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 S&P 500 index options. We use a proprietary data set on price estimates for S&P500 index option provided by major broker-dealers to a consensus pricing service to estimate a structural model of learning about uncertain asset values. In the model, market participants treat consensus prices as public signals about latent fundamental values. We construct model-implied measures of the informational content of broker-dealers' price estimates and the informational value of the consensus price feedback for its subscribers. We find that institutions' price estimates contain a significant amount of new information about option valuations for all strike prices and times-to-maturities. Furthermore, the feedback provided by the consensus pricing service is a valuable source of pricing information over the entire volatility surface and significantly reduces market participants' valuation uncertainty.

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1 Introduction

Many important asset classes, such as corporate bonds or a majority of derivatives contracts, currently do not trade on centralised exchanges. Instead, they are traded on over-the-counter (OTC) markets. In such markets, price and volume data typically remain the private information of those directly involved in the transaction and are not made publicly available to other parties. 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 over-the-counter 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. This paper studies the informational value of such consensus prices for market participants trading in the over-the-counter market for equity index derivatives.

Consensus pricing services typically specialise in a specific asset class and tend to focus on the most prominent financial instruments traded within that class. The London interbank offered rate (LIBOR) service is perhaps the best known example. In the wake of the LIBOR scandal of 2012, however, 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] This paper focuses on 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. We have access to a panel of price estimates that major financial institution 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. 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

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

then construct two 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 captures the amount of information that is contained in the price estimates that market participants provide to the consensus pricing service. Our measure of the informational content is the Kalman gain of their price estimates, that is the weight Totem submitters put on new information rather than their prior in these price estimates. The higher the Kalman gain, the informationally richer are price estimates.

The second informational measure gauges the value market participants attach to consensus prices itself, that is, how strongly their asset valuations rely on the price information provided by the consensus pricing service. To do so, we compare the model-implied posterior variances of market participants' 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.

We find that the price estimates provided by market participants are informationally rich: updates of individual price estimates appear to contain precise information about changes in asset values. Their informational content varies across the strike and time-to-maturity space of the options. For option contracts for which we would expect more trading activity in the over-the-counter market, we also identify a higher informational content of price estimates. This evidence is consistent with our model identifying information flows derived from unobservable over-the-counter trades. For almost all option contracts broker-dealer price estimates put a weight of at least 50% on new valuation information received over the month preceding the submission date.

Concerning the informational value of consensus prices, we find that consensus prices receive a lower weight in institutions' valuations relative to other informational sources for contracts that we would expect to be less actively traded. Yet, we consistently find that access to the consensus price significantly reduces posterior uncertainty about fundamentals, by a factor of four for at-the-money options at all times-to-maturity and by a factor of two for most out-of-the-money option contracts.

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 preopening 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-sectional dispersion of forecasts and their dynamics. Barillas and Nimark (2017) and

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

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.

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, Dworczak, 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 section 2 we provide a detailed description of the Totem consensus pricing service with a focus on the S&P 500 index options. We also provide summary statistics for the different contracts. In section 3 we 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 4 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 5 concludes.

2 The Totem consensus pricing service

In this paper we use a proprietary data set to study the informational value of consensus prices for option valuations in OTC derivatives markets. The analysis is based on consensus prices collected by IHS Markit's Totem consensus pricing service.[3] Totem 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. Totem collects estimates for the midquote from active market participants. At Markit, a team of specialists then cleans these midquote submissions and returns to its subscribers various aggregate statistics of the midquote submissions, so-called consensus data.[4] This allows Totem subscribers to gauge the position of their prices in relation to the market consensus prices.

2.1 Index option consensus prices

The empirical analysis in this paper is based on the individual midquote submissions for S&P 500 index options of Totem subscribers as well as the aggregated consensus prices derived from these submissions. 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

[3]Data provided by IHS Markit^{TM} - 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.

[4]In 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.

in terms of moneyness[5] 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.[6]

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 service. 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).

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.[7] As is well known empirically, the implied volatility is not equal across the whole range of moneyness.[8] The IV for

[5]The 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.

[6]Tables 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.

[7]When 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.

[8]To 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

	moneyness								
term	**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 devided 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.

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&P 500 index options.

2.2 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 1 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

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.

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.

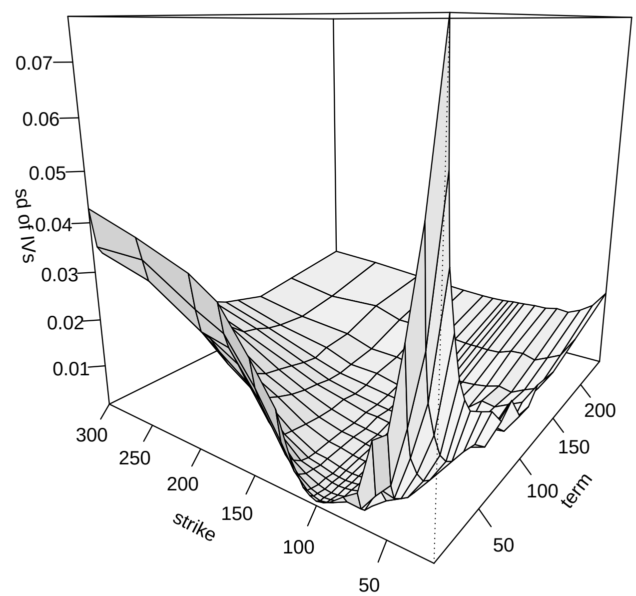


Figure 1: Cross-sectional dispersion of IVs (S&P 500)

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-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.

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 the transaction-based OptionMetrics data.[9] Figure 9 depicts the bid-ask spread of the latter and the range of Totem submissions for a European put option on the S&P 500 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 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.

3 Measuring the informational content of consensus prices

In this section we set up a simple model of consensus pricing based on subscribers who share a common prior about an asset of uncertain value, and receive noisy private and public signals about this asset value at discrete points in time. Based on the prior and the signals received, each subscriber submits her best current estimate for the asset value to the consensus pricing service. We then show how to construct measures for the informational content of consensus price data based on the structural parameters of the model.

3.1 A model of learning from public and private information

There are N financial institutions which participate in a consensus pricing service. At discrete submission dates, indexed $t = 1, 2, 3...$, each institution submits its best estimate for the current value of an unobservable stochastic process $\{\theta_t\}$ to the service. The unobservable stochastic process evolves according to

$$\theta_t = (1-\rho)\bar{\theta} + \rho\,\theta_{t-1} + \varepsilon_t,$$

where innovations ε_t are independent across time and normally distributed

$$\varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right).$$

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

Initially, all submitters start with a common prior for θ_0, $N(\mu_0, \sigma_0^2)$. At each subsequent submission date t they receive a noisy public signal S_t about θ_t,

$$S_t = \alpha + \beta\,\theta_t + \eta_t,$$

where $\eta_t \sim N(0, \sigma_\eta^2)$.[10] In addition to the public signal S_t each institution receives a noisy private signal $s_{i,t}$ about θ_t,

$$s_{i,t} = \theta_t + \nu_{i,t},$$

where $\nu_{i,t} \sim N(0, \sigma_\nu^2)$. Conditional on θ_t all period t signals are independent. Also, all noise components $\{\eta_t\}$ and $\{\nu_{i,t}\}$ are independent across time.

