

The Informational Value of Consensus Prices: Evidence from the OTC Derivatives Market

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Abstract

This paper provides empirical evidence on the ability of consensus prices to reduce valuation uncertainty in the over-the-counter market for financial derivatives. The analysis is based on a proprietary data set of price estimates for S&P500 index options provided by major broker-dealers to a consensus pricing service. We develop and estimate a model of learning about fundamental asset values from consensus prices. The panel dimension of the data set allows us to estimate Bayesian updating dynamics at the individual broker-dealer level. We find that uncertainty about index option values, as measured by the variance of broker-dealers' posterior beliefs about the options' fundamental value, is substantial across the volatility surface of S&P500 index options that are traded over-the-counter. The 95% confidence intervals around posterior means can be as large as 10 volatility points for index options with strike prices that correspond to extreme moves of the S&P500 index. Having access to consensus pricing data is found to significantly reduce broker-dealers' strategic uncertainty, that is uncertainty about the positioning of their option valuations in relation to other market participants' valuations.

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1 Introduction

This paper studies the informational value of consensus prices for market participants trading in the over-the-counter (OTC) market for financial derivatives. OTC trading is the dominant market structure for many important financial assets, including corporate bonds and a majority of financial derivatives contracts. Unlike on centralised exchanges, in OTC markets price and volume data are proprietary information of the parties directly involved in a given transaction and, typically, are not made available to other market participants. Problematically, these data are a crucial input for asset valuation and risk management and their public availability can facilitate efficient risk transfers by reducing informational asymmetries between market participants. As a market response to this problem, consensus pricing services have sprung up in many important OTC markets. Consensus pricing services collect estimates of an asset’s mid-market value from market participants, aggregate these estimates, and then return an aggregate “consensus price” to their subscribers. Using a proprietary dataset of consensus prices provided by a large consensus pricing service for the OTC derivatives market, we study the ability of the service to reduce market participants’ valuation uncertainty. We consider two dimensions of valuation uncertainty: fundamental uncertainty, that is uncertainty about fundamental asset values, and strategic uncertainty, by which we understand uncertainty about the relative position of ones asset valuations in relation to competitors’ valuations.

In the wake of the LIBOR scandal of 2012 the usefulness of consensus pricing services as information aggregation devices has come under close scrutiny. There has been an ongoing regulatory effort to switch important financial benchmarks from using consensus prices to using transaction prices and firm quotes.¹ It is, however, unclear whether a complete switch, if at all feasible, is also desirable. Particularly during episodes of extreme market stress, transaction- or quote-based price data might become unavailable due to market illiquidity. In such situations, consensus prices will often be the only available source of valuation data. But these are exactly the periods during which pricing information can be most valuable, both for risk management purposes and for reducing informational asymmetries in the affected market.

Apart from their practical importance as a source of information in opaque financial markets, consensus prices also provide an ideal data source to study how market participants extract information from asset prices and how these learning dynamics

¹For an overview of the current regulatory debate see [Wheatley \(2012\)](#), [IOSCO \(2013\)](#), [Financial Stability Board \(2014\)](#).

are reflected in the dynamics of asset prices. This is due to the specific design of the consensus pricing mechanism: at regular intervals, market participants provide their own price estimates to a central actor that then averages these individual estimates and returns an average value back to the participants. Having access to individual submission data allows us to track the time series of price estimates of each individual participant as well as the common feedback participants receive in the form of the consensus price. This enables us to estimate Bayesian updating dynamics directly at the individual participant's level, something that is impossible to do with transaction prices that are the outcome of a market equilibrium.

The paper studies a consensus pricing service for equity index options run by IHS Markit's Totem service. Totem is a large consensus pricing service specialising in the over-the-counter market for financial derivatives. We use a novel proprietary dataset to study the informational value of S&P500 index option consensus prices collected by the Totem service. We have access to a panel of price estimates that major financial institutions have provided to this service. To gauge the informational content of these price data, we develop a model of learning about fundamental asset values from public and private information. We treat the consensus price as a publicly observable signal about fundamental values and explicitly model the endogeneity of this signal which is both an input and an output of the learning process of users of the consensus pricing service. We estimate this structural model exploiting both the time-series and cross-section of individual financial institutions' price estimates and the corresponding consensus prices. We then construct three empirical measures for the informational value of the consensus prices from the estimates of the structural parameters of our model.

The first of these measures is based on the posterior variance of submitters' beliefs. Here, we focus on submitters' first and second order beliefs about fundamental asset values, and refer to these as fundamental and strategic uncertainty, respectively. Fundamental uncertainty, as measured by the posterior variance of submitters' first order beliefs, measures submitters' uncertainty about asset values. The higher the posterior variance of these beliefs, the less certain are submitters' about the current fundamental value of the asset. Strategic uncertainty, as measured by the posterior variance of submitters' second order beliefs, measures submitters' uncertainty about the asset valuation of other market participants. The higher the posterior variance of second order beliefs, the more uncertain is a given submitter about the position of his valuation relative to other market participants' asset valuations.

The second informational measure gauges by how much submitters' fundamental and strategic uncertainty is reduced by having access to the consensus price information. To do so, we compare the model-implied posterior variances of market participants' first and second order beliefs concerning the mid-market value of an asset for two informational conditions. In the first setting, market participants have access to private information and the consensus price signal. In the second setting, we construct the posterior variance of beliefs for the counterfactual situation in which market participants do not have access to the consensus price signal and have to exclusively rely on their private signal to form estimates for the mid-market value. We use the ratio of these two variances as a measure for the informational value of the consensus price.

The last measure captures the amount of new valuation information that is contained in the price estimates that market participants provide to the consensus pricing service. Our measure of the informational content is derived from the Kalman gains of their price estimates, that is the weight consensus price submitters put on new information concerning fundamental asset values relative to their prior beliefs. The higher these weights, the more novel valuation information is contained in submitters' price submissions and, consequently, the corresponding consensus prices.

We find that valuation uncertainty, both fundamental and strategic, varies substantially across the strike and time-to-expiration space (the volatility surface) of S&P500 index options. The 95% confidence bands around market participants' mean estimates of implied volatilities can be as wide as 10 volatility points for deep out-of-the-money put options with short times-to-expiration, but tend to be below 1 volatility point for option contracts with strike price close to the current index level and out-of-the-money options with longer times-to-expiration. Confidence bands gauging market participants' uncertainty about their competitors' valuation show similar qualitative patterns. Strategic uncertainty is highest for option contracts with strike prices that correspond to extreme index moves. This result is intuitive, as valuations for such option contracts will be more dependent on proprietary pricing models and privately observed OTC trades, and less on data shared among market participants. Similarly, we find that access to the consensus price feedback is most valuable for such extreme option contract, and it is particularly important for reducing strategic uncertainty. For such extreme contract the consensus feedback appears to provide a commonly shared signal that helps to reduce uncertainty about where the current average valuation is located. Lastly, we find that consensus price submissions contain significant amounts of novel pricing information. Monthly changes in price submission appear to put a weight typically in excess of 50% on new information

about fundamental asset values that broker-dealers have received over the preceding month.

Related literature

This paper adds to a large existing literature on learning about asset values in the presence of informational frictions.² Due to data availability issue in many of the most affected asset markets, the majority of work has been theoretical. The main contributions of this paper lies in the development of a structural model of learning from prices that can be brought to the data and its estimation using a unique dataset of price estimates by major financial institution for assets that are predominately traded on an over-the-counter market.

An early empirical contribution studying learning in financial markets is [Biais, Hillion, and Spatt \(1999\)](#). Building on theoretical insights into the speed of learning in financial markets by [Vives \(1993, 1995\)](#), the authors study the informational content of pre-opening prices at the Paris Bourse and quantify the speed of learning by traders. The study uses reduced form regression techniques to identify the informational content of these indicative prices, somewhat similar in nature to our consensus prices, however originating from an arguably much more informationally transparent market place. Additionally, they provide an indirect measure of valuation uncertainty in the form of the variance of the residuals from their reduced form regressions. In contrast, the estimation of the structural model allows us to directly measure valuation uncertainty under varying market transparency conditions.

A set of more recent papers has studied the informational content of survey forecasts. While survey forecasts focus on macroeconomic aggregates, most importantly GDP growth and inflation, they bear some similarity to our consensus prices. Forecasters provide a series of best estimates for a well defined outcome. And, like consensus prices, survey forecasts tend to have non-trivial cross-sectional dispersion which can be used to estimate the precision of forecasters' information. A study closely related to our paper using survey forecasts is [Coibion and Gorodnichenko \(2012\)](#). While the aim of their paper is to use inflation forecasts to differentiate between sticky price models and models of sluggish price adjustment due to informational frictions, as part of this exercise the authors develop a structural model of informational frictions based on [Woodford \(2003\)](#). They estimate this model exploiting both the cross-

²For summaries of the large literature on learning and information in financial markets see, for example, [Chamley \(2004\)](#) and [Veldkamp \(2011\)](#).

sectional dispersion of forecasts and their dynamics. [Barillas and Nimark \(2017\)](#) and [Struby \(2016\)](#) make use of the information contained in the cross-sectional dispersion of survey forecasts to estimate an affine factor model of the interest rate term structure. Their models also exploit the cross-sectional dispersion to identify the precision of signals that market participants receive.

Another common feature shared by the present paper with the above mentioned work is that market participants extract information from prices that are, in turn, the outcome of their equilibrium behavior. As first pointed out by [Townsend \(1983\)](#), learning from such endogenous variables has the well-known consequence of potentially infinite state spaces: agents have to keep track of higher order beliefs in order to extract the relevant information from prices. Some progress has recently been made to address such problems, either by showing that in certain cases the original problem can be approximated arbitrarily well with a finite state space ([Huo and Takayama \(2015\)](#), [Nimark \(2017\)](#); see [Sargent \(1991\)](#) for earlier work using similar ideas) or by working with frequency domain techniques ([Kasa \(2000\)](#), [Kasa, Walker, and Whiteman \(2014\)](#), [Rondina and Walker \(2014\)](#)). In our model we adapt the iterative procedure developed in [Nimark \(2017\)](#) to the context of consensus pricing in order to deal with the endogeneity of the information contained in consensus prices.

Our paper also contributes to the discussion on the informational value of benchmarks in search markets. [Duffie and Stein \(2015\)](#) provide a good summary of the debate with a focus on interest rate benchmarks in the wake of the Libor scandal. [Duffie, Dworzak, and Zhu \(2017\)](#) build a theoretical model in which they show how benchmarks can help reduce informational asymmetries in search markets and thereby improve allocational efficiency. Unlike benchmarks, consensus prices do not serve to index financial contracts. However, their construction is analogous to benchmarks: market participants are polled for their best estimates of a price. Our study on the informational content of consensus price thus provides empirical evidence for the ability of this mechanism to aggregate information in opaque search markets.

Lastly, the empirical results in our paper can inform modelling choices in the theoretical literature on search and information friction in over-the-counter markets (e.g. [Duffie, Malamud, and Manso \(2009\)](#), [Duffie, Gârleanu, and Pedersen \(2007\)](#), [Babus and Kondor \(2017\)](#)). We provide insights into the relative importance of private versus public informational sources for asset valuations in over-the-counter markets. Furthermore, to the extent that the source of private information in our model is interpreted as deriving from trades in the over-the-counter market, the estimates of

the precision of these private signals can be seen as a proxy for the meeting frequency in the respective market segment.

The plan of the paper is as follows. In the section 2 we provide a detailed description of the Totem consensus pricing service and develop a theoretical model of learning about asset values from public and private information. The model structures the way we think about financial institutions' price submissions to the consensus pricing service and how these institutions, in turn, learn from the consensus price feedback. In section 3 we introduce the data for the empirical analysis and provide summary statistics for the individual contracts which make up the volatility surface. The Kalman filter which we use to estimate the parameters of our structural model is discussed in section 4. In section 5 we use the estimates of the structural parameters of the model to compute the previously developed comparative statistics of the informational content of price submissions and consensus price. Section 6 concludes.

2 Consensus Pricing

We start by providing a short introduction to consensus pricing and explain how IHS Markit’s consensus pricing service operates. We then develop a theoretical model of consensus pricing based on consensus service subscribers who learn about an unobservable time-varying fundamental asset value from a sequence of noisy private signals and the consensus price. From this model we derive two measures for the informational content of consensus prices. These measures will then be at the center of the empirical analysis in the following sections.

2.1 The Totem Service

Consensus pricing services collect estimates of an asset’s mid-market value from market participants, aggregate these estimates, and then return an aggregate “consensus price” to their subscribers. Consensus pricing services typically specialise in a specific asset class and tend to focus on the most prominent financial instruments traded within that class. IHS Markit’s Totem service is a leading industry source for asset valuations and price verification data in the OTC derivatives markets. Most broker-dealers that participate in these markets subscribe and contribute to the Totem service. The origins of the service date back to the 1998 Russian financial crisis when a range of important derivatives markets became illiquid following the catastrophic losses suffered by a large hedge fund, LTCM. Totem addressed the demand for reliable price information by financial institutions who needed to mark their books and manage their risk exposures.

