# The Implied Volatility Skew of Single Stock Options and the Predictability of Jumps - Robustness Analysis 

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#### Abstract

In this thesis, we try to understand whether the observed implied volatility skew of single stock options is significantly related to the probability of observing future return jumps in the underlying single stock. In particular, our main aim is to verify whether the skew-jump relationship persists during normal periods without any pre-scheduled information disclosure event or it is confined to earnings announcement periods. Using S\&P 100 daily stock and option data from January 1996 to December 2017, we model the statistical relationship between ex-ante skew and ex-post jump using a probit model. To ensure robustness, we define skew in two ways as the difference between out-of-the-money (OTM) implied volatility and at-the-money (ATM) or in-the-money (ITM) implied volatility. We find that the statistical significance of the skew-jump relationship is preserved during normal periods with no earnings announcement: more positive put skews are related to a higher probability of observing future negative jumps and more negative call OTM-ATM skews are related to a higher probability of observing future positive jumps, both in the full period and the normal period. To improve the robustness, we repeat our analysis raising the probability threshold for jump identification and we find that while the statistical relationships do not change, the predictive accuracy improves.


Keywords: single stocks, options, implied volatility skew, jumps, earnings announcements

To my parents and grandparents.

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## Introduction

The main purpose of this robustness analysis is to verify that a change in the probability threshold used to predict future return jumps from single stock options' implied volatility skew dynamics changes the predictive accuracy of our probit model.

Plain-vanilla equity options are derivative securities whose price depends on several factors: the underlying price, S; the strike price, K, at which one can exercise the option; the time to expiry, T ; the dividend yield of the underlying stock, d ; the risk free rate, $r$; the level of volatility of the stock, $\sigma$.

Equity options can be American or European in their simplest form. American options can be exercised any time prior to expiry, even if in practice early exercise is only convenient prior to dividends and for well in the money options, which makes the time value component of the option premium irrelevant. European options can only be exercised at expiry. We have both call and put options, which respectively give the holder the right to buy and sell the underlying stock at the given strike price.

Given the Black-Scholes pricing model, one can back-solve for the level of volatility implied by the observed option market price. Theory states that implied volatility should be uniform across different strike prices. However, when we observe real-world option market prices, we notice that implied volatility changes depending on strike prices, producing what we define as implied volatility curve, also known as skew or smile depending on its shape.


Figure 1: Example of implied volatility skew

Variables: implied volatility $=$ volatility that makes the observed option market price equal to the theoretical Black-Scholes price; moneyness = strike price / spot price; ATM, ITM, OTM respectively at the money, in the money, out of the money. The chart shows a stylized implied volatility curve. As moneyness increases, implied volatility usually first decreases and then may increase again for the tails of the curve, forming what is defined as smile.

In our empirical thesis work, we ask ourselves whether observed single stock option skews are statistically related to subsequent extreme returns in the underlying stock. The basis of our empirical study is the observation that stock returns are not normally distributed as they exhibit higher kurtosis and negative skewness than the normal, so that extreme returns, also defined as jumps, happen more frequently than a normal distribution would imply. Furthermore, given options' higher built-in leverage (Easley, O'Hara and Srinivas, 1998), given the finding that demand and supply pressures get incorporated into option implied volatilities (Garleanu, Pedersen and Poteshman, 2009) and given that stock returns exhibit jumps and influence option prices (Pan, 2002; Eraker, 2004; Heston, 1993), demand pressures of informed traders carry valuable information for the expectation about future stock returns and, therefore, also jumps.

Given implied volatilities (IV), we define skew as:

$$
\text { Skew }=I V_{\text {ОTM }}-I V_{\text {ITM or ATM }}
$$

Previous research shows that a more positive put skew, i.e. a higher put OTM implied volatility relative to the ATM implied volatility, is associated with future negative returns of the underlying equity. This is observed both before significant information events, such as earnings announcements for single stocks (Xing, Zhang and Zhao, 2010) and during normal periods (Jin, Livnat and Zhang, 2012). Usually, ATM implied volatility rises before information events as uncertainty about the event outcome builds up and market participants start bidding up the price of uncertainty, i.e. implied volatility of options (Dubinsky and Johannes, 2006). We therefore would like to ask whether such findings persist with jumps or are only confined to normal returns.

We rely on the methodology adopted for the study of the statistical relation between equity index option skews and index jumps (Doran, Peterson and Tarrant, 2007), where time-series data for option skews and jumps is used.

We ask ourselves four research questions. First, we ask whether the probability of observing negative jumps in the underlying stocks is positively related to a more positive put skew over the time series, as market participants should bid up the price of OTM puts to get protection if they expect future negative jumps. Second, we ask whether the probability of observing positive jumps in the underlying stocks is positively related to a more positive call skew over the time series, as market participants expecting positive jumps in the underlying should buy OTM calls to profit. Third, we ask whether the statistical relationship skew-jumps (if found) characterizes normal periods without any earnings announcements or it is limited to earnings announcement periods. Finally, we ask whether the significance of the skew in explaining future jumps is incremental with respect to using only ATM implied volatility.

All data are downloaded through the Wharton Research Data Services (WRDS) online database. The sample period extends from January 1, 1996 to December 31, 2017. ${ }^{1}$ Using the Compustat Capital IQ database, data about the S\&P 100 index constituents from the North America - Annual Updates section is downloaded. This gives information on all firms included in the index over the sample period and on the dates of inclusion and/or exclusion from the index: 207 unique company tickers are retrieved, of which only those that have been included continuously throughout the period are used for the empirical test. ${ }^{2}$ This reduces the sample to 26 of the 207 stocks. Using OptionMetrics, we then download daily data on stock prices, returns, volumes and shares outstanding for the 26 stocks. After cleaning for missing data (shares outstanding), 24 stocks are retained. For each stock, we retrieve data on the quarterly earnings announcement dates from the Compustat North America - Fundamental Quarterly database. For each stock, we get option data from OptionMetrics: we retrieve option type (call/put), expiration date, strikes, bid, ask, volume, open interest, implied volatility, on a daily frequency. Observations for which IV is not available are eliminated.

Small (big) negative jumps are those daily stock returns that are in the bottom 5\% (1\%) of the returns distribution, conditional on returns being negative. Small (big)

[^0]positive jumps are those daily stock returns that are in the top $5 \%$ (1\%) of the returns distribution, conditional on returns being positive. we keep only those options with a mid-price greater than $\$ 0.25$ and a bid different than zero. We further keep only options with non-zero volume and with days to expiration between 10 and 90 . We check that option bids and asks respect basic no-arbitrage conditions and eliminate those that fail the test.

Following Doran, Peterson and Tarrant (2007), we group options' observations by maturity into 3 categories: (1) short-term (ST) options with between 10 and 30 days to expiry; (2) medium-term (MT) options with between 31 and 60 days to expiry; and (3) long-term (LT) options with between 61 and 90 days to expiry. Furthermore, always following Doran, Peterson and Tarrant (2007), we group options according to moneyness into 7 categories: (1) Deep-Deep-Out-of-The-Money (DDOTM) options, which are puts with moneyness smaller than $87.5 \%$ and calls with moneyness larger than 112.5\%; (2) Deep-Out-of-The-Money (DOTM) options, which are puts with moneyness between $87.5 \%$ and $92.5 \%$ and calls between $107.5 \%$ and $112.5 \%$; (3) OTM options, which are puts between 92.5\% and 97.5\% and calls between 102.5\% and 107.5\%; (4) ATM options, which are both puts and calls between $97.5 \%$ and 102.5\%; (5) ITM options, which are puts between $102.5 \%$ and $107.5 \%$ and calls between 92.5\% and 97.5\%; (6) DITM options, which are puts between 107.5\% and $112.5 \%$ and calls between $87.5 \%$ and $92.5 \%$; and (7) DDITM options, which are puts with moneyness larger than $112.5 \%$ and calls with moneyness smaller than $87.5 \%$.

We then filter the dataset in order to keep only a unique observation per trading day and per call/put maturity-moneyness bin: for instance, on a Monday, we can observe a maximum of 42 implied volatilities. ${ }^{3}$ Following previous research which shows that the options containing the best information regarding jump risk are the shorter-dated ones (Pan, 2002; Doran, Peterson and Tarrant, 2007), we impose a further filter and keep only ST contracts (10 to 30 days to expiry). In addition, given that far from the money contracts display much fewer observations, we retain only

[^1]OTM, ATM and ITM contracts. At this point, we compute skews. For each option type call/put, as already announced, we define skew in two different ways:

$$
\begin{gathered}
\text { skew }_{\text {OTM-ATM }}=I V_{\text {OTM }}-I V_{A T M} \\
\text { skew }_{\text {OTM-ITM }}=I V_{\text {OTM }}-I V_{I T M ~}
\end{gathered}
$$

The skews are defined for each trading day in which the necessary IVs are available. All days where we previously identified a jump are assigned a 1, as in that day a jump happened with probability $100 \%$. All days without a jump are assigned a 0 , as in that day a jump happened with probability $0 \%$. Of course, we differentiate among small negative, big negative, small positive and big positive jumps as previously defined. Using data on the report date of quarterly earnings, we distinguish between earnings announcement date (EAD) periods and normal/non-EAD periods. We also place controls on jumps to avoid market microstructure effects and reverse-causality issues.

We use a probit model in order to estimate parameters measuring the predictive ability of skews and ATM IV on future jumps. The most general specification of the probit is:

$$
\operatorname{Prob}\left(D_{t+1 \rightarrow t+T}=1 \mid \text { skew }_{t}, I V_{t}\right)=\Phi\left(\alpha+\beta_{1} \text { skew }_{t}+\beta_{2} I V_{t}\right)+\varepsilon_{t}
$$

The probability of observing a jump during the option window (from the day following the current day $t+1$ to option expiry $t+T$ ) is equal to a non-linear function $\Phi$ of the regressor, plus estimation errors $\varepsilon_{t}$. In a probit model, the function $\Phi$ is a cumulative standard normal distribution function, which is chosen because, given a value of the linear expression, it always returns a value which is between 0 and 1 . This is paramount, as we are trying to regress a binary variable which should represent a probability.

To sum up, we want to understand how skews and ATM IVs influence the probability of observing future positive or negative jumps. Below, we present the main conclusions of our empirical work.

First, on average for at least two thirds of the sample 24 S\&P 100 stocks in the period 1996-2017, a more positive put implied volatility skew, i.e. a higher put OTM implied volatility relative to put ATM or ITM implied volatility, is related to a higher probability of observing future negative return jumps in the underlying equity within the option life. ${ }^{4}$ This result provides support for our first hypothesis, according to which informed traders expecting a negative return jump are likely to buy OTM puts. Furthermore, it is in line with previous literature demonstrating that options are an important avenue for informed trading (Easley, O'Hara and Srinivas, 1998) and that positive demand pressures on OTM puts convey a negative news signal for the cash asset (Doran, Peterson and Tarrant, 2007; Garleanu, Pedersen and Poteshman, 2009; Xing, Zhang and Zhao, 2010).

Second, on average for at least two thirds of the sample 24 S\&P 100 stocks in the period 1996-2017, a more negative call OTM-ATM implied volatility skew, i.e. a higher call ATM implied volatility relative to call OTM implied volatility, is significantly related to a higher probability of observing future positive return jumps in the underlying equity within the option life. This result contradicts our second hypothesis, according to which a less negative (or more positive) call OTM-ATM implied volatility skew should have been related with a higher probability of observing future positive return jumps in the underlying equity. The ex-ante hypothesis was based on the theory that informed traders with positive directional information on the underlying equity are likely to go long OTM calls to exploit the best leverage. However, this is not what is found. A possible intuitive reason that might help explaining the result is the following. On average, investors are long equities and like positive return jumps in their holdings. Therefore, stock investors are not likely to buy OTM calls to get further directional exposure to rising equity prices. On the other hand, if they expect a positive jump, they may try to profit from the volatility move. Therefore, they may buy ATM calls (and, possibly, also puts in order to form straddles) since these options have the highest Vega and Gamma. Hence, one may hypothesize that call trading prior to expected positive return jumps in the underlying equity is dominated by volatility

[^2]traders buying ATM implied volatility rather than directional traders exploiting the greater leverage in OTM options. This intuition is partially supported by the finding that the percentage of sample stocks for which the call OTM-ATM skew coefficients are significantly negative is much greater for small positive return jumps (87.50\%) than for big positive return jumps (58.30\%). This makes sense since if volatility traders expected huge moves, they might use OTM strangles and not ATM straddles, thus bidding up call OTM implied volatility and not call ATM implied volatility. ${ }^{5}$ At this point, one might ask why we do not observe the same put ATM implied volatility buying before negative jumps. A possible explanation, deriving directly from the average net long positioning in equity markets, is the following. Investors dislike negative jumps as they are net long equity. Hence, they are likely to buy insurance in the form of OTM puts if they expect negative jumps. Therefore, put trading prior to negative jumps is likely to be dominated by directional hedgers buying put OTM implied volatility rather than pure volatility traders buying put ATM implied volatility. Now, looking at the call OTM-ITM implied volatility skew, we find that for slightly less than half of the sample 24 S\&P 100 stocks in the period 1996-2017 a less negative (or more positive) call OTMITM implied volatility skew is related to a higher probability of observing future positive return jumps in the underlying equity within the option life. This provides only weak support for our ex-ante hypothesis, since only less than $50 \%$ of the sample behaves as expected. Therefore, we can affirm that the skew-jump relationship for calls is less well defined than for puts.

Third, looking at put skews, on average for slightly less than $60 \%$ of the sample 24 S\&P 100 stocks in the period 1996-2017, the skew-jump relationship maintains its statistical significance even in the normal periods, i.e. those sub-sample periods which do not contain earnings announcements. ${ }^{6}$ This finding corroborates our third and main hypothesis and provides support to the idea that the skew-jump relationship is not

[^3]driven exclusively by earnings announcements: on average, traders seem to behave as if their trading were informed, bidding up put OTM implied volatility relative to the rest of the skew prior to negative return jumps in the underlying stock. Our result adds to the existing literature, since it shows that option traders engage in fruitful information discovery outside of earnings announcement periods also for randomly arriving events that generate extreme returns and not only for non-extreme returns, as already demonstrated in previous research (Jin, Livnat and Zhang, 2012). Looking at call skews, we shall differentiate between the two skew definitions, as we have already done in trying to answer research question II. As far as call OTM-ATM implied volatility skews are concerned, the analysis of normal sub-sample periods confirms the results found for the full sample period 1996-2017. In fact, on average 60\% of the 24 S\&P 100 sample stocks exhibit significantly negative skew coefficients, meaning that also during normal sub-sample periods a more negative call OTM-ATM skew is significantly associated with a higher probability of observing future positive return jumps in the underlying stock. Furthermore, while this is true for only $45.80 \%$ of the sample stocks when analyzing big jumps, the percentage increases to $75 \%$ for small jumps, providing some support to the intuition that call ATM implied volatility buying pressures are somewhat stronger if traders expect relatively small jumps. As far as call OTM-ITM implied volatility skews are concerned, we find that, even during the normal sub-sample period, on average $40 \%$ of the 24 S\&P 100 sample stocks display significantly positive skew coefficients, in line with the results of the full sample period. ${ }^{7}$ Again, as for puts, the call results provide some support to the hypothesis that the skew jump relationship is not limited to earnings announcement periods, in line with previous research on non-extreme returns (Jin, Livnat and Zhang, 2012).

Fourth and last, adding the ATM implied volatility as independent variable makes skews mostly insignificant in more than $80 \%$ of the 24 S\&P 100 sample stocks during the period 1996-2017, on average across all jump-skew specifications and put-call models. Furthermore, the sign of the ATM implied volatility is significantly positive in more than two thirds of the sample stocks on average. This is valid across all periods:

[^4]full, normal and earnings announcements. This finding corroborates our fourth and last hypothesis, according to which a higher ATM implied volatility is related to a higher probability of observing a return jump in the underlying stock. ${ }^{8}$ Intuitively, traders seem to have better information on whether a jump will occur rather than on the jump's precise direction: the information they impound in prices is more important for ATM options as these are natural candidates to trade pure volatility moves, given their bigger Vegas and Gammas. Therefore, when coupled with ATM implied volatility in trying to identify future jumps, skew loses much of its statistical significance. It is interesting to compare this result with what is found by Doran, Peterson and Tarrant (2007) regarding equity index options. Our result for single stocks agrees with their finding for equity indices that higher ATM IV significantly increases the probability of observing both negative and positive return jumps. In Doran, Peterson and Tarrant (2007), after including ATM IV, the significance of the index skew is lost for mediumand long-dated options and it is maintained, even if decreased, for short-term maturities. On the other hand, our single stock skew loses much of its significance for short-term maturities. A possible explanation for this inconsistency may be found in previous research. Garleanu, Pedersen and Poteshman (2009) find that index options (in particular OTM puts) seem overpriced, whereas single stock options (in particular OTM calls) seem underpriced. Dubinsky and Johannes (2006) and Bakshi, Kapadia and Madan (2003) find that single stock options tend to exhibit a smiling implied volatility as function of moneyness in around $30 \%$ of cases, whereas index options exhibit a more skewed implied volatility as function of moneyness. Therefore, the signal given by index skew may be stronger than that given by single stock skew, especially before negative return jumps, since the index skew is more pronounced.

[^5]
## Robustness Analysis

One of the practical issues encountered in the thesis work was the determination of the threshold to study the ex-post forecasting ability of the model. In fact, in order to measure the goodness-of-fit and forecasting ability of our model we used positive predicted value (ppv) and negative predicted value (npv) statistics (Bruno, 2016). Below we will frame the general problem.

In general, we decide a probability threshold over which our model predicts a return to be a jump:

$$
\widehat{D}_{\iota}=\left\{\begin{array}{cc}
1 \text { if } \Phi\left(x^{\prime} \hat{\beta}\right) \geq X \% \\
0 & \text { else }
\end{array}\right\}
$$

The above equation means that if the predicted probability of jump is greater than $\mathrm{X} \%$, then we identify a jump; otherwise, we identify a normal return (Bruno, 2016). In the original empirical work, we used $20 \%$. This choice was dictated by an attempt to optimize the results between ppv and npv. However, ex-post, we thought of this choice as quite arbitrary and we decided to conduct a robustness analysis following the existing literature in adopting a 50\% probability threshold. Below we will present these new empirical results and confront them with the original empirical work. We find that the choice of threshold influences the results in terms of predictive accuracy.

Ppv shows the probability of our model correctly predicting a jump - given the model predicts a future jump day, what is the probability of observing a jump insample. On the other hand, npv shows the probability of our model correctly predicting a normal day - given the model predicts a normal day, what is the probability of observing a normal day in-sample.

First, we will start comparing the ppv and npv of the put skew model to predict negative jumps in the underlying stocks.

| Skew type Jump type | Mean ppv* |  |
| :--- | :--- | :--- |
| OTM-ATM big negative | $18.20 \%$ |  |
| OTM-ATM small negative | $24.50 \%$ |  |
| OTM-ITM | big negative | $21.20 \%$ |
| OTM-ITM | small negative | $24.00 \%$ |

[^6]Table 1: Mean ppv with 20\% threshold: negative jumps, put skews, all periods
Variables: skew = implied volatility OTM - implied volatility ATM or ITM; big negative jump in the bottom $1 \%$ and small negative jump in the bottom $5 \%$ of the negative return distribution; mean ppv is the average positive predicted value across the 24 sample stocks.

Table 1 is quite discouraging. On average across the sample stocks, our models can predict jumps correctly only one in five times for big jumps (more rare) and one in four times for small jumps. However, this result may be caused by the $20 \%$ probability threshold choice: in fact, this may influence downwards the ppv, since whereas on the one hand a lower initial threshold allows the model to identify more future days as jump, on the other hand the predicted jumping days have a lower probability of showing an actual jump.

In order to test whether the forecasting ability depends on the initial choice of threshold, we repeat the analysis with a 50\% probability threshold.

| Skew type | Jump type | Mean ppv* |
| :--- | :--- | ---: |
| OTM-ATM | big negative | NA |
| OTM-ATM | small negative | $55.60 \%$ |
| OTM-ITM | big negative | $0.00 \%$ |
| OTM-ITM | small negative | $31.00 \%$ |

* Only homoscedastic models.

Table 2: Mean ppv with $50 \%$ threshold: negative jumps, put skews, all periods

Variables: skew = implied volatility OTM - implied volatility ATM or ITM; big negative jump in the bottom $1 \%$ and small negative jump in the bottom 5\% of the negative return distribution; mean ppv is the average positive predicted value across the 24 sample stocks.

Table 2 immediately shows that the ppv changed. Using a 50\% threshold, the positive predicted value increases. This means that the probability of our model correctly predicting a jump increases when we rise the probability threshold for jump identification. The finding is well supported by statistical intuition: by raising our threshold, fewer future trading days will be classified as jumping, but the signal of the model will be stronger so that the likelihood of observing future jumps after the model predicts those jumps rises. To provide a practical example, on average across the 24 sample stocks $55.60 \%$ of the predictions of future small negative jumps in the underlying stocks obtained by using the OTM-ATM put skew model turn out to be correct, with a small negative jump actually happening in-sample. This is a good
improvement relative to the original 20\% threshold modeling choice. The same is true for OTM-ITM put skews and small negative jumps, even if the forecasting ability is worse. The opposite happens with big negative jumps. This result may be explained by the fact that by setting a more demanding probability threshold, fewer jumps will be predicted even if with a higher accuracy. Hence, given the smaller number of big negative jumps in sample, it does not come as completely unexpected to see our model being worse at predicting those more statistically extreme events.

| Skew type Jump type | Mean npv* |  |
| :--- | :--- | :--- |
| OTM-ATM | big negative | $95.40 \%$ |
| OTM-ATM | small negative | $75.30 \%$ |
| OTM-ITM | big negative | $94.30 \%$ |
| OTM-ITM | small negative | $83.40 \%$ |

* Only homoscedastic models.

Table 3: Mean npv with 20\% threshold: negative jumps, put skews, all periods
Variables: skew = implied volatility OTM - implied volatility ATM or ITM; big negative jump in the bottom $1 \%$ and small negative jump in the bottom $5 \%$ of the negative return distribution; mean npv is the average negative predicted value across the 24 sample stocks.

Table 3 shows that the models are good at predicting normal days.

| Skew type | Jump type | Mean npv* |
| :--- | :--- | ---: |
| OTM-ATM | big negative | $95.40 \%$ |
| OTM-ATM | small negative | $80.40 \%$ |
| OTM-ITM | big negative | $94.30 \%$ |
| OTM-ITM | small negative | $78.70 \%$ |

* Only homoscedastic models.

Table 4: Mean npv with 50\% threshold: negative jumps, put skews, all periods

Variables: skew = implied volatility OTM - implied volatility ATM or ITM; big negative jump in the bottom $1 \%$ and small negative jump in the bottom $5 \%$ of the negative return distribution; mean npv is the average negative predicted value across the 24 sample stocks.

We can see that changing the probability threshold does not change significantly the results for negative predicted values. This is reasonable from an intuitive perspective since normal days represent the majority of the trading days. Given these results for npv, we will go on presenting only the comparisons for positive predicted values.

We therefore approach the same problem of evaluating the forecasting ability of our call skew models for predicting positive jumps.

| Skew type Jump type | Mean ppv* |  |
| :--- | ---: | ---: |
| OTM-ATM big positive | $10.80 \%$ |  |
| OTM-ATM small positive | $29.10 \%$ |  |
| OTM-ITM | big positive | $7.14 \%$ |
| OTM-ITM small positive | $25.50 \%$ |  |
| * Only homoscedastic models. |  |  |

Table 5: Mean ppv with 20\% threshold: positive jumps, call skews, all periods
Variables: skew = implied volatility OTM - implied volatility ATM or ITM; big positive jump in the top $1 \%$ and small positive jump in the top $5 \%$ of the positive return distribution; mean ppv is the average positive predicted value across the 24 sample stocks.

Table 5 shows that the positive predicted value remains low also for the call skew / positive jump models. Furthermore, it is even lower for big jumps, consistent with jumps being rare events difficult to correctly predict.

| Skew type | Jump type | Mean ppv* |
| :--- | :--- | ---: |
| OTM-ATM | big positive | NA |
| OTM-ATM | small positive | $51.20 \%$ |
| OTM-ITM | big positive | $100.00 \%$ |
| OTM-ITM | small positive | $38.90 \%$ |

Table 6: Mean ppv with 50\% threshold: positive jumps, call skews, all periods
Variables: skew = implied volatility OTM - implied volatility ATM or ITM; big positive jump in the top $1 \%$ and small positive jump in the top $5 \%$ of the positive return distribution; mean ppv is the average positive predicted value across the 24 sample stocks.

Raising the probability threshold to $50 \%$ improves the positive predicted value also for call skew models used to predict positive jumps: on average across the 24 sample stocks $51.20 \%$ of the predictions of future small positive jumps in the underlying stocks obtained by using the OTM-ATM call skew model turn out to be correct, with a small positive jump actually happening in-sample. Similarly to our results for put skew models, the forecasting ability is lower for OTM-ITM call skews, thus suggesting that the bulk of forecasting ability is obtained by looking at the OTMATM portion of the implied volatility curves. Contrary to our put results, this time the results for big positive jumps are contradictory. Using OTM-ATM call skews, results are similar to put models. However, using OTM-ITM call skews returns an unexpected $100 \%$ ppv. This result is likely given by the binary nature of predictions regarding the most extreme returns of the distribution: we believe the big jump numbers may not
be reliably interpreted as indicators of goodness of fit and forecasting ability for our models.

In our third research question we ask ourselves whether the statistical relationship between skews and jumps characterizes also periods without earnings announcements of the underlying stocks or it is limited to earnings announcement periods.

| Option type | Skew type | Sample | Jump type | Mean ppv* |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Call | OTM-ATM | Full | big positive |  | 10.80\% |
| Call | OTM-ATM | Full | small positive |  | 29.10\% |
| Call | OTM-ATM | EAD | big positive |  | 15.10\% |
| Call | OTM-ATM | EAD | small positive |  | 30.00\% |
| Call | OTM-ATM | Normal | big positive |  | 18.80\% |
| Call | OTM-ATM | Normal | small positive |  | 30.40\% |
| Call | OTM-ITM | Full | big positive |  | 7.14\% |
| Call | OTM-ITM | Full | small positive |  | 25.50\% |
| Call | OTM-ITM | EAD | big positive |  | 21.00\% |
| Call | OTM-ITM | EAD | small positive |  | 25.90\% |
| Call | OTM-ITM | Normal | big positive |  | 16.10\% |
| Call | OTM-ITM | Normal | small positive |  | 27.20\% |
| Put | OTM-ATM | Full | big negative |  | 18.20\% |
| Put | OTM-ATM | Full | small negative |  | 24.50\% |
| Put | OTM-ATM | EAD | big negative |  | 38.40\% |
| Put | OTM-ATM | EAD | small negative |  | 28.10\% |
| Put | OTM-ATM | Normal | big negative |  | 8.76\% |
| Put | OTM-ATM | Normal | small negative |  | 24.90\% |
| Put | OTM-ITM | Full | big negative |  | 21.20\% |
| Put | OTM-ITM | Full | small negative |  | 24.00\% |
| Put | OTM-ITM | EAD | big negative |  | 31.20\% |
| Put | OTM-ITM | EAD | small negative |  | 26.90\% |
| Put | OTM-ITM | Normal | big negative |  | 13.90\% |
| Put | OTM-ITM | Normal | small negative |  | 21.30\% |

* Only homoscedastic models.

Table 7: Mean ppv with $20 \%$ threshold: full vs EAD vs normal periods
Variables: skew = implied volatility OTM - implied volatility ATM or ITM; full sample includes both earnings announcement periods (EAD) and normal periods without earnings releases; big positive jump in the top $1 \%$ and small positive jump in the top $5 \%$ of the positive return distribution; big negative jump in the bottom $1 \%$ and small negative jump in the bottom $5 \%$ of the negative return distribution; mean ppv is the average positive predicted value across the 24 sample stocks.

Table 7 shows that the predictive ability of our models remain low across the sample stocks. On average, we are able to ex-ante identify correctly a jump only one in four times. Two interesting observations are the following: (1) for put skews, the predictive ability in terms of ppv is higher during EAD periods, despite the statistical significance being lower as previously shown; and (2) for call skews, the predictive ability does not depend on the sample period, but on the jump definition, with the positive predicted value for small positive jumps being almost double the one for big
positive jumps, especially for OTM-ATM call skews: this provides some evidence on the intuition about informed long straddle trading before small positive jumps ${ }^{9}$. The ppv results are similar between the full sample and the normal sub-sample, supporting the reasoning that the skew-jump relationship is not EAD-driven.

| Option type | Skew type Sample Jump type | Mean ppv* |  |  |
| :--- | :--- | :--- | :--- | ---: |
| Call | OTM-ATM | Full | big positive | NA |
| Call | OTM-ATM | Full | small positive | $51.20 \%$ |
| Call | OTM-ATM | EAD | big positive | $37.50 \%$ |
| Call | OTM-ATM | EAD | small positive | $34.40 \%$ |
| Call | OTM-ATM | Normal | big positive | NA |
| Call | OTM-ATM | Normal | small positive | $64.50 \%$ |
| Call | OTM-TM | Full | big positive | $100.00 \%$ |
| Call | OTM-TM | Full | small positive | $38.90 \%$ |
| Call | OTM-TM | EAD | big positive | $50.00 \%$ |
| Call | OTM-TM | EAD | small positive | $64.70 \%$ |
| Call | OTM-TM | Normal | big positive | NA |
| Call | OTM-TM | Normal | small positive | $40.00 \%$ |
| Put | OTM-ATM | Full | big negative | NA |
| Put | OTM-ATM | Full | small negative | $55.60 \%$ |
| Put | OTM-ATM | EAD | big negative | $41.70 \%$ |
| Put | OTM-ATM | EAD | small negative | $57.20 \%$ |
| Put | OTM-ATM | Normal | big negative | $0.00 \%$ |
| Put | OTM-ATM | Normal | small negative | $42.20 \%$ |
| Put | OTM-TM | Full | big negative | $0.00 \%$ |
| Put | OTM-TM | Full | small negative | $31.00 \%$ |
| Put | OTM-TM | EAD | big negative | NA |
| Put | OTM-TM | EAD | small negative | $36.60 \%$ |
| Put | OTM-TM | Normal | big negative | NA |
| Put | OTM-TM | Normal | small negative | $70.00 \%$ |

* Only homoscedastic models.