We denote institution i's period t information set by $\Omega_{i,t}$. We assume that this information set consists of the history of public and private signals that i has observed up to period t, that is[11]

$$\Omega_{i,t} = \{s_{i,j}, S_j, \Omega_{i,t-1}\}.$$

To characterise institution i's submission to the consensus service in period t we need to calculate its best estimate of θ_t which is given by $\mu_{i,t} \equiv \mathbb{E}\,(\theta_t|\Omega_{i,t})$. Under our above assumption of normal priors in combination with normally distributed signals and we know that i's beliefs will be normally distributed as well,

$$\theta_t|\Omega_{i,t} \sim N(\mu_{i,t}, \sigma_{i,t}^2).$$

We can now derive $\mu_{i,t}$ and $\sigma_{i,t}^2$ using standard Kalman filtering techniques.[12]

We obtain the following updating equation for posterior means and variances

[10]In the estimation the private signal will be treated as a latent variable, while the public signal will be treated as observable, namely the consensus price. This is why the public signal is parameterised by α and β, while no such parameterisation is used for the private signal.

[11]In principle the information set in our setting should also include past consensus prices, i.e. the cross-sectional averages of the individual institutions' submissions to the consensus pricing service. This, however, would be a set-up in which submitters learn from endogenous variables with the well-known consequence of potentially infinite state spaces due to having to keep track of higher order beliefs for signal extraction purposes (see Townsend (1983), Sargent (1991)). Some progress has recently been made to address such problems, either by using truncation methods for the state space (Nimark (2017)) or working in the frequency domain (Kasa (2000), Kasa, Walker, and Whiteman (2014), Rondina and Walker (2014)). Endogenizing the public signal adapting Nimark (2017)'s iterative procedure to the above setup is work-in-progress.

[12]See e.g. Durbin and Koopman (2012).

$$\mu_{i,t} = (1-k_t)\rho\,\mu_{i,t-1} + k_t\,\theta_t + k_t\,[(1-\gamma)\nu_{i,t} + (\gamma/\beta)\,\eta_t] \tag{1}$$

$$\sigma_t^2 = (1-k_t)\left(\rho^2\,\sigma_{t-1}^2 + \sigma_\varepsilon^2\right) \tag{2}$$

where k_t is the Kalman gain with

$$k_t = \frac{\rho^2\,\sigma_{t-1}^2 + \sigma_\varepsilon^2}{\rho^2\,\sigma_{t-1}^2 + \sigma_\varepsilon^2 + \zeta} \tag{3}$$

and

$$\zeta = \frac{\sigma_\nu^2\,\sigma_\eta^2}{\beta^2\,\sigma_\nu^2 + \sigma_\eta^2} \quad \text{and} \quad \gamma = \frac{\beta^2\,\sigma_\nu^2}{\beta^2\,\sigma_\nu^2 + \sigma_\eta^2}.$$

Note that the common prior assumption together with the assumption of identical signal distributions across submitters results in all submitters' posterior beliefs having the same variance, σ_t^2.

Equations (2) and (3) define a globally stable dynamic system in (k_t, σ_t^2) that for any prior σ_0^2 converges to a unique fixed point (k, σ^2) given by

$$k = \frac{1}{2} + \frac{1}{2\rho^2}\left\{\left[(1-\rho)^2 + \frac{\sigma_\varepsilon^2}{\zeta}\right]^{\frac{1}{2}}\left[(1+\rho)^2 + \frac{\sigma_\varepsilon^2}{\zeta}\right]^{\frac{1}{2}} - \left(1 + \frac{\sigma_\varepsilon^2}{\zeta}\right)\right\} \tag{4}$$

and

$$\sigma^2 = \left(\frac{1-k}{1-(1-k)\rho^2}\right)\sigma_\epsilon^2. \tag{5}$$

In our empirical analysis we will concentrate on this steady-state of the learning dynamics in which all submitters have constant Kalman gain k and posterior variance σ^2.

3.2 Two measures of informational content

To analyse the informational content of our consensus price data, we will estimate the structural parameters of the above model, namely $\psi = \{\bar{\theta}, \rho, \sigma_\varepsilon^2, \sigma_\nu^2, \sigma_\eta^2, \alpha, \beta\}$, treating the time series of price estimates submitted by financial institution i as their best estimate $\mu_{i,t}$ of the current market value of the given contract θ_t. This estimation is carried out for each option contract (defined by time-to-maturity and moneyness) separately, that is we will obtain an estimate $\hat{\psi}$ for each option. Based on these estimates of the structural parameters of the above learning model, we construct 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 two specific questions. First, how much information do the price estimates that financial institutions submit to the consensus pricing service contain? Second, how much weight do these institution put on the consensus price feedback relative to other private informational sources in their valuations of the option contract?

3.2.1 How much information do institutions' price estimates contain?

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, given in equation (1), can be expressed as follows:

$$\underbrace{\mathbb{E}(\theta_t|\Omega_{i,t})}_{\text{new estimate}} = \underbrace{\mathbb{E}(\theta_t|\Omega_{i,t-1})}_{\text{previous estimate}} + \underbrace{k(\psi)}_{\text{Kalman gain}} \times \underbrace{\xi_{i,t}}_{\text{new information}} .$$

The higher the precision of the signals, the higher is the Kalman gain k and, consequently, the more weight is put on new information relative to the institution's prior estimate. A higher k thus implies informationally richer price estimates.

It is important to note that the persistence in institutions' price estimates can derive from two distinct sources. It can either come from persistent fundamentals, that is a high ρ, or it can be the consequence of poor signals which imply a low Kalman gain k. The structural model allows us to separate these two channels. Simply basing ourselves on the persistence of the price estimates to draw conclusions about the informational content of these estimates would not be a feasible avenue.

3.2.2 How important is the consensus price feedback?

The second question we want to address is the importance of the feedback financial institutions receive from the consensus pricing service, as given by the current consensus price, for their valuation of this option contract. 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 public signal, which in our estimation is the consensus price, keeping its information acquisition strategy constant?

The posterior uncertainty about the fundamental value of an institution that has access to the history of both private and public signal is given by

$$\sigma^2(\psi) = Var(\theta_t|\{S_k, S_{i,k}\}_{k=t_0}^{t-1}; \psi).$$

A informative comparative statistic to derive is the posterior variance of an institution without access to the public signal. This is achieved by setting the variance of the public signal, σ_η^2, to infinity, keeping all other parameters values unchanged. This yields

$$\sigma_p^2(\psi) = Var(\theta_t | \{S_{i,k}\}_{k=t_0}^{t-1}; \psi).$$

The ratio of the two variances, which we call λ, is then our measure of the informational value of the consensus price,

$$\lambda(\psi) = \frac{\sigma^2(\psi)}{\sigma_p^2(\psi)}. \tag{6}$$

A lower λ implies a larger reduction in posterior uncertainty due to the introduction of the consensus price.

4 Results

The estimation, described in appendix 6.1, yields maximum likelihood estimates for the structural parameter ψ of the model developed in section 3. 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 $\hat{\psi}(c)$. 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 3.2. We first show the variation of the estimated Kalman gains of individual institutions' price submissions across the volatility surface. We then analyse how the relative informational importance of the consensus price feedback varies across this space.

4.1 Posterior uncertainty

To gauge the extent of uncertainty about option valuations across the volatility surface, a natural metric is the posterior variance of submitters' beliefs σ^2. Given the parameter estimates $\hat{\psi}(c)$ for contract c, we can calculate an estimate of the corresponding steady-state posterior variance of beliefs $\hat{\sigma}^2(c)$ using equation (5). As institutions' posterior beliefs are normally distributed, $\pm 2\,\hat{\sigma}^2(c)$ gives a 95% confidence interval around an institution's current mean belief about the fundamental value θ_t. An intuitive way to display these estimates is as "confidence intervals" around the estimate of the long-run mean $\hat{\bar{\theta}}(c)$.

