

# Strategic Uncertainty in Financial Markets: Evidence from a Consensus Pricing Service\*

Lerby M. Ergun<sup>1,2</sup> and Andreas Uthemann<sup>1,2</sup>

<sup>1</sup>*Bank of Canada*

<sup>2</sup>*Systemic Risk Centre, LSE*

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## Abstract

Consensus pricing services are a popular information aggregation mechanism in over-the-counter (OTC) markets to anonymously share price information among market participants. We study the informational value of consensus prices for market participants. The analysis employs a novel dataset of price estimates that dealer banks, highly sophisticated market participants, provide to the main consensus pricing service in the OTC derivatives market. We develop and structurally estimate a model of learning from prices to obtain empirical measures of uncertainty based on banks' model-implied beliefs. We show how consensus price information impacts banks' uncertainty about asset values and market conditions. We also measure how efficiently consensus prices aggregate dispersed information. The main contribution of consensus price information is to reduce strategic uncertainty, meaning uncertainty about competitors' valuations. The results stress the importance of public price data, such as financial benchmarks, for a shared understanding of market conditions in markets with limited price transparency.

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\*Uthemann (corresponding author): Financial Markets Department, Bank of Canada, 234 Wellington St W, Ottawa, ON K1A 0G9 ([authemann@bank-banque-canada.ca](mailto:authemann@bank-banque-canada.ca)). Ergun: Financial Markets Department, Bank of Canada ([mergun@bank-banque-canada.ca](mailto:mergun@bank-banque-canada.ca)). We are grateful for comments from Jason Allen, Enrique Salvador Aragón (discussant), Jón Daníelsson, Darrell Duffie, Jean-Sébastien Fontaine, Yifan Gong (discussant), Antonio Guarino, Emanuel Mönch (discussant), Myra Mohnen, Christine Parlour, Dongho Song, Haoxiang Zhu, Jean-Pierre Zigrand, IHS Markit's Totem team and seminar participants at the 2020 Econometric Society World Congress, 2018 Paris December Finance meeting, 2018 NBER-NSF SBIES Conference, 2018 Econometric Society North American Summer Meeting, 2018 CEPR Spring Meeting in Financial Economics, 2017 Econometric Society European Summer Meeting, Bank of Canada, Bank of England, Federal Reserve Board, Tinbergen Institute, Cass Business School, University of Sussex, Católica Lisbon, NOVA Lisbon, University of Bristol, King's College, London, École Polytechnique, Paris, and the University of Copenhagen. The views expressed in this paper are solely those of the authors and do not necessarily represent those of the Bank of Canada.

# 1 Introduction

Prices serve a dual purpose. They aggregate dispersed information about gains from trade. At the same time, they help market participants to coordinate their actions. Empirical work on the informational value of prices typically focuses on the first aspect. However, the ability of prices to reduce uncertainty about market participants' actions and beliefs, that is, strategic uncertainty, can be of equal importance. This is especially true in markets with strong coordination motives ([Angeletos and Pavan \(2007\)](#)). Intermediated markets are an important example. Intermediaries have to form beliefs about the gain from trades that they intermediate. But they also have to take into account the behaviour of other intermediaries. The aggregate level of intermediation activity influences the number of trading parties that can be linked. It also determines the ability to share the risk that comes with the holding of inventory during the intermediation process. Therefore, an intermediary needs to form beliefs about both valuations and other intermediaries' behavior.

Public price data can help to coordinate these beliefs by establishing important reference points for trading and risk management. A lack of price transparency, a common problem in intermediated markets, threatens the common understanding of market conditions and can lead to costly coordination failures ([Morris and Shin 2012](#)). Episodes of financial market freezes provide ample evidence for this fact.<sup>1</sup> In response to the temporary or permanent shortage of trading-based price data, so-called consensus pricing services have emerged in many markets. These services collect price estimates from market participants and aggregate the estimates into a consensus price. A consensus price is supposed to give the current market value of a specific asset, for example, a 2015 Honda Civic LX with 50,000 km mileage in the used car market or the interest rate for an unsecured 6-month US dollar loan in the London inter-bank market at 11 a.m. London time. A major advantage of consensus prices is that they can be generated irrespective of whether the asset has been traded recently. As the last example shows, consensus prices are a much used mechanism in financial markets to calculate important benchmark prices. It is thus crucial to understand whether, and how, the consensus pricing mechanism works in practice.

In this paper, we study the informational value of the consensus pricing mechanism for market participants. To tackle this question, we develop and structurally estimate a model of learning from prices. The empirical analysis is based on a new data set of price submissions that large dealer banks, highly sophisticated market participants, make to the main consensus pricing service in the over-the-counter (OTC) options market. We use a structural estimation to obtain empirical measures of uncertainty

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<sup>1</sup>[Lowenstein \(2000\)](#) (p. 159), for example, gives a vivid account of the bond market at the height of the LTCM crisis on August 31, 1998: "It was as if a bomb had hit; traders looked at their screens, and the screens stared blankly back. [...] So few issues traded, you had to guess where they were."

that are based on dealer banks’ model-implied beliefs. We also measure how efficient the consensus price is in aggregating dispersed information. In the model, dealer banks learn about a latent and time-varying option value from two types of signals: a noisy private signal and a consensus price. The consensus price is modelled as an endogenous signal: it is the average expectation across dealers of an option’s value plus noise. Each dealer bank is uncertain about the current value of the option and other dealers’ expectations of this value. We use the variance of a dealer bank’s posterior beliefs about option value and competing dealers’ average expectations to measure these two dimensions of uncertainty. Having access to a panel of individual dealer banks’ price submissions allows us to identify the structural parameters that determine dealers’ beliefs. To gauge the informational value of consensus prices, we perform counterfactual experiments on the option market’s information structure.

We find that dealer banks’ uncertainty about option values and strategic uncertainty varies substantially across the different segments of the options market. There is higher uncertainty for option contracts that are not listed on centralized exchanges but are exclusively traded over-the-counter. We infer from our counterfactual experiments that dealer banks do not rely heavily on the consensus price feedback to reduce their uncertainty about option values. The reduction in valuation uncertainty, that is uncertainty about option values, is at most 4.36 percent in the most opaque market segment. We find that the information the consensus price contains is most important for reducing strategic uncertainty, i.e., their uncertainty about competitors’ valuations. This effect is strongest, up to 27.33 percent, in the most opaque segments of the options market and reflects the scarcity of public valuation information in these market segments. It stresses the importance of publicly observed market data, such as financial benchmarks, to establish a shared understanding of market conditions in markets with limited price transparency.

The estimation framework developed in this paper makes a methodological contribution by showing how to structurally identify the informativeness and informational efficiency of prices. The modern theoretical framework for these questions dates back to the early 1980s, with seminal contributions by [Grossman and Stiglitz \(1980\)](#), [Hellwig \(1980\)](#) and [Diamond and Verrecchia \(1981\)](#).<sup>2</sup> [Vives \(1997\)](#) highlights the importance of the mix between public and private information for the speed of information aggregation. However, as pointed out by [Townsend \(1983\)](#), determining the informational content of the price process in a dynamic equilibrium context poses significant technical challenges. Most structural empirical analyses of price formation avoid these problems by assuming that asset values become common knowledge after

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<sup>2</sup>The modern literature on information aggregation is too large to do justice to here. Important contributions have focused on auctions ([Pesendorfer and Swinkels \(1997\)](#); [Kremer \(2002\)](#)), decentralized trading ([Gale \(1986\)](#), [Goloso et al. \(2014\)](#)), asset design ([Ostrovsky \(2012\)](#)) or the trade-off between market size and information heterogeneity ([Rostek and Weretka \(2012\)](#)).

a finite number of periods, e.g., following [Easley et al. \(1996\)](#)’s information structure. But this assumption prevents long-lasting belief heterogeneity. A time-varying latent fundamental value paired with privately informed market participants is a key source of belief heterogeneity and, hence, strategic uncertainty in our model. To solve the dynamic signal extraction problem and structurally estimate the model, we adopt an iterative algorithm previously used in [Nimark \(2014\)](#) and [Barillas and Nimark \(2017\)](#). We show that observing belief updating dynamics at the level of the individual institution is key for identifying the structural parameters of the model. Modelling the consensus price as an endogenous public signal allows us to conduct counterfactual experiments on the market’s information structure to evaluate the strength of informational externalities caused by public information ([Amador and Weill \(2012\)](#)).

There is a large literature that uses the cross-sectional dispersion among professional forecasters to study informational frictions ([Coibion and Gorodnichenko \(2012\)](#), [Andrade et al. \(2016\)](#)). A major aim of this literature is to understand the expectation formation process. The insights gained are then used to discriminate between alternative models, extrapolate to a wider group of market participants than just professional forecasters, and study macroeconomic consequences. In this paper we have a different objective. We want to measure uncertainty among market participants in an opaque market structure. For this, we assume that our units of observation, highly sophisticated financial market participants, are fully rational Bayesian agents. We then use this structural assumption to derive measurement devices for uncertainty based on market participants’ model-implied beliefs. An additional novel aspect of our empirical approach is the focus on strategic uncertainty. Here, the structural approach is particularly useful as data on market participants’ higher-order beliefs are typically not available. [Hortaçsu and Kastl \(2012\)](#) and [Hortaçsu et al. \(2018\)](#), for example, use model-implied beliefs derived from a structural estimation to gauge the strategic value dealers derive from being able to observe client demand in Treasury auctions. Similarly, [Boyarchenko et al. \(2019\)](#) use a calibrated model to perform counterfactual informational experiments in the US Treasury market to evaluate the welfare implications of different order flow information-sharing arrangements among dealers and clients. However, the source of strategic information in these models is order flow information rather than price data. More generally, we see the counterfactual experiments we perform on the market’s information structure as an illustration of the usefulness of a structural approach for empirical work on information design ([Bergemann and Morris \(2019\)](#)).

This paper also advances the understanding of the role financial benchmarks have for market functioning. [Duffie et al. \(2017\)](#) show how benchmarks can reduce informational asymmetries in search markets and thereby increase the participation of less-informed agents. Here, we focus on the informational content of the benchmark itself. This paper is, to our knowledge, the first to provide an empirical evaluation

of the informational properties of a consensus pricing mechanism.<sup>3</sup> While the importance of benchmarks for financial markets is widely appreciated, the attempted manipulation of major interest rate benchmarks has led to a regulatory push to base benchmarks on transaction prices or firm quotes rather than expert judgment (IOSCO (2013)). However, in illiquid markets and during crisis times, this might not always be possible. During the COVID-19 turmoil in March 2020, for example, three out of four candidate forward-looking term rate benchmark providers were unable to publish benchmarks during a three-day period due to the lack of transactions data (Risk.net). More generally, this paper illustrates the informational value of non-transaction based price information for decentralized financial markets. Previous work in this area has focused on information aggregation mechanisms predominately used in centralized stock markets, in particular pre-opening prices (Biais et al. (1999), Cao et al. (2000)) and opening auctions (Madhavan and Panchapagesan (2000)).

The plan of the paper is as follows. Section 2 provides a brief explanation of the option market structure and the Totem consensus pricing service and presents the data. Section 3 develops the structural model of learning from consensus prices. Section 4 presents the structural estimation of the model and discusses identification and robustness. Section 5 explains our approach to measuring valuation and strategic uncertainty and presents results. Section 6 concludes.

## 2 Market structure and data

We start by providing a short overview of the structure of the options markets. We then introduce the Totem consensus pricing service and explain the submission process. At the end of the section, we provide some stylized facts of the consensus price data that motivate our structural modelling approach.

### 2.1 Options market structure

Options on the S&P 500 index are arguably the central derivatives contracts for the US stock market. Option prices contain rich information on market participants’ beliefs about future stock market movements and risk premia.<sup>4</sup> The VIX index, a popular measure of risk perception in financial markets, is based on S&P 500 option prices. The dominant market structure for options trading depends on the terms of

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<sup>3</sup>Many important financial benchmarks are consensus prices. It is also employed by information providers, such as Bloomberg, to calculate “generic prices” for a wide range of financial products.

<sup>4</sup>An option contract on an asset gives the owner the right (but not the obligation) to buy (call option) or sell (put option) the asset. The time-to-expiration of (European style) contracts specifies the date at which the option can be exercised; the strike price specifies the price at which the asset can be bought or sold. The strike price is often expressed as a ratio to the current price of the asset times 100. This is also called the moneyness of the option.

the contract. Option contracts with times-to-expiration of less than 6 months and strike prices close to the current index value (moneyness close to 100) are typically traded via limit order books on options exchanges such as the Chicago Board Options Exchange (CBOE). Price quotes, transaction prices and volumes are fully transparent and are available to all market participants. For options with more extreme contract terms, the dominant market structure is OTC trading. Figure 1 displays the average on-exchange trading activity for S&P 500 index option over the period 2002 to 2015 for contract terms covered in this paper. On-exchange trading activity is decreasing with the time-to-expiration and the extremeness of the strike price of an option. For option contracts with times-to-expiration of more than 3 years, trading is almost exclusively OTC.<sup>5</sup>

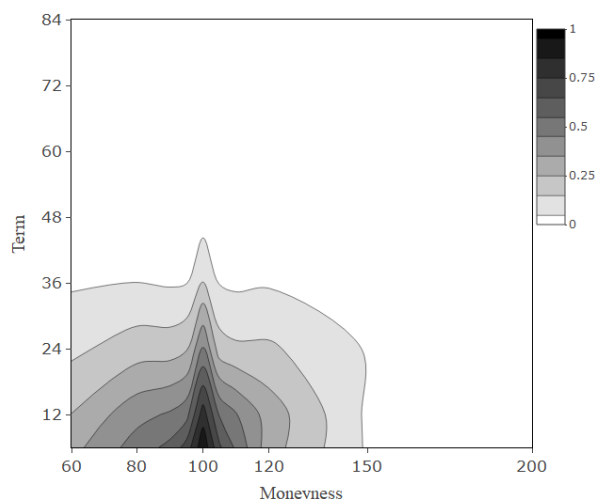


Figure 1: This figure displays the percentage of trading days on which an S&P500 option contract has an aggregate trading volume of at least 10 contract on US options exchange according. Volumes for exchange-traded contracts in proximity to a given Totem contract are aggregated and mapped to the corresponding moneyness/term combination. The x-axis gives the moneyness of the contracts, the y-axis times-to-expiration in months. The sample period is 2002 to 2015 (Data: OptionMetrics).