## Table 8: Mean ppv with $50 \%$ threshold: full vs EAD vs normal periods

Variables: skew = implied volatility OTM - implied volatility ATM or ITM; full sample includes both earnings announcement periods (EAD) and normal periods without earnings releases; big positive jump in the top $1 \%$ and small positive jump in the top $5 \%$ of the positive return distribution; big negative

[^7]jump in the bottom 1\% and small negative jump in the bottom 5\% of the negative return distribution; mean ppv is the average positive predicted value across the 24 sample stocks.

Focusing our attention on small jumps and on the difference between earnings periods (EAD) and normal periods and comparing the new results with the $50 \%$ probability threshold and the previous results with $20 \%$ threshold, we immediately notice that the 50\% threshold improves the positive predicted value both for EAD and normal periods. For instance, for OTM-ATM put skew models with small negative jumps in normal periods the ppv rises from $24.90 \%$ to $42.20 \%$. There is a similar improvement for all periods and models. We can thus affirm that the improvement in ppv is not dependent on the model or period chosen but is simply a function of the chosen probability threshold.

Finally, we add ATM implied volatility to skew as control variable in our probit models.

| Option type | Skew typ | Sample | Jump type | Mean ppv* |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Call | OTM-ATM | Full | big positive |  | 29.90\% |
| Call | OTM-ATM | Full | small positive |  | 39.80\% |
| Call | OTM-ATM | EAD | big positive |  | 19.90\% |
| Call | OTM-ATM | EAD | small positive |  | 36.40\% |
| Call | OTM-ATM | Normal | big positive |  | 30.20\% |
| Call | OTM-ATM | Normal | small positive |  | 37.50\% |
| Call | OTM-ITM | Full | big positive |  | 25.20\% |
| Call | OTM-ITM | Full | small positive |  | 39.80\% |
| Call | OTM-ITM | EAD | big positive |  | 22.80\% |
| Call | OTM-ITM | EAD | small positive |  | 36.70\% |
| Call | OTM-ITM | Normal | big positive |  | 27.20\% |
| Call | OTM-ITM | Normal | small positive |  | 37.20\% |
| Put | OTM-ATM | Full | big negative |  | 35.70\% |
| Put | OTM-ATM | Full | small negative |  | 32.60\% |
| Put | OTM-ATM | EAD | big negative |  | 40.00\% |
| Put | OTM-ATM | EAD | small negative |  | 33.20\% |
| Put | OTM-ATM | Normal | big negative |  | 42.00\% |
| Put | OTM-ATM | Normal | small negative |  | 39.00\% |
| Put | OTM-ITM | Full | big negative |  | 23.00\% |
| Put | OTM-ITM | Full | small negative |  | 35.70\% |
| Put | OTM-ITM | EAD | big negative |  | 36.90\% |
| Put | OTM-ITM | EAD | small negative |  | 32.80\% |
| Put | OTM-ITM | Normal | big negative |  | 27.90\% |
| Put | OTM-ITM | Normal | small negative |  | 36.90\% |

* Only homoscedastic models.

Table 9: Mean ppv with 20\% threshold: ATM IV control
Variables: skew = implied volatility OTM - implied volatility ATM or ITM; full sample includes both earnings announcement periods (EAD) and normal periods without earnings releases; big positive jump in the top $1 \%$ and small positive jump in the top $5 \%$ of the positive return distribution; big negative
jump in the bottom 1\% and small negative jump in the bottom 5\% of the negative return distribution; mean ppv is the average positive predicted value across the 24 sample stocks.

Table 9 above shows that adding the ATM IV variable improves the forecasting power of our models, even before raising the probability threshold: we go from correctly forecasting a jump only on approximately $20 \%$ of times without the ATM IV variable to $30 \% / 35 \%$, on average across our sample stocks. Interestingly, for call skews, the best predictive accuracy is for small positive jumps, consistent with our prior results about informed short-term ATM straddle trading before small positive jumps.

| Option type | Skew type Sample Jump type | Mean ppv* |  |  |
| :--- | :--- | :--- | :--- | :--- |
| Call | OTM-ATM | Full | big positive | $53.50 \%$ |
| Call | OTM-ATM | Full | small positive | $63.30 \%$ |
| Call | OTM-ATM | EAD | big positive | $90.40 \%$ |
| Call | OTM-ATM | EAD | small positive | $64.50 \%$ |
| Call | OTM-ATM | Normal | big positive | $50.50 \%$ |
| Call | OTM-ATM | Normal | small positive | $57.60 \%$ |
| Call | OTM-ITM | Full | big positive | $44.40 \%$ |
| Call | OTM-ITM | Full | small positive | $55.00 \%$ |
| Call | OTM-ITM | EAD | big positive | $40.50 \%$ |
| Call | OTM-ITM | EAD | small positive | $64.70 \%$ |
| Call | OTM-ITM | Normal | big positive | $58.90 \%$ |
| Call | OTM-ITM | Normal | small positive | $53.30 \%$ |
| Put | OTM-ATM | Full | big negative | $68.50 \%$ |
| Put | OTM-ATM | Full | small negative | $60.50 \%$ |
| Put | OTM-ATM | EAD | big negative | $60.80 \%$ |
| Put | OTM-ATM | EAD | small negative | $70.00 \%$ |
| Put | OTM-ATM | Normal | big negative | $76.80 \%$ |
| Put | OTM-ATM | Normal | small negative | $55.10 \%$ |
| Put | OTM-ITM | Full | big negative | $65.00 \%$ |
| Put | OTM-ITM | Full | small negative | $49.50 \%$ |
| Put | OTM-ITM | EAD | big negative | $94.40 \%$ |
| Put | OTM-ITM | EAD | small negative | $66.80 \%$ |
| Put | OTM-ITM | Normal | big negative | $73.30 \%$ |
| Put | OTM-ITM | Normal | small negative | $64.60 \%$ |

* Only homoscedastic models.

Table 10: Mean ppv with 50\% threshold: ATM IV control
Variables: skew = implied volatility OTM - implied volatility ATM or ITM; full sample includes both earnings announcement periods (EAD) and normal periods without earnings releases; big positive jump in the top $1 \%$ and small positive jump in the top $5 \%$ of the positive return distribution; big negative jump in the bottom 1\% and small negative jump in the bottom 5\% of the negative return distribution; mean ppv is the average positive predicted value across the 24 sample stocks.

Raising the threshold to 50\% greatly improves the predictive power of our models, even after accounting for the added ATM IV variable. This is true for both EAD and normal periods. For all our models with ATM IV incorporated and a threshold of $50 \%$, the positive predicted value is well above $50 \%$. We also notice that the predictive
ability does not seem to be caused by the inclusion of earnings periods into the sample since the ppv is similar between the full and normal samples, with no discernible patterns.

## Conclusions

In this empirical extension to our main research work we demonstrated that raising the probability threshold from $20 \%$ to $50 \%$ in the computation of positive predicted value influences the results, thus showing that the predictive accuracy depends on this choice. This result is well supported by intuition since a higher probability threshold implies that fewer stock return jumps will be identified by the model but the forecasting accuracy will be higher since the signal will be stronger. The model specification with the greatest predictive power is the probit version incorporating both the skew and ATM implied volatility explanatory variables.

Hence, not only our model demonstrates that there exists a statistical relationship between the steepness of single stock implied volatility skew and the probability of observing future return jumps - adding to the literature on index skew and jumps (Doran, Peterson and Tarrant, 2007) - but that this statistical relationship is able to accurately predict jumps if a proper probability threshold for jump identification is chosen. We have thus overcome one of the limits that we identified in our main research work, namely the choice of the probability threshold.

Other remaining limitations include: the sample size of 24 stocks drawn from the S\&P 100 universe, the chosen period that stretches between 1996 and 2017 and the absence of a back-tested trading strategy trying to exploit the predictive findings of this thesis.

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## Appendix

## Greeks definitions

Greeks are the key sensitivities (i.e. derivatives) of option prices to changes in key pricing inputs and are fundamental for risk-managing option books. Below a brief and basic description of the most important Greeks.
Delta: change in option price for a change in underlying equity price. It is comprised between 0 and 1 in absolute value, with 0 if the option is OTM, $\sim 0.5$ if ATM and 1 if ITM. It is positive for long calls and negative for long puts. It is similar to the probability of exercising the option: for a call, Delta is slightly higher than the probability of exercising; for a put, Delta is slightly lower than the probability of exercising. It also represents the hedge ratio, i.e. the equivalent stock position that must be bought or sold to protect the overall position from changes in the stock price. It increases in absolute value with the passage of time and with a decrease in implied volatility for ITM options; the opposite behavior is true for OTM options.
Gamma: change in option delta for a change in underlying equity price. It is always positive for buyers of options. It peaks ATM when time to expiry is short and implied volatility is low.
Theta: change in option price for a 1-day passage of time. It is always negative for buyers of options. It peaks ATM when time to expiry is short.
Vega: change in option price for a change in underlying implied volatility. It is always positive for buyers of options. It peaks ATM when time to expiry is long.
Rho: change in option price for a change in risk-free interest rates. It is positive for call buyers and negative for put buyers.

# The Implied Volatility Skew of Single Stock Options and the Predictability of Jumps 

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#### Abstract

In this thesis, we try to understand whether the observed implied volatility skew of single stock options is significantly related to the probability of observing future return jumps in the underlying single stock. In particular, our main aim is to verify whether the skew-jump relationship persists during normal periods without any pre-scheduled information disclosure event or it is confined to earnings announcement periods. Using S\&P 100 daily stock and option data from January 1996 to December 2017, we model the statistical relationship between exante skew and ex-post jump using a probit model. To ensure robustness, we define skew in two ways as the difference between out-of-the-money (OTM) implied volatility and at-themoney (ATM) or in-the-money (ITM) implied volatility. We find that the statistical significance of the skew-jump relationship is preserved during normal periods with no earnings announcement: more positive put skews are related to a higher probability of observing future negative jumps and more negative call OTM-ATM skews are related to a higher probability of observing future positive jumps, both in the full period and the normal period. Interestingly, the sign of the relationship we find for call OTM-ATM is opposite to our ex-ante expectation. A possible explanation is that call trading prior to jumps may be dominated by ATM volatility trading and not by OTM directional trading.


To my parents and grandparents.

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## Introduction

The returns of public equity securities follow a non-normal distribution, with observed daily returns often more extreme than those predicted by a normal distribution. In fact, they display a higher kurtosis than the normal: this means that the real-world probability of observing extreme returns ${ }^{1}$, both positive and negative, is higher than the probability under a normality assumption. Furthermore, equity returns are usually characterized by a negative skewness, which means that negative returns are more extreme and frequent than positive returns. Therefore, it is evident that equity prices present jumps in their evolution over time.

Equity options ${ }^{2}$ are derivative securities whose price depends on several parameters, among which the most important are the underlying price, its volatility and dividend yield, the time to expiration and strike price of the contract and the risk-free interest rate $^{3}$. Since option prices are influenced by the price process of the underlying, which displays jumps, then it follows that jumps are important in the correct pricing of equity options (Heston, 1993; Eraker, 2004; Pan, 2002). Furthermore, equity options display some advantages over the underlying equities, for instance they have a higher builtin leverage. Therefore, traders with accurate information can decide to trade in options rather than in the underlying equity (Easley, O'Hara and Srinivas, 1998).

Since option implied volatilities ${ }^{4}$ are also affected by demand and supply (Bollen and Whaley, 2004; Garleanu, Pedersen and Poteshman, 2009), and since option prices depend also on the underlying equity price process, then the demand pressures by informed traders carry valuable information for the expectations about future underlying returns and, potentially, also jumps. In particular, higher demand for an option tends to increase its implied volatility.

[^8]When a market participant buys a put, he hopes that the underlying price will fall; when a call is bought, the expectation is for a price increase. Therefore, if demand is informed and affects implied volatility, higher call implied volatility incorporates positive information regarding the underlying and higher put implied volatility incorporates negative information. In fact, previous research show that higher and/or increasing call implied volatility is a leading indicator for higher underlying returns, whereas higher and/or increasing put implied volatility anticipates lower underlying returns (An et al., 2014; Yan, 2011).

By plotting option prices for a given time to expiration in terms of implied volatilities against the moneyness ${ }^{5}$ of the contracts, one can notice that implied volatilities are not constant: they form a curve, called implied volatility curve or function, which can be a "skew ${ }^{6 "}$ or a "smile"". The more "smiling" the implied volatility curve, the higher the kurtosis implied by the options. The more "skewed" the implied volatility curve, the higher the negative skewness implied by the options (Bennett, 2014; Bakshi, Kapadia and Madan, 2003).

Not only implied volatilities, but also skews or smiles carry information about future returns. Skews can be defined in many ways, but commonly represent the difference between the OTM and ATM implied volatilities of options ${ }^{8}$. Previous research shows that a more positive skew, i.e. a higher put OTM implied volatility relative to the ATM implied volatility, is associated with future negative returns of the underlying equity. This effect is registered both before significant information events, such as earnings announcements for single stocks (Xing, Zhang and Zhao, 2010), and during normal periods (Jin, Livnat and Zhang, 2012). Regarding earnings announcements, option ATM implied volatility is also found to increase prior to them, as market participants price in a higher uncertainty prior to significant disclosure events (Dubinsky and

[^9]Johannes, 2006). It is then natural to ask ourselves whether a similar relationship can be found for jumps, and not only normal returns, and whether this is caused by specific information, such as earnings announcements for single stocks, or it is persistent even during periods without such specific information events.

An answer to the above question has already been attempted for equity index options. In fact, the skew of equity index options is found to be significantly related to the probability of observing a following jump in the underlying index (Doran, Peterson and Tarrant, 2007). In particular, a higher put OTM implied volatility relative to put ATM implied volatility is related to a higher probability of observing a future negative jump; on the other hand, a higher call OTM implied volatility relative to call ATM implied volatility is related to a higher probability of observing a future positive jump, as one would expect under informed directional trading by option market participants.

However, studies on the relationship between the skew and future jumps in the underlying seem to be limited to index options. This thesis tries to close the gap in the literature about the relationship between single stock options' skew and future jumps in the single stocks. In particular, we are interested in studying the statistical relationship existing between the ex-ante dynamics of observed single stock options' skews and the ex-post probability of observing future jumps in the underlying single stock.

Therefore, drawing on the statistical methodology applied by Doran, Peterson and Tarrant (2007), and given an early check to understand if the skew-jump relationship found in equity index options exists also in single stock options, our main aim is to ascertain whether the skew-jump relationship is driven only by earnings announcements' information or it exists even during periods without such prescheduled disclosure events. Finally, we include the ATM implied volatility besides the skew as another explanatory variable in order to check whether the statistical relationship skew-jump resists to the addition of a further control variable, which has been found to price in uncertainty about the future.

To answer our research questions, we use a sample of 24 S\&P 100 components stocks, retrieving daily underlying and option data from January 1996 to December 2017 and applying a probit model. We separate between call and put skews, respectively related
to ex-post positive and negative jumps. We also define skews in two ways to check whether the results are robust to different specifications, as a difference of OTM implied volatilities and ATM or ITM implied volatilities. We define jumps in two ways too, as big or small in order to make results robust to different jump specifications. Finally, to answer our main research question, we separate the sample period in two sub-samples: earnings announcement periods and normal periods without any prescheduled single stock disclosure event.

Our early checks confirm prior evidence on equity index options and our ex-ante hypotheses for puts, but not entirely for calls. We find that on average for at least two thirds of the sample, a more positive put implied volatility skew, i.e. a higher put OTM implied volatility relative to put ATM or ITM implied volatility, is related in a significant way to a higher probability of observing future negative return jumps in the underlying equity within the option life. This result is in line with the findings of Doran, Peterson and Tarrant (2007) for equity index options and provides support to the intuition that the skew-jump relationship holds also for single stocks.

On the other hand, we find that on average for at least two thirds of the sample, a more negative call OTM-ATM implied volatility skew, i.e. a higher call ATM implied volatility relative to call OTM implied volatility, is related in a significant way to a higher probability of observing future positive return jumps in the underlying equity within the option life. This finding goes against our ex-ante hypothesis and what Doran, Peterson and Tarrant (2007) find for indices. Our interpretation rests upon the intuition that trading in calls prior to jumps may be dominated by volatility traders and not by directional traders. As far as the call OTM-ITM skew specification is concerned, the results provide only weak support for our hypothesis.

As far as our main research question is concerned, we find that on average around $60 \%{ }^{9}$ of the sample displays a skew-jump relationship which maintains its statistical significance ${ }^{10}$ even during normal periods, i.e. those sub-sample periods which do not contain earnings announcements. This finding corroborates our third and main

[^10]hypothesis and adds to the existing literature, since it shows that option traders engage in useful information discovery outside of earnings announcement periods also for extreme returns and not only for normal, non-extreme returns, as demonstrated in previous research (Jin, Livnat and Zhang, 2012).

Finally, by including the ATM implied volatility as control variable, we find that skews become mostly insignificant in more than $80 \%$ of the sample and that the sign of the ATM implied volatility is significantly positive in more than two thirds of the sample, on average, independently on the period analyzed. This finding shows that when the ATM IV increases, the probability of observing future jumps, both positive and negative, rises: traders seem to have better information on whether a jump will occur rather than on the jump's precise direction. Previous literature (Garleanu, Pedersen and Poteshman, 2009; Bakshi, Kapadia and Madan, 2003; Dubinsky and Johannes, 2006) suggests that the index skew is more pronounced than the single stock skew and this may cause the signal given by index skew to be stronger than that given by single stock skew.

The rest of the thesis is organized as follows.
In Section 1, we review existing literature on the impact of jumps and demand on option pricing, on the information contained in option prices and on how this information may predict future underlying returns.

In Section 2, we present the main research questions.
In Section 3, we explain the data collection, cleaning, summarization and analysis process and the statistical modeling methodology.

In Section 4, we discuss the main empirical results of our analysis, including diagnostics and controls.

In Section 5, we interpret the results, we present the main limits of the thesis, we suggest possible topics deserving further research and we conclude.

## 1. Literature review

This thesis builds upon three main streams of research concerning equity options: (1) models for equity option pricing, with a special attention to how the inclusion of jumps and demand pressures is able to explain implied volatility skew dynamics; (2) the literature studying whether option markets are a venue for informed equity trading and the subsequent ability of equity options' skew, spread and implied volatility to predict underlying equity returns; and (3) the literature studying earnings announcements and the predictive ability of options around earnings dates.

### 1.1 The dynamics of implied volatility across option pricing models

In the earlier academic literature, options are seen as redundant securities whose price is determined in conditions of no-arbitrage with respect to the underlying price (Black and Scholes, 1973). According to the classic Black-Scholes intuition, markets are complete and frictionless and, therefore, European options can be perfectly replicated with dynamic portfolios of underlying assets and by borrowing or lending. The pricing of European options can thus be achieved through a relatively simple closed-formula solution, which rests on the usual six inputs: underlying equity spot price $S$, strike price K, time to expiration of the option $T$, equity volatility $\sigma$, interest rate $r$ and dividend yield q (all taken at time zero) (Hull, 2012):

$$
\begin{gathered}
c=S e^{-q T} N\left(d_{1}\right)-K e^{-r T} N\left(d_{2}\right) \\
p=K e^{-r T} N\left(-d_{2}\right)-S e^{-q T} N\left(-d_{1}\right) \\
d_{1}=\frac{\ln \left(\frac{S}{K}\right)+\left(r-q+\frac{1}{2} \sigma^{2}\right) T}{\sigma \sqrt{T}} \\
d_{2}=d_{1}-\sigma \sqrt{T}
\end{gathered}
$$

However, this ground-breaking approach fails to explain a common and fundamental feature in equity option markets: implied volatility (i.e., the volatility incorporated in closing option prices according to the appropriate Black-Scholes-type option pricing model) is not constant across strikes and expirations. In fact, in equity option markets, both for index and single stocks options (with some differences that will be later explained), we see a so-called volatility surface: the volatility implied by the Black-

Scholes price (implied volatility IV $^{11}$ ) is usually increasing as time to expiration increases (upward sloping term structure of IV for ATM options ${ }^{12}$ ) and decreasing as strike price increases (skew/smile/smirk of IV) (Bennett, 2014).

In order to try to explain these empirical regularities, many models have been developed over the past decades. The Constant Elasticity of Variance (CEV) (Emanuel and MacBeth, 1982) and implied trees models (Dupire, 1994; Rubinstein, 1994; Derman and Kani, 1994) succeed in explaining the cross-sectional distribution of option prices across strikes and expirations. Both the CEV and implied trees are an example of deterministic volatility models, which assume that equity volatility between current time t and future expiry date T is a time-series average of the instantaneous local volatility rate, which is a function of the underlying spot price and time. Therefore, they can explain skew and term structure, but they cannot explain the dynamics of the surface over the time-series of observed option prices ${ }^{13}$ (Bollen and Whaley, 2004).

A second group of models has left behind deterministic volatility and has adopted a stochastic volatility approach. This class of models assumes that volatility too, like price, is driven by a stochastic process. In its simplest form (Heston, 1993), these models let the variance process be a diffusion process, characterized by its own meanreverting drift and its own volatility of volatility term that interacts with the usual Brownian motion for the returns of the underlying asset. In particular, the following equation drives the underlying spot price process, with the generic drift $a$, the square root of variance $\sqrt{V_{t}}$ (i.e. volatility) and the price-process Brownian motion $W_{t}^{s}$ :

$$
\frac{d S_{t}}{S_{t}}=a d t+\sqrt{V_{t}} d W_{t}^{s}
$$

The second equation expresses the variance process, with $k$ being the speed of meanreversion, i.e. the speed at which volatility reverts back to its long-term average

[^11]estimate $\theta, \sigma_{v}$ being the volatility of volatility parameter and $W_{t}^{v}$ representing the variance-process Brownian motion:
$$
d V_{t}=k\left(\theta-V_{t}\right)+\sigma_{v} \sqrt{V_{t}} d W_{t}^{v}
$$

Finally, we let the two Brownian motions be correlated:

$$
E\left[d W_{t}^{s} W_{t}^{v}\right]=\rho d t
$$

Something important to be considered is the volatility of volatility parameter. In fact, this is the parameter which determines the fatness of the tails of the distribution of returns: higher volatility of volatility means fatter tails (Eraker, 2004). Therefore, the volatility of volatility parameter gives a rough measure of the fourth central moment of the distribution of returns, which is kurtosis. In options trading, one can take a view on volatility of volatility (hence, kurtosis) by initiating a long strangle or long-wings butterfly position. In practice, using calls as an example for the butterfly position, a trader can go long kurtosis ${ }^{14}$ by selling one ITM call (with low strike K1), selling another OTM call (with high strike K2) and buying two ATM calls (with intermediate strike K3 $=$ mean(K1, K2)). In this way, if the underlying spot either plummets below K1 or jumps above K3, gains are realized. The key Greek ${ }^{15}$ measuring kurtosis is Volga (volatility gamma, also called Vomma), which measures the change of Vega ${ }^{16}$ for a given change in IV. Volga can be thought of as the Gamma of IV. Just like an option with high Gamma ${ }^{17}$ benefits if the underlying spot realizes high volatility, then an option with high Volga gains from an increase of the volatility of volatility (Bennett, 2014). Volatility of volatility can be estimated by taking log changes in the historical realized volatility and applying the same procedure that one normally applies to

[^12]estimate the volatility of the underlying spot. The options which have the highest exposure to Volga, hence kurtosis, are OTM options. Volga is always positive for long options positions and peaks for OTM options: in fact, a big change in volatility changes time value of one option by a greater amount if the option is OTM as the probability of ending up ITM jumps higher, so that Vega is very sensitive to changes in IV for OTM options. These results are corroborated by findings that the higher the risk-neutral kurtosis (i.e. the kurtosis implied by option prices), the higher the prices and so IVs of OTM and ITM options: this means that the skew described by IV as a function of moneyness flattens and becomes a U-shaped smile (Bakshi, Kapadia and Madan, 2003).

The second key parameter in stochastic diffusive volatility models is $\rho$, i.e. the correlation between the Brownian motion shocks driving the underlying spot and the variance. $\rho$ is usually found to be negative, which means that when underlying spot falls the volatility will increase. This is a recurrent finding in the options literature and is sometimes called "leverage effect" (Eraker, 2004). This implies that the conditional return distribution is negatively skewed. This leads to the finding that the more leftskewed the return distribution, the steeper volatility smiles, which become skews (Bakshi, Kapadia and Madan, 2003). The key Greek in this case is Vanna. Vanna measures the change in Vega for a change in spot or, equivalently, the change in Delta for a change in IV. Hence, Vanna represents the slope of the Vega curve in the Vegaspot plane. Therefore, since Vega peaks for ATM options, Vanna will be positive until the Vega peak is reached (i.e. for K/S < 100\%) and will then turn negative for K/S > $100 \%$. As Volga expresses the size of the volatility of volatility (kurtosis) position, Vanna expresses the size of the skew ${ }^{18}$ position. The easiest way to trade skew is to go long a bearish risk reversal, i.e. to buy one OTM put and sell one OTM call. If the skew steepens, i.e. if the OTM put IV increases relative to the OTM call IV as market participants expect more negatively-skewed returns and demand protection for that, the bearish risk reversal makes money ${ }^{19}$ (Bennett, 2014).

[^13]Despite improving the description of skew dynamics with respect to deterministic models, stochastic volatility models lead to wrong predictions: namely, stochastic diffusive volatility models predict flatter skews for both very long and short maturities (Eraker, 2004). However, short-dated IVs are more volatile than long-dated IVs. This happens because realized volatility spikes as equities fall and, since spikes of realized volatility tend to be short-lived yet clustered over time, traders price in a higher shortdated IV following a realized volatility spike as they expect current high realized volatility to last over the short-run. However, realized volatility is expected to meanrevert over time. Therefore, short-dated IVs track the realized volatility spike, whereas long-dated IVs remain more stable as the long-run expectation is for a more constant level of volatility. This is also the reason why the IV skew is steeper for short-dated options (Das and Sundaram, 1999): for the same \% move in spot, we expect a larger IV move for short-dated options than for long-dated options ${ }^{20}$ (Bennett, 2014).

A further improvement in option pricing comes from adding a randomly-arriving Poisson-driven jump component in the price process (Bates, 2000):

$$
\begin{gathered}
\frac{d S_{t}}{S_{t}}=a d t+\sqrt{V_{t}} d W_{t}^{s}+d J_{t}^{s} \\
d V_{t}=k\left(\theta-V_{t}\right)+\sigma_{v} \sqrt{V_{t}} d W_{t}^{v} \\
d J_{t}^{s}=Z_{t}^{s} d N_{t}^{s} \\
E\left[d W_{t}^{s} W_{t}^{v}\right]=\rho d t
\end{gathered}
$$

The innovation here is given by the $d J_{t}^{s}$ jump process added to the stochastic diffusive price process. In particular, $d J_{t}^{s}$ has size $Z_{t}^{s}$ and occurs with a frequency determined by $d N_{t}^{s}$, which is a Poisson counting process. The size of the jump is assumed to be normally distributed:

$$
Z_{t}^{S} \sim N\left(\mu_{y}, \sigma_{y}^{2}\right)
$$

$\mu_{y}$ is the mean size of the jump and $\sigma_{y}^{2}$ represents the variance of the jump size. A more negative mean jump size increases the probability of seeing a negative jump,

[^14]hence it increases the negative skewness in returns. On the other hand, a higher jump size variance raises the likelihood of observing both big negative and positive jumps, thus increasing kurtosis (Eraker, 2004). Thanks to the addition of the jump component, this model is able to explain the empirically observed steeper IV skew for short-dated options whenever the mean jump size is negative. Furthermore, the magnitude of the wings of the IV skew is increasing in jump size variance, as would be expected for a more leptokurtic distribution.

The next step in option pricing comes from turning the volatility process into a jumping one (Pan, 2002). In the simplest form, both price and volatility jumps are driven by a common Poisson process:

$$
\begin{gathered}
\frac{d S_{t}}{S_{t}}=a d t+\sqrt{V_{t}} d W_{t}^{s}+d J_{t}^{s} \\
d V_{t}=k\left(\theta-V_{t}\right)+\sigma_{v} \sqrt{V_{t}} d W_{t}^{v}+d J_{t}^{v} \\
d J_{t}^{i}=Z_{t}^{i} d N_{t}^{i} \\
E\left[d W_{t}^{s} W_{t}^{v}\right]=\rho d t
\end{gathered}
$$

Above, $d J_{t}^{v}$ is the jumping process for volatility. In particular:

$$
\begin{gathered}
Z_{t}^{v} \sim e^{\mu_{v}} \\
Z_{t}^{s} \mid Z_{t}^{v} \sim N\left(\mu_{y}+\rho_{J} Z_{t}^{v}, \sigma_{s}^{2}\right)
\end{gathered}
$$

As in Eraker (2004), this class of models is usually defined as stochastic volatility with correlated jumps. With respect to the naïve diffusive volatility plus jumping price processes, this specification makes the volatility distribution positively-skewed through the mean volatility jump size component $\mu_{v}$. This increases the fatness of the tails of the return distribution, further improving the description of short-dated non-ATM IV skew (Pan, 2002). Moreover, the term $\rho_{J}$ explains the correlation between jumps to volatility and jumps in the underlying spot: this correlation is usually positive, so that jumps in returns are accompanied by jumps in volatility, reinforcing skewness in the distribution.