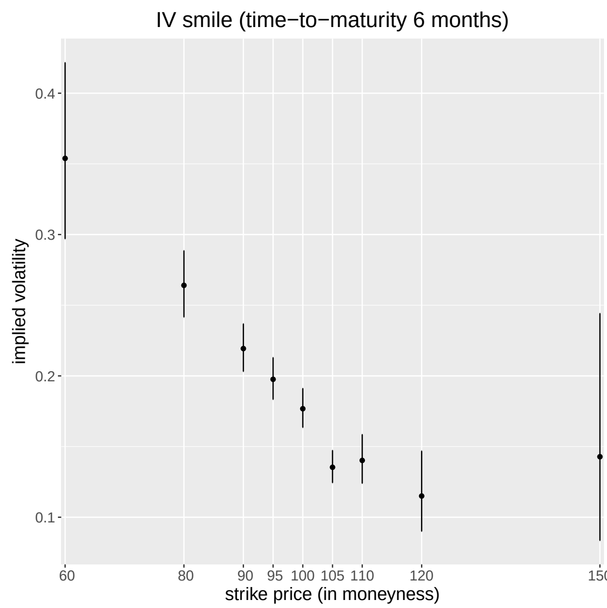
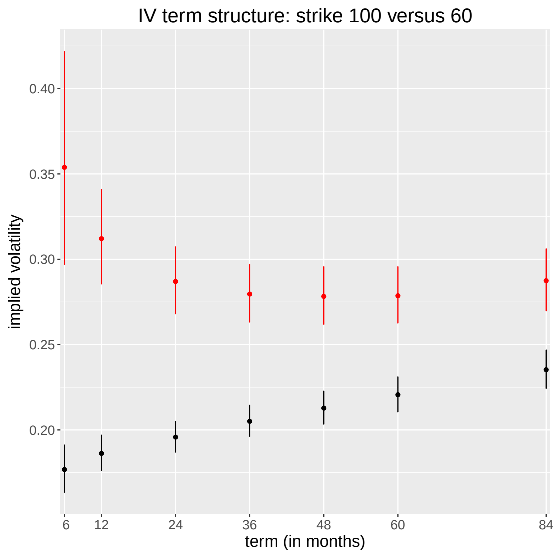


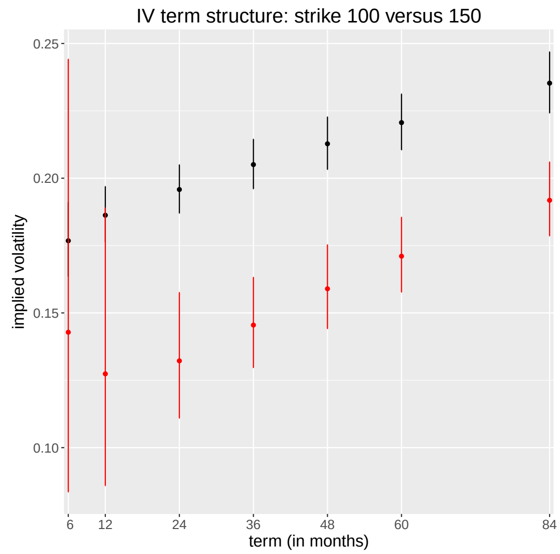
Figure 2: This figure presents the submitters steady-state beliefs of the long-run implied volatility mean, $\bar{\theta}$. The horizontal axis denotes the moneyness of the options under consideration. To estimate the model we log the implied volatility. The black dots represent the point estimates of the exponentiated point estimates. The bounds around the point estimates are the 95% confidence intervals. The confidence intervals are derived by the delta-method. We consider the option contracts with a time-to-maturity of **6 months**. The data sample is from December 2002 till February 2015 for the option contracts on the SPX provided by Markit's Totem service.

Figure 2 plots these "confidence intervals" centred around the long-run mean for option contracts with time-to-maturity of 6 months.[13] This gives the model-implied stead-state uncertainty of Totem submitters around the well-known volatility smile. The volatility curve displays the familiar smile with highest IV for the deep out-of-the-money (OTM) put option (moneyness 60), and the IV curve sloping upwards

[13]The units of the y-axis have been rescaled to display results in terms of implied volatilities rather than the logarithm of implied volatilities.



strike price at 60 in red



strike price at 150 in red

Figure 3: These figures present the term structure of submitters steady-state beliefs of the long-run implied volatility mean, $\bar{\theta}$. In the left figure we introduce the term structure of an at-the-money option (in black) and an out-of-money put option with a moneyness of 60 (in red). In the right figure the at-the-money option (in black) is contrasted with an out-of-money call option with a moneyness of 150 (in red). The horizontal axis denotes the time-to-maturity in months. To estimate the model we log the implied volatility. The dots represent the point estimates of the exponentiated point estimates. The bounds around the point estimates are the 95% confidence intervals. The confidence intervals are derived by the delta-method from the likelihood function. The data sample is from December 2002 till February 2015 for the option contracts on the SPX provided by Markit's Totem service.

again for the deep OTM call option (moneyness 150). Posterior uncertainty mirrors this smile. Uncertainty about fundamental values increases as we move out of the money. This results agrees with intuition: strike prices of 60 or 150 for terms of 6 month refer to extreme movements in the index. We expect valuations of options referring to such extreme events to come with higher uncertainty.

Figure 3 illustrates how the posterior uncertainty varies with the time-to-maturity of the option contracts. It displays the term structure of posterior uncertainty for option contracts with fixed moneynesses. In both plots options with moneyness 100 appear in black. Time-to-maturity varies from 6 months to 7 years. The left plot displays OTM puts with moneyness 60 in red. The right plot shows the posterior uncertainty for OTM calls with moneyness 150. While posterior uncertainty remains roughly constant for the options with moneyness 100 as the time-to-maturity increases, the term structure for the OTM options is downward sloping, that is the confidence intervals narrow as time-to-maturity increases. Again, this narrowing agrees with intuition as moneynesses 60 and 150 correspond to less extreme events as the time-to-maturity of the option lengthens.

4.2 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 3.2.1, 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 $\hat{\psi}(c)$ for option contract c, we can obtain an estimate for the stationary Kalman gain using equation (4).

Figure 4 displays estimates of $\hat{k}(c)$ for option contracts with a time-to-maturity of 6 months and moneynesses varying from 60 to 150. The plot shows a clear inverted U-shape pattern with a significantly lower Kalman gain for OTM options than close to at-the-money (ATM) options. The deep OTM call option with moneyness 150 has the lowest Kalman gain, and hence informational content. This is in line with expectations: extreme upward movements of the index within a 6 months term are rare and, unlike for deep OTM put options, insurance motives will be less relevant. Hence, as we expect such options to trade infrequently we would expect little new valuation information to arrive at a monthly time interval.

Figure 5 displays the term structure of the Kalman gain for options with fixed moneynesses 60, 100, and 150. Black corresponds to options with moneyness 100, red to options with moneyness 60 (left) and 150 (right). Across the term structure of options, the OTM options have lower Kalman gains than the ATM options. It appears that the price estimates for ATM options are informationally richer than those for the OTM options for all times-to-maturity. While the OTM call options have an increasing term structure, the OTM put options' term structure has an inverted U-shape. The increasing term structure of the OTM call options appears intuitive: a moneyness of 150 corresponds to a less extreme move of the underlying for an horizon of several years than for 6 months. Consequently, one would expect more trading activity for the longer times-to-maturity, and, correspondingly, a more frequent flow of new valuation information in the longer termed contracts. The reason for inverted U-shape pattern for the OTM put is less obvious. According to our model-implied