At regular intervals, typically monthly, Totem collects estimates of the midquote for a large range of financial derivatives contracts from its subscribers. Totem subscribers are active market participants in the derivatives contracts they submit to. They can decide which derivatives contracts they want to participate in and pay a subscription fee for each derivative product. At IHS Markit, a team of specialists process subscribers’ midquote submissions and returns various aggregate statistics of the midquote submissions, so-called consensus data, to the Totem subscribers, normally on the same or the following day. This then allows subscribers to gauge the position of their prices in relation to the market consensus prices.

In the cleaning process, midquotes are checked for basic arbitrage violations and attempts to manipulate the consensus price. Submissions are rejected if they meet these criteria and the excluded submitter does not receive any consensus data for

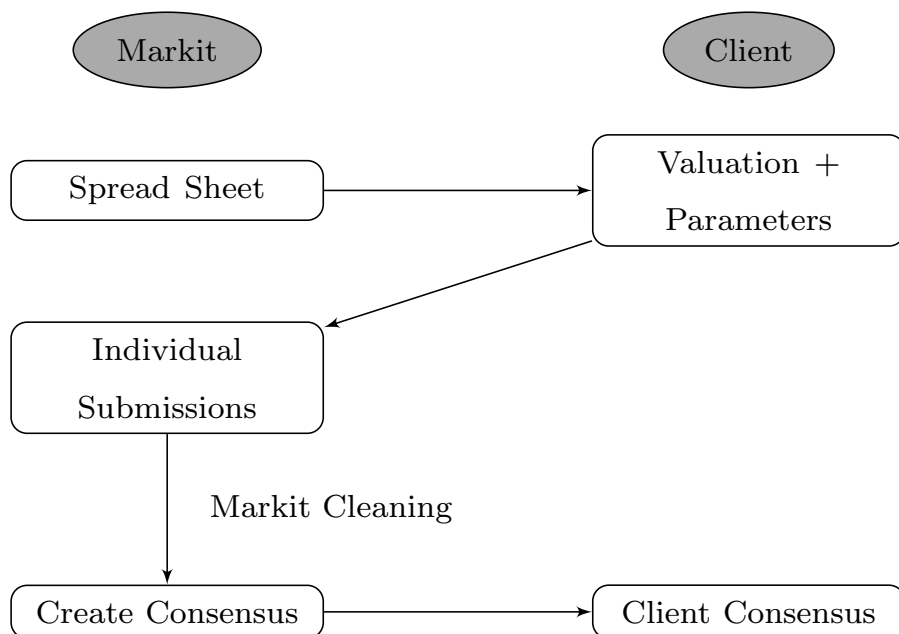


Figure 1: Totem submission process

the affected submission date. This mechanism is meant to incentivize submitters to provide their best estimate of the current midquote. Figure 1 gives a schematic description of the consensus pricing process. For each derivative product, Totem provides submitters with a spreadsheet into which they input the relevant prices using the going market convention for price quotes. Often submitters provide additional information in these spreadsheet, such as discount factors or dividend used in calculating their prices. At Markit, these data are then “cleaned” after which submitters whose prices have been accepted on the given submission date receive the consensus data.³

2.2 A Model of Consensus Pricing

We now develop a theoretical model of consensus pricing that is intended to capture the way market participants use consensus prices to learn about latent fundamental asset values.

³For a more detailed description see the Appendix.

A large number of financial institutions, modelled as a continuum indexed by $i \in [0, 1]$, participate in a consensus pricing service. At discrete submission dates, indexed by t , each institution submits its best estimate for the current value of an unobservable stochastic process (θ_t) to the service. The unobservable stochastic process itself evolves according to

$$\theta_t = (1 - \rho)\bar{\theta} + \rho\theta_{t-1} + \sigma_u u_t \quad (1)$$

with $-1 < \rho < 1$ and where the innovations u_t are independent across time and standard normally distributed, $u_t \sim N(0, 1)$.

At each subsequent submission date t , submitters observe two signals. Firstly, each institution receives a noisy private signal $s_{i,t}$ about θ_t ,

$$s_{i,t} = \theta_t + \sigma_\eta \eta_{i,t},$$

where $\eta_{i,t} \sim N(0, 1)$. Secondly, each institution can observe the consensus price p_t which is the average of all institutions' previous period's first-order beliefs about θ_{t-1} plus an aggregate noise shock $\varepsilon_t \sim N(0, 1)$,

$$p_t = \int_0^1 \mathbb{E}_{i,t-1}(\theta_{t-1}) di + \sigma_\varepsilon \varepsilon_t. \quad (2)$$

All shocks (u_t), (ε_t), and ($\eta_{i,t}$) are uncorrelated across institutions and time.

Institution i 's information set in period t , denoted $\Omega_{i,t}$, thus consists of the (infinite) history of public and private signals that i has observed up to period t , that is

$$\Omega_{i,t} = (\{s_{i,t}, p_t\}, \Omega_{i,t-1}).$$

In order to characterise institution i 's submission to the consensus pricing service, we need to calculate the institution's best estimate of θ_t , given by $\mathbb{E}(\theta_t | \Omega_{i,t})$, for all periods t . Its information set $\Omega_{i,t}$, however, depends on all other institutions' submissions via the consensus price process (p_t).

2.3 Learning from Prices

We now show how to apply the method developed in [Nimark \(2017\)](#) to the above consensus pricing problem. We adopt the following standard notation for higher-

order beliefs, defining recursively⁴

$$\begin{aligned}\theta_t^{(0)} &= \theta_t - \bar{\theta}, \\ \theta_{i,t}^{(k+1)} &= \mathbb{E}\left(\theta_t^{(k)} | \Omega_{i,t}\right) \quad \text{and} \quad \theta_t^{(k+1)} = \int_0^1 \theta_{i,t}^{(k+1)} di \quad \text{for all } k \geq 0.\end{aligned}$$

We denote institution i 's hierarchy of beliefs up to order k by

$$\theta_{i,t}^{(1:k)} = \left(\theta_{i,t}^{(1)}, \dots, \theta_{i,t}^{(k)}\right)^\top$$

and for the hierarchy of average beliefs up to order k , including the fundamental value $\theta_t^{(0)}$ as first element,

$$\theta_t^{(0:k)} = \left(\theta_t^{(0)}, \theta_t^{(1)}, \dots, \theta_t^{(k)}\right)^\top.$$

The solution procedure proceeds recursively. It starts with a fixed order of beliefs $k \geq 0$ and postulates that the dynamics of average beliefs $\theta_t^{(0:k)}$ are given by the VAR(1)

$$\theta_t^{(0:k)} = M_k \theta_{t-1}^{(0:k)} + N_k w_t \tag{3}$$

with $w_t = (u_t, \varepsilon_t)^\top$ and $\theta_t^{(n)} = \theta_t^{(k)}$ for all $n \geq k$.

Institution i 's signal can be expressed in terms of $\theta_t^{(0:k)}$ and period t shocks w_t and $n_{i,t}$. The (demeaned)⁵ private signal can be written as

$$\hat{s}_{i,t} = e_1^\top \theta_t^{(0:k)} + \sigma_\eta \eta_{i,t}$$

where e_j denotes a column vector of conformable length with a 1 in position j , all other elements being 0. Similarly, we can express the (demeaned) consensus price \hat{p}_t as⁶

$$\hat{p}_t = \theta_{t-1}^{(1)} + \sigma_\varepsilon \varepsilon_t = e_{\min\{k+1,2\}}^\top M_k^{-1} \theta_t^{(0:k)} - e_{\min\{k+1,2\}}^\top M_k^{-1} N_k w_t + \sigma_\varepsilon \varepsilon_t$$

⁴Here we express the fundamental in terms of deviations from its mean $\bar{\theta}$ to lighten notation. Defining $\theta_t^{(0)} = \theta_t$ and carrying forward a constant or deterministically changing mean would not cause any conceptual difficulties.

⁵We define $\hat{z}_{i,t} = z_{i,t} - \bar{\theta}$ as deviations from the mean $\bar{\theta}$ for a generic random variable $z_{i,t}$.

⁶Note that for $k = 0$, M_k and N_k will be scalars and $\theta_{t-1}^{(1)} = \theta_{t-1}^{(0)}$ by assumption. This explains the subscript $\min\{k+1, 2\}$ for the unit vector.

where the last equality follows from inverting (3) to obtain $\theta_{t-1}^{(1)}$ in term of $\theta_t^{(0:k)}$ and shocks w_t . Denote the vector of signals by $y_{i,t} = (\hat{s}_{i,t}, \hat{p}_t)^\top$. We can now express the signals in terms of current average beliefs and shocks,

$$y_{i,t} = D_k \theta_t^{(0:k)} + R_{k,w} w_t + R_\eta \eta_{i,t} \quad (4)$$

where

$$D_k = \begin{bmatrix} e_1^\top \\ e_{\min\{k+1,2\}}^\top M_k^{-1} \end{bmatrix}, R_\eta = \begin{bmatrix} \sigma_\eta \\ 0 \end{bmatrix},$$

$$\text{and } R_{k,w} = \begin{bmatrix} (0, 0) \\ -e_{\min\{k+1,2\}}^\top M_k^{-1} N_k + (0, \sigma_\varepsilon) \end{bmatrix}. \quad (5)$$

We thus obtain a state space representation of the system from the perspective of institution i . Equation (3) describes the dynamics of the latent state variable $\theta_t^{(0:k)}$, equation (4) is the observation equation that provides the link between the current state and i 's signals. Standard Kalman filtering arguments now imply that institution i 's beliefs conditional on the information contained in $\Omega_{i,t}$ are given by

$$\theta_{i,t}^{(1:k+1)} = M_k \theta_{i,t-1}^{(1:k+1)} + K_k \left[y_{i,t} - D_k M_k \theta_{i,t-1}^{(1:k+1)} \right] \quad (6)$$

where K_k is the (stationary) Kalman gain. Substituting out the signal vector in terms of current state and shocks, this can equivalently be written as

$$\begin{aligned} \theta_{i,t}^{(1:k+1)} &= [I_k - K_k D_k] M_k \theta_{i,t-1}^{(1:k+1)} + K_k D_k M_k \theta_t^{(0:k)} \\ &\quad + [K_k D_k N_k + K_k R_{k,w}] w_t + K_k R_\eta \eta_{i,t}. \end{aligned}$$

Averaging this expression across all submitters, assuming that by a law of large numbers $\int_0^1 \eta_{i,t} di = 0$, average beliefs are then given by

$$\theta_t^{(1:k+1)} = [I_k - K_k D_k] M_k \theta_{t-1}^{(1:k+1)} + K_k D_k M_k \theta_t^{(0:k)} + [K_k D_k N_k + K_k R_{k,w}] w_t. \quad (7)$$

Combined with the fact that $\theta_t^{(0)} = \rho \theta_{t-1}^{(0)} + \sigma_u u_t$ we now obtain a new law of motion for the state

$$\theta_t^{(0:k+1)} = M_{k+1} \theta_t^{(0:k+1)} + N_{k+1} w_t$$

with

$$M_{k+1} = \begin{bmatrix} \rho e_1^\top & 0 \\ K_k D_k M_k & 0_{k \times 1} \end{bmatrix} + \begin{bmatrix} 0 & 0_{1 \times k} \\ 0_{k \times 1} & (I_k - K_k D_k) M_k \end{bmatrix} \quad (8)$$

and

$$N_{k+1} = \begin{bmatrix} \sigma_u e_1^\top \\ K_k D_k N_k + K_k R_{k,w} \end{bmatrix}. \quad (9)$$

Note, however, that now the state space has increased by one dimension from $k + 1$ to $k + 2$. This is a consequence of the well-known infinite regress problem when filtering endogenous signals. When filtering average beliefs of order k , institutions have to form beliefs about average beliefs of order k . But this implies that equilibrium dynamics will be influenced by average beliefs of order $k + 1$, and so on for all orders $k \geq 0$.

In practice, the solution algorithm works as follows. We initialise the iteration at $k = 0$ with $M_0 = \rho$ and $N_0 = \sigma_u$ which implies that $\theta_t^{(1)} = \theta_t^{(0)}$ for all t . Consequently, the consensus price of the first iteration is given by⁷

$$\hat{p}_t^{[1]} = \theta_{t-1}^{(0)} + \sigma_\varepsilon \varepsilon_t = \frac{1}{\rho} \theta_t^{(0)} - \frac{\sigma_u}{\rho} u_t + \sigma_\varepsilon \varepsilon_t.$$

This will yield a Kalman gain K_0 (here a two-dimensional vector) which can then be used to obtain M_1 and N_1 via equations (8) and (9) and so on until convergence of the process $\hat{p}_t^{[n]}$ has been achieved according to a pre-specified convergence criteria after n steps. The highest order belief that is not trivially defined by lower order beliefs is then of order n .