Finally, the most refined class of models are those that incorporate jumps in both the price and volatility processes and allow the jump frequency ${ }^{21}$ to depend on the level of volatility (Eraker, 2004). In fact, previous models had still an important issue: in high-volatility regimes the diffusive Gaussian part of the process tends to suppress the jumping Poisson part. Therefore, they produce an empirical irregularity that makes short-dated IV skews flatten as IV increases (in contrast to what we see in markets). Thanks to the last class of models, jumps arrive more frequently when IV is high, so that the issue seems solved. Furthermore, this model produces estimated volatility and jump risk premia that are consistent with investors being averse to both phenomena, as one would expect. As also demonstrated by Pan (2002), jump risk premium is a short-term phenomenon: for short-dated options, as realized volatility spikes, jump risk premium spikes too, whereas volatility risk premium stays more subdued. It follows that using short-dated options should be more useful in order to capture the expectations about jumps.

One would think that the last class of models would be able to describe all behaviors witnessed in markets. Unluckily, that is not the case. As Eraker (2004) shows, even this class of models encounters a problem: it cannot explain the drop in IVs following a jump.

Demand and supply drivers factored into option pricing try to solve this issue. A seminal paper is the one by Bollen and Whaley (2004). They examine whether net buying pressure (i.e. demand) and the shape of the skew for index and equity options are related.

The core idea in Bollen and Whaley (2004) is that market makers are not risk-neutral agents that stand ready to buy and sell at whatever market condition. Furthermore, they cannot delta-hedge ${ }^{22}$ continuously with a known constant volatility as in a BlackScholes world: discrete-time hedging with unknown and time-varying future volatility gives rise to path-dependency in returns (Bennett, 2014). On the one hand, unknown

[^15]future volatility obliges traders to estimate future realized volatility using e.g. IV and applying this IV in the estimation of Delta. This means that profits will be depending on the path taken by the spot price, unless realized volatility equals IV. In the latter (unlikely) situation, a long IV position will simply make money if realized volatility > IV and lose money if realized volatility < IV. On the other hand, discrete time deltahedging will make profits dependent on the frequency and timing of hedging. The higher the frequency of delta-hedging, the lower will be the error in realized profits ${ }^{23}$ : this means that the closer to theoretical continuous-time hedging we are, the more our profits from a long IV position will depend simply on realized volatility minus IV, and not on the path taken by the spot price. As a general rule, hedging less frequently is more profitable in trending markets (Bennett, 2014). As a consequence, the errors from real-world hedging are a sum of the errors of hedging discretely and with unknown future realized volatility.

Given this situation, market makers will have to risk-manage their books with an eye to diversification. If end-users ${ }^{24}$ of options demand only a particular option series (put/call, certain strike and maturity), then market makers will have their books heavily tilted towards that option series. Therefore, market makers will be very exposed to that particular IV. Hence, they will be asking a compensation to sell that series as they are risk-averse and need to cover hedging costs and under-diversification. The typical example is given by S\&P 500 index options. End users are net long index puts (especially OTM) as portfolio insurance (Bollen and Whaley, 2004; Garleanu, Pedersen and Poteshman, 2009). Market makers step in to fill the demand imbalance. They quote an IV for OTM index puts that incorporates an insurance premium: hence, market makers have an upward sloping supply curve.

Given this premise, Bollen and Whaley (2004) investigate how demand pressures affect the shape of the S\&P 500 index skew and of the skews of 20 individual equity options. They define net buying pressure as the difference between the number of trades with execution prices greater than mid and the number of trades with execution prices lower than mid, calculated on a series-by-series basis and then multiplied by the

[^16]absolute value of Delta to express the net buying pressure in stock/index equivalent units. Consistently with what stated above and with other studies (Shleifer and Vishny, 1997; Liu and Longstaff, 2003), Bollen and Whaley (2004) find that the effect of net buying pressure on the change of IV reflects a "limits to arbitrage" story.

Their main findings are as follows:

1. Net buying pressure at time $t$ directly impacts the change in IV between time $t$ and $t+1$, with higher net buying pressure leading to increasing IV;
2. Demand for index puts mostly affects index IV changes;
3. Demand for equity calls mostly affects equity IV changes;
4. It is options' own demand that mostly affects changes in IV: e.g. changes in OTM IV are mainly driven by changes in OTM net demand as changes in ATM IV are mainly driven by changes in ATM net demand.

After this seminal paper by Bollen and Whaley (2004), Garleanu, Pedersen and Poteshman (2009) formalize an option pricing model where net demand is explicitly considered in the pricing equations. They show that "demand pressure in one option contract increases its price by an amount proportional to the variance of the unhedgeable part of the option. Similarly the demand pressure increases the price of any other option by an amount proportional to the covariance of their unhedgeable parts" (Garleanu, Pedersen and Poteshman, 2009). They also demonstrate that incorporating demand pressures explains the expensiveness and skew dynamics of both index options and equity options.

In particular, they divide market participants among "end users", market makers and proprietary traders. End users are those who trade options for a fundamental reason, for instance hedging their delta one exposures or speculating on certain market events. However, when perfect hedging is not possible due to real-world market frictions such as discontinuous trading hours, transaction costs, non-constant volatility processes and jumps in the underlying return distribution, then market makers cannot price options as perfectly replicable contingent claims. Another caveat to be kept in mind is the fact that market makers are not risk neutral agents, as it is assumed in the classic option pricing framework: therefore, they require a risk premium, especially if they are taking positions which exacerbate their risk aversion and are pushing them towards their
allocated risk capital boundaries. For these reasons, their pricing will be influenced by demand pressures of clients.

Very interestingly and consistently with market wisdom and previous research (Bollen and Whaley, 2004), they document that non-market-makers are net buyers of S\&P 500 index options: in particular, they are long index puts with low strikes (OTM) ${ }^{25}$. Therefore, it must be true that market makers are net short index options and, especially, net short OTM index puts. As one would expect, they also find that the higher the net positive demand by non-market-makers, the higher the difference between IV and volatility estimated with stochastic models (Bates, 2000): low strike index options are the most overpriced (driven by OTM puts), with the overpricing decreasing as strike increases. A different story is found for equity options: non-market-makers are net short single stock options ${ }^{26}$ and the difference between IV and a GARCH ${ }^{27}(1,1)$ expected volatility is negative across almost all moneyness categories and it gets more negative the higher the option strike. Therefore, whereas index options appear to be relatively overpriced, driven by non-market-makers buying OTM index puts, single stock options appear to be relatively underpriced, driven by non-market-makers selling OTM equity calls ${ }^{28}$.

Garleanu, Pedersen and Poteshman (2009) also find other evidence on the fact that demand for options influences their price. In fact, they show that S\&P 500 index option prices are more sensitive to demand following periods during which market makers experienced losses than following profitable periods: this shows that when market makers become more risk-averse, they take into higher consideration demand pressures from their clients.

At the end of this discussion, there are two main conclusions relevant for the aim of this paper.

[^17]The first one is that prices follow a diffusive and jumping process and volatility too is stochastic and jumping. Hence, as jumps are very important in pricing correctly options, we can deduce that by observing option prices (IVs) we should be able in some way to extrapolate information about what the market expects for jumps.

The second conclusion is that also option prices are sensitive to the simple mechanics of supply and demand. Intuitively, if option demand pressures change option IVs and option IVs carry information about the distribution of underlying returns (in particular, jumps) and, at the same time, a substantial portion of the demand pressures is informed, then we should be able to predict returns of the underlying by looking at changes in IVs.

In the next section of the literature review, we will analyze research on informed trading in options in order to understand whether the above intuitions have some empirical evidence.

### 1.2 Informed trading in option markets

Fisher Black (1975) was the first to acknowledge that a trader who wants to take a long or short position in a stock has two choices: first, he can trade directly in the equity; second, he can trade in the options whose underlying is the equity itself. In fact, it might be preferable to trade in options for many reasons (Black, 1975):

1. The commission is lower than with an equivalent stock position;
2. Shorting the stock is difficult and expensive, so that selling calls ${ }^{29}$ or buying puts is convenient;
3. Capital availability is limited so that the leverage implicit in options is an important advantage;
4. Option trading may lead to favorable tax treatment, depending on the tax bracket of the trader.

For the purpose of this thesis, the second and third motivations are the most important. In fact, if a trader happens to be informed about a particular fundamental event ${ }^{30}$ that

[^18]is likely to influence the price of the underlying equity, then he has more incentives to trade in options given the higher leverage and asymmetric payoff.

Building on Black's (1975) seminal intuition, a stream of research has developed on the role of informed trading in options markets, testing whether option prices may anticipate underlying asset returns, either in normal days or in coincidence with major fundamental events.

To the author's knowledge, the first such attempt has been carried out in 1981 by Patell and Wolfson. They study how equity option IV changes around earnings announcement dates (EADs) for single stocks. First, they confirm Beaver's (1968) original finding that equity returns are more volatile on and straight after EADs than in normal days ${ }^{31}$. Furthermore, they demonstrate that the volatility implied by preannouncement option prices rises before EADs and then falls. In addition to this, the magnitude of the subsequent realized stock price volatility seems to be positively correlated to larger pre-EAD increases in implied volatilities (Patell and Wolfson, 1981). The finding is quite clear: ex-ante, option traders seem to price a higher volatility when the ex-post realized EAD volatility is actually higher. This paper provides the first comforting evidence that options markets do convey significant information. Further evidence on the informative role of options came from the finding that the prices of stocks which have listed options require much less time to adjust after EADs than prices of stocks without listed options (Jennings and Starks, 1986).

But is there a theoretical model that can explain how informed trading develops in the options and underlying markets? This question is addressed by Easley, O'Hara and Srinivas (1998), whose model supports the view that markets are indeed in a pooling equilibrium, whereby traders will trade in options or underlying stocks depending on certain relative features of the two assets. Some informed traders will use options if: (1) the relative leverage given by options is high, i.e. if the number of shares underlying

[^19]an option contract is high relative to the number of shares bought or sold ${ }^{32}$; (2) the liquidity in the stock is low, i.e. stocks have a high bid-ask; and (3) there are many informed traders in the market (Easley, O'Hara and Srinivas, 1998). They also conduct an empirical investigation to test whether signed ${ }^{33}$ option volume can predict future stock returns. The study covers 44 trading days in October and November 1990 and uses the 50 most liquid CBOE $^{34}$ stocks. Interestingly and consistently with more recent findings (Garleanu, Pedersen and Poteshman, 2009), Easley, O'Hara and Srinivas (1998) find that trading in calls makes up more than $70 \%$ of transactions, so that traders in single stock options mostly trade calls. Furthermore, trading is concentrated in near term and near the money options and volumes have the typical u-shaped function, being highest near open and close of the market. The most important finding is that signed option volumes can predict future returns up to 20 minutes: positive news (buy call - sell put) leads to higher positive returns than negative news (sell call - buy put). Furthermore, consistent with Black's (1975) suggestion that options may be particularly useful in place of shorting the stock, the signed volume is more informative for negative news.

Easley, O'Hara and Srinivas (1998) opens the way for a very rich branch of research focusing on informed trading in options and the predictability of future equity returns ${ }^{35}$.

Chakravarty, Gulen and Mayhew (2004) confirm Easley, O'Hara and Srinivas (1998) intuition and results. Using a modified version of the "information share" approach (Hasbrouck, 1995), they find that the contribution of the option market to price discovery in the underlying is $17 \%$ on average. Furthermore, they find that in the cross-section of 60 stocks over 5 years, the "information share" of options in price

[^20]discovery is higher the higher the liquidity and leverage offered by options ${ }^{36}$, thus strengthening previous empirical findings.

Given the evidence that options do carry significant information for underlying prices, is this information evenly distributed over time or is the informative power of options stronger during certain periods?

In this section, we will review literature on options' overall predictive power. In the following section, we will focus on particular fundamental events for single stocks and mainly on earnings announcement dates (EADs).

Traders may find interesting information looking at put-call parity deviations. Noarbitrage pricing predicts that European options on non-dividend paying equities should be priced respecting the so-called put-call parity (Stoll, 1969; Klemkosky and Resnick, 1979; Hull, 2012):

$$
c-p=S-K e^{-r T}
$$

The renowned relation states that buying a European call and selling a European put with equal strike and maturity should cost as much as buying the underlying equity and borrowing with maturity equal to the maturity of the options ${ }^{37}$.

However, most times traders deal with dividend-paying equities. In such a case, the put-call parity becomes:

$$
c-p=S-D-K e^{-r T}
$$

In this case, $D$ represents the present value of the dividends on the underlying equity during the life of the option.

Finally, single stock options are American, so that they can be exercised freely ${ }^{38}$ before expiration. The put-call parity now becomes an inequality, both for the non-dividendpaying case and for the dividend-paying case (Hull, 2012):

[^21]\[

$$
\begin{gathered}
S-K \leq C-P \leq S-K e^{-r T} \\
S-D-K \leq C-P \leq S-K e^{-r T}
\end{gathered}
$$
\]

Furthermore, whereas early exercise of American calls on non-dividend-paying stocks is never optimal, early exercise of American puts on non-dividend-paying stocks can be optimal, especially if the put is sufficiently ITM. For dividend-paying stocks, early exercise can become favorable also for American calls just prior to ex-dividend dates. Therefore, American calls on non-dividend-paying stocks are worth the same as European calls; American puts are always worth more than European puts, given their early exercise premium is independent on whether the underlying pays or not dividends.

However, in real markets, enforcing the above mentioned no-arbitrage relations can become impossible due to transaction costs, margin requirements, taxes, differing borrowing and lending rates and restrictions to short-selling the underlying stock if it becomes too expensive relative to what is implied by the put-call parity relation: this can give rise to powerful information for underlying returns.

Ofek, Richardson and Whitelaw (2004) study the put-call parity relation for single stocks when there are short-sales restrictions. They find that the stronger the restrictions to short selling, the greater the deviations from put-call parity: traders who cannot short sell overpriced stocks will bid up excessively the price of OTM puts. Interestingly for this thesis, they find that the magnitude of put-call parity deviations is a significant predictor of future stock returns.

In order to gauge the difficulty of short selling, they use the overnight rebate rate, which is the interest rate received by the short seller on the proceeds of the sale deposited in margin account as collateral. When short selling is easy ${ }^{39}$, the short seller will get a high rebate rate close to the risk free rate; when short selling is difficult, the rebate rate will be low. To understand the relative difficulty of short selling a stock one can easily compare the rebate rate on that stock on that day with the average rebate

[^22]rate on all examined stocks on the same date (i.e. the cold rate): the lower the rebate rate on the stock relative to the cold rate, the tougher short selling.

Given this premise, stocks that are costly to short sell happen to be overpriced relative to put-call parity implied price significantly more often than stocks that are easy to short sell (Ofek, Richardson and Whitelaw, 2004).

Consequently, and without delving into the reasons that make these violations persist over time, we expect that shorting overpriced stocks that have put-call parity violations ${ }^{40}$ and going long comparable stocks without such issues should deliver positive excess returns. This is exactly what Ofek, Richardson and Whitelaw (2004) find.

Cremers and Weinbaum (2010) continue analyzing the informative ability of put-call parity deviations. Put-call parity deviations are measured as the difference in IV between calls and puts with equal strike and maturity, which we will call volatility spread (VS). Hence, VS is averaged over time for each stock; then each time-series average VS is averaged across all stocks; finally, 25 portfolios are created, first sorting stocks into five groups based on the change in VS over one week and then into five groups based on the level of the VS at the end of the week. Buying the portfolio that contains the stocks with both the highest level and change in VS (relatively expensive calls ${ }^{41}$ ) and selling the portfolio that contains the stocks with both the lowest level and change in VS (relatively expensive puts ${ }^{42}$ ) produces risk-adjusted ${ }^{43}$ excess returns of 50 bps per week (Cremers and Weinbaum, 2010). Furthermore, as would be expected given the model by Easley, O'Hara and Srinivas (1998), the predictability is higher when option liquidity is higher and stock liquidity is lower (Cremers and Weinbaum, 2010). Finally, they find that also the long side of the long/short strategy earns significantly positive risk-adjusted excess returns: therefore, the result is not driven by

[^23]short-selling constraints. Hence, we can say that IVs of both calls and puts carry information for subsequent returns.

Pan and Poteshman (2006) provide further evidence on the relative informative ability of calls and puts, using in this case volumes and not IVs. Volume initiated by buyers to open new positions is used to construct put-call ratios, dividing open-buy put volume by open-buy call volume ${ }^{44}$. Given previous research (Easley, O'Hara and Srinivas, 1998), open-buy call volume should carry positive information for subsequent underlying returns whereas open-buy put volume should carry negative information. In fact, buying stocks in the lowest quintile of put-call ratios and selling stocks in the highest quintile of put-call ratios generates an excess return of more than $0.4 \%$ during the following day and of more than $1 \%$ during the following week (Pan and Poteshman, 2006). Volume is also segmented according to the type of investor who initiated the trade: proprietary traders, public customers of discount brokers, public customers of full service brokers and other public customers. Not surprisingly, the volume initiated by clients of full service brokers (which include hedge funds) is much more informative for future stock returns than volume initiated by clients of discount brokers: this corroborates the hypothesis that the source of predictability lies in access to better information or superior ability to process public information. Finally, the predictive ability is stronger for OTM options and shorter-dated options (Pan and Poteshman, 2006), which are both types of options with higher leverage, consistent with Easley, O'Hara and Srinivas (1998) finding that the informative ability is higher for options which provide traders with higher leverage.

It is not just volumes or the differential between put and call IVs that provide valuable information to market participants. In fact, also IV dynamics and the shape and dynamics of the skew lead stock returns.

Firstly, let us investigate the effect of IV dynamics on future underlying returns: as one would expect, stocks with past sizeable increases in call IV tend to have high future

[^24]returns; stocks with past sizeable increases in put IV tend to have low future returns. Using stocks with IVs with 30 days to maturity and 50\% Deltas over 1996-2011 and controlling for a multitude of factors usually predicting returns ${ }^{45}$, An et al. (2014) find that sorting stocks in deciles based on previous month change in call IV, buying the equally weighted highest decile and selling the equally weighted lowest decile generates significantly positive monthly excess returns of $1.09 \%$ with an annualized Sharpe of 0.90 . Again, it appears that it is superior information about the single stock that leads to this predictability: in fact, decomposing call IV into idiosyncratic and systematic ${ }^{46}$, it is the change in idiosyncratic call IV that predicts returns (An et al., 2014).

Secondly, evidence on the predictive ability of skew measures is provided. Doran and Krieger (2010) use a sample of 4161 stocks in the CRSP ${ }^{47}$ database with available option data on OptionMetrics ${ }^{48}$. They compute five skew measures on the last trading day of each month from 1996 to September 2008. Then, they compute returns for the underlying stocks during the following month. In particular, for the purposes of this thesis, four measures are important:

$$
\begin{gathered}
\text { COMA }=\sigma_{c, o t m}-\sigma_{c, a t m} \\
\text { POMA }=\sigma_{p, o t m}-\sigma_{p, a t m} \\
C W=\sigma_{c, a t m}-\sigma_{p, a t m} \\
Z Z X=\sigma_{p, o t m}-\sigma_{c, a t m}
\end{gathered}
$$

COMA is the difference between call OTM and ATM IVs, hence it represents the right side of the call skew. POMA is the difference between put OTM and ATM IVs, hence it represents the left side of the put skew. CW stands for Cremers and Weinbaum (2010) and is the difference between the call and put ATM IVs, hence it represents the central

[^25]part of the skew. Finally, ZZX stands for Zhang, Zhao and Xing (2010) and is the difference between the put OTM and the call ATM IVs.

Interestingly, $74 \%$ of the value of the positive difference between put OTM and call ATM IVs is originated by the difference between OTM and ATM put IVs and only the remaining $26 \%$ by the difference between put and call ATM IVs (Doran and Krieger, 2010). They find that COMA is not significant in predicting next-month underlying returns ${ }^{49}$, whereas the higher POMA the higher next-month returns and Fama-French alphas. This means that, on the one hand, the right side of the skew is less informative than the left side and, on the other hand, the POMA result is counterintuitive. One would expect that the higher the price of OTM puts relative to ATM puts, the higher the probability of following negative returns, if a substantial part of OTM put trading is informed. However, according to Doran and Krieger (2010) this does not seem the case. ZZX has the expected effect: the higher ZZX, the lower next-month returns. This means that the higher put OTM IV versus call ATM IV, the worse the following returns. This also implies that CW is more important in driving ZZX than POMA ${ }^{50}$. Two motivations can be found for these results: firstly, as options trading is informed, then buying calls (puts) provides market makers with positive (negative) information, so that IVs will be adjusted accordingly; and, secondly, the POMA result may be explained by hedging pressures ${ }^{51}$.

What about jump risk? Can option prices provide information on jump risk too? The problem of estimating with precision jump sizes is a so-called "peso" problem ${ }^{52}$ : jumps are rare events for the underlying return distribution and, therefore, it is very difficult to both estimate and predict them. It would be required to have a huge sample size and, even with a large sample, the distribution of jumps may be time-varying (Yan,

[^26]2011). Hence, a possible approach may rely on extracting information regarding jumps from quoted option prices, which provide for a large sample.

Yan (2011) uses as a proxy for jump risk the difference between 1 month IVs of puts and calls with $50 \%$ absolute Delta. They conjecture that the steeper this "slope", the most negative the information priced in by markets regarding a future negative jump. Indeed, using a sample period from 1996 to 2015, stocks in the lowest quintile of IV slope significantly outperform stocks in the highest quintile of IV slope by $1.8 \%$ monthly ${ }^{53}$ (Yan, 2011). This outperformance is robust to risk-adjustment using different factors. Finally, as in An et al. (2014) with IVs, Yan (2011) decomposes the "slope" into its idiosyncratic and systematic components ${ }^{54}$ and finds that it is the idiosyncratic component of the "slope" that explains most of the future outperformance of stocks in the quintile with the highest $50 \%$ Delta call IV relative to put IV: again, specific information on the stocks seems to be driving the findings.

Through option prices, one can also estimate the probability of observing jumps in the future. To the author's knowledge, this approach has been applied only to index options. The paramount example of this line of research is Doran, Peterson and Tarrant (2007) ${ }^{55}$. They do not focus on explaining the reasons behind a negative skew in option IVs; instead, they investigate whether observed index option skew can forecast index crashes or positive jumps. A steeper put skew implies higher OTM put IV relative to ATM put IV and, as we have already seen in past research, this is likely to be synonym of negative expectations about future underlying events. Therefore, one would expect a higher probability of observing crashes when the put skew steepens, i.e. becomes more positive. Conversely, a flatter ${ }^{56}$ call skew, when OTM call IV is relatively more expensive than ATM call IV, should be associated with an increased probability of future positive extreme returns. Using index option data on the S\&P 100 from 1984 to 2006, this is what is found by Doran, Peterson and Tarrant (2007). Furthermore, since jump risk premium is mainly priced in the short-term (Pan, 2002), one would expect

[^27]to see shorter-dated options predicting more accurately jumps in the underlying price: in fact, one finds that options with a maturity of 10 to 30 days are related to future jumps in a more statistically significant way than options with a maturity of 31 to 60 days or 61 to 90 days (Doran, Peterson and Tarrant, 2007). Furthermore, the results are robust to different specifications of moneyness ${ }^{57}$ and to the inclusion of control variables: percentage OTM bid-ask spread, OTM option volume, OTM option open interest and term structure of interest rates are mostly insignificant in predicting jumps (both positive and negative). The most significant control variable is ATM IV: as one would expect, higher ATM IV implies that market participants are pricing in a higher uncertainty about the future and jumps in both directions should be more likely if the bidding up of ATM IV is driven by informed trading. Doran, Peterson and Tarrant (2007) verify that higher ATM IV significantly increases the probability of seeing both crashes and positive spikes; however, for index options, the skew explanatory variables remain significant for shorter-dated maturities. Interestingly, whereas for longer-dated maturities the skew regressor loses statistical significance, the ATM IV regressor keeps it: this is consistent with the fact that jump risk is a short term phenomenon, whereas volatility risk a longer term issue (Das and Sundaram, 1999). Finally, for index options, the statistical significance is higher for put skew predicting negative jumps than for call skew forecasting positive jumps (Doran, Peterson and Tarrant, 2007): this is further evidence that most of trading in index options is concentrated in puts, which drives the typical shape of the skew and the expensiveness across strikes (Garleanu, Pedersen and Poteshman, 2009).

At the end of this discussion, there are three main conclusions relevant for the aim of this paper.

First, options represent a venue for informed trading, especially the ones with the highest leverage and liquidity relative to the underlying.

Second, given the informed nature of trading, higher open-buy call volume and higher call IV provide positive information on the underlying and, conversely, higher openbuy put volume and higher put IV provide negative information on the underlying.

[^28]Third, this information is contained also in the skew and can be applied to improve predictions regarding jumps.

In this section, we analyzed informed option trading over time, without focusing on specific events. In the following section, we will focus on whether options can be used to improve decision-making regarding the underlying before scheduled and/or unscheduled events.

### 1.3 Options' predictive power around significant information events

Whereas indexes react not only to scheduled earnings announcements (which are in any case dispersed over time) but also to macro events, for single stocks major information events (i.e. earnings) are pre-announced and single stock prices reflect less general macro data. Therefore, the majority of research on the predictive ability of option prices around major information events has been done looking at single stock options and earnings announcement dates (EADs).

EADs are dates during which listed companies declare to the investors' community key quarterly performance results and earnings. During the EAD week, the trading volume in stocks is usually much higher than during non-EAD periods (Beaver, 1968). This provides evidence about the fact that earnings announcements bring information to the market, which is relevant at least for individual investors ${ }^{58}$. Furthermore, Beaver (1968) finds that also the magnitude of price changes during EAD weeks is much larger ( $67 \%$ on average) than the average during the non-EAD periods: hence, EADs bring also price-relevant information for the entire market.

It is not only earnings that carry information: stock prices are determined discounting future cash flows at the appropriate discount rate ${ }^{59}$. Hence, information on everything that can affect estimates of future cash flows or discount rate will bring information to

[^29]the market and allow investors to update their valuations, possibly causing adjustments of positioning in portfolios and thus buying / selling pressures and price changes. For instance, dividends, even when taken alone, carry significant pricing information. Theory goes that since dividend policy is discretionary, management can use dividend announcements to signal their view on future firm performance (Aharony and Swary, 1980). Furthermore, dividends are sticky: once management raises dividends, they are very reluctant to scale them back as this would represent a very bad signal for expectations about future cash generation capacity. Aharony and Swary (1980) find that stocks of companies which announced dividend increases earned positive excess returns over the 20 days surrounding announcement dates, on average. This is independent on whether or not there are contemporaneous EADs. Conversely, as one would expect, when companies decrease their dividends, their stocks earn significantly negative excess returns during the same 20 days. The magnitude of the negative reaction to downward revision to dividends is much greater than the magnitude of the positive reaction to upward revision to dividends (Aharony and Swary, 1980): this further corroborates the stickiness of dividends hypothesis.

However, the effect of EADs is not limited to the days straight after the announcements. In fact, plenty of literature investigated the so-called Post Earnings Announcement Drift (PEAD), according to which estimated cumulative returns in excess of standard factor models continue to drift up for "good news" stocks and down for "bad news" stocks (Bernard and Thomas, 1989; Ball and Brown, 1968). It is out of the scope of this thesis to investigate the reasons behind the PEAD ${ }^{60}$ : the important point here is that earnings announcements do bring new information to the market that not only impact prices immediately afterwards but also in the longer term.

While it is true that EADs spread fundamental information about firm future prospects to the market, they also increase the variability of returns during immediately following days, as investors need time to adjust the consensus on valuations and, therefore, will increase volumes and will move prices more than during normal days. Ball and Kothari

[^30](1991) finds that the average return, across stocks and over time, on the EAD is larger than the average return on any of the 10 prior or 5 following days; also standard deviation of returns increases during EADs, with EAD standard deviation being 30\% larger than its average over days -10 through -2 and +2 through +10 (Ball and Kothari, 1991). This finding is another proof that one expects greater than usual price moves during EAD periods. However, nothing assures us that these larger-than-normal moves are as extreme as to be categorized as jumps.

Demers and Vega (2010) find that it is not only hard numeric information about sales, margins, capex, working capital, leverage or earnings that moves prices. In fact, soft information, which is related to the type and frequency of words used during earnings announcement releases, is found to move prices. Using language-processing software to extract different linguistic dimensions of managerial net optimism ${ }^{61}$ from more than 20,000 corporate earnings releases over the period 1998 to 2006, Demers and Vega (2010) find that unanticipated net optimism in managers' language affects EAD returns and forecasts PEAD in the following 60 days. This is robust to the contemporaneous release of hard information (i.e. accounting numbers). Moreover, the incremental predictive power of soft information is stronger when: (1) hard information is noisier, i.e. for high-tech stocks, for stocks with high P/E ratios, for stocks with high R\&D expenses and for stocks with lower quality accounting data; (2) the language used in the release is more credible, i.e. when hard accounting information is more precise; (3) stocks enjoy a higher media coverage and more numerous analyst coverage; and (4) firms are governed by managements with better forecasting reputations.

For all these reasons, EADs are crucial moments during the life of listed companies. It is then natural to ask whether option prices can provide particularly important information about future returns around these events.

Dubinsky and Johannes (2006) introduce a reduced-form option pricing model and estimators to distinguish volatility during EADs and normal days. Their first important finding is that shorter-dated ATM IV is systematically higher and concentrated during EADs, which also confirms prior research (Patell and Wolfson, 1981). Jumps are not

[^31]assumed to arrive following a Poisson counting process: they are assumed to arrive deterministically during pre-scheduled EADs. Furthermore, option IV increases prior to EADs, then IV falls afterwards and the term structure of IV ${ }^{62}$ is upward-sloping before an EAD (Dubinsky and Johannes, 2006). For large stocks, Dubinsky and Johannes (2006) find that $8 \%$ of the total variance in their returns is realized during the four EADs: assuming volatility realizes evenly over trading days, and knowing there are approximately 252 trading days in one year, then four days should account for approximately $4 / 252=1.6 \%$ of total variance. Clearly, during EADs, stocks realize a disproportionately high percentage of their total variance, consistent with the notion that EADs increase lack of consensus by bringing to markets new information (Ball and Kothari, 1991).