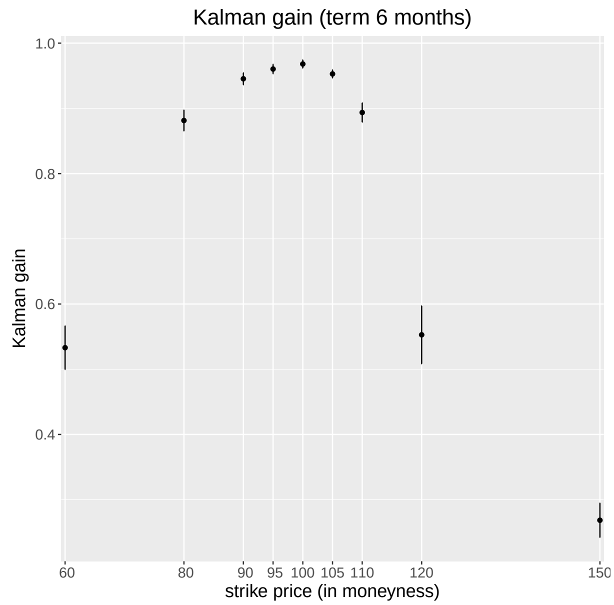
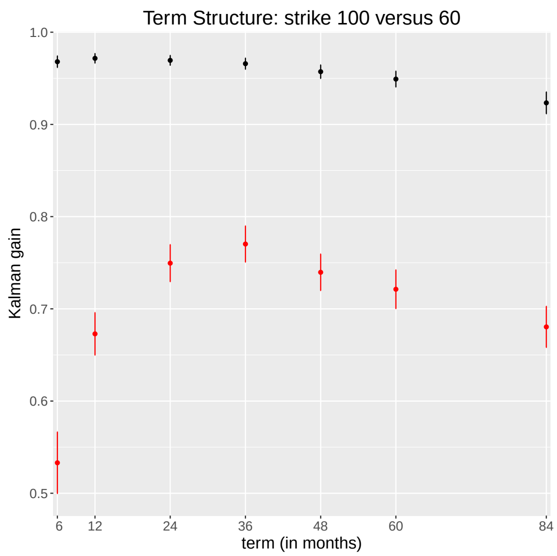


Figure 4: This figure presents the estimated kalman gain, given by k in (4), for our dynamic bayesian learning model. The horizontal axis denotes the moneyness of the options under consideration. To estimate the model we log the implied volatility. The black dots represent the point estimates of k. The bounds around the point estimates are the 95% confidence intervals. The confidence intervals are derived by the delta-method. We consider the option contracts with a time-to-maturity of **6 months**. The data sample is from December 2002 till February 2015 for the option contracts on the SPX provided by Markit's Totem service.

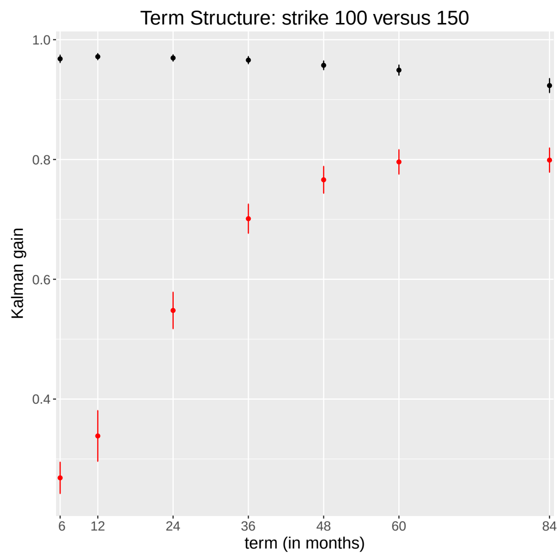
measure of information content, among the put options with moneyness 60, the option with time-to-maturity of three years appears to put the highest weight on new valuation information relative to prior beliefs.[14]

It is worth noting that for most of option contracts the Kalman gain lies above 0.5, that is institutions' price estimates put at least half of their weight on new information, private or public, received over the preceding month. For ATM options this weight is even higher and lies above 0.9 for all maturities with the highest values reached at the one year horizon.

[14]See figure 12 in the Appendix for a 3D plot of the Kalman gain estimates.



strike price at 60 in red



strike price at 150 in red

Figure 5: These figures present the term structure of the estimated kalman gain, given by k in (4), for our dynamic Bayesian learning model. In the left figure we introduce the term structure of an at-the-money option (in black) and an out-of-money put option with a moneyness of 60 (in red). In the right figure the at-the-money option (in black) is contrasted with an out-of-money call option with a moneyness of 150 (in red). The horizontal axis denotes the time-to-maturity in months. To estimate the model we log the implied volatility. The dots represent the point estimates of the exponentiated point estimates. The bounds around the point estimates are the 95% confidence intervals. The confidence intervals are derived by the delta-method from the likelihood function. The data sample is from December 2002 till February 2015 for the option contracts on the SPX provided by Markit's Totem service.

4.3 Variance ratios

Next we consider the variance ratio developed in section 3.2.2 to gauge the relative importance of the consensus price feedback when compared to other private information that the submitting institutions have access to for valuation purposes. Given the estimate $\hat{\psi}(c)$ for contract c we obtain an estimate for the variance ratio $\hat{\lambda}(c)$ using equation (6). The lower this ratio, the more important is the consensus price as a source of valuation information for the submitting institutions when compared to other information sources.

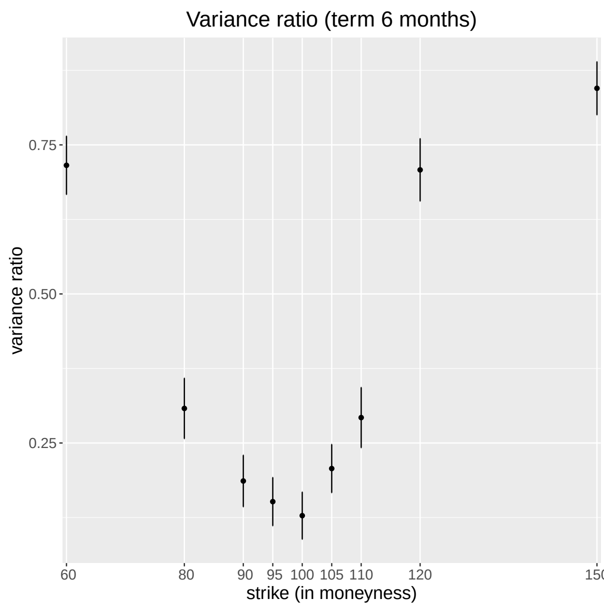
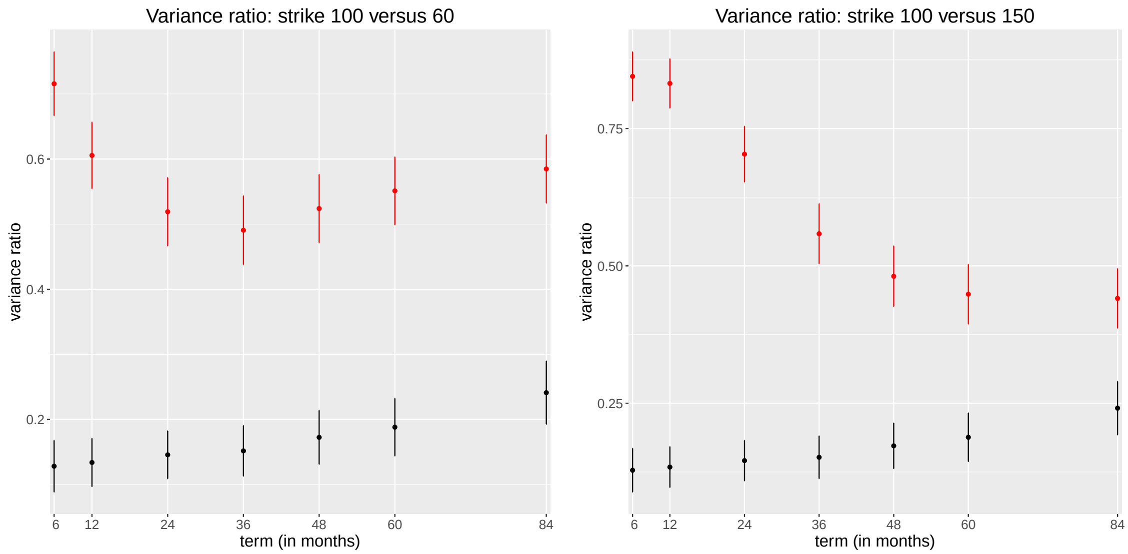


Figure 6: This figure presents the estimate of the variance ratio, given by $\sigma^2(\psi)/\sigma_p^2(\psi)$ in (6). Here $\sigma^2(\psi)$ is the posterior uncertainty about the fundamental value when there is access to both the public and private signal. $\sigma_p^2(\psi)$ is the posterior uncertainty about the fundamental value when there is only access to the private signal. 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 k. The bounds around the point estimates are the 95% confidence intervals. The confidence intervals are derived by the delta-method. We consider the option contracts with a time-to-maturity of **6 months**. The data sample is from December 2002 till February 2015 for the option contracts on the SPX provided by Markit's Totem service.

