure

[34] Notice that comparison only makes sense for the restricted sample, since we need to be able to calculate betas.

with few firms in the subportfolios[35]. On the contrary, the portfolio with the highest average idiosyncratic jump risk and highest ivol has a monthly Fama-French alpha of at least -1.0% that is significant at the 0.1% level. This result is independent of the particular put time-series. Next, we reverse the sort order. Table 24 reports the corresponding results. The ivol difference portfolio returns are significant for four out of five beta portfolios. Only the beta portfolio with the highest betas (lowest absolute idiosyncratic jump risk) does not exhibit an ivol pricing effect.

To interpret our results, notice that a higher exposure to idiosyncratic jump risk leads to a higher ivol because, by construction, (1) yields a decomposition of the residuals into a jump-related and diffusion-related part.[36] This can be seen in Table 23. Since we first sort on ivol, we control for the absolute effect of idiosyncratic risk. For instance, a small ivol limits the size of the idiosyncratic jump exposure. Therefore, the difference portfolios of the first lines for all put time series have very small alphas. Next, recall that an omitted factor materializes in the residuals of the benchmark model (e.g. Fama-French or Cahart model).[37] Consequently, if exposure to idiosyncratic jump risk is related to an omitted factor, then stocks with high idiosyncratic jump risk should also have a high ivol. This is suggested by the results reported in Table 24. The difference portfolios of the first lines for all put time series (high absolute exposure to idiosyncratic jump risk) have large significant alphas. Besides, the magnitude of the alphas is decreasing across subportfolios. Therefore, the exposure to idiosyncratic jump risk determines the size of ivol. Otherwise, there would not be a monotonous pattern in the data and we should find stocks with high ivol and low exposure to idiosyncratic jump risk. However, Tables 25 and 26 do not indicate that a lot of these stocks exist: First, Table 25 reports the average portfolio numbers of stocks in portfolios based on otm put sensitivities. It also reports the fraction of exact matches. There is a remarkable overlap in the portfolios sorted on put sensitivies and ivol. Second, Table 26 shows that the difference portfolios (ivol, put, call) are highly correlated over the full period. The absolute value of their correlations is at least 90%. To put these correlations into perspective, we also report the correlations with the Fama-French factor that are around around 60% to 70%. To summarize, our findings suggest that the exposure to idiosyncratic jump is related to an omitted factor in the benchmark models.

[35] For the otm put close sensitivities, there are on average 44.45 stocks in each of the 25 portfolios

[36] As a robustness check, we have also runs formation regressions including the Fama-French size and book factors. The results however do not change.

[37] See, e.g., Chen and Petkova (2012).

7 Conclusion

We use prices of options on individual stocks to estimate returns of different option strategies. Using a linear factor model, we determine the sensitivities of stock prices to these option characteristics. In particular downwards jump risks are proxied by sensitivities to otm put returns and upward jump risks are proxied by sensitivities to otm call returns. We examine how these different risks are priced using portfolio sorts. We also study pre- and post-formation sensitivities to verify that our sorting is consistent through time. It is documented that the smallest 40% of all companies carry a negative risk-premium on downward jump risk. We also find that most firms have similar exposures to up- and downward jumps. Controlling for systematic volatility and systematic jump risk it is shown that the negative premium is due to idiosyncratic risk. It is reasonable that this effect is not significant for big companies, as their price jumps are mostly systematic.

We also relate our results to the ivol anomaly. If ivol captures an omitted factor, then our findings suggest that idiosyncratic jump risk is related to this factor. In particular, there are few stocks with high ivol and low exposure to idiosyncratic jump risk. We also show that firms with a higher idiosyncratic jump risk have on average higher cds spreads. The pricing effect is not present in the consumer and manufacturing industries. The pricing of idiosyncratic jump risk is however very strong in the remaining industries (high tech, health and others).

References

Ang, Andrew, Joseph Chen, and Yuhang Xing, 2005, Downside Risk, *Working Paper*.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The Cross-Section of Volatility and Expected Returns, *Journal of Finance* LXI, 259–299.

Bali, Turan G., and Nusret Cakici, 2008, Idiosyncratic Volatility and the Cross Section of Expected Returns, *Journal of Financial and Quantitative Analysis* 43, 29–58.

Bali, Turan G., Nusret Cakici, Xuemin (Sterling) Yan, and Zhe Zhang, 2005, Does Idiosyncratic Risk Really Matter?, *Journal of Finance* LX, 905–929.

Cao, Melanie, and Jason Wei, 2010, Option market liquidity: Commonality and other characteristics, *Journal of Financial Markets* 13, 20–48.

Carhart, Mark M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance* 52, 57–82.

Chen, Zhanhui, and Ralitsa Petkova, 2012, Does Idiosyncratic Volatility Proxy for Risk Exposure?, *Review of Financial Studies (forthcoming)*.

Christoffersen, Peter, Ruslan Goyenko, Kris Jacobs, and Mehdi Karoui, 2011, Illiquidity Premia in the Equity Options Markets, *Working Paper*.

Coval, Joshua D., and Tyler Shumway, 2001, Expected Option Returns, *Journal of Finance* LVI, 983–1009.

Cremers, Martijn, Michael Halling, and David Weinbaum, 2010, In Search of Aggregate Jump and Volatility Risk in the Cross-Section of Stock Returns, *Working Paper*.

Dennis, Patrick, Stewart Mayhew, and Chris Stivers, 2006, Stock Returns, Implied Volatility Innovations, and the Asymmetric Volatility Phenomenon, *Journal of Financial and Quantitative Analysis* 41, 381–406.

Driessen, Joost, and Pascal J. Maenhout, 2006, The World Price of Jump and Volatility Risk, *Working Paper, AFA 2005 Philadelphia Meetings*.

Elkamhi, Redouane, Yong Lee, and Tong Yao, 2009, Idiosyncratic Volatility and Stock Returns: Does Option Trading Reduce Stock Market Mispricing?, *Working Paper*.

Fama, Eugene F., and Kenneth R. French, 1992, The Cross-Section of Expected Stock Returns, *Journal of Finance* 47, 427–465.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fu, Fangjian, 2009, Idiosyncratic Risk and the Cross-Section of Expected Stock Returns, *Journal of Financial Economics* 91, 24–37.

Huang, Wei, Qianqiu Liu, S. Ghon Ree, and Liang Zhang, 2010, Return Reversals, Idiosyncratic Risk, and Expected Returns, *Review of Financial Studies* 23, 147–168.

Lintner, John, 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economics and Statistics* 47, 13–37.

Merton, Robert C., 1976, Option Pricing when Underlying Stock Returns are Discontinuous, *Journal of Financial Economics* 3, 125–144.

Mossin, Jan, 1966, Equilibrium in a Capital Asset Market, *Econometrica* 34, 768–783.

Newey, Whitney K, and Kenneth D. West, 1987, A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703–708.

Pan, Jun, 2002, The jump-risk premia implicit in options: evidence from an integrated time-series study, *Journal of Financial Economics* 63, 3–50.

Sharpe, William F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *The Journal of Finance* 19, 425–442.

Wooldridge, Jeffrey M., 2010, *Econometric Analysis of Cross Section and Panel Data*. MIT Press.

Yan, Shu, 2011, Jump risk, stock returns, and slope of implied volatility smile, *Journal of Financial Economics* pp. 216–233.

Figure 1: Theoretical Betas of Stock Returns With Respect to OTM Put and Call Returns. This figure depicts theoretical betas of stock returns with respect to otm put and otm call returns from a Merton option pricing model for different constant jump sizes L and different constant jump intensities λ. Betas with respect to put returns are in the upper two figures, betas with respect to call returns are in the lower two figures. The options are 15% otm. The parameters are: $r = 0$, $\sigma = 0.4$, $\tau = \frac{100}{360}$. The left figures use a jump intensity of $\lambda = 1$, the right figures use a jump size of $L = -0.25$ for put betas and $L = 0.25$ for call betas.