Donders, Kouwenberg and Vorst (2000) use one call and one put for every stock in their sample, with the shortest expiry date (as long as it is greater than 10 days) and closest to being ATM forward. They study the five days before an EAD, the EAD and the five days after the EAD. They define good news as when the cumulative abnormal return (CAR) for a stock during EAD and EAD+1 is positive; bad news when the CAR is negative. They find that stock returns are significantly more volatile from EAD-2 to EAD+2 and the effects are stronger for negative news (Donders, Kouwenberg and Vorst, 2000), consistent with both a short-selling restrictions story (Ofek, Richardson and Whitelaw, 2004) and with higher volatility during EADs (Ball and Kothari, 1991)

Option skew, too, can provide useful information regarding stock returns around EADs.
Xing, Zhang and Zhao (2010) demonstrate that stocks with the steepest (i.e. more positive) volatility skews are those that experience the worst earnings shocks (i.e. lowest standardized earnings surprises) in the subsequent quarter ${ }^{63}$. IV skew is defined

[^32]as the difference between OTM put and ATM call IVs, calculated daily and averaged over one week. Their results are consistent with research stating that informed traders with negative news prefer to trade OTM puts (Garleanu, Pedersen and Poteshman, 2009; Doran and Krieger, 2010). The standardized earnings surprise variable is the difference between reported earnings and the latest consensus earnings forecast before the EAD, divided by the standard deviation of the forecasts, taken from IBES (Institutional Brokers' Estimate System). Finally, the skew predictability is increasing in stock market illiquidity and option leverage (proxied by OTM Delta), consistent with previous theoretical models (Easley, O'Hara and Srinivas, 1998).

If option prices are influenced by changing expectations regarding jump risk (Pan, 2002), Diavatopoulos et al. (2012) demonstrate that implied skewness prior to EADs gives information about the direction of future stock returns and implied kurtosis prior to EADs predicts the size of future stock returns ${ }^{64}$. If traders expect a positive jump to occur, then the implied skewness should become more positive; conversely, for negative jumps, it should become more negative. This happens because traders will bid up OTM put prices when expecting bad news and OTM call prices when expecting good news. Furthermore, also the size of the jump is important: if traders are scared about a huge movement in the underlying but do not have enough information on the direction, then they will buy strangles ${ }^{65}$, bidding up the prices and IVs of OTM options. This translates into higher implied density in the tails of the returns distribution, which becomes more leptokurtic. Hence, higher implied kurtosis anticipates larger jumps (Diavatopoulos et al., 2012). In particular, one can compute the change in implied

[^33]moments between two dates preceding EADs. They use daily data from 1996 to 2007. Computing changes in implied skewness and kurtosis from 30 to 20,10 and 5 days prior to EADs, controlling for changes in implied volatility ${ }^{66}$ and sorting stocks into deciles based on cumulative buy-and-hold returns over the EAD and EAD+1, Diavatopoulos et al. (2012) find that both the implied skewness and kurtosis changes are significantly larger for the decile with the largest positive returns than for the low return decile, as expected. Furthermore, as one would expect, the more informative implied skewness and kurtosis changes are the most recent ones, i.e. the changes between 30 and 5 days prior to EADs, consistent with markets learning information as time passes. Consistent with literature stating that jumps are a short-term worry for markets (Pan, 2002), Diavatopoulos et al. (2012) find that shorter-dated options are more informative for EAD period returns than longer-dated options ${ }^{67}$.

As we have already said, earnings announcements are not the only significant information events for single stocks. It remains to be seen whether options can provide valuable information regarding those other events.

To this end, the recent study by Jin, Livnat and Zhang (2012) provides some clarity. Firstly, they confirm abundant research demonstrating that options ${ }^{\prime 68}$ skews $^{69}$ and spreads have predictive ability for returns around EADs, with steeper ${ }^{70}$ skews predicting more negative returns ${ }^{71}$. Secondly, they examine whether options' predictive ability is not lost for returns around extreme returns or unscheduled events. For any event studied, the event date is day 0 ; the base window is days -50 to -11 included and the pre window is days -10 to -2 included. Average IV skew and spreads are measured during these two windows. Excess returns are measured cumulatively over days -1 to +1 , minus the cumulative returns on a portfolio of stocks of similar size, book-to-market and 12-month momentum (Jin, Livnat and Zhang, 2012). They demonstrate improved forecasting ability for skews and spreads measured during the

[^34]pre-window, consistently with traders acquiring more and/or better information as the event date approaches. For what concerns extreme returns, they can be generated both by firm-specific, industry-wide or macroeconomic events. Jin, Livnat and Zhang (2012) compute 3-day cumulative excess ${ }^{72}$ returns for every day from 1996 to 2010 and they keep them if they are greater in absolute value than $10 \%$. They find that options' skews and spreads during the pre-window are significant in explaining extreme returns, with steeper skews predicting more negative returns: this is evidence that options' traders not only engage in fruitful information discovery for EADs, but also for random events that generate extreme returns. Finally, when looking at unscheduled events, they use data from the Key Developments database ${ }^{73}$ by Capital IQ. Again, pre-window skews and spreads significantly predict returns around unscheduled announcements (Jin, Livnat and Zhang, 2012), providing support to the notion that option traders have comparatively better information processing skills.

Finally, Cao, Chen and Griffin (2005) examine option volumes' informative ability prior to takeovers, which are not pre-scheduled. Across the sample of stocks announcing takeovers ${ }^{74}$, the larger the increase in preannouncement ${ }^{75}$ call volume imbalance ${ }^{76}$, the larger the two-day cumulative excess announcement return (and vice versa for puts). Furthermore, prior to announcements, traders focus their buying pressures in the shorter-dated OTM calls, which give the highest leverage (Cao, Chen and Griffin, 2005), consistent with prior research on informed trading in options (Easley, O'Hara and Srinivas, 1998).

[^35]At the end of this discussion, there are three main conclusions relevant for the aim of this paper.

First, options' implied volatility, skew and kurtosis provide valuable information about future returns around EADs.

Second, this predictability is found also for unscheduled events, such as extreme returns or takeover announcements.

Third, not only prices, but also changes in signed option volumes can predict returns around information events.

## 2. Research questions

The literature review in the previous section has shown the existence of a gap as far as the relationship between single stock options' skew or implied volatility and jumps in the underlying stock is concerned. Many papers examine the power of single stock options in predicting returns during normal days or around major information events, particularly EADs. However, to the author's knowledge, no such study has been attempted on the link between skew or implied volatility and single-day jumps in the returns distribution of individual stocks.

Therefore, following the methodology applied by Doran, Peterson and Tarrant (2007) in order to study the relationship between S\&P 100 index options' skew and subsequent S\&P 100 jumps, we will study the phenomenon for single stock options over the time-series. Furthermore, in order to check our main hypothesis, we will also differentiate between earnings announcements periods and normal periods, where we do not observe EADs. Skews are defined as follows ${ }^{77}$ :

$$
\begin{gathered}
\text { skew }_{\text {OTM-ATM }}=I V_{\text {OTM }}-I V_{\text {ATM }} \\
\text { skew }_{\text {OTM-ITM }}=I V_{\text {OTM }}-I V_{\text {ITM }}
\end{gathered}
$$

Using the above definitions of skews, we will try to answer to the following four research questions.
I. Is the probability of observing negative jumps in the underlying stocks positively related to a more positive put skew over the time-series?

Based on Garleanu, Pedersen and Poteshman (2009) and many other papers as previously shown, if informed traders choose options and they are able on average to anticipate future jumps of the underlying, we should expect to see relatively higher demand for OTM puts than for ATM puts prior to negative jumps, since OTM puts provide the greatest leverage to hedge / speculate on future negative extreme events.

[^36]Hypothesis I: We expect a more positive put skew to be positively related to a higher probability of observing a future negative jump.
II. Is the probability of observing positive jumps in the underlying stocks positively related to a less negative (or more positive) call skew over the time-series?
In a specular way, we should expect to see relatively higher demand for OTM calls than for ATM calls prior to positive jumps, since OTM calls provide the greatest leverage to hedge / speculate on future positive extreme events. Hypothesis II: We expect a less negative (or more positive, in cases of smiling IV function $)^{78}$ call skew to be positively related to a higher probability of observing a future positive jump.
III. If the skew proves to be significantly related to following jumps, does this statistical relationship characterize normal periods or is it limited to earnings announcement periods?
Prior research shows that the skew of single stock options carries information for underlying returns both for normal periods and earnings announcement periods (Xing, Zhang and Zhao, 2010). However, jumps are rare events ${ }^{79}$ and, as such, how we define jumps may affect results. In fact, given that earnings announcement periods extend over a limited amount of time with respect to normal periods, we may find that few jumps happen during earnings announcement periods, thus reducing the statistical significance of the results. Hypothesis III: We expect the statistical significance of the skew-jump relationship to persist during normal periods; furthermore, during earnings announcement periods, the smaller sample size may decrease the statistical significance.
IV. Is the significance of the skew incremental with respect to ATM implied volatility?

[^37]Plenty of research, from Patell and Wolfson (1981) to Donders, Kouwenberg and Vorst (2000), demonstrates that prior to major information events single stock option ATM implied volatility rises. In fact, ATM implied volatility represents a gauge about how markets are pricing future uncertainty.

Hypothesis IV: If option traders do have some information also on jumps ${ }^{80}$, we expect higher ATM implied volatility to be linked with a higher probability of observing following jumps, both positive and negative ${ }^{81}$. Since jumps are rare events and tougher-to-predict with respect to scheduled information, we also expect the incremental significance of the skew coefficient to be negligible with respect to ATM implied volatility: in fact, while having an informed view on whether future jumps will happen is tough business, correctly predicting also the direction of the jumps is certainly even tougher.

Some caveats to be kept in mind are as follows:

1. Trading volume in single stock options is concentrated in calls and non-market makers are usually and on average net short single stock options (Garleanu, Pedersen and Poteshman, 2009; Pan and Poteshman, 2006). We would expect that calls' skew and ATM implied volatility do better at predicting positive jumps than the equivalent puts' measures do for negative jumps: this would be true assuming that retail and professional investors are distributed evenly between call and put volumes.
2. Stock volatility is higher on average than index volatility; on the other hand, index jumps are larger than single stock jumps ${ }^{82}$ (Dubinsky and Johannes, 2006). Therefore, individuating and predicting jumps using skew and ATM IV may be easier for index options as the underlying index is likely to have more identifiable jumps.
3. The skew of single stock options is flatter (i.e. less positive) or more "smiling" than index options' skew: single stock skews may sometimes be upward sloping

[^38]in strike (even if less than 30\% of times), whereas index skews are always negatively sloped in strike (Dubinsky and Johannes, 2006; Bakshi, Kapadia and Madan, 2003). Several motivations can be given for the relatively flatter single stock skew: (1) index returns distributions are more negatively skewed; (2) correlation skew steepens index implied volatility skew (while not impacting single stock implied volatility skew): this happens because implied correlation ${ }^{83}$ tends towards $100 \%$ for low strikes since during a crash all stocks are expected to be almost perfectly positively correlated and fall together; on the other hand, high-strikes implied correlations are lower, thus originating an implied correlation skew (Bennett, 2014); and (3) there is a heavy institutional investors' buying pressure for OTM index puts as portfolio insurance against market-wide crashes: this does not happen for single stock options. Therefore, we may expect that OTM-ATM skews will be more significant in predicting future jumps than OTM-ITM skews, since the single stock skew is more smiling and hence the differential of information carried by OTM options is likely to be greater with respect to ATM than ITM options. Furthermore, as other evidence in favor of the latter hypothesis, prior research found that when traders have some information about a future event but are unsure about the direction of the underlying returns, they will buy strangles ${ }^{84}$, bidding up both OTM and ITM IVs (Diavatopoulos et al., 2012). A possible counterfactual to this intuition is that, if traders buy more straddles expecting only small jumps and not huge jumps, then OTM-ITM is expected to be more significant, as with straddles ATM IV is bid up a lot.

After pinpointing the key research questions, we will delve into the methodology used for the empirical test of the thesis and into the data collection, cleaning and summarization process.

[^39]
## 3. Data and methodology

All data are downloaded through the Wharton Research Data Services (WRDS) online database. The sample period extends from January 1, 1996 to December 31, $2017{ }^{85}$. We will study a selection of single stocks that are components of the S\&P 100 index (from now on, simply "the index") ${ }^{86}$, which comprises the 100 largest listed companies by market capitalization in the US. Firstly, using the Compustat Capital IQ database, data about the S\&P 100 index constituents from the North America - Annual Updates section is downloaded. This gives information on all firms included in the index over the sample period and on the dates of inclusion and/or exclusion from the index: 207 unique company tickers are retrieved, of which only those that have been included continuously throughout the period are used for the empirical test ${ }^{87}$. This reduces the sample to 26 of the 207 stocks.

Using OptionMetrics, we then download daily data on stock prices, returns, volumes and shares outstanding for the 26 stocks. After cleaning for missing data (shares outstanding), 24 stocks $^{88}$ are retained.

For each stock, we retrieve data on the quarterly earnings announcement dates from the Compustat North America - Fundamental Quarterly database. For each stock, we get option data from OptionMetrics: we retrieve option type (call/put), expiration date, strikes, bid, ask, volume, open interest, implied volatility ${ }^{89}$, on a daily frequency. Observations for which IV is not available are eliminated.

We will now explain in detail the data cleaning and summarization procedure for a sample stock ${ }^{90}$, Halliburton Company (HAL), which is one of the largest oil field service companies in the world.

[^40]Small (big) negative jumps are those daily stock returns ${ }^{91}$ that are in the bottom 5\% (1\%) of the returns distribution, conditional on returns being negative. Small (big) positive jumps are those daily stock returns that are in the top $5 \%(1 \%)$ of the returns distribution, conditional on returns being positive. One could argue that this absolute definition of jumps that does not adjust for the prevalent level of volatility in the market is not adequate; however, Doran, Peterson and Tarrant (2007) confronted a similar absolute definition and a relative definition scaled by volatility and found no differences in their findings. Hence, we proceed with the absolute definition.

We then test the returns distribution for normality using QQ plots and the Jarque-Bera test and we reject the normality hypothesis at conventional significance levels ${ }^{92}$ : as expected, tails are much fatter than the normal would command. Using a KolmogorovSmirnov test, we test whether a t-Student distribution could describe well the returns and cannot reject the hypothesis that a t-Student could fit well the data. Hence, we estimate a rolling t -Student $\operatorname{NAGARCH}(1,1)^{93}$, starting the estimate after the first 2 trading years ${ }^{94}$ and recursively refitting every 6 trading months ${ }^{95}$. In Figure 1, we plot the estimated volatilities, adjusted close prices for HAL and jump days over time.

[^41]

Figure 1: HAL adjusted close price and t-Student NAGARCH(1,1) volatility

As we can see, periods of high volatility usually coincide with stock price drops and a high concentration of jump days, as defined earlier. This behavior is consistent across all analyzed stocks and is in line with previous research (Bennett, 2014; Doran, Peterson and Tarrant, 2007).

We then merge the option and stock datasets retrieved from OptionMetrics and proceed with the cleaning. First, we compute days to expiration, mid-price and moneyness as strike price divided by closing spot price ${ }^{96}$. As it is common practice in previous research (Doran, Peterson and Tarrant, 2007; Xing, Zhang and Zhao, 2010), we keep only those options with a mid-price greater than $\$ 0.25$ and a bid different than zero. We further keep only options with non-zero volume ${ }^{97}$ and with days to

[^42]expiration between 10 and 90 . We check that option bids and asks respect basic noarbitrage conditions ${ }^{98}$ and eliminate those that fail the test.

We compute the bid-ask spread as a percentage of mid-price. Following Doran, Peterson and Tarrant (2007), we group options' observations by maturity into 3 categories: (1) short-term (ST) options with between 10 and 30 days to expiry; (2) medium-term (MT) options with between 31 and 60 days to expiry; and (3) long-term (LT) options with between 61 and 90 days to expiry. Furthermore, always following Doran, Peterson and Tarrant (2007), we group options according to moneyness into 7 categories: (1) Deep-Deep-Out-of-The-Money (DDOTM) options, which are puts with moneyness smaller than $87.5 \%$ and calls with moneyness larger than 112.5\%; (2) Deep-Out-of-The-Money (DOTM) options, which are puts with moneyness between 87.5\% and $92.5 \%$ and calls between $107.5 \%$ and $112.5 \%$; (3) OTM options, which are puts between $92.5 \%$ and $97.5 \%$ and calls between $102.5 \%$ and 107.5\%; (4) ATM options, which are both puts and calls between 97.5\% and 102.5\%; (5) ITM options, which are puts between $102.5 \%$ and $107.5 \%$ and calls between $92.5 \%$ and $97.5 \%$; (6) DITM options, which are puts between $107.5 \%$ and $112.5 \%$ and calls between 87.5\% and 92.5\%; and (7) DDITM options, which are puts with moneyness larger than $112.5 \%$ and calls with moneyness smaller than $87.5 \%$.

Hence, we obtain a matrix dataset with cleaned observations and options observations identified by a maturity and moneyness group.

The charts describe the HAL dataset (similar charts have been produced for all stocks but are not reported for brevity).

To obtain Figure 2, we averaged IV for all options inside the same maturity and moneyness bin for each day, a methodology that is used also in previous research (Xing, Zhang and Zhao, 2010; Doran, Peterson and Tarrant, 2007). For instance, there can be days during which we observe more than one contract traded for the category ST, OTM puts: in this case, to get a single IV quote for the ST, OTM put bin we simply average the IVs of the traded contracts. Interestingly in Figure 2, we see that as the

[^43]maturity decreases, IV becomes more volatile, consistent with prior research (Bennett, 2014).


Figure 2: HAL IV mean by option type, across maturity and moneyness
Figure 3 below shows that the great majority of high IV options are ST contracts, both for puts and calls and across different moneyness bins. Again, this is consistent with the fact that ST options react more to underlying returns and are more volatile, exhibiting the highest spikes of IV. Hence, ST contracts seem to be the ideal candidates to predict jumps, as shown in previous work (Doran, Peterson and Tarrant, 2007).

In non-reported analysis, we also confirm the usual positively skewed IV distribution. In the Appendix, similar charts for HAL are also presented for volumes and open interests.


Figure 3: HAL IV mean frequency by maturity, across option type and moneyness
In order to summarize data, we compute the time-series average ( M ) and standard deviation (SD) of mean IVs and number of observations ${ }^{99}(\mathrm{~N})$ for each unique call/put maturity-moneyness bin (Panel A). Furthermore, we compute also the time-series average for the percentage bid-ask spread (BA), option volume (V) and open interest (OI) (Panel B). Results are presented in Table 1. Furthermore, in Figure 4, Figure 5 and Figure 6, we present a graphical representation of the descriptive statistics. In Figure 4 we can easily see the typical skew/smirk pattern for IVs of single stock options (Bakshi, Kapadia and Madan, 2003). We see that the smirk pattern is more pronounced for ST maturities, as one would expect and consistently with abundant evidence (Bennett, 2014). Furthermore, there are many more observations for ST and closer to the money options: as we get farther away from being ATM and we pick longer-dated contracts, the number of traded contracts falls.

[^44]

Table 1: Descriptive statistics for HAL, January 1, 1996 to December 31, 2017


Figure 4: Descriptive statistics for HAL - IV mean and number of observations


Figure 5: HAL descriptive statistics - bid-ask mean and number of observations
Figure 5 shows that bid-ask spreads monotonically decrease as options become more in the money, consistent with previous research (Chakravarty, Gulen and Mayhew, 2004); furthermore, they are higher the shorter the maturity of the contracts.

Figure 6 below shows that volumes for ST contracts are on average higher the more OTM the options are. In general, ST contracts have higher peak volumes than MT or LT contracts. Furthermore, volumes for MT and LT contracts tend to peak for OTM and ATM options and are, in general, lower than those of ST options. Finally, open interest tends to be higher for LT contracts: this makes perfectly sense since, as time passes, traders acquire more/better information and either early exercise or close their positions with an offsetting one, thus decreasing open interest (Donders, Kouwenberg and Vorst, 2000).


Figure 6: HAL descriptive statistics - volume and open interest means
We then filter the dataset in order to keep only a unique observation per trading day and per call/put maturity-moneyness bin: for instance, on a Monday, we can observe a maximum of 42 implied volatilities ${ }^{100}$.

Following previous research which shows that the options containing the best information regarding jump risk are the shorter-dated ones (Pan, 2002; Doran, Peterson and Tarrant, 2007), we impose a further filter and keep only ST contracts (10 to 30 days to expiry). In addition, given that far from the money contracts display much fewer observations, we retain only OTM, ATM and ITM contracts ${ }^{101}$.

[^45]At this point, we compute skews. For each option type call/put, as already announced, we define skew in two different ways:

$$
\begin{gathered}
\text { skew }_{\text {OTM-ATM }}=I V_{\text {OTM }}-I V_{\text {ATM }} \\
\text { skew }_{\text {OTM-ITM }}=I V_{\text {OTM }}-I V_{\text {ITM }}
\end{gathered}
$$

The skews are defined for each trading day in which the necessary IVs are available.
All days where we previously identified a jump are assigned a 1, as in that day a jump happened with probability $100 \%$. All days without a jump are assigned a 0 , as in that day a jump happened with probability 0\%. Of course, we differentiate among small negative, big negative, small positive and big positive jumps as previously defined.

We then extend option expiry dates over trading days as long as the time to expiry is not zero: for instance, for an option with maturity 2000-01-22, all days between the first skew observation (e.g. on 2000-01-05) and 2000-01-22 shall have expiry date equal to 2000-01-22, as that is the closest available maturity date. Of course, some trading days will not have any valid expiry date, since if the latest expiry is on 2000-01-22 and the next valid option observation is on 2000-01-28, then all days between 2000-01-22 and 2000-01-28 will not have any expiry date.

At this point, using data on the report date of quarterly earnings, we distinguish between earnings announcement date (EAD) periods and normal/non-EAD periods ${ }^{102}$ :

1. If the expiry date for that day is valid (i.e. not missing), then a trading day is defined as part of an EAD period if the date following the report date of the quarterly earnings is between the current trading day and the valid expiry date. For instance, for a report date on 2000-04-12, all trading days up to 2000-0413 (included) are assigned in the EAD period if they have an expiry date on 2000-04-21. In fact, by trading in the contracts with expiry 2000-04-21, one can get exposure to the EAD on 2000-04-12; the pricing (IV/skew) of the

[^46]options will be influenced by the EAD until 2000-04-12 ${ }^{103}$ and any eventual stock jump is likely to be determined by EAD-specific information until the day after the EAD, 2000-04-13. Jumps happening two or more days after the EAD are assumed to be not likely to be caused by EAD-specific information.
2. If the expiry date is not available, then a trading day is defined as part of an EAD period if the date following the report date of the quarterly earnings is after the current trading day and the year and month of the report date are equal to the year and month of the current trading day. For instance, if we have the contracts with expiry 2000-04-21, and the report date is on 2000-04-24, then the trading day 2000-04-24 will not have any available expiry date ${ }^{104}$, but since the 2000-04-21 contracts are the closest, we assume that the pricing of the contracts will be partially influenced by the upcoming EAD. Therefore, we will consider all days up to and including 2000-04-24 as part of the EAD period, since IV/skew will be influenced and any jump in the underlying before 2000-$04-24$ is likely to be caused by EAD-specific information ${ }^{105}$.

Now, following Doran, Peterson and Tarrant (2007), we place controls on jumps. Jumps are identified by a binary variable, which will be the dependent variable: $D=1$ identifies jump days and $\mathrm{D}=0$ identifies normal days. Firstly, we eliminate a jump (i.e. we consider it as a non-jump day, assigning a 0 value) if there has been a jump, at least of the same magnitude ${ }^{106}$, in the opposite direction in the previous 5 trading days. In fact, the second in a stretch of two close consecutive and opposite jumps is likely due to market microstructure reasons. For instance, covering a big short in the stock when there is little liquidity may cause a positive jump, which is likely not to be

[^47]driven by new information but by risk management and/or profit taking. On the other hand, selling after a positive jumps may cause a negative jumps which is not driven by new information but by profit-taking. Secondly, we eliminate the 3 trading days after a valid jump, following a reasoning similar to Doran, Peterson and Tarrant (2007). In fact, a jump may influence option prices in the subsequent days ${ }^{107}$ : since we are trying to verify which is the statistical relation between ex-ante skews and ex-post jumps and whether skews can predict jumps, we do not want to retain skews that may be influenced by jumps that have already happened, i.e. those skews that incorporate past information but do not price in expectations about future jumps.

Again, as a further control to avoid reverse causality, we eliminate (i.e. assign a 0 value to) those jumps that happen on the same day of an option skew observation. We do this in order to avoid that the observed skew is influenced by the already happened jump: only future jumps should influence current skew pricing ${ }^{108}$.

Following Doran, Peterson and Tarrant (2007), we identify as jumping days those trading days that do not see a jump but that are prior to the jump day and within the option expiration. For instance, if the first skew observation is on 2000-04-05, the contracts expire on 2000-04-21, and the jump is observed on 2000-04-12, then we will assign $\mathrm{D}=1$ (i.e. consider as a jumping day) to all days between 2000-04-05 and 2000-04-11.

Finally, to test research question IV, put ATM IV is retained as a control variable in the negative jumps - put model and call ATM IV is retained as a control variable in the positive jumps - call model.

[^48]Below, in Table $2^{109}$, we show some descriptive statistics for skews, always taking HAL as example. The statistics are reported for the dataset before controls on jumps and ATM IV controls are applied, since we want to present the broadest dataset.

Some interesting observations are as follows: (1) as expected in our research question I, the put IV skews, both for the small negative jump and big negative jump datasets, are significantly ${ }^{110}$ more positive during jump days than during normal days. This is consistent with our ex-ante expectation that if informed traders expect a negative jump in the stock, they will purchase more OTM puts relative to ATM / ITM puts; (2) unexpectedly, and contrary to our research question II, call IV skews, for both categories of positive jumps, are significantly more negative (and not less negative, as we would have expected) during jump days than during normal days. This apparently means that when traders expect positive jumps, they purchase more ATM / ITM calls than OTM calls. This sounds surprising and will later be analyzed more in depth through our model, applied to the other stocks too. Furthermore, consistently with our caveat 3 in the research questions and with prior evidence (Diavatopoulos et al., 2012), the significance of the difference between mean skews is higher for the OTM-ATM skew than for the OTM-ITM skew, both for puts and calls. However, this is just a preliminary descriptive finding.

[^49]| Descriptive statistics of volatility skew for HAL |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | Put |  | Call |  |
|  |  | skew OTM-ATM | skew OTM-ITM | skew OTM-ATM | skew OTM-ITM |
|  |  | small negative jumps (5\%) |  | small positive jumps (95\%) |  |
| Normal days | M | 2.02\% | 2.95\% | -0.99\% | -2.88\% |
|  | SD | 1.08\% | 2.13\% | 0.92\% | 2.23\% |
|  | N | 1656 | 1740 | 1636 | 1832 |
| Jump days | M | 2.54\% | 3.54\% | -1.76\% | -2.92\% |
|  | SD | 1.14\% | 2.75\% | 1.19\% | 3.41\% |
|  | N | 214 | 255 | 172 | 266 |
|  | t-statistic | (6.4)*** | (3.32)*** | $(-8.19)^{* * *}$ | (-0.19) |
|  |  | big negative jumps (1\%) |  | big positive jumps (99\%) |  |
| Normal days | M | 2.06\% | 2.99\% | -1.04\% | -2.84\% |
|  | SD | 1.09\% | 2.19\% | 0.96\% | 2.40\% |
|  | N | 1823 | 1935 | 1757 | 2024 |
| Jump days | M | 2.62\% | 3.94\% | -1.87\% | -4.05\% |
|  | SD | 1.25\% | 3.17\% | 0.90\% | 2.51\% |
|  | N | 47 | 60 | 51 | 74 |
|  | t-statistic | $(3.01) * * *$ | (2.29)** | $(-6.44)^{* * *}$ | $(-4.09)^{* * *}$ |

* Significant at $10 \%$. ${ }^{* *}$ Significant at 5\%. *** Significant at $1 \%$.

Table 2: Descriptive statistics for HAL, IV skew, January 1, 1996 to December 31, 2017
Figure 7 depicts Table 2 findings for an easier graphical representation.


Figure 7: HAL mean skew and observations by jump, across skew and option type
Figure 8 shows skew descriptive statistics for HAL, differentiating between EAD and non-EAD periods.


Figure 8: HAL mean skew and observations by EAD-jump, across skew and option type
We can notice that the difference between mean skews during normal and jump days seems to persist regardless of whether we consider normal or EAD periods. We also find that not all categories are always represented: for instance, HAL misses OTM-ATM skew observations for big jump days during EAD periods ${ }^{111}$. Our statistical model will try to shed light on this.

Figure 9 plots the number of days per calendar quarter during which we observe a skew, small jump or big jump, divided across the two skew definitions and option types. As usual, in the Appendix there is a similar chart for the cross-section.

[^50]

Figure 8: HAL observed skew days and jump days, across skew and option type
We see that in the first years of our sample there are very few skew observations ${ }^{112}$ for HAL. This could weaken the reliability of our model because in the first periods, even if jumps were observed, then these will not be included in the estimation as the days would not be included due to missing skew observations.

### 3.1 Model

We use a probit model ${ }^{113}$ in order to estimate parameters measuring the predictive ability of skews and ATM IV on future jumps. The most general specification of the probit is:

[^51]$$
\operatorname{Prob}\left(D_{t+1 \rightarrow t+T}=1 \mid \text { skew }_{t}, I V_{t}\right)=\Phi\left(\alpha+\beta_{1} \text { skew }_{t}+\beta_{2} I V_{t}\right)+\varepsilon_{t}
$$

The probability of observing a jump during the option window (from the day following the current day $t+1$ to option expiry $t+T$ ) is equal to a non-linear function $\Phi$ of the regressor, plus estimation errors $\varepsilon_{t}$.

