How much information is incorporated in financial asset prices? Experimental Evidence*

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ABSTRACT
We propose a new estimation method and use experimental data from multiple double auction experiments in the literature to directly estimate how much information is incorporated in financial market prices. We find that public information is almost completely reflected in prices, but that surprisingly little private information—less than 50%—is incorporated in prices. Our estimates therefore suggest that while semi-strong informational efficiency is consistent with the data, financial market prices may be very far from strong-form efficiency. We compare our estimates with beliefs of economists surveyed at the Econometric Society Meetings, and find that economists and finance researchers alike expect market prices to reflect considerably more private information than what we estimated.

JEL classification: C92, D82, D84, G14.

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“Few engineers would ever consider performing a statistical test to determine whether or not a given engine is perfectly efficient such an engine exists only in the idealized frictionless world of the imagination. But measuring relative efficiency—relative, that is, to the frictionless ideal—is commonplace.” (Lo 2008)

The efficient market hypothesis (EMH) is one of the most influential concepts in economics. It combines the Hayekian idea that market prices aggregate information held by economic agents (Hayek 1945) and Samuelson’s principles of agents’ rationality and market equilibrium (Samuelson 1965). As stated by Fama, a market is said to be informationally efficient if its prices “fully reflect” the available information (Fama 1970).

Market efficiency has important consequences for our understanding of how financial markets work, and how prices can be used to inform the decisions of economic agents from traders to governments. Therefore, whether and to what degree are markets indeed informationally efficient has been the object of intense theoretical and empirical research (Malkiel 2005; Lim and Brooks 2011). While the EMH links prices to the available information, the informational content of prices is hard to assess if trader information sets are not observed. As a consequence, the bulk of the empirical research has focused on the observable consequences of market efficiency: the fact that prices should follow random walks and be unpredictable thereby preventing the possibility of systematically profitable trading strategies.

In the present study, we directly estimate the informational content of prices. We collected the data of 664 experimental asset markets from 5 different experiments in the literature. In these experimental markets with Arrow-Debreu securities, all information sets and distributions are known, and the theoretical model prices for the information realizations can be computed. Consistent with findings from prior studies from the literature, we develop a method to estimate the share of information—as a percentage number between 0 and 100—which is reflected in the observed asset prices.

Our results are striking. First, we find evidence supporting semi-strong efficiency. Between 90% and 100% of public information is reflected in prices. Indeed, the hypothesis of all public information being incorporated cannot be rejected, at least when we consider late transaction prices. Second, our main finding is that experimental asset prices reflect surprisingly little private information. Estimates for the share of private information used by the market range between 0% and 30%, depending on the experiment. Thus, the estimates suggest that market prices are far away from the ideal of strong-form informationally efficient markets or fully revealing rational expectations equilibrium prices. Indeed, we can reject the hypothesis that 50% of private information or more is incorporated in asset prices for any of the experiments we use.

But while the share of private information incorporated in prices is small, we also demonstrate that the ensuing mispricing is smaller than these low estimates might suggest, due to a concavity in the Bayesian posterior probability function. Thus, even though markets incorporated less than 50% of private information, the prices can nevertheless be closer to the “full information price” than to the “no information price.” In a sense made precise in the paper, market prices are more than twice as close to the ideal of strong-form efficient prices as the underlying information set is to the ideal of full information.

We also compare the unexpectedly small share of information inherent in prices to the
average belief on market efficiency among economists. We conducted a survey among all 2017 Econometric Society Meeting participants—overall more than 300 academic economists responded—to see whether the estimates and their beliefs differ about how much information is reflected in asset prices. In particular, we asked academics how much information they believe is reflected in real world financial markets, and how much in the experimental asset markets we are studying (this part was incentivized with a quadratic scoring rule). On average, economists believe that real financial markets incorporate 77% of information, and that experimental markets incorporate 71% of information. These beliefs markedly overestimate our results. Indeed, only 4% of respondents had a belief equal to or less than the maximal experimental estimate (30%). These responses suggest that economists overestimate the ability of financial markets to incorporate private information; they certainly overestimate the ability of experimental markets to do so.

Our estimates are not only of academic interest, because policy proposals regularly call for relying more on market information, for example in the cases of banking supervision (e.g., Flannery, 1998; Greenspan, 2001; Flannery et al., 2010) or contingent capital with market triggers (e.g., Flannery, 2016). Since the merits of such proposals depend on how much information is incorporated in prices, the results and techniques of this paper might help in these debates. Moreover, our method can help to identify the markets and conditions that reveal more information, which tells regulators and market participants where to look for the most information. Finally, the question of whether prediction markets should be used for decision and policy making (e.g., Wolfers and Zitzewitz, 2004; Cowgill and Zitzewitz, 2015) depends on how much information the prices in these markets reveal. In this vein, our method and estimates can be used to compare prediction markets to alternative information aggregation and prediction mechanisms.