The OTC segment of the options market is centred around a network of dealers. These are typically large investment banks that act as market-makers and trade with each other and with so-called clients: hedge funds, asset managers, insurance companies, and pension funds that need to manage portfolio risk or intend to establish speculative positions. In terms of clientele, the market segment with times-to-expiration below one year is typically dominated by hedge funds trading short-term stock market volatility. The one- to three-year segment tends to be the domain of “real money,” asset managers such as BlackRock that use options in their portfolio insurance strategies. Client demand in the market segment with times-to-expiration beyond 3 years

<sup>5</sup>Clearing house data (see, e.g., [OOC](#)) shows that in overlapping regions, traders often choose an OTC over an on-exchange trade. This can be because of greater flexibility in contract terms, lower trading fees, or market impact considerations. Large trades can be difficult to hedge if the trade is publicized. Here the transparency that comes with on-exchange trading is undesirable.

tends to come from pension funds and life insurance companies that have long-term commitments linked to the evolution of the stock market. In the OTC market, trades are negotiated bilaterally, often over the phone, by email or instant messaging. Both transaction price and volume remain proprietary information of the two parties involved in the trade.<sup>6</sup> Rather than having to rely on pricing models to hedge option exposures, dealer banks typically prefer to conduct offsetting trades with each other in the inter-dealer segment of the options market. Hence, when trading with clients, a dealer bank not only has to form a view on the fundamental drivers of option values. It also has to consider the valuations of other dealer banks with whom it can enter into offsetting trades. In the online Appendix we develop a stylized model of this market structure to illustrate the value of information for dealer banks.

## 2.2 Consensus Price Data

The empirical analysis is based on data from the main consensus pricing service for the OTC derivatives market, IHS Markit’s Totem service. The service started in February 1997 with 6 major OTC derivatives dealers. Since then, Totem has become the leading platform for OTC consensus price data, with around 120 participants and a coverage of all major asset classes and types of derivatives contracts. In this paper, we focus on the consensus prices for call and put options on the S&P 500 index. We have access to the full history of Totem contributors’ price submissions. The individual institutions are anonymized, but we can track each institution’s submissions over time and across contracts. We restrict our sample to the period December 2002 to February 2015 to achieve a consistent set of option contracts and a stable group of submitting institutions. Table 1 reports the set of option contracts we consider (by time-to-expiration and moneyness) as well as the average number of institutions submitting price estimates for a given contract over our sample period.<sup>7</sup>

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<sup>6</sup>Some dealers run proprietary electronic trading platforms on which they post price quotes. In 2010, various electronic trading platforms introduced request-for-quote systems to further increase pre-trade price transparency. The regulatory reforms after the financial crisis have also introduced mandatory post-trade reporting to trade repositories for all OTC derivatives transactions. But these are regulatory data and not available to market participants. Another source for price and volume information in OTC markets is central counterparties (CCPs). However, unlike for interest rate and credit derivatives, OTC equity derivatives trades are currently not subject to a central clearing mandate. The current proportion of OTC equity derivatives trades that is centrally cleared is negligible (see [Financial Stability Board \(2018\)](#)).

<sup>7</sup>For contracts with time-to-expiration of 6 and 12 months, we exclude the contracts with a moneyness of 200. For these contracts, prices are close to zero and crucially depend on the numerical precision used by Totem submitters when reporting prices. Additionally, the inversion of the prices to Black-Scholes implied volatilities can become numerically unstable.

Table 1: Average number of submitters

<i>term</i>	<i>moneyness</i>										
	60	80	90	95	100	105	110	120	130	150	200
6	27	31	31	31	31	31	31	31	29	27	.
12	27	30	30	30	30	30	30	30	28	27	.
24	27	30	30	30	30	30	30	30	28	26	19
36	26	29	29	29	29	29	29	29	27	26	18
48	26	29	29	29	29	29	29	29	26	25	18
60	25	28	28	28	28	28	28	28	26	25	18
84	24	25	25	25	25	25	25	25	24	23	17

This table provides the average number of dealer banks that submit to a given S&P 500 options contract. The numbers are based on accepted submissions for the given date. The data sample is from December 2002 to February 2015.

### The consensus pricing process

The Totem pricing service typically operates at a monthly frequency. At the end of a month, all submitters are asked to provide their best estimates of the mid-quotes for the set of derivatives contracts to which they contribute. In addition to their estimate of the contract price itself, this includes other auxiliary information, such as discount factors, dividend yields, and the price of the underlying asset. Totem indicates the precise time at which valuations are to be made on the so-called valuation day.

Manipulation incentives for consensus prices of OTC derivatives are generally weaker than for benchmark interest rates, such as LIBOR, that are compiled using a similar methodology. Unlike for interest rate benchmarks, there are no financial products that are indexed to OTC derivatives consensus prices. Hence, changes in consensus prices do not immediately impact an institution’s profits and losses from other investments. Furthermore, the Totem consensus pricing service has significantly more submitters than interest rate benchmarks. Even for the most extreme contract on average 17 institutions contribute prices, which makes manipulation of the consensus price strategically challenging. Nevertheless, Totem uses a range of formal and informal procedures to discourage price manipulation and incentivize high-quality price submissions. For the S&P 500 option service, each submitter is obligated to contribute to the contracts with time-to-expiration of 6 months and moneyness, expressed as the ratio of the option’s strike price to the current index level, between 80 and 120. ‘No-arbitrage’ arguments between contracts allow for consistency checks between contracts. In case of doubt, additional private conversation between submitters and IHS Markit employees (often former market participants) can take place to gather additional information on individual prices and market conditions. Price submissions that are deemed of low quality do not enter the consensus price calculation, and the submitting institution does not receive the consensus price for that submission period. This serves as a formal punishment mechanism for low-quality



submissions.

Accepted price submissions are then used to calculate consensus prices, one for each derivatives contract. The highest and lowest accepted price are dropped from the sample before the mean is calculated. Totem provides contributors with the new consensus prices within 5 hours of their initial price submissions. The consensus price for a given option contract is the arithmetic mean of the accepted price estimates. Totem submitters only receive aggregated data from the service. They do not observe data on other institutions' individual submissions. We provide a detailed description of the submission process and the quantities submitted in the online Appendix.

### Valuation differences among dealers

To provide a sense of the cross-sectional dispersion in Totem submitters' option valuations, the left panel of Figure 2 depicts the cross-sectional standard deviation of price submissions averaged over the sample period.<sup>8</sup> There is considerable variation in the dispersion of dealers' submitted prices across the contract space. It is highest for short-dated options with extreme strike prices. For a given time-to-expiration, the dispersion is lowest for strike prices close to the current index level, that is a moneyness of 100. The price dispersion across dealers tends to decrease with time-to-expiration. These cross-sectional differences are economically meaningful; they are of similar magnitude to bid-ask spreads observed on option exchanges in regions where OTC and on-exchange trading overlaps, but they display a low level of correlation with these bid-ask spreads over time, as can be seen in Figure 6 of the Appendix.

The right panel of Figure 2 shows the persistence of individual dealers' deviations from the consensus price. For each option contract, we estimate the following AR(1) regressions to quantify this persistence:

$$p_{i,t}^c - p_t^c = \beta^c (p_{i,t-1}^c - p_{t-1}^c) + \epsilon_{i,t}^c. \quad (1)$$

Here  $p_{i,t}^c$  is institution  $i$ 's price submission for contract  $c$  in period  $t$  and  $p_t^c$  is the corresponding consensus price. The right panel of Figure 2 reports the estimated  $\beta$  coefficients expressed as half-lives, i.e., the number of months it takes to close half of the gap between an individual dealer's price estimate and the consensus price. Dealers' deviations from consensus are persistent for all contracts. The U-shaped persistence pattern in moneyness partially mirrors the cross-sectional dispersion in the left panel of Figure 2.

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<sup>8</sup>Throughout the paper, we express option prices in terms of Black-Scholes implied volatilities (IVs). This is the market convention for quoting option prices and facilitates the comparison of option prices across times-to-expiration and strike prices.

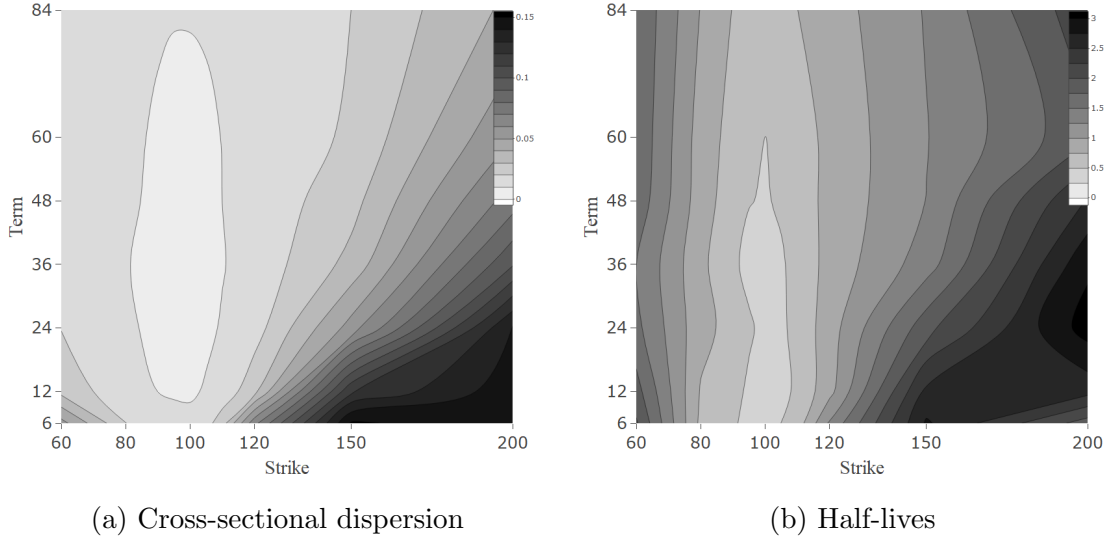


Figure 2: The **left figure** displays the time-series average of the cross-sectional standard deviation of submitters' implied volatility estimates for S&P 500 OTC index options. The **right figure** presents estimates for the half-life (in months) of the individual deviations from the contemporaneous consensus price. Half-lives derive from AR1 coefficients estimates of (1):  $\hat{t}^c = \log(0.5)/\log(\hat{\beta}^c)$ . The estimates are from a pooled ordinary least squares regression. The y-axes show times-to-expiration in months, the x-axes moneyness. The sample period is December 2002 to February 2015.

From these statistics of the raw data, we draw some preliminary observations that guide our structural modelling. First, all dealers are asked to provide their best estimate for the mid-quote of a given contract, i.e. a market-wide price. If all dealers had access to the same information and used the same models, they should all provide the same price estimate. In this paper we abstract from model disagreement or model uncertainty and assume that dealers form expectations by updating beliefs using a model that itself is common knowledge. Under this interpretation of the data, the observed cross-sectional dispersion necessarily reveals informational frictions in the OTC market. Furthermore, these frictions vary across market segments.

Second, these informational frictions have to derive from dealer banks' private information. Imperfect information that is observed by all dealer banks does not induce cross-sectional dispersion. However, the cross-sectional dispersion alone cannot identify the precision of private valuation information, as both very precise and very imprecise private information imply low cross-sectional dispersion. This illustrates the conceptual problem of using the cross-sectional dispersion of the raw data for the measurement of informational frictions.

Last, if the consensus price perfectly aggregates dispersed information, all bank dealers should have the same expectation about the current mid-quote after observing the current consensus price. Any deviation from the consensus price in the next period

has to be the result of new private information. But this implies that a dealer’s past relative position to the consensus price has no predictive power for its future relative position; individual deviations from consensus cannot be persistent. This is clearly rejected by the data. The positive persistence points to imperfect information aggregation and, consequently, long-lived private information at the level of individual dealers.

### 3 A Model of Consensus Pricing

We model the consensus pricing process as a social learning problem. Dealers learn about a time-varying fundamental value from private signals and the consensus price. We derive the consensus price process as an equilibrium outcome of the model and show what structure this imposes on dealers’ belief updating dynamics.

#### 3.1 The model

A large number of dealers, modelled as a continuum indexed  $i \in (0, 1)$ , participate in a consensus pricing service. At discrete submission dates  $t = \{\dots, -1, 0, 1, \dots\}$  each dealer  $i$  submits its best estimate for the current value of an option,  $\theta_t$ , to the service.  $\theta_t$  is latent and follows an AR(1) process,

$$\theta_t = \rho \theta_{t-1} + \sigma_u u_t \text{ with } u_t \sim N(0, 1), \quad (2)$$

and  $-1 < \rho < 1$ . We do not explicitly model the economic forces responsible for the variation in fundamental option values. A possible interpretation is based on a demand-based option pricing model in the spirit of [Gârleanu et al. \(2009\)](#).<sup>9</sup>

At each submission date  $t$ , dealers observe two signals about the fundamental option value, a noisy private signal and the consensus price. Dealer  $i$ ’s noisy private signal is

$$s_{i,t} = \theta_t + \sigma_\eta \eta_{i,t} \text{ with } \eta_{i,t} \sim N(0, 1), \quad (3)$$

where  $1/\sigma_\eta^2$  measures the precision of the private signal. The precision does not depend on  $i$ , that is all dealers receive signals of equal quality. The private signal structure implies that dealers are able to infer the current fundamental value if they

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<sup>9</sup>Under a demand-based interpretation, changes in the fundamental value derive from time-varying client demand that is satisfied by risk-averse broker-dealers.  $u_t$  is an aggregate demand shock for options with a given strike price and time-to-expiration. The AR(1) process for the fundamental value can be obtained in a setting in which the underlying asset follows a geometric Brownian motion, as is assumed in the Black-Scholes model ([Black and Scholes \(1973\)](#)). All time variation in fundamental option prices (expressed in terms of implied volatilities) is then driven by client demand shocks that cannot be perfectly hedged using the underlying, for example because of an inability to trade continuously. We provide a derivation of this setup in the online Appendix.

pool their private information; there is no aggregate noise in private signals. Taking a demand-based pricing view for our OTC market setting, this is a natural assumption. Trades with clients are the primary source of a dealer’s private information. These trades provide an imperfect signal of aggregate demand conditions. Pooling client demands across dealers reveals current aggregate demand.

In addition to the private signal, each dealer observes last period’s consensus price  $p_{t-1}$ . The timing of the consensus pricing process under which dealers only obtain the consensus price once they have submitted their estimates is a key difference to standard rational expectations equilibrium (REE) models. As the consensus price is a signal of the market’s past state, it does not supplant a dealer’s noisy private signal even if it is perfectly revealing. We model the current consensus price  $p_t$  as a noisy signal of the average estimate of  $\theta_t$  across dealers. Dealer  $i$ ’s information set at the time of period  $t$ ’s price submission consists of the (infinite) history of previous consensus prices and the private signals that  $i$  has observed up to period  $t$ , that is  $\Omega_{i,t} = \{s_{i,t}, p_{t-1}, \Omega_{i,t-1}\}$ . All dealers submit their best estimate of  $\theta_t$  to the service. For each dealer, we take this to mean its conditional expectation of  $\theta_t$  given  $\Omega_{i,t}$ . We denote this conditional expectation by

$$\theta_{i,t} = \mathbb{E}(\theta_t | \Omega_{i,t}),$$

and the corresponding cross-sectional average across dealers by

$$\bar{\theta}_t = \int_0^1 \theta_{i,t} di.$$

The consensus price itself is a noisy signal of this average expectation,

$$p_t = \bar{\theta}_t + \sigma_\varepsilon \varepsilon_t \text{ with } \varepsilon_t \sim N(0, 1). \quad (4)$$

We do not specify dealers’ preferences, which would determine why they value the consensus price information. Certain preference specifications could create an incentive to strategically manipulate the consensus price, for example in order to experiment (e.g. [Brancaccio et al. \(2020\)](#)) or to gain a competitive advantage. However, given the assumption of a continuum of dealers (and mild technical restrictions on admissible submissions), no single submitter can influence the consensus price. Hence, asking dealers to submit their best estimate of  $\theta_t$  is compatible with their incentives.<sup>10</sup>

Modelling the consensus price as a noisy public signal of average expectations is motivated by two considerations. First, as previously discussed, Totem eliminates the

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<sup>10</sup>[Raith \(1996\)](#) gives a theoretical analysis of the incentives for competitive firms to participate in (truthful) information-sharing arrangements. In the online Appendix we develop a stylized model that illustrates the value of consensus pricing information for dealers that operate in an OTC market.

lowest, the highest, and problematic price submissions from the consensus price calculations. Hence, the consensus price itself does not exactly correspond to the average submission. Second, while we assume a continuum of dealers, we want to allow for the possibility that the consensus price does not fully reveal the average expectation and, consequently, last period’s fundamental value.<sup>11</sup> Knowing last period’s fundamental value rules out long-lived private information. But such long-lived private information is needed to capture the persistence of the deviations of individual price submissions from the consensus price, a feature we observe in the data.