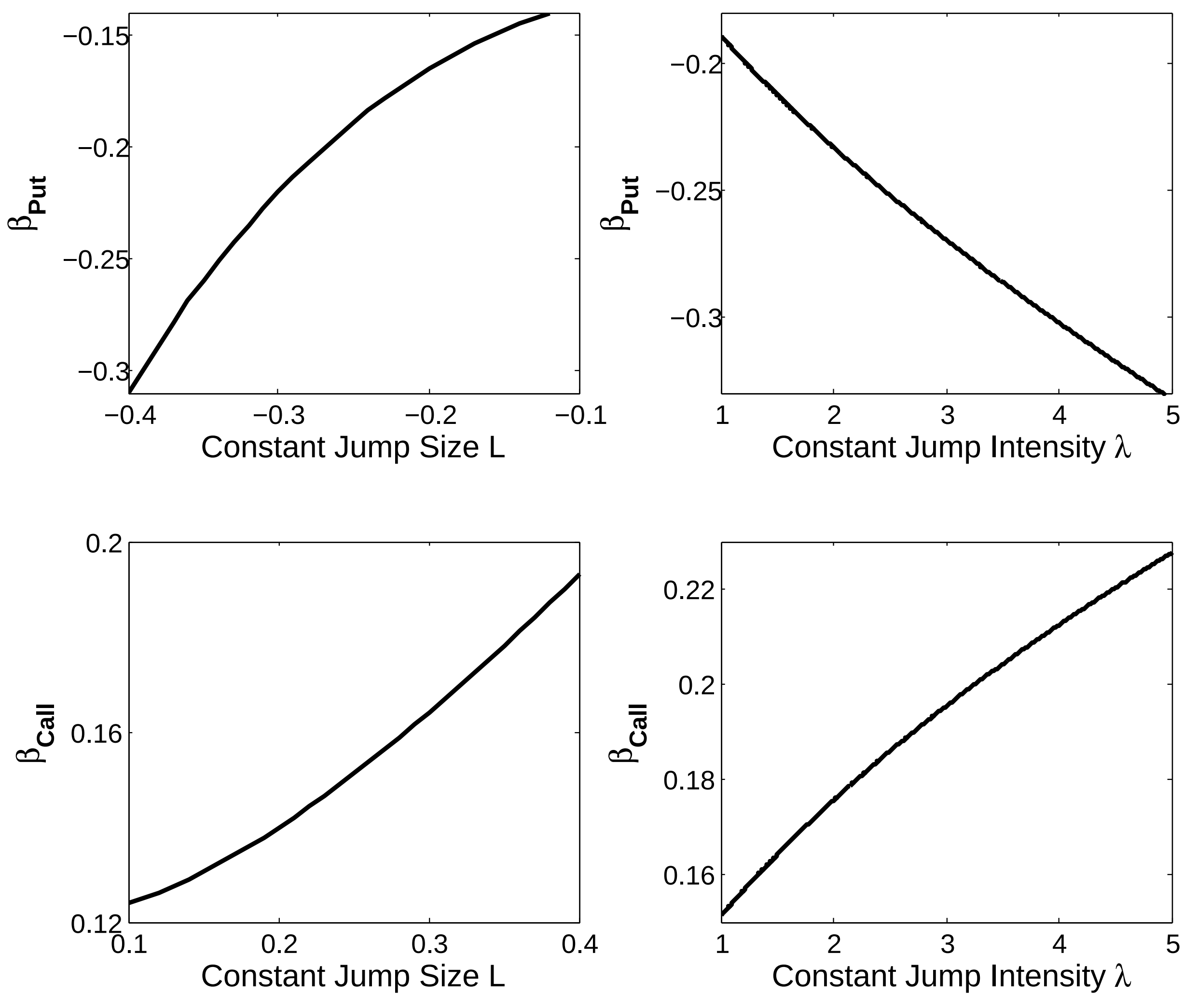

Figure 2: Histogram of Option Quotes. Histogram of the number of option quotes in the final dataset from which the different time series are constructed. The x-axis depicts the maturity of the quote in actual days, the y-axis depicts the moneyness (strike-to-spot ratio) of the quote as a percentage. The top figure shows call option quotes, the bottom figure shows put option quotes.

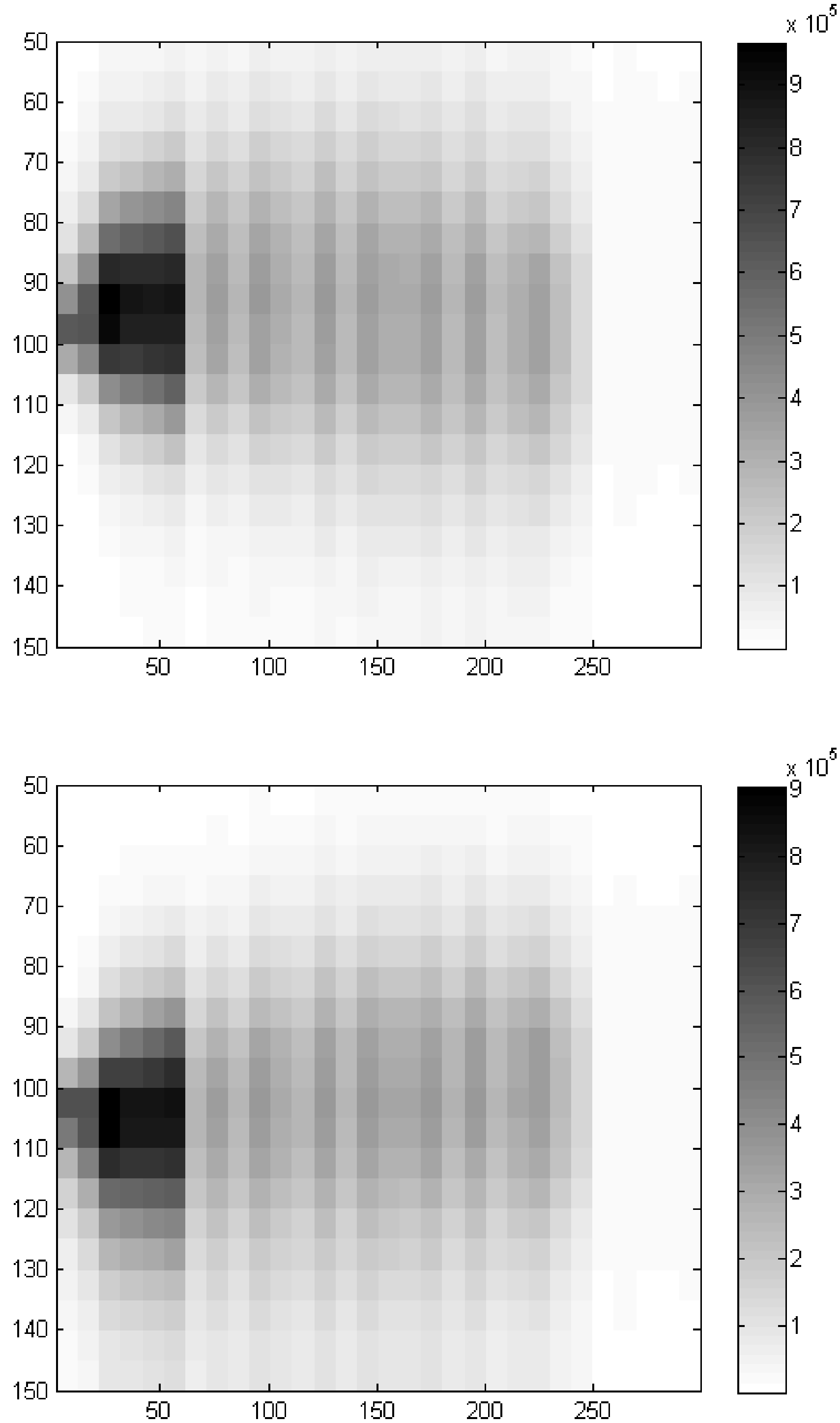

Table 1: Number of Option Quotes. The row *Remaining quotes* reports the number of quotes remaining after cleaning the data. We drop quotes due to several reasons: underlying not common stock, non-standard settlement, illiquid positions (relative bid-ask spread above 40%), bid/ask problems (bid or ask is zero, or bid above ask), excluded underlyings (multiple CUSIPs at the same time for one secid), or no underlying price quote (neither closing value nor average of closing bid and closing ask). Note that the number of options quotes is shown, not the number of option contracts.

Total quotes	586,132,584
Underlying not common stock	129,086,018
Non-std settlement	121,078,902
Bid/ask issues	30,845,031
Relative bid-ask spread too high	59,050,546
Excluded underlying	273,708
No underlying price quote	21,721
Remaining quotes	245,776,658

Table 2: Number of Option Contracts in each Year and in the Whole Sample. Contracts are identified by unique *OptionIds* from OptionMetrics. The numbers refer to the cleaned data set. Note that options with the same strike and maturity can have multiple issuers. The data ends at 31 October 2010. In every year, there is at least one stock that serves as underlying for only one option.

Year	Stocks	Options	Options per Stock: Average	Maximum
1996	1,256	132,813	105.74	473
1997	1,592	182,169	114.43	542
1998	1,842	239,069	129.79	852
1999	2,026	286,813	141.07	1,300
2000	2,164	392,009	181.15	1,348
2001	2,087	332,505	159.32	1,045
2002	2,154	298,729	138.69	596
2003	2,141	268,387	125.36	526
2004	2,348	307,712	131.05	745
2005	2,481	325,595	131.24	1,608
2006	2,686	364,477	135.70	1,829
2007	2,870	439,324	153.07	1,678
2008	2,873	543,101	189.04	1,956
2009	2,778	503,935	181.40	1,811
2010	2,821	480,770	170.43	2,056
All	4,671	3,943,187	844.18	8,123

Table 3: Conflicts between OptionMetrics and CRSP. These conflicts arise when OptionMetrics is merged with CRSP using the date and the corresponding CUSIP on that date. In all cases the CRSP quote is preferred. Note that 263,082 quotes from OptionMetrics could not be matched to CRSP. We treat these cases as if the CRSP quote was missing and use the OptionMetrics data. Both, CRSP and OptionMetrics use holding period returns. If the price on the previous day is missing in one dataset, the next day's returns will obviously not match. In this case, we use the return quotes from the dataset that had a price quote on the previous day. This procedure is also used for consecutively missing data points.