2.4 Informational Measures

To analyse the informational content of our consensus price data, we estimate the structural parameters of the above model. We denoted the parameters of the model by $\Phi = \{\bar{\theta}, \rho, \sigma_\varepsilon^2, \sigma_u^2, \sigma_\eta^2, \alpha, \beta\}$ and treat the time series of price estimates submitted by financial institution i as their best estimate of the current fundamental value, that is $\bar{\theta} + \theta_{i,t}^{(1)}$. This estimation is carried out for each option contract (defined by time-to-maturity and moneyness) separately, that is we obtain an estimate $\hat{\Phi}$ for each option. Based on these estimates, we construct model-implied measures of the informational content of the consensus price data for each option contract. In particular, we construct statistical measure that allow us to address three specific questions. First, how uncertain are consensus price submitters about the valuations of their peers? Second, how much weight do these institution put on the consensus price feedback relative to other private informational sources in their valuations of the

⁷Superscripts in square brackets denote iterations of the algorithm.

option contract? Lastly, how much information do the price estimates that financial institutions submit to the consensus pricing service contain?

2.4.1 Measuring fundamental and strategic uncertainty

We denote the (stationary) covariance matrix of an individual submitter's posterior beliefs about the average beliefs up to order k by

$$\Sigma \equiv Var \left(\theta_t^{(0:k)} | \Omega_{i,t} \right).$$

The variance of posterior beliefs about the current value of the fundamental, $\theta_t^{(0)}$ are then given by

$$\Sigma_{11} \equiv Var \left(\theta_t^{(0)} | \Omega_{i,t} \right) = \mathbb{E} \left\{ \left[\theta_t^{(0)} - \mathbb{E} \left(\theta_t^{(0)} | \Omega_{i,t} \right) \right]^2 | \Omega_{i,t} \right\}.$$

This posterior variance is a natural measure of the uncertainty of submitters concerning the fundamental value. We refer to this uncertainty as *fundamental uncertainty*. A convenient way to display this uncertainty is via confidence intervals. As posterior beliefs are normally distributed, an individual submitter's $x\%$ confidence interval for the fundamental value $\theta_t^{(0)}$ having observed all signals up to and including t is

$$\left[\mathbb{E} \left(\theta_t^{(0)} | \Omega_{i,t} \right) - \alpha_x \sqrt{\Sigma_{11}}, \mathbb{E} \left(\theta_t^{(0)} | \Omega_{i,t} \right) + \alpha_x \sqrt{\Sigma_{11}} \right]. \quad (10)$$

where α_x is the critical value of the standard normal distribution such that $\Phi(\alpha_x) = x/2$.

Knowing submitters' higher order beliefs allows us to go beyond measures of fundamental uncertainty. We can also measure how uncertain a given submitter i is about the mean valuations of his peers using the variance of his second order beliefs, that is

$$\Sigma_{22} \equiv Var \left(\theta_t^{(1)} | \Omega_{i,t} \right) = \mathbb{E} \left\{ \left[\int \theta_{j,t}^{(1)} dj - \mathbb{E} \left(\int \theta_{j,t}^{(1)} dj | \Omega_{i,t} \right) \right]^2 | \Omega_{i,t} \right\}.$$

The more uncertain a submitter is about the average position of his co-submitters in terms of first order beliefs about the current fundamental value, $\theta_t^{(0)}$, the higher is Σ_{22} . If the average valuation is common knowledge, then this variance is zero. This would, for example, be the case if the only informative signal was the consensus price which is a public signal and, consequently, common to all submitters. Σ_{22} is

a measure of *strategic uncertainty*, that is uncertainty about the relative position of the average market participant.⁸ Again, as beliefs are normally distributed we can express this strategic uncertainty in terms of a submitter's confidence intervals around his current second order beliefs $\theta_{i,t}^{(2)} = \mathbb{E} \left(\int \theta_{j,t}^{(1)} dj \mid \Omega_{i,t} \right)$.

Obviously, such confidence intervals can also be obtained for beliefs of order higher than 2. Our focus in what follows, however, will be on the first two orders which we will consistently refer to as fundamental and strategic uncertainty, respectively.

2.4.2 Informational value of consensus prices

Finally, we want to measure the importance of the feedback financial institutions receive from the consensus pricing service for the valuation of their options contracts. To do so we carry out the following counterfactual experiment: by how much would an institution's posterior uncertainty increase if it did not have access to the consensus price keeping its information acquisition strategy constant?

The (stationary) posterior uncertainty about the average belief of order $n \geq 0$, $\theta_t^{(n)}$, of an institution that has access to the history of both private signals and consensus prices is given by

$$\Sigma_{nn} = \text{Var} \left(\theta_t^{(n)} \mid \Omega_{i,t} \right).$$

An informative comparative statistic to derive is the posterior variance of an institution that can only observe the history of private signals, but not the consensus price. The information set of such an institution is given by $\tilde{\Omega}_{i,t} = \{s_{i,t-j}\}_{j=0}^{\infty}$ with corresponding counterfactual covariance matrix⁹

$$\tilde{\Sigma} \equiv \text{Var} \left(\theta_t^{(0:k)} \mid \tilde{\Omega}_{i,t} \right).$$

The institution's posterior variance for the fundamental value is then

$$\tilde{\Sigma}_{nn} = \text{Var} \left(\theta_t^{(n)} \mid \tilde{\Omega}_{i,t} \right).$$

The ratio of the two variances, denoted λ , is a natural measure for the informational value of the consensus price,

$$\lambda_n = \frac{\Sigma_{nn}}{\tilde{\Sigma}_{nn}} \tag{11}$$

⁸This notion is not to be confused with informational asymmetries - in our model all submitters are symmetrically informed about asset values.

⁹This can be easily computed by setting the variance of the consensus price signal, σ_ε^2 , to infinity, keeping all other parameter values unchanged.

A lower λ implies a larger reduction in posterior uncertainty about average order n beliefs due to having access to the consensus price.

2.4.3 Information content of price submissions

A natural measure for the informational content of the submitted price estimates to the consensus price service is the Kalman gain K of their price updates. The standard logic of Bayesian updating, used in equation (6), can be expressed as follows:

$$\underbrace{\mathbb{E}(\theta_t|\Omega_{i,t})}_{\text{posterior belief}} = \underbrace{\mathbb{E}(\theta_t|\Omega_{i,t-1})}_{\text{prior belief}} + \underbrace{K_k}_{\text{Kalman gain}} \times \underbrace{\xi_{i,t}}_{\text{new information}} .$$

For the above developed model this updating equation can be restated as

$$\mathbb{E}(\theta_t|\Omega_{i,t}) = (I_k - K_k D_k) \mathbb{E}(\theta_t|\Omega_{i,t-1}) + (K_k D_k) \theta_t + \epsilon_{i,t},$$

with some appropriately specified error term $\epsilon_{i,t}$ such that $\mathbb{E}(\epsilon_{i,t}^{(j)}|\Omega_{i,t-1}) = 0$ for all $j = 1, \dots, k$. The higher the precision of the signals, the more weight is put on new information relative to the institution's prior estimate. We can see this more clearly focusing on submitters first order beliefs, $\theta_{i,t}^{(1)}$, which we take to be their submissions to the consensus pricing service. The Kalman gain for submitters' first order beliefs consists of two components, the Kalman gain for the private signal $s_{i,t}$, denoted by k_s , and the Kalman gain for the consensus price p_t , denoted k_p . Define the $(k+1)$ -element vector κ as

$$\kappa \equiv e_1^\top (K_k D_k) = k_s e_1^\top + k_p e_2^\top M_k^{-1}. \quad (12)$$

The j th element of this vector, κ_j , is the weight submitters' first order beliefs put on the current average belief of order j , $1 - \kappa_j$ is the weight put on their prior beliefs about this average belief. We can thus write a submitter's updated first order beliefs as a weighted average of current average beliefs and the submitter's prior beliefs about these average beliefs plus a mean zero noise term,

$$\theta_{i,t}^{(1)} = \mathbb{E}(\theta_t^{(0)}|\Omega_{i,t}) = \sum_{j=0}^k \left[(1 - \kappa_j) \mathbb{E}(\theta_t^{(j)}|\Omega_{i,t-1}) + \kappa_j \theta_t^{(j)} \right] + \epsilon_{i,t}^{(1)}.$$

It can be shown that $0 \leq \kappa_j \leq 1$. Thus, κ_j determines how much information current price submissions contain about current average beliefs of order j .

3 Data

3.1 Index option consensus prices

The empirical analysis in this paper is based on the individual midquote submissions for S&P500 index options of Totem subscribers as well as the aggregated consensus prices derived from these submissions.¹⁰ Totem collects estimates for the midquote from active market participants. At Markit, a team of specialists then cleans these midquote submissions.¹¹ The data allows us to track individual submissions by institutions across time. The focus of the paper is on plain vanilla European put and call options for which we have monthly Totem data for the period of November 1998 to February 2015. These plain vanilla contracts are stated in terms of moneyness¹² and time-to-maturity. Moneyness ranges from 20 to 300 and the time-to-maturity of the contracts range from 1 month to 300 months.¹³

Initially, contracts with moneyness between 80 and 120 and terms varying from 6 to 60 months were introduced in 1998. Later, as demand for more extreme contracts and a finer grid increased, additional standardized contracts were added to the ser-

¹⁰Data provided by IHS MarkitTM - Nothing in this publication is sponsored, endorsed, sold or promoted by Markit or its affiliates. Neither Markit nor its affiliates make any representations or warranties, express or implied, to you or any other person regarding the advisability of investing in the financial products described in this report or as to the results obtained from the use of the Markit Data. Neither Markit nor any of its affiliates have any obligation or liability in connection with the operation, marketing, trading or sale of any financial product described in this report or use of the Markit Data. Markit and its affiliates shall not be liable (whether in negligence or otherwise) to any person for any error in the Markit Data and shall not be under any obligation to advise any person of any error therein.

¹¹In the cleaning process midquotes are checked for arbitrage violations and attempts to manipulate the consensus price. Submissions are rejected if they meet these criteria. A feedback mechanism is in place that allows submitters to justify their rejected submissions and ask for reconsideration. In case a submission is rejected, its submitter does not receive any consensus feedback for the concerned product. This mechanism provides incentives to submit high quality data and deters manipulation of the consensus price. When the number of accepted submissions exceeds six, the highest and lowest midquote submissions are excluded from the consensus price aggregate statistics. The submitters of the highest and lowest quote do receive the consensus data feedback.

¹²The moneyness definition used by Totem is the strike price of the option, K , divided by the spot price of the underlying index, S , times 100, that is $(K/S) \times 100$. All options in Totem are at-of-the-money or out-of-the-money options. Options with moneyness smaller than 100 are put options, options with moneyness greater than 100 are call options and for moneyness 100 we both have put and call options.

¹³Tables 2 and 3 give an overview of the coverage of the options available to us, their corresponding sample period, and the number of submitters per contract.

vice. The sample we use to estimate our structural model consists of option contracts with moneyness between 60 and 150 and time-to-maturity between 6 months and 7 years. We focus on the sample period between January 2002 and February 2015. This selection is motivated by the trade-off between having access to a long time-series of price submissions while maximizing the range of option contracts available for analysis.

We have access to the full history of price submissions by the financial institutions. The institutions are anonymised, but we can track each institutions' submissions over time and across contracts. We use all monthly individual price submissions to Totem for out-of-the-money and at-the-money European call and put option contracts. In total we consider 63 distinct option contracts. There are about 30 submitters per month on average for each option contract (see Table 1).

| <i>term</i> | <i>moneyness</i> | | | | | | | | |
|-------------|------------------|-----------|-----------|-----------|------------|------------|------------|------------|------------|
| | 60 | 80 | 90 | 95 | 100 | 105 | 110 | 120 | 150 |
| 6 | 27 | 31 | 31 | 31 | 31 | 31 | 31 | 31 | 19 |
| 12 | 27 | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 26 |
| 24 | 27 | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 26 |
| 36 | 26 | 29 | 29 | 29 | 29 | 29 | 29 | 29 | 26 |
| 48 | 26 | 29 | 29 | 29 | 29 | 29 | 29 | 29 | 25 |
| 60 | 25 | 28 | 28 | 28 | 28 | 28 | 28 | 28 | 25 |
| 84 | 23 | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 23 |

Table 1: This table reports the average average number of Totem submitters for a particular option contract to the Totem Service. The time-to-maturity in months of the option contract is given in the first column. The moneyness of the option contract is given in first row in bold numbers. Moneyness is defined as the strike price divided by the spot price times 100. All contracts are out of the money contracts, except the moneyness 100 contracts which are at the money. The data sample is from December 2002 till February 2015 for the option contracts on the SPX.