A remaining question is how commonly observed exchange-based option price data, for example prices listed on the Chicago Board Options Exchange (CBOE), fit into the above framework. A way to think about such data within our model is to interpret a dealer’s submission,  $\theta_{i,t}$ , as the difference between the dealer’s best estimates of the current fundamental value of the OTC contract and the current corresponding exchange-based price for the option. If no exchanged-based prices are available for a given Totem contract, an industry-standard, and hence commonly known, option pricing model calibrated to exchange-based prices for other contracts could be used instead. To map our data into the model, a dealer  $i$ ’s Totem submission and the corresponding consensus price are then  $\theta_{i,t}$ , respectively  $p_t$ , plus the price for the contract as given by exchange-based trading activity. An important assumption under this interpretation of the data is that exchange-based prices do not contain any information about  $u_t$ ,  $\eta_{i,t}$ , and  $\varepsilon_t$  that is not already contained in a dealer’s history of private signals and past consensus prices. In that sense, these shocks should be seen as specific to OTC market conditions, which is consistent with the stated purpose of the Totem consensus pricing service.<sup>12</sup>

## 3.2 Learning from consensus prices

In order to characterize dealer  $i$ ’s submission to the consensus pricing service, we need to calculate the dealer’s conditional expectation  $\mathbb{E}(\theta_t|\Omega_{i,t})$ . Its information set  $\Omega_{i,t}$  depends on all other dealers’ submissions via the consensus price process  $p_t$ . This information set is endogenous as  $p_t$  is both an input and an output of the joint learning process of the consensus pricing participants. As first pointed out by [Townsend \(1983\)](#), signal extraction problems in which signals are equilibrium variables, such as prices, typically do not admit representations in which a finite number of variables can summarize the current state of the system. For very restrictive settings, frequency domain techniques have been successfully employed to obtain exact finite state space

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<sup>11</sup>We estimate  $\sigma_\varepsilon$  and allow the parameter to be 0. This implies that full revelation is a possible outcome.

<sup>12</sup>In our estimation, we treat exchange-based prices as latent and use contract fixed effects. Explicitly incorporating exchange-based price data for option contracts that are exclusively OTC-traded would require specifying the option pricing model that is used by all dealers and taking a stand on how to calibrate this model to observed prices.

representations, e.g. [Kasa \(2000\)](#). However, a popular direction of attack is truncation, i.e. to show that the original problem is well approximated by a finite state space even if the actual solution requires an infinite number of states (e.g. [Sargent \(1991\)](#), [Lorenzoni \(2009\)](#), [Huo and Pedroni \(2020\)](#)).

This is the approach taken here. We adopt an iterative algorithm previously used in [Nimark \(2014\)](#) and [Barillas and Nimark \(2017\)](#) to solve our filtering problem. The algorithm works as follows:

1. Start with any covariance-stationary process  $(p_t^0)$  that lies in the space spanned by linear combinations of current and past aggregate shocks  $(u_t)$  and  $(\varepsilon_t)$ .
2. This consensus price process  $(p_t^0)$  yields information sets for all  $i$  and  $t$  defined recursively by  $\Omega_{i,t}^0 = \{s_{i,t}, p_{t-1}^0, \Omega_{i,t-1}^0\}$ .
3. Given information set  $\Omega_{i,t}^0$ , dealer  $i$  can compute the conditional expectation  $\mathbb{E}(\theta_t | \Omega_{i,t}^0)$  for period  $t$  under the assumed stochastic process for  $(p_t^0)$ .
4. Averaging the expectations across submitters yields a new consensus price process

$$p_t^1 = \int_0^1 \mathbb{E}(\theta_t | \Omega_{i,t}^0) di + \sigma_\varepsilon \varepsilon_t \text{ for all } t.$$

5. If the distance (in m.s.e.) between  $(p_t^0)$  and  $(p_t^1)$  is smaller than some pre-specified stopping criterion, stop. Otherwise, go to step 2 with  $(p_t^1)$  as the new consensus price process and so on.

For any initial choice of  $(p_t^0)$ , the sequence of price processes  $\{(p_t^n)\}_n$  converges (in m.s.e.) to a unique limit process  $(p_t)$ , the solution of the original filtering problem, when the integral in step 4 is a contraction on the space of covariance-stationary price processes. Starting with the initial guess  $p_t^0 = \theta_t + \sigma_\varepsilon \varepsilon_t$  allows the problem to be solved by a sequential application of the Kalman filter. It also provides an upper bound on the approximation error if the algorithm is stopped after a finite number of steps.

After  $n$  steps, the equilibrium learning dynamics are approximated by a linear state-space system with an  $n+1$  dimensional state vector  $x_t$ . The first and second element of  $x_t$  are the fundamental value  $\theta_t$  and the cross-sectional average expectation  $\bar{\theta}_t$ , respectively.<sup>13</sup> The state evolves according to

$$x_t = Mx_{t-1} + Nv_t \text{ with } v_t = (u_t, \varepsilon_{t-1})^\top, \quad v_t \sim N(0, I_2). \quad (5)$$

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<sup>13</sup>The  $k$ -th element of  $x_t$  is the cross-sectional average of dealers'  $k$ -th order expectation of  $\theta_t$  given their information in period  $t$ . The average  $k$ -th order expectation is defined recursively as  $\theta_t^{(k)} = \int \mathbb{E}(\theta_t^{(k-1)} | \Omega_{i,t}) di$  with  $\theta_t^{(1)} = \bar{\theta}_t$ . The online Appendix provides a more detailed explanation of these higher-order expectations and the solution algorithm.

The matrices  $M$  and  $N$  are known functions of the model parameters, namely  $\{\rho, \sigma_u, \sigma_\varepsilon, \sigma_\eta\}$ . A dealer's signals in period  $t$  can be expressed as noisy observations of the state,<sup>14</sup>

$$\begin{aligned} s_{i,t} &= e_1^\top x_t + \sigma_\eta \eta_{i,t} = \theta_t + \sigma_\eta \eta_{i,t}, \\ p_{t-1} &= e_2^\top x_{t-1} + \sigma_\varepsilon \varepsilon_{t-1} = \bar{\theta}_{t-1} + \sigma_\varepsilon \varepsilon_{t-1}. \end{aligned}$$

The two signals can be written in vector form as

$$z_{i,t} = D_1 x_t + D_2 x_{t-1} + B \epsilon_{i,t},$$

with  $z_{i,t} = (s_{i,t}, p_{t-1})^\top$  and  $\epsilon_{i,t} = (v_t^\top, \eta_{i,t})^\top$ .

We can now use the Kalman filter to obtain dealer  $i$ 's beliefs about  $\theta_t$  and  $\bar{\theta}_t$ , the first two elements of  $x_t$ , given the information in  $\Omega_{i,t}$ . The linear-normal structure of the state-space system implies that dealer  $i$ 's beliefs are normally distributed,

$$x_t \mid \Omega_{i,t} \sim N(x_{i,t}, \Sigma^p), \quad (6)$$

where the conditional expectations about the state evolve according to

$$x_{i,t} = M x_{i,t-1} + K(z_{i,t} - (D_1 M + D_2) x_{i,t-1}), \quad (7)$$

and  $K$  is a  $(n+1) \times 2$  dimensional matrix of Kalman gains. Here  $K$  and the covariance matrix of dealers' beliefs  $\Sigma^p$  are known functions of the model parameters.<sup>15</sup>

## 4 Estimation

We estimate the model's parameter vector  $\phi = \{\rho, \sigma_u, \sigma_\varepsilon, \sigma_\eta\}$  separately for each contract. This contract-by-contract approach is consistent with the above model and we can prove that the structural parameters of the model are identified. Furthermore, estimating each contract separately allows us to verify that coefficients estimates do not vary substantially across adjacent contracts. This is a reasonable a priori assumption in our context and provides an additional sanity check for the estimation results. A joint estimation, on the other hand, would require imposing a correlation structure on fundamental shocks and signals across contracts. As not all participating dealer banks submit to all contracts, modelling compositional effects would add an additional layer of complexity to a joint estimation framework.

<sup>14</sup>Here,  $e_n^\top$  is a vector with 1 in the  $n^{th}$  position, 0 otherwise.

<sup>15</sup>Given the infinite history of past signals, the covariance matrix  $\Sigma^p$  and the matrix of Kalman gains  $K$  are not time dependent. Also,  $\Sigma^p$  and  $K$  are not dealer-specific as dealers are symmetrically informed. They all receive signals of the same quality. Superscripts, here  $p$ , are used to index information structures. Later, we modify the information structure of the market in counterfactual experiments.

For a given contract, our data consists of the panel of Totem price submissions by individual dealers and the corresponding consensus price. We denote by  $\iota_t \subset \{1, 2, \dots, S\}$  the set of dealers active in  $t$ .  $S$  is the total number of distinct dealers that have submitted to Totem over the course of our sample period. The time series of submissions is given by  $(\mathbf{p}_t)_{t=1}^T$ , where  $\mathbf{p}_t = (p_{i,t})_{i \in \iota_t}$  is a  $|\iota_t|$ -dimensional vector consisting of the individual period  $t$  consensus price submissions. Our data set for a given contract,  $(\mathbf{y})_{t=1}^T$ , then consists of the time series of dealers' price submissions for this contract and the corresponding consensus price, i.e.  $\mathbf{y}_t = (p_t, \mathbf{p}_t)^\top$ .<sup>16</sup>

## 4.1 Likelihood function and estimation

To estimate the model for a given contract, we cast it into state-space form. The panel of individual price submissions and the time series of consensus prices constitute the available observations of the system. Based on Section 3, the latent state space has the following dynamics:

$$x_t = M(\phi) x_{t-1} + N(\phi) v_t, \quad v_t \sim N(\mathbf{0}, I_2),$$

where  $v_t = (u_t \ \varepsilon_{t-1})^\top$ .  $M(\phi)$  and  $N(\phi)$  are obtained by employing the previously explained solution algorithm for a given parameter vector  $\phi$ . We assume that dealer  $i$ 's price submission for period  $t$  is its conditional expectation of  $\theta_t$ , i.e.  $p_{i,t} = \theta_{i,t}$ .

Dealer  $i$ 's conditional expectations of the current state  $x_t$  are updated as follows,

$$x_{i,t} = M(\phi) x_{i,t-1} + K(\phi) \left[ \begin{pmatrix} s_{i,t} \\ p_{t-1} \end{pmatrix} - (D_1 M(\phi) + D_2) x_{i,t-1} \right]. \quad (8)$$

In the estimation, we treat a dealer  $i$ 's private signal  $s_{i,t}$  as a latent variable. It is observed by the dealer but not by the econometrician. The noise in the private signal is assumed to be uncorrelated across submitting dealers and time. The consensus price  $p_t$  is observed by both the dealers and the econometrician. The econometrician only observes the first element of dealer  $i$ 's conditional expectations  $x_{i,t}$  which is  $\theta_{i,t}$ , dealer  $i$ 's conditional expectation of the current fundamental value. We assume that it is this expectation that the dealer submits to the Totem service.

Equation (8) provides us with a disciplined way of modelling the belief updating dynamics at the level of the individual dealer. It illustrates both the usefulness of the model to impose structure on belief data and the importance of observing a time series of beliefs at the individual level to estimate dynamic social learning models. A more

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<sup>16</sup>To be precise, we take the natural logarithm of the implied volatility (IV) corresponding to, respectively, dealer  $i$ 's price submission and IHS Markit's consensus price for each time  $t$ . We then subtract the time series average of the logged consensus IV series from all individual logged IV time series and the consensus IV series itself to remove a contract specific level. The resulting objects are series of  $p_{i,t}$  for each dealer  $j$  and the consensus series  $p_t$ .



simplistic approach that estimates belief-updating dynamics using only first-order expectations without taking into account the importance of higher-order expectations in the filtering problem will suffer from an omitted variable bias.

Given the linearity of the above system and the joint normality of all shocks, the likelihood function for the observed data  $(\mathbf{y}_t)_{t=1}^T$  can be derived using the Kalman filter. We obtain estimates for the parameter vector  $\phi$  using MCMC methods with diffuse priors.<sup>17</sup> We constrain  $\sigma_u, \sigma_\varepsilon$ , and  $\sigma_\eta$  to be positive and  $0 < \rho < 1$ . For each contract we run chains of length 100,000 with the Metropolis-Hastings algorithm and disregard the first 10,000 draws. We subsequently pick every 10<sup>th</sup> draw to construct the posterior distribution of the parameters. Appendix 7.1 provides a detailed derivation of the filter for the above model. Table 3 in the Appendix reports parameter estimates and standard errors for  $\rho, \sigma_u, \sigma_\varepsilon$ , and  $\sigma_\eta$  for all contracts.

## 4.2 Identification

The online Appendix provides a formal proof of identification for the model. Here, we give a short summary of which moments of the data help us to identify the structural parameters of the model. The time-series variance of the differences between  $p_t$  and cross-sectional average of submission identifies  $\sigma_\varepsilon$ . The speed at which individual deviations from the average submission mean-revert determines the weight dealers put on their prior expectations (as opposed to weight put on news in the current signal and consensus price). Knowing this weight allows us to isolate changes in price submissions that are due to new information a dealer received in a given period. As these news are linked to the current fundamental, the autocorrelation of these expectation updates that have been “cleaned” of prior expectations allow us to identify  $\rho$ , the persistence in the fundamental value process. The weight dealers put on their prior depends on how persistent the fundamental is and how high the quality of their new information is, i.e. the signal-to-noise ratio of their signals. Having identified  $\rho$ , we can now identify this signal-to-noise ratio from the weight dealers put on their prior expectations. The signal-to-noise ratio depends on the variance of the fundamental shocks,  $\sigma_u^2$ , and the precision of private signals and the consensus price as determined by  $\sigma_\eta$  and  $\sigma_\varepsilon$ . We have already identified  $\sigma_\varepsilon$ . The relative weight dealers put on the consensus price as opposed to the private signal depends on the relative precision of these two signals. This allows us to identify  $\sigma_\eta$  and, finally,  $\sigma_u$  from the signal-to-noise ratio.