Return	No conflict	11,585,272
	OptionMetrics missing, CRSP available	2,676
	CRSP missing, OptionMetrics available	398
	Difference less than 0.005	4,638
	Difference more than 0.005	4,096
	Previous price missing in OptionMetrics	44,350
	Previous price missing in CRSP	287,189
Price	No conflict	11,621,697
	OptionMetrics missing, CRSP available	39,701
	CRSP missing, OptionMetrics available	266,394
	Difference less than 10%	601
	Difference more than 10%	226
Shares Outstanding	No conflict	6,625,781
	OptionMetrics missing, CRSP available	155,901
	CRSP missing, OptionMetrics available	255,247
	Difference less than 20%	4,707,162
	Difference more than 20%	184,528

Table 4: Summary Statistics for Option-derived Time Series. Below are the mean, standard deviation, skewness and kurtosis of the daily values for all option-derived time series over the whole sample period and the whole cross-section. The average moneyness (strike-to-spot ratio) and maturity (in actual days) of the option positions are reported. The last column reports the average number of stocks that have more than 14 observation for the time series in a month. This is the number of available stocks that are used to form portfolios.

	Mean	SD	Skew	Kurt	Mnn	Mat	avail
OTM Put, Close	0.63%	18.77%	8.26	646.59	0.922	100.98	1082.56
OTM Put, Close, Short Term	2.01%	28.33%	7.92	439.70	0.933	44.20	605.34
OTM Put, Close, Long Term	0.55%	16.63%	4.40	130.12	0.921	107.98	1069.46
OTM Put, Far	0.98%	20.03%	10.64	793.31	0.843	106.62	657.65
OTM Put, Far, Short Term	3.16%	32.80%	9.32	397.04	0.854	45.36	225.89
OTM Put, Far, Long Term	0.89%	18.50%	9.62	856.98	0.842	110.55	649.03
OTM Call, Close	1.28%	21.97%	8.28	828.82	1.081	100.98	1113.82
OTM Call, Close, Short Term	3.30%	31.99%	6.24	329.09	1.069	44.20	607.76
OTM Call, Close, Long Term	1.13%	19.55%	6.29	693.68	1.082	107.98	1099.04
OTM Call, Far	1.82%	24.29%	12.56	1340.45	1.173	106.62	675.20
OTM Call, Far, Short Term	5.13%	39.34%	17.80	2117.38	1.157	45.36	212.39
OTM Call, Far, Long Term	1.69%	22.39%	9.79	1057.75	1.174	110.55	664.40

Table 5: Summary Statistics for OTM Put based Portfolios. Below are the (arithmetic) mean, standard deviation, Sharpe ratio, skewness and kurtosis of monthly excess returns of equal weighted portfolios based on stocks' sensitivities to otm put option returns. Portfolio one consists of stocks with the smallest β_{put}, while stocks in portfolio five have the highest β_{put}. "Close" refers to a moneyness between 80% and 98%, "Far" to a moneyness between 50% and 90%. "Long Term" uses only options with a maturity of 60 to 150 actual days, otherwise all maturities from 10 to 150 actual days are included. All values are expressed in percentages, except for kurtosis.

Time Series	PF	Mean	Std Dev	Sharpe	Skew	Kurt
Close	1	0.173	10.912	1.588	7.13	3.83
	2	0.339	8.197	4.133	-36.06	3.50
	3	0.617	6.341	9.727	-72.59	4.15
	4	0.539	5.210	10.347	-82.24	5.00
	5	0.517	4.476	11.561	-86.25	5.32
Close, Long Term	1	0.054	11.635	0.460	4.98	3.95
	2	0.415	8.396	4.938	-31.64	3.60
	3	0.581	6.315	9.197	-71.79	4.36
	4	0.584	5.103	11.451	-93.69	5.26
	5	0.540	4.374	12.356	-84.56	5.29
Far	1	0.059	11.781	0.504	10.50	3.79
	2	0.224	9.177	2.444	-25.09	3.22
	3	0.473	7.466	6.334	-44.40	3.61
	4	0.587	6.153	9.547	-78.49	4.47
	5	0.498	5.060	9.835	-89.91	5.24
Far, Long Term	1	-0.022	12.263	-0.178	5.31	3.75
	2	0.259	9.608	2.699	-15.41	3.64
	3	0.558	7.541	7.406	-43.95	3.39
	4	0.544	5.931	9.168	-88.47	4.88
	5	0.507	4.790	10.592	-93.06	5.63

Table 6: Alphas, Market Capitalizations, Pre-Formation and Post-Formation Betas for OTM Put based Portfolios. Below are the alphas and their p-values (in brackets) of monthly portfolio returns of equal weighted portfolios based on sensitivities to otm put returns. The respective factor models are run using Newey and West (1987) regressions with one lag. For portfolio one to five we use excess returns, for the long-short portfolio $5-1$ we use simple returns. Also reported are the average market caps, the average pre-formation betas, and the average post-formation betas in equal weighted portfolios. The market cap is expressed relative to the market cap of all assets in the respective portfolio on the last day of the pre-formation period, averaged across months. The pre-formation beta is the average beta of stocks in a portfolio in the pre-formation period. These are the betas the stocks are ranked on. They are averaged using equal weights across months and cross-sectionally. The post-formation beta is the average beta of the stocks in a portfolio in the month in which they contribute to the portfolio returns. "Close" refers to a moneyness between 80% and 98%, "Far" to a moneyness between 50% and 90%. "Long Term" uses only options with a maturity of 60 to 150 actual days, otherwise all maturities from 10 to 150 actual days are included. All values except betas are expressed in percentages.

Time Series	PF	CAPM	FF 3-F	Carhart 4-F	M-Cap	Pre-F. β_c	Post-F. β_c
	1	-0.590 [17.5]	-0.625 [00.2]	-0.522 [00.9]	3.63	-0.2778	-0.2306
Close	2	-0.268 [32.8]	-0.350 [02.9]	-0.297 [06.3]	7.51	-0.1869	-0.1804
	3	0.121 [46.6]	-0.020 [87.0]	0.002 [98.7]	13.45	-0.1451	-0.1505
	4	0.131 [35.4]	-0.018 [87.8]	-0.013 [91.6]	25.37	-0.1131	-0.1240
	5	0.175 [21.5]	0.060 [58.7]	0.045 [70.0]	50.04	-0.0768	-0.1030
	5-1	0.765 [14.0]	0.685 [00.7]	0.567 [02.9]			
	1	-0.754 [11.5]	-0.727 [00.2]	-0.619 [00.6]	4.54	-0.3134	-0.2724
Close,	2	-0.202 [48.8]	-0.273 [07.4]	-0.245 [11.7]	8.38	-0.2101	-0.2055
Long Term	3	0.090 [61.7]	-0.063 [65.6]	-0.039 [78.2]	14.93	-0.1619	-0.1668
	4	0.195 [26.0]	0.019 [88.2]	0.019 [89.2]	26.64	-0.1252	-0.1341
	5	0.229 [21.3]	0.082 [54.0]	0.087 [54.3]	45.51	-0.0862	-0.1077
	5-1	0.983 [10.7]	0.810 [00.8]	0.706 [02.4]			
	1	-0.749 [12.9]	-0.753 [00.3]	-0.593 [01.6]	3.59	-0.2978	-0.2441
Far	2	-0.444 [16.9]	-0.463 [01.2]	-0.409 [02.6]	7.11	-0.2021	-0.1924
	3	-0.084 [73.9]	-0.181 [29.5]	-0.166 [33.6]	12.55	-0.1586	-0.1635
	4	0.109 [52.3]	0.020 [89.2]	0.004 [97.9]	24.15	-0.1232	-0.1374
	5	0.101 [44.2]	0.024 [85.3]	-0.022 [87.6]	52.59	-0.0816	-0.1135
	5-1	0.850 [11.2]	0.777 [01.3]	0.571 [06.6]			
	1	-0.867 [09.0]	-0.835 [00.2]	-0.673 [00.9]	4.01	-0.3219	-0.2731
Far,	2	-0.422 [26.0]	-0.431 [03.4]	-0.384 [06.1]	7.51	-0.2180	-0.2092
Long Term	3	-0.007 [97.5]	-0.088 [59.0]	-0.084 [61.2]	12.82	-0.1701	-0.1752
	4	0.089 [64.1]	-0.035 [83.4]	-0.059 [73.0]	24.10	-0.1309	-0.1437
	5	0.147 [37.1]	0.039 [79.3]	0.011 [94.4]	51.55	-0.0871	-0.1142
	5-1	1.013 [09.2]	0.874 [01.2]	0.684 [05.0]			

Table 7: Summary Statistics for OTM Call based Portfolios. Below are the (arithmetic) mean, standard deviation, Sharpe ratio, skewness and kurtosis of monthly excess return of equal weighted portfolios based on stocks' sensitivities to otm call option returns. Portfolio one consists of stocks with the smallest β_{call}, while stocks in portfolio five have the highest β_{call}. "Close" refers to a moneyness between 102% and 120%, "Far" to a moneyness between 110% and 150%. "Long Term" uses only options with a maturity of 60 to 150 actual days, otherwise all maturities from 10 to 150 actual days are included. All values are expressed in percentages, except for kurtosis.

