Volatility Leadership Among Index Options *

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Abstract

Equity options are not only an attractive trading vehicle due to the high leverage they offer, they also enable investors to trade their volatility expectations. With high-resolution option data, we analyze the volatility information embedded in index options with different moneyness and maturity. We tackle the question of how to characterize the volatility process of cointegrated assets by including options on cointegrated underlyings in a cross-sectional options analysis. For the S&P 500 index market, we find that on both the price as well as the volatility level, the ETF market seems to offer the most dominant security with regard to transmitting price and volatility information. Looking at the options separately, our study suggests that slightly out-of-the-money put options contain more volatility information than either at-the-money put or call options.

Keywords: Volatility Leadership; Implied Volatilities; Index Options; Information Shares
JEL Classification: G13, G14

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1 Introduction

Numerous markets and financial instruments are tied to the S&P 500 index. Among others, the E-mini futures contracts as well as the SPDR ETFs offer investors opportunities to trade expectations on the S&P 500 index, each differing in their individual contract specifications. Hence, prices of these assets should all be interconnected by arbitrage subject to limits imposed by transaction costs. Essentially, there is a single "true" price which should be reflected by all markets, each containing an individual noise term added to the true efficient price. The true price can be assumed to follow a random walk and causes the prices of the cointegrated markets to move when the true price itself moves.

New information that leads to a change in the "true" price may regularly enter one of the markets first before being observed in all prices of the interconnected assets. Consequently, this market appears to lead price changes in the index and other markets follow along. Previous studies of stock market index-related securities such as the S&P 500, the DJIA or the DAX have generally found that it is either the futures or the ETF market that incorporates information first and the index itself follows.

Extending the analysis of price discovery to the second moment is the next logical step in the present analysis. Specifically, if we assume the volatility of the true price to be a random walk from an intra-day perspective, it is possible to decompose the volatility discovery process and allocate a proportional value to a market's contribution to volatility discovery. This paper investigates the question of volatility leadership among different options, each of them priced on an underlying that aims to depict the efficient, unobservable price process of an index. Specifically, in the context of this paper, we analyze the price discovery process of the S&P 500 index by including the index itself, the E-mini and the SPDR ETF in order to determine each market's informational contribution using two different price discovery measures. From the analysis of the first moment, we go one step further and extend the discussion to the second moment, namely the corresponding volatility. This paper aims to identify how and where new information is first integrated into an option's volatility. However, instead of focusing on the historical volatility or estimating a volatility model, we make use of traded options on the three mentioned assets and extract the market's (risk-neutral) implied volatility assumption from option data. To compare the informational contribution of each option to the unobservable volatility process, in a first step, options on the same underlying that only differ according to moneyness and put call-character are included. From there, the option with the highest informational power is chosen for the subsequent comparison across the whole sample of options. This discussion might be particularly relevant to questions regarding hedging strategies as well as regarding risk management associated with adverse selection, as equity options are a popular and important vehicle used by institutional investors to hedge against risk and speculate on the financial market.

To the best of our knowledge, this is the first study that transfers the often-cited and applied price discovery measures to the second moment in consideration of different option characteristics such as moneyness, put-call parity and expiration. Our results suggest that both on the price as well as on the volatility level, the ETF market dominates the price and volatility formation. We differentiate between moneyness and expiration date and find for both index options, E-mini and the ETF options, that slightly out-the-money (OTM) put options contribute most to the volatility information transmission.

The remainder of this note is organized as follows. The next section briefly presents related literature. Section 3 delivers insights into the model setup as well as the volatility extraction methods applied. Section 4 provides a description of the data set and the descriptive statistics. Section 5 presents the empirical results, thereby differentiating between price and volatility leadership. The last section concludes the paper.

2 Literature Review

The price discovery process and information assessment of cointegrated assets has been extensively studied over the last two decades. In his 1995 paper, Hasbrouck (1995) introduced the information share measure, which is based on the assumption that an unobservable, efficient price underlies the various market prices of a specific asset. To analyze this assumption, he looks at several time series which reflect the price movements of this asset; such as, for instance, an index and its corresponding futures or stocks on the same entity, which are traded on different exchanges. Hasbrouck's information share measure quantifies the informational content of the included price series under consideration of the assets' innovation variance. Closely related to this, Schwarz and Szakmary (1994) suggest measuring price discovery solely by means of the adjustment coefficients of a cointegrated VAR, hence, do not include the innovation variance of the price series; this measure is known as the common factor weights. Earlier studies addressing the question of price leadership among assets related to equity index markets mostly suggest that the futures market is the fastest to embody new information. Hasbrouck (2003) calculates the price discovery process of the S&P 500 index including the floor-traded and electronically-traded (E-mini) futures as well as the ETF and concludes that the E-mini contributes most to price discovery. In their studies on the price discovery process on the DJIA, Tse (1999) and Tse et al. (2006) conclude from their bivariate analysis, that most of price discovery occurs in the regular futures index. In an extended study, they estimate the multivariate setup adding the electronically-traded mini-futures and the DJIA ETF and find that the mini-futures incorporates information the fastest.

With the increased data availability of option quotes and prices, this field of literature has been extended to examine the role of option markets in the price discovery process. However, there is no clear consensus on whether the options market contains additional information and contributes to price discovery. Early studies such as Manaster and Rendleman (1982), Bhattacharya (1987) and Easley et al. (1998) identify that some information embedded in options markets serves, for example, as a vehicle to spread investors' information across several options. One of the first and influential studies in this specific area of research is Chakravarty et al. (2004) who translate the information share measure from Hasbrouck (1995) to the options market. They characterize the price discovery process of U.S. stocks by means of both the stock prices as well as their corresponding call options and estimate the information share contributed by call options at between 17.5% and 18.3%. Using a slightly different extraction method for obtaining the stock price underlying the observed option price, Holowczak et al. (2006) use an options sample which consists of 40 U.S. stocks and options and estimate the information share of the NYSE options in their sample as being between 12.7% and 14% and the share corresponding to NASDAQ options being between 3.1% and 15.3%, respectively. They find that there is more price discovery in the options market at times when trading activity in the options market is higher and also when there is a large price movement in the underlying asset. With a data sample assorted with U.S. stocks and stock options, Pan and Poteshman (2006), applying an information-based model, support the positive relationship between the level of options market trading activity and the price discovery of the underlying. However, when looking at S&P 500 index options, the evidence indicating that the options market contains information on the respective underlying's price development vanishes. They attribute this finding to the functional specification that the equity index market serves hedging more than speculation.

Instead of including only one call option into the price discovery analysis as in Chakravarty et al. (2004), Rourke (2013) looks at the relative price discovery of options differing in moneyness. As each individual option contributes to the consecutive price discovery process with a positive information share, he is able to conclude that the options are not redundant, but instead contain different degrees of informational contribution. Averaging over his one-year-sample of NYSE- and Nasdaq-traded stocks and their corresponding options, he assigns more than 17% informational contribution to the options market. In a recent study, Patel et al. (2014) look at the price discovery shares of U.S. options and their corresponding underlying stocks. They apply a slightly adjusted price discovery measure first introduced by Yan and Zivot (2007) which is basically a combination of the common factor weights and Hasbrouck's information share measure. The authors argue that their resulting new measure is compatible with different noise levels in the time series under consideration; however, is limited to the bivariate case. Patel et al. find that the options market's informational content, evaluated with the adjusted information share measure, is about 33% compared to the stock market, which is considerably higher than the estimates made in earlier research. They justify their result by the argument that the option price series contain a higher noise level compared to the stock market which leads to an underestimation of the common information share and common factor weight measure.