Our paper contributes to the literature by developing a method and estimating how much information is incorporated in asset prices. A vast literature surrounding the efficient market hypothesis performs tests of informational efficiency by looking at the observable consequences of efficiency on prices. We will not attempt to review this large body of literature here, overview articles can be found for example in Fama (1998), Malkiel (2003, 2005), Yen and Lee (2008), or Lo (2008). Overall, while most of this existing empirical literature contributes to the question “Are market prices informationally efficient?” by testing the empirical implications of the efficient market hypothesis, our paper instead contributes to answer the question “How informationally efficient are financial market prices?,” which the initial quote illustrates. An advantage of the experimental approach taken here is that, first, all relevant variables such as information sets of traders and asset values are observed, second, a common prior can be established, and third, causal effects are easily identified via random assignment to treatment, all of which allows for very clean and direct tests, whereas analyses based on stock market data typically have to rely on indirect tests.

Our paper also contributes to the literature on market experiments. This literature has played a substantial role in building economists’ confidence in market mechanisms by finding that even in small laboratory settings, markets are able to converge to competitive equilibrium prices (Smith, 2007). Early on, several experiments with one-period lived assets tested whether rational expectations equilibrium (REE)—a formalization of strong-form informational efficiency or the $\lambda = 1$ special case for our model—fits the experimental market data. In these studies, the REE concept was typically able to outperform competing theories such
as Walrasian equilibrium price predictions (e.g., Forsythe et al., 1982; Plott and Sunder 1982, 1988; Copeland and Friedman, 1987; Forsythe and Lundholm, 1990). However, almost all of these early studies use simple information structures, such as perfect signals for insiders that reveal the realized asset value, while we consider more complex but arguably also more realistic information structures where signals are imperfect and stochastically informative. Indeed, Plott and Sunder (1988) also features imperfect private signals, and while the REE model arguably fits their data best in some conditions, the experimental prices never fully converge to the REE price.

Later studies using similar designs have found more evidence of deviations from REE prices, indicating that the information dispersed in the market was imperfectly incorporated in the experimental prices (Biais et al., 2005; Hanson et al., 2006; Veiga and Vorsatz, 2010; Corgnet et al., 2015). Other experimental papers using different market designs, for example in the context of decentralized markets, have also found deviations from full informational efficiency (Huber et al., 2011; Bossaerts et al., 2013; Goeree and Zhang, 2015; Asparouhova et al., 2017). None of these studies estimate how much information is incorporated in prices, nor do they have a metric for it.

Our approach is related to at least one prior study which in some way quantified information in an experimental market. Bossaerts (2009, section 9) reports results from a lab experiment where 2 out of 16 traders were informed of the asset value while the remaining traders only knew the prior distribution. The author found that the Walrasian equilibrium prediction had a poor fit to the data. He then generated counterfactual predictions of Walrasian equilibria where more than the 2 traders are informed of the asset value. The equilibrium prediction with 8 out of 16 traders being informed fits the data best, i.e., transaction prices behave as if 8 of the traders are informed even though only 2 are informed. While this approach does not directly quantify how much information is used by the market, it can be viewed as quantifying how far perfect information spreads or is transmitted from informed to uninformed traders. The numbers suggest that information spreads to 6 out of 14 uninformed traders, or approximately to 43% of uninformed traders.

Our paper is structured as follows. Section I describes the market setting we use to derive our estimates and explains the designs of the experiments whose data we use. Section II explains and derives the method used to estimate how much information is incorporated in the asset prices. Section III presents the estimates and results. Section IV reports on the survey among economists, and the last section concludes. The appendices contain several robustness analyses.

I. Market setting and experimental design

A. Arrow-Debreu securities

We investigate experimental markets with Arrow-Debreu state contingent securities, also called binary options. In such markets, the asset traded has a payoff of 1 if event $A$ occurs in the near future, and a payoff of 0 if event $B$ (i.e., not $A$) occurs. Such assets are also typically used by prediction markets, which have attracted a lot of attention from economists (Arrow et al., 2008). The prices of such assets are meant to aggregate the trader information on the
likelihood of event $A$, providing an approximation for the probability of $A$ happening (Pen-nock et al., 2001; Wolfers and Zitzewitz, 2004). These markets have been used as forecasting tools for political elections (Snowberg et al., 2007), for business related variables inside corporations (Cowgill and Zitzewitz, 2015), and for macro-economic outcomes (Snowberg et al., 2012).