In a probit model, the function $\Phi$ is a cumulative standard normal distribution function, which is chosen because, given a value of the linear expression, it always returns a value which is between 0 and 1 . This is paramount, as we are trying to regress a binary variable which should represent a probability: of course, a probability must be between 0 and 1.

In order to answer research question I, we will use the probit without the control variable ATM IV and we will apply it to put skew and negative jumps. Hence, we will run 4 probit regressions for each stock: 2 put skews times 2 definitions of negative jumps.

In order to answer research question II, we will use the probit without the control variable ATM IV and we will apply it to call skew and positive jumps. Hence, we will run 4 probit regressions for each stock: 2 call skews times 2 definitions of positive jumps.

To answer research question III, we will use the probit without the control variable ATM IV and we will apply it both to put and call skew, negative and positive jumps, respectively. Furthermore, we will distinguish between EAD and normal period regressions, thus running 16 regressions for each stock: 2 option types times 2 periods times 2 skew types times 2 definitions of jumps.

Finally, to answer research question IV, we repeat the whole procedure inserting ATM IV as a control variable, thus running further 24 regressions for each stock.

Given we have a sample of 24 stocks, this returns 48 regressions times 24 stocks, which equals 1152 regressions.

Below, a brief discussion of the theory underpinning the probit model.
As noted in Bruno (2016), we can characterize any probit model as a latent regression model. Let us take a generic probit:

$$
y=\Phi\left(x^{\prime} \beta\right)+\varepsilon
$$

Then, we can express this through a latent regression, with $y^{*}$ being a continuous random variable:

$$
y^{*}=x^{\prime} \beta+u
$$

with $u$ being a zero mean random variable that is independent from $x$ and with $u \sim \Phi$, such that $\Phi$ is a distribution function symmetric around zero (in our case, a standard normal CDF).

Then, let $y=1$ correspond to $y^{*}>0$. This happens only if $u>-x^{\prime} \beta$. Therefore:

$$
\operatorname{Prob}(y=1 \mid x)=\operatorname{Prob}\left(u>-x^{\prime} \beta \mid x\right)
$$

Since $u$ and $x$ are independent, $\operatorname{Prob}\left(u \leq x^{\prime} \beta \mid x\right)=\Phi\left(x^{\prime} \beta\right)$. Since $\Phi$ is symmetric around zero, it is also true that $\operatorname{Prob}\left(u>-x^{\prime} \beta \mid x\right)=\Phi\left(x^{\prime} \beta\right)$. Hence:

$$
\operatorname{Prob}(y=1 \mid x)=\Phi\left(x^{\prime} \beta\right)
$$

which is equivalent to the probit model.
In probit estimation, $\operatorname{Var}(u)=\sigma^{2}$ and $\beta$ cannot be separately identified. Therefore, we must first fix $\sigma^{2}$ to some value to be able to get $\beta$. In probit, $\sigma^{2}=1$. By so doing, the classic estimation assumes homoscedastic errors. As we will see, that is not always the case. If we are in presence of heteroscedastic errors, then we should adjust the estimation method so that the variance of the errors in the latent regression is no more fixed to some value.

Probit coefficients are estimated by maximizing the log-likelihood function of the sample, yielding a consistent estimate.

In order to allow for heteroscedastic errors, we can set $\sigma_{i}^{2}=e^{z_{i}^{\prime} \delta}$. Therefore:

$$
\operatorname{Prob}\left(y_{i}=1 \mid x\right)=\Phi\left(\frac{x_{i}^{\prime} \beta}{e^{z_{i}^{\prime} \delta}}\right)
$$

Now, running this probit, we can capture heteroscedastic errors to avoid any estimate is inconsistent. Moreover, we can get a Likelihood Ratio (LR) test for the null of homoscedastic errors, i.e. $\delta=0^{114}$.

Another important characteristic of probit models is that marginal effects do not coincide with estimated model coefficients and they vary over the sample, differently from linear regression. In fact, when we estimate the $\beta \mathrm{s}$, these are the coefficients of the latent regression, which tell us the effect of a change in $x$ on $y^{*}$, which is not the predicted probability $y$. The $y^{*}$ is the $z$-value, which is the input of the $\Phi$ function. Since $\Phi$ is not linear, then the marginal effect of $y^{*}$ on the predicted probability $y$ is not constant over the entire sample. If $x$ is large and $\beta$ is different from zero, then also fitted $y^{*}$ will be large. As $y^{*}(=$ zvalue $) \rightarrow+\infty$, the CDF $\Phi$ tends to 1 , so that marginal effects of changes in regressors on the predicted probability become negligible (Bruno, 2016).

This technical excursus is useful to understand that we will estimate coefficients which are not interpretable as in a linear regression as fixed marginal effects across the entire sample. Hence, we will not say that "a change in a regressor will change the predicted probability of a future jump by $\mathrm{x} \%{ }^{1115}$.

We do not have any issue of endogeneity; we do not have any issue of one- or twoway causation in our estimation samples, as we do not have dummies as regressor or a regressor perfectly predicting a binary event (Bruno, 2016).

As a reminder, below the two definitions of skew ${ }^{116}$ :

$$
\begin{aligned}
\text { skew }_{\text {OTM-ATM }} & =I V_{\text {OTM }}-I V_{A T M} \\
\text { skew }_{\text {OTM-ITM }} & =I V_{\text {OTM }}-I V_{I T M ~}
\end{aligned}
$$

In the next section, we will present the main results of the empirical test.

[^52]
## 4. Empirical results, discussion and diagnostics

### 4.1 Research question I: is the probability of observing negative jumps in the underlying stocks positively related to a more positive put skew over the

## time-series?

In order to answer this question, we collect the results of 96 probit regressions for puts: 24 stocks times 2 skew types times 2 jump definitions, for the sample that includes both normal and EAD periods, using jump controls but not the ATM IV control.

Importantly, for each regression, we ran both the specification assuming homoscedasticity and the one allowing for heteroscedasticity. Then, looking at the Likelihood Ratio test ${ }^{117}$, we verify which regressions are best specified as homo- or heteroscedastic. For those regressions that are best specified as heteroscedastic, we keep the coefficients estimated using heteroscedastic probits.

| Skew type Jump type | Homoscedastic \% |
| :--- | :--- |
| OTM-ATM | big negative |
| OTM-ATM | small negative |

Table 3: Percentage of homoscedastic probits ${ }^{118}$ : negative jumps, put skews, all periods

As we can see in Table 3, most often across our 24 stocks the homoscedastic specification well specifies the underlying data, with the notable exception of small negative jumps regressed on put OTM-ATM skew, for which the homoscedastic specification is correct for less than $50 \%$ of times.

But is the sign of the skew coefficient changing by specifying probits as heteroscedastic?

| Skew type | Jump type | Same skew coefficient sign $\%$ |
| :--- | :--- | ---: |
| OTM-ATM | big negative | $100.00 \%$ |
| OTM-ATM | small negative | $100.00 \%$ |
| OTM-ITM | big negative | $100.00 \%$ |
| OTM-ITM | small negative | $83.30 \%$ |

[^53]Table 4: Percentage of heteroscedastic skew coefficients that have the same sign as homoscedastic skew coefficients: negative jumps, put skews, all periods

As we can see in Table 4, the sign of the skew coefficients estimated with heteroscedastic probit is almost always equal to the sign obtained using a homoscedastic specification. Hence, we can state that the vast majority of times, the economic sense of the relationship between skews and jumps does not change depending on the statistical specification.

As in previous research (Garleanu, Pedersen and Poteshman, 2009; An et al., 2014), we average the estimated time-series coefficients across the 24 stocks in our sample.

| Skew type Jump type | Mean \# of obs | Mean constant coef | Mean skew coef |
| :--- | :---: | :---: | ---: |
| OTM-ATM | big negative | 1582 | -1.86 |
| OTM-ATM | small negative | 1528 | -0.98 |
| OTM-ITM | big negative | 1384 | -1.78 |
| OTM-ITM | small negative | 1321 | -0.97 |

Table 5: Mean \# of observations ${ }^{119}$, constant and skew coefficients: negative jumps, put skews, all periods

| Skew type Jump type | Skew coef \% positive signif* |
| :--- | ---: |
| OTM-ATM big negative | $66.70 \%$ |
| OTM-ATM small negative | $70.80 \%$ |
| OTM-ITM | big negative |
| OTM-ITM | small negative |

* Significant at least at 10\%.

Table 6: Percentage of significantly positive skew coefficients ${ }^{120}$ : negative jumps, put skews, all periods

Results in Table 5 and Table 6 are encouraging. For at least two thirds of our 24 stocks in the period 1996-2017 a more positive put skew has been associated with a higher probability of observing future negative jumps within the option expiration window. In

[^54]fact, all mean skew coefficients are positive ${ }^{121}$. Hence, evidence cannot reject hypothesis I.

This finding adds to previous research, since it shows that single stock option skews contain information that is significant not only for normal returns (Xing, Zhang and Zhao, 2010), but also for jumps, extending the methodology used for index options by Doran, Peterson and Tarrant (2007).

Below, we explain and report some goodness of fit measures for the probit regressions.
Firstly, we can compute (Mc Fadden's) pseudo R squared (Bruno, 2016):

$$
R^{2}=1-\frac{L(\beta)}{L(y)}
$$

$L(\beta)$ is the value of the maximized log-likelihood and $L(y)$ is the value of the loglikelihood function evaluated for the model with only the intercept. Therefore, $0<R^{2}<$ 1 and the closer $R^{2}$ to 1 , the better the fit ${ }^{122}$.

| Skew type Jump type | Mean pseudo R squared* |  |
| :--- | :--- | :--- |
| OTM-ATM | big negative | $1.71 \%$ |
| OTM-ATM | small negative | $0.98 \%$ |
| OTM-ITM | big negative | $1.50 \%$ |
| OTM-ITM | small negative | $0.93 \%$ |

* Only homoscedastic models.

Table 7: Mean pseudo $R^{2}$ : negative jumps, put skews, all periods
In Table 7 we can easily spot the low overall explanatory power. This result does not come unexpected, since jumps are rare events and, hence, it is far from easy to precisely predict them.

Other goodness-of-fit statistics include sensitivity, specificity, positive predicted value (ppv) and negative predicted value (npv) (Bruno, 2016).

[^55]In general, we decide a probability threshold over which our model predicts a return to be a jump:

$$
\widehat{D}_{\iota}=\left\{\begin{array}{cc}
1 \text { if } \Phi\left(x^{\prime} \hat{\beta}\right) \geq 0.5 \\
0 & \text { else }
\end{array}\right\}
$$

The above equation means that if the predicted probability is greater than $50 \%$, then we identify a jump; otherwise, we identify a normal return (Bruno, 2016). Usually, a $50 \%$ threshold is used. In this thesis, we will use $20 \%$, a threshold that will be used to compute sensitivity, specificity, ppv and npv ${ }^{123}$.

Sensitivity shows the true positive rate ${ }^{124}$ and it explains, given the existence of a jump in-sample, what is the probability of classifying it correctly as a jump using the model.

Specificity shows the true negative rate ${ }^{125}$, which explains, given that we do not observe a jump in-sample, what is the probability of classifying it correctly as a normal day using the model.

Ppv shows the probability of our model correctly predicting a jump, i.e. given the model predicts a future jump day, what is the probability of observing a jump in-sample.

Finally, npv shows the probability of our model correctly predicting a normal day (given the model predicts a normal day, what is the probability of observing a normal day insample).

I focus on reporting only ppv and npv, since when we observe a jump, we know it has been a jump according to our definition. Hence, there is less need to verify sensitivity and specificity. On the other hand, we would like to understand whether there will be a jump, given that our model predicts a jump ex-ante.

[^56]One relevant caveat is the following: the ppv and npv reported are only those of the homoscedastic models. Hence, they will represent the means across fewer than 24 stocks ${ }^{126}$.

| Skew type Jump type $\quad$ Mean ppv* |  |
| :--- | :--- |
| OTM-ATM big negative | $18.20 \%$ |
| OTM-ATM small negative | $24.50 \%$ |
| OTM-ITM big negative | $21.20 \%$ |
| OTM-ITM small negative | $24.00 \%$ |
| * Only homoscedastic models. |  |

Table 8: Mean ppv for homoscedastic models: negative jumps, put skews, all periods
Table 8 is quite discouraging. On average across the sample stocks, our models can predict jumps correctly only one in five times for big jumps (more rare) and one in four times for small jumps. This may be a problem due to the nature itself of jumps: they are very rare events and one should compare these models to our models used in order to predict jumps to properly assess their relative performance. However, the choice of a $20 \%$ threshold may influence downwards the ppv, since whereas on the one hand a lower initial threshold allows the model to identify more future days as jump, on the other hand the predicted jumping days may have a lower probability of showing an actual jump. In any case, these results suggest that while there exists a statistically significant relationship between current put skews and following negative jumps for single stocks, the economic significance may be low.

| Skew type Jump type $\quad$ Mean npv* |  |
| :--- | :--- |
| OTM-ATM big negative | $95.40 \%$ |
| OTM-ATM small negative | $75.30 \%$ |
| OTM-ITM big negative | $94.30 \%$ |
| OTM-ITM small negative | $83.40 \%$ |
| * Only homoscedastic models. |  |

## Table 9: Mean npv for homoscedastic models: negative jumps, put skews, all periods

Table 9 shows that the models are good at predicting normal days. This is obvious and irrelevant for practical purposes, given that normal days represent the vast majority of days for stocks.

[^57]Finally, we will present a chart to give a more intuitive explanation of what is happening in the background.


Figure 9: HAL probability of observing small negative jumps on OTM-ITM put skew, all periods

Figure 9 depicts a HAL example. We can see the fitted (predicted) probability of observing a small negative jump increasing as OTM-ITM put skew becomes more positive, as one would expect. The prediction by the probit model reflects in-sample data ${ }^{127}$ : after dividing observed OTM-ITM put skews in deciles, we compute the mean jump probability per skew decile and plot them. The model does a decent job in fitting the jumps. However, we can notice that probabilities are always very low, given the rare nature of jumps.

The main conclusions of the results for research question I are:

[^58]1. The ex-ante hypothesis cannot be rejected: we find that a higher probability of observing future negative jumps in single stocks is positively related to a previous steepening of put skew (i.e. more positive), for at least two thirds of the stocks examined in a significant way;
2. However, the pseudo $R$ squared and the positive predicted value warn us that the economic significance may be low: predicting negative jumps is tough business;
3. A caveat: ex-ante, we would have expected a stronger statistical significance / economic significance for OTM-ATM skews, since single stocks exhibit a smirk and not a monotonically downward sloping skew. However, we do not find strong evidence for this intuition.

In the Appendix, we present tables reporting results and diagnostics for all 96 regressions separately.

### 4.2 Research question II: is the probability of observing positive jumps in the underlying stocks positively related to a less negative (or more positive) call skew over the time-series?

In order to answer this question, we collect the results of 96 probit regressions for calls: 24 stocks times 2 skew types times 2 jump definitions, for the sample that includes both normal and EAD periods, using jump controls but not the ATM IV control. As with research question I, we run both homoscedastic and heteroscedastic specifications.

| Skew type Jump type | Homoscedastic $\%$ |
| :--- | ---: |
| OTM-ATM | big positive |$\quad 54.20 \%$

Table 10: Percentage of homoscedastic probits: positive jumps, call skews, all periods
Table 10 shows that, relative to put data, call models exhibit much more heteroscedasticity in errors. Table 11 below shows that the sign of skew coefficients in heteroscedastic models is almost always equal to the sign estimated in homoscedastic models, as in the put case.

| Skew type Jump type | Same skew coefficient sign \% |
| :--- | ---: |
| OTM-ATM | big positive |
| OTM-ATM | small positive |

Table 11: Percentage of heteroscedastic skew coefficients that have the same sign as homoscedastic skew coefficients: positive jumps, call skews, all periods

| Skew type Jump type | Mean \# of obs Mean constant coef | Mean skew coef |  |
| :--- | :---: | :---: | ---: |
| OTM-ATM | big positive | 1325 | -2.04 |
| OTM-ATM | small positive | 1269 | -1.09 |
| OTM-ITM | big positive | 1375 | -1.59 |
| OTM-ITM | small positive | 1309 | -0.76 |

Table 12: Mean \# of observations ${ }^{128}$, constant and skew coefficients: positive jumps, call skews, all periods

| Skew type Jump type | Skew coef \% positive signif* |
| :--- | ---: |
| OTM-ATM big positive | $12.50 \%$ |
| OTM-ATM small positive | $8.33 \%$ |
| OTM-ITM | big positive |
| OTM-ITM | small positive |

Table 13: Percentage of significantly positive skew coefficients: positive jumps, call skews, all periods

| Skew type Jump type | Skew coef \% negative signif* |
| :--- | ---: |
| OTM-ATM big positive | $58.30 \%$ |
| OTM-ATM | small positive |
| OTM-ITM | big positive |
| OTM-ITM | small positive |

* Significant at least at 10\%.

Table 14: Percentage of significantly negative skew coefficients: positive jumps, call skews, all periods

Tables 12, 13 and 14 show unexpected results, which vary depending on the skew used in the probit regressions. Firstly, the better news. The mean skew coefficients for OTM-ITM call skew are positive as posited in hypothesis II. Only around 40\% of them are significantly positive, though. Hence, on average across our sample a less negative

[^59](or more positive) OTM-ITM call skew is positively related to a higher probability of observing future positive jumps ${ }^{129}$. A big caveat is that the statistical significance is much smaller than for put skews and negative jumps, which goes against the initial hypothesis ${ }^{130}$. The situation dramatically worsens for OTM-ATM call skew. Here, we see that mean skew coefficients are even negative and Table 14 shows that the negative relationship is statistical significant for around two thirds of stocks, depending on jump definition. This goes in the opposite direction of our initial hypothesis. Data are telling us that the more negative the OTM-ATM call skew, the higher the probability of observing a future positive jump. This suggests that when traders bid up ATM call IV relative to OTM call IV, they are expecting a higher probability of positive jumps. This finding goes also against previous literature demonstrating that OTM contracts exhibit the highest leverage and thus should be the preferred avenue for informed trading (Easley, O'Hara and Srinivas, 1998).

A possible explanation that would be still consistent with previous research on informed trading is the following. If traders expect a positive jump, they may act in three ways: (1) if they play on Delta, they will likely buy a Delta-positive structure, the simplest of which is long OTM call; but (2) if they play on Vega/Gamma in expectation of higher IV/RV ${ }^{131}$ due to the jump, they will likely buy a Vega/Gamma positive structure with minimum Delta risk: (2a) if they expect a large jump and increase in IV/RV, they are more likely to buy strangles, thus bidding up OTM call IV; (2b) however, if they expect a smaller jump and increase in IV/RV, then they should buy straddles, thus bidding up ATM call IV ${ }^{132}$. If the majority of traders chose strategy (2b), then we would observe

[^60]an increase in ATM call IV relative to OTM call IV, i.e. a more negative call skew would be consistent with a higher probability of observing a future positive jump. This is what the results seem to tell us. In particular, as one would expect in the (2a) situation, Table 14 shows that the statistical significance is much higher for the OTM-ATM regressions with small jumps as dependent variable.

The above discussion tells us that call skew brings a rather weak and ambiguous signal for the probability of observing a future positive jump in the stock. Hence, evidence in favor of hypothesis II is ambiguous and not clear enough to arrive at a clear-cut conclusion. Of course, a problem may be given by relatively uninformed traders (e.g. retails) trading call options on stocks. As far as this point is concerned, one would need a categorization similar to the one used in previous research e.g. Garleanu, Pedersen and Poteshman (2009).

Below, the usual goodness of fit measures for the probit regressions.

| Skew type Jump type | Mean pseudo R squared* |
| :--- | ---: |
| OTM-ATM big positive | -Inf |
| OTM-ATM small positive | $4.34 \%$ |
| OTM-ITM big positive | $1.12 \%$ |
| OTM-ITM small positive | $0.57 \%$ |
| O Only homoscedastic models. |  |

Table 15: Mean pseudo $R^{2}$ : positive jumps, call skews, all periods
Table 15 shows that, as for the put case, the fit of the model is rather weak. Interestingly, it is by far highest for the OTM-ATM small positive regressions, suggesting that traders expecting a small positive jump might be used to buying ATM call IV using straddles.

| Skew type Jump type | Mean ppv* |  |
| :--- | :--- | ---: |
| OTM-ATM | big positive | $10.80 \%$ |
| OTM-ATM | small positive | $29.10 \%$ |
| OTM-ITM | big positive | $7.14 \%$ |
| OTM-ITM | small positive | $25.50 \%$ |

* Only homoscedastic models.

Table 16: Mean ppv for homoscedastic models: positive jumps, call skews, all periods
Table 16 shows that the positive predicted value remains low also for the call skew / positive jump models. Furthermore, it is even lower for big jumps, consistent with
jumps being rare events difficult to correctly predict. Interestingly, the predictive power improves for call small jumps models relative to put models.

| Skew type Jump type | Mean npv* |  |
| :--- | :--- | :--- |
| OTM-ATM big positive | $95.20 \%$ |  |
| OTM-ATM small positive | $85.10 \%$ |  |
| OTM-ITM big positive | $95.10 \%$ |  |
| OTM-ITM small positive | $84.90 \%$ |  |
| * Only homoscedastic models. |  |  |

Table 17: Mean npv for homoscedastic models: positive jumps, call skews, all periods Table 17 shows that, as with puts, normal days are the rule in stocks.

The main conclusions of the results for research question II are:

1. The evidence supporting our ex-ante hypothesis is ambiguous: we find that the sign and significance of the relationship between the prior observation of the steepness of call skew and the following higher probability of observing positive jumps depends on both skew specification and jump definition;
2. Furthermore, the pseudo R squared and the positive predicted value warn us that the economic significance may be low: predicting positive jumps is tough business (as it is with negative jumps);
3. Call skew does not seem better at predicting positive jumps than put skew is at predicting negative jumps; furthermore, considerations about possible alternative Vega/Gamma strategies around jumps influence the results and would merit further research.

In the Appendix, we present tables reporting results and diagnostics for all 96 regressions separately.

### 4.3 Research question III: if the skew proves to be significantly related to following jumps, does this statistical relationship characterize normal periods or is it limited to earnings announcement periods?

To answer this third research question, we collect data on 384 probit regressions: 24 stocks times 2 skew definitions times 2 jump definitions times 2 periods (EAD vs
normal/NO-EAD) times 2 option types (call vs put), keeping only regressions without the ATM IV control.

| Option type | Skew type Sample Jump type | Homoscedastic $\%$ |  |  |
| :--- | :--- | :--- | :--- | :--- |
| Call | OTM-ATM | Full | big positive | $54.20 \%$ |
| Call | OTM-ATM | Full | small positive | $37.50 \%$ |
| Call | OTM-ATM | EAD | big positive | $83.30 \%$ |
| Call | OTM-ATM | EAD | small positive | $70.80 \%$ |
| Call | OTM-ATM | Normal | big positive | $62.50 \%$ |
| Call | OTM-ATM | Normal | small positive | $37.50 \%$ |
| Call | OTM-ITM | Full | big positive | $79.20 \%$ |
| Call | OTM-ITM | Full | small positive | $58.30 \%$ |
| Call | OTM-ITM | EAD | big positive | $87.50 \%$ |
| Call | OTM-ITM | EAD | small positive | $70.80 \%$ |
| Call | OTM-ITM | Normal | big positive | $87.50 \%$ |
| Call | OTM-ITM | Normal | small positive | $58.30 \%$ |
| Put | OTM-ATM | Full | big negative | $70.80 \%$ |
| Put | OTM-ATM | Full | small negative | $45.80 \%$ |
| Put | OTM-ATM | EAD | big negative | $91.70 \%$ |
| Put | OTM-ATM | EAD | small negative | $79.20 \%$ |
| Put | OTM-ATM | Normal | big negative | $79.20 \%$ |
| Put | OTM-ATM | Normal | small negative | $50.00 \%$ |
| Put | OTM-ITM | Full | big negative | $91.70 \%$ |
| Put | OTM-ITM | Full | small negative | $75.00 \%$ |
| Put | OTM-ITM | EAD | big negative | $95.80 \%$ |
| Put | OTM-ITM | EAD | small negative | $87.50 \%$ |
| Put | OTM-ITM | Normal | big negative | $100.00 \%$ |
| Put | OTM-ITM | Normal | small negative | $83.33 \%$ |

Table 18: Percentage of homoscedastic probits: full vs EAD vs normal periods
Table 18 shows that, except for put OTM-ITM specifications, it is more likely that homoscedastic models are the best specification for EAD periods rather than normal periods. Full and normal samples are comparable. The analysis on the sign of skew coefficients shows that, as usual, signs do not change between homo- and heteroscedastic specifications ${ }^{133}$.

[^61]| Option type | Skew type | Sample | Jump type | Mean \# of obs | Mean constant coef | Mean skew coef |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Call | OTM-ATM | Full | big positive | 1325 | -2.04 | -8.84 |
| Call | OTM-ATM | Full | small positive | 1269 | -1.09 | -17 |
| Call | OTM-ATM | EAD | big positive | 355 | -2.01 | -4.72 |
| Call | OTM-ATM | EAD | small positive | 342 | -1.12 | -12.3 |
| Call | OTM-ATM | Normal | big positive | 970 | -2.20 | -9.3 |
| Call | OTM-ATM | Normal | small positive | 927 | -1.17 | -15.4 |
| Call | OTM-ITM | Full | big positive | 1375 | -1.59 | 4.29 |
| Call | OTM-ITM | Full | small positive | 1309 | -0.76 | 4.5 |
| Call | OTM-ITM | EAD | big positive | 372 | -1.43 | 4.31 |
| Call | OTM-ITM | EAD | small positive | 357 | -0.62 | 5.62 |
| Call | OTM-ITM | Normal | big positive | 1003 | -1.91 | 2.4 |
| Call | OTM-ITM | Normal | small positive | 952 | -0.82 | 4.44 |
| Put | OTM-ATM | Full | big negative | 1582 | -1.86 | 4.58 |
| Put | OTM-ATM | Full | small negative | 1528 | -0.98 | 0.505 |
| Put | OTM-ATM | EAD | big negative | 434 | -2.04 | 2.71 |
| Put | OTM-ATM | EAD | small negative | 421 | -0.77 | 2.32 |
| Put | OTM-ATM | Normal | big negative | 1148 | -2.24 | 2.79 |
| Put | OTM-ATM | Normal | small negative | 1107 | -1.12 | 1.36 |
| Put | OTM-ITM | Full | big negative | 1384 | -1.78 | 4.81 |
| Put | OTM-ITM | Full | small negative | 1321 | -0.97 | 4.35 |
| Put | OTM-ITM | EAD | big negative | 381 | -1.69 | 2.66 |
| Put | OTM-ITM | EAD | small negative | 365 | -0.77 | 0.48 |
| Put | OTM-ITM | Normal | big negative | 1003 | -1.90 | 4.43 |
| Put | OTM-ITM | Normal | small negative | 956 | -1.05 | 3.82 |

Table 19: Mean \# of observations ${ }^{134}$, constant and skew coefficients: full vs EAD vs normal periods

| Option type | Skew type | Sample | Jump type | Skew coef \% positive signif* |
| :---: | :---: | :---: | :---: | :---: |
| Call | OTM-ATM | Full | big positive | 12.50\% |
| Call | OTM-ATM | Full | small positive | 8.33\% |
| Call | OTM-ATM | EAD | big positive | 16.70\% |
| Call | OTM-ATM | EAD | small positive | 0.00\% |
| Call | OTM-ATM | Normal | big positive | 8.33\% |
| Call | OTM-ATM | Normal | small positive | 12.50\% |
| Call | OTM-ITM | Full | big positive | 41.70\% |
| Call | OTM-ITM | Full | small positive | 45.80\% |
| Call | OTM-ITM | EAD | big positive | 25.00\% |
| Call | OTM-ITM | EAD | small positive | 37.50\% |
| Call | OTM-ITM | Normal | big positive | 33.30\% |
| Call | OTM-ITM | Normal | small positive | 54.20\% |
| Put | OTM-ATM | Full | big negative | 66.70\% |
| Put | OTM-ATM | Full | small negative | 70.80\% |
| Put | OTM-ATM | EAD | big negative | 33.30\% |
| Put | OTM-ATM | EAD | small negative | 29.20\% |
| Put | OTM-ATM | Normal | big negative | 62.50\% |
| Put | OTM-ATM | Normal | small negative | 66.70\% |
| Put | OTM-ITM | Full | big negative | 66.70\% |
| Put | OTM-ITM | Full | small negative | 66.70\% |
| Put | OTM-ITM | EAD | big negative | 20.80\% |
| Put | OTM-ITM | EAD | small negative | 33.30\% |
| Put | OTM-ITM | Normal | big negative | 54.20\% |
| Put | OTM-ITM | Normal | small negative | 50.00\% |

* Significant at least at $10 \%$.