Using implied volatilities in order to make a statement about the information transmission of the corresponding underlying time series has also been the fundamental idea applied in Yuhang Xing and Zhao (2014). In contrast to our approach, but still supportive of our basic idea, they calculate implied volatilities from option prices originating from different moneyness and use these to construct a volatility smile. With their results, they can show that the degree of the derived smirk contains predictive power for the future stock price movement. Cremers and Weinbaum (2010) also exploit implied volatility rates of put and call options and find that deviations in the implied volatilities of a put and call pair can contain information about the performance of the future's underlying asset.

Nonetheless, there is also a stream of literature that does not necessarily confirm that the options market contains any additional information that is not already reflected in the prices of the corresponding underlying price series: One proponent of this theory is Stephan and Whaley (1990). More recently, Muravyev et al. (2013) analyze the price adjustment behavior of U.S. stocks and options for situations where the observed stock price and the implied stock price extracted from option-price data using the put-call parity clearly disagree. They look at the adjustment behavior of the two time series shortly after the disagreement effect and find that it is the options market that adjusts towards the stock price, indicating that the options price does not contribute to the price discovery process of the underlying. Also, they calculate the mean information share averaged over the option sample to be roughly 5%, which strengthens the earlier conclusions. In Ansi and Ben Ouda (2009), the literature on the question whether options contain additional information is presented in more detail.

3 Methodology

3.1 Price Discovery Measure

For time series that are cointegrated and stationary in their first differences, a cointegrated VAR is a natural way to analyze the long-term behavior of the data, as the individual time series cannot drift apart from each other arbitrarily. For a system consisting of n time series, where each series is the logarithm of an asset's price at time t, an error correction model can be set up:

$$\Delta S_t = c + \sum_{i=1}^{k} \Gamma_i \, \Delta S_{t-i} + \Pi \, S_{t-1} + \epsilon_t, \tag{1}$$

where S_t is an $(n \times 1)$ vector containing the log price of the n assets included in the price series analysis. c is the regression's constant, whereas the second segment of the RHS of equation 1 is the VAR term of the model including k lags. $\Pi = \alpha\, \beta'$, with α being an $n \times h$ matrix representing the error correction term between the n first-difference stationary time series with h being the total number of cointegration relations. β is the cointegration matrix with the dimension $n \times h$. We follow the literature, e.g., Hasbrouck (1995), Hasbrouck (2003) or Chakravarty et al. (2004), and predefine the cointegration relation between the n log price series as $[\, \iota_{(n-1)} \;\; -I_{(n-1)}]'$, where $\iota_{(n-1)}$ is a column unit vector and $I_{(n-1)}$ is the identity matrix, assuming $n-1$ linear cointegrating relationships. The error term ϵ_t corresponds to a $(n \times 1)$ vector of time-independent innovations with zero mean and covariance matrix Ω.

Equation 1 can be estimated using ordinary least squares for the log of the price series using Newey-West (Newey and West (1987)) standard errors. The number of lags in the VAR term originate from Schwartz information criteria. Specifically, under the consideration of three securities in the system, equation 1 can be formulated as:

$$\begin{aligned}
\Delta S_{1,t} &= c_1 + \sum_{i=1}^{k} \sum_{n=1}^{3} \gamma_{1,i,n}\, \Delta S_{n,t-i} + \alpha_{1,1}(S_{1,t-1} - S_{3,t-1}) + \alpha_{1,2}(S_{2,t-1} - S_{3,t-1}) + \epsilon_{1,t} \\
\Delta S_{2,t} &= c_2 + \sum_{i=1}^{k} \sum_{n=1}^{3} \gamma_{2,i,n}\, \Delta S_{n,t-i} + \alpha_{2,1}(S_{1,t-1} - S_{3,t-1}) + \alpha_{2,2}(S_{2,t-1} - S_{3,t-1}) + \epsilon_{2,t} \qquad (2) \\
\Delta S_{3,t} &= c_3 + \sum_{i=1}^{k} \sum_{n=1}^{3} \gamma_{3,i,n}\, \Delta S_{n,t-i} + \alpha_{3,1}(S_{1,t-1} - S_{3,t-1}) + \alpha_{3,2}(S_{2,t-1} - S_{3,t-1}) + \epsilon_{3,t}.
\end{aligned}$$

In order to quantify both the price discovery process of the price series, as well as the volatility leadership of the corresponding index options, both common factor weights (CFW), first introduced by Schwarz and Szakmary (1994), as well as Hasbrouck (1995)'s information share measure (IS), are applied. The common factor weights measure a market's informational contribution solely based on the adjustment coefficients in the cointegration relation, α:

$$\mathrm{CFW}' = \kappa' \times \mathrm{K}^{-1}, \qquad (3)$$

where κ is a $(n \times 1)$ vector with a 1-scalar at position n, and zero anywhere else. K is a symmetric $(n \times n)$ matrix constructed with the adjustment coefficient matrix α and a $(n \times 1)$ vector of ones, such that the CFWs sum up to one. A more thorough motivation of the common factor weights based on Gonzalo and Granger (1995) is given in Theissen (2002). The information shares require additional input of the variables' innovation variance measured by the covariance matrix Ω of the error terms as well as of the VAR coefficients in equation 1:

$$\mathrm{IS}^{\,i} = \frac{([\psi\, F]_i)^2}{\psi\, \Omega\, \psi'}. \qquad (4)$$

ψ is a vector of dimension $n \times 1$ and can be calculated based on the moving average representation of ΔS_t. F_i originates from a Cholesky factorization and is the lower triangular matrix, such that $\mathrm{F} \cdot \mathrm{F}' = \Omega$ holds. Here, the index i refers to the i-th ordering of the time series, as the resulting triangular matrix F might change depending on which time series is put first in the error correction model.

Comparing the two price discovery measures above, it can be concluded that the efficient price as the product of CFWs multiplied by the corresponding assets' prices is restricted to an average of the current observations in $t-1$, as the CFWs only depend on the adjustment coefficients. Therefore, it might not completely account for bid-ask bounce or overshooting. In this respect, Hasbrouck's information share measure is more flexible, as it includes past observations through the covariance matrix of the error terms Ω as well as the VAR coefficients.