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<sup>17</sup>While we use Bayesian methods to obtain the posterior parameter distributions, using diffuse priors implies the estimates can also be thought of as classical maximum-likelihood point estimates with the standard deviations corresponding to classical standard errors.

### 4.3 Model fit and robustness checks

To judge how well the model fits the data, we compare the model-implied cross-sectional dispersion of price submissions and the time-series volatility of the consensus price to their empirical analogues. In the online Appendix, the ratio of the model-implied cross-sectional standard deviation and the empirical cross-sectional standard deviation are displayed. This ratio for the different contracts is between 0.909 and 1.125, which implies that the model is able to reproduce the size of the cross-sectional dispersion for the different contracts. We also do not find a statistically significant difference between the model-implied and the empirical consensus price volatility.

The sample period includes two peculiar periods: the low volatility period from 2002 to 2006 and the Great Recession from 2007 to 2010. The parameter estimates for these periods might be very different. However, we find that results do not change if we consider these two periods separately. Another potential split is that of dealers that participate for a limited time frame and routine dealers. We therefore re-estimate the model excluding dealers who have submitted for less than 40% of the total sample period. The parameter estimates are comparable to the results for the entire sample. Including only the ‘routine’ dealers makes the contrast between the at-the-money (ATM) and the out-of-the-money (OTM) options slightly larger. The estimation results for these three additional data treatments are reported in the online Appendix.

## 5 Results

This section derives model-implied measures of valuation and strategic uncertainty based on dealers’ posterior beliefs. The estimates of the structural model parameters provide us with estimates for these uncertainty measures and we show how dealer uncertainty varies across market segments. Counterfactual experiments on the option market’s information structure allow us to quantify the informational value of the consensus prices for dealer banks.

### 5.1 Valuation and strategic uncertainty

At the time of the period  $t$  consensus price submission, dealer  $i$ ’s posterior beliefs about the current fundamental value of a contract,  $\theta_t$ , and the cross-sectional average expectation of this value,  $\bar{\theta}_t$ , are jointly normally distributed with

$$\begin{pmatrix} \theta_t \\ \bar{\theta}_t \end{pmatrix} | \Omega_{i,t} \sim N \left( \begin{pmatrix} \theta_{i,t} \\ \bar{\theta}_{i,t} \end{pmatrix}, \begin{pmatrix} (\sigma_{11}^p)^2 & \sigma_{12}^p \\ \sigma_{12}^p & (\sigma_{22}^p)^2 \end{pmatrix} \right). \quad (9)$$

The dealer’s conditional expectations about  $\theta_t$  and  $\bar{\theta}_t$  are updated according to

$$\theta_{i,t} = \rho \theta_{i,t-1} + k_s (s_{i,t} - \rho \theta_{i,t-1}) + k_p (p_{t-1} - \bar{\theta}_{i,t-1}), \quad (10)$$

$$\bar{\theta}_{i,t} = m_2 \cdot x_{i,t-1} + \bar{k}_s (s_{i,t} - \rho \theta_{i,t-1}) + \bar{k}_p (p_{t-1} - \bar{\theta}_{i,t-1}). \quad (11)$$

The covariance matrix in (9) corresponds to the top left  $2 \times 2$  sub-matrix of  $\Sigma^p$  given in (6). The parameters  $k_s$  and  $k_p$  in (10) are the Kalman gains for the private signal and the consensus price, respectively. The Kalman gains are the weights a dealer puts on the “news” contained in the signals when updating expectations about the fundamental value  $\theta_t$ . They correspond to the first row of  $K$  in (7). Similarly,  $\bar{k}_s$  and  $\bar{k}_p$  in (11) are the Kalman gains for the private signal and consensus price for the average expectation  $\bar{\theta}_t$ . They correspond to the second row of  $K$ .

Our measures of valuation uncertainty and strategic uncertainty are the variance of a dealer’s forecast errors for the fundamental value,  $\theta_{i,t} - \theta_t$ , and the variance of its forecast error for the average expectation,  $\bar{\theta}_{i,t} - \bar{\theta}_t$ , at the time of the consensus price submission. These variances are  $(\sigma_{11}^p)^2$ , respectively  $(\sigma_{22}^p)^2$ , as given in (9). The correlation between the two forecast errors,  $\rho_{12} = \sigma_{12}^p / (\sigma_{11}^p \sigma_{22}^p)$ , is a natural measure for what [Angeletos and Pavan \(2007\)](#) call the “commonality of information”: higher correlations imply that different dealers interpret new valuation information in a similar way.

We start by developing some intuition for the relationship between valuation uncertainty, strategic uncertainty and the commonality of information before presenting the estimation results. To do so, we split up the expectation updating for  $\theta_t$  into two steps. First, the dealer updates its expectations about  $\theta_{t-1}$  after observing the consensus price  $p_{t-1}$ . Call this updated expectation  $\theta_{i,t-1}^+$ . Next, the dealer receives the private signal  $s_{i,t}$  and updates its expectation to  $\theta_{i,t}$ . This is what the dealer submits to the Totem service. We can therefore decompose the submission as follows,

$$\theta_{i,t} = (1 - k_s)\rho\theta_{i,t-1}^+ + k_s s_{i,t}.$$

Averaging across dealers and noting that idiosyncratic noise cancels out, the average expectation across dealers can now be expressed as

$$\bar{\theta}_t = (1 - k_s)\rho\bar{\theta}_{t-1}^+ + k_s \theta_t.$$

Finally, taking expectations of the above expression conditioning on  $\Omega_{i,t}$  and subtracting the original equation allows us to link the forecast errors for  $\theta_t$  and  $\bar{\theta}_t$ ,

$$\bar{\theta}_{i,t} - \bar{\theta}_t = (1 - k_s) [\mathbb{E}(\rho\bar{\theta}_{t-1}^+ | \Omega_{i,t}) - \rho\bar{\theta}_{t-1}^+] + k_s (\theta_{i,t} - \theta_t).$$

The above expression shows that the forecast error for  $\bar{\theta}_t$  is a weighted sum of the forecast error for  $\theta_t$  and the forecast error for the average prior expectation about  $\theta_t$  before observing the private signal in period  $t$ . Dealer  $i$ ’s forecast errors for  $\bar{\theta}_t$  and  $\theta_t$  are perfectly correlated, i.e.  $\rho_{12} = 1$ , if the dealer knows the average expectation  $\bar{\theta}_{t-1}^+$ . In our model this can only happen if the consensus price perfectly aggregates all dispersed information. In that case, all dealers have the same expectation after

observing the consensus price, namely  $\bar{\theta}_{t-1}^+ = p_{t-1}$ , and the average posterior expectation is given by  $\bar{\theta}_t = (1 - k_s)\rho p_{t-1} + k_s \theta_t$ . It follows that dealers are less uncertain about  $\bar{\theta}_t$  than about  $\theta_t$  as  $\sigma_{22}^p = k_s^2 \sigma_{11}^p$  and  $|k_s^2| < 1$ .

If dealers are uncertain about the average expectation  $\bar{\theta}_{t-1}^+$ , this simple relationship no longer holds. (10) can be written as

$$\theta_{i,t} = (1 - k)\rho \theta_{i,t-1} + k_s s_{i,t} + k_p p_{t-1} + k_p (\theta_{i,t-1} - \bar{\theta}_{i,t-1}) \quad \text{with } k = k_s + \frac{k_p}{\rho}. \quad (12)$$

We see that if dealers put strictly positive weight on their individual prior expectations, that is  $1 - k > 0$ , their expectations are partially dependent on their individual history of private signals. Hence, dealers do not return to a common market perception after observing the consensus price. A lack of common perspective on past market conditions partially feeds into uncertainty about current market conditions as given by  $\bar{\theta}_t$ .

### 5.1.1 Price versus private information

Figure 3 displays estimates of the Kalman gains for the private signal and consensus price for both the fundamental value, that is  $k_s$  and  $k_p$ , and for the average expectation, that is  $\bar{k}_s$  and  $\bar{k}_p$ . The graphs show the variation in Kalman gains across moneyness for options with a fixed time-to-expiration of 12 months. For contracts with moneyness close that 100, dealers almost put full weight on their private signal both when updating their expectations about the current fundamental value (top left panel) and their expectation about the location of the current average expectation across dealers (bottom left panel). The consensus price signal receives correspondingly low weight in the updating of expectations about fundamental values (top right panel) and expectations about the location of average expectations (bottom right panel). As we move towards OTM contracts, both put and call options, the consensus price increases in importance and the weight on private signals decreases. Table 4 in the Appendix reports estimates for all contracts. They confirm the pattern observed for contracts with 12 months to expiration. The Kalman gains for the consensus price are higher for more extreme options contracts that are predominately OTC-traded. In market segments that overlap with exchange-based trading, dealers' private signals receive a higher weight in updating expectations and the consensus price is relatively less important. Lastly, note that for a given contract the Kalman gain for the consensus price is always higher for updating expectations about the location of the average expectation than for updating expectations about the fundamental value.

A key structural parameter for understanding this variation in Kalman gains across market segments is  $1/\sigma_\eta$ , the precision of the private signal. The estimates for  $\sigma_\eta$ , given in the fourth row of Table 2, show that dealers receive very precise private

signals for contracts that overlap with active exchange-based trading activity.<sup>18</sup> Consequently, the implied Kalman gains for these contracts in Figure 3 show that dealers put essentially full weight on their private signal and largely ignore the information contained in the consensus price when updating expectations about  $\theta_t$ . For option contracts with low exchange-based trading activity, the private signals are estimated to be noisier. Therefore, increasingly more weight is given to the consensus price. When updating expectations about  $\bar{\theta}_t$ , the consensus price receives relatively higher weight for all contracts. This highlights the scarcity of information in these market segments, but it also illustrates the strategic value of the consensus price as a focal public signal. Row five of Table 2 reports that 1- $k$ , the weight dealers put on their prior expectation as given in (12), is estimated to be strictly positive for all contracts. Hence, dealers do not put full weight on new information, especially not for exclusively OTC-traded contracts. Furthermore,  $\rho_{12}$  is estimated to be strictly smaller than 1. This implies that a dealer's forecast errors for fundamental and average expectation are not perfectly correlated. As explained in Section 5.1, this leads to long-lived private information and, consequently, dispersed priors among dealers.

Table 2: Sample parameter estimates and implied quantities

	60	80	90	95	100	105	110	120	150
$\rho$	0.967 (0.015)	0.930 (0.024)	0.939 (0.027)	0.949 (0.028)	0.941 (0.022)	0.930 (0.025)	0.949 (0.022)	0.967 (0.013)	0.969 (0.017)
$\sigma_u$	0.047 (0.001)	0.076 (0.004)	0.082 (0.005)	0.086 (0.005)	0.091 (0.005)	0.095 (0.005)	0.095 (0.005)	0.073 (0.002)	0.135 (0.003)
$\sigma_\varepsilon$	0.055 (0.004)	0.004 (0.000)	0.006 (0.000)	0.007 (0.000)	0.009 (0.001)	0.011 (0.001)	0.014 (0.001)	0.036 (0.003)	0.262 (0.016)
$\sigma_\eta$	0.041 (0.001)	0.014 (0.000)	0.010 (0.000)	0.010 (0.000)	0.010 (0.000)	0.011 (0.000)	0.015 (0.000)	0.036 (0.001)	0.281 (0.011)
$k$	0.733 (0.011)	0.998 (0.000)	0.996 (0.001)	0.996 (0.001)	0.995 (0.001)	0.993 (0.001)	0.989 (0.001)	0.901 (0.010)	0.490 (0.014)
$\rho_{12}$	0.974 (0.002)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	0.997 (0.001)	0.922 (0.003)

This table presents the mean and standard deviation of the model parameter estimates and implied quantities for contracts with time-to-expiration of 12 months. The header gives the moneyness of contracts. Rows 1 to 6 show estimates for the persistence of the process for the fundamental,  $\rho$ , and the standard deviation of the shock to the fundamental,  $\sigma_u$ , the standard deviation of noise in consensus price,  $\sigma_\varepsilon$ , the standard deviation of noise of the private signal,  $\sigma_\eta$ , the weight dealers put on new information,  $k$ , and the correlation between the forecast error for fundamental value and average expectations,  $\rho_{12}$ . Estimates are obtained using MCMC methods assuming diffuse priors for all parameters. The standard deviation of the posterior distribution of the parameter is given in parentheses below its mean (0.000 signifies standard deviations below 0.0005). The sample period is December 2002 to February 2015.

<sup>18</sup>Table 2 provides the parameter estimates for the contracts with time-to-expiration of 12 months. In the Appendix we provide the estimates for the complete contract space. Table 3 provides estimates for  $\rho$ ,  $\sigma_u$ ,  $\sigma_\varepsilon$  and  $\sigma_\eta$ , and Table 5 for  $k$  and  $\rho_{12}$ .