Figure 6 displays estimates of these variance ratios for option contracts with a fixed time-to-maturity of 6 months. The estimates imply that the consensus price is a significantly more important source of valuation information for ATM options than



strike price at 60 in red

strike price at 150 in red

Figure 7: these figures present the estimate of the variance ratio, given by $\sigma^2(\psi)/\sigma_p^2(\psi)$ in (6). Here $\sigma^2(\psi)$ is the posterior uncertainty about the fundamental value when there is access to both the public and private signal. $\sigma_p^2(\psi)$ is the posterior uncertainty about the fundamental value when there is only access to the private signal. In the left figure we introduce the term structure of an at-the-money option (in black) and an out-of-money put option with a moneyness of 60 (in red). In the figure on the right the at-the-money option (in black) is contrasted with an out-of-money call option with a moneyness of 150 (in red). The horizontal axis denotes the time-to-maturity in months. To estimate the model we log the implied volatility. The dots represent the point estimates of the exponentiated point estimates. The bounds around the point estimates are the 95% confidence intervals. The confidence intervals are derived by the delta-method from the likelihood function. The data sample is from December 2002 till February 2015 for the option contracts on the SPX provided by Markit's Totem service.

for OTM options, both puts and calls. While the posterior uncertainty more that quadruples for options close to at-the-money when depriving the institutions of the consensus price feedback, this reduction in uncertainty is far less severe, yet still sizeable, for OTM options. This results suggest that private sources of valuation information are a relatively more important for OTM options.

Figure 7 displays the term structure of the variance ratio estimates, again for fixed moneynesses of 60 (red; left), 100 (black), 150 (red; right). The consensus price feedback appears to be more important for the close to at-the-money options than for the OTM options across the whole term structure. For the OTM call option, the importance of the consensus price feedback increases for longer terms. For the OTM put options the term structure is non-monotonic. The consensus price has the highest value for options with times-to-maturity of around three years. Depriving subscribers of the consensus price feedback would lead to a doubling of posterior uncertainty for these put option contracts.[15]

5 Conclusion

In this paper we have provided 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 has been based on estimation of a structural model of learning in financial markets using a unique panel of price estimates that large-broker dealer have provided to a consensus pricing service for OTC derivatives. From the model we have derived two measures of the informational content of the consensus data. The first was targeted towards measuring the informational content of the price estimates that the financial institutions submit to the consensus pricing service. The second measure was used to judge the importance these institutions attach to the feedback provided by the consensus pricing service for the valuation of the options contracts.

We found that the price estimates that broker-dealers provide to the consensus pricing service are informationally rich. For almost all option contracts broker-dealer price estimates put a weight of at least 50% on new valuation information received over the month preceeding the submission date. For at-the-money options this weight is close to 95%. Concerning the importance broker-dealers attach to the consensus price feedback, we find that its value is highest for options close to at-the-money across all times-to-maturity. For these contracts our model estimates imply that losing access to the consensus price would increase posterior uncertainty (measured as the variance of the institutions' posterior beliefs) about the fundamental value of the option by a factor of 4. However, also for OTM options, both puts and calls, this increase in posterior uncertainty due to a counterfactual loss of the consensus price feedback is found to be sizeable. For OTM options with times-to-maturity beyond two year, for example, posterior uncertainty would approximately double. The consensus price mechanism thus appears to play an important informational role in these segments of the OTC derivatives market.

[15] See figure 14 in the Appendix for a 3D plot of the variance ratio estimates.

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6 Appendix

6.1 Estimation

We estimate the structural parameters of our model, $\psi = \{\bar{\theta}, \rho, \sigma_\varepsilon^2, \sigma_\nu^2, \sigma_\eta^2, \alpha, \beta\}$, by maximum likelihood using the Kalman filter. This estimation is done contract-by-contract, that is for each option contract, e.g. an out-of-the-money put option with time-to-maturity of 1 year and moneyness 80, we obtain a separate parameter estimate $\hat{\psi}$.

The state space of the Kalman filter consists of the fundamental value, θ_t, and the current best estimates $\mu_{i,t}$ of θ_t for each institution $i \in \{1, 2, ..., N\}$. Institutions' best estimates $\{\mu_{1,t}, ..., \mu_{N,t}\}$ are part of the state space as they constitute the prior in the following period's Bayesian updating step. Having access to individual submissions is therefore key for estimating the learning dynamics. We call the current state $\mathbf{x}_t = \{\theta_t, \mu_{1,t}, ..., \mu_{N,t}\}$. The transition equations for the state space are given by the dynamics of the fundamental value θ_t and the updating equations of the individual price estimates $\mu_{i,t}$:

$$\begin{aligned} \theta_t &= (1-\rho)\bar{\theta} + \rho\,\theta_{t-1} + \varepsilon_t \\ \mu_{i,t} &= (1-k)\rho\,\mu_{i,t-1} + k\,\theta_t + k(\gamma/\beta)\,\eta_t + k(1-\gamma)\nu_{i,t}\ , \quad i = 1, ..., N. \end{aligned}$$

In terms of measurement variables for the Kalman filter, we assume that $\mu_{i,t}$ corresponds to the natural logarithm of the IV of institution i's price submission and is thus observed by the econometricians. Furthermore, we assume that the public signal corresponds to the natural logarithm of the IV of the current consensus price for the given option contract, denoted by IV_t, and is also observed. Call $\mathbf{y}_t \in \mathbb{R}^{N+1}$ the measurement variables for the Kalman filter. The measurement equations are then

$$\begin{aligned} y_{i,t} &= \mu_{i,t}\ \ , \ \ i = 1, ..., N \\ y_{N+1,t} &= \alpha + \beta\,\theta_t + \eta_t. \end{aligned}$$

We can write the transition and measurement equations for the Kalman filter in matrix form as

$$\begin{aligned} \mathbf{y}_t &= \mathbf{c} + D\,\mathbf{x}_t + \mathbf{w}_t \quad \text{with } \ \mathbf{w}_t \sim N(\mathbf{0}, \Gamma) \\ \mathbf{x}_t &= \mathbf{a} + B\,\mathbf{x}_{t-1} + \mathbf{u}_t \quad \text{with } \ \mathbf{u}_t \sim N(\mathbf{0}, \Sigma). \end{aligned}$$

As the shocks are assumed to be normally distributed we can now obtain the likelihood of the observed data $\{\mathbf{y}_t\}_{t=t_0}^{T}$ for a given parameter vector ψ using standard results from Kalman filtering. We obtain the parameter estimate, $\hat{\psi}$, by maximising this likelihood over the parameter vector ψ.[16]

[16]See Appendix 6.1 for details of the estimation routine. Some care has to be taken in implementing the Kalman filter as the error vectors of transition and measurement equation, $\mathbf{u}_t$ and $\mathbf{w}_t$, are correlated due to the presence of the shock η_t in both.