3.2 Volatility Extraction

In order to make a statement about our main question, namely which option contains most of the information on volatilities across time, in a first step it is essential to extract volatility assumptions from option price data. The implied volatility assumption underlying each quote update can be extracted numerically using a suitable option pricing model and the real-time asset price of each option's underlying. Basically, the following problem has to be solved:

$$\hat{\sigma}_t = f^{-1}\left(S_t, X, T, r, D, P_t\right), \tag{5}$$

such that the function $L = \min\limits_{\hat{\sigma}_t}\left(P_t - f(S_t, X, T, r, D, \hat{\sigma}_t)\right)^2$ is minimized wrt $\hat{\sigma}$ for every time stamp t. $f(\ )$ specifies an option pricing algorithm; in the context of this paper, the Black-Scholes pricing model is applied for the SPX options which are of European character, and the binomial tree option pricing routine in the spirit of Cox et al. (1979) with 500 steps is applied for the ES and the SPY options due to their American character. The input parameters required for the option pricing model are the real-time underlying price, S_t, the option's strike price, X and its maturity, T, the risk-free interest rate, r, as well as the dividend yield, D.

In the context of implied volatility calculation, it is important to mention that both the price as well as volatility leadership analysis only require knowledge of the changes in the variables over one discrete instant in time. Hence, even though the applied option pricing models might not work perfectly given the empirical evidence, the resulting changes in the obtained implied volatility rates may be virtually identical to those from the perfect model.

4 Data

This paper comprises tick data on the S&P 500 index, its mini futures and ETF and additionally, each security's corresponding option; all of which are obtained from Bloomberg. Specifically, we use transaction data on the S&P 500 index (SPX) and the E-mini index futures (ES), the latter being one of the most popular index futures in the world. Furthermore, we use trade prices from the SPDR S&P 500 Trust ETF (SPY) which is designed to track the S&P 500 index and is traded mainly on NYSE Amex. Due to liquidity aspects, best bid and offer quote data are used for the options dataset. The big data volume and the resulting computational time required limited the time frame that we could consider to the period of May 27 to June, 30, 2015; i.e., 25 trading days.

The S&P 500 is one of the most important total return stock indices which provides an impression of the condition on the U.S. stock market. It is composed of the 500 biggest listed U.S. companies according to their market capitalization on the NYSE, the NYSE Amex and the NASDAQ. The index is traded during the opening hours of the NYSE, beginning at 9.30 am and closing at 4.00 pm. The index level is recalculated every second, and hence, might exhibit stale prices.

The E-mini futures is an electronically traded futures contract on the S&P 500 with a notional value of 50 times the index itself. It is traded on the Chicago Mercantile Exchange (CME) Globex platform from 6 pm until 5 pm from Sunday until Friday. For the subsequent analysis, however, we neglect over-night trading and only consider the regularly traded ES quotes published from 9.35 am until 4.00 pm. The ES has quarterly expiration cycles in March, June, September and December. For our analysis, we use the futures contract which is closest to maturity and roll over to the next maturity contract two weeks before the final settlement date. Specifically, for the futures contracts included, we use the June contract which expires on June 18, 2015 until June 5th and subsequently, switch to the September expiration.

SPX options are traded on the Chicago Board Options Exchange (CBOE) and are listed as a multiple of USD100 on the underlying index. They are cash settled and expire on the third Friday of the expiry month. As SPX options are European options, early exercise is not possible. We only include quotes originating from regular trading hours, that is, from 9.30 am until 4.15 pm, thereby excluding extended trading hours that last from 3 am until 9.15 am. In contrast to SPX options, options on the SPY are American options and deliver the underlying upon settlement. Furthermore, the notional contract size is only one-tenth of that of SPX options; SPY options usually also expire on the third Friday of the expiration month, and their underlying corresponds to 100 SPY ETFs. ES options are American style options that expire quarterly on the third Friday of the respective month. They are exclusively traded on the CME and are subject to the identical trading hours as the E-mini.

For the main analysis, we adopt the same procedure applied to the E-mini contract, and choose SPX and SPY option contracts that expire on a quarterly basis, and at the same time, restrict the number of days to expiration to be a minimum of 14 calendar days. Options on the SPX are European options, i.e., there is no possibility of early exercise. Options on the SPY and the ES, on the contrary, are American options and need to be treated differently when it comes to the extraction of implied volatilities.

The range in the strike prices chosen for the options on the SPX, the ES and the SPY are chosen such that there always exists at least one put and call option that is slightly in- as well as out-the-money. Specifically, on the first day under consideration, the strike price range is fixed according to the moneyness of the option relative to the opening prices of the SPX, the ES and the SPY on May 27. The respective moneyness is chosen to be between 0.95 and 1.05. In order to circumvent microstructural noise in the opening phase of the exchanges, we only include price and quote data from 9.35 am (Eastern Time Zone) onwards. Rare observations with a negative bid-ask-spread or a best bid or offer quote that deviates greatly from the previous 1-minute moving average (for example, quote prices of zero) are eliminated. Subsequently, we calculate a series of midquotes on a 1-second time resolution for every option and apply the previous tick-method in case neither the bid nor the ask quote is updated. The latter procedure basically fills in missing price records with the most recently observed price, thereby assuming that no new information has occurred on that specific market.

For the extraction of implied volatilities from option prices, data on the risk-free interest rate as well on the underlying's dividend yield are required. We use daily Libor rates for maturities between 1 and 30 calendar days and interpolate the rated for the respective maturity of the considered option. For the ES and SPX option, the dividend yield of the SPX is used, and for the SPY option, we use the dividend yield of the SPY. The Libor rates as well as the dividend yields are all obtained from Bloomberg.

[Insert Table 1 about here]

Table 1 summarizes the descriptive statistics for the SPX, the SPY and the ES. Since the SPX is constructed to tick regularly every second, and hence might be subject to stale prices, its return standard deviation is the lowest compared with the other two securities. The return series on which the measures are built are constructed using a 1-second data resolution and applying the previous tick method when no trade update has been registered. The positive coefficient of the serial correlation of the SPX arises due to the lags in the calculation of the index, as explained above. The negative coefficients for the ES and SPY, however, imply overshooting of the price series. The ES shows the highest average daily percentage number of zero returns, indicating that its prices do not change much from one second to the next. This in turn might be caused by less frequent trading. It is interesting to see that there are on average more transactions in the E-mini market than in the SPY market; still, the daily average absolute number of contracts traded is higher in the ETF market.

[Insert Table 2 about here]

Table 2 serves to give a first brief overview on the included option data. The measures presented are calculated as an average over the 25 trading days considered. Furthermore, they are averaged across the four strike prices which are available for each instrument. The average bid-ask spread values, weighted by the ask price of the respective time stamp, are small for the SPY and ES options, and higher in the case of the SPX options. The higher bid-ask spread of the SPX option is accompanied by a considerably lower average number of quote-updates per day, indicating that the SPX options are less actively traded compared to the SPY and the ES options.

Comparing the standard deviations of the implied volatility rates across the chacateristics of moneyness and put-call character, it can be concluded for all options that the OTM put options exhibit the highest standard deviation. Although the OTM put options tend to have a lower average number of midquote changes, the changes in the resulting implied volatilities seem to fluctuate more, thereby suggesting that if the quotes in these markets are updated, new information deviates more from previous prices.