Table 20: Percentage of significantly positive skew coefficients: full vs EAD vs normal periods

[^62]| Option type | Skew type | Sample | Jump type | Skew coef \% negative signif* |
| :---: | :---: | :---: | :---: | :---: |
| Call | OTM-ATM | Full | big positive | 58.30\% |
| Call | OTM-ATM | Full | small positive | 87.50\% |
| Call | OTM-ATM | EAD | big positive | 37.50\% |
| Call | OTM-ATM | EAD | small positive | 54.20\% |
| Call | OTM-ATM | Normal | big positive | 45.80\% |
| Call | OTM-ATM | Normal | small positive | 75.00\% |
| Call | OTM-ITM | Full | big positive | 8.33\% |
| Call | OTM-ITM | Full | small positive | 16.70\% |
| Call | OTM-ITM | EAD | big positive | 4.17\% |
| Call | OTM-ITM | EAD | small positive | 16.70\% |
| Call | OTM-ITM | Normal | big positive | 20.80\% |
| Call | OTM-ITM | Normal | small positive | 20.80\% |
| Put | OTM-ATM | Full | big negative | NA |
| Put | OTM-ATM | Full | small negative | NA |
| Put | OTM-ATM | EAD | big negative | 20.80\% |
| Put | OTM-ATM | EAD | small negative | 16.70\% |
| Put | OTM-ATM | Normal | big negative | 12.50\% |
| Put | OTM-ATM | Normal | small negative | 16.70\% |
| Put | OTM-ITM | Full | big negative | NA |
| Put | OTM-ITM | Full | small negative | NA |
| Put | OTM-ITM | EAD | big negative | 4.17\% |
| Put | OTM-ITM | EAD | small negative | 8.33\% |
| Put | OTM-ITM | Normal | big negative | 4.17\% |
| Put | OTM-ITM | Normal | small negative | 0.00\% |

* Significant at least at $10 \%$.

Table 21: Percentage of significantly negative skew coefficients: full vs EAD vs normal periods

Consistent with our hypothesis for research question III, we find in Table 19 that the signs of the skew-jump relationship are stable across the full sample and the EAD and normal sub-samples, as commented previously. In Table 20, we observe that the statistical significance only slightly deteriorates when we consider the normal subsample: for put skews and the OTM-ITM call skew, the percentage of significantly positive coefficients decreases by $5 \%-10 \%$ on average, remaining around or above $50 \%$. This provides support for the hypothesis that the skew-jump relationship is not EAD-driven. Furthermore, as expected, on average across our sample stocks coefficients are more likely to be significant for normal periods rather than for EAD periods. This is likely to be determined by a problem of sample size for the estimation of EAD-period coefficients. As can be seen in Table 19, the mean number of observations for EAD periods is substantially smaller than for normal periods something to be expected since EAD periods span fewer trading days. This is likely to affect the stability of estimated coefficients, weakening the statistical significance.

The situation changes drastically for OTM-ATM call skews (as should be expected given the results to research question II). The coefficients are negative and most often
significantly so. Again, the percentage of significantly negative coefficients slightly falls from the full sample to the normal sub-sample, but always remains above $50 \%$ on average. Interestingly, and further supporting the intuition developed in trying to explain results to research question III, stocks are much more likely to display significantly negative OTM-ATM call skew coefficients for small positive jumps than for big positive jumps. This is consistent with the intuition that traders will especially favor buying ATM structures (outright or straddles) when expecting small jumps, in accordance with prior research and the payoff structure of straddles versus strangles (Bennett, 2014).

Overall, these results say that we cannot reject hypothesis III, and support the hypothesis that informed trading in options markets is useful also for unscheduled events (jumps in this specific test) and not only for scheduled announcements (e.g. EADs) (Jin, Livnat and Zhang, 2012).

| Option type | Skew type | Sample | Jump type | Mean pseudo R squared* |
| :---: | :---: | :---: | :---: | :---: |
| Call | OTM-ATM | Full | big positive | -Inf |
| Call | OTM-ATM | Full | small positive | 4.34\% |
| Call | OTM-ATM | EAD | big positive | -Inf |
| Call | OTM-ATM | EAD | small positive | -Inf |
| Call | OTM-ATM | Normal | big positive | -Inf |
| Call | OTM-ATM | Normal | small positive | 5.31\% |
| Call | OTM-ITM | Full | big positive | 1.16\% |
| Call | OTM-ITM | Full | small positive | 0.57\% |
| Call | OTM-ITM | EAD | big positive | 2.11\% |
| Call | OTM-ITM | EAD | small positive | 2.05\% |
| Call | OTM-ITM | Normal | big positive | -Inf |
| Call | OTM-ITM | Normal | small positive | 1.04\% |
| Put | OTM-ATM | Full | big negative | 1.71\% |
| Put | OTM-ATM | Full | small negative | 0.98\% |
| Put | OTM-ATM | EAD | big negative | -Inf |
| Put | OTM-ATM | EAD | small negative | 0.94\% |
| Put | OTM-ATM | Normal | big negative | -Inf |
| Put | OTM-ATM | Normal | small negative | 1.63\% |
| Put | OTM-ITM | Full | big negative | 1.50\% |
| Put | OTM-ITM | Full | small negative | 0.93\% |
| Put | OTM-ITM | EAD | big negative | 1.43\% |
| Put | OTM-ITM | EAD | small negative | 1.12\% |
| Put | OTM-ITM | Normal | big negative | 1.82\% |
| Put | OTM-ITM | Normal | small negative | 0.82\% |

Table 22: Mean pseudo $R^{2}$ : full vs EAD vs normal periods
Table 22 confirms prior results for the overall sample period. The fit of the model remains unluckily low. Consistently with mean pseudo $R$ squared results found for
research question II, OTM-ATM call skew during normal periods provides the best fit by far.

| Option type | Skew type Sample Jump type | Mean ppv* |  |
| :--- | :--- | :--- | :--- |
| Call | OTM-ATM | Full | big positive |
| Call | OTM-ATM | Full | small positive |
| Call | OTM-ATM | EAD | big positive |
| Call | OTM-ATM | EAD | small positive |
| Call | OTM-ATM | Normal | big positive |
| Call | OTM-ATM | Normal | small positive |
| Call | OTM-ITM | Full | big positive |
| Call | OTM-ITM | Full | small positive |
| Call | OTM-ITM | EAD | big positive |
| Call | OTM-ITM | EAD | small positive |
| Call | OTM-ITM | Normal | big positive |
| Call | OTM-ITM | Normal | small positive |
| Put | OTM-ATM | Full | big negative |
| Put | OTM-ATM | Full | small negative |
| Put | OTM-ATM | EAD | big negative |
| Put | OTM-ATM | EAD | small negative |
| Put | OTM-ATM | Normal | big negative |
| Put | OTM-ATM | Normal | $30.80 \%$ |
| Put | OTM-ITM | Full | big negative |
| Put | OTM-ITM | Full | small negative |
| Put | OTM-ITM | EAD | big negative |
| Put | OTM-ITM | EAD | small negative |
| Put | OTM-ITM | Normal | big negative |
| Put | OTM-ITM | Normal | $25.50 \%$ |

* Only homoscedastic models.

Table 23: Mean ppv for homoscedastic models: full vs EAD vs normal periods
Table 23 shows that the predictive ability of our models remain low across the sample stocks. On average, we are able to ex-ante identify correctly a jump only one in four times. Two interesting observations are the following: (1) for put skews, the predictive ability in terms of ppv is higher during EAD periods, despite the statistical significance being lower as previously shown; and (2) for call skews, the predictive ability does not depend on the sample period, but on the jump definition, with the positive predicted value for small positive jumps being almost double the one for big positive jumps, especially for OTM-ATM call skews: this provides further evidence on the intuition about informed long straddle trading before small positive jumps ${ }^{135}$. The ppv results

[^63]are similar between the full sample and the normal sub-sample, supporting the reasoning that the skew-jump relationship is not EAD-driven.

| Option type | Skew type | Sample | Jump type | Mean npv* |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Call | OTM-ATM | Full | big positive |  | 95.20\% |
| Call | OTM-ATM | Full | small positive |  | 85.10\% |
| Call | OTM-ATM | EAD | big positive |  | 92.90\% |
| Call | OTM-ATM | EAD | small positive |  | 87.60\% |
| Call | OTM-ATM | Normal | big positive |  | 96.00\% |
| Call | OTM-ATM | Normal | small positive |  | 87.60\% |
| Call | OTM-ITM | Full | big positive |  | 95.10\% |
| Call | OTM-ITM | Full | small positive |  | 84.90\% |
| Call | OTM-ITM | EAD | big positive |  | 92.10\% |
| Call | OTM-ITM | EAD | small positive |  | 75.10\% |
| Call | OTM-ITM | Normal | big positive |  | 96.00\% |
| Call | OTM-ITM | Normal | small positive |  | 86.80\% |
| Put | OTM-ATM | Full | big negative |  | 95.40\% |
| Put | OTM-ATM | Full | small negative |  | 75.30\% |
| Put | OTM-ATM | EAD | big negative |  | 93.80\% |
| Put | OTM-ATM | EAD | small negative |  | 72.10\% |
| Put | OTM-ATM | Normal | big negative |  | 96.50\% |
| Put | OTM-ATM | Normal | small negative |  | 87.00\% |
| Put | OTM-ITM | Full | big negative |  | 94.30\% |
| Put | OTM-ITM | Full | small negative |  | 83.40\% |
| Put | OTM-ITM | EAD | big negative |  | 92.60\% |
| Put | OTM-ITM | EAD | small negative |  | 79.50\% |
| Put | OTM-ITM | Normal | big negative |  | 95.40\% |
| Put | OTM-ITM | Normal | small negative |  | 85.10\% |

Table 24: Mean npv for homoscedastic models: full vs EAD vs normal periods
Table 24 confirms usual results for the negative predicted value.
The main conclusions of the results for research question III are:

1. The evidence supporting the ex-ante hypothesis is quite strong: we find that the significance of the relationship between the prior observation of the steepness of skew and the following higher probability of observing jumps is comparable between the full sample and the normal sub-sample. Therefore, the skew-jump relationship is likely to be not entirely EAD-driven. Furthermore, but less interestingly, more coefficients are significant during normal periods than during EAD periods, most likely due to sample size issues;

[^64]2. Positive predicted value results show that for puts the predictive ability is higher during EAD periods and for calls is higher for small positive jumps. Ppv between the full sample and the normal sub-sample is very similar;
3. Taking the evidence from both the statistical significance and sign of the coefficients and the predictive ability, we can say that our intuition about different informed ATM IV trading for calls and puts before positive and negative jumps, respectively, would deserve future research.

In the Appendix, we present tables reporting results and diagnostics for all 384 regressions separately.

### 4.4 Research question IV: is the significance of the skew incremental with respect to ATM implied volatility?

To answer our last research question, we collect data on 576 probit regressions: 24 stocks times 2 skew definitions times 2 jump definitions times 3 periods (all days, EAD, normal) times 2 option types (call vs put), keeping only regressions with the ATM IV control.

| Option type | Skew type Sample | Jump type | Homoscedastic \% |
| :--- | :--- | :--- | :--- |
| Call | OTM-ATM |  |  |
| Call | OTM-ATM | Full | big positive |
| Call | OTM-ATM | EAD | big positive |
| Call | OTM-ATM | EAD | small positive |
| Call | OTM-ATM | Normal | big positive |
| Call | OTM-ATM | Normal | small positive |
| Call | OTM-ITM | Full | big positive |
| Call | OTM-ITM | Full | small positive |
| Call | OTM-ITM | EAD | big positive |
| Call | OTM-ITM | EAD | small positive |
| Call | OTM-ITM | Normal | big positive |
| Call | OTM-ITM | Normal | small positive |
| Put | OTM-ATM | Full | big negative |
| Put | OTM-ATM | Full | small negative |
| Put | OTM-ATM | EAD | big negative |
| Put | OTM-ATM | EAD | small negative |
| Put | OTM-ATM | Normal | big negative |
| Put | OTM-ATM | Normal | small negative |
| Put | OTM-ITM | Full | big negative |
| Put | OTM-ITM | Full | small negative |
| Put | OTM-ITM | EAD | big negative |
| Put | OTM-ITM | EAD | small negative |
| Put | OTM-ITM | Normal | big negative |
| Put | OTM-ITM | Normal | $75.00 \%$ |

Table 25: Percentage of homoscedastic probits: ATM IV control

In Table 25, the usual results on the percentage of models that are homoscedastic.
Contrary to our univariate model, by including the ATM IV control variable, the sign of the skew coefficients is subject to much higher noise between homo- and heteroscedastic specifications. This can be seen in Table 26 below.

| Option type | Skew type | Sample | Jump type | Same skew coefficient sign \% |
| :---: | :---: | :---: | :---: | :---: |
| Call | OTM-ATM | Full | big positive | 90.00\% |
| Call | OTM-ATM | Full | small positive | 73.70\% |
| Call | OTM-ATM | EAD | big positive | 75.00\% |
| Call | OTM-ATM | EAD | small positive | 66.70\% |
| Call | OTM-ATM | Normal | big positive | 87.50\% |
| Call | OTM-ATM | Normal | small positive | 77.80\% |
| Call | OTM-ITM | Full | big positive | 40.00\% |
| Call | OTM-ITM | Full | small positive | 68.80\% |
| Call | OTM-ITM | EAD | big positive | 33.30\% |
| Call | OTM-ITM | EAD | small positive | 80.00\% |
| Call | OTM-ITM | Normal | big positive | 40.00\% |
| Call | OTM-ITM | Normal | small positive | 66.70\% |
| Put | OTM-ATM | Full | big negative | 54.50\% |
| Put | OTM-ATM | Full | small negative | 37.50\% |
| Put | OTM-ATM | EAD | big negative | 72.70\% |
| Put | OTM-ATM | EAD | small negative | 69.20\% |
| Put | OTM-ATM | Normal | big negative | 54.50\% |
| Put | OTM-ATM | Normal | small negative | 55.60\% |
| Put | OTM-ITM | Full | big negative | 28.60\% |
| Put | OTM-ITM | Full | small negative | 50.00\% |
| Put | OTM-ITM | EAD | big negative | 71.40\% |
| Put | OTM-ITM | EAD | small negative | 50.00\% |
| Put | OTM-ITM | Normal | big negative | 40.00\% |
| Put | OTM-ITM | Normal | small negative | 91.70\% |

Table 26: Percentage of heteroscedastic skew coefficients that have the same sign as homoscedastic skew coefficients: ATM IV control

Before presenting results for the bivariate probit regressions, we check whether the two independent variables - skew and ATM IV - are in some way correlated. Importantly, if two independent variables happen to be much correlated, this will cause issues of multicollinearity for our model. In order to perform this check, we compute Variance Inflation Factors (VIFs): if the VIF is lower than 10, then we can assume that the regressor variables are not correlated and there are no issues of multicollinearity. Results relative to multicollinearity checks are presented in Table 27 below. We find that no model suffers from these issues.

| Option type | Skew type | Sample Jump type | Multicollinear \% |  |
| :--- | :--- | :--- | :--- | :--- |
| Call | OTM-ATM | Full | big positive | $0.00 \%$ |
| Call | OTM-ATM | Full | small positive | $0.00 \%$ |
| Call | OTM-ATM | EAD | big positive | $0.00 \%$ |
| Call | OTM-ATM | EAD | small positive | $0.00 \%$ |
| Call | OTM-ATM | Normal | big positive | $0.00 \%$ |
| Call | OTM-ATM | Normal small positive | $0.00 \%$ |  |
| Call | OTM-ITM | Full | big positive | $0.00 \%$ |
| Call | OTM-ITM | Full | small positive | $0.00 \%$ |
| Call | OTM-ITM | EAD | big positive | $0.00 \%$ |
| Call | OTM-ITM | EAD | small positive | $0.00 \%$ |
| Call | OTM-ITM | Normal big positive | $0.00 \%$ |  |
| Call | OTM-ITM | Normal small positive | $0.00 \%$ |  |
| Put | OTM-ATM | Full | big negative | $0.00 \%$ |
| Put | OTM-ATM | Full | small negative | $0.00 \%$ |
| Put | OTM-ATM | EAD | big negative | $0.00 \%$ |
| Put | OTM-ATM | EAD | small negative | $0.00 \%$ |
| Put | OTM-ATM | Normal big negative | $0.00 \%$ |  |
| Put | OTM-ATM | Normal small negative | $0.00 \%$ |  |
| Put | OTM-ITM | Full | big negative | $0.00 \%$ |
| Put | OTM-ITM | Full | small negative | $0.00 \%$ |
| Put | OTM-ITM | EAD | big negative | $0.00 \%$ |
| Put | OTM-ITM | EAD | small negative | $0.00 \%$ |
| Put | OTM-ITM | Normal big negative | $0.00 \%$ |  |
| Put | OTM-ITM | Normal small negative | $0.00 \%$ |  |

Table 27: Percentage of models suffering from multicollinearity issues: ATM IV control

| Option type | Skew type | Sample | Jump type | Mean \# of obs | Median constant coef M | Median skew coef | Median ATM IV coef |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Call | OTM-ATM | Full | big positive | 1325 | -2.99 | 7.23 | 0.63 |
| Call | OTM-ATM | Full | small positive | 1269 | -4.4 | 6.38 | 8.15 |
| Call | OTM-ATM | EAD | big positive | 355 | -2.15 | 0.24 | 1.95 |
| Call | OTM-ATM | EAD | small positive | 342 | -2.14 | -0.51 | 3.79 |
| Call | OTM-ATM | Normal | big positive | 970 | -4.35 | 7.26 | 6.53 |
| Call | OTM-ATM | Normal | small positive | 927 | -4.92 | 9.00 | 9.15 |
| Call | OTM-ITM | Full | big positive | 1019 | -2.9 | 2.01 | 3.79 |
| Call | OTM-ITM | Full | small positive | 979 | -3.66 | 2.49 | 7.60 |
| Call | OTM-ITM | EAD | big positive | 282 | -2.38 | 0.08 | 2.36 |
| Call | OTM-ITM | EAD | small positive | 273 | -1.96 | 2.25 | 5.71 |
| Call | OTM-ITM | Normal | big positive | 738 | -4.18 | 0.00 | 4.87 |
| Call | OTM-ITM | Normal | small positive | 706 | -3.46 | 2.42 | 7.47 |
| Put | OTM-ATM | Full | big negative | 1582 | -3.2 | 0.43 | 3.71 |
| Put | OTM-ATM | Full | small negative | 1528 | -2.94 | -0.14 | 5.46 |
| Put | OTM-ATM | EAD | big negative | 434 | -2.6 | -0.57 | 2.28 |
| Put | OTM-ATM | EAD | small negative | 421 | -1.56 | 0.82 | 4.06 |
| Put | OTM-ATM | Normal | big negative | 1148 | -4.16 | 0.22 | 3.74 |
| Put | OTM-ATM | Normal | small negative | 1107 | -3.25 | 0.00 | 6.74 |
| Put | OTM-ITM | Full | big negative | 1042 | -3.24 | 0.00 | 4.08 |
| Put | OTM-ITM | Full | small negative | 1005 | -2.74 | -1.16 | 5.73 |
| Put | OTM-ITM | EAD | big negative | 296 | -3.05 | -0.06 | 2.89 |
| Put | OTM-ITM | EAD | small negative | 287 | -1.91 | -1.90 | 4.60 |
| Put | OTM-ITM | Normal | big negative | 746 | -3.64 | 0.43 | 5.44 |
| Put | OTM-ITM | Normal | small negative | 718 | -3.42 | 0.24 | 6.69 |

Table 28: Mean \# of observations ${ }^{136}$, median of constant, skew, ATM IV coefficients:

## ATM IV control

[^65]| Option type | Skew type Sample | Jump type | Skew coef $\%$ positive signif* |
| :--- | :--- | :--- | ---: |
| Call | OTM-ATM | Full | big positive |
| Call | OTM-ATM | Full | small positive |

* Significant at least at $10 \%$.

Table 29: Percentage of significantly positive skew coefficients: ATM IV control

| Option type | Skew type | Sample | Jump type |
| :--- | :--- | :--- | :--- |
| Call | Skew coef $\%$ negative signif* |  |  |
| Call | OTM-ATM | Full | big positive |
| Call | OTM-ATM | Full | small positive |

* Significant at least at $10 \%$.

Table 30: Percentage of significantly negative skew coefficients: ATM IV control

Starting from Table 28, we present median coefficients because the bivariate models lead to huge estimated coefficients and means would be heavily influenced. Median skew coefficients are close to zero and have changing signs, on average. ATM IV coefficients are all positive and quite different from zero. In Table 29 and Table 30, we see that, after inserting the ATM IV as a further explanatory variable, skew coefficients lose much of their statistical significance and their signs become more unstable across all specifications.

| Option type | Skew type | Sample | Jump type | ATM IV coef \% positive signif* |
| :---: | :---: | :---: | :---: | :---: |
| Call | OTM-ATM | Full | big positive | 79.20\% |
| Call | OTM-ATM | Full | small positive | 70.80\% |
| Call | OTM-ATM | EAD | big positive | 54.20\% |
| Call | OTM-ATM | EAD | small positive | 62.50\% |
| Call | OTM-ATM | Normal | big positive | 70.80\% |
| Call | OTM-ATM | Normal | small positive | 75.00\% |
| Call | OTM-ITM | Full | big positive | 66.70\% |
| Call | OTM-ITM | Full | small positive | 75.00\% |
| Call | OTM-ITM | EAD | big positive | 45.80\% |
| Call | OTM-ITM | EAD | small positive | 54.20\% |
| Call | OTM-ITM | Normal | big positive | 54.20\% |
| Call | OTM-ITM | Normal | small positive | 75.00\% |
| Put | OTM-ATM | Full | big negative | 62.50\% |
| Put | OTM-ATM | Full | small negative | 83.30\% |
| Put | OTM-ATM | EAD | big negative | 54.20\% |
| Put | OTM-ATM | EAD | small negative | 75.00\% |
| Put | OTM-ATM | Normal | big negative | 54.20\% |
| Put | OTM-ATM | Normal | small negative | 75.00\% |
| Put | OTM-ITM | Full | big negative | 79.20\% |
| Put | OTM-ITM | Full | small negative | 83.30\% |
| Put | OTM-ITM | EAD | big negative | 62.50\% |
| Put | OTM-ITM | EAD | small negative | 66.70\% |
| Put | OTM-ITM | Normal | big negative | 75.00\% |
| Put | OTM-ITM | Normal | small negative | 75.00\% |

[^66]Table 31: Percentage of significantly positive ATM IV coefficients: ATM IV control

| Option type | Skew type | Sample | Jump type | ATM IV coef \% negative signif* |
| :---: | :---: | :---: | :---: | :---: |
| Call | OTM-ATM | Full | big positive | 0.00\% |
| Call | OTM-ATM | Full | small positive | 0.00\% |
| Call | OTM-ATM | EAD | big positive | 4.17\% |
| Call | OTM-ATM | EAD | small positive | 0.00\% |
| Call | OTM-ATM | Normal | big positive | 4.17\% |
| Call | OTM-ATM | Normal | small positive | 0.00\% |
| Call | OTM-ITM | Full | big positive | 0.00\% |
| Call | OTM-ITM | Full | small positive | 0.00\% |
| Call | OTM-ITM | EAD | big positive | 4.17\% |
| Call | OTM-ITM | EAD | small positive | 0.00\% |
| Call | OTM-ITM | Normal | big positive | 0.00\% |
| Call | OTM-ITM | Normal | small positive | 0.00\% |
| Put | OTM-ATM | Full | big negative | 0.00\% |
| Put | OTM-ATM | Full | small negative | 0.00\% |
| Put | OTM-ATM | EAD | big negative | 0.00\% |
| Put | OTM-ATM | EAD | small negative | 0.00\% |
| Put | OTM-ATM | Normal | big negative | 0.00\% |
| Put | OTM-ATM | Normal | small negative | 0.00\% |
| Put | OTM-ITM | Full | big negative | 0.00\% |
| Put | OTM-ITM | Full | small negative | 0.00\% |
| Put | OTM-ITM | EAD | big negative | 0.00\% |
| Put | OTM-ITM | EAD | small negative | 0.00\% |
| Put | OTM-ITM | Normal | big negative | 0.00\% |
| Put | OTM-ITM | Normal | small negative | 0.00\% |

* Significant at least at 10\%.

Table 32: Percentage of significantly negative ATM IV coefficients: ATM IV control
Table 31 provides quite strong evidence in favor of our hypothesis for research question IV. In fact, across the vast majority of our sample stocks, higher ATM IV is significantly and positively related to a higher probability of observing future jumps, when the effect of skew is included. This is valid for both put-negative and call-positive specifications and is valid across different skew definitions and sub-periods. Furthermore, as in Table 32, almost no model across the sample stocks returns significantly negative coefficients for the ATM IV regressor: hence, either we have a strongly significant and positive coefficient or we have insignificance.

The results of Table 29 through Table 32 tell us that we cannot reject hypothesis IV: after controlling for ATM IV - which has the expected sign and significance, skew loses much of its significance in explaining single stock jumps.

| Option type | Skew type | Sample | Jump type | Mean pseudo R squared* |
| :--- | ---: | :--- | :--- | ---: |
| Call | OTM-ATM | Full | big positive | -Inf |
| Call | OTM-ATM | Full | small positive | $18.80 \%$ |
| Call | OTM-ATM | EAD | big positive | -Inf |
| Call | OTM-ATM | EAD | small positive | -Inf |
| Call | OTM-ATM | Normal | big positive | -Inf |
| Call | OTM-ATM | Normal | small positive | $18.50 \%$ |
| Call | OTM-ITM | Full | big positive | -Inf |
| Call | OTM-ITM | Full | small positive | $17.50 \%$ |
| Call | OTM-ITM | EAD | big positive | -Inf |
| Call | OTM-ITM | EAD | small positive | -Inf |
| Call | OTM-ITM | Normal | big positive | -Inf |
| Call | OTM-ITM | Normal small positive | $18.80 \%$ |  |
| Put | OTM-ATM | Full | big negative | $12.80 \%$ |
| Put | OTM-ATM | Full | small negative | $8.73 \%$ |
| Put | OTM-ATM | EAD | big negative | - Inf |
| Put | OTM-ATM | EAD | small negative | $7.54 \%$ |
| Put | OTM-ATM | Normal | big negative | - Inf |
| Put | OTM-ATM | Normal | small negative | $16.30 \%$ |
| Put | OTM-ITM | Full | big negative | $13.00 \%$ |
| Put | OTM-ITM | Full | small negative | $11.60 \%$ |
| Put | OTM-ITM | EAD | big negative | - Inf |
| Put | OTM-ITM | EAD | small negative | $9.62 \%$ |
| Put | OTM-ITM | Normal | big negative | - Inf |
| Put | OTM-ITM | Normal | small negative | $14.60 \%$ |

* Only homoscedastic models.

Table 33: Mean pseudo $R^{2}$ : ATM IV control
As one would expect, the inclusion of the highly significant ATM IV variable also improves the fit of our models. Table 22 confirms this. Pseudo $R^{2}$ is on average greater than $10 \%$. Results for the medians ${ }^{137}$, not influenced by outliers which produce the Inf values, show similar results.

Positive predicted value results confirm that adding the ATM IV variable improves the forecasting power of our models: we go from correctly forecasting a jump only on approximately $20 \%$ of times without the ATM IV variable to $30 \% / 35 \%$, on average across our sample stocks. This is shown in Table 34 below. Interestingly, for call skews, the best predictive accuracy is for small positive jumps, consistent with our prior results about informed short-term ATM straddle trading before small positive jumps.

[^67]| Option type | Skew type | Sample | Jump type | Mean ppv* |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Call | OTM-ATM | Full | big positive |  | 29.90\% |
| Call | OTM-ATM | Full | small positive |  | 39.80\% |
| Call | OTM-ATM | EAD | big positive |  | 19.90\% |
| Call | OTM-ATM | EAD | small positive |  | 36.40\% |
| Call | OTM-ATM | Normal | big positive |  | 30.20\% |
| Call | OTM-ATM | Normal | small positive |  | 37.50\% |
| Call | OTM-ITM | Full | big positive |  | 25.20\% |
| Call | OTM-ITM | Full | small positive |  | 39.80\% |
| Call | OTM-ITM | EAD | big positive |  | 22.80\% |
| Call | OTM-ITM | EAD | small positive |  | 36.70\% |
| Call | OTM-ITM | Normal | big positive |  | 27.20\% |
| Call | OTM-ITM | Normal | small positive |  | 37.20\% |
| Put | OTM-ATM | Full | big negative |  | 35.70\% |
| Put | OTM-ATM | Full | small negative |  | 32.60\% |
| Put | OTM-ATM | EAD | big negative |  | 40.00\% |
| Put | OTM-ATM | EAD | small negative |  | 33.20\% |
| Put | OTM-ATM | Normal | big negative |  | 42.00\% |
| Put | OTM-ATM | Normal | small negative |  | 39.00\% |
| Put | OTM-ITM | Full | big negative |  | 23.00\% |
| Put | OTM-ITM | Full | small negative |  | 35.70\% |
| Put | OTM-ITM | EAD | big negative |  | 36.90\% |
| Put | OTM-ITM | EAD | small negative |  | 32.80\% |
| Put | OTM-ITM | Normal | big negative |  | 27.90\% |
| Put | OTM-ITM | Normal | small negative |  | 36.90\% |

* Only homoscedastic models.

Table 34: Mean ppv for homoscedastic models: ATM IV control
$\left.\begin{array}{llll}\hline \text { Option type } & \text { Skew type Sample Jump type } & \text { Mean npv* } & \\ \hline \text { Call } & \text { OTM-ATM } & \text { Full } & \text { big positive } \\ \text { Call } & \text { OTM-ATM } & \text { Full } & \text { small positive }\end{array}\right] 96.40 \%$

* Only homoscedastic models.

Table 35: Mean npv for homoscedastic models: ATM IV control

Table 35 confirms the usual results for the npv.
The main conclusions of the results for research question IV are:

1. The evidence supporting our ex-ante hypothesis is quite strong: we find that after inserting ATM IV as regressor, skew loses much of its significance. Furthermore, ATM IV has the positive sign we expected ex-ante, consistently with previous literature: it is also significantly positive for the vast majority of our sample stocks. Traders seem to have better information on whether there will be a jump or not, rather than on its precise direction;
2. Including ATM IV greatly improves the fit and the forecasting ability of our models.

In the Appendix, we present tables reporting results and diagnostics for all 576 regressions separately.

In the next and last section, we will present the final conclusions of this thesis, as well as its limitations and suggestions for potential future research.

## 5. Conclusions and limitations

In this final section, we (1) provide the main results of the empirical work presented above and their collocation within existing literature; and (2) we discuss the limits of the thesis and possible suggestions for future research on the topic.