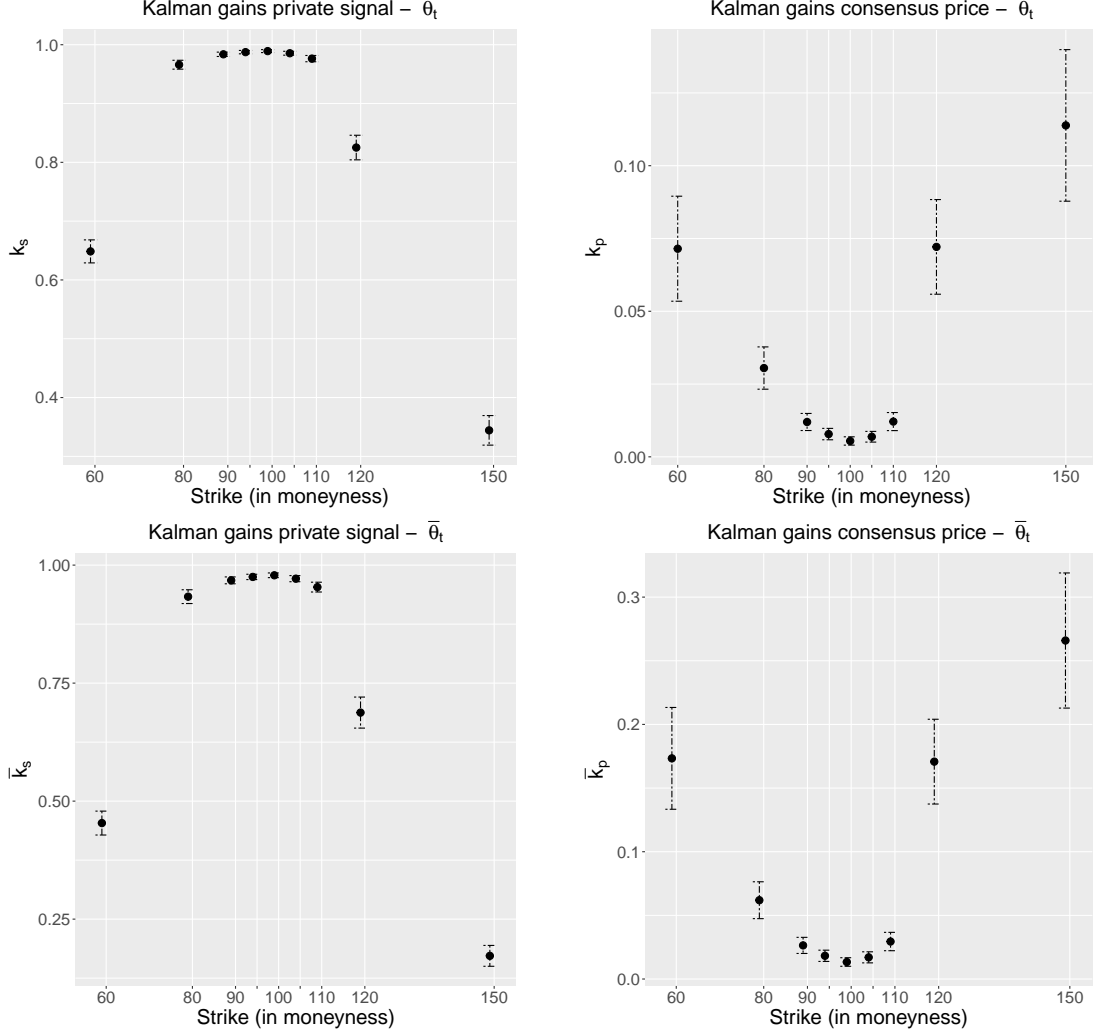


Figure 3: These figures present a dealer’s Kalman gains for private signals and consensus prices. The horizontal axis denotes the moneyness of the option contracts. The black dots in the figures represent the Kalman gain extracted from the  $K$  matrix in Equation (9). The *top* figures depict  $k_s$  and  $k_p$ . From left to right, these are the weights put on the private signal and consensus price when updating the posterior expectation about the fundamental  $\theta_t$ . The *bottom* figures depict  $\bar{k}_s$  and  $\bar{k}_p$ . From left to right, these are the weights put on the private signal and consensus price when updating the posterior expectation about average expectations  $\bar{\theta}_t$ . The 95% centred interval of the posterior distribution of Kalman gain estimates are given by the dotted lines surrounding the dots. The Kalman gains are for the option contracts with a **time-to-expiration** of **12 months**. The sample period is December 2002 to February 2015.

### 5.1.2 Uncertainty smile and term structure

As dealers’ beliefs are normal distributions, we display valuation and strategic uncertainty in terms of 95% posterior intervals. That is, having observed past period’s consensus price and the current private signal, a dealer attributes a probability of 0.95 to the event that the current fundamental value lies in an interval of length  $3.92 \sigma_{11}^p$  centered around its current expectation  $\theta_{i,t}$ . The length of this posterior in-

terval thus gauges a dealer’s uncertainty about the fundamental value  $\theta_t$  at the time of submission. Similarly, for strategic uncertainty, the length of the posterior interval is  $3.92 \sigma_{22}^p$  and it is centred around  $\bar{\theta}_{i,t}$ . It measures a dealer’s uncertainty about the location of the average expectation for  $\theta_t$  across dealers.

Figure 4 shows these posterior intervals for valuation uncertainty (left panels) and strategic uncertainty (right panels). As dealers’ expectations are varying over time, we center all posterior intervals around the time-series mean of the corresponding consensus price. For our purpose, this is immaterial. Given the stationarity of the model, the lengths of the posterior intervals do not vary over time. The top panels show the “uncertainty smile”, that is posterior intervals for fixed times-to-expiration of 12 months (black) and 5 years (red) across moneyness. The bottom panels display the term structure of uncertainty, i.e. they show how posterior intervals for ATM puts with moneyness 100 (black) and OTM put with moneyness 60 (red) vary by times-to-expiration. Table 6 in the Appendix reports the length of 95% posterior intervals for all contracts. The two top panels in Figure 4 show the well-known “smile” of the implied volatility curve. OTM put options (moneyness below 100) tend to be relatively more expensive than ATM put options or OTM call options reflecting market participants’ demand for insurance against drops in the S&P 500 index. The width of the posterior intervals shows that for options with more extreme strike prices (further away from moneyness 100), valuation and strategic uncertainty are higher. These areas correspond to market segments in which trading is predominantly or exclusively OTC, as was previously shown in Figure 1. For options with moneyness 150 and time-to-expiration of 12 months, for example, the posterior intervals are on the order of 8 volatility points. This is substantial given that the time-series average and standard deviation of the consensus price for this contract are 13 and 3.8 volatility points, respectively. While the term structure of uncertainty is relatively flat for ATM options (black posterior intervals in bottom panels), it is downward sloping for OTM puts (red posterior intervals in bottom panels).

These results reflect the estimated lower precision of the private signal,  $\sigma_\eta$ , for OTM contracts and especially OTM call options, as can be seen in row four of Table 2. Given the relatively low precision of private signals, more weight is put on prior expectations. This, in turn, is the source of “long-lived” private information and sizable strategic uncertainty. It contrasts to posterior intervals well below one volatility point for options in market segments with likely more trading activity. Here, private signals are precise, which implies lower values of  $\sigma_{11}^p$ . As all dealers are symmetrically informed and receive private signals from the same distribution, strategic uncertainty is small as well. This difference in results illustrates that for the exclusively OTC-traded areas of the option market, dealers are not only relatively uncertain about the correctness of their own option valuations, but also face substantial uncertainty about the relative position of their valuation to the average market valuation.

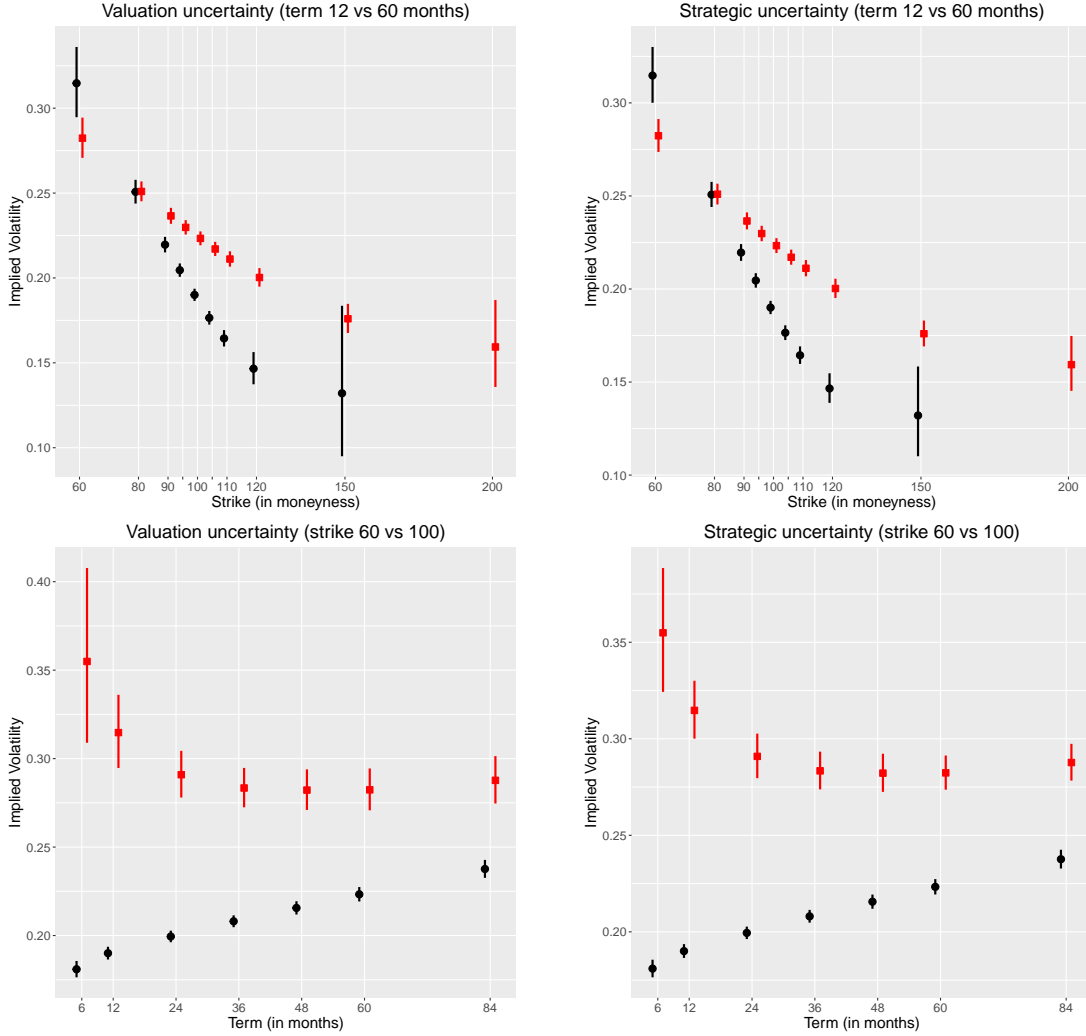


Figure 4: These figures display the variance of dealers’ posterior beliefs expressed in terms of posterior intervals centred on the sample mean of the corresponding consensus price. The *left* figures depict the 95% posterior intervals for the fundamental value  $\theta_t$ ,  $[p \pm 1.96 \cdot \sigma_{11}^p]$ , as given in (9). The figures on the *right* display the posterior intervals for the average expectation  $\bar{\theta}_t$ ,  $[p \pm 1.96 \cdot \sigma_{22}^p]$ .  $p$  is the time-series average of the corresponding consensus price. The two *top* panels depict the posterior intervals by moneyness for the option contracts with a fixed **time-to-expiration** of **12 months** and **60 months**. The two *bottom* panels show the term structure of the uncertainties for ATM options with fixed moneyness **100** and OTM options with fixed moneyness of **60**. The sample period is December 2002 to February 2015

## 5.2 The informational properties of consensus prices

We now consider two counterfactual information structures for the options markets to gauge the informational content of the consensus price and its influence on dealer banks’ uncertainty. We assume that the structural parameters of the model are invariant to these informational experiments. In particular, we assume that dealer banks do not adjust their information acquisition strategy, which would affect the



precision of the private signal.<sup>19</sup> This assumption is not problematic when we use the counterfactual settings to measure the informational value of the consensus price in the current market setting. However, it becomes important when we consider the implications of changing the market’s information structure.

To study the informativeness of the consensus price for dealer banks, we consider an information structure under which dealers only receive private signals. Denote by  $\Sigma^s$  the covariance matrix of dealer  $i$ ’s posterior beliefs under this counterfactual information set, namely  $\Omega_{i,t}^s = \{s_{i,t}, \Omega_{i,t-1}^s\}$ . This covariance matrix can be obtained by solving a standard single-agent learning problem and evaluating it at our parameter estimates for  $\{\rho, \sigma_u, \sigma_\eta\}$ .<sup>20</sup> We use the percentage reduction in uncertainty that results from having access to the consensus price as a measure of price informativeness,

$$\Delta_i^p = \frac{(\sigma_{ii}^s - \sigma_{ii}^p)}{\sigma_{ii}^s}.$$

Note that we evaluate the informativeness of the consensus price both with respect to valuation information, that is information about  $\theta_t$ , as given by  $\Delta_1^p$  and with respect to strategic information, that is information about  $\bar{\theta}_t$ , as given by  $\Delta_2^p$ .

To elicit the efficiency of the consensus price mechanism in aggregating dispersed information, we introduce a counterfactual setting with a fully efficient consensus price that perfectly reveals last period’s fundamental value. As the price reveals  $\theta_{t-1}$ , it is a common prior shared by all dealers before they receive new private signals in  $t$ . In addition to providing a benchmark for efficiency, this counterfactual also helps us understand how big an impediment the lack of a common prior is for creating a common understanding of market conditions. We denote by  $\Sigma^\theta$  the counterfactual covariance matrix of posterior beliefs for a dealer who receives a fully efficient consensus price in the above sense. We measure the inefficiency of the consensus price by the increase in the standard deviation of posterior beliefs when moving from a fully efficient price to the current consensus price. We express this increase as a ratio to the standard deviation of posterior beliefs without consensus price,

$$\Delta_i^\theta = \frac{(\sigma_{ii}^p - \sigma_{ii}^\theta)}{\sigma_{ii}^s}.$$

We use this somewhat unusual definition of inefficiency to obtain the following de-

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<sup>19</sup>If private signals derive from OTC trading activity this would, for example, imply that dealers do not change their trading activity to generate more valuation information through experimentation.

<sup>20</sup>In the online Appendix we derive the stationary posterior covariance matrices for first- and second-order beliefs for all counterfactual informational scenarios.

composition,

$$1 = \underbrace{\frac{(\sigma_{ii}^s - \sigma_{ii}^p)}{\sigma_{ii}^s}}_{\Delta_i^p} + \underbrace{\frac{(\sigma_{ii}^p - \sigma_{ii}^\theta)}{\sigma_{ii}^s}}_{\Delta_i^\theta} + \underbrace{\frac{\sigma_{ii}^\theta}{\sigma_{ii}^s}}_{\Delta_i^R} \quad (13)$$

Price informativeness                      Price inefficiency                      Residual informational friction

Given the lagged nature of the consensus pricing mechanism, even a fully efficient price does not eliminate all uncertainty about asset values. We also quantify the potential for further uncertainty reduction that is outside the scope of this specific information aggregation mechanism and refer to it as the residual informational friction. The potential for uncertainty reduction in a market structure without consensus prices can thus be decomposed into (consensus) price informativeness, (consensus) price inefficiency, and residual informational frictions.

### The influence of information structure on uncertainty

Figure 5 displays the percentage reductions in uncertainty under the different informational settings for contracts with a fixed time-to-expiration of 12 months. The dark gray regions show price informativeness measures  $\Delta_1^p$  and  $\Delta_2^p$  across contracts, that is the percentage reduction in valuation, respectively, strategic uncertainty that results from having access to the consensus price. The lack of uncertainty reduction in the moneyness range from 80 to 110 is to be expected as dealers receive very precise private signal for these contracts. This mirrors the previously shown estimates of the Kalman gain  $k_s$  and  $\bar{k}_s$  which are both close to 1 (see Figure 3). In the mostly OTC-traded market segments  $\Delta_1^p$  is higher, which implies that the consensus price is more informative about  $\theta_t$ . Here, the Kalman gains for the consensus price,  $k_p$ , are also higher. Table 7 in the Appendix shows similar patterns for other times-to-expiration. For all contracts under consideration, the reduction in valuation uncertainty is between 0% for the ATM contracts to 4.36% for the more extreme contracts. The comparison between  $\Delta_1^p$  and  $\Delta_2^p$ , that is the left and right panel in Figure 5, shows that the consensus price signal is much more informative about  $\bar{\theta}_t$ .  $\Delta_2^p$ , the reduction in strategic uncertainty that results from having access to the consensus price, ranges from 0.02% to 27.33% (see Table 7). The relative larger decrease in strategic uncertainty in comparison to valuation uncertainty points to the importance of the consensus price for learning about strategic aspects of the market. This is also echoed in the difference between  $k_p$  and  $\bar{k}_p$ . Given the scarcity of shared trade data in market segments that are dominated by OTC trading, the ability of the consensus price to significantly reduce strategic uncertainty is both intuitive and important.