It is often more convenient to state option prices in terms of the volatility of the underlying implied by the price of the option. The standard model to compute the implied volatility (IV) from the price of the option is the [Black and Scholes \(1973\)](#) model. We transform these prices into implied volatilities (IVs) using the Black-Scholes formula, spot price, interest rate, and dividend yield data provided by the

Totem submitters as part of their price submission.¹⁴ As is well known empirically, the implied volatility is not equal across the whole range of moneyness.¹⁵ The IV for deep out-of-the-money (OTM) options tends to be higher than that of at-the-money (ATM) options. This so called volatility smirk in index options first appeared after the 1987 stock market crash. The implied volatility for a fixed time-to-maturity shows the well documented smile. For the longer-dated options this pattern is less severe. [Cont and Da Fonseca \(2002\)](#) provide a detailed analysis of the dynamic behavior of the implied volatility surface of S&P500 index options.

3.2 Valuation dispersion

To form an initial idea of the degree of dispersion in valuations in these OTC markets we examine the cross-sectional distribution of individual midquote submissions. The standard deviation of the cross-sectional distribution allows us to gauge the dispersion of submitters' option valuations across the implied volatility surface at given points in time, in our case at monthly time intervals. Figure 2 depicts the time-series average of the standard deviation of submissions for given points on the volatility surface. One immediate observation is that the dispersion in submitters' IVs attains its highest level for short-dated deep OTM options. This is true for both OTM call and put options. There appears to be more agreement on the value of long-dated deep OTM option. For short-dated deep OTM option one needs to estimate a low probability high impact event to estimate the value of the option. This is not a trivial matter given the scarcity for data on extreme outcomes. This gives scope for sizable disagreement among market participants.

To provide perspective on the magnitude of the cross sectional dispersion we make a comparison between the typical bid-ask spread in the exchange-traded index options market and the range of the Totem submissions. Whenever both sides are available, contracts submitted to Totem are matched with corresponding options in

¹⁴When estimating the parameters of the model we treat the natural logarithm of an institution's IV as the institution's best estimate of the current fundamental value.

¹⁵To verify the quality of the data, we compare the implied volatilities from Totem to the standard data source for option price data, OptionMetrics. The volatility surface provided by OptionMetrics is stated in terms of the Black and Scholes delta as a definition of moneyness. Totem uses $(K/S) \times 100$. Additionally, the terms of the contracts in both databases are not exactly the same. To compare the two different data sets, we linearly interpolate between the points on the implied volatility surface. The comparison of the IV of an option contract with a maturity of 6 month and a moneyness of 90 shows a near perfect correlation. Moneyness 90 is the deepest OTM option contract we can consistently find in OptionMetrics.

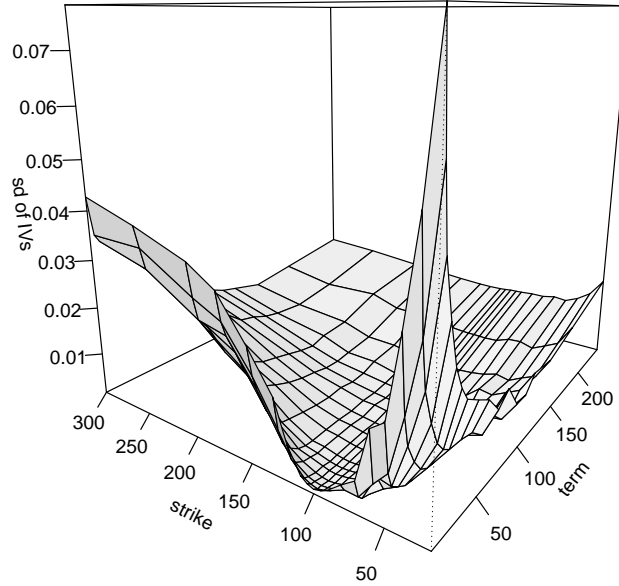


Figure 2: Cross-sectional dispersion of IVs (S&P500)

This figure depicts the monthly time-series average of the cross sectional standard deviation for the submissions of the midquote estimates. The midquote estimates are provided by large broker dealers who submit to Markit's totem service. The midquote estimates are expressed as implied volatilities. The axis labeled term indicates the time-to-maturity of the option contract in months. The axis labeled strike indicates the moneyness of the option contract. Moneyness is defined as the strike price divided by the spot price multiplied by 100. All contracts are out-of-the-money contracts, except contracts with the moneyness 100 which are at-the-money. The data sample is from December 2002 till February 2015 for the option contracts on the S&P500.

the transaction-based OptionMetrics data.¹⁶ Figure 12 depicts the bid-ask spread of the latter and the range of Totem submissions for a European put option on the S&P500 with a time-to-maturity of 1 month and moneyness 95. The range in the midquote quote dispersion is on the same level as the bid-ask spread. From this

¹⁶We only use option prices and bid-ask spreads from OptionMetrics if the last occurred trade is on the same day.

figure we can also deduce that the two are not perfectly correlated. This indicates that the disagreement is economically important and does not move proportionally to the bid-ask spread. A perhaps surprising finding is that for a relatively liquid option the disagreement on the midquote is substantial.

4 Estimation

We estimate the parameters of the model presented in section 2, namely $\Phi = \{\rho, \bar{\theta}, \sigma_u, \sigma_\varepsilon, \sigma_\eta\}$, by maximum likelihood separately for each options contract. For a given contract, that is fixed time-to-maturity, moneyness, and option type (put or call), our data consist of two series. First, the time-series of submissions by the institutions participating in the Totem consensus pricing service for the specified contract; second, the consensus price time-series. If an institution does not submit a price in t , we treat this as a missing value. However, it is assumed that this institution received both the consensus price and the private signal about the fundamental in that period. As we will use the Kalman filter to derive the likelihood function, the treatment of such missing values is straightforward.¹⁷ Let S be the total number of institutions that have submitted to Totem over the course of our sample and let $\iota_t \subset \{1, 2, \dots, S\}$ be the set of institutions active in t . Our sample of submissions is then given by $(\mathbf{m}_t)_{t=1}^T$, where $\mathbf{m}_t = (m_{j,t})_{j \in \iota_t}$ is a $|\iota_t|$ -dimensional vector consisting of the individual period t consensus price submissions. We assume that consensus price submissions are institution i 's best estimate of θ_t plus uncorrelated measurement error, i.e.

$$m_{i,t} = \bar{\theta} + \theta_{i,t}^{(1)} + \sigma_\psi \psi_{i,t} \quad \text{with } \psi_{i,t} \sim N(0, 1). \quad (13)$$

Following our model, we assume that the consensus price of period $t - 1$, which we call p_t , equals the average first order belief of period $t - 1$ plus aggregate noise, that is

$$p_t = \bar{\theta} + \theta_{t-1}^{(1)} + \sigma_\varepsilon \varepsilon_t.$$

Our data set for a given contract, $(\mathbf{y})_{t=1}^T$, then consists of the time-series of institutions' price submissions for this contract and the corresponding consensus price, i.e. $\mathbf{y}_t = (p_t, \mathbf{m}_t)^\top$.¹⁸

To estimate the model, we fix the maximum order of beliefs at $\bar{k} = 4$ and assume that the system has reached its stationary limit.¹⁹ Average beliefs then evolve according to (3), namely

$$\theta_t^{(0:\bar{k})} = M_{\bar{k}} \theta_{t-1}^{(0:\bar{k})} + N_{\bar{k}} w_t,$$

¹⁷For the treatment of missing values in the Kalman filter see, for example, Durbin and Koopman (2012), Chapter 4.10.

¹⁸To be precise, $m_{j,t}$ is the natural logarithm of the Black-Scholes implied volatility of submitter j 's time t price submission, and p_t is the natural logarithm of the consensus Black-Scholes implied volatility calculated by Totem for the corresponding contract.

¹⁹Allowing \bar{k} greater than 4 does not change the estimates noticeably.

where $M_{\bar{k}}$ and $N_{\bar{k}}$ are functions of the parameters Φ defined recursively by equations (8) and (9) and $w_t = (u_t, \varepsilon_t)^\top \sim N(\mathbf{0}_2, I_2)$.²⁰ The dynamics of institutions i 's conditional beliefs $\theta_{i,t}^{(1:\bar{k})}$ can be expressed in terms of deviations from average beliefs, $x_{i,t}^{(1:\bar{k})} \equiv \theta_{i,t}^{(1:\bar{k})} - \theta_t^{(1:\bar{k})}$, as

$$x_{i,t}^{(1:\bar{k})} = Q_{\bar{k}} x_{i,t-1}^{(1:\bar{k})} + V_{\bar{k}} \eta_{i,t},$$

where

$$Q_{\bar{k}} = [I_{\bar{k}} - K_{\bar{k}} D_{\bar{k}}] M_{\bar{k}} \quad \text{and} \quad V_{\bar{k}} = K_{\bar{k}} R_\eta.$$

$K_{\bar{k}}$ is the stationary Kalman gain, $D_{\bar{k}}$ and R_η are defined in (5) and $\eta_{i,t} \sim N(0, 1)$.

Given the linearity of the above system and the assumed normality of shocks the likelihood function for the observed data $(\mathbf{y})_{t=1}^T$ with $\mathbf{y}_t = (p_t, \mathbf{m}_t)^\top$ can be derived using the Kalman filter. We define $\alpha_t = (\theta_t^{(0:\bar{k})}, x_{1,t}^{(1:\bar{k})}, \dots, x_{S,t}^{(1:\bar{k})}, u_t, \varepsilon_t)^\top$ to be the state of the system in t .

The *transition equation* of the system in state space form is then given by

$$\alpha_t = T \alpha_{t-1} + R \epsilon_t$$

where

$$T = \begin{pmatrix} M_{\bar{k}}, 0_{\bar{k}+1 \times S\bar{k}+2} \\ 0_{S\bar{k} \times \bar{k}+1}, I_S \otimes Q_{\bar{k}}, 0_{S\bar{k} \times 2} \\ 0_{2 \times \bar{k}+1+S\bar{k}+2} \end{pmatrix}, \quad R = \begin{pmatrix} N_{\bar{k}}, 0_{\bar{k}+1 \times S} \\ 0_{S\bar{k} \times 2}, I_S \otimes \sigma_\eta V_{\bar{k}} \\ I_2, 0_{2 \times S} \end{pmatrix}$$

and $\epsilon_t = (u_t, \varepsilon_t, \eta_{1,t}, \dots, \eta_{S,t})^\top \sim N(\mathbf{0}_{2+S}, I_{2+S})$.

We now derive the *observation equation* for the system given by

$$\mathbf{y}_t = c_t + Z_t \alpha_t + \phi_t.$$

First note that the consensus price p_t can be expressed in terms of the current state vector α_t as

$$p_t = \bar{\theta} + \theta_{t-1}^{(1)} + \sigma_\varepsilon \varepsilon_t = \bar{\theta} + e_2^\top M_{\bar{k}}^{-1} \theta_t^{(0:\bar{k})} - e_2^\top M_{\bar{k}}^{-1} N_{\bar{k}} w_t + \sigma_\varepsilon \varepsilon_t.$$

Next, note that we can write institution i 's submission $m_{i,t}$ as

$$m_{i,t} = \bar{\theta} + \theta_{i,t}^{(1)} + \sigma_\psi \psi_{i,t} = \bar{\theta} + \theta_t^{(1)} + x_{i,t}^{(1)} + \sigma_\psi \psi_{i,t}.$$

²⁰We use $0_{n \times m}$ to denote a $n \times m$ matrix of zeros, 1_n is a (column) vector containing n ones, and I_n is an n -dimensional identity matrix.

The above derivations allow us to write c_t and Z_t in terms of the parameters of the model. We start by defining an auxiliary matrix J_t that allows us to deal with missing submissions by some institutions in period t . Recall that $\iota_t \subset \{1, 2, \dots, S\}$ is the set of institutions submitting in t . Let $\iota_{k,t}$ designate the k -th element of the index ι_t . J_t is a $(|\iota_t| \times S)$ matrix whose k -th row has a 1 in position $\iota_{k,t}$ and zeros otherwise.

We thus have

$$c_t = J_t \mathbf{1}_{S+1} \bar{\theta} \quad \text{and}$$

$$\phi_t = \begin{pmatrix} 0 \\ \sigma_\psi J_t (\psi_{1,t}, \dots, \psi_{N,t})^\top \end{pmatrix} \quad \text{with} \quad \Gamma_t = \mathbb{E}(\phi_t \phi_t^\top) = \begin{pmatrix} 0 & \mathbf{0}_{|\iota_t|}^\top \\ \mathbf{0}_{|\iota_t|} & \sigma_\psi^2 I_{|\iota_t|} \end{pmatrix}.$$

Furthermore, we have $Z_t = J_t Z$ where

$$Z = \begin{pmatrix} e_2^\top M_{\bar{k}}^{-1}, 0_{1 \times S\bar{k}}, e_2^\top M_{\bar{k}}^{-1} N_{\bar{k}} + (0 \sigma_\varepsilon) \\ 0, 1, e_1^\top \\ 0, 1, e_{\bar{k}+1}^\top \\ \vdots \\ 0, 1, e_{(S-1)\bar{k}+1}^\top \end{pmatrix}.$$

Given a prior for the state of the system at $t = 1$, $\alpha_1 \sim N(\mathbf{a}_1, P_1)$, we can now apply the usual Kalman filter recursion to derive the likelihood function for our data $(\mathbf{y}_t)_{t=1}^T$ given the parameter vector Φ denoted $L((\mathbf{y}_t)_{t=1}^T | \Phi)$. We obtain maximum likelihood estimates for Φ by maximising the corresponding log-likelihood function numerically.