### 5.1 Conclusions and interpretation

After checking whether the skew-jump statistical relationship exists also in single stock options, the main aim of this thesis is to ascertain whether the skew-jump relationship is confined to periods where significant information is disclosed to the market, i.e. earnings announcement periods, or it exists even during normal periods where no new pre-scheduled information is announced. Finally, as a last check, ATM implied volatility is introduced as a second explanatory variable besides skew in order to understand whether the skew significance persists after the addition of that control variable.

In order to verify the hypotheses posed in this thesis, the research has been organized along four main research questions: the first two represent the early checks, the third develops the main topic and the fourth concludes with the inclusion of the control variable. Below, the main results to the four research questions are presented.

First, on average for at least two thirds of the sample 24 S\&P 100 stocks in the period 1996-2017, a more positive put implied volatility skew ${ }^{138}$, i.e. a higher put OTM implied volatility relative to put ATM or ITM implied volatility, is related in a significant way ${ }^{139}$ to a higher probability of observing future negative return jumps in the underlying equity within the option life. This result provides support for our first hypothesis, according to which informed traders expecting a negative return jump are likely to buy OTM puts. Furthermore, it is in line with previous literature demonstrating that options are an important avenue for informed trading (Easley, O'Hara and Srinivas, 1998) and that positive demand pressures on OTM puts convey a negative news signal for the cash asset (Doran, Peterson and Tarrant, 2007; Garleanu, Pedersen and Poteshman, 2009; Xing, Zhang and Zhao, 2010).

[^68]Second, on average for at least two thirds of the sample 24 S\&P 100 stocks in the period 1996-2017, a more negative call OTM-ATM implied volatility skew, i.e. a higher call ATM implied volatility relative to call OTM implied volatility, is related in a significant way to a higher probability of observing future positive return jumps in the underlying equity within the option life. This result goes against our second hypothesis, according to which a less negative (or more positive) call OTM-ATM implied volatility skew should have been related with a higher probability of observing future positive return jumps in the underlying equity. The ex-ante hypothesis was based on the theory that informed traders with positive directional information on the underlying equity are likely to go long OTM calls to exploit the best leverage. However, this is not what is found. A possible intuitive reason that might help explaining the result is the following. On average, investors are long equities and like positive return jumps in their holdings. Therefore, stock investors are not likely to buy OTM calls to get further directional exposure to rising equity prices. On the other hand, if they expect a positive jump, they may try to profit from the volatility move. Therefore, they may buy ATM calls (and, possibly, also puts in order to form straddles) since these options have the highest Vega and Gamma. Hence, one may hypothesize that call trading prior to expected positive return jumps in the underlying equity is dominated by volatility traders buying ATM implied volatility rather than directional traders exploiting the greater leverage in OTM options. This intuition is partially supported by the finding that the percentage of sample stocks for which the call OTM-ATM skew coefficients are significantly negative is much greater for small positive return jumps (87.50\%) than for big positive return jumps (58.30\%). This makes sense since if volatility traders expected huge moves, they might use OTM strangles and not ATM straddles, thus bidding up call OTM implied volatility and not call ATM implied volatility ${ }^{140}$. At this point, one might ask why we do not observe the same put ATM implied volatility buying before negative jumps. A possible explanation, deriving directly from the average net long positioning in equity markets, is the following. Investors dislike negative jumps as they are net long equity. Hence, they are likely to buy insurance in the form of OTM

[^69]puts if they expect negative jumps. Therefore, put trading prior to negative jumps is likely to be dominated by directional hedgers buying put OTM implied volatility rather than pure volatility traders buying put ATM implied volatility.

Now, looking at the call OTM-ITM implied volatility skew, we find that for slightly less than half of the sample 24 S\&P 100 stocks in the period 1996-2017 a less negative (or more positive) call OTM-ITM implied volatility skew is related in a significant way to a higher probability of observing future positive return jumps in the underlying equity within the option life. This provides only weak support for our ex-ante hypothesis, since only less than $50 \%$ of the sample behaves as expected. Therefore, we can affirm that the skew-jump relationship for calls is less well defined than for puts.

Third, looking at put skews, on average for slightly less than $60 \%$ of the sample 24 S\&P 100 stocks in the period 1996-2017, the skew-jump relationship maintains its statistical significance ${ }^{141}$ even in the normal periods, i.e. those sub-sample periods which do not contain earnings announcements. This finding corroborates our third and main hypothesis and provides support to the idea that the skew-jump relationship is not driven exclusively by earnings announcements: on average, traders seem to behave as if their trading were informed, bidding up put OTM implied volatility relative to the rest of the skew prior to negative return jumps in the underlying stock. Our result adds to the existing literature, since it shows that option traders engage in fruitful information discovery outside of earnings announcement periods also for randomly arriving events that generate extreme returns and not only for non-extreme returns, as already demonstrated in previous research (Jin, Livnat and Zhang, 2012).

Looking at call skews, we shall differentiate between the two skew definitions, as we have already done in trying to answer research question II. As far as call OTM-ATM implied volatility skews are concerned, the analysis of normal sub-sample periods confirms the results found for the full sample period 1996-2017. In fact, on average $60 \%$ of the 24 S\&P 100 sample stocks exhibit significantly negative skew coefficients, meaning that also during normal sub-sample periods a more negative call OTM-ATM

[^70]skew ${ }^{142}$ is significantly associated with a higher probability of observing future positive return jumps in the underlying stock. Furthermore, while this is true for only $45.80 \%$ of the sample stocks when analyzing big jumps, the percentage increases to $75 \%$ for small jumps, providing some support to the intuition that call ATM implied volatility buying pressures are somewhat stronger if traders expect relatively small jumps.

As far as call OTM-ITM implied volatility skews are concerned, we find that, even during the normal sub-sample period, on average $40 \%$ of the 24 S\&P 100 sample stocks display significantly positive skew coefficients ${ }^{143}$, in line with the results of the full sample period.

Again, as for puts, the call results provide some support to the hypothesis that the skew-jump relationship is not limited to earnings announcement periods, in line with previous research on non-extreme returns (Jin, Livnat and Zhang, 2012).

Fourth and last, adding the ATM implied volatility as independent variable makes skews mostly insignificant in more than $80 \%$ of the 24 S\&P 100 sample stocks during the period 1996-2017, on average across all jump-skew specifications and put-call models. Furthermore, the sign of the ATM implied volatility is significantly positive in more than two thirds of the sample stocks on average. This is valid across all periods: full, normal and earnings announcements. This finding corroborates our fourth and last hypothesis, according to which a higher ATM implied volatility is related to a higher probability of observing a return jump in the underlying stock ${ }^{144}$. Intuitively, traders seem to have better information on whether a jump will occur rather than on the jump's precise direction: the information they impound in prices is more important for ATM options as these are natural candidates to trade pure volatility moves, given their bigger Vegas and Gammas. Therefore, when coupled with ATM implied volatility in trying to identify future jumps, skew loses much of its statistical significance. It is interesting to compare this result with what is found by Doran, Peterson and Tarrant (2007) regarding equity index options. Our result for single stocks agrees with their finding for equity indices

[^71]that higher ATM IV significantly increases the probability of observing both negative and positive return jumps. In Doran, Peterson and Tarrant (2007), after including ATM IV, the significance of the index skew is lost for medium- and long-dated options and it is maintained, even if decreased, for short-term maturities. On the other hand, our single stock skew loses much of its significance for short-term maturities. A possible explanation for this inconsistency may be found in previous research. Garleanu, Pedersen and Poteshman (2009) find that index options (in particular OTM puts) seem overpriced, whereas single stock options (in particular OTM calls) seem underpriced. Dubinsky and Johannes (2006) and Bakshi, Kapadia and Madan (2003) find that single stock options tend to exhibit a smiling implied volatility as function of moneyness in around $30 \%$ of cases ${ }^{145}$, whereas index options exhibit a more skewed implied volatility as function of moneyness ${ }^{146}$. Therefore, the signal given by index skew may be stronger than that given by single stock skew, especially before negative return jumps, since the index skew is more pronounced.

### 5.2 Limits and suggestions for future research

This thesis presents the following main limitations.
The sample size of stocks used ${ }^{147}$ has been limited by the choice of the S\&P 100 index as original stock universe and by successive checks and eliminations. Hence, the results apply to those analyzed stocks and we cannot infer with certainty that the same skewjump relationship holds in different samples, even if that might sound reasonable. Therefore, it would be certainly useful to perform the same analysis on a larger crosssectional sample of stocks, for instance starting from the S\&P 500 universe or even using non-US single stocks, such as those in the Eurostoxx indices.

We used a sample period extending from 1996 to $2017^{148}$. However, as we noticed in the data summarization and analysis section, the first years of the sample period display very few valid skew observations, likely due to the fact that there has been a growth in single stock option trading over the last years. Therefore, future research

[^72]may focus on a shorter and more recent period to check whether the model can be improved.

The analysis has been carried out for each single stock over the time-series. Starting from a broader cross-section of single stocks, one could apply a cross-sectional or panel analysis, under whose lenses the results may be seen in a different light.

To check the predictive performance of the models, an ex-ante threshold of $20 \%$ probability for identifying jumps has been chosen. However, different choices of threshold may lead to slightly different interpretations. Hence, it would be interesting to perform further analyses by changing that threshold. Furthermore, future research may extend the analysis to out-of-sample applications, testing whether the model estimated in-sample is able to predict in a meaningful way jumps out-of-sample.

Unluckily, the fit of the models, as estimated using the mean pseudo R squared, is low and below $5 \%$ in the univariate specifications. However, adopting the bivariate specification, it increases to an improved 10\%-20\%, depending on the model. This would suggest that the ATM IV, when used together with the skew, better explains the occurrence of future single stocks' jumps.

No trading strategy has been proposed. This is certainly a big limitation. In order to check the economic significance of the model and to ascertain whether the ATM IV or the skew are better predictors of underlying single stock jumps, future research could concentrate on back-testing a reasonable strategy using as signal the jump probability predicted by models using either ATM IV, skew or both. For instance, for situations in which the model predicts a jumps over a certain probability threshold, one might decide to "buy the jump" using delta-hedged straddles or strangles; another possible strategy could trade the underlying's directionality as predicted by the model using the single stock ${ }^{149}$.

Another topic that may be interesting for future research is the analysis of the dynamics of Greeks around information events such as earnings announcements. For instance, given the results on the skew-jump relationship of this thesis, analyzing the

[^73]behavior of higher-order Greeks such as Vanna, expressing the size of the skew position, or Volga, measuring the size of the kurtosis position, prior to and after earnings might provide useful insights for the risk management of books of single stock options.

Finally, we believe that this thesis provides further support in favor of the hypothesis that informed traders may choose options over the underlying, especially for shortand medium-term strategies. Therefore, it would be certainly interesting and useful to extend this analysis to options on other assets, for instance, analyzing the dynamics of the implied volatility curve of options on short-term interest rate futures around major central bank announcements.

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## Appendix

| Ticker | Ticker |
| :--- | :--- |
| HAL | BMY |
| F | DIS |
| INTC | UTX |
| TXN | MMM |
| FDX | CL |
| SLB | SO |
| BA | GE |
| IBM | VZ |
| AXP | JNJ |
| RTN | XOM |
| MCD | KO |
| GD | WMT |

Table 36: Tickers of selected sample stocks

| Cross-sectional descriptive statistics* |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Option | Maturity | Moneyness | IV mean | IV SD mean ${ }^{\text {N }}$ | ${ }^{\circ}$ | BA mean | mean | OI mean |
| C | ST | DDOTM | 51.20\% | 14.50\% | 223 | 30.60\% | 1113 | 6441 |
| C | ST | DOTM | 37.60\% | 10.30\% | 662 | 26.30\% | 814 | 5528 |
| C | ST | OTM | 25.50\% | 9.22\% | 4538 | 17.80\% | 746 | 4522 |
| C | ST | ATM | 20.80\% | 7.34\% | 12250 | 8.14\% | 516 | 3609 |
| C | ST | ITM | 25.50\% | 8.92\% | 5685 | 5.89\% | 375 | 3681 |
| C | ST | DITM | 34.60\% | 10.80\% | 2313 | 4.53\% | 335 | 3338 |
| C | ST | DDITM | 60.30\% | 30.70\% | 2493 | 2.97\% | 278 | 2135 |
| C | MT | DDOTM | 41.60\% | 11.70\% | 1262 | 22.80\% | 401 | 4648 |
| C | MT | DOTM | 30.60\% | 8.95\% | 2171 | 18.80\% | 523 | 5144 |
| C | MT | OTM | 23.30\% | 8.47\% | 6391 | 13.00\% | 609 | 5014 |
| C | MT | ATM | 22.00\% | 7.93\% | 9144 | 6.98\% | 480 | 4223 |
| C | MT | ITM | 25.60\% | 8.80\% | 5379 | 5.00\% | 255 | 3920 |
| C | MT | DITM | 30.20\% | 9.68\% | 2982 | 4.08\% | 179 | 3155 |
| C | MT | DDITM | 44.30\% | 19.40\% | 3557 | 2.92\% | 241 | 2122 |
| C | LT | DDOTM | 36.00\% | 10.20\% | 1202 | 18.40\% | 286 | 7360 |
| C | LT | DOTM | 26.20\% | 8.52\% | 1365 | 12.00\% | 415 | 8038 |
| C | LT | OTM | 23.00\% | 8.13\% | 2340 | 6.87\% | 545 | 8522 |
| C | LT | ATM | 23.40\% | 7.94\% | 2637 | 4.18\% | 430 | 7565 |
| C | LT | ITM | 25.00\% | 8.01\% | 2265 | 3.74\% | 183 | 5773 |
| C | LT | DITM | 27.70\% | 8.41\% | 1498 | 3.70\% | 114 | 4667 |
| C | LT | DDITM | 38.50\% | 15.60\% | 2262 | 2.87\% | 184 | 2919 |
| P | ST | DDOTM | 60.20\% | 18.80\% | 424 | 27.10\% | 594 | 5198 |
| P | ST | DOTM | 40.30\% | 11.70\% | 1349 | 24.60\% | 480 | 3780 |
| P | ST | OTM | 26.60\% | 8.96\% | 6471 | 15.30\% | 430 | 3056 |
| P | ST | ATM | 21.00\% | 7.53\% | 11284 | 7.85\% | 359 | 2509 |
| P | ST | ITM | 23.80\% | 9.29\% | 4081 | 6.28\% | 237 | 2876 |
| P | ST | DITM | 32.00\% | 10.40\% | 1306 | 4.91\% | 187 | 3211 |
| P | ST | DDITM | 53.40\% | 23.90\% | 1372 | 3.38\% | 241 | 3315 |
| P | MT | DDOTM | 47.60\% | 16.10\% | 2267 | 19.90\% | 261 | 3607 |
| P | MT | DOTM | 32.00\% | 9.72\% | 3591 | 16.20\% | 303 | 3525 |
| P | MT | OTM | 25.10\% | 8.38\% | 7402 | 11.00\% | 366 | 3441 |
| P | MT | ATM | 22.40\% | 8.18\% | 8087 | 6.55\% | 332 | 2858 |
| P | MT | ITM | 23.80\% | 9.28\% | 4120 | 5.17\% | 190 | 2699 |
| P | MT | DITM | 27.80\% | 9.95\% | 1795 | 4.35\% | 122 | 2475 |
| P | MT | DDITM | 40.40\% | 16.10\% | 1923 | 3.14\% | 123 | 2721 |
| P | LT | DDOTM | 39.80\% | 13.60\% | 2220 | 15.20\% | 170 | 5145 |
| P | LT | DOTM | 28.40\% | 8.31\% | 1952 | 9.17\% | 225 | 5705 |
| P | LT | OTM | 25.10\% | 8.01\% | 2514 | 5.92\% | 282 | 5836 |
| P | LT | ATM | 23.40\% | 8.03\% | 2423 | 4.08\% | 268 | 4858 |
| P | LT | ITM | 23.30\% | 8.63\% | 1654 | 3.74\% | 132 | 3720 |
| P | LT | DITM | 25.70\% | 9.50\% | 825 | 3.91\% | 82 | 3508 |
| P | LT | DDITM | 35.60\% | 14.00\% | 1092 | 3.03\% | 79 | 4124 |

* First, we compute time-series means for implied volatility (IV), bid-ask spread (BA), volume (V) and open interest (OI) of each stock and time-series standard deviation (SD) for IV. Then, we average across the stocks in our sample.
${ }^{\circ} \mathrm{N}$ is the number of observed contracts: first we compute the observed contracts over the timeseries for each stock and the we average across the stocks in our sample to get the mean number of observed contracts for each option-maturity-moneyness bin.


Figure 10: Cross-sectional IV mean and mean number of observed contracts by moneyness, across maturity and option type


Figure 11: Cross-sectional bid-ask mean and mean number of observed contracts by moneyness, across maturity and option type


Figure 12: Cross-sectional volume mean and open interest mean by moneyness, across maturity and option type

| Cross-sectional descriptive statistics for skews* |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Option | Skew | Jump type | Jump |  | Skew mean | mean |  | \% sign? ${ }^{\circ}$ |
| C | OTM_ATM | big_positive |  | 0 | -1.02\% | 1.49\% | 1271 | 66.70\% |
| C | OTM_ATM | big_positive |  | 1 | -1.60\% | 2.09\% | 71 | 69.60\% |
| C | OTM_ATM | small_positive |  | 0 | -0.92\% | 1.38\% | 1045 | 83.30\% |
| C | OTM_ATM | small_positive |  | 1 | -1.43\% | 1.87\% | 295 | 83.30\% |
| C | OTM_ITM | big_positive |  | 0 | -3.46\% | 2.98\% | 1307 | 50.00\% |
| C | OTM_ITM | big_positive |  | 1 | -3.52\% | 3.33\% | 86 | 50.00\% |
| C | OTM_ITM | small_positive |  | 0 | -3.46\% | 2.87\% | 1042 | 50.00\% |
| C | OTM_ITM | small_positive |  | 1 | -3.48\% | 3.39\% | 352 | 50.00\% |
| P | OTM_ATM | big_negative |  | 0 | 2.60\% | 1.54\% | 1526 | 54.20\% |
| P | OTM_ATM | big_negative |  | 1 | 3.02\% | 1.95\% | 71 | 54.20\% |
| P | OTM_ATM | small_negative |  | 0 | 2.56\% | 1.46\% | 1286 | 70.80\% |
| P | OTM_ATM | small_negative |  | 1 | 2.86\% | 1.90\% | 311 | 70.80\% |
| P | OTM_ITM | big_negative |  | 0 | 3.26\% | 3.01\% | 1322 | 75.00\% |
| P | OTM_ITM | big_negative |  | 1 | 4.20\% | 3.06\% | 83 | 75.00\% |
| P | OTM_ITM | small_negative |  | 0 | 3.14\% | 2.98\% | 1081 | 91.70\% |
| P | OTM_ITM | small_negative |  | 1 | 3.87\% | 3.06\% | 323 | 91.70\% |

* First, we compute the time-series mean and standard deviation (SD) for skew for each stock, differentiating among option types, skew types, jump types, and whether the days are normal days or jump days. We also compute the number of observed skews ( N ) in the time-series. Then, we average the time-series skew mean, SD and N across the sample stocks.
${ }^{\circ}$ Skew diff \% sign: this shows the percentage of stocks for which the difference between the mean skews for the jump (1) versus normal (0) days - taken inside each option-skew-jump type category is significantly different from zero at least at a $10 \%$ level. The higher the percentage, the higher the probability that true population skews are different during normal and jump days.

Table 38: Cross-sectional descriptive statistics for skews


Figure 13: Cross-sectional mean skew and number of observed contracts by jump, across skew type and option type

| Cross-sectional descriptive statistics for skews, EAD vs normal periods* |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Option | Skew Jump type | Sub-samp | Jump | w mean | mean |  |
| C | OTM_ATM big_positive | EAD | 0 | -0.99\% | 1.47\% | 328 |
| C | OTM_ATM big_positive | EAD | 1 | -1.56\% | 1.90\% | 32 |
| C | OTM_ATM big_positive | NO_EAD | 0 | -1.03\% | 1.48\% | 943 |
| C | OTM_ATM big_positive | NO_EAD | 1 | -1.65\% | 2.22\% | 40 |
| C | OTM_ATM small_positive | EAD | 0 | -0.88\% | 1.41\% | 258 |
| C | OTM_ATM small_positive | EAD | 1 | -1.42\% | 1.73\% | 104 |
| C | OTM_ATM small_positive | NO_EAD | 0 | -0.95\% | 1.36\% | 787 |
| C | OTM_ATM small_positive | NO_EAD | 1 | -1.42\% | 1.91\% | 195 |
| C | OTM_ITM big_positive | EAD | 0 | -3.36\% | 2.76\% | 340 |
| C | OTM_ITM big_positive | EAD | 1 | -3.55\% | 3.14\% | 36 |
| C | OTM_ITM big_positive | NO_EAD | 0 | -3.50\% | 3.06\% | 967 |
| C | OTM_ITM big_positive | NO_EAD | 1 | -3.58\% | 3.37\% | 52 |
| C | OTM_ITM small_positive | EAD | 0 | -3.33\% | 2.68\% | 258 |
| C | OTM_ITM small_positive | EAD | 1 | -3.38\% | 3.11\% | 119 |
| C | OTM_ITM small_positive | NO_EAD | 0 | -3.51\% | 2.95\% | 784 |
| C | OTM_ITM small_positive | NO_EAD | 1 | -3.46\% | 3.45\% | 233 |
| P | OTM_ATM big_negative | EAD | 0 | 2.62\% | 1.51\% | 408 |
| P | OTM_ATM big_negative | EAD | 1 | 3.08\% | 1.61\% | 31 |
| P | OTM_ATM big_negative | NO_EAD | 0 | 2.60\% | 1.53\% | 1118 |
| P | OTM_ATM big_negative | NO_EAD | 1 | 3.17\% | 2.06\% | 43 |
| P | OTM_ATM small_negative | EAD | 0 | 2.59\% | 1.44\% | 326 |
| P | OTM_ATM small_negative | EAD | 1 | 2.74\% | 1.69\% | 112 |
| P | OTM_ATM small_negative | NO_EAD | 0 | 2.56\% | 1.44\% | 960 |
| P | OTM_ATM small_negative | NO_EAD | 1 | 2.92\% | 1.94\% | 199 |
| P | OTM_ITM big_negative | EAD | 0 | 3.30\% | 2.81\% | 353 |
| P | OTM_ITM big_negative | EAD | 1 | 3.90\% | 3.10\% | 33 |
| P | OTM_ITM big_negative | NO_EAD | 0 | 3.27\% | 3.06\% | 968 |
| P | OTM_ITM big_negative | NO_EAD | 1 | 4.27\% | 2.90\% | 49 |
| P | OTM_ITM small_negative | EAD | 0 | 3.19\% | 2.78\% | 277 |
| P | OTM_ITM small_negative | EAD | 1 | 3.73\% | 2.93\% | 109 |
| P | OTM_ITM small_negative | NO_EAD | 0 | 3.15\% | 3.04\% | 804 |
| P | OTM_ITM small_negative | NO_EAD | 1 | 3.93\% | 3.07\% | 213 |

* First, we compute the time-series mean and standard deviation (SD) for skew for each stock, differentiating among option types, skew types, jump types, EAD vs normal periods and whether the days are normal days or jump days. We also compute the number of observed skews ( N ) in the time-series. Then, we average the time-series skew mean, SD and N across the sample stocks.

Table 39: Cross-sectional descriptive statistics for skews, EDA vs normal periods


Figure 14: Cross-sectional mean skew by EAD group - jump group, across skew type and option type


Figure 15: Cross-sectional mean observed skew days and jump days, across skew and option type


Figure 16: HAL volume mean frequency by maturity, across option type and moneyness


Figure 17: HAL OI mean frequency by maturity, across option type and moneyness


Table 40: Research question I, Part A: negative jumps, put skews, all periods


Table 41: Research question I, Part B: negative jumps, put skews, all periods


Table 42: Research question II, Part A: positive jumps, call skews, all periods


Table 43：Research question II，Part B：positive jumps，call skews，all periods


Table 44: Research question III, Part A: EAD vs normal periods


Table 45: Research question III, Part B: EAD vs normal periods


Table 46: Research question III, Part C: EAD vs normal periods


Table 47: Research question III, Part D: EAD vs normal periods


Table 48: Research question III, Part E: EAD vs normal periods


Table 49: Research question III, Part F: EAD vs normal periods


Table 50: Research question III, Part G: EAD vs normal periods


Table 51: Research question III, Part H: EAD vs normal periods


Table 52: Research question IV, Part A: ATM IV control


Table 53: Research question IV, Part B: ATM IV control


Table 54: Research question IV, Part C: ATM IV control


Table 55: Research question IV, Part D: ATM IV control


Table 56: Research question IV, Part E: ATM IV control


Table 57: Research question IV, Part F: ATM IV control


Table 58: Research question IV, Part G: ATM IV control


Table 59: Research question IV, Part H: ATM IV control


[^0]:    ${ }^{1}$ This is the longest period during which options data from the OptionMetrics database is available.
    ${ }^{2}$ We chose to keep only those stocks for two reasons: (1) to ensure consistent estimation of the model over a common sample period; and (2) for computational ease.

[^1]:    ${ }^{3} 2$ call or put $\times 3$ ST or MT or LT $\times 7$ DDOTM or DOTM or OTM or ATM or ITM or DITM or DDITM

[^2]:    ${ }^{4}$ As a reminder, in this work, skews are always defined as differences between out-of-the-money (OTM) implied volatilities and at-the-money (ATM) or in-the-money (ITM) implied volatilities, not taken in absolute value.

[^3]:    ${ }^{5}$ A caveat: despite the small- and big-jump sample sizes are similar, big jumps are observed more rarely than small jumps. Hence, the less frequent (across sample stocks) statistical significance of the bigjump specifications may be at least partially caused by the recurrent "peso" problem in estimating rare events.
    ${ }^{6}$ On average, the sign of the put skew-jump relationship remains positive during normal sub-sample periods, indicating that a more positive put skew (i.e. higher put OTM implied volatility relative to put ATM or ITM implied volatility) is associated with a higher probability of observing future negative jumps in the underlying stock.

[^4]:    ${ }^{7}$ Less negative (or more positive) call OTM-ITM implied volatility skew, i.e. higher call OTM implied volatility relative to call ITM implied volatility, is associated with a higher probability of observing future positive return jumps.

[^5]:    ${ }^{8}$ Higher call ATM implied volatility prior to positive jumps; higher put ATM implied volatility prior to negative jumps.

[^6]:    * Only homoscedastic models.

[^7]:    ${ }^{9}$ If the reasoning is correct for calls, one may expect traders predicting small negative jumps buying ATM puts and calls, thus driving up ATM put IV relative to OTM put IV and flattening the skew before negative jumps happen - this would go against our findings about a put skew steepening prior to negative jumps. Our intuitive explanation is as follows: (1) stock investors like positive jumps; (2) since the market is net long stocks, the majority of people already owns stocks; (3) therefore, stock investors may not be likely to buy OTM calls to get further exposure to the stocks; (4) on the other hand, option traders who do not want to bet on Delta, but on Vega/Gamma have the incentives to buy straddles in expectation of small positive jumps; (5) hence, call trading prior to positive stock jumps may be likely to be dominated by volatility traders buying ATM IV rather than delta traders buying OTM IV. On the other hand, for negative jumps: (1) stock investors dislike negative jumps; (2) they are likely to buy insurance in the form of OTM puts if they expect negative jumps; (3) hence, put trading prior to negative jumps is likely to be dominated by delta traders buying OTM IV rather than volatility traders buying ATM IV.

[^8]:    ${ }^{1}$ For instance, a $-10 \%$ daily return can be categorized as extreme; a $-0.2 \%$ daily return is not extreme. Later, we will provide a probabilistic definition of "extreme". Extreme returns are often called "jumps". ${ }^{2}$ There are two types of vanilla equity options: puts, which give the option buyer the right to sell the underlying equity to the option seller within a certain time at a certain price decided today (the strike); and calls, which give the option buyer the right to buy the underlying equity from the option seller within a certain time at the strike price.
    ${ }^{3}$ The standard inputs for a Black-Scholes (1973) pricing.
    ${ }^{4}$ Implied volatility is the input volatility that makes the observed option market price equal to the theoretical Black-Scholes option price. Options are quoted in terms of implied volatilities rather than prices, as the former are more stable than the latter.

[^9]:    ${ }^{5}$ A measure of how close an option is to be exercised. For puts: if the underlying equity price (the spot) is lower than the strike, the option is in the money (ITM); if the spot equals the strike, the option is at the money (ATM) (valid also for calls); and if the spot is higher than the strike, the option is out of the money (OTM). For calls: if the spot is lower than the strike, the option is out of the money (OTM); and if the spot is higher than the strike, the option is in the money (ITM).
    ${ }^{6}$ The implied volatilities of OTM puts / ITM calls are higher than those of ATM options and ITM puts / OTM calls.
    ${ }^{7}$ The implied volatilities of OTM and ITM options are higher than those of ATM options.
    ${ }^{8}$ A typical definition is the difference between put OTM implied volatility and call ATM implied volatility, or between put OTM and ATM implied volatilities.

[^10]:    ${ }^{9}$ The results display minor variation in the percentage of the sample which maintains its statistical significance depending on the option type (call/put) and skew definition (OTM-ATM/OTM-ITM). However, the essence of the finding does not change.
    ${ }^{10}$ At least at $10 \%$.

[^11]:    ${ }^{11}$ Implied volatility IV is the volatility that makes the observed option market price equal to the theoretical Black-Scholes price; therefore, if the assumptions behind Black-Scholes were true, IV should be constant. In reality, it is not.
    ${ }^{12}$ ATM $=$ At-The-Money (spot): moneyness $=$ K/S ~ 100\%. ATMf $=$ At-The-Money forward: K/F~100\%, with $S$ being the spot price and F being the forward equity price, $F=S e^{(r-q) T}$ for expiry T . In general, OTM = Out-of-The-Money and ITM = In-The-Money.
    ${ }^{13}$ Throughout this thesis, we will refer interchangeably to option prices and IVs, as it is common market practice to quote option prices in terms of IVs, given that IVs are much more stable than prices.