6.2 Additional figures

6.2.1 Descriptives

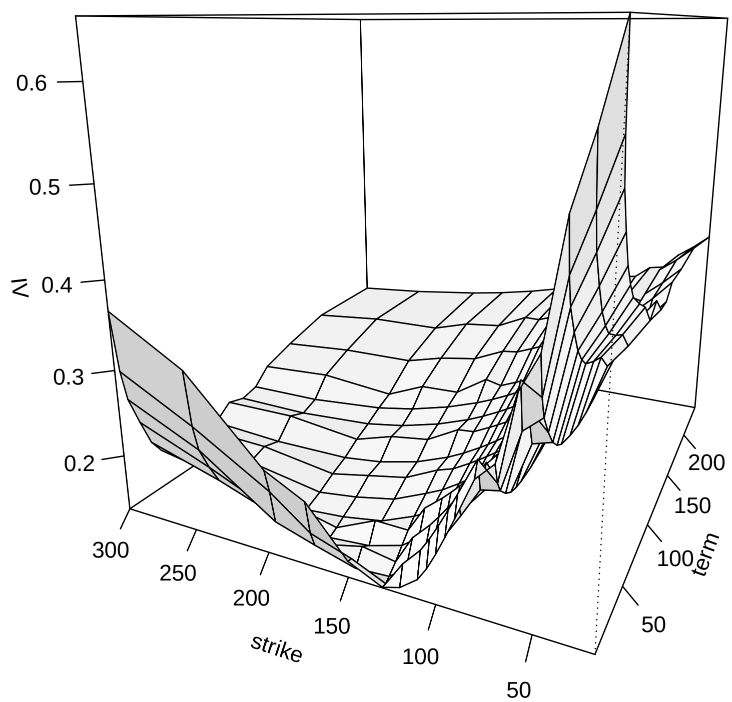

Figure 8: Average consensus IV (S&P 500)

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 devised by the spot price multiplied by 100. All contracts are out-of-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.

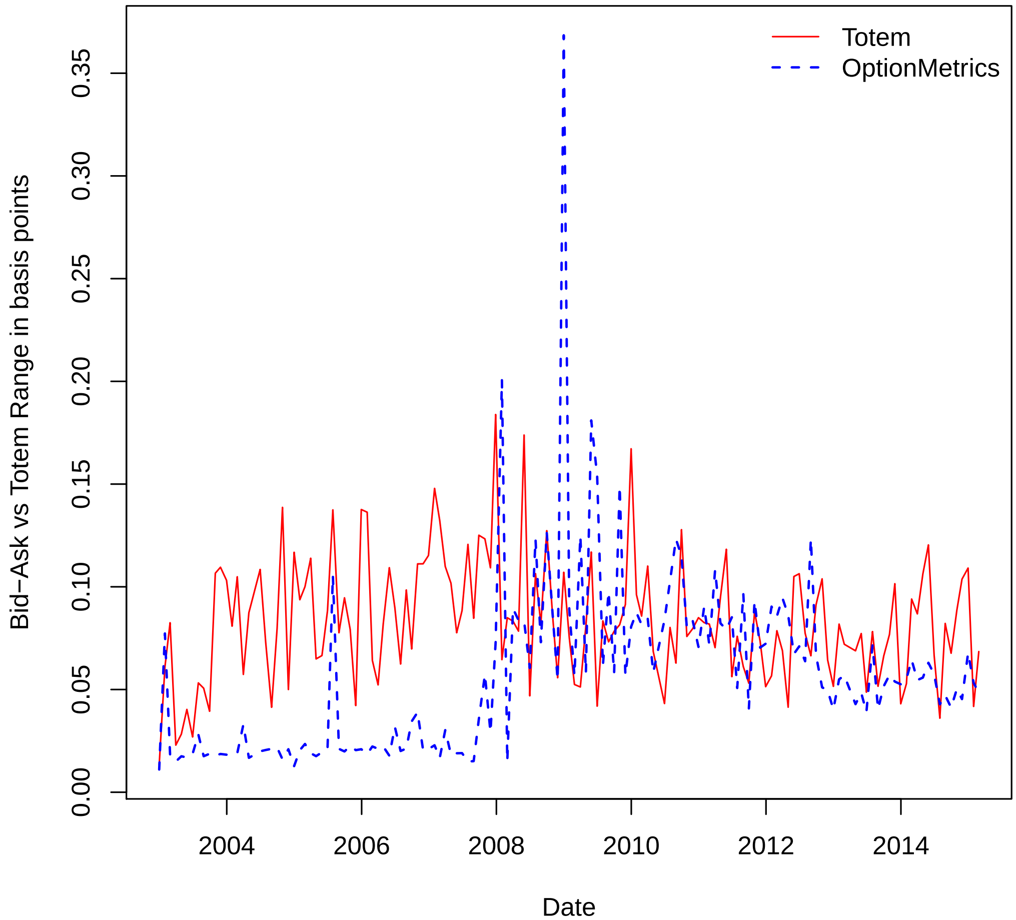

Figure 9: Bid-Ask spread vs Submission Range IV (S&P 500)

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 $\pm$ 10 days-to-maturity and a ± 1 moneyness value. When multilple options match the criteria an average is taken of their bid-ask spread.

6.2.2 Posterior uncertainty

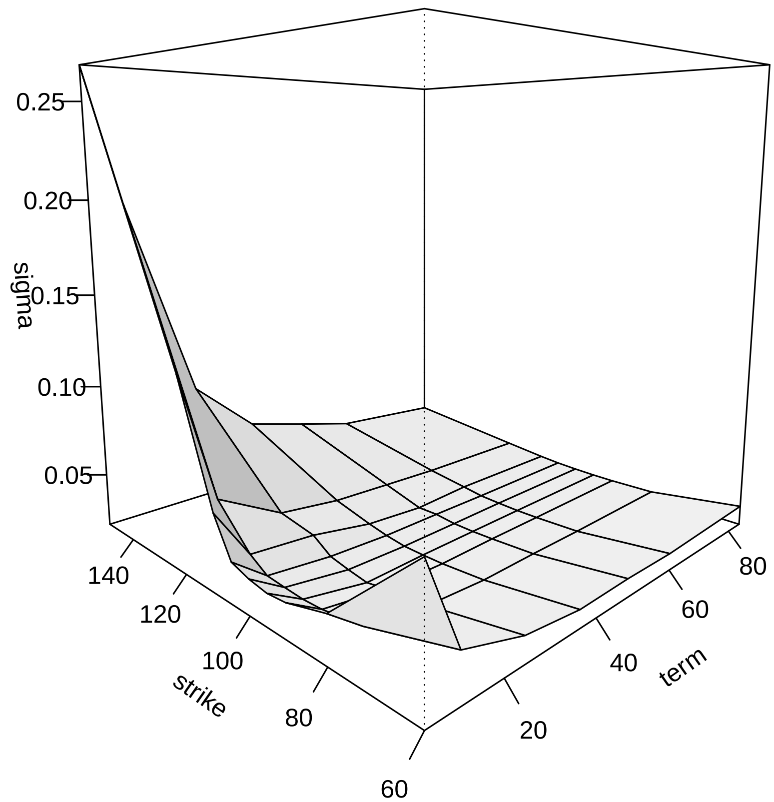

Figure 10: This figure depicts the posterior uncertainty about the fundamental, given by $\sigma^2(\psi)$ in (5). The axis labeled term indicates the time-to-maturity of the option contract in months. We consider contracts with a time-to-maturity of 6, 12, 24, 36, 48, 60, 84 months. The axis labeled strike indicates the moneyness of the option contract. Moneyness is defined as the strike price devised by the spot price multiplied by 100. We consider contracts with a moneyness of 60, 80, 90, 95, 100, 105, 110, 120 and 150. All contracts are out-of-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.