Time Series	PF	Mean	Std Dev	Sharpe	Skew	Kurt
Close	1	0.550	4.290	12.808	-91.34	5.05
	2	0.479	5.186	9.231	-89.09	5.18
	3	0.731	6.361	11.497	-71.41	4.19
	4	0.412	8.104	5.085	-37.81	3.55
	5	0.284	10.814	2.623	-7.53	3.55
Close, Long Term	1	0.545	4.224	12.911	-95.51	5.53
	2	0.600	5.165	11.615	-82.80	5.01
	3	0.702	6.320	11.104	-76.76	4.37
	4	0.529	8.314	6.367	-37.02	3.53
	5	0.089	11.411	0.776	-9.05	3.64
Far	1	0.545	4.965	10.977	-73.83	4.24
	2	0.503	6.352	7.913	-66.90	4.18
	3	0.362	7.638	4.742	-51.81	3.55
	4	0.222	9.598	2.317	-36.35	3.17
	5	0.023	11.820	0.195	0.70	3.40
Far, Long Term	1	0.541	4.826	11.202	-76.58	4.62
	2	0.630	6.213	10.140	-71.30	4.33
	3	0.410	7.561	5.422	-49.94	3.48
	4	0.184	9.870	1.868	-28.67	3.21
	5	-0.091	12.332	-0.740	-5.86	3.47

Table 8: Alphas, Market Capitalizations, Pre-Formation and Post-Formation Betas for OTM Call based Portfolios. Below are the alphas and their p-values (in brackets) of monthly portfolio returns of equal weighted portfolios based on sensitivities to otm call returns. The respective factor models are run using Newey and West (1987) regressions with one lag. For portfolio one to five we use excess returns, for the long-short portfolio $5-1$ we use simple returns. Also reported are the average market cap, the average pre-formation betas, and the average post-formation betas in equal weighted portfolios. The market cap is expressed relative to the market cap of all assets in the respective portfolio on the last day of the pre-formation period, averaged across months. The pre-formation beta is the average beta of stocks in a portfolio in the pre-formation period. These are the betas the stocks are ranked on. They are averaged using equal weights across months and cross-sectionally. The post-formation beta is the average beta of stocks in a portfolio in the month in which they contribute to the portfolio returns. "Close" refers to a moneyness between 80% and 98%, "Far" to a moneyness between 50% and 90%. "Long Term" uses only options with a maturity of 60 to 150 actual days, otherwise all maturities from 10 to 150 actual days are included. All values except betas are expressed in percentages.

Time Series	PF	CAPM	FF 3-F	Carhart 4-F	M-Cap	Pre-F. β_c	Post-F. β_c
	1	0.220 [12.3]	0.098 [37.7]	0.078 [52.0]	51.23	0.0677	0.0880
Close	2	0.078 [62.5]	-0.087 [48.3]	-0.095 [46.7]	24.49	0.0977	0.1061
	3	0.233 [13.0]	0.088 [49.6]	0.114 [37.8]	13.19	0.1232	0.1266
	4	-0.195 [45.9]	-0.308 [04.1]	-0.248 [10.3]	7.36	0.1541	0.1492
	5	-0.490 [22.5]	-0.516 [01.6]	-0.359 [07.4]	3.72	0.2125	0.1810
	5-1	-0.710 [14.2]	-0.614 [01.9]	-0.436 [09.7]			
	1	0.244 [18.5]	0.098 [46.7]	0.089 [54.1]	47.16	0.0754	0.0911
Close,	2	0.209 [25.2]	0.017 [90.3]	0.025 [86.4]	25.39	0.1073	0.1136
Long Term	3	0.211 [24.0]	0.034 [79.7]	0.046 [73.2]	14.37	0.1363	0.1392
	4	-0.092 [73.2]	-0.168 [25.6]	-0.113 [45.0]	8.55	0.1712	0.1679
	5	-0.718 [10.5]	-0.694 [00.2]	-0.554 [01.1]	4.53	0.2354	0.2099
	5-1	-0.962 [09.3]	-0.792 [00.8]	-0.643 [03.7]			
	1	0.156 [26.7]	0.062 [63.4]	0.048 [72.8]	56.02	0.0733	0.0974
Far	2	0.014 [94.3]	-0.120 [49.1]	-0.079 [64.5]	22.06	0.1082	0.1193
	3	-0.217 [35.6]	-0.302 [08.8]	-0.234 [18.1]	11.72	0.1366	0.1405
	4	-0.475 [17.8]	-0.529 [01.8]	-0.409 [05.6]	6.83	0.1689	0.1620
	5	-0.802 [09.1]	-0.813 [00.7]	-0.543 [05.1]	3.37	0.2313	0.1967
	5-1	-0.959 [06.5]	-0.876 [01.0]	-0.592 [07.4]			
	1	0.180 [32.1]	0.058 [71.4]	0.068 [68.0]	54.69	0.0778	0.0965
Far,	2	0.155 [45.3]	0.001 [99.8]	0.044 [81.2]	22.40	0.1147	0.1239
Long Term	3	-0.165 [45.7]	-0.246 [12.9]	-0.175 [26.6]	11.88	0.1457	0.1497
	4	-0.526 [16.3]	-0.552 [01.6]	-0.448 [04.7]	7.22	0.1806	0.1753
	5	-0.948 [05.7]	-0.934 [00.2]	-0.680 [01.6]	3.81	0.2463	0.2157
	5-1	-1.128 [05.6]	-0.991 [00.6]	-0.748 [03.7]			

Table 9: Overlaps of Portfolios Based on OTM Put and Portfolios Based on OTM Call. Below are the average portfolio numbers induced by OTM call return betas for stocks that are in a portfolio based on OTM put return betas (*Avg Call PF in Put PF*). We also report the average OTM call portfolio numbers for stocks that are in no OTM put portfolio (*No PF*). Additionally the percentage of exact matches of portfolio indicators is reported. An exact match is a situation where a stock in call portfolio 1 is also in put portfolio 5 (2 in 4, and 3 in 3). The exact matches are reported for put portfolios 1 and 5 only. All these items are also quoted for the opposite situation: Put-based portfolio numbers of stocks in call-based portfolios (*Avg Put PF in Call PF*). We report the numbers for close and far moneyness, all maturities and long term maturities only.

Portfolio	Time Series	1	2	3	4	5	No PF	Exact Match	PF 1	PF 5
	Close	4.42	3.69	2.96	2.22	1.60	3.04	47.2%	61.4%	61.1%
Avg Call Pf	Close, LT	4.61	3.79	2.97	2.13	1.42	2.93	54.2%	69.3%	69.1%
in Put PF	Far	4.30	3.50	2.84	2.17	1.63	3.01	43.8%	54.8%	62.2%
	Far LT	4.45	3.58	2.84	2.10	1.47	2.93	48.0%	60.3%	68.5%
	Close	4.37	3.71	2.97	2.25	1.58	3.17	47.2%	58.8%	62.7%
Avg Put PF	Close, LT	4.56	3.79	2.97	2.15	1.41	3.28	54.2%	66.2%	70.1%
in Call PF	Far	4.22	3.46	2.79	2.14	1.56	3.61	43.8%	51.0%	65.2%
	Far LT	4.38	3.53	2.77	2.07	1.44	3.64	48.0%	55.9%	70.3%

Table 10: Average 5yr CDS Spread in Equal-weighted Portfolios Based on OTM Put Sensitivities. Below are the (arithmetic) mean monthly returns, alphas, p-values (in brackets), and average cds spreads (5yr maturity) of equal weighted portfolios based on otm put sensitivities. The sensitivities are from (1). The fraction of firms in each portfolio from which we calculated the average CDS spread are also reported. We use only data from 2001 onwards. We use excess returns for portfolio one to five. All values are expressed in percentages.

Time Series	PF	Mean	FF 3-F	CDS Spread	Fraction of Firms
	1	-0.007	-0.560 [01.8]	5.03	13.62
OTM Put	2	0.062	-0.437 [01.5]	2.37	17.20
Close	3	0.418	-0.062 [58.4]	1.49	26.34
	4	0.414	0.038 [71.8]	1.04	37.68
	5	0.394	0.154 [12.1]	0.75	50.04
	1	-0.298	-0.793 [00.3]	5.22	14.24
OTM Put	2	0.194	-0.319 [05.8]	2.24	18.15
Close	3	0.422	-0.054 [67.2]	1.48	25.73
Long Term	4	0.457	0.068 [55.0]	1.01	37.75
	5	0.457	0.190 [08.2]	0.72	50.17

Table 11: Mean Returns and Alphas for Systematic Volatility Based Portfolios. Below are the (arithmetic) means, alphas and p-values (in brackets) of monthly returns from portfolios based on sensitivities to changes in VIX and on sensitivities to market-neutral atm straddle returns. The respective factor models use Newey and West (1987) regressions with one lag. For portfolio one to five we use excess returns, for the long-short portfolio $5-1$ we use simple returns. All values are expressed in percentages.