In order to set up the error correction model and conduct the price discovery analysis, the time series have to be stationary in their first differences. Table 3 presents the results for the stationarity tests conducted both for the log price series of the underlying assets, as well as for implied volatility rates of the OTM put options.

[Insert Table 3 about here]

Table 3 gives the number of days under consideration for which the null hypothesis of the existence of a unit root can be rejected. Both the augmented Dickey-Fuller (ADF) and the Phillips-Perron test statistics suggest that the relevant time series are stationary after taking first differences. Additionally, to meet the assumptions of the model described above, the time series have to be tested for their degree of cointegration, and ideally, n time series are cointegrated of order $n-1$. For the price discovery analysis which includes three log price series, as well as for the volatility leadership analysis which looks in a first step at four 4 and afterward at 3 markets, Johansen cointegration test suggests at most 2 cointegration relations for the trivariate analysis and 3 cointegration relations for the four-asset case.

5 Empirical Results

5.1 Price Leadership

Having performed stationarity and cointegration tests, in a next step, the cointegrated VAR model for the price series of the S&P 500, the E-mini and the ETF, as well as for the extracted volatility series of the corresponding options is estimated using ordinary least squares. Table 4 summarizes the mean results of the parameter estimates from the VECM. As the model is estimated separately for each day, the coefficients in Table 4 show the result for each coefficient averaged over the 25 days under consideration. For each coefficient, the number of days for which the coefficient can be considered to be significantly different from zero are summarized below the coefficient estimates. Ideally, we expect the signs of the cointegration parameters to be positive for one market and negative for the second market in the cointegration relation, indicating that the markets adjust, such that they do not drift too far apart from each other.

[Insert Table 4 about here]

Looking at the error correction terms in rows 4 and 8 and keeping in mind the predefined cointegration relation $[(S_{1,t} - S_{3,t}), (S_{2,t} - S_{3,t})]'$, the reported coefficients have the expected sign. The adjustment coefficient for the return series of the SPX is negative for all 25 trading days, such that in case the index exceeds the SPY in one instance, due to the nature of the system and the negative adjustment coefficient, the index is expected to be pulled back in magnitude within the next time stamps. The same holds for the other adjustment coefficients. The impact of each series' own history is negative for the first lag and significant for all days for the index and the E-mini. The short-term history of the other assets appears to positively affect the return of the asset. The results suggest an explanatory power of the model of 3.9% for the index, 15.8% for the E-mini, and even more than 42% for the SPY.

With the results from the cointegrated VAR, it is now possible to go one step further in the analysis of price leadership. Table 5 presents the results for the price discovery measures of the three underlying securities. Both the Common Factor Weights (CFW) as well as Hasbrouck's information share measure are shown.

[Insert Table 5 about here]

The results on both measures clearly suggest that the SPY dominates the price discovery process of the efficient, non-observable index. With an average CFW of 58% and an information share raning between 57% and 89%, the SPY is observed to lead the price discovery process over the 25 trading days under consideration. For the SPX and the ES, however, the results are not as clear. Going back to the definitions formulated in equations 3 and 4 and comparing the two measures, the CFWs only depend on the adjustment coefficients from the VECM, whereas the information shares include the recent history of the autoregressive part as well as the innovation matrix from the error terms. Therefore, the different outcomes from our analysis are probably caused by the innovations in the price series which do not play any role in the CFW calculation and hence, slightly diverge for the two assets.

5.2 Volatility Leadership

In a next step, the cointegrated VAR is estimated for the implied volatility series in the same way as above. Table 6 summarizes the average ECM results and suggests very similar conclusions to those drawn for the model estimated from the underlying price series. The adjustment coefficients for both cointegration relations, on average, have the expected sign, although the coefficients for the implied SPY volatility is significant only for a couple of days, meaning that the SPY does not necessarily adjust to the other time series.

[Insert Table 6 about here]

The implied volatilities are negatively related to their own history; however, owing to the dependency of a time series on the first lag of the other time series, no clear picture can be drawn, as there are mixed results with respect to the coefficients' signs. Although the explanatory power of the error correction model is rather low compared to the results presented above, it still ranges from about 3% for the SPX and the SPY options, and up to 7% for the ES options. Note, that the results presented in Table 6 are based on OTM put options only, because, as seen further down, these options seem to play a key role in volatility leadership among the three option groups.

For the implied volatility series of the SPX, ES and SPY options, a similar analysis is conducted. However, before comparing the options' informational contribution across the three securities, in a first step, the option type which has the highest explanatory power within an asset class has to be determined. Therefore, we estimate the CFWs and Hasbrouck's information shares for different moneyness and put and call combinations for every security.

[Insert Table 7 about here]

From the results in Table 7, it can be concluded that the OTM put and call options contribute most to the process of the efficient implied volatility of each option series. For the ES and SPY options market, both the CFWs as well as the information shares support the OTM put options as containing most of the information of the efficient implied volatility discovery, with the OTM call options following very close behind. For the SPX options, OTM call and put options seem to dominate the volatility process. Reported upper and lower bounds for the information shares do not diverge much: however, for the SPX options, the average lower bound for the OTM put clearly lies below the average upper bound of the OTM call option, thus suggesting that OTM put and call options take turn in leading the volatility process. Based on these outcomes, we continue the quest for volatility leadership between the SPX, ES and SPY options - which all have the same unobservable efficient index as the underlying asset in common by comparing the CFWs as well as the information share bounds across the three OTM put options.

[Insert Table 8 about here]

The top results presented in Table 8 are averaged over the 25 trading days and are based on the implied volatilities of the SPX, ES and SPY OTM put options with a 1-second data resolution. The results for both the common factor weights and the bounds of the information shares suggest that the implied volatility of the SPY OTM put option on average contributes the most to the evolution of the common volatility underlying all the options. Note, that the difference between the upper and the lower information share bound is very small throughout all options, whereas the standard deviation of the CFWs across the 25 trading days is comparatively high. These slight disagreements, once again, arise because of the different methods underlying the calculation of these two measures. However, when it comes to volatility and the often observed mean reversion over a longer time horizon, the results appear slightly more reasonable when at least the recent history is included; i.e. by involving the lagged VAR coefficients as well as the innovation variance.

With respect to the choice of option type for the volatility leadership discussion, we calculate the informational contribution of OTM call options in the same spirit as for the OTM put options. The bottom part of Table 8 summarizes the CFWs as well as the information share bounds averaged over the 25 trading days considered. The results once again suggest that the options on the ETF dominate the volatility discovery process which is supported by both the CFWs as well as Hasbrouck's information share measure. Compared to the analysis based on OTM put options, OTM call options on the E-mini contribute considerably less to the volatility discovery than the ES put options do.

For the sake of completeness, the volatility leadership analysis is conducted separately for the options' expiration. The corresponding results are in line with the findings above and are presented in Appendix A.

Regarding the different expirations of the options comprised in our dataset, it is reasonable to consider the informativeness of close-to-maturity versus next-to-maturity options. Intuitively, the closer the option to maturity, the less trading activity there is, and the more investors roll over to the next expiration.