The light gray areas in Figure 5 display price inefficiency measures  $\Delta_1^\theta$  and  $\Delta_2^\theta$ , that is the additional percentage reductions in valuation, respectively, strategic uncertainty that could be achieved by moving from the current consensus price to a consensus

price that perfectly reveals  $\theta_{t-1}$ . Knowing the previous period's option value eliminates two sources of uncertainty. First, it eliminates the uncertainty that originates from the additive noise component of the consensus price,  $\varepsilon_t$ . Second, dealers no longer have to take into account the dispersion in prior expectations across dealers. With a perfect consensus price, they all start from a common prior before observing their new private signals. In the top and bottom panel of Figure 5, the lack of uncertainty reduction in the moneyness range from 80 to 110 is mainly due to the high precision of private signals, as was the case for  $\Delta_1^p$  and  $\Delta_2^p$ . The signal-to-noise ratio  $\sigma_u/\sigma_\eta$  puts an upper bound on the weight the consensus price can receive when updating expectations. The consensus price can at most reveal the past value, while the private signal is a signal about the current value. This limits the potential impact of a fully efficient price on valuation uncertainty. For contracts with intermediate moneyness, little weight is put on prior expectations, thus limiting the potential of a fully efficient price to reduce uncertainty by providing a common prior. For contracts with extreme moneyness, the relative imprecision of the private signal shifts weight towards the consensus price and the prior. This explains the up to 33.46% drop in valuation uncertainty and 62.69% drop in strategic uncertainty for the deep OTM call options, as seen in Table 7 in the Appendix. A focal point, such as the commonly observed consensus price, helps to reduce dispersion in priors among dealers. It thereby lowers strategic uncertainty and fosters a common understanding of market conditions.

The white areas in the figures show the residual informational frictions  $\Delta_1^R$  and  $\Delta_2^R$ , that is the potential percentage reduction in valuation, respectively, strategic uncertainty that is outside of the scope of this consensus pricing mechanism. The reduced size of this area for more extreme contracts illustrates the importance of public information in the opaque parts of the market, especially in providing information about other dealers' valuations. For contracts with moneyness between 80 and 110, informational frictions that could not be remedied by a perfectly efficient consensus pricing mechanism dominate. Reducing the remaining uncertainty would require changing the design parameters of the consensus pricing service. Increasing the frequency of the consensus service, for example, can be thought of as lowering the variance of the fundamental shocks,  $\sigma_u^2$ , in our model. However, given the labour-intensive nature of the consensus pricing process, running a more frequent service is costly. It appears that the marginal cost of increasing the frequency of the service exceeds the dealers' willingness to pay for a marginal reduction in uncertainty.

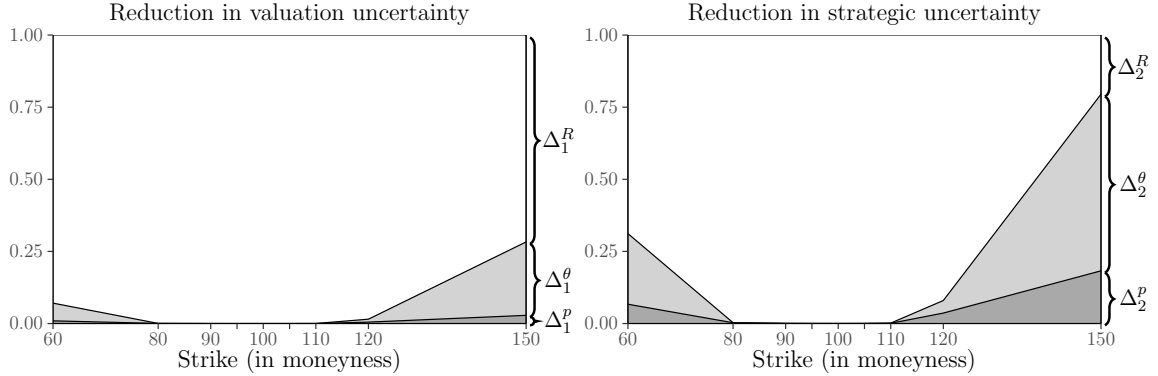


Figure 5: These two figures present the percentage reductions in valuation and strategic uncertainty under different informational settings. The left figure shows the percentage reduction in **valuation uncertainty** (y-axis) and the right figure shows the percentage reductions in **strategic uncertainty** (y-axis) by moneyness (x-axis) for the option contracts with a **time-to-expiration** of **12 months**. In the base case setting, dealers only observe private signals. This is indicated by the lower horizontal axis. The dark grey area is the percentage reduction in uncertainty due to observing the consensus price, i.e.,  $\Delta_i^p$  in (13). The light grey area indicates the further reduction in uncertainty due to observing the past state, i.e.,  $\Delta_i^\theta$ . The white area is the further reduction in uncertainty that can be achieved from an information structure that eliminates informational frictions, i.e.,  $\Delta_i^R$ . The sample period is from December 2002 to February 2015.

## 6 Conclusion

In this paper we provide empirical evidence on the ability of consensus prices to reduce valuation and strategic uncertainty among major dealer banks in the over-the-counter options market. This evidence is based on a structural model of learning from prices. The estimation uses a proprietary 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 uncertain are dealer banks that participate in the OTC derivatives market about the values of S&P 500 index options? Here we consider two dimensions of uncertainty: a dealer bank’s uncertainty about fundamental values and its uncertainty about its relative position with respect to other market participants’ valuations. Second, does the consensus price feedback help to reduce market participants’ uncertainty? Last, how well does the consensus pricing mechanism aggregate dispersed information?

We find that both valuation and strategic valuation uncertainty vary substantially across the different market segments. Dealers are more uncertain about option valuations for contracts that are predominately or exclusively traded in the OTC segment of the options market. For these contracts, they are also less certain about their relative position in relation to other market participants. Dealer banks do not appear to rely heavily on the consensus price feedback to reduce valuation uncertainty. The consensus price feedback is found to be most important for reducing strategic uncertainty, and particularly so for options with extreme contract terms. This result is consistent with the scarcity of shared valuation information 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 can be particularly valuable during episodes of market stress where high levels of strategic uncertainty can cause financial markets to freeze.

## 7 Appendix

### 7.1 Kalman Filter for Estimation

For a given contract, that is, a given time-to-expiration, moneyness, and option type (put or call), our data consists of two time series. 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  $t$ .<sup>21</sup> Our sample of submissions is then given by  $(\mathbf{p}_t)_{t=1}^T$ , where  $\mathbf{p}_t = (p_{j,t})_{j \in \iota_t}$  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 conditional expectation of  $\theta_t$ ,

$$p_{i,t} = \theta_{i,t}. \quad (14)$$

Following our model, we assume that the consensus price of period  $t$ ,  $p_t$ , equals the average expectation of period  $t$  plus aggregate noise, that is,

$$p_t = \bar{\theta}_t + \sigma_\varepsilon \varepsilon_t.$$

Our data set for a given contract,  $(\mathbf{y}_t)_{t=1}^T$ , then consists of the time-series of institutions' price submissions for this contract and the corresponding consensus price of the previous period, i.e.  $\mathbf{y}_t = (p_{t-1}, \mathbf{p}_t)^\top$ .<sup>22</sup>

To estimate the model, we fix the maximum order of beliefs at  $\bar{k} = 4$ .<sup>23</sup> Average expectations then evolve according to (5), namely,

$$x_t = M_{\bar{k}} x_{t-1} + N_{\bar{k}} v_t,$$

where  $x_t$  is the  $\bar{k} + 1$  dimensional state vector,  $M_{\bar{k}}$  and  $N_{\bar{k}}$  are functions of the parameters  $\phi$  defined recursively (see online Appendix for solution algorithm) and  $v_t = (u_t, \varepsilon_{t-1})^\top \sim N(\mathbf{0}_2, I_2)$ .<sup>24</sup> The dynamics of institution  $i$ 's conditional expectations  $x_{i,t}$  can be expressed in terms of deviations from average expectations,  $\hat{x}_{i,t} \equiv x_{i,t}(1 : \bar{k}) - x_t(2 : (\bar{k} + 1))$ ,<sup>25</sup>

$$\hat{x}_{i,t} = Q_{\bar{k}} \hat{x}_{i,t-1} + V_{\bar{k}} \eta_{i,t},$$

where

$$Q_{\bar{k}} = [M_{\bar{k}} - K_{\bar{k}}(D_{1,\bar{k}}M_{\bar{k}} + D_{2,\bar{k}})] \quad \text{and} \quad V_{\bar{k}} = K_{\bar{k}} R_\eta.$$

<sup>21</sup>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.

<sup>22</sup>This timing convention of lagging the consensus price simplifies the expression for the likelihood function in terms of  $\mathbf{y}_t$ .

<sup>23</sup>Allowing  $\bar{k}$  greater than 4 does not change the estimates noticeably.

<sup>24</sup>We 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.

<sup>25</sup> $x(j : k)$  denotes a subvector of  $x$  containing elements  $j$  to  $k$ .

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  $\mathbf{y}_t = (p_{t-1}, \mathbf{p}_t)^\top$  can be derived using the Kalman filter. We define  $\alpha_t = (x_t^\top, x_{1,t}^\top, \dots, x_{S,t}^\top, \varepsilon_{t-1})^\top$  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

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

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

We now derive the *observation equation* for the system. First note that the consensus price  $p_{t-1}$  can be expressed in terms of the past state vector  $\alpha_{t-1}$  as

$$p_{t-1} = \bar{\theta}_{t-1} + \sigma_\varepsilon \varepsilon_{t-1} = e_2^\top \alpha_{t-1} + \sigma_\varepsilon e_{\text{last}}^\top \alpha_t.$$

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

$$p_{i,t} = \theta_{i,t} = e_2^\top \alpha_t + e_n^\top \alpha_t,$$

where  $n$  corresponds to the position of the first element of  $x_{i,t}$  in  $\alpha_t$ . It follows that our observations of the system,  $\mathbf{y}_t$ , can be expressed in terms of the latent state of the system, namely

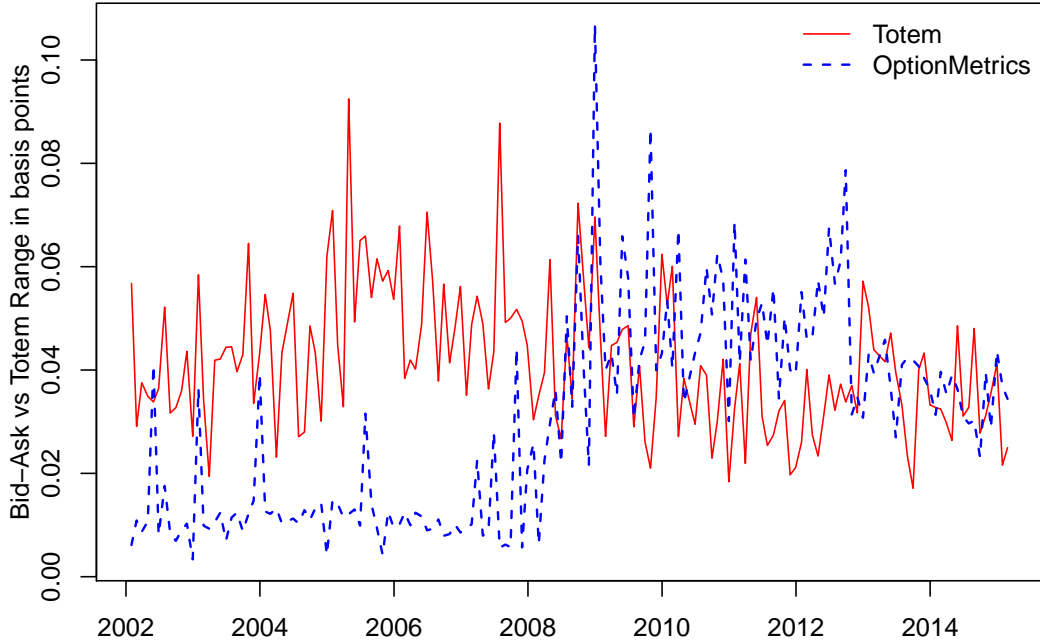
$$\mathbf{y}_t = Z_{1,t} \alpha_t + Z_{2,t} \alpha_{t-1}.$$

$Z_{1,t}$ , and  $Z_{2,t}$  are matrices that depend on the parameters of the model. To derive these matrices, 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  $\iota_t$ .  $J_t$  is a  $(|\iota_t| \times S)$  matrix whose  $k$ -th row has a 1 in position  $\iota_{k,t}$  and zeros otherwise. We have  $Z_{1,t} = J_t Z_1$  and  $Z_{2,t} = J_t Z_2$ , where

$$Z_1 = \begin{pmatrix} 0_{1 \times 1 + \bar{k} + S\bar{k}}, \sigma_\varepsilon \\ 0, 1, e_1^\top \\ 0, 1, e_{\bar{k}+1}^\top \\ \vdots \\ 0, 1, e_{(S-1)\bar{k}+1}^\top \end{pmatrix}, \quad \text{and} \quad Z_2 = \begin{pmatrix} 0, 1, 0_{1 \times (\bar{k}-2) + S\bar{k}+1} \\ 0_{1 \times 1 + \bar{k} + S\bar{k}+1} \\ \vdots \\ 0_{1 \times 1 + \bar{k} + S\bar{k}+1} \end{pmatrix}.$$

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  $\phi$  denoted  $L((\mathbf{y}_t)_{t=1}^T | \phi)$ .

Figure 6: Bid-Ask spread vs Totem's submission range



The figure above displays the cross-sectional range (the difference between the highest and lowest submitted price) of the submissions to IHS Markit's Totem service and the bid-ask spread on traded options from OptionMetrics data. The series on display are for an option contract with time-to-expiration of 6 months and moneyness 100. The bid-ask spread is given by the difference between the best closing bid price and best closing ask price across all US option exchanges. On a given Totem valuation date, we match OptionMetrics option contracts that are a close proxy to a time-to-expiration of 6 months and moneyness 100. In the OptionMetrics database we search for contracts with a  $\pm 10$  days-to-maturity and a  $\pm 1$  moneyness on Totem's valuation date. When multiple options match the criteria, an average of their bid-ask spread is taken.