Time Series	PF	Mean	CAPM	Fama-French 3-F	Carhart 4-F
Changes in VIX, Equal Weighted	1	0.944	0.407 [09.3]	0.213 [13.6]	0.296 [03.6]
	2	0.850	0.426 [01.8]	0.198 [08.7]	0.268 [01.9]
	3	0.812	0.401 [02.0]	0.172 [10.0]	0.209 [04.3]
	4	0.810	0.357 [03.6]	0.134 [12.4]	0.144 [10.8]
	5	0.831	0.244 [44.3]	0.047 [74.8]	0.066 [64.9]
	5-1	-0.112	-0.163 [52.1]	-0.166 [45.3]	-0.230 [29.9]
Changes in VIX, Value Weighted	1	0.594	0.139 [48.4]	0.167 [39.9]	0.225 [24.0]
	2	0.389	0.001 [99.0]	0.025 [79.2]	0.049 [61.7]
	3	0.483	0.119 [20.0]	0.106 [19.8]	0.094 [26.4]
	4	0.476	0.049 [69.7]	0.033 [79.6]	-0.040 [73.4]
	5	0.168	-0.380 [09.2]	-0.392 [04.6]	-0.419 [03.7]
	5-1	-0.426	-0.519 [16.0]	-0.559 [11.0]	-0.644 [06.4]
Market-Neutral ATM Straddle, Equal Weighted	1	1.065	0.513 [07.4]	0.331 [02.5]	0.371 [01.3]
	2	0.983	0.555 [00.4]	0.319 [00.5]	0.345 [00.3]
	3	0.827	0.421 [01.2]	0.198 [04.7]	0.235 [01.7]
	4	0.758	0.317 [06.4]	0.089 [36.3]	0.138 [13.0]
	5	0.614	0.029 [90.8]	-0.174 [17.4]	-0.108 [40.0]
	5-1	-0.451	-0.484 [02.6]	-0.505 [01.7]	-0.479 [03.1]
Market-Neutral ATM Straddle, Value Weighted	1	0.784	0.315 [09.6]	0.345 [07.7]	0.388 [05.0]
	2	0.692	0.327 [00.3]	0.300 [00.4]	0.284 [00.6]
	3	0.395	0.035 [73.1]	0.036 [66.1]	0.028 [74.1]
	4	0.399	-0.011 [90.8]	-0.012 [90.3]	-0.036 [72.2]
	5	-0.156	-0.706 [00.1]	-0.707 [00.1]	-0.683 [00.2]
	5-1	-0.940	-1.021 [00.3]	-1.052 [00.3]	-1.071 [00.4]

Table 12: Mean Returns, Alphas, and Betas for OTM Put Based Portfolios. Below are the (arithmetic) means, alphas, p-values (in brackets), pre-formation betas, and post-formation betas of monthly portfolio returns of equal weighted portfolios based on sensitivities to otm put returns. The sensitivities are obtained from the formation regression (6) including a proxy for systematic volatility. The respective factor models use Newey and West (1987) regressions with one lag. For portfolio one to five we use excess returns, for the long-short portfolio $5-1$ we use simple returns. All values are expressed in percentages except for pre- and post-formation betas.

Time Series	PF	Mean	CAPM	FF 3-F	Carhart 4-F	Pre-F β_c	Post-F β_c
	1	-0.591 [17.5]	-0.614 [00.3]	-0.504 [01.0]	3.73	-0.2797	-0.2316
Close	2	-0.237 [37.1]	-0.331 [03.0]	-0.285 [06.6]	7.65	-0.1880	-0.1816
	3	0.094 [57.9]	-0.043 [73.7]	-0.013 [91.5]	13.58	-0.1460	-0.1515
	4	0.128 [38.0]	-0.030 [79.8]	-0.027 [82.4]	25.48	-0.1139	-0.1252
	5	0.175 [21.8]	0.065 [56.8]	0.046 [70.9]	49.57	-0.0773	-0.1042
	5-1	0.765 [14.1]	0.679 [00.8]	0.550 [03.5]			
	1	-0.742 [11.8]	-0.710 [00.2]	-0.600 [00.6]	4.55	-0.3151	-0.2733
Close,	2	-0.188 [52.0]	-0.252 [10.1]	-0.218 [16.4]	8.58	-0.2112	-0.2065
Long Term	3	0.074 [69.0]	-0.095 [50.4]	-0.072 [61.0]	15.17	-0.1626	-0.1678
	4	0.196 [25.6]	0.022 [87.0]	0.022 [87.1]	26.89	-0.1259	-0.1351
	5	0.219 [23.4]	0.074 [57.9]	0.070 [61.8]	44.81	-0.0865	-0.1088
	5-1	0.961 [11.4]	0.784 [00.9]	0.671 [02.8]			
	1	-0.753 [12.5]	-0.754 [00.3]	-0.597 [01.4]	3.62	-0.3003	-0.2459
Far	2	-0.352 [26.5]	-0.379 [03.0]	-0.311 [07.2]	7.38	-0.2037	-0.1937
	3	-0.183 [47.4]	-0.264 [15.0]	-0.256 [16.6]	12.77	-0.1599	-0.1651
	4	0.094 [57.8]	-0.008 [95.7]	-0.019 [89.3]	24.51	-0.1242	-0.1385
	5	0.128 [34.2]	0.052 [69.1]	-0.003 [98.5]	51.71	-0.0823	-0.1156
	5-1	0.881 [09.4]	0.806 [00.8]	0.594 [04.8]			
	1	-0.853 [10.0]	-0.814 [00.3]	-0.650 [01.4]	4.07	-0.3242	-0.2746
Far,	2	-0.372 [31.9]	-0.379 [05.4]	-0.333 [09.4]	7.72	-0.2195	-0.2104
Long Term	3	-0.112 [63.2]	-0.201 [21.9]	-0.193 [24.5]	13.08	-0.1714	-0.1769
	4	0.119 [51.6]	-0.008 [96.2]	-0.028 [85.9]	24.58	-0.1319	-0.1447
	5	0.158 [33.4]	0.053 [72.2]	0.017 [91.8]	50.54	-0.0877	-0.1161
	5-1	1.010 [09.2]	0.868 [01.2]	0.666 [05.7]			

Table 13: Mean Returns, Alphas and Significances for Systematic Jump Risk Based Portfolios. Below are the (arithmetic) means, alphas and p-values (in brackets) of monthly portfolio returns of equal weighted portfolios based on sensitivities to changes in downward smile and on sensitivites to otm put returns. The respective factor models use Newey and West (1987) regressions with one lag. We use excess returns for portfolio one to five, and simple returns for the long-short portfolio $5-1$. All values are expressed in percentages.

Time Series	PF	Mean	CAPM	Fama-French 3-F	Carhart 4-F
OTM Put	1	1.082	0.549 [03.1]	0.325 [05.4]	0.422 [01.1]
	2	0.905	0.481 [00.7]	0.256 [01.8]	0.291 [00.8]
	3	0.832	0.431 [01.2]	0.200 [06.2]	0.244 [01.9]
	4	0.743	0.289 [09.8]	0.081 [38.2]	0.114 [19.8]
	5	0.686	0.088 [78.5]	-0.097 [52.0]	-0.088 [56.6]
	5-1	-0.396	-0.461 [09.6]	-0.423 [09.5]	-0.510 [04.6]
Changes in Downward Smile	1	1.122	0.554 [06.2]	0.363 [03.3]	0.446 [00.5]
	2	0.867	0.437 [01.8]	0.193 [08.2]	0.250 [01.6]
	3	0.853	0.451 [00.9]	0.219 [02.9]	0.246 [01.5]
	4	0.744	0.303 [08.1]	0.072 [41.8]	0.086 [35.2]
	5	0.662	0.091 [72.5]	-0.082 [50.0]	-0.047 [69.8]
	5-1	-0.460	-0.464 [04.2]	-0.446 [04.1]	-0.493 [01.8]

Table 14: Mean Returns, Alphas, Significances, and Betas for OTM Put Based Portfolios. Below are the (arithmetic) means, alphas, p-values (in brackets), pre-formation betas, and post-formation betas of monthly portfolio returns of equal weighted portfolios based on sensitivities to otm put returns. The sensitivities are obtained from the formation regression (8) that includes a proxy for systematic volatility (market-neutral atm straddle returns from S&P 500 options) and a proxy for systematic jump risk (changes in the downward smile implied by 30 day S&P 500 options). The respective factor models use Newey and West (1987) regressions with one lag. We use excess returns for portfolio one to five, and simple returns for the long-short portfolio $5-1$. All values are expressed in percentages except for pre- and post-formation betas.

Time Series	PF	Mean	CAPM	FF 3-F	Carhart 4-F	Pre-F β_c	Post-F β_c
Close	1	-0.606 [16.6]	-0.631 [00.2]	-0.529 [00.8]	3.74	-0.2801	-0.2310
	2	-0.276 [28.5]	-0.372 [01.4]	-0.318 [03.7]	7.68	-0.1879	-0.1810
	3	0.141 [40.1]	0.013 [92.0]	0.035 [77.7]	13.70	-0.1458	-0.1513
	4	0.127 [40.3]	-0.031 [80.0]	-0.027 [82.9]	25.36	-0.1137	-0.1254
	5	0.183 [19.1]	0.068 [54.5]	0.056 [64.1]	49.52	-0.0768	-0.1043
	5-1	0.789 [12.8]	0.700 [00.7]	0.585 [02.5]			
Close, Long Term	1	-0.775 [10.1]	-0.744 [00.1]	-0.639 [00.5]	4.55	-0.3149	-0.2722
	2	-0.205 [47.2]	-0.276 [06.8]	-0.239 [11.9]	8.57	-0.2107	-0.2059
	3	0.112 [54.0]	-0.047 [74.1]	-0.026 [85.5]	15.16	-0.1623	-0.1674
	4	0.225 [18.8]	0.052 [68.9]	0.051 [70.4]	26.84	-0.1255	-0.1351
	5	0.201 [27.1]	0.054 [69.2]	0.055 [69.9]	44.89	-0.0860	-0.1088
	5-1	0.977 [10.5]	0.798 [00.9]	0.695 [02.8]			
Far	1	-0.795 [10.1]	-0.806 [00.1]	-0.650 [00.6]	3.70	-0.3003	-0.2448
	2	-0.373 [25.2]	-0.391 [04.0]	-0.327 [08.5]	7.31	-0.2033	-0.1932
	3	-0.131 [57.6]	-0.209 [19.0]	-0.200 [21.3]	12.79	-0.1595	-0.1650
	4	0.102 [55.7]	0.005 [97.5]	-0.011 [94.0]	24.78	-0.1238	-0.1382
	5	0.130 [34.2]	0.049 [71.5]	0.002 [98.7]	51.41	-0.0816	-0.1153
	5-1	0.925 [07.3]	0.855 [00.5]	0.653 [02.9]			
Far, Long Term	1	-0.904 [07.4]	-0.880 [00.1]	-0.708 [00.5]	4.11	-0.3241	-0.2731
	2	-0.389 [29.3]	-0.396 [04.5]	-0.364 [06.6]	7.69	-0.2189	-0.2095
	3	0.025 [91.3]	-0.041 [79.4]	-0.029 [85.4]	13.23	-0.1708	-0.1764
	4	0.081 [66.1]	-0.050 [74.4]	-0.075 [63.3]	24.48	-0.1315	-0.1448
	5	0.126 [43.0]	0.019 [89.8]	-0.013 [93.7]	50.49	-0.0870	-0.1161
	5-1	1.029 [07.7]	0.899 [00.7]	0.695 [03.8]			