5 Results

The estimation described in the preceding section yields maximum likelihood estimates for the structural parameter Φ of the model developed in section 2. For each option contract c , where a contract c is defined by the time-to-maturity (in months) and strike price (in moneyness), we obtain a corresponding estimate $\hat{\Phi}(c) = \{\hat{\rho}(c), \hat{\theta}(c), \hat{\sigma}_u(c), \hat{\sigma}_\varepsilon(c), \hat{\sigma}_\eta(c)\}$. In this section we discuss these estimates with a focus on their variation across the time-to-maturity/moneyness space. This focus allows us to draw inference about the variation of the informational content of the consensus price data in different segments of the index options market.

We start by discussing what our estimates imply about the extent of posterior uncertainty about fundamental values and we show how this uncertainty varies across the volatility surface. We then move on to the two measures for the informational content of the consensus price data developed in section 2.4. We first show the variation of the estimated Kalman gains for individual institutions' first order beliefs, which we take to be their price submissions, across the volatility surface. We then analyse to what extent the consensus price feedback helps reduce submitters fundamental and strategic valuation uncertainty across this surface.

5.1 Fundamental and strategic uncertainty

Figures 3 and 4 display 95% confidence intervals for fundamental and strategic uncertainty based on the expression in (10) derived in section 2. Here, the confidence intervals are centered around the estimate of the unconditional expectation for first and second order beliefs, which is $\hat{\theta}(c)$. Figure 3 displays option contracts with a fixed time-to-expiration of 6 months, figure 4 shows option contracts with a time-to-expiration of 5 years. Strike prices range from a moneyness of 60 to 150. The plots on the left show 95% confidence intervals around $\hat{\theta}(c)$ for submitters' first order beliefs, what we call fundamental uncertainty. The plots on the right display 95% around the same value confidence intervals for submitters' second order beliefs, that is strategic uncertainty.

As $\hat{\theta}(c)$ are Black-Scholes implied volatilities for the option contract c , both figures show the well-known “smirk” of the volatility curve. Out-of-the money (OTM) put options (moneyness below 100) tend to be relatively more expensive than at-the-money (ATM) put option (moneyness around 100), or OTM call options (moneyness above 100) due to risk premia for providing insurance against downward moves of

the index. For both figure 3 and 4 we can see that option contracts that are deeper out-of-the-money (further away from moneyness 100) fundamental and strategic valuation uncertainty is also higher - the confidence intervals are wider. Confidence intervals for deep OTM put options with moneyness 60 and time-to-expiration of 6 months are on the order of ten volatility points. This contrasts with confidence intervals of the order of one volatility point for ATM options with the same time-to-expiration.

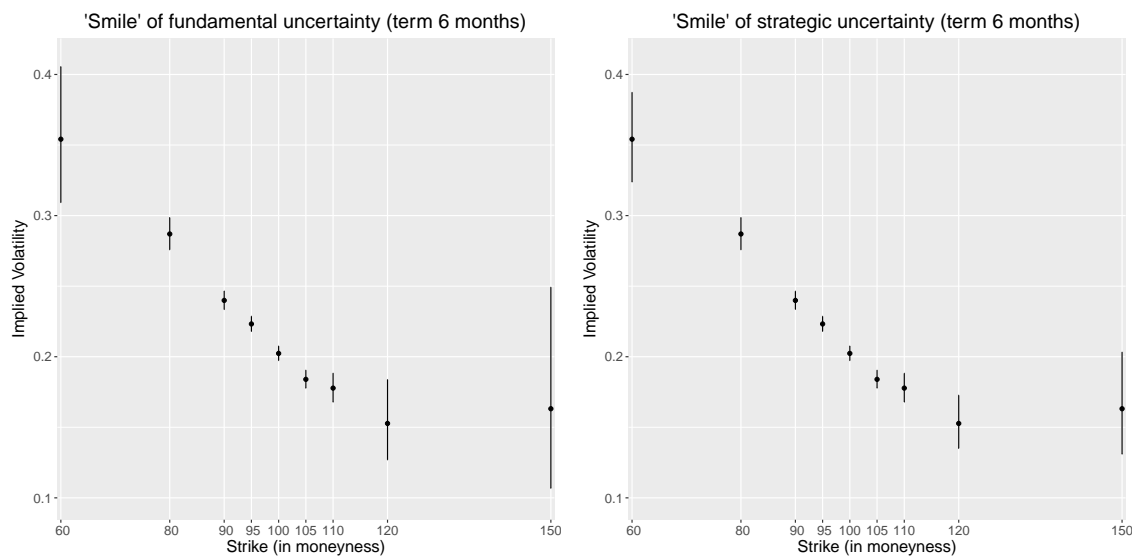


Figure 3: These figures present the submitters steady-state beliefs of the long-run implied volatility mean, θ . The horizontal axis denotes the moneyness of the options under consideration. The model is estimated in terms of the log of the implied volatilities. The black dots in both figures represent the exponentiated point estimates. The *left* figure depicts the "volatility smirk" with the error bounds created from the variance of the believes of θ , as stated in equation (10), i.e. **fundamental uncertainty**. The figure on the *right* incorporates the variance of the first order believes, i.e. **strategic uncertainty**, as error bounds around θ . We consider the option contracts with a time-to-maturity of **6 months**. The data sample is from December 2002 to February 2015 for the option contracts on the SPX provided by Markit's Totem service.

This variation in valuation uncertainty across the volatility curve is intuitive: option contracts closer to ATM tend to trade more often than deep OTM options. Particular deep OTM call options with short times-to-expirations are expected to be very illiquid. Furthermore, by necessity, it is more difficult to assess the objective likelihood of large index moves. Both of these facts would increase fundamental

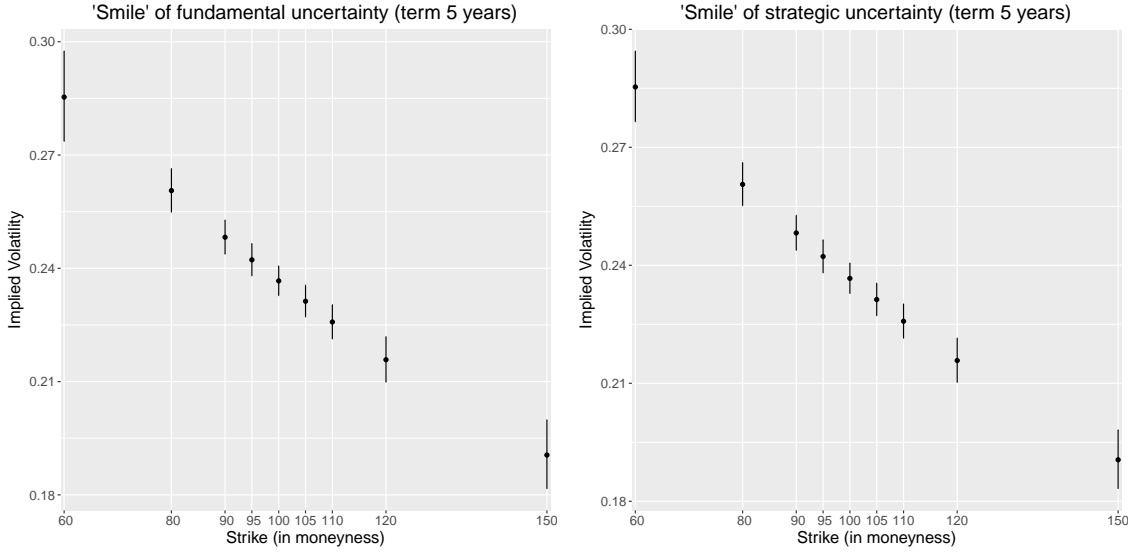


Figure 4: These figures present the submitters steady-state beliefs of the long-run implied volatility mean, $\bar{\theta}$. The horizontal axis denotes the moneyness of the options under consideration. The model is estimated in terms of the log of the implied volatilities. The black dots in both figures represent the exponentiated point estimates. The *left* figure depicts the "volatility smirk" with the error bounds created from the variance of the believes of θ , as stated in equation (10), i.e. **fundamental uncertainty**. The figure on the *right* incorporates the variance of the first order believes, i.e. **strategic uncertainty**, as error bounds around $\bar{\theta}$. We consider the option contracts with a time-to-maturity of **5 years**. The data sample is from December 2002 to February 2015 for the option contracts on the SPX provided by Markit's Totem service.

valuation uncertainty for deep OTM options. The absence of trading is expected to increase the uncertainty about other market participants' valuation, i.e. strategic uncertainty. Similarly, we would expect rarity of extreme S&P500 index moves in historical data to lead to stronger reliance on proprietary pricing models. This should also be consistent with higher strategic uncertainty for option contracts with more extreme strike prices.

While strategic uncertainty is visibly smaller than fundamental uncertainty for deep OTM put and call options with time-to-expiration of 6 months, this effect is much less pronounced for option contracts with longer times-to-expiration and closer to ATM. This is confirmed in figures 5 and 6 which plot the term structure of fundamental and strategic uncertainty. Figure 5 shows this term structure for OTM put options with moneyness 60 in black and, for comparison, the corresponding term structure

for ATM put options. Figure 6 provides the same comparison for OTM call options with moneyness 150. Again, plots on the left display fundamental uncertainty, plots on the right strategic uncertainty.

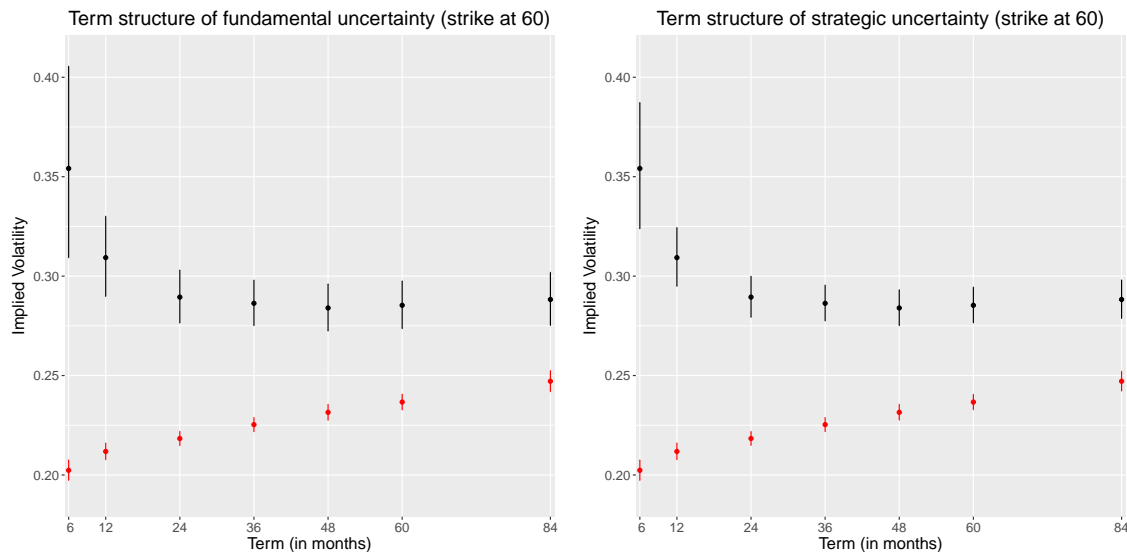


Figure 5: These figures present the term structure of submitters steady-state beliefs of the long-run implied volatility mean, $\bar{\theta}$. The horizontal axis denotes the time-to-maturity in months of the contracts under consideration. The model is estimated in terms of the log of the implied volatilities. The black dots in both figures represent the exponentiated point estimates. The *left* figure depicts the term structure with the error bounds created from the variance of the believes of θ , i.e **fundamental uncertainty**. The figure on the *right* incorporates the variance of the first order believes, i.e. **strategic uncertainty**, as error bounds around $\bar{\theta}$. The term structure for the contracts with moneyness of 60 are in **black**. The term structure for the contracts with **moneyness of 100** are in **red**. We consider the option contracts with a **moneyness of 60**. The data sample is from December 2002 to February 2015 for the option contracts on the SPX provided by Markit's Totem service.