[Insert Table 9 about here]

Table 9 presents the results for a comparison of the volatility informativeness of options which only differ according to their expirations. Daily minimum and maximum values for both the common factor weights and the mean information share are calculated for the time period, during which our option data overlaps with respect to the options' maturity. The OTM put and OTM call options of each of the three option classes are included in the bivariate volatility leadership analysis. The findings for the SPX and ES options favor the above described suppposition about the transfer of information from the closest to the next maturity option. The CFWs as well as mean information shares suggest that the options which are close to expiration options to only contain only a small amount of information about the true underlying volatility process. The lowest and highest values of each measure do not deviate much from each other. However, this does not necessarily hold for the informativeness of the SPY volatilities. The values for the minimum and maximum CFWs as well as information shares do not permit a dominant role in volatility leadership to be assigned to either the closest-to-expiration or the next-to-expiration options.

[Insert Figure 1 about here]

These findings are confirmed when looking at the graph illustrating the obtained CFWs (Table 1) and information shares (Table 2). Especially for the OTM put options of the SPX and ES, it becomes apparent that the informativeness of the option that is closest to maturity decreases over the 10 overlapping days under consideration during which options data of both June as well as September is available.

[Insert Figure 2 about here]

Although there is no clear conclusion that can be drawn from the findings of the SPY volatilities, for all of the included OTM options, the volatilites for the options with September maturity seem to contribute more to the volatility discovery process than the volatilities obtained from June options.

6 Conclusion

This paper analyzes price and volatility transmission on the S&P 500 index market by including high-frequency data on the index itself and on its options, the E-mini and the SPDR ETF, and their corresponding options. Evidence from volatility smirks (i.e., indicating that option's implied volatility varies across moneyness) already gives some justification that option series are priced individually on different information and assumptions. In extending the price discovery literature to the second moment by drawing on the extracted implied volatility rates of the options, this paper delivers complementary findings which are potentially important for a better understanding of hedging strategies and managing risk.

On the first moment, price discovery measures for the index, the E-mini (ES) and the SPD ETF (SPY) are calculated on a daily basis, applying both Hasbrouck's information share measure as well as the common factor weights. We find that on the first moment, the SPY dominates the price discovery process of the S&P 500. After having extracted implied volatility rates for all option series categorized by moneyness and put-call character, we find that for all three securities new volatility information tends to be assimilated first in the OTM put and call options. Exploiting this fact, we conduct an across-securities comparison of OTM put options on the SPX, the ES and the SPY. Our results for the volatility transmission suggest that on the second moment, the SPY once again assmilates new information the fastest, manifesting this in trading activity.

As the data sample only ranges over a limited number of days, a next sensible step to take is to extend the time period of the data in order to more precisely evaluate the time series behavior of the volatility transmission across options. With a longer time horizon, the volatility information transmission could be checked for dependencies with the market environment and micro-structure-specific variables.

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A Subsample for Different Expirations

Since the option dataset comprises both June and September options, the volatility leadership measures are calculated separately for both expiration types. Following the procedure above, in a first step, the informational contribution of the different option types within one security are calculated. For the June options, we find that the OTM put options across all securities dominate the volatility discovery process. For the SPX and the ES options, both CFWs and information shares suggest the OTM call options to be the second most dominant option type. For the SPY, in contrast, the ATM call options seem to be more important than the OTM calls.

[Insert Table 10 about here]

More striking results can be found when looking at the SPX and the ES September options in the bottom half of Table 10. For the SPX options, the CFW results suggest the OTM put option dominates the volatility discovery process, whereas Hasbrouck's information shares evidence the dominance of the OTM call options. For the ES, the OTM put option remains the most dominant option within the option set, while the ATM call option is more important and has a higher CFW and information share compared to the OTM call option. For the SPY option, the ATM put option replaces the OTM put option and has higher information share bounds, whereas the CFW still suggests that the OTM put option dominates the SPY volatility process.

The striking results for the September expiration might be due to the long time horizon of the options compared to the June expiration. For the September options, the maturity is almost 3 months, suggesting a comparatively lower trading activity leading to less pronounced results in terms of volatility leadership.

Additionally, the constituents in the volatility discovery process are calculated separately with the implied volatilities extracted from June and September options. For purposes of comparison, we continue to conduct the analysis using OTM put and OTM call options, thereby slightly neglecting the intermediate results presented in Table 10.

For the OTM put options, our earlier findings seem to be robust, independent of which option maturity we select. The SPY option still dominates the volatility discovery process, confirmed by both the CFWs as well as by the upper and lower information share bound. The SPX option remains more important with respect to its informational contribution compared to the ES put option.

Similar results are obtained when looking at the OTM call options. The SPY option clearly dominates the volatility discovery, followed by the SPX option. As before, the options on the E-mini do not seem to play an important role.

B Tables

Table 1: Descriptive Statistics 1

	SPX	ES	SPY
Return Standard Deviation (%)	.00146	.00606	.00379
1st-Order Serial Correlation	.282	$-.230$	$-.117$
Percentage Zero Returns (%)	44.4	76.1	54.5
Avg. Daily Trading Size	-	$9.97e05$	$8.41e07$
Avg. Daily Number of Transactions	-	$3.16e05$	$2.81e05$
Index Factor	-	1	10
Contract Size	-	50	-
Tick Size	0.01	0.25	0.01

The table displays summary statistics for the underlying dataset which includes S&P 500 (SPX), the E-mini (ES) and the SPY. The calculation of the return standard deviation as well as 1st-order serial correlation is based on the assets' return series. The returns are calculated using available trade prices on a 1-second data resolution using the previous tick method. Percentage zero return presents the number of entries in the return series for which there is no trade recorded; that is, for which the return equals zero. The average daily trading size corresponds to the average number of contracts traded on a sample day, whereas the average daily number of transactions describes how many trades were recorded per day on average.

Table 2: Descriptive Statistics 2

	ATM Call	OTM Call	ATM Put	OTM Put
	SPX Options			
Percentage Bid-Ask Spread	4.13	8.74	4.17	8.36
Avg. Numb. of Midquote Changes	6,404	4,174	6,631	4,138
Impl. Volatility Standard Dev. (%)	.0825	.0824	.0916	.1027
1st-Order Serial Correlation	.994	.996	.995	.996
Tick Size	0.10 (Index multiplier: $100)			
	ES Options			
Percentage Bid-Ask Spread	1.62	2.91	1.82	2.39
Avg. Numb. of Midquote Changes	51,630	42,594	57,659	40,440
Impl. Volatility Standard Dev. (%)	.0845	.0910	.0945	.1027
1st-Order Serial Correlation	.983	.990	.964	.988
Tick Size	0.01 (Index multiplier: $100)			
	SPY Options			
Percentage Bid-Ask Spread	1.33	2.33	1.51	2.29
Avg. Numb. of Midquote Changes	60,521	40,668	60,521	38,878
Impl. Volatility Standard Dev. (%)	.0961	.0883	.1043	.111
1st-Order Serial Correlation	.994	.996	.995	.997
Tick Size	0.25 (Index multiplier: $50)			

The table briefly displays summary statistics for the options dataset including SPX options, SPY options and E-mini (ES) options. The statistics are averaged over the 25 trading days under consideration. The percentage bid-ask spread resembles the average spread between ask and bid quotes weighted by the ask quote. The average number of changes in the midquote shows the average number of quote updates per day.