Table 15: Fama-French Alphas of Double-sorted Portfolios, First Sorted on Market Capitalizations (Rows) and Second on OTM Put Return Sensitivities (Columns). Below are the alphas and p-values (in brackets) of monthly portfolio returns of equal weighted and value weighted portfolios based on market cap and sensitivities to otm put returns. The sensitivities to otm put returns are obtained from the formation regression (8) that includes a proxy for systematic volatility and systematic jump risk. We first sort the stocks based on their market cap into five portfolios (rows), then we sort with respect to sensitivities to otm put returns (columns). Portfolio one consists of stocks with small market caps/sensitivities, portfolio five consists of stocks with high market caps/sensitivities. The respective factor models are estimated using Newey and West (1987) regressions with one lag. We use excess returns for portfolio one to five, and simple returns for the long-short portfolio $5-1$. We report results for "close" moneyness (80% to 98%). "Long term" refers to options with a maturity of 60 to 150 actual days, otherwise all maturities from 10 to 150 actual days are included. All values are expressed in percentages.

			1	2	3	4	5	5-1
Equal Weighted	All	1	-1.111 [00.2]	-0.396 [12.5]	-0.219 [38.4]	-0.420 [09.1]	-0.077 [73.5]	1.034 [01.0]
		2	-0.710 [01.5]	-0.800 [00.2]	-0.340 [12.9]	-0.164 [44.0]	0.010 [95.5]	0.720 [05.2]
		3	-0.355 [25.0]	-0.431 [05.9]	0.104 [57.5]	-0.216 [33.0]	0.013 [94.7]	0.368 [36.2]
		4	-0.133 [63.5]	0.157 [42.5]	0.041 [78.8]	-0.055 [73.6]	0.298 [07.6]	0.431 [21.5]
		5	-0.133 [56.3]	-0.055 [66.8]	0.026 [83.1]	0.218 [04.3]	0.018 [88.4]	0.151 [62.6]
			1	2	3	4	5	5-1
	Long Term	1	-1.333 [00.1]	-0.384 [19.3]	-0.132 [61.7]	-0.236 [27.0]	-0.107 [64.9]	1.226 [00.3]
		2	-0.955 [00.2]	-0.676 [00.6]	-0.437 [10.0]	-0.070 [76.3]	0.045 [79.5]	1.001 [01.1]
		3	-0.349 [29.1]	-0.426 [04.2]	0.046 [80.6]	-0.025 [90.6]	-0.022 [91.6]	0.328 [44.5]
		4	-0.024 [94.2]	-0.175 [35.6]	0.134 [46.5]	0.022 [90.8]	0.262 [14.9]	0.286 [50.6]
		5	-0.028 [91.5]	-0.130 [33.3]	0.050 [70.9]	0.107 [38.8]	0.065 [64.9]	0.093 [79.6]
			1	2	3	4	5	5-1
Value Weighted	All	1	-1.024 [00.6]	-0.493 [06.1]	-0.262 [31.9]	-0.497 [03.7]	-0.108 [62.7]	0.915 [02.4]
		2	-0.727 [01.5]	-0.793 [00.2]	-0.402 [07.3]	-0.163 [44.3]	-0.030 [86.8]	0.697 [06.4]
		3	-0.283 [38.5]	-0.430 [05.8]	0.050 [78.1]	-0.142 [51.1]	0.065 [74.3]	0.348 [41.0]
		4	-0.188 [51.6]	0.192 [35.5]	0.118 [43.5]	-0.058 [72.1]	0.296 [07.7]	0.484 [18.1]
		5	0.076 [76.2]	-0.043 [81.5]	0.192 [13.6]	0.106 [39.8]	-0.033 [79.8]	-0.109 [73.9]
			1	2	3	4	5	5-1
	Long Term	1	-1.188 [00.2]	-0.545 [06.6]	-0.247 [32.7]	-0.270 [21.1]	-0.144 [53.4]	1.043 [01.2]
		2	-0.895 [00.4]	-0.740 [00.5]	-0.436 [10.8]	-0.137 [54.6]	-0.007 [97.0]	0.889 [02.4]
		3	-0.320 [34.9]	-0.400 [06.2]	0.049 [78.6]	-0.004 [98.5]	0.014 [94.6]	0.334 [45.0]
		4	-0.015 [96.4]	-0.201 [30.6]	0.165 [38.5]	0.061 [73.9]	0.251 [17.1]	0.267 [54.6]
		5	0.057 [83.9]	-0.005 [97.8]	0.053 [71.8]	-0.062 [64.2]	0.020 [88.8]	-0.036 [92.3]

Table 16: Pre-Formation Betas of Double-sorted Portfolios, First Sorted on Market Capitalizations (Rows) and Second on OTM Put Return Sensitivities (Columns). Below are the average pre-formation betas, β_c, of stocks in portfolios based on market cap and sensitivities to otm put returns. We first sort the stocks based on their market cap into five portfolios (rows), then we sort within each portfolio with respect to sensitivities to otm put returns (columns). The sensitivities to otm put returns are obtained from the formation regression (8) that includes a proxy for systematic volatility and systematic jump risk. Portfolio one consists of stocks with small market caps/sensitivities, portfolio five consists of stocks with high market caps/sensitivities. The pre-formation beta is the average beta of stocks in a portfolio in the pre-formation period. These are the betas the stocks are ranked on. They are averaged using equal weights across months and equal weights or value weights cross-sectionally (depending on the portfolio weighting). We report results for "close" moneyness (80% to 98%). "Long term" refers to options with a maturity of 60 to 150 actual days, otherwise all maturities from 10 to 150 actual days are included.

			1	2	3	4	5
Equal Weighted	All	1	-0.3528	-0.2532	-0.2086	-0.1701	-0.1161
		2	-0.2886	-0.2082	-0.1701	-0.1386	-0.0969
		3	-0.2548	-0.1786	-0.1447	-0.1174	-0.0821
		4	-0.2220	-0.1565	-0.1267	-0.1031	-0.0728
		5	-0.1751	-0.1247	-0.1035	-0.0862	-0.0626
			1	2	3	4	5
	Long Term	1	-0.3877	-0.2762	-0.2268	-0.1852	-0.1280
		2	-0.3263	-0.2303	-0.1865	-0.1504	-0.1058
		3	-0.2928	-0.2004	-0.1591	-0.1277	-0.0897
		4	-0.2601	-0.1779	-0.1405	-0.1128	-0.0802
		5	-0.2112	-0.1443	-0.1175	-0.0978	-0.0731
			1	2	3	4	5
Value Weighted	All	1	-0.3493	-0.2530	-0.2085	-0.1700	-0.1168
		2	-0.2884	-0.2081	-0.1701	-0.1385	-0.0970
		3	-0.2543	-0.1786	-0.1447	-0.1174	-0.0821
		4	-0.2216	-0.1565	-0.1267	-0.1031	-0.0728
		5	-0.1713	-0.1244	-0.1031	-0.0861	-0.0613
			1	2	3	4	5
	Long Term	1	-0.3847	-0.2761	-0.2266	-0.1850	-0.1285
		2	-0.3261	-0.2303	-0.1865	-0.1504	-0.1057
		3	-0.2924	-0.2004	-0.1591	-0.1276	-0.0896
		4	-0.2596	-0.1778	-0.1405	-0.1128	-0.0801
		5	-0.2050	-0.1436	-0.1170	-0.0977	-0.0730

Table 17: Mean Returns and Alphas of Equal-weighted Portfolios Based on Betas From Longer Formation Periods. Below are the (arithmetic) mean monthly returns, alphas, and p-values (in brackets) of equal weighted portfolios based on betas from formation regression (8) where we include a systematic volatility and systematic jump risk proxy. The formation regressions are done using two and three months of data. The respective factor models are estimated using Newey and West (1987) regressions with one lag. We use excess returns for portfolio one to five. All values except betas are expressed in percentages.