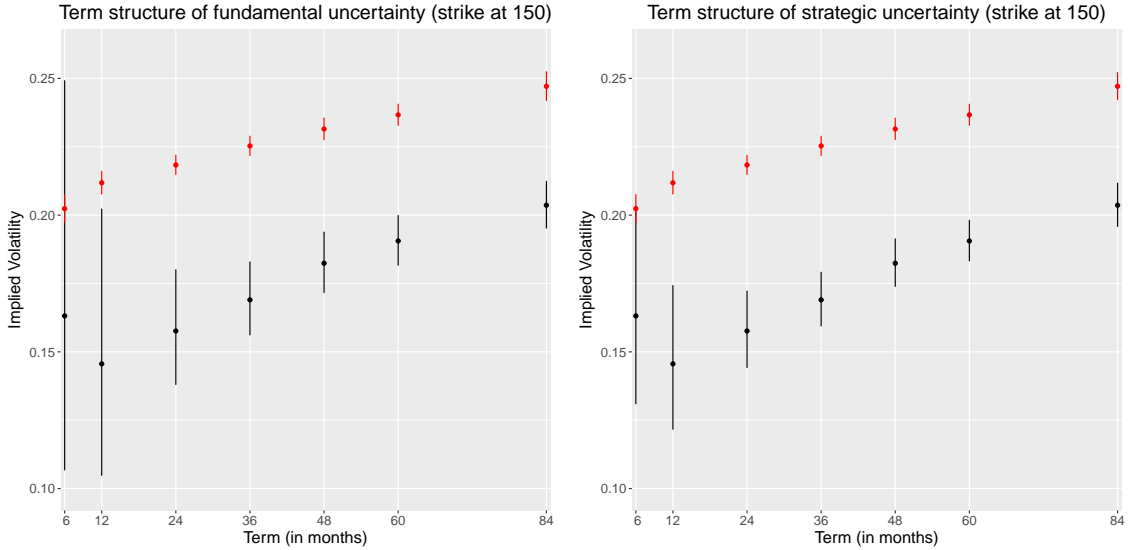


Figure 6: These figures present the term structure of submitters steady-state beliefs of the long-run implied volatility mean, $\bar{\theta}$. The horizontal axis denotes the time-to-maturity in months of the contracts under consideration. The model is estimated in terms of the log of the implied volatilities. The black dots in both figures represent the exponentiated point estimates. The *left* figure depicts the term structure with the error bounds created from the variance of the beliefs of θ , as stated in equation (10), i.e **fundamental uncertainty**. The figure on the *right* incorporates the variance of the first order beliefs, i.e. **strategic uncertainty**, as error bounds around $\bar{\theta}$. The term structure for the contracts with moneyness of 60 are in **black**. The term structure for the contracts with **moneyness of 100** are in **red**. We consider the option contracts with a **moneyness of 150**. The data sample is from December 2002 to February 2015 for the option contracts on the SPX provided by Markit's Totem service.

5.2 Variance ratios

We now consider the variance ratio developed in section 2.4.2 to gauge the relative importance of the consensus price feedback to reduce subscribers' fundamental and strategic valuation uncertainty. Given the estimate $\hat{\Phi}(c)$ for contract c we obtain estimate for the variance ratios $\hat{\lambda}_1(c)$ and $\hat{\lambda}_2(c)$ using equation (11). The lower this ratios, the more important is the consensus price as a source of valuation information for the submitting institutions when compared to other information sources these submitters have access to.

Figures 7 display estimates for these variance ratios for option with a time-to-expiration of 6 months. The plot on the left shows the relative reduction in the

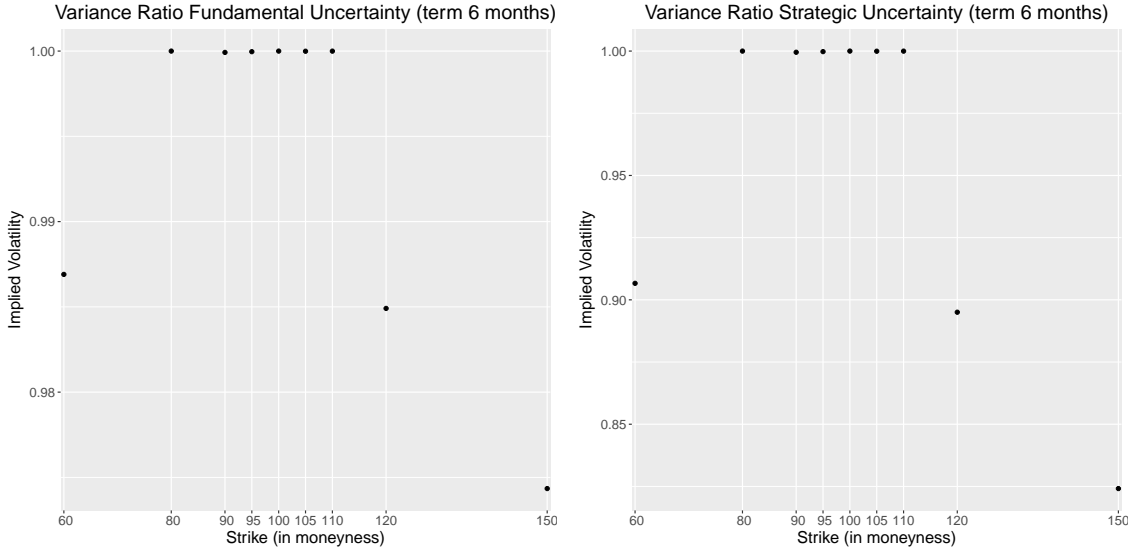


Figure 7: These figures present the estimate of the variance ratios, given by $\Sigma_{nn}/\tilde{\Sigma}_{nn}$ in (11). Here Σ_{nn} is the posterior uncertainty about the n^{th} order believe when there is access to both the public and private signal. $\tilde{\Sigma}_{NN}$ is the posterior uncertainty about the n^{th} when there is only access to the private signal. The horizontal axis denotes the moneyness of the options under consideration. In the left figure we depict the variance ratio of the fundamental value, i.e. **fundamental uncertainty**, for the **6 months** contracts. In the right figure we depict the variance ratio of the first order believe, i.e. **strategic uncertainty**, for the 6 month contracts. The data sample is from December 2002 to February 2015 for the option contracts on the SPX provided by Markit’s Totem service.

posterior variance of first order beliefs due to the availability of the consensus price feedback, that is $\hat{\lambda}_1(c)$. The plot on the right shows the reduction in the posterior variance of second order beliefs, $\hat{\lambda}_2(c)$. Figure 8 displays estimates of these ratios for options with times-to-expiration of 5 years.

We see that the consensus price feedback mostly helps reduce strategic valuation uncertainty for deep OTM put and call options. For put options with moneyness 60 and times-to-expiration, for example, having access to the consensus price for this contract is estimated to reduce the posterior variance of second order beliefs by 10%.

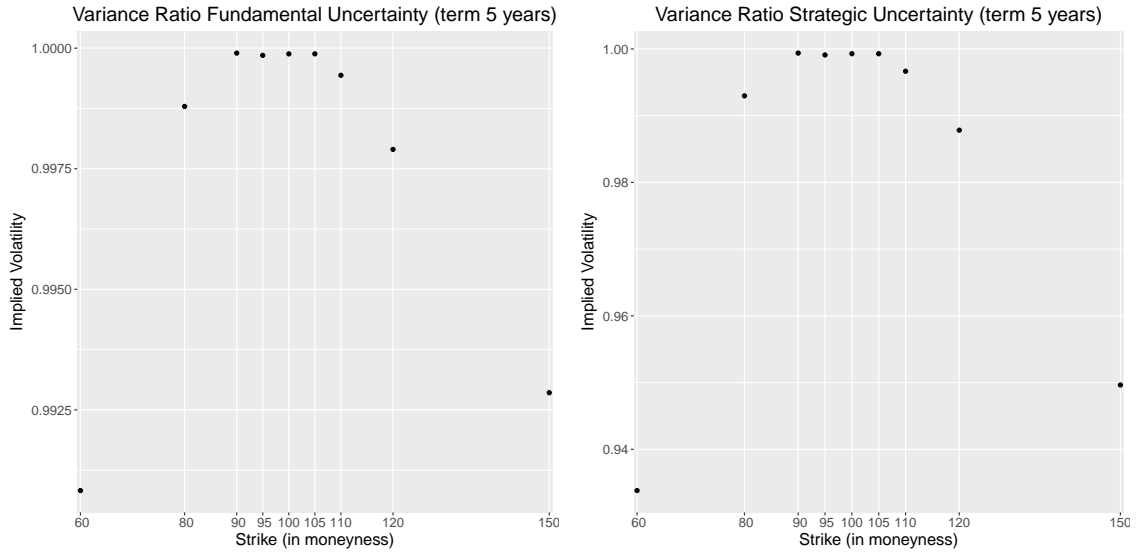


Figure 8: These figures present the estimate of the variance ratios, given by $\Sigma_{nn}/\hat{\Sigma}_{nn}$ in (11). Here Σ_{nn} is the posterior uncertainty about the n^{th} order believe when there is access to both the public and private signal. $\hat{\Sigma}_{NN}$ is the posterior uncertainty about the n^{th} when there is only access to the private signal. The horizontal axis denotes the moneyness of the options under consideration. In the left figure we depict the variance ratio of the fundamental value, i.e. **fundamental uncertainty**, for the **5 years** contracts. In the right figure we depict the variance ratio of the first order believe, i.e. **strategic uncertainty**, for the 6 month contracts. The data sample is from December 2002 to February 2015 for the option contracts on the SPX provided by Markit's Totem service.

5.3 Kalman gain

We now turn to the informational content of the price estimates that financial institutions submit to the Totem service. As discussed in section 2.4.3, we use the Kalman gain of the institutions' price updates to quantify the amount of new valuation information contained in their submissions. Given the parameter estimate $\hat{\Phi}(c)$ for option contract c and using equation (12), we can obtain an estimate for the weights submitters' beliefs put on current average beliefs $\theta_t^{(1:k)}$.

The following figures display estimates for the relative weight a submitter' price estimate for the given contract c puts on the current fundamental value $\theta_t^{(0)}$ of the contract, that is $\hat{\kappa}_1(c)$. $1 - \hat{\kappa}_1(c)$ is then the weight put on his prior estimate for $\theta_t^{(0)}$, that is $\mathbb{E}(\theta_t^{(0)}|\Omega_{i,t-1})$. Figure 9 display $\hat{\kappa}_1(c)$ for fixed times-to-maturity of 6 months (left) and 5 years (right). Figure 10 displays the term structure of these weights for put options with moneyness 60 (left) and call options with moneyness 150 (right). For comparison, the corresponding weight for ATM put options are given in red in both plots.

We see that for all contracts, price submissions put non-negligible weight on new information. Price submissions tend to contain more novel valuation information for ATM options and options with longer times-to-expiration. The term structure of informational content is upward sloping for deep OTM call option, but non-monotonic for deep OTM put options, first upward sloping up to terms of three years, then downward sloping.

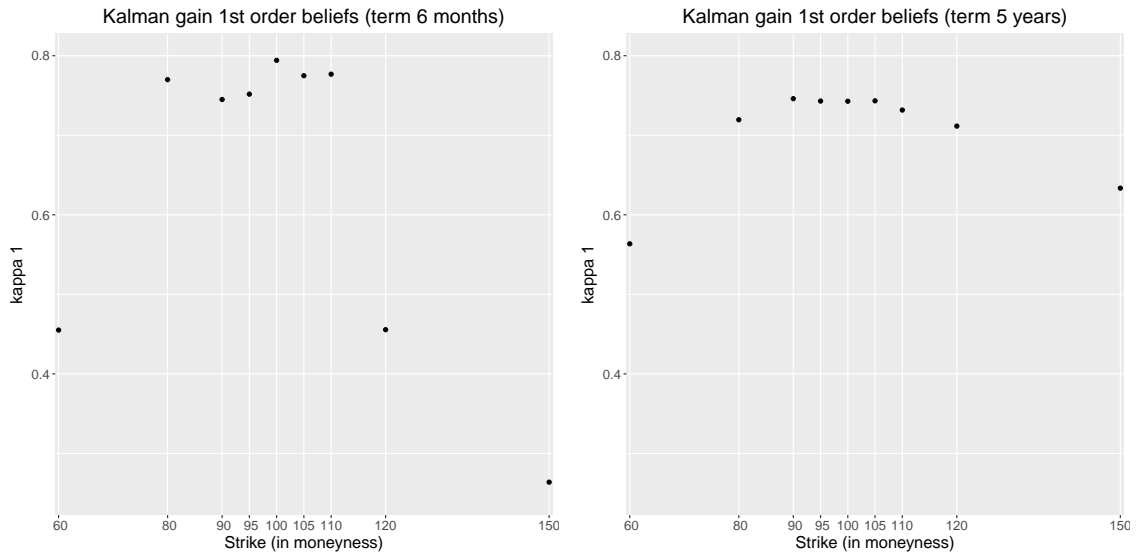


Figure 9: This figure presents the estimated Kalman gain, given by κ_1 in (12). The horizontal axis denotes the moneyness of the options under consideration. To estimate the model we log the implied volatility. The black dots represent the point estimates of κ_1 . The left figure considers option contracts with a time-to-maturity of **6 months**. The right figure considers option contracts with a time-to-maturity of **5 years**. The data sample is from December 2002 to February 2015 for the option contracts on the SPX provided by Markit's Totem service.