Table 3: Stationarity Test

	Level		First Differences	
	ADF	Phillips-Perron	ADF	Phillips-Perron
log(S&P500))	0	1	25	25
log(E-mini)	0	1	25	25
log(ETF)	0	1	25	25
$\log(\sigma_{\text{SPX}}))$	0	0	25	25
$\log(\sigma_{\text{ES}}))$	0	0	25	25
$\log(\sigma_{\text{SPY}}))$	0	0	25	25

The table presents the number of days for which the null hypothesis of the existence of a unit root at significance level of 0.05 is rejected. The number of rejections over the 25 days under consideration is reported for the levels as well as first differences of the time series obtained from the augemented Dickey-Fuller (ADF) test as well as Phillips-Perron test.

Table 4: Error Correction Model - Underlyings

	D(log(S&P500))	D(log(E-MINI))	D(log(ETF))
Average Constant	−.00004	−.00002	.00008
	[−1.7950]	[−2.8432]	[14.3850]
	(16)	(24)	(25)
Average EC term 1	−.0479	.1440	.0330
	[−6.7020]	[14.3152]	[13.2904]
- of which positive	0 (0)	25 (24)	25 (25)
- of which negative	25 (25)	0 (0)	0 (0)
Average EC term 2	.0274	−.1330	.0020
	[6.0114]	[−19.9604]	[1.3520]
- of which positive	25 (25)	0 (0)	17 (17)
- of which negative	0 (0)	25 (25)	8 (8)
$D(\log(S\&P500))_{-1}$	−.148	.211	.131
	[−12.1870]	[12.6787]	[20.3602]
	(25)	(25)	(25)
$D(\log(E\text{-MINI}))_{-1}$	.0699	−.302	.0390
	[9.6346]	[−29.6874]	[12.8985]
	(25)	(25)	(24)
$D(\log(ETF))_{-1}$	.125	.150	−.553
	[3.1963]	[3.0384]	[−.3466]
	(19)	(18)	(7)
Average R^2	.039	.158	.421
Average F Statistic	42.11	192.41	764.55
	(25)	(25)	(25)

This table presents the mean results for the OLS regression estimated for each day separately using Newey-West standard errors (Newey and West (1987)). Rows 4-11 summarize the mean cointegration terms and the corresponding t-statistics for the estimated model; rows 12-20 show the coefficients on the first lag. All reported values are averaged over the 25 days under consideration. The model is estimated using the price series of the S&P500, the E-mini and the SPDR ETF with a 1-second resolution. Average daily t-statistics are presented in brackets. The number of days, where the coefficients are significantly different from zero, are reported in parentheses at the 5% significance level. The cointegration matrix is predefined as $\beta' = [\,\iota_{(n-1)} \;\; -\mathrm{I}_{(n-1)}]$, with $\iota_{(n-1)}$ being a column unit vector and $\mathrm{I}_{(n-1)}$ the identity matrix. The total number of rejections of the F-statistic in row 23 refers to the 5% significance level.

Table 5: Price Leadership - Underlying

	S&P500	E-mini	ETF
CFW	.2899	.1248	.5856
Upper IS	.0737	.3706	.8951
Lower IS	.0271	.0594	.5740

The table displays the common factor weights (CFWs) of the S&P500, the E-mini and the ETF calculated over the time period from May 27 to June 30, 2015. The common factors are averaged over the 25 trading days. They are calculated based on transaction data with a 1-second data resolution. Upper and lower IS display the respective upper and lower bounds of Hasbrouck's information share measure.

Table 6: Error Correction Model - Implied Volatilities

	$D(\log(\sigma_{SPX}))$	$D(\log(\sigma_{ES}))$	$D(\log(\sigma_{SPY}))$
Average Constant	.00011	.00063	$-.0011$
	[-1.1026]	[-2.9626]	[-4.5733]
	(15)	(17)	(23)
Average EC term 1	$-.0043$	.0099	.003
	[-4.8225]	[5.6201]	[2.4412]
- of which positive	0 (0)	25 (20)	20 (16)
- of which negative	25 (23)	0 (0)	5 (5)
Average EC term 2	.004	$-.00150$	.0027
	[4.1665]	[-8.4783]	[1.5610]
- of which positive	25 (24)	0 (0)	18 (3)
- of which negative	0 (0)	25 (25)	7 (1)
$D(\log(S\&P500))_{-1}$	$-.092$	$-.0131$	.0071
	[-6.3637]	[$-.2310$]	[$-.7374$]
	(21)	(4)	(18)
$D(\log(\text{E-MINI}))_{-1}$	.0069	$-.199$	$-.0268$
	[.5250]	[-8.9774]	[-3.2451]
	(11)	(25)	(19)
$D(\log(ETF))_{-1}$	.0048	.0093	$-.114$
	[.5637]	[.10]	[-3.9704]
	(1)	(0)	(22)
Average R^2	.0263	.0683	.0315
Average F Statistic	28.81	80.00	35.27
	(25)	(25)	(25)

This table presents the mean results for the OLS regression estimated for each day separately using Newey-West standard errors (Newey and West (1987)). Rows 4-11 summarize the mean cointegration terms and the corresponding t-statistics for the estimated model; rows 12-20 show the coefficients on the first lag. All reported values are averaged over the 25 days under consideration. The model is estimated using the implied volatility series of the SPX options, the ES options and the SPY options with a 1-second resolution. Average daily t-statistics are presented in brackets. The number of days, where the coefficients are significantly different from zero, are reported in parentheses at the 5% significance level. The cointegration matrix is predefined as $\beta' = [\,\iota_{(n-1)} \;\; -\mathrm{I}_{(n-1)}]$, with $\iota_{(n-1)}$ being a column unit vector and $\mathrm{I}_{(n-1)}$ the identity matrix. The total number of rejections of the F-statistic in row 23 refers to the 5% significance level.

Table 7: Volatilty Leadership - Within Securities for All Expirations

	ATM Call	OTM Call	ATM Put	OTM Put
SPX Options				
CFW	.2248	.2605	.1539	.3607
Upper IS	.3400	.3762	.1891	.3679
Lower IS	.2034	.1331	.1172	.2285
ES Options				
CFW	.2160	.1918	.1494	.4428
Upper IS	.2410	.1945	.1875	.5249
Lower IS	.1613	.1331	.1172	.4405
SPY Options				
CFW	.1987	.2075	.1594	.4345
Upper IS	.2517	.2410	.2143	.4475
Lower IS	.1652	.1680	.1321	.3809

The table displays the common factor weights of the implied volatilities extracted from different SPX, ES and SPY options calculated over the time period from May 27 to June 30, 2015. The common factor weights are calculated across different options within one asset class and are averaged over the 25 trading days. The ATM option is the option that is closest to ATM over the time period considered. Common factor weights are calculated based on best bid and best offer quote data with a 1-second data resolution. Upper and lower IS display the upper and lower bounds of Hasbrouck's information share measure.