Formation	Time-Series	PF	Mean	FF 3-F	Pre-F. β_c	Post-F. β_c
Two Months	OTM Put Close	1	0.206	-0.586 [00.4]	-0.2708	-0.2503
		2	0.393	-0.295 [05.5]	-0.1830	-0.1807
		3	0.550	-0.085 [52.2]	-0.1431	-0.1455
		4	0.540	-0.026 [84.1]	-0.1122	-0.1166
		5	0.567	0.119 [28.0]	-0.0776	-0.0889
		5-1	0.360	0.705 [00.6]		
	OTM Call Close	1	0.548	0.109 [28.5]	0.0680	0.0765
		2	0.647	0.076 [55.5]	0.0967	0.1003
		3	0.597	-0.041 [75.9]	0.1214	0.1231
		4	0.488	-0.217 [19.4]	0.1513	0.1494
		5	0.159	-0.659 [00.2]	0.2078	0.1942
		5-1	-0.389	-0.769 [00.4]		
Three Months	OTM Put Close	1	0.072	-0.685 [00.1]	-0.2668	-0.2543
		2	0.386	-0.282 [08.5]	-0.1810	-0.1796
		3	0.514	-0.112 [43.1]	-0.1420	-0.1432
		4	0.621	0.066 [61.8]	-0.1116	-0.1140
		5	0.571	0.125 [29.4]	-0.0778	-0.0843
		5-1	0.499	0.810 [00.3]		
	OTM Call Close	1	0.545	0.104 [33.5]	0.0681	0.0729
		2	0.696	0.128 [33.3]	0.0963	0.0983
		3	0.601	-0.018 [89.0]	0.1206	0.1215
		4	0.419	-0.264 [13.2]	0.1499	0.1490
		5	0.052	-0.727 [00.1]	0.2050	0.1969
		5-1	-0.492	-0.831 [00.2]		

Table 18: Mean Returns and Alphas of Equal-weighted Portfolios Based on Betas With Implicit Volatility Proxy. Below are the (arithmetic) mean monthly returns, alphas, and p-values (in brackets) of equal weighted portfolios based on put and call betas from formation regression (9) where we include a systematic volatility, a systematic jump risk proxy and daily changes in firm specific implied volatility. The respective factor models are estimated using Newey and West (1987) regressions with one lag. We use excess returns for portfolio one to five. All values except betas are expressed in percentages.

Time-Series	PF	Mean	FF 3-F	Pre-F. β_c	Post-F. β_c
OTM Put Close	1	0.236	-0.456 [01.6]	-0.2636	-0.2174
	2	0.349	-0.295 [05.8]	-0.1814	-0.1743
	3	0.599	0.021 [87.6]	-0.1421	-0.1471
	4	0.456	-0.093 [43.6]	-0.1115	-0.1229
	5	0.537	0.092 [38.7]	-0.0754	-0.1041
	5-1	0.301	0.548 [02.2]		
OTM Call Close	1	0.529	0.094 [38.7]	0.0654	0.0844
	2	0.513	-0.010 [93.8]	0.0933	0.1014
	3	0.601	-0.019 [88.9]	0.1164	0.1197
	4	0.421	-0.221 [11.0]	0.1441	0.1386
	5	0.242	-0.471 [01.5]	0.1953	0.1667
	5-1	-0.287	-0.566 [01.9]		

Table 19: Mean Returns and Alphas of Equal-weighted Portfolios Based on OTM Put Sensitivities by Period. Below are the (arithmetic) mean monthly returns, alphas, and p-values (in brackets) of equal weighted difference portfolios $(5-1)$ based on otm put sensitivities. We split the sample into three subperiods. The sensitivities are from (8) where we include a systematic volatility and systematic jump risk proxy. The respective factor models are estimated using Newey and West (1987) regressions with one lag. We use excess returns for portfolio one to five. All values are expressed in percentages.

Period	Time-Series	Mean	CAPM	FF 3-F	Carhart 4-F
1996-200	Put Close	0.140	1.220 [35.5]	-0.088 [82.9]	0.111 [78.7]
	Put Close, Long Term	-0.096	1.261 [42.0]	-0.321 [50.3]	-0.003 [99.5]
2001-2005	Put Close	0.598	0.798 [20.1]	0.506 [21.8]	0.531 [20.8]
	Put Close, Long Term	0.957	1.185 [08.9]	0.608 [16.3]	0.633 [15.3]
2006-2010	Put Close	0.368	0.453 [21.3]	0.665 [02.1]	0.727 [00.3]
	Put Close, Long Term	0.578	0.674 [06.9]	0.862 [00.7]	0.930 [00.1]

Table 20: Mean Returns and Alphas of Equal-weighted portfolios Based on OTM Put by Industry. Below are the (arithmetic) mean monthly returns, alphas, p-values (in brackets) of equal weighted portfolios based on otm put sensitivities. We split the sample into five different industries and also report the average fraction of firms in each industry. The sensitivities are from (8) that involves a systematic volatility and systematic jump risk proxy. The respective factor models are estimated using Newey and West (1987) regressions with one lag. We use excess returns for portfolio one to five. All values are expressed in percentages.

Industry	Time-Series	Pct Firms	Mean	CAPM	FF 3-F	Carhart 4-F
Consumer	Put Close	17.89	-0.169	0.141 [68.1]	0.301 [30.6]	0.153 [60.8]
	Put Close, Long Term	17.91	-0.106	0.237 [49.6]	0.338 [25.7]	0.181 [55.0]
Manufacturing	Put Close	21.00	-0.118	0.251 [60.3]	0.288 [49.5]	0.177 [67.3]
	Put Close, Long Term	21.02	0.025	0.446 [39.8]	0.466 [28.5]	0.362 [41.5]
High Tech	Put Close	26.85	0.137	0.510 [27.7]	0.435 [13.3]	0.294 [30.9]
	Put Close, Long Term	26.87	0.487	0.941 [11.0]	0.740 [04.2]	0.652 [09.3]
Health	Put Close	12.53	0.801	1.116 [15.2]	1.143 [02.5]	1.190 [01.7]
	Put Close, Long Term	12.53	1.242	1.598 [02.6]	1.538 [00.2]	1.538 [00.2]
Others	Put Close	24.55	0.947	1.195 [00.4]	1.349 [00.1]	1.243 [00.1]
	Put Close, Long Term	24.52	0.819	1.124 [00.9]	1.255 [00.1]	1.117 [00.1]

Table 21: Mean Returns, Alphas, and IVols for Portfolios Based on Fama-French IVols, Full Sample. Below are the (arithmetic) means, alphas, p-values (in brackets), pre-formation ivols, and post-formation ivols of monthly portfolio returns of equal weighted and value weighted portfolios based on idiosyncratic volatility with respect to the Fama-French three-factor model (3). The respective factor models are estimated using Newey and West (1987) regressions with one lag. We use excess returns for portfolio one to five, and simple returns for the long-short portfolio $5 - 1$. The sample includes all stocks that can be matched from OptionMetrics to CRSP and that pass our filtertering process. All values are expressed in percentages, except for ivols.

Time Series	PF	Mean	CAPM	FF 3-F	Carhart 4-F	Pre-F IVol	Post-F IVol
Equal Weights	1	0.791	0.517 [00.9]	0.293 [01.9]	0.298 [02.2]	0.0105	0.0141
	2	0.812	0.434 [02.5]	0.183 [13.1]	0.210 [08.8]	0.0160	0.0190
	3	0.930	0.466 [01.4]	0.217 [05.1]	0.267 [01.5]	0.0216	0.0237
	4	0.923	0.354 [19.0]	0.152 [15.8]	0.192 [07.1]	0.0291	0.0287
	5	0.794	0.066 [88.0]	-0.080 [63.1]	0.016 [92.3]	0.0484	0.0351
	5-1	0.003	-0.450 [40.4]	-0.373 [13.3]	-0.282 [27.3]		
Value Weights	1	0.609	0.309 [02.1]	0.290 [00.3]	0.239 [02.0]	0.0104	0.0127
	2	0.333	-0.061 [57.4]	-0.078 [39.0]	-0.095 [28.5]	0.0158	0.0163
	3	0.486	0.003 [98.0]	0.016 [89.6]	0.071 [56.1]	0.0213	0.0203
	4	0.451	-0.151 [50.3]	-0.117 [45.4]	-0.091 [56.8]	0.0287	0.0253
	5	0.196	-0.560 [16.0]	-0.462 [06.6]	-0.429 [08.9]	0.0454	0.0320
	5-1	-0.413	-0.869 [08.3]	-0.752 [01.3]	-0.668 [02.9]		

Table 22: Mean Returns, Alphas, Significances, and IVols for Portfolios Based on Fama-French IVols, Restricted Sample. Below are the (arithmetic) means, alphas, p-values (in brackets), pre-formation ivols, and post-formation ivols of monthly portfolio returns of equal weighted and value weighted portfolios based on idiosyncratic volatility with respect to the Fama-French three-factor model (3). The respective factor models are estimated using Newey and West (1987) regressions with one lag. We use excess returns for portfolio one to five, and simple returns for the long-short portfolio $5-1$. We reduce the sample to stocks for which we can estimate a beta with respect to otm put close returns. All values are expressed in percentages, except for ivols.