Table 3: Model parameter estimates  $\phi = \{\rho, \sigma_u, \sigma_\varepsilon, \sigma_\eta\}$ 

	60	80	90	95	100	105	110	120	150	200
6	0.950 (0.019)	0.911 (0.031)	0.930 (0.028)	0.923 (0.026)	0.920 (0.028)	0.945 (0.030)	0.949 (0.022)	0.956 (0.015)	0.950 (0.021)	.
12	0.967 (0.015)	0.930 (0.024)	0.939 (0.027)	0.949 (0.028)	0.941 (0.022)	0.930 (0.025)	0.949 (0.022)	0.967 (0.013)	0.969 (0.017)	.
24	0.935 (0.025)	0.940 (0.021)	0.943 (0.020)	0.956 (0.026)	0.947 (0.028)	0.938 (0.024)	0.945 (0.023)	0.962 (0.020)	0.970 (0.015)	0.971 (0.017)
36	0.939 (0.022)	0.943 (0.026)	0.941 (0.023)	0.969 (0.026)	0.952 (0.023)	0.932 (0.021)	0.958 (0.025)	0.948 (0.021)	0.963 (0.017)	0.946 (0.021)
48	0.935 (0.022)	0.949 (0.025)	0.947 (0.022)	0.938 (0.021)	0.944 (0.024)	0.942 (0.022)	0.953 (0.026)	0.945 (0.020)	0.959 (0.017)	0.943 (0.022)
60	0.982 (0.012)	0.956 (0.028)	0.951 (0.022)	0.941 (0.021)	0.948 (0.021)	0.941 (0.025)	0.945 (0.024)	0.956 (0.027)	0.963 (0.016)	0.937 (0.026)
84	0.968 (0.011)	0.947 (0.025)	0.949 (0.026)	0.947 (0.023)	0.939 (0.019)	0.945 (0.019)	0.940 (0.022)	0.945 (0.024)	0.941 (0.023)	0.954 (0.017)

(a) Mean and standard deviation  $\rho$

	60	80	90	95	100	105	110	120	150	200
6	0.079 (0.001)	0.092 (0.005)	0.099 (0.005)	0.106 (0.006)	0.116 (0.006)	0.120 (0.007)	0.115 (0.006)	0.111 (0.002)	0.166 (0.005)	.
12	0.047 (0.001)	0.076 (0.004)	0.082 (0.005)	0.086 (0.005)	0.091 (0.005)	0.095 (0.005)	0.095 (0.005)	0.073 (0.002)	0.135 (0.003)	.
24	0.064 (0.003)	0.065 (0.003)	0.070 (0.004)	0.072 (0.004)	0.075 (0.004)	0.078 (0.004)	0.080 (0.004)	0.073 (0.004)	0.078 (0.001)	0.135 (0.005)
36	0.056 (0.002)	0.059 (0.003)	0.063 (0.003)	0.065 (0.004)	0.067 (0.004)	0.069 (0.004)	0.070 (0.004)	0.068 (0.004)	0.061 (0.001)	0.110 (0.003)
48	0.054 (0.002)	0.056 (0.003)	0.059 (0.003)	0.061 (0.003)	0.062 (0.003)	0.064 (0.003)	0.065 (0.004)	0.065 (0.003)	0.057 (0.002)	0.097 (0.002)
60	0.033 (0.001)	0.055 (0.003)	0.055 (0.003)	0.057 (0.003)	0.058 (0.003)	0.059 (0.003)	0.060 (0.003)	0.061 (0.003)	0.051 (0.002)	0.089 (0.002)
84	0.033 (0.001)	0.050 (0.003)	0.051 (0.003)	0.052 (0.003)	0.053 (0.004)	0.054 (0.003)	0.055 (0.003)	0.056 (0.003)	0.062 (0.003)	0.058 (0.001)

(b) Mean and standard deviation  $\sigma_u$

	60	80	90	95	100	105	110	120	150	200
6	0.121 (0.008)	0.004 (0.000)	0.007 (0.000)	0.009 (0.001)	0.011 (0.001)	0.016 (0.001)	0.021 (0.002)	0.151 (0.010)	0.328 (0.013)	.
12	0.055 (0.004)	0.004 (0.000)	0.006 (0.000)	0.007 (0.000)	0.009 (0.001)	0.011 (0.001)	0.014 (0.001)	0.036 (0.003)	0.262 (0.016)	.
24	0.002 (0.000)	0.004 (0.000)	0.006 (0.000)	0.007 (0.000)	0.008 (0.000)	0.009 (0.001)	0.010 (0.001)	0.015 (0.001)	0.114 (0.008)	0.270 (0.016)
36	0.003 (0.000)	0.004 (0.000)	0.005 (0.000)	0.006 (0.000)	0.007 (0.000)	0.008 (0.000)	0.008 (0.000)	0.011 (0.001)	0.054 (0.004)	0.183 (0.012)
48	0.003 (0.000)	0.004 (0.000)	0.005 (0.000)	0.006 (0.000)	0.006 (0.000)	0.007 (0.000)	0.007 (0.000)	0.009 (0.001)	0.034 (0.003)	0.121 (0.009)
60	0.032 (0.002)	0.002 (0.000)	0.004 (0.000)	0.005 (0.000)	0.005 (0.000)	0.006 (0.000)	0.006 (0.000)	0.007 (0.000)	0.024 (0.003)	0.083 (0.006)
84	0.034 (0.002)	0.003 (0.000)	0.003 (0.000)	0.004 (0.000)	0.004 (0.000)	0.004 (0.000)	0.004 (0.000)	0.005 (0.000)	0.005 (0.000)	0.069 (0.005)

(c) Mean and standard deviation  $\sigma_\varepsilon$

	60	80	90	95	100	105	110	120	150	200
6	0.096 (0.002)	0.022 (0.000)	0.015 (0.000)	0.013 (0.000)	0.013 (0.000)	0.018 (0.000)	0.030 (0.000)	0.131 (0.003)	0.380 (0.020)	.
12	0.041 (0.001)	0.014 (0.000)	0.010 (0.000)	0.010 (0.000)	0.011 (0.000)	0.015 (0.000)	0.015 (0.000)	0.036 (0.001)	0.281 (0.011)	.
24	0.024 (0.000)	0.012 (0.000)	0.009 (0.000)	0.008 (0.000)	0.008 (0.000)	0.009 (0.000)	0.013 (0.000)	0.018 (0.000)	0.093 (0.002)	0.395 (0.023)
36	0.021 (0.000)	0.011 (0.000)	0.009 (0.000)	0.008 (0.000)	0.008 (0.000)	0.009 (0.000)	0.010 (0.000)	0.015 (0.000)	0.049 (0.001)	0.231 (0.011)
48	0.022 (0.000)	0.012 (0.000)	0.010 (0.000)	0.009 (0.000)	0.009 (0.000)	0.009 (0.000)	0.011 (0.000)	0.014 (0.000)	0.035 (0.001)	0.155 (0.006)
60	0.025 (0.000)	0.012 (0.000)	0.010 (0.000)	0.009 (0.000)	0.009 (0.000)	0.010 (0.000)	0.011 (0.000)	0.014 (0.000)	0.027 (0.001)	0.116 (0.004)
84	0.029 (0.001)	0.014 (0.000)	0.011 (0.000)	0.011 (0.000)	0.011 (0.000)	0.011 (0.000)	0.012 (0.000)	0.014 (0.000)	0.023 (0.000)	0.069 (0.002)

(d) Mean and standard deviation  $\sigma_\eta$

The panels in this table present the means and standard deviations (in parentheses) of the model parameter estimates. Panel (a) displays estimates of the persistence  $\rho$  of the AR1 process for the fundamental value. Panel (b) displays estimates of the standard deviation  $\sigma_u$  of the shock to the fundamental. Panel (c) displays the estimates of the standard deviation  $\sigma_\varepsilon$  of the noise in the consensus price. Panel (d) displays the estimates of the standard deviation of the noise  $\sigma_\eta$  in private signal. Estimates are obtained using MCMC methods assuming diffuse priors for all parameters. The first row and first column of each panel give moneyness and time-to-expiration, respectively, of the option contracts under consideration. The standard deviation of the posterior distribution of the parameter is given in parenthesis below its mean (0.000 signifies standard deviations below 0.0005). The sample period of the data is December 2002 to February 2015.

Table 4: Kalman gains for  $\theta_{i,t}$  and  $\bar{\theta}_{i,t}$ 

	60	80	90	95	100	105	110	120	150	200
6	0.522 (0.012)	0.945 (0.006)	0.977 (0.003)	0.984 (0.002)	0.988 (0.001)	0.978 (0.002)	0.937 (0.007)	0.531 (0.011)	0.309 (0.015)	·
12	0.649 (0.010)	0.966 (0.004)	0.984 (0.002)	0.987 (0.001)	0.989 (0.001)	0.986 (0.002)	0.976 (0.003)	0.825 (0.010)	0.344 (0.013)	·
24	0.875 (0.013)	0.967 (0.004)	0.983 (0.002)	0.987 (0.002)	0.988 (0.001)	0.986 (0.002)	0.975 (0.003)	0.945 (0.006)	0.531 (0.011)	0.248 (0.014)
36	0.878 (0.012)	0.966 (0.004)	0.981 (0.002)	0.984 (0.002)	0.986 (0.002)	0.983 (0.002)	0.978 (0.002)	0.955 (0.005)	0.672 (0.011)	0.330 (0.015)
48	0.860 (0.014)	0.957 (0.005)	0.974 (0.003)	0.979 (0.002)	0.981 (0.002)	0.978 (0.002)	0.973 (0.003)	0.954 (0.005)	0.751 (0.012)	0.414 (0.015)
60	0.689 (0.010)	0.955 (0.005)	0.967 (0.004)	0.973 (0.003)	0.975 (0.003)	0.974 (0.003)	0.968 (0.004)	0.950 (0.006)	0.797 (0.012)	0.480 (0.016)
84	0.640 (0.010)	0.930 (0.008)	0.953 (0.005)	0.958 (0.005)	0.959 (0.005)	0.958 (0.011)	0.954 (0.005)	0.939 (0.007)	0.882 (0.012)	0.529 (0.013)

(a)  $k_s$

	60	80	90	95	100	105	110	120	150	200
6	0.081 (0.010)	0.051 (0.006)	0.018 (0.002)	0.010 (0.001)	0.006 (0.001)	0.012 (0.001)	0.040 (0.005)	0.096 (0.011)	0.116 (0.009)	·
12	0.071 (0.009)	0.030 (0.004)	0.012 (0.001)	0.008 (0.001)	0.005 (0.001)	0.007 (0.001)	0.012 (0.002)	0.072 (0.008)	0.114 (0.013)	·
24	0.132 (0.015)	0.028 (0.003)	0.012 (0.001)	0.008 (0.001)	0.006 (0.001)	0.007 (0.001)	0.014 (0.002)	0.030 (0.003)	0.089 (0.011)	0.152 (0.017)
36	0.126 (0.015)	0.029 (0.003)	0.013 (0.002)	0.010 (0.001)	0.008 (0.001)	0.009 (0.001)	0.013 (0.002)	0.028 (0.003)	0.096 (0.011)	0.139 (0.016)
48	0.147 (0.017)	0.037 (0.004)	0.019 (0.002)	0.014 (0.002)	0.012 (0.002)	0.014 (0.002)	0.017 (0.002)	0.031 (0.004)	0.102 (0.013)	0.160 (0.020)
60	0.079 (0.010)	0.045 (0.005)	0.026 (0.003)	0.020 (0.002)	0.018 (0.002)	0.019 (0.002)	0.023 (0.003)	0.038 (0.005)	0.099 (0.013)	0.190 (0.022)
84	0.093 (0.012)	0.067 (0.008)	0.042 (0.005)	0.037 (0.004)	0.035 (0.004)	0.036 (0.013)	0.039 (0.005)	0.054 (0.014)	0.117 (0.015)	0.117 (0.015)

(b)  $k_p$

	60	80	90	95	100	105	110	120	150	200
6	0.318 (0.013)	0.893 (0.012)	0.955 (0.005)	0.969 (0.003)	0.976 (0.003)	0.957 (0.005)	0.878 (0.012)	0.324 (0.012)	0.146 (0.012)	·
12	0.454 (0.013)	0.933 (0.007)	0.968 (0.004)	0.975 (0.003)	0.978 (0.002)	0.971 (0.003)	0.953 (0.005)	0.688 (0.016)	0.172 (0.011)	·
24	0.766 (0.022)	0.936 (0.007)	0.966 (0.004)	0.973 (0.003)	0.977 (0.003)	0.972 (0.003)	0.951 (0.005)	0.894 (0.011)	0.327 (0.012)	0.110 (0.009)
36	0.771 (0.022)	0.932 (0.007)	0.962 (0.004)	0.969 (0.003)	0.972 (0.003)	0.967 (0.004)	0.957 (0.005)	0.912 (0.009)	0.475 (0.015)	0.157 (0.012)
48	0.740 (0.024)	0.916 (0.009)	0.949 (0.006)	0.958 (0.005)	0.961 (0.004)	0.957 (0.005)	0.948 (0.006)	0.910 (0.010)	0.575 (0.018)	0.213 (0.014)
60	0.501 (0.013)	0.911 (0.010)	0.936 (0.007)	0.948 (0.006)	0.951 (0.005)	0.948 (0.006)	0.938 (0.007)	0.903 (0.011)	0.642 (0.019)	0.262 (0.016)
84	0.439 (0.013)	0.865 (0.015)	0.909 (0.010)	0.918 (0.009)	0.920 (0.009)	0.918 (0.019)	0.911 (0.010)	0.882 (0.013)	0.779 (0.022)	0.318 (0.015)

(c)  $\bar{k}_s$

	60	80	90	95	100	105	110	120	150	200
6	0.196 (0.022)	0.101 (0.012)	0.038 (0.004)	0.023 (0.003)	0.015 (0.002)	0.028 (0.003)	0.091 (0.010)	0.227 (0.024)	0.271 (0.018)	·
12	0.173 (0.020)	0.062 (0.007)	0.026 (0.003)	0.018 (0.002)	0.013 (0.002)	0.017 (0.002)	0.029 (0.004)	0.171 (0.017)	0.266 (0.027)	·
24	0.248 (0.027)	0.059 (0.007)	0.026 (0.003)	0.019 (0.002)	0.015 (0.002)	0.017 (0.002)	0.033 (0.004)	0.072 (0.008)	0.212 (0.024)	0.335 (0.030)
36	0.240 (0.026)	0.061 (0.007)	0.030 (0.004)	0.023 (0.003)	0.019 (0.002)	0.022 (0.003)	0.030 (0.004)	0.065 (0.007)	0.226 (0.024)	0.318 (0.032)
48	0.277 (0.030)	0.077 (0.009)	0.043 (0.005)	0.032 (0.004)	0.028 (0.003)	0.031 (0.004)	0.039 (0.005)	0.070 (0.008)	0.234 (0.025)	0.359 (0.037)
60	0.190 (0.022)	0.088 (0.011)	0.056 (0.007)	0.044 (0.005)	0.040 (0.005)	0.041 (0.005)	0.051 (0.006)	0.083 (0.010)	0.226 (0.024)	0.412 (0.039)
84	0.220 (0.025)	0.133 (0.016)	0.086 (0.010)	0.076 (0.009)	0.072 (0.008)	0.075 (0.023)	0.081 (0.010)	0.110 (0.013)	0.227 (0.025)	0.272 (0.031)

(d)  $\bar{k}_p$

This table presents the means and standard deviations (in parantheses) of the weight dealers put on “news” in the private signal and the consensus price when updating expectations about the fundamental value and the average expectation across dealers. The top panels display the Kalman gain for private signal ( $k_s$ ; Panel (a)) and the consensus price ( $k_p$ ; Panel (b)) w.r.t. the fundamental value as given in (10). The bottom panels display the Kalman gains for private signal ( $\bar{k}_s$ ; Panel (c)) and consensus price ( $\bar{k}_p$ ; Panel (d)) w.r.t. the average expectation, as given in (11). The first row and first column of each table give moneyness and time-to-expiration, respectively, of the options under consideration. The sample period of the data is December 2002 to February 2015.