[^12]:    14 "Going long kurtosis" means betting on the realization of extreme returns, i.e. jumps: the position gains if realized kurtosis increases, i.e. if the tails of the return distribution become fatter as we observe more extreme returns, both positive and negative. The position also gains if future realized volatility will be higher than implied volatility.
    ${ }^{15}$ Greeks are the key sensitivities (i.e. derivatives) of option prices to changes in key pricing inputs and are fundamental for risk-managing option books. The main first-order Greeks are: Delta, Gamma, Vega, Theta and Rho. Other important second-order Greeks are Volga and Vanna. Finally, so-called shadow Greeks are Vol-Slide Theta and Anchor Delta (Bennett, 2014). To these, we can add Shadow Gamma, Bleed and other third- or fourth- order Greeks. We will focus on kurtosis and skew Greeks Volga and Vanna as the core of this thesis is investigating how skew and kurtosis are related to jumps.
    ${ }^{16}$ Vega is the change in the option price for a given change of IV and measures the size of the IV position in options. Vega peaks for ATM, long-dated options.
    ${ }^{17}$ Gamma is the change in Delta for a given change in spot or, equivalently, the change in option price for a given change in realized spot volatility. Gamma peaks for ATM, short-dated options.

[^13]:    ${ }^{18}$ Skew can be measured in different ways, but usually is taken as the difference between $90 \%$ put IV and $100 \%$ or $110 \%$ put or call IV.
    ${ }^{19}$ Actually, in real markets that would depend on the kind of market regime in which we are: (1) sticky delta; (2) sticky strike; (3) sticky local volatility; or (4) jumpy volatility. For a complete review, see Bennett (2014).

[^14]:    ${ }^{20}$ This is also the reason why term structure is usually downward-sloping for low strikes whereas it is upward-sloping for high strikes above $100 \%$ moneyness.

[^15]:    ${ }^{21}$ The intensity $\lambda$ in the Poisson counting process.
    ${ }^{22}$ Delta-hedging means covering the Delta risk of an option position. For instance, if I buy a put, my Delta will be negative, which means that I gain if the spot falls. To cover my Delta, I need to purchase Delta units of the underlying spot (or another Delta-one payoff such as futures). However, as spot changes, Delta changes due to the Gamma effect: hence, Delta-hedging is precise only for small changes in spot.

[^16]:    ${ }^{23}$ However, one must take into account that more frequent delta-hedging increases transaction costs.
    ${ }^{24}$ In this case, we define end-users slightly differently than in other research (Garleanu, Pedersen and Poteshman, 2009): they are all clients of market makers.

[^17]:    ${ }^{25}$ This is driven by demand for portfolio insurance.
    ${ }^{26}$ Of course, market-makers are net long options on single stocks.
    ${ }^{27}$ Generalized Auto-Regressive Conditional Heteroscedasticity model. Details about this econometric model will be provided in Section 3.
    ${ }^{28}$ This is consistent with market wisdom regarding call overwriting, a strategy whereby investors who are long underlying stocks sell OTM calls on the same stocks in order to enhance the yield of their portfolios (Bennett, 2014). However, this strategy underperforms in highly volatile bull markets as by call overwriting we would be short Delta, Gamma and Vega.

[^18]:    ${ }^{29}$ In this case, one could also place the proceeds of the sale in an interest-earning account.
    ${ }^{30}$ For an index, particularly important events are: 1) release of macroeconomic data (e.g. monetary policy meetings and minutes, wages, inflation, commodities' prices, balance of trade data...); 2) inclusion or exclusion of some component stocks; 3) during earnings season, performance at a sector-level; and

[^19]:    4) regulatory changes. For single stocks: 1) quarterly earnings announcements; 2) dividend announcements; 3) changes in capital structure (e.g. takeovers, mergers, spin-offs, rights issues, buybacks...); 4) changes in the financing structure (e.g. issuance of new debt, conversion of hybrids, draw-down of major credit lines...); 5) operating changes (JVs, R\&D breakthroughs, discovery of important resources, new major contracts...); 6) changes at the top management level; and 7) regulatory changes.
    ${ }^{31}$ This does not necessarily imply the frequency of extreme returns (i.e. jumps, depending on their definition) is higher around EADs.
[^20]:    ${ }^{32}$ Also, OTM options provide higher leverage given the limited initial investment and asymmetric payoffs.
    ${ }^{33}$ Signed means buyer- or seller-initiated volume: buyer-initiated is defined as when the trade happens at a price greater than mid; seller-initiated is defined as when the trade happens at a price lower than mid.
    ${ }^{34}$ Chicago Board Options Exchange.
    ${ }^{35}$ We believe that a strong assumption of their model is the one about market makers: in fact, they assume that market makers are risk-neutral and, therefore, they can ignore the effect of inventory on the pricing of options (Easley, O'Hara and Srinivas, 1998). However, real-world market makers are risk averse and their pricing seems to be affected by demand pressures and recent inventory performance (Bollen and Whaley, 2004; Garleanu, Pedersen and Poteshman, 2009).

[^21]:    ${ }^{36}$ They use volume and bid-ask spreads to proxy for the relative liquidity of options and stocks; they find that OTM options have the highest leverage and thus contribute most to price discovery.
    ${ }^{37}$ Buying spot and borrowing at the risk-free with maturity T is equivalent to go long futures with the same maturity.
    ${ }^{38}$ Even if early exercise is rare, since the realized intrinsic value does not provide enough compensation for the loss of time value. That is why early exercise is most likely for deep ITM options.

[^22]:    ${ }^{39}$ Short selling is easy when the supply of shares of a stock available to be lent is high relative to the free float of that stock.

[^23]:    ${ }^{40}$ Stocks that are costly to short sell will have relatively overpriced OTM puts.
    ${ }^{41}$ As explained, demand for calls increases the IV of calls, which conveys a "good news" message for the underlying stock (Easley, O'Hara and Srinivas, 1998; Garleanu, Pedersen and Poteshman, 2009).
    ${ }^{42}$ As explained, demand for puts increases the IV of puts, which conveys a "bad news" message for the underlying stock (Easley, O'Hara and Srinivas, 1998; Garleanu, Pedersen and Poteshman, 2009).
    ${ }^{43}$ Cremers and Weinbaum (2010) adjust returns using a five-factor model based on Fama and French three factors (market, size, book-to-market), Carhart momentum and Harvey and Siddique skewness factor.

[^24]:    ${ }^{44}$ Buyer-initiated put and call option volume is backed out from publicly observable trade and quote records from the CBOE using a classic algorithm (Lee and Ready, 1991). Furthermore, an interesting finding that corroborates previous research (Garleanu, Pedersen and Poteshman, 2009) is that the putcall ratio is on average $30 \%$ for the stocks in their sample, meaning that in the single stock options market the trading volume for calls is much higher than the volume of puts.

[^25]:    ${ }^{45}$ Market, size, book-to-market, momentum, illiquidity, short-term reversal, realized volatility, riskneutral skew (An et al., 2014).
    ${ }^{46}$ First, estimate historical beta of the stock by regressing stock returns on market returns, on a daily frequency over the last year; then multiply the estimated beta by the IV of the market (index) to get the systematic component of single stock IV; finally, compute idiosyncratic single stock IV by subtracting the systematic components from the overall IV (An et al., 2014)..
    ${ }^{47}$ The Center for Research in Security Prices.
    ${ }^{48}$ OptionMetrics is the database we will extensively use for the empirical part of this thesis.

[^26]:    ${ }^{49}$ They build usual quintile portfolios and long/short Q5-Q1 portfolios.
    ${ }^{50}$ ZZX can be decomposed in POMA - CW.
    ${ }^{51}$ When put OTM-ATM skew becomes more positive, OTM put IV increases relative to ATM put IV. Therefore, for someone long both OTM and ATM put IV, this means increased hedging pressure. In fact, as the OTM put IV increases, its time value rises; the probability of ending up ITM increases and hence the Delta becomes more negative, shifting closer to $-50 \%$. For this reason, delta-hedged traders will need to purchase more shares of the underlying stock in order to delta-neutral. This will cause positive demand pressure on the underlying and lead to positive returns (Doran and Krieger, 2010).
    52 The origins of the term "peso" problem are uncertain; to the author's knowledge, it refers to the "unexpected", sudden and one-off unpegging of the Mexican Peso relative to the US Dollar in 1976, which caused a huge sell-off in the Mexican currency.

[^27]:    ${ }^{53}$ Still outperform by $1.1 \%$ monthly assuming $0.5 \%$ one-way transaction costs (Yan, 2011). A long/short portfolio is created.
    ${ }^{54}$ Yan (2011) uses the S\&P 500 index option "slope" as a proxy for market jump risk.
    ${ }^{55}$ We will rely on their methodology for the empirical part of this thesis, applying it to single stock options instead of index options.
    ${ }^{56}$ Flatter, i.e. more positive or less negative.

[^28]:    ${ }^{57}$ Doran, Peterson and Tarrant (2007) define moneyness both as $\frac{K}{S e^{r T}}$ and using options' Delta.

[^29]:    ${ }^{58}$ As Beaver (1968) says, price changes reflect changes in expectations of the market as a whole, as the majority of individual market participants agrees on the direction of price. On the other hand, volume changes without major price changes reflect changes in expectations of individual investors only, so that there is a lack of consensus about the future direction of price.
    ${ }^{59}$ If we want to obtain an Enterprise Value (EV), we should discount free cash flows to the entire firm by the Weighted Average Cost of Capital (WACC), reflecting the fact that those cash flows are available for both debt holders and equity holders. If we want to use a dividend discount model, then we should discount dividends (and cash flows to equity after debt repayment / issuance) at the levered cost of equity, arriving at an estimated equity value. This last modeling approach is mostly used for financial institutions, since for them debt is an operating and not financing flow.

[^30]:    ${ }^{60}$ Just to name the most cited explanations: (1) delayed price response due to transaction costs; (2) misspecification of factor models used to judge excess returns; and (3) at least a portion of investors are affected by behavioral biases so that they fail to fully recognize the implications of current earnings results for future prospects of the firm, since they are slow in updating their past information set (anchoring bias) (Bernard and Thomas, 1989).

[^31]:    ${ }^{61}$ Net optimism is defined as the number of optimistic words, minus the number of pessimistic words, divided by the total number of words in the releases (Demers and Vega, 2010).

[^32]:    ${ }^{62}$ IV term structure can be intuitively thought of as the "yield curve" for implied volatilities. ATM term structure is usually upward sloping, so that longer-dated ATM options have higher IVs. However, following a big decline in underlying price, the IV term structure can become inverted, with shorterdated IVs being larger than longer-dated IVs. This happens because the recent fall in underlying causes a spike of realized volatilities which gets priced into higher IVs for the short-term. However, as volatility is mean-reverting and alternates long periods of low realizations to brief clusters of high realizations, longer-dated IVs are sticky to a lower and more stable level, as they should represent estimates of longrun expected realized volatilities (Bennett, 2014).
    ${ }^{63}$ Furthermore, using the same sample period 1996-2005, each week, stocks are sorted into quintiles based on previous week average IV skew. Going long stocks in the quintile with the flattest skew (i.e. less positive) and going short the quintile with the steepest skew, rebalancing weekly and computing

[^33]:    weekly returns delivers an annualized excess return of $10.90 \%$ on a risk-adjusted basis, using the FamaFrench 3-factor model (Xing, Zhang and Zhao, 2010). Therefore, the results not only apply for the specific EADs but also in general for all trading days. Interestingly, volumes on stocks with the least positive IV skews are much higher than volumes on stocks with the most positive IV skews: this would suggest that during "panic" times when the market expects negative news, stock trading volume is lower. Furthermore, Xing, Zhang and Zhao (2010) demonstrate that this predictability lasts for the 6 months following the sorting week: this proves the fact that equity markets are slow in incorporating information impounded in IVs.
    ${ }^{64}$ The calculation of implied skewness and kurtosis is based on the non-parametric approach of Bakshi, Kapadia and Madan (2003); options with the shortest maturity are used, conditioning on maturity including the EAD, i.e. on making sure to include EADs within option windows.
    ${ }^{65}$ A strangle is a strategy which entails buying an OTM put and an OTM call on the same underlying, with the same expiry date, usually with strikes symmetric relative to ATM (Bennett, 2014). This strategy minimizes Delta risk and is long both Gamma and Vega risks: hence, it makes money for big jumps in the underlying.

[^34]:    ${ }^{66}$ Implied volatility is computed as the moneyness-weighted IV where ATM options carry the highest weight (Diavatopoulos et al., 2012).
    ${ }^{67}$ Their results are robust to common factors: size, book-to-market and momentum.
    ${ }^{68}$ Options used have between 10 and 60 days to expiration.
    ${ }^{69}$ Skew defined as difference between OTM put IV and ATM call IV.
    ${ }^{70}$ Higher OTM put IV relative to ATM call IV, i.e. more positive skew.
    ${ }^{71}$ Interestingly, they find that the predictive ability for EAD returns is stronger for negative news (Jin, Livnat and Zhang, 2012).

[^35]:    72 Always adjusted for size, book-to-market and momentum.
    73 This database includes most of unscheduled corporate information events, starting in 2002. Interestingly, these are announcements on: clients (17.5\%), products (14.0\%), management changes (14.1\%), litigations (4.2\%), corporate guidance (4.1\%), M\&A (2.8\%) and strategic alliances (2.4\%) (Jin, Livnat and Zhang, 2012).
    ${ }^{74}$ All companies that were targets of merger or tender offers and had options listed on the CBOE between 1986 and 1994. Announcement day is defined as the day during which the bidder sends the first bid to the target (Cao, Chen and Griffin, 2005).
    ${ }^{75}$ Preannouncement period goes between days -30 and -1 , where day 0 is the announcement day (Cao, Chen and Griffin, 2005). Benchmark period goes between days -200 and -100 . Option volumes significantly increase during the preannouncement period, relative to the benchmark period: both buyerinitiated call volume and seller-initiated put volume increase.
    ${ }^{76}$ Buyer- minus seller-initiated call volume divided by total option volume (Cao, Chen and Griffin, 2005). Buyer-initiated volume if the trade occurs above the mid; seller-initiated if below the mid.

[^36]:    ${ }^{77}$ Differences between OTM and ATM implied volatilities or OTM and ITM implied volatilities, not in absolute value. The same definition applies to both calls and puts. Hence, for puts, the skew definition considers the left side of the skew; on the other hand, for calls, the skew definition considers the right side of the skew.

[^37]:    ${ }^{78}$ Higher OTM call IV relative to ATM call IV.
    ${ }^{79}$ Remember the "peso" problem in estimating jumps (Yan, 2011).

[^38]:    ${ }^{80}$ Jumps are, of course, unscheduled events; hence, it is inherently tough to gather information in order to estimate their likelihood. However, option traders do seem to possess some information gathering / processing skills also regarding unscheduled events (Jin, Livnat and Zhang, 2012).
    ${ }^{81}$ For negative jumps, we will use put skew and put ATM IV. For positive jumps, we will use call skew and ATM IV.
    ${ }^{82}$ Especially, negative jumps.

[^39]:    ${ }^{83}$ An implied correlation surface can be extracted by index and single stocks' volatility surfaces (Bennett, 2014).
    ${ }^{84}$ Or also straddles, if they expect a smaller move. A straddle is identical to a strangle except that the two strikes should be ATM for both the purchased call and put option.

[^40]:    ${ }^{85}$ This is the longest period during which options data from the OptionMetrics database is available.
    ${ }^{86}$ This choice is dictated by the fact that Doran, Peterson and Tarrant (2007) use index options data on the S\&P 100 index. Since we are applying a similar methodology to single stock options, we wanted to use components of that index. Furthermore, for computational ease and statistical reasons, it is better to include those stocks for which options are more likely to be traded and liquid.
    ${ }^{87}$ We chose to keep only those stocks for two reasons: (1) to ensure consistent estimation of the model over a common sample period; and (2) for computational ease.
    ${ }^{88}$ In the Appendix, tickers of the selected 24 stocks are available.
    ${ }^{89}$ IV is computed by OptionMetrics using a standard binomial tree model (Cox, Ross and Rubinstein, 1979) to price American options on dividend-paying stocks.
    ${ }^{90}$ The same procedure is recycled for all 24 stocks. We will then present only the final results for the 24 stocks, without entering into details for sake of brevity. However, in the Appendix, we report the

[^41]:    cross-sectional statistics for all 24 stocks, which confirm the findings for HAL. All statistics are computed for the sample before controls on jumps or ATM IV are imposed.
    ${ }^{91}$ Linear, as they will be used only to define the jumps. We will then compute $\log$ returns for econometrics, due to their well-known better statistical properties.
    ${ }^{92}$ The results of these tests are not reported as these are not the focus of the empirical work. However, they are available on demand.
    ${ }^{93}$ t-Student Non-linear Asymmetric Generalized Auto-Regressive Conditional Heteroscedasticity model, which generates volatility estimates by properly taking into account: (1) the leptokurtic nature of returns; and (2) the non-linear asymmetric nature of volatility responses to returns, where volatility spikes more after negative jumps than after positive jumps. $\sigma_{t+1}^{2}=\omega+\alpha\left(r_{t}-\delta \sigma_{t}\right)^{2}+\beta \sigma_{t}^{2}$, where the next period variance $\sigma_{t+1}^{2}$ is equal to a constant $\omega$, current period shock $\left(r_{t}-\delta \sigma_{t}\right)^{2}$ multiplied by parameter $\alpha$ and current period variance $\sigma_{t}^{2}$ multiplied by parameter $\beta$. We can notice that when returns are negative, the effect on next period variance is magnified, whereas when returns are positive, the effect is reduced, thus giving rise to asymmetry.
    ${ }^{94} 252$ trading days for each year.
    ${ }^{95}$ This means that the first estimate of the parameters will be done using 2 years of daily data; then these estimated parameters will be used to estimate daily volatility for the following 6 months, after which the algorithm will add the 6 months to the initial estimation window of 2 years and re-estimate a new set of parameters using 2.5 years of daily data. The procedure is carried forward until December 31, 2017. Latest estimates will be more stable and robust given the progressively longer estimation window used.

[^42]:    ${ }^{96}$ Doran, Peterson and Tarrant (2007) compute moneyness either as strike over forward or using the Delta of the options. However, they find that results are not sensitive to moneyness specifications and, hence, we will simplify the procedure by computing spot moneyness, despite forward moneyness being a better market practice.
    ${ }^{97}$ In order to ensure that, at the quoted prices, there is trading and, hence, information dissemination and price discovery.

[^43]:    ${ }^{98}$ For calls, the bid must be smaller than the stock close price; for puts, the bid must be smaller than the strike price (Hull, 2012).

[^44]:    ${ }^{99}$ The number of observations ( N ) refers to the number of contracts, not the number of days: in fact, for any given trading day, more than one contract may be within each call/put maturity-moneyness bin.

[^45]:    1002 call or put $\times 3$ ST or MT or LT $\times 7$ DDOTM or DOTM or OTM or ATM or ITM or DITM or DDITM
    ${ }^{101}$ Doran, Peterson and Tarrant (2007) keep also DOTM contracts; however, since they work with index options data, it is likely that observations abound also for the DOTM category. Hence, since DOTM contracts have higher leverage, we expect that the predictive ability of our model will be somewhat worsened by not using those contracts. However, a trade-off between predictive power and statistical significance advises not to include them.

[^46]:    ${ }^{102}$ Consistent with previous literature (Diavatopoulos et al., 2012), we consider the effect of the EAD to last also for the trading day following the EAD, i.e. EAD+1. In fact, immediate market reactions to earnings releases last more than during the same day of the release. Hence, when we refer to EAD, we mean EAD and EAD+1.

[^47]:    ${ }^{103}$ IV usually rises before EADs and then decreases; skews steepen or flatten in expectation of the EAD and then, after the information is disseminated to the market, they revert back to normal (Patell and Wolfson, 1981; Jin, Livnat and Zhang, 2012; Xing, Zhang and Zhao, 2010).
    ${ }^{104}$ The next option series will start in May.
    ${ }^{105}$ This is not strictly speaking an EAD period, as the EAD does not happen inside the life of the option. However, to be more conservative and prudent, we assume that the underlying returns in the last trading days of the option contract will be partially influenced by the very close and upcoming EAD. The main reason for this choice is prudence: since we want to check whether the skew has explanatory power for following jumps also during normal periods with no EADs, we treat quasi-EAD periods as EAD periods to further limit the possible effect of the EAD in the analysis of the normal periods. These cases are few and are unlikely to influence the results.
    ${ }^{106}$ This means that in order to eliminate a big negative jump, we must have observed a big positive jump. Observing a small positive jump does not eliminate the following big negative jump.

[^48]:    ${ }^{107}$ Previous research has found some links between past returns and current IVs (An et al., 2014).
    ${ }^{108}$ Due to a shortcut that has been used to speed up the execution of the code, there are inadvertently few cases in which the issue of daily simultaneity of jumps and observed skews persists. Ex-ante, the goal was to avoid any possible reverse causality flowing from jumps influencing same-day closing option IVs and, hence, skews. However, after an ex-post check on one stock, approximately $4 \%-6 \%$ of skew days identified as jumping days have been found to suffer from this simultaneity issue. This could bias the results, since the statistical significance may be artificially improved by reverse causality. However, assuming that the error percentage is similar across all stocks, reverse causality issues should not spoil results in a tangible way. Finally, since the check has been done ex-post when concluding the thesis, no change in the original code has been possible.

[^49]:    ${ }^{109}$ The same statistics are available for the cross-section of all stocks in the Appendix.
    ${ }^{110}$ A standard t-test for the difference of the means of the two skew populations of jump days and normal days with unequal variances is performed. The null hypothesis is of equal means. Rejection of the null implies there is statistical evidence about the two means being different.

[^50]:    ${ }^{111}$ This is a recurring phenomenon across our sample of 24 stocks. This is in line with our intuition that jumps shall not necessarily happen in proximity of EADs: whereas it is undeniable that new information arrives to the market during EADs (Beaver, 1968), the magnitude of the stock price reaction does not necessarily generate a jump, as we define it.

[^51]:    ${ }^{112}$ Again, before controls on jumps are imposed. Hence, the dataset which will be used for model estimation will contain even fewer observations. Similar findings with fewer skew observations during the first period are obtained for the cross-section, available in the Appendix. An interesting refinement of this thesis would be to limit the analysis to the most recent sub-sample, in order to incorporate more observed skew days.
    ${ }^{113}$ In order to be able to perform probit estimation, we relied on teaching notes for the econometrics course by Bocconi Professor Bruno (Bruno, 2016).

[^52]:    ${ }^{114}$ If $\delta=0$, the exponential collapses to 1 , as in the homoscedastic specification.
    ${ }^{115}$ It would be possible to compute marginal effects at any observation i for each regressor, Average Marginal Effects (AMEs) or Marginal Effects at the Means (MEMs) but it is outside of the scope of this thesis. As in Bruno (2016), the probit marginal effect of $x$ at observation $i$ is: $\phi\left(x_{i}^{\prime} \widehat{\beta_{\text {probit }}}\right) \hat{\beta_{\text {probit }}}$, where $\phi$ is the PDF and $\widehat{\beta_{\text {probit }}}$ is the estimated probit coefficient.
    ${ }^{116}$ Calculated not in absolute value.

[^53]:    ${ }^{117}$ If the p-value of the LR test is below $10 \%$, we reject the null hypothesis of homoscedasticity.
    ${ }^{118}$ The percentage is calculated dividing the number of stocks whose models are homoscedastic by the total number of stocks in each skew type - jump type category.

[^54]:    ${ }^{119}$ Observations are daily observed skews. If one trading day we can observe a traded skew with nonzero volumes, then we will count one observation.
    ${ }^{120}$ The percentage is calculated dividing the number of stocks whose models determine a significantly positive skew coefficient by the total number of stocks in each skew type - jump type category.

[^55]:    ${ }^{121}$ As previously explained, these coefficients cannot be interpreted as marginal effects as in a linear regression model. In order to say: "when put skew changes by 1 -sigma, the probability of observing a future negative jump within the option expiration window changes by $\mathrm{x} \%$ ", one should use the method described in Bruno (2016).
    ${ }^{122}$ However, it is not interpretable as the usual R squared for linear regression models, which is the portion of total variance of the dependent variable explained by the independent variables.

[^56]:    ${ }^{123}$ The threshold equal to $20 \%$ has been chosen after some simulations with different thresholds, since it has produced decent results. However, this choice is of course done ex-ante and different choices could lead to different (and potentially better) interpretations. The results are commented in relation to this choice of threshold. Ex-post, using other thresholds e.g. 50\% may improve the results and future research could use that different threshold to further verify the predictability of jumps.
    ${ }^{124}$ The power of the model.
    125 The confidence of the model.

[^57]:    ${ }^{126}$ IT issues dictated this choice. Results should not change meaningfully if heteroscedastic statistics were added. The same reporting is applied for all research questions.

[^58]:    ${ }^{127}$ We do not check out-of-sample. This is certainly something valuable that could be tested in future research.

[^59]:    ${ }^{128}$ Observations are daily observed skews. If one trading day we can observe a traded skew with nonzero volumes, then we will count one observation.

[^60]:    ${ }^{129}$ When OTM call IV increases relative to ITM call IV, the OTM-ITM call skew becomes less negative. If trading is at least partially informed, this skew dynamic should be associated with traders expecting a higher probability of observing a positive jump in the underlying stock. From this reasoning, the positive coefficient, if statistically significant, confirms the hypothesis.
    ${ }^{130}$ We expected a higher statistical / economic significance for call skews given that there is prior literature documenting that trading in single stock options is mainly driven by calls (Garleanu, Pedersen and Poteshman, 2009). This is likely to mean that call trading, despite dominating single stock options trading, does not carry better information: possibly, retail volumes make up a great portion of call trading.
    ${ }^{131}$ RV stands for realized volatility.
    ${ }^{132}$ Of course, with every strategy focused on Gamma, Theta costs shall be factored in. Most often, a trader needs to pay Theta daily to have the chance to be long Gamma. Hence, even if the options are pricing in little Gamma (i.e. Gamma is cheap) relative to one's expectations and so it would be convenient to buy Gamma by buying straddles or strangles, if Theta is relatively more expensive, then the strategy might not make sense. For more on the Gamma-Theta trade-off, see Bennett (2014).

[^61]:    ${ }^{133}$ We do not report the table for brevity reasons.

[^62]:    ${ }^{134}$ Observations are daily observed skews. If one trading day we can observe a traded skew with nonzero volumes, then we will count one observation.

[^63]:    ${ }^{135}$ If the reasoning is correct for calls, one may expect traders predicting small negative jumps buying ATM puts and calls, thus driving up ATM put IV relative to OTM put IV and flattening the skew before negative jumps happen - this would go against our findings about a put skew steepening prior to negative jumps. Our intuitive explanation is as follows: (1) stock investors like positive jumps; (2) since the market is net long stocks, the majority of people already owns stocks; (3) therefore, stock investors may not be likely to buy OTM calls to get further exposure to the stocks; (4) on the other hand, option traders who do not want to bet on Delta, but on Vega/Gamma have the incentives to buy straddles in expectation of small positive jumps; (5) hence, call trading prior to positive stock jumps may be likely to be dominated by volatility traders buying ATM IV rather than delta traders buying OTM IV. On the

[^64]:    other hand, for negative jumps: (1) stock investors dislike negative jumps; (2) they are likely to buy insurance in the form of OTM puts if they expect negative jumps; (3) hence, put trading prior to negative jumps is likely to be dominated by delta traders buying OTM IV rather than volatility traders buying ATM IV.

[^65]:    ${ }^{136}$ Observations are daily observed skews. If one trading day we can observe a traded skew with nonzero volumes, then we will count one observation.

[^66]:    * Significant at least at 10\%.

[^67]:    ${ }^{137}$ In the Appendix.

[^68]:    ${ }^{138}$ As a reminder, in this work, skews are always defined as differences between out-of-the-money (OTM) implied volatilities and at-the-money (ATM) or in-the-money (ITM) implied volatilities, not taken in absolute value.
    ${ }^{139}$ At least at $10 \%$ significance.

[^69]:    ${ }^{140}$ A caveat: despite the small- and big-jump sample sizes are similar, big jumps are observed more rarely than small jumps. Hence, the less frequent (across sample stocks) statistical significance of the big-jump specifications may be at least partially caused by the recurrent "peso" problem in estimating rare events.

[^70]:    ${ }^{141}$ On average, the sign of the put skew-jump relationship remains positive during normal sub-sample periods, indicating that a more positive put skew (i.e. higher put OTM implied volatility relative to put ATM or ITM implied volatility) is associated with a higher probability of observing future negative jumps in the underlying stock.

[^71]:    ${ }^{142}$ Higher call ATM implied volatility relative to call OTM implied volatility.
    ${ }^{143}$ Less negative (or more positive) call OTM-ITM implied volatility skew, i.e. higher call OTM implied volatility relative to call ITM implied volatility, is associated with a higher probability of observing future positive return jumps.
    ${ }^{144}$ Higher call ATM implied volatility prior to positive jumps; higher put ATM implied volatility prior to negative jumps.

[^72]:    ${ }^{145}$ Implied volatility rises with increasing strikes, for same-maturity options.
    ${ }^{146}$ Implied volatility falls with increasing strikes, for same-maturity options.
    ${ }^{147}$ After all checks performed for various reasons, 24 S\&P 100 stocks have been retained for the analysis. ${ }^{148}$ The longest period available for which we had option data retrievable from the WRDS OptionMetrics database.

[^73]:    ${ }^{149}$ A caveat: (1) one should always consider that information may be already priced in the options, so that trading in the options may reveal unprofitable even before transaction costs: timings is crucial; and (2) two-way transactions costs shall always be factored in.