Table 8: Volatility Leadership - OTM Options for All Expirations

	SPX	ES	SPY
	OTM Put Options		
CFW	.2750	.2003	.5247
Upper IS	.2661	.2568	.5210
Lower IS	.2493	.2199	.4867
	OTM Call Options		
CFW	.3358	.1184	.5458
Upper IS	.3500	.0973	.5807
Lower IS	.3308	.0827	.5585

The table displays common factor weights for the OTM put and call options of SPX, ES and SPY. The options included in this across-asset analysis are selected according to their ranking in the information processing compared with comparable options that have the same underlying asset. The common factor weights are calculated over the time period from May 27 to June 30, 2015. They are averaged over the 25 trading days and are calculated based on quote data with a 1-second data resolution. Upper and lower IS display the respective upper and lower bounds of Hasbrouck's information share measure.

Table 9: Volatility Leadership - June vs. September Options

	June Expiration	September Expiration
SPX Call Options		
Min(CFW)	.000	.7412
Max(CFW)	.2588	1.0
Min(Mean IS)	.004	.7414
Max(Mean IS)	.2586	.9960
SPX Put Options		
Min(CFW)	.000	.7176
Max(CFW)	.2824	1.0
Min(Mean IS)	.002	.7963
Max(Mean IS)	.2037	.9980
ES Call Options		
Min(CFW)	.0594	.6580
Max(CFW)	.3420	.9406
Min(Mean IS)	.0292	.7271
Max(Mean IS)	.2729	.9708
ES Put Options		
Min(CFW)	.000	.7176
Max(CFW)	.2824	1.0
Min(Mean IS)	.002	.7960
Max(Mean IS)	.2040	.9980
SPY Call Options		
Min(CFW)	.000	.2274
Max(CFW)	.7726	1.0
Min(Mean IS)	.0024	.0379
Max(Mean IS)	.9621	.9976
SPY Put Options		
Min(CFW)	.0571	.1905
Max(CFW)	.8095	.9429
Min(Mean IS)	.0185	.060
Max(Mean IS)	.9400	.9815

This table displays the daily minimum and maximum of the common factor weights and the mean information share of implied volatilities compared for different expiration dates. Model in 1 is estimated for the bivariate case, including options with the same characteristics wrt to moneyness and put and call character, and only distinguished by their expiration date. The volatility leadership analysis is conducted for the volatility series derived from OTM put and OTM call SPX, ES and SPY options. For the SPX and the ES options, the presented measures are calculated over a time period from June 08 until June 18; for the SPY option from June 08 until June 26, 2015.

Table 10: CFW - Separated by Expiration

	ATM Call	OTM Call	ATM Put	OTM Put
		June Expiration		
SPX Options				
CFW	.1743	.2701	.1165	.4392
Upper IS	.2746	.3441	.1678	.4078
Lower IS	.1670	.2548	.0730	.3110
ES Options				
CFW	.1163	.2621	.0405	.5811
Upper IS	.1573	.2538	.0600	.6256
Lower IS	.1015	.2160	.0277	.5582
SPY Options				
CFW	.1792	.1451	.1402	.5356
Upper IS	.2304	.1333	.1708	.5686
Lower IS	.1657	.0954	.1072	.5287
		September Expiration		
SPX Options				
CFW	.2518	.2688	.1607	.3186
Upper IS	.3669	.3716	.1971	.3440
Lower IS	.2234	.2214	.0800	.1963
ES Options				
CFW	.2609	.2084	.1874	.3411
Upper IS	.2889	.2120	.2320	.4257
Lower IS	.2016	.1490	.1532	.3381
SPY Options				
CFW	.1879	.2097	.2581	.3442
Upper IS	.1975	.2740	.3929	.3160
Lower IS	.1433	.1549	.2378	.2249

The table displays the common factor weights of the implied volatilities extracted from different SPX, ES and SPY options calculated over the time period from May 27 to June 18, 2015, for the June expiration and from June 8 to June 30, 2015, for the September expiration. The common factor weights are calculated across different options within one asset class and are averaged over each of the 17 trading days. The ATM option is the option that is closest to ATM over the time period considered. Common factor weights are calculated based on best bid and best offer quote data with a 1-second data resolution. Upper and lower IS display the respective upper and lower bounds of Hasbrouck's information share measure.

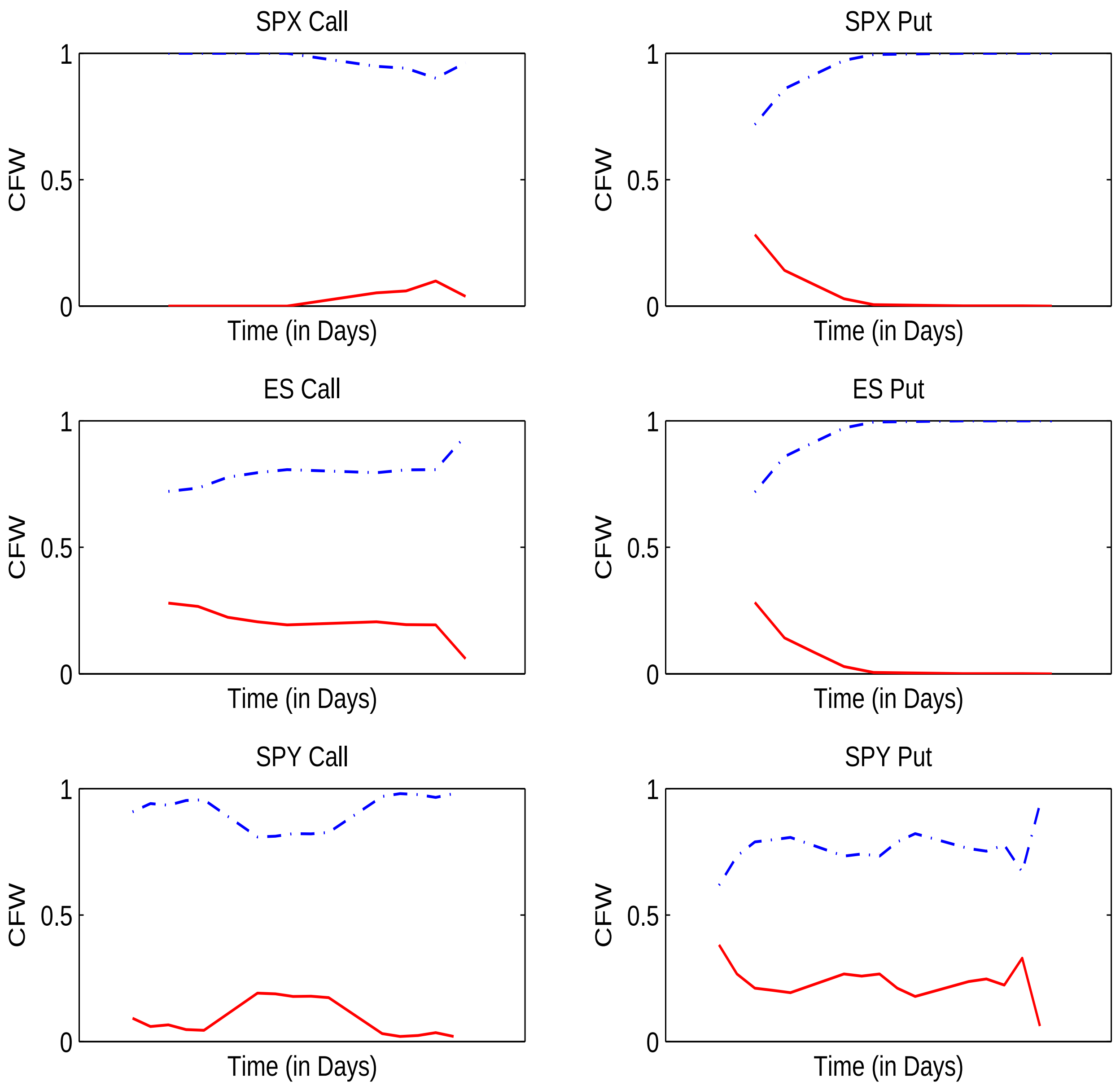
Table 11: Volatility Leadership - OTM Put Separated wrt Expiration