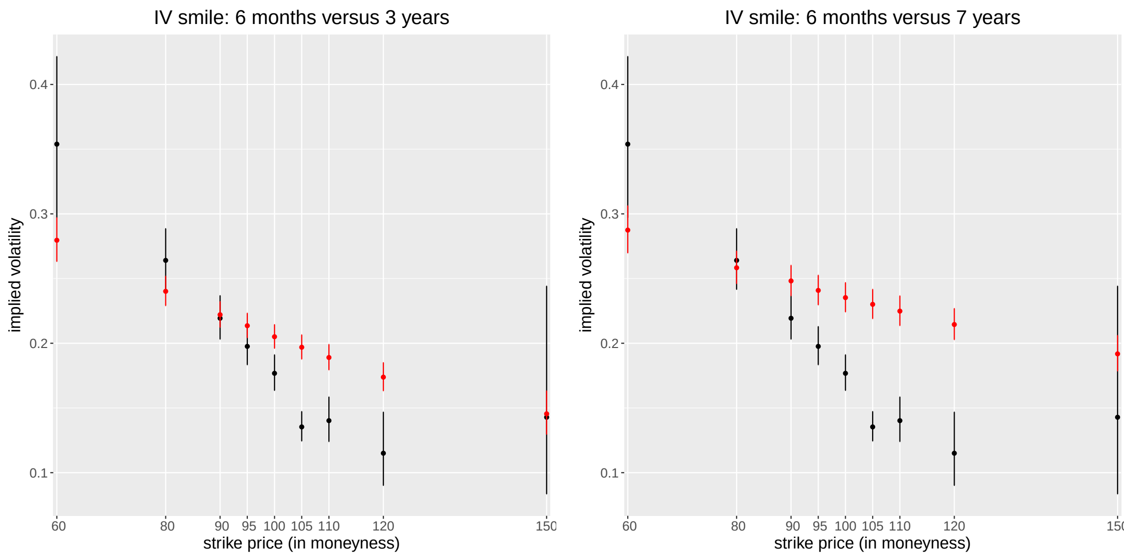

Figure 11: These figures present the submitters steady-state beliefs of the long-run implied volatility mean, $\bar{\theta}$, for different levels of moneyness. In the left figure we present the volatility smile for options with a time-to-maturity of 6 month (in black) and the volatility smile with a time-to-maturity of 36 months (in red). In the right figure we benchmark the volatility smile with a time-to-maturity of 84 months (in red) against the volatility smile for options with a time-to-maturity of 6 month (in black). The horizontal axis denotes the time-to-maturity in months. To estimate the model we log the implied volatility. The dots represent the point estimates of the exponentiated point estimates. The bounds around the point estimates are the 95% confidence intervals. The confidence intervals are derived by the delta-method from the likelihood function. The data sample is from December 2002 till February 2015 for the option contracts on the SPX provided by Markit's Totem service.

6.2.3 Kalman gain

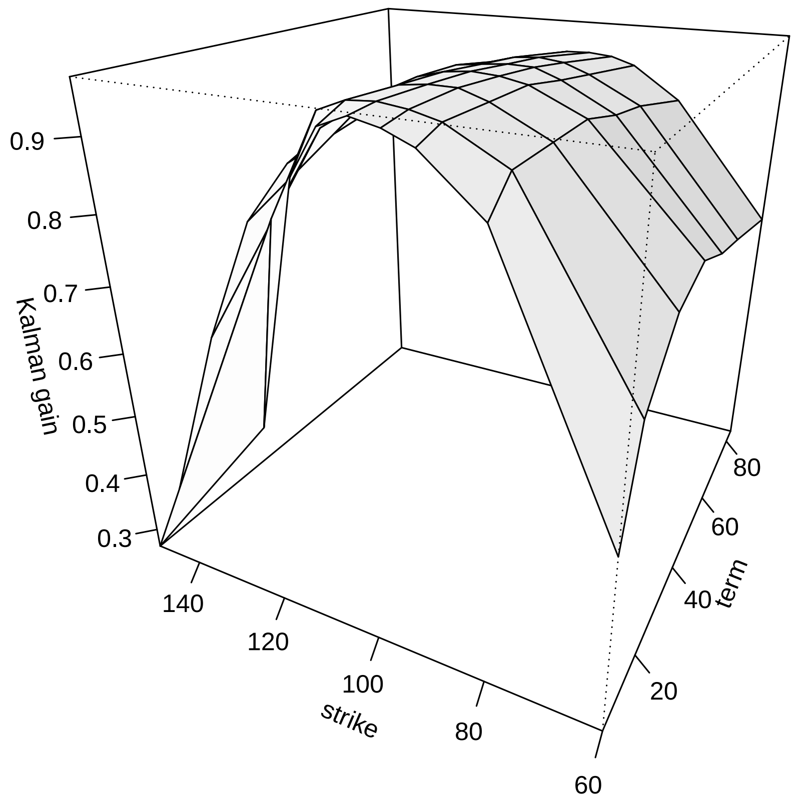

Figure 12: This figure presents the estimated kalman gain, given by k in (4), for our dynamic bayesian learning model. The axis labeled term indicates the time-to-maturity of the option contract in months. We consider contracts with a time-to-maturity of 6, 12, 24, 36, 48, 60, 84 months. The axis labeled strike indicates the moneyness of the option contract. Moneyness is defined as the strike price devised by the spot price multiplied by 100. We consider contracts with a moneyness of 60, 80, 90, 95, 100, 105, 110, 120 and 150. All contracts are out-of-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.

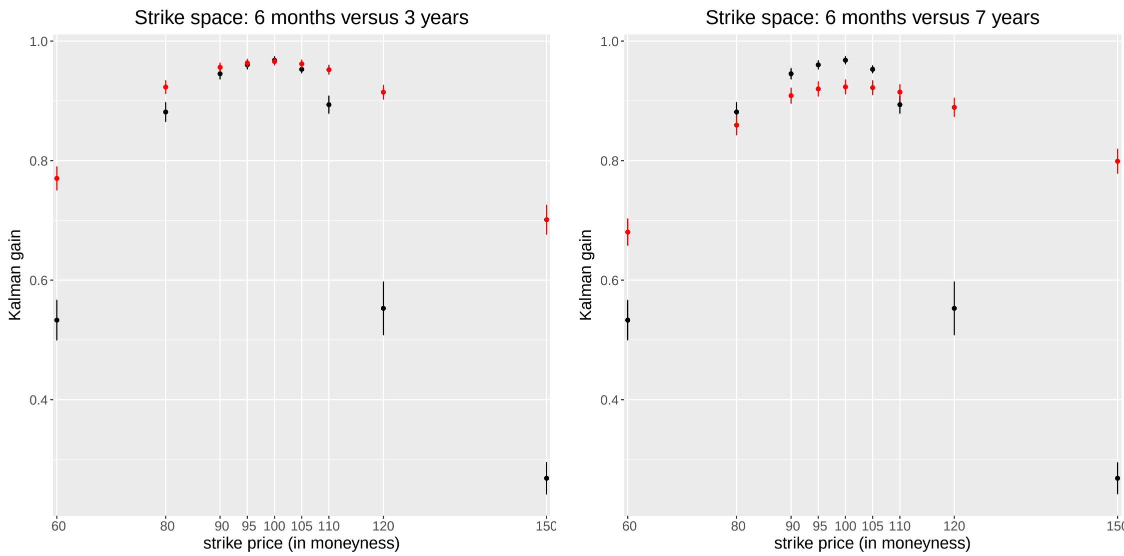

Figure 13: These figures present the estimated kalman gain, given by k in (4), for our dynamic bayesian learning model, for different levels of moneyness. In the left figure we present the Kalman estimates for options with a time-to-maturity of 6 month (in black) and time-to-maturity of 36 months (in red). In the right figure we benchmark kalman estimates with a time-to-maturity of 84 months (in red) against the kalman estimates from options with time-to-maturity of 6 month (in black). The horizontal axis denotes the time-to-maturity in months. To estimate the model we log the implied volatility. The dots represent the point estimates of the exponentiated point estimates. The bounds around the point estimates are the 95% confidence intervals. The confidence intervals are derived by the delta-method from the likelihood function. The data sample is from December 2002 till February 2015 for the option contracts on the SPX provided by Markit's Totem service.