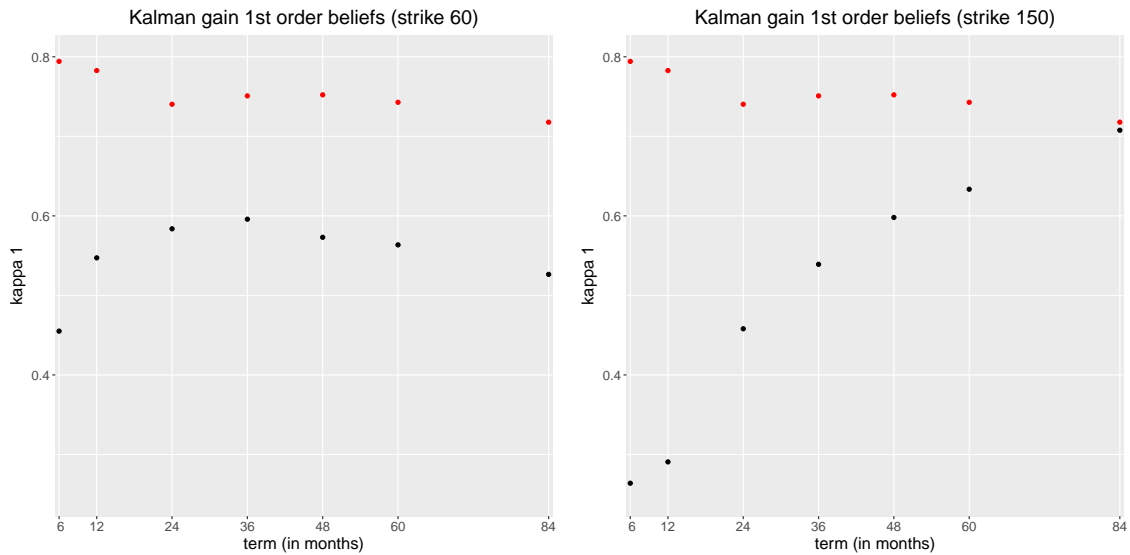


Figure 10: This figure presents the term structure of the estimated Kalman gain, given by κ_1 in (12). The horizontal axis denotes the term of the options under consideration. To estimate the model we log the implied volatility. The red dots represent the point estimates of κ_1 for the contracts with a moneyness of 100. The left figure considers option contracts with a moneyness of 60. The right figure considers option contracts with a moneyness of 150 in red. The data sample is from December 2002 to February 2015 for the option contracts on the SPX provided by Markit's Totem service.

6 Conclusion

In this paper we provide empirical evidence on the informational value of consensus prices for the valuation of illiquid S&P 500 index options that are predominately traded in the over-the-counter market. This evidence is based on the estimation of a structural model of learning in financial markets. For this, we use a unique panel of price estimates that large broker-dealers have provided to a consensus pricing service for OTC derivatives. The structural model allows us to address three questions. First, how large is the valuation uncertainty of broker-dealers participating in the OTC market for S&P500 index options? Here, we consider two dimensions of uncertainty: fundamental uncertainty about correctly pricing index options, and strategic uncertainty, that is how uncertain is a given broker-dealer about the position of his option valuations in relation to other market participants? Second, how helpful is having access to the consensus price feedback in reducing fundamental and strategic uncertainty? Last, how much novel valuation information do broker-dealers' consensus price submissions to the pricing service contain?

We find both fundamental and strategic valuation uncertainty to be pervasive across the volatility surface of S&P500 options that are traded in the OTC market, with higher uncertainty for option contracts with strike prices that correspond to more extreme moves in the S&P500 index. Broker-dealers do not appear to heavily rely on the consensus price feedback to reduce fundamental uncertainty. A perhaps somewhat counter-intuitive consequence of this fact is that their price submissions to the service contain significant amounts of novel valuation information. The consensus price feedback is found to be most important for reducing strategic uncertainty, and particularly so for extreme option contracts. This result is consistent with the scarcity of shared valuation information and, typically, heavy reliance on proprietary pricing models for such extreme contracts. It stresses the importance of publicly observable valuation data, such as benchmarks, to establish a shared understanding of market conditions in OTC markets. Such a shared understanding will be particularly valuable during episodes of market stress where high levels of strategic uncertainty might cause derivatives markets to freeze up.

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7 Appendix

7.1 Additional figures

7.1.1 Descriptives

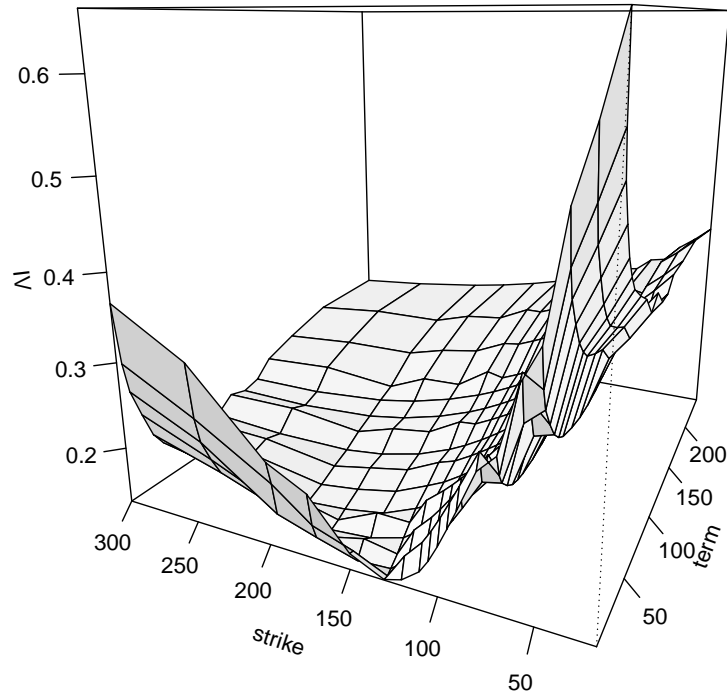


Figure 11: Average consensus IV (S&P 500)

This figure depicts the time-series average of the consensus price derived from the submitted midquotes. These midquotes are submitted by large broker dealers to Markit's Totem service. The midquote estimates are expressed as implied volatilities. The axis labeled term indicates the time-to-maturity of the option contract in months. The axis labeled strike indicates the moneyness of the option contract. Moneyness is defined as the strike price divided by the spot price multiplied by 100. All contracts are out-of-the-money contracts, except contracts with the moneyness 100 which are at-the-money. The data sample is from December 2002 till February 2015 for the option contracts on the S&P 500 index.

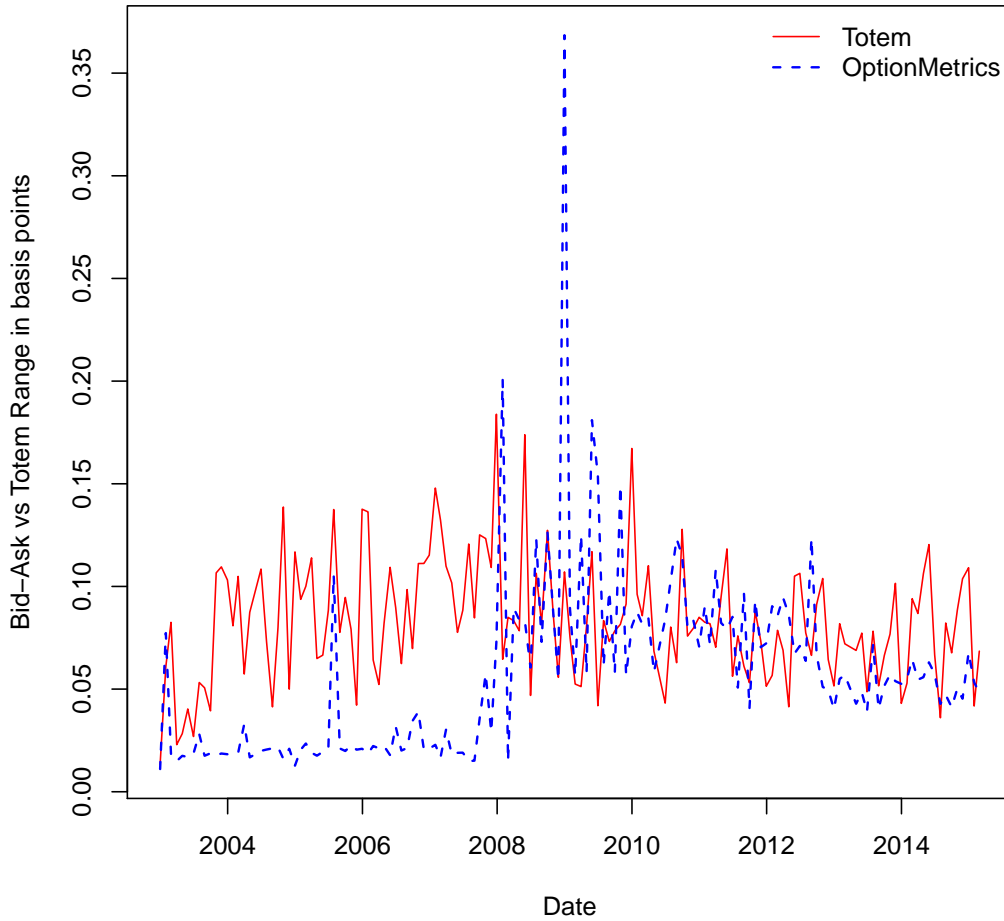


Figure 12: Bid-Ask spread vs Submission Range IV (S&P 500)

The figure above displays the difference between the range of the price submissions to the Totem service and bid-ask spread on traded options from OptionMetrics. The bid-ask spread is given by the best difference between the best closing bid price and best closing ask price across all US option exchanges. The options in the Totem service are matched to the traded options in the OptionMetrics database. On a given Totem valuation date we match OptionMetrics option contracts that are a close proxy for the totem option contracts. We search for contracts with a ± 10 days-to-maturity and a ± 1 moneyness value. When multiple options match the criteria an average is taken of their bid-ask spread.

7.2 Valuation submission process

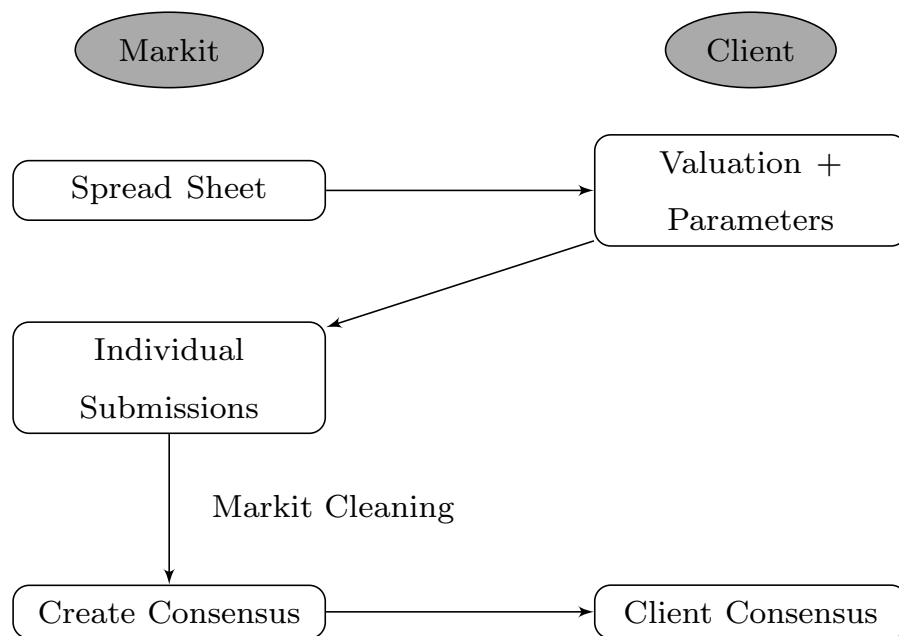


Figure 13: Diagram: Submission process

Figure 13 depicts a diagram of the submission process to Markit's Totem service for plain vanilla index options. Totem issues at the end of each month a spread sheet to $N_{K,T}$ submitters. Here K is the moneyness of the contract defined as the strike price divided by the spot price multiplied by 100 and T is the time-to-maturity of the contract in months. participating submitters are required to submit their mid-price estimate for a range of put option with a moneyness between 80 and 100 and a range of call option with a moneyness ranging from 100 to 120 with a time to maturity of 6 months. Submitters which want to submit to any other contracts with a different maturity or/and different moneyness are required to submit to all the available terms and strikes which lie in between the required contracts and the additionally demanded contracts.