Table 5: Weight  $k$  on new information and belief correlation  $\rho_{12}$ 

	60	80	90	95	100	105	110	120	150	200
6	0.625 (0.012)	0.998 (0.000)	0.996 (0.001)	0.995 (0.001)	0.995 (0.001)	0.990 (0.001)	0.978 (0.003)	0.649 (0.013)	0.465 (0.012)	· ·
12	0.733 (0.011)	0.998 (0.000)	0.996 (0.001)	0.996 (0.001)	0.995 (0.001)	0.993 (0.001)	0.989 (0.001)	0.901 (0.010)	0.490 (0.014)	· ·
24	0.999 (0.000)	0.997 (0.001)	0.995 (0.001)	0.995 (0.001)	0.995 (0.001)	0.993 (0.001)	0.990 (0.001)	0.976 (0.003)	0.639 (0.013)	0.440 (0.017)
36	0.997 (0.001)	0.995 (0.001)	0.995 (0.001)	0.995 (0.001)	0.994 (0.001)	0.993 (0.001)	0.991 (0.001)	0.984 (0.002)	0.781 (0.012)	0.513 (0.017)
48	0.996 (0.001)	0.995 (0.001)	0.994 (0.001)	0.994 (0.001)	0.993 (0.001)	0.993 (0.001)	0.991 (0.001)	0.986 (0.002)	0.860 (0.013)	0.613 (0.019)
60	0.778 (0.011)	0.999 (0.000)	0.994 (0.001)	0.994 (0.001)	0.994 (0.001)	0.993 (0.001)	0.992 (0.001)	0.989 (0.002)	0.900 (0.015)	0.703 (0.018)
84	0.747 (0.012)	0.997 (0.001)	0.996 (0.001)	0.996 (0.001)	0.995 (0.001)	0.995 (0.001)	0.994 (0.001)	0.993 (0.001)	0.994 (0.001)	0.671 (0.016)

(a)  $k$ 

	60	80	90	95	100	105	110	120	150	200
6	0.954 (0.002)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	0.958 (0.002)	0.915 (0.003)	· ·
12	0.974 (0.002)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	0.997 (0.001)	0.922 (0.003)	· ·
24	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	0.956 (0.002)	0.909 (0.004)
36	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	0.982 (0.002)	0.925 (0.004)
48	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	0.993 (0.001)	0.947 (0.003)
60	0.981 (0.002)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	0.996 (0.001)	0.964 (0.003)
84	0.976 (0.002)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)	0.962 (0.003)

(b)  $\rho_{12}$ 

This table presents means and standard deviations (in parantheses) of  $k$ , the Kalman gain as given in (12) and  $\rho_{12}$ , the correlation between  $\theta_t$  and  $\bar{\theta}_t$  according to a dealer's posterior beliefs.  $1-k$  measures how much weight a dealer puts on their prior when updating expectations about the fundamental value  $\theta_t$ . The first row and first column of each table give moneyness and time-to-expiration, respectively, of the options under consideration. The sample period of the data is December 2002 to February 2015.

Table 6: 95% posterior intervals  $\theta_t$  and  $\bar{\theta}_t$ 

	60	80	90	95	100	105	110	120	150	200
6	5.280 (0.094)	1.185 (0.014)	0.673 (0.007)	0.540 (0.006)	0.467 (0.005)	0.588 (0.006)	0.887 (0.011)	2.831 (0.048)	7.927 (0.281)	· ·
12	2.135 (0.031)	0.708 (0.008)	0.462 (0.005)	0.398 (0.004)	0.364 (0.004)	0.406 (0.004)	0.488 (0.005)	0.979 (0.013)	5.156 (0.136)	· ·
24	1.349 (0.020)	0.579 (0.006)	0.402 (0.004)	0.353 (0.004)	0.329 (0.004)	0.351 (0.004)	0.459 (0.005)	0.580 (0.007)	2.053 (0.035)	6.734 (0.274)
36	1.135 (0.017)	0.537 (0.006)	0.393 (0.004)	0.355 (0.004)	0.337 (0.004)	0.358 (0.004)	0.400 (0.004)	0.530 (0.006)	1.271 (0.020)	4.353 (0.139)
48	1.171 (0.018)	0.574 (0.007)	0.439 (0.005)	0.397 (0.004)	0.378 (0.004)	0.394 (0.004)	0.430 (0.005)	0.536 (0.006)	1.042 (0.016)	3.296 (0.088)
60	1.209 (0.018)	0.591 (0.007)	0.475 (0.006)	0.428 (0.005)	0.411 (0.005)	0.420 (0.005)	0.457 (0.005)	0.552 (0.007)	0.878 (0.013)	2.765 (0.070)
84	1.370 (0.021)	0.694 (0.009)	0.555 (0.007)	0.525 (0.007)	0.512 (0.006)	0.513 (0.010)	0.535 (0.007)	0.611 (0.008)	0.857 (0.013)	1.864 (0.040)

(a)  $3.92 \cdot \sigma_{11}^p$ 

	60	80	90	95	100	105	110	120	150	200
6	3.353 (0.049)	1.118 (0.012)	0.658 (0.007)	0.532 (0.006)	0.461 (0.005)	0.575 (0.006)	0.830 (0.009)	1.779 (0.025)	3.692 (0.088)	· ·
12	1.535 (0.018)	0.684 (0.007)	0.454 (0.005)	0.392 (0.004)	0.360 (0.004)	0.400 (0.004)	0.477 (0.005)	0.816 (0.009)	2.629 (0.056)	· ·
24	1.177 (0.014)	0.560 (0.006)	0.395 (0.004)	0.348 (0.004)	0.325 (0.003)	0.346 (0.004)	0.448 (0.005)	0.548 (0.006)	1.318 (0.019)	2.852 (0.079)
36	0.994 (0.012)	0.519 (0.006)	0.385 (0.004)	0.349 (0.004)	0.332 (0.004)	0.352 (0.004)	0.391 (0.004)	0.506 (0.005)	0.915 (0.011)	2.103 (0.052)
48	1.004 (0.013)	0.549 (0.006)	0.427 (0.005)	0.388 (0.004)	0.370 (0.004)	0.385 (0.004)	0.418 (0.004)	0.511 (0.006)	0.803 (0.010)	1.744 (0.037)
60	0.898 (0.011)	0.564 (0.006)	0.459 (0.005)	0.417 (0.005)	0.401 (0.004)	0.409 (0.004)	0.442 (0.005)	0.524 (0.006)	0.708 (0.009)	1.545 (0.032)
84	0.968 (0.012)	0.645 (0.008)	0.529 (0.006)	0.502 (0.006)	0.491 (0.006)	0.491 (0.012)	0.510 (0.006)	0.574 (0.007)	0.754 (0.010)	1.168 (0.019)

(b)  $3.92 \cdot \sigma_{22}^p$ 

This table presents the means and standards deviations (in parentheses) of the 95% posterior intervals, as implied by a dealer's posterior beliefs, for the fundamental value,  $[3.92 \cdot \sigma_{11}^p]$ , as given in (9) and for the average expectation,  $[3.92 \cdot \sigma_{22}^p]$ . The lengths of the posterior intervals are given in terms of volatility points. The first row and first column of each table give moneyness and time-to-expiration, respectively, of the options under consideration. The sample period of the data is December 2002 to February 2015.

Table 7: Counterfactual experiments - change in uncertainty

	60	80	90	95	100	105	110	120	150	200		60	80	90	95	100	105	110	120	150	200
6	1.38 (0.17)	0.12 (0.03)	0.02 (0.00)	0.01 (0.00)	0.00* (0.00)	0.01 (0.00)	0.11 (0.02)	1.58 (0.18)	2.91 (0.29)	.	6	9.65 (1.02)	0.70 (0.16)	0.12 (0.03)	0.05 (0.01)	0.03 (0.01)	0.09 (0.02)	0.77 (0.16)	10.82 (1.08)	19.17 (1.40)	.
12	0.93 (0.12)	0.05 (0.01)	0.01 (0.00)	0.00* (0.00)	0.00* (0.00)	0.00* (0.00)	0.01 (0.00)	0.50 (0.07)	2.85 (0.32)	.	12	6.70 (0.75)	0.28 (0.06)	0.06 (0.01)	0.03 (0.01)	0.02 (0.01)	0.04 (0.01)	0.10 (0.02)	3.63 (0.42)	18.27 (1.66)	.
24	0.62 (0.12)	0.04 (0.01)	0.01 (0.00)	0.01 (0.00)	0.00* (0.00)	0.00* (0.00)	0.02 (0.00)	0.07 (0.02)	1.52 (0.18)	4.36 (0.50)	24	3.48 (0.66)	0.26 (0.06)	0.06 (0.01)	0.04 (0.01)	0.03 (0.01)	0.12 (0.01)	0.54 (0.03)	10.37 (0.11)	27.33 (1.09)	(2.33)
36	0.59 (0.12)	0.04 (0.01)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.06 (0.01)	1.14 (0.14)	3.20 (0.38)	36	3.33 (0.63)	0.28 (0.06)	0.08 (0.02)	0.05 (0.01)	0.04 (0.01)	0.05 (0.01)	0.09 (0.02)	7.98 (0.09)	20.69 (0.83)	(1.93)
48	0.76 (0.15)	0.07 (0.02)	0.02 (0.01)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.02 (0.00)	0.06 (0.01)	0.92 (0.12)	3.06 (0.36)	48	4.25 (0.79)	0.44 (0.10)	0.15 (0.03)	0.10 (0.02)	0.08 (0.02)	0.10 (0.02)	0.15 (0.03)	6.50 (0.10)	19.34 (0.73)	(1.84)
60	0.93 (0.12)	0.09 (0.02)	0.04 (0.01)	0.02 (0.01)	0.02 (0.00)	0.02 (0.01)	0.03 (0.01)	0.09 (0.02)	0.76 (0.10)	3.06 (0.34)	60	6.63 (0.75)	0.53 (0.12)	0.25 (0.06)	0.16 (0.04)	0.14 (0.03)	0.15 (0.03)	0.22 (0.05)	5.29 (0.12)	19.08 (0.61)	(1.70)
84	1.21 (0.15)	0.20 (0.04)	0.09 (0.02)	0.07 (0.02)	0.06 (0.01)	0.07 (0.10)	0.08 (0.02)	0.14 (0.03)	0.53 (0.11)	1.90 (0.24)	84	8.45 (0.93)	1.18 (0.26)	0.53 (0.12)	0.43 (0.10)	0.39 (0.09)	0.44 (0.52)	0.49 (0.11)	3.08 (0.19)	12.67 (0.60)	(1.35)
(a) Reduction in valuation uncertainty: $\Delta_1^p$											(b) Reduction in strategic uncertainty: $\Delta_2^p$										
	60	80	90	95	100	105	110	120	150	200		60	80	90	95	100	105	110	120	150	200
6	12.02 (0.52)	0.01 (0.00)	0.00* (0.00)	0.00* (0.00)	0.00* (0.00)	0.01 (0.00)	0.07 (0.02)	11.35 (0.52)	27.01 (1.03)	.	6	41.31 (1.43)	0.02 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.04 (0.01)	0.27 (0.07)	38.80 (1.49)	62.69 (1.09)	.
12	6.15 (0.35)	0.00* (0.00)	0.00* (0.00)	0.00* (0.00)	0.00* (0.00)	0.00* (0.00)	0.01 (0.00)	1.02 (0.16)	25.45 (0.84)	.	12	24.49 (1.28)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.02 (0.00)	0.05 (0.01)	4.35 (0.74)	61.23 (1.52)	.
24	0.01 (0.00)	0.01 (0.00)	0.00* (0.00)	0.00* (0.00)	0.00* (0.00)	0.00* (0.00)	0.01 (0.00)	0.07 (0.02)	11.99 (0.52)	33.46 (1.21)	24	0.03 (0.01)	0.02 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.02 (0.01)	0.05 (0.07)	0.27 (1.48)	40.68 (1.95)	62.10
36	0.02 (0.01)	0.01 (0.00)	0.00* (0.00)	0.00* (0.00)	0.00* (0.00)	0.01 (0.00)	0.01 (0.00)	0.03 (0.01)	4.71 (0.34)	24.14 (1.00)	36	0.07 (0.02)	0.03 (0.01)	0.02 (0.00)	0.02 (0.00)	0.02 (0.01)	0.04 (0.01)	0.13 (0.04)	18.68 (1.31)	57.87 (1.75)	
48	0.03 (0.01)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.03 (0.01)	2.19 (0.27)	16.80 (0.82)	48	0.09 (0.03)	0.03 (0.01)	0.03 (0.01)	0.02 (0.01)	0.02 (0.01)	0.03 (0.01)	0.04 (0.01)	0.12 (0.03)	8.94 (1.16)	46.67 (1.89)
60	4.60 (0.33)	0.00* (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.03 (0.01)	1.24 (0.24)	11.55 (0.74)	60	18.72 (1.29)	0.01 (0.00)	0.03 (0.01)	0.02 (0.01)	0.02 (0.01)	0.03 (0.01)	0.04 (0.01)	5.06 (0.03)	35.14 (1.05)	
84	6.13 (0.39)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.02 (0.01)	0.04 (0.01)	10.88 (0.63)	84	23.65 (1.41)	0.04 (0.01)	0.03 (0.01)	0.03 (0.01)	0.03 (0.01)	0.04 (0.01)	0.07 (0.02)	0.13 (0.04)	36.56 (1.82)	
(c) Reduction in valuation uncertainty: $\Delta_1^\theta$											(d) Reduction in strategic uncertainty: $\Delta_2^\theta$										

The panels in this table present the counterfactual percentage decreases in valuation and strategic uncertainty. The two top panels display the reductions in uncertainties when comparing a setting without consensus price to a setting with consensus price. Panel (a) presents the results for the percentage decrease in **valuation uncertainty**,  $\Delta_1^p$  in (13). Panel (b) shows the percentage increase in **strategic uncertainty**,  $\Delta_2^p$ . The lower panels show the counterfactual percentage reductions in valuation and strategic uncertainty when comparing the current information structure to an information structure with a consensus price that perfectly reveals last period's state. Panel (c) shows percentage reduction in **valuation uncertainty**,  $\Delta_1^\theta$  in (13). Panel (d) shows the percentage reduction in **strategic uncertainty**,  $\Delta_2^\theta$ . The first row and first column of each table give moneyness and time-to-expiration, respectively, of the options under consideration. The standard deviations of the posterior distribution of the parameter is given in parentheses below the means (0.00 signifies standard deviations below 0.005). The sample period is from December 2002 to February 2015.

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