6.2.4 Variance ratios

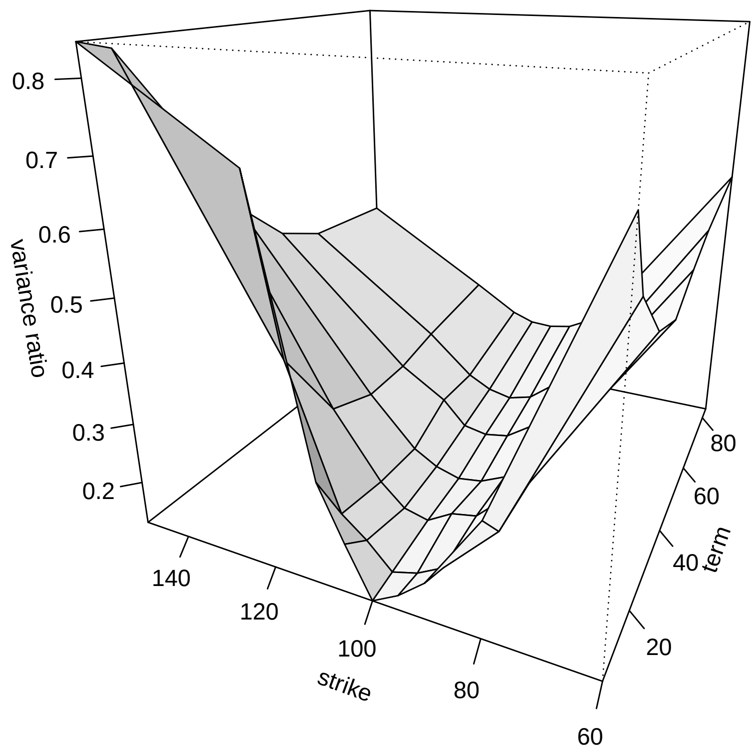

Figure 14: This figure presents the estimate of the variance ratio, given by $\sigma^2(\psi)/\sigma_p^2(\psi)$ in (6). Here $\sigma^2(\psi)$ is the posterior uncertainty about the fundamental value when there is access to both the public and private signal. $\sigma_p^2(\psi)$ is the posterior uncertainty about the fundamental value when there is only access to the private signal. The axis labeled term indicates the time-to-maturity of the option contract in months. We consider contracts with a time-to-maturity of 6, 12, 24, 36, 48, 60, 84 months. The axis labeled strike indicates the moneyness of the option contract. Moneyness is defined as the strike price devised by the spot price multiplied by 100. We consider contracts with a moneyness of 60, 80, 90, 95, 100, 105, 110, 120 and 150. All contracts are out-of-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.

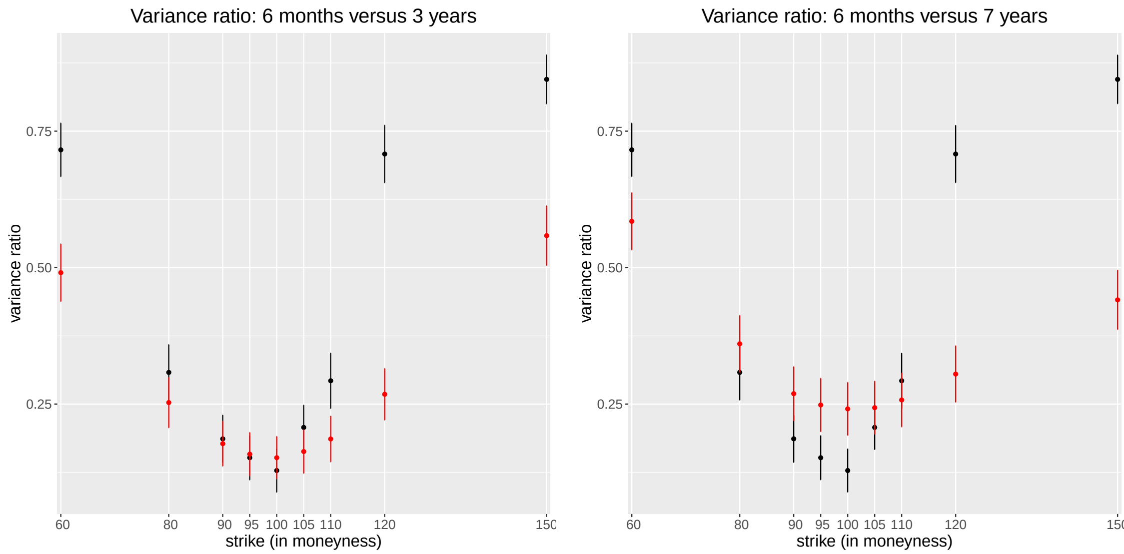

Figure 15: This figure presents the estimate of the variance ratio, given by $\sigma^2(\psi)/\sigma_p^2(\psi)$ in (6). Here $\sigma^2(\psi)$ is the posterior uncertainty about the fundamental value when there is access to both the public and private signal. $\sigma_p^2(\psi)$ is the posterior uncertainty about the fundamental value when there is only access to the private signal. In the left figure we present the variance ratio for options with a time-to-maturity of 6 month (in black) and time-to-maturity of 36 months (in red). In the right figure we benchmark variance ratios with a time-to-maturity of 84 months (in red) against variance ratios from options with time-to-maturity of 6 month (in black). The horizontal axis denotes the time-to-maturity in months. To estimate the model we log the implied volatility. The dots represent the point estimates of the exponentiated point estimates. The bounds around the point estimates are the 95% confidence intervals. The confidence intervals are derived by the delta-method from the likelihood function. The data sample is from December 2002 till February 2015 for the option contracts on the SPX provided by Markit's Totem service.

6.3 Data

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

	moneyness																		
term	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	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	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	09/15	07/15	09/15	07/15	-	-
6	08/15	08/15	08/15	13/15	98/15	13/15	98/15	98/15	98/15	98/15	98/15	98/15	98/15	09/15	99/15	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	09/15	07/15	09/15	07/15	08/15	08/15
12	08/15	08/15	08/15	13/15	98/15	13/15	98/15	98/15	98/15	98/15	98/15	98/15	98/15	09/15	99/15	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	09/15	07/15	09/15	07/15	08/15	08/15
24	08/15	08/15	08/15	13/15	98/15	13/15	98/15	98/15	98/15	98/15	98/15	98/15	98/15	09/15	99/15	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	09/15	07/15	09/15	07/15	08/15	08/15
36	08/15	08/15	08/15	13/15	98/15	13/15	98/15	98/15	98/15	98/15	98/15	98/15	98/15	09/15	99/15	09/15	02/15	08/15	08/15
48	08/15	08/15	08/15	13/15	98/15	13/15	98/15	98/15	98/15	98/15	98/15	98/15	98/15	09/15	99/15	09/15	02/15	08/15	08/15
60	08/15	08/15	08/15	13/15	98/15	13/15	98/15	98/15	98/15	98/15	98/15	98/15	98/15	09/15	99/15	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
84	08/15	08/15	08/15	13/15	99/15	13/15	99/15	99/15	99/15	99/15	99/15	99/15	99/15	09/15	99/15	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
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
120	08/15	08/15	08/15	13/15	99/15	13/15	99/15	99/15	99/15	99/15	99/15	99/15	99/15	09/15	99/15	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	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	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

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

	moneyness																		
term	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	18	-	-
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.