Time Series	PF	Mean	CAPM	FF 3-F	Carhart 4-F	Pre-F IVol	Post-F IVol
Equal Weights	1	0.620	0.295 [09.8]	0.147 [26.0]	0.147 [28.5]	0.0112	0.0151
	2	0.574	0.165 [28.2]	0.009 [94.4]	0.025 [84.4]	0.0165	0.0196
	3	0.608	0.101 [56.1]	-0.045 [70.2]	-0.023 [84.8]	0.0216	0.0240
	4	0.425	-0.196 [48.7]	-0.269 [05.2]	-0.244 [08.0]	0.0282	0.0288
	5	-0.043	-0.800 [06.1]	-0.798 [00.1]	-0.691 [00.1]	0.0451	0.0350
	5-1	-0.663	-1.095 [04.5]	-0.945 [00.1]	-0.839 [00.3]		
Value Weights	1	0.525	0.205 [11.2]	0.229 [02.5]	0.172 [10.3]	0.0109	0.0131
	2	0.317	-0.081 [46.7]	-0.052 [61.6]	-0.058 [57.5]	0.0163	0.0168
	3	0.306	-0.189 [22.5]	-0.122 [43.4]	-0.096 [54.4]	0.0213	0.0206
	4	0.341	-0.274 [23.8]	-0.193 [24.5]	-0.167 [33.0]	0.0279	0.0250
	5	0.039	-0.704 [08.6]	-0.542 [05.9]	-0.525 [06.6]	0.0426	0.0307
	5-1	-0.486	-0.909 [07.1]	-0.771 [02.5]	-0.697 [04.3]		

Table 23: Fama-French Alphas and Significances for Double-sorted Portfolios, First Sorted on Idiosyncratic Volatility (Rows) and Second on OTM Put Return Sensitivities (Columns). Below are the alphas and p-values (in brackets) of monthly portfolio returns of equal weighted portfolios based on idiosyncratic volatility with respect to the Fama-French three-factor model and sensitivities to otm put option returns. The sensitivities to otm put returns are obtained from the formation regression (8) that includes a proxy for systematic volatility and systematic jump risk. We first sort the stocks based on their idiosyncratic volatility into five portfolios (rows), then we sort with respect to betas, β_c^i. Portfolio ome consists of stocks with small sensitivities/ivols, portfolio five consists of stocks with high sensitivities/ivols. The respective factor models is estimated using Newey and West (1987) regressions with one lag. We use excess returns for portfolio one to five, and simple returns for the long-short portfolio $5-1$. We report results for "close" moneyness (102% to 120%). "Long term" refers to options with a maturity of 60 to 150 actual days, otherwise all maturities from 10 to 150 actual days are included. All values are expressed in percentages.

			1	2	3	4	5	5-1
Equal Weighted	Close	1	0.167 [33.4]	0.250 [10.3]	0.064 [71.1]	0.095 [50.8]	0.163 [27.0]	-0.004 [98.3]
		2	-0.127 [52.3]	0.081 [63.7]	0.037 [84.6]	0.021 [88.2]	0.033 [81.8]	0.160 [46.5]
		3	-0.213 [32.0]	0.018 [92.6]	0.097 [58.1]	-0.095 [61.3]	-0.024 [87.9]	0.189 [49.9]
		4	-0.272 [30.3]	-0.324 [11.5]	-0.540 [00.9]	-0.068 [74.9]	-0.140 [41.9]	0.133 [64.2]
		5	-1.289 [00.1]	-0.790 [00.9]	-0.645 [01.2]	-0.718 [01.4]	-0.538 [05.4]	0.751 [10.1]
			1	2	3	4	5	5-1
	Close, LT	1	0.089 [61.1]	0.379 [02.1]	0.102 [55.1]	0.019 [90.4]	0.122 [40.9]	0.034 [84.1]
		2	-0.145 [43.7]	0.146 [44.2]	-0.005 [97.4]	-0.086 [61.0]	0.119 [42.7]	0.264 [21.3]
		3	-0.243 [30.5]	-0.229 [17.6]	0.216 [29.0]	0.025 [89.0]	-0.054 [76.6]	0.189 [56.7]
		4	-0.501 [12.6]	-0.138 [51.1]	-0.204 [30.2]	-0.469 [02.2]	-0.002 [99.2]	0.499 [21.0]
		5	-1.328 [00.2]	-1.009 [00.2]	-0.672 [02.5]	-0.485 [08.9]	-0.447 [10.9]	0.880 [08.7]

Table 24: Fama-French Alphas and Significances for Double-sorted Portfolios, First Sorted on OTM Put Return Sensitivities (Rows) and Second on Idiosyncratic Volatility (Columns). Below are the alphas and p-values (in brackets) of monthly portfolio returns of equal weighted portfolios based on sensitivities to option returns and idiosyncratic volatility with respect to the Fama-French three-factor model. The sensitivities to otm put returns are obtained from the formation regression (8) that includes a proxy for systematic volatility and systematic jump risk. We first sort stocks based on their betas, β_c^i, into five portfolios (rows), then we sort with respect to ivol (columns). Portfolio one consists of stocks with small sensitivities/ivols, portfolio five consists of stocks with high sensitivities/ivols. The respective factor models use Newey and West (1987) regressions with one lag. We use excess returns for portfolio one to five, and simple returns for the long-short portfolio $5-1$. We report results for "close" moneyness (102% to 120%). "Long term" refers to options with a maturity of 60 to 150 actual days, otherwise all maturities from 10 to 150 actual days are included. All values are expressed in percentages.

			1	2	3	4	5	5-1
Equal Weighted	Close	1	-0.369 [11.6]	-0.324 [21.9]	-0.405 [14.3]	-0.902 [00.3]	-1.157 [00.1]	-0.787 [02.6]
		2	-0.027 [89.5]	-0.022 [91.0]	-0.396 [04.8]	-0.648 [00.4]	-0.776 [00.8]	-0.749 [02.3]
		3	0.218 [26.2]	-0.047 [77.5]	0.069 [70.3]	0.088 [62.4]	-0.271 [26.6]	-0.489 [09.7]
		4	0.218 [16.4]	-0.019 [90.6]	0.078 [65.2]	-0.106 [53.5]	-0.334 [08.0]	-0.552 [01.6]
		5	0.173 [24.6]	0.156 [31.9]	0.058 [70.0]	-0.085 [56.2]	0.035 [84.1]	-0.137 [50.2]
			1	2	3	4	5	5-1
	Close, LT	1	-0.300 [21.3]	-0.651 [02.8]	-0.372 [19.1]	-0.860 [01.1]	-1.548 [00.1]	-1.249 [00.1]
		2	-0.100 [61.0]	-0.207 [32.1]	-0.332 [11.7]	-0.151 [51.0]	-0.599 [03.3]	-0.499 [09.8]
		3	0.064 [71.8]	-0.074 [71.1]	0.066 [71.2]	0.224 [24.4]	-0.522 [02.7]	-0.586 [01.8]
		4	0.286 [10.3]	0.055 [73.2]	0.088 [55.1]	-0.022 [90.7]	-0.155 [43.5]	-0.441 [03.7]
		5	0.114 [46.9]	0.264 [10.2]	-0.061 [68.6]	0.096 [54.1]	-0.145 [46.7]	-0.258 [17.4]

Table 25: Overlaps of Portfolios Based on Ivol with Portfolios Based on OTM Put and OTM Call Sensitivities. Below are the average portfolio numbers induced by different sorting criteria for stocks that are in a particular portfolio based on otm put or otm call return betas. We also report the average portfolio numbers for stocks that are in no otm put/call portfolio (*No PF*). Additionally the percentage of exact matches of portfolio indicators is reported. An exact match is a situation where a stock in ivol portfolio 1 is also in put portfolio 5 (2 in 4, and 3 in 3). For ivol portfolios numbers in call portfolios, we count an exact match if a stock in ivol portfolio 1 is also in call portfolio 1, etc. The exact matches are also reported for put/call portfolios 1 and 5 only.

Portfolio	Time Series	1	2	3	4	5	No PF	Exact Match	PF 1	PF 5
Avg Ivol PF in Put PF	Close	4.21	3.49	2.91	2.28	1.79	3.04	40.1%	46.7%	54.2%
	Close, LT	4.27	3.54	2.92	2.25	1.69	3.04	42.4%	49.2%	57.4%
	Far	4.33	3.69	3.16	2.58	2.01	2.95	39.4%	52.9%	44.7%
	Far LT	4.38	3.72	3.18	2.56	1.92	2.95	40.9%	55.0%	46.9%
Avg Ivol PF in Call PF	Close	1.80	2.32	2.93	3.53	4.21	3.03	39.7%	52.2%	47.4%
	Close, LT	1.68	2.29	2.95	3.58	4.28	3.03	42.2%	55.7%	49.9%
	Far	2.14	2.78	3.35	3.84	4.41	2.89	38.1%	37.3%	57.9%
	Far LT	2.03	2.77	3.37	3.88	4.46	2.90	39.6%	39.6%	60.3%

Table 26: Correlations of Long-Short Portfolios. Below are the correlations of monthly returns of the difference portfolios $(5-1)$ corresponding to different pricing anomalies. The portfolios are equal weighted and monthly rebalanced. For the difference portfolio of the ivol anomaly, we use both weighting schemes, equal- and value-weighted. We also include the Fama-French factors.

	put	call	ivol, ew	ivol, vw	mktrf	smb	hml
put	1.000						
call	-0.967	1.000					
ivol, ew	-0.969	0.954	1.000				
ivol, vw	-0.921	0.903	0.934	1.000			
mktrf	-0.588	0.635	0.618	0.625	1.000		
smb	-0.737	0.689	0.738	0.666	0.246	1.000	
hml	0.676	-0.641	-0.667	-0.644	-0.254	-0.373	1.000