Submitter i submits its mid-price estimate for different out of the money put and call options, $P_t^i(p, K, T)$ and $P_t^i(c, K, T)$ respectively. The inputs which are required in addition to the mid-price estimates are:

- Their discount factor $\beta_t^i(T)$.
- Reference level R_t^i (This is the price of a futures contract with maturity date closest to the valuation date, i.e t .)
- Implied spot level $S_t^i(K, T)$ (Implied level of the underlying index of the futures contract)

There are strict instructions on the timing of the valuation of the contract and the reference level used. To address any issues which might still arise with respect to valuation timing and the effect it could have on the comparability of the prices, the various prices are aligned according to the following mechanism.

1. $\text{Basis}_i = R_t^i - S_t^i(K = 100, T = 6)$
2. $S_t^{i*}(K, T) = \text{mode}_i [R_t^i] - \text{Basis}_i$
3. Remove from $S_t^{i*}(K, T)$ the lowest, highest and erroneous adjusted spot levels.
4. $\bar{S}_t(K, T) = \text{mode}_i [R_t^i] - \frac{1}{N^*(K, T)} \sum_{i=1}^{N^*(K, T)} S_t^i(K, T)$

This consensus implied spot from the at-the-money 6 month option is used for all other combinations of K and T . The submitted prices are restated in terms of $\bar{S}_t(K, T)$, giving: $\hat{p}_t^i(\{c, p\}, K, T) = P_t^i(\{c, p\}, K, T) / \bar{S}_t(K, T)$.

Given the submitted quantities a security analyst calculates various implied quantities to validate the individual submissions. The security analyst utilizes put-call parity on ATM options to retrieve the relative forward, i.e

$$f_t^i(K, T) = \frac{\hat{p}_t^i(c, K, T) - \hat{p}_t^i(p, K, T)}{\beta_t^i(K, T)} + 1$$

The above inputs are then used in the Black and Scholes model,

$$\hat{p}_t^i(c, K, T) = \beta_t^i(K, T) [f_t^i(K, T) N(d_1) - KN(d_2)]$$

$$d_1 = \frac{\ln\left(\frac{f}{K}\right) + \left(\frac{\sigma^2}{2}\right) \Delta T_t}{\sigma \sqrt{\Delta T_t}}, \text{ where } \Delta T_t = \frac{\text{days}(T)}{365.25}$$

$$d_2 = d_1 - \sigma\sqrt{\Delta T_t}$$

to back-out the implied volatility, $\sigma_i(K, T)$.

When reviewing submissions security analysts compare the implied volatilities against other submitted prices and market conditions by taking the following points into consideration:

- The number of contributors
- Market activity & news
- Frequency of change of variables
- Market conventions
- In a one way market, is the concept of a mid-market price clearly understood?
- The distribution and spread of contributed data

In addition to these criteria security analyst also visually inspect the ATM implied volatility term structure and the implied volatility along the moneyness for a given term.²¹ After the vetting process the security analyst proceeds to the aggregation of the individual submissions into the consensus data.

Given the Black and Scholes model they back out $\sigma_i(K, T)$ and aggregate it into the consensus implied volatility.

$$\bar{\sigma}(K, T) = \frac{1}{n_{(K, T)} - n^r} \sum_{i=1}^{n_{K, T} - n^r} \sigma_i(K, T)$$

Here n^r are the number of excluded prices. The exclusions consist of the lowest, highest and rejected prices. The highest and lowest acceptable $\sigma_i(K, T)$ are consistent and reasonable IV's, but are excluded to safeguard the stability of the consensus IV.²² The same process takes place for the submitted prices.

²¹Also referred to as the skew or smile.

²²If the number of acceptable prices is 6 or below the highest and lost submissions are included in the calculations.

The submitters of which the pricing information is not rejected receive from the security analyst the consensus information.²³ The consensus data includes the average, standard deviation, skewness and kurtosis of the distribution of acceptable prices and implied volatility. They also include the number of submitters to the consensus data.

²³The time between submission of the mid-price estimate and receiving the consensus price back normally takes less than half a day.

7.3 Data

Table 2: Available data for plain vanilla option on the S&P 500

| <i>term</i> | <i>moneyness</i> | | | | | | | | | | | | | | | | | | | |
|-------------|------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 95 | 100 | 105 | 110 | 120 | 130 | 150 | 175 | 200 | 250 | 300 | |
| 1 | 08/09 | 08/09 | 08/15 | 13/15 | 07/15 | 13/15 | 02/15 | 02/15 | 02/15 | 02/15 | 02/15 | 02/15 | 02/15 | 02/15 | 09/15 | 07/15 | 09/15 | 07/15 | - | - |
| 2 | 08/09 | 08/09 | 08/15 | 13/15 | 08/15 | 13/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 09/15 | 08/15 | 09/15 | 08/15 | - | - |
| 3 | 08/09 | 08/09 | 08/15 | 13/15 | 07/15 | 13/15 | 02/15 | 02/15 | 02/15 | 02/15 | 02/15 | 02/15 | 02/15 | 02/15 | 09/15 | 07/15 | 09/15 | 07/15 | - | - |
| 6 | 08/15 | 08/15 | 08/15 | 13/15 | 08/15 | 13/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 09/15 | 09/15 | 09/15 | 02/15 | 08/15 | 08/15 |
| 9 | 08/15 | 08/15 | 08/15 | 13/15 | 07/15 | 13/15 | 07/15 | 07/15 | 07/15 | 07/15 | 07/15 | 07/15 | 07/15 | 07/15 | 09/15 | 07/15 | 09/15 | 07/15 | 08/15 | 08/15 |
| 12 | 08/15 | 08/15 | 08/15 | 13/15 | 08/15 | 13/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 09/15 | 09/15 | 09/15 | 02/15 | 08/15 | 08/15 |
| 18 | 08/15 | 08/15 | 08/15 | 13/15 | 07/15 | 13/15 | 07/15 | 07/15 | 07/15 | 07/15 | 07/15 | 07/15 | 07/15 | 07/15 | 09/15 | 07/15 | 09/15 | 07/15 | 08/15 | 08/15 |
| 24 | 08/15 | 08/15 | 08/15 | 13/15 | 08/15 | 13/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 09/15 | 09/15 | 09/15 | 02/15 | 08/15 | 08/15 |
| 30 | 08/15 | 08/15 | 08/15 | 13/15 | 07/15 | 13/15 | 07/15 | 07/15 | 07/15 | 07/15 | 07/15 | 07/15 | 07/15 | 07/15 | 09/15 | 07/15 | 09/15 | 07/15 | 08/15 | 08/15 |
| 36 | 08/15 | 08/15 | 08/15 | 13/15 | 08/15 | 13/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 09/15 | 09/15 | 09/15 | 02/15 | 08/15 | 08/15 |
| 48 | 08/15 | 08/15 | 08/15 | 13/15 | 08/15 | 13/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 09/15 | 09/15 | 09/15 | 02/15 | 08/15 | 08/15 |
| 60 | 08/15 | 08/15 | 08/15 | 13/15 | 08/15 | 13/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 08/15 | 09/15 | 09/15 | 09/15 | 02/15 | 08/15 | 08/15 |
| 72 | 10/15 | 10/15 | 10/15 | 13/15 | 10/15 | 13/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 |
| 84 | 08/15 | 08/15 | 08/15 | 13/15 | 09/15 | 13/15 | 09/15 | 09/15 | 09/15 | 09/15 | 09/15 | 09/15 | 09/15 | 09/15 | 09/15 | 09/15 | 09/15 | 02/15 | 08/15 | 08/15 |
| 96 | 10/15 | 10/15 | 10/15 | 13/15 | 10/15 | 13/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 |
| 108 | 10/15 | 10/15 | 10/15 | 13/15 | 10/15 | 13/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 | 10/15 |
| 120 | 08/15 | 08/15 | 08/15 | 13/15 | 09/15 | 13/15 | 09/15 | 09/15 | 09/15 | 09/15 | 09/15 | 09/15 | 09/15 | 09/15 | 09/15 | 09/15 | 09/15 | 03/15 | 08/15 | 08/15 |
| 144 | 08/15 | 08/15 | 08/15 | 13/15 | 05/15 | 13/15 | 05/15 | 05/15 | 05/15 | 05/15 | 05/15 | 05/15 | 05/15 | 05/15 | 09/15 | 05/15 | 09/15 | 05/15 | 08/15 | 08/15 |
| 180 | 08/15 | 08/15 | 08/15 | 13/15 | 05/15 | 13/15 | 05/15 | 05/15 | 05/15 | 05/15 | 05/15 | 05/15 | 05/15 | 05/15 | 09/15 | 05/15 | 09/15 | 05/15 | 08/15 | 08/15 |
| 240 | 11/15 | 11/15 | 11/15 | 13/15 | 11/15 | 13/15 | 11/15 | 11/15 | 11/15 | 11/15 | 11/15 | 11/15 | 11/15 | 11/15 | 11/15 | 11/15 | 11/15 | 11/15 | 11/15 | 11/15 |

This table gives the coverage of the data for the specific contracts on the S&P 500 Index. The table reports the start and end year that a contract covers.

Table 3: Average number of submitters for plain vanilla option on the S&P 500

| <i>term</i> | <i>moneyness</i> | | | | | | | | | | | | | | | | | | |
|-------------|------------------|----|----|----|----|----|----|----|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 95 | 100 | 105 | 110 | 120 | 130 | 150 | 175 | 200 | 250 | 300 |
| 1 | 14 | 14 | 17 | 18 | 18 | 21 | 21 | 21 | 21 | 21 | 21 | 21 | 21 | 18 | 18 | 18 | 17 | - | - |
| 2 | 14 | 14 | 17 | 18 | 18 | 21 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 18 | 18 | 18 | 17 | - | - |
| 3 | 14 | 14 | 17 | 19 | 18 | 21 | 21 | 21 | 21 | 21 | 21 | 21 | 21 | 19 | 18 | 18 | 17 | - | - |
| 6 | 17 | 17 | 21 | 24 | 27 | 30 | 31 | 31 | 31 | 31 | 31 | 31 | 31 | 29 | 27 | 24 | 19 | 13 | 12 |
| 9 | 16 | 16 | 21 | 24 | 26 | 30 | 29 | 29 | 29 | 29 | 29 | 29 | 29 | 29 | 26 | 24 | 22 | 13 | 12 |
| 12 | 16 | 16 | 21 | 24 | 27 | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 28 | 27 | 23 | 19 | 13 | 12 |
| 18 | 16 | 16 | 21 | 24 | 25 | 29 | 28 | 28 | 28 | 28 | 28 | 28 | 28 | 28 | 25 | 23 | 21 | 13 | 12 |
| 24 | 16 | 16 | 21 | 24 | 27 | 29 | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 28 | 26 | 23 | 19 | 13 | 12 |
| 30 | 16 | 16 | 21 | 23 | 25 | 29 | 27 | 27 | 27 | 27 | 27 | 27 | 27 | 28 | 25 | 23 | 20 | 13 | 12 |
| 36 | 16 | 16 | 20 | 23 | 26 | 28 | 29 | 29 | 29 | 29 | 29 | 29 | 29 | 27 | 26 | 23 | 18 | 13 | 11 |
| 48 | 16 | 16 | 20 | 22 | 26 | 27 | 29 | 29 | 29 | 29 | 29 | 29 | 29 | 26 | 25 | 22 | 18 | 12 | 11 |
| 60 | 16 | 16 | 20 | 22 | 25 | 26 | 28 | 28 | 28 | 28 | 28 | 28 | 28 | 26 | 25 | 22 | 18 | 12 | 11 |
| 72 | 16 | 16 | 19 | 21 | 25 | 24 | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 24 | 24 | 21 | 20 | 13 | 12 |
| 84 | 15 | 15 | 18 | 20 | 24 | 24 | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 24 | 23 | 21 | 17 | 12 | 11 |
| 96 | 15 | 15 | 18 | 19 | 22 | 23 | 23 | 23 | 23 | 23 | 23 | 23 | 23 | 22 | 22 | 19 | 19 | 12 | 11 |
| 108 | 14 | 14 | 17 | 17 | 21 | 20 | 22 | 22 | 22 | 22 | 22 | 22 | 22 | 21 | 21 | 18 | 18 | 12 | 11 |
| 120 | 13 | 13 | 16 | 17 | 20 | 20 | 21 | 21 | 21 | 21 | 21 | 21 | 21 | 21 | 20 | 17 | 15 | 11 | 10 |
| 144 | 11 | 11 | 13 | 13 | 13 | 14 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 14 | 13 | 14 | 12 | 9 | 8 |
| 180 | 10 | 10 | 11 | 12 | 11 | 12 | 11 | 11 | 11 | 11 | 11 | 11 | 11 | 12 | 11 | 12 | 11 | 8 | 8 |
| 240 | 5 | 5 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 5 | 5 |

This table provides the average number of submitters for the specific options on the S&P 500 Index. These are the accepted prices per contract for the dates that the contract is polled. In our analysis we ignore submissions with a price of 0. The data sample is from December 2002 till February 2015.