	SPX	ES	SPY
	OTM Put Options		
June Expiration			
CFW	.2675	.2385	.4940
Upper IS	.2503	.2838	.5112
Lower IS	.2371	.2424	.4752
September Expiration			
CFW	.2920	.1767	.5313
Upper IS	.3004	.2231	.5107
Lower IS	.2831	.1983	.4843
	OTM Call Options		
June Expiration			
CFW	.3271	.1165	.5565
Upper IS	.3567	.0880	.5760
Lower IS	.3458	.0738	.5577
September Expiration			
CFW	.3616	.1244	.5140
Upper IS	.3775	.0956	.5571
Lower IS	.3548	.0821	.5330

The table displays common factor weights for the OTM put and call options of SPX, ES and SPY separately for the different expiration dates. The options included in this across-asset analysis are selected according to their ranking in the information processing compared with comparable options that have the same underlying asset. The common factor weights are calculated over the time period from May 27 to June 30, 2015. They are averaged over the 17 trading days for each split-off period and are calculated based on quote data with a 1-second data resolution. Upper and lower IS display the upper and lower bounds of Hasbrouck's information share measure.

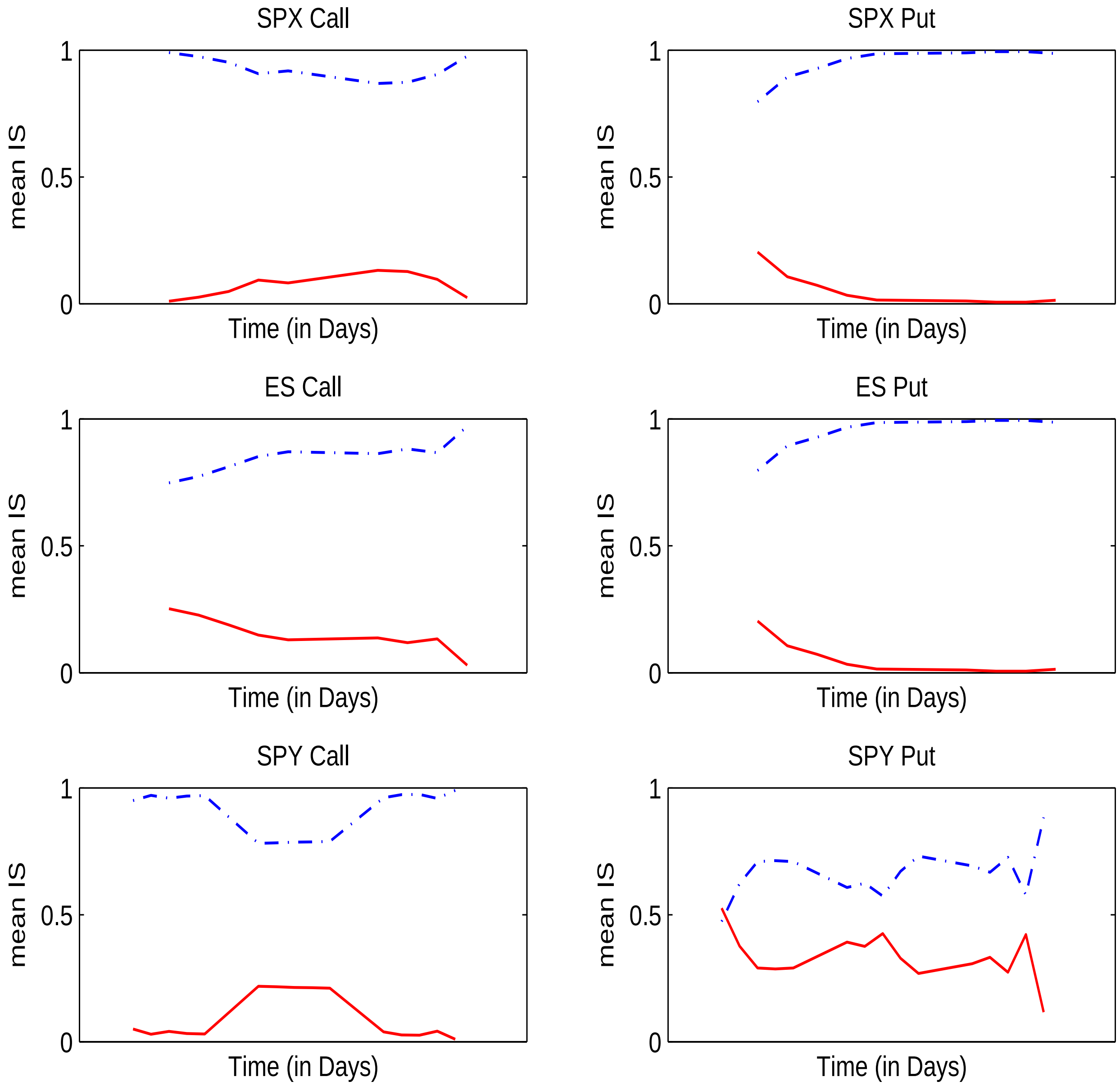
C Figures

Figure 1: CFWs for Expiration Overlap



This figure plots the common factor weights (CFWs) for implied volatilities of options with same the identification, excepting expiration. The CFWs are calculated for the overlapping time period from June 08 until June 18, 2015, during which data for both June as well as September options is available. The dashed line corresponds to the options with September expiration, and the straight line to the June expiration.

Figure 2: Mean IS for Expiration Overlap



This figure plots the mean information share (IS) for implied volatilities from options with the same identification, excepting expiration. The mean information share is calculated for the overlapping time period from June 08 until June 18, 2015, during which data for both June as well as September options is available. The mean IS corresponds to the average between Hasbrouck's upper and lower information share measure. The dashed line corresponds to the options with September expiration, and the straight line to the June expiration, respectively.