In this paper, we look at experiments where traders are given noisy signals about the state of nature. By design, event $A$ occurs half of the time (i.e., the prior probability of $A$ is 0.5). Information is modeled as a signal $s$ that indicate $A$ or $B$, with a $s = A$ being more likely if the state of nature is $A$, and $s = B$ being more likely if the state of nature is $B$. A signal is therefore stochastically informative about the asset value, but not perfectly so. Each trader may receive several signals, which are independently and identically distributed conditional on the state.

This setting has two natural benchmarks. First, a market price of $p = 0.5$ corresponds to the case of 0% information—it is the expected asset value ignoring all information, just based on the prior probability distribution. Second, the 100%-benchmark is the expected asset value based on all information in the market (full informational efficiency). To illustrate, suppose the entire market possesses 5 signals, which can be written as the realization vector $s = (A, A, A, A, B)$. By Bayes’ rule, the posterior probability of $A$ (and thus the asset paying off 1) given $s$ is $Pr(A|s) \approx 0.77$. Based on a simple risk neutral asset pricing model, 100% information therefore corresponds to an asset price of $p \approx 0.77$. In general, as there are more signals in $s$ in favor of $A$, the larger the posterior probability $Pr(A|s)$, and hence the more “extreme” is the asset price, i.e., closer to 1. Similarly, as there are more signals in favor of $B$, the smaller the posterior probability of $A$, and hence the more extreme and closer to 0 the asset price. Consequently, prices based on more information should be closer to 0 or 1 and farther away from the “0% price” of 0.5, which is what we exploit in our estimation.

The prices on such markets have been extensively studied. Two important properties have been observed:

**Calibration**

The empirical research on such markets has found that their prices are well calibrated (Deck and Porter, 2013; Page and Clemen, 2013 for short time to maturity; Page and Siemroth, 2017). This means that in all the situations where market prices are, say, 0.6, then in 60% of these cases the asset value is really equal to 1; when market prices are 0.7, then in 70% of these cases the asset value is equal to 1, and so on. Formally, for state of the world $\theta$ and observed prices $p_m$, well calibrated prices require $p_m = Pr(\theta = A|p_m)$. Thus, market prices of an asset paying 1 if $\theta = A$ on average equal the conditional probability of $\theta = A$ in this binary setting. This result is often interpreted as indicating that these markets provide a good estimate of the probability of event $A$.

But calibration is not equivalent to informational efficiency. The concept of calibration is closely linked with weak-form informational efficiency, because miscalibrated prices are not weak-form efficient: If the asset value is equal to 1 in 80% of the cases whenever market

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1While the underlying asset pricing model is based on risk neutrality, the appendix allows for other risk preferences with an additional risk parameter to be estimated, and generally confirms the magnitude of estimates obtained from the simpler risk neutral model.
prices are 0.7, then it would be profitable in expectation to buy at these prices, i.e., it is possible to use past price information to make profits. Thus, well calibrated prices are necessary (but not sufficient) for weak-form informational efficiency. And the fact that prices are well calibrated does not mean that they are strongly efficient and incorporate all private information.

**Underreaction to information**

The second common finding is underreaction of prices to information. Formally, market prices underreact to information and differ from the Bayesian posterior taking into account all the information present among traders. Underreaction has been observed in other settings for financial market prices (e.g., Gillette et al. 1999; Stevens and Williams 2004; Kirchler 2009). In Page and Siemroth (2017), we simply compared the full information price (2) with the observed prices and found significant differences. However, besides rejecting the hypothesis that 100% of information is used, this “reduced form” analysis cannot tell us how much information is in fact used. In the present study, we derive a structural model to do just that and estimate it on a large sample of more than 600 experimental markets with public and private information.

**B. Experimental designs**

Given the very general principles of markets with binary options, many experiments exist with this market design. We collected the market data from five experimental studies in total, all from different sets of authors. This data collection allows us to build a large data set in terms of number of observations and also to conduct our analysis over different experiments in order to have more external validity.

We start with the design of Page and Siemroth (2017)’s experiment and explain the existing differences with the other experiments afterward. In each session of the experiment, 9-12 traders participated in 12 (rounds) markets, plus one practice round in the beginning. There are overall 108 markets. The state of the world $\theta$ was binary with $\theta \in \{A, B\}$. The risky asset paid off 1 ($\theta = A$) or 0 ($\theta = B$). Thus, the task of the traders was to figure out whether the state of the world was $A$ or $B$, and trade accordingly. Each trader had an initial endowment of cash and risky assets. In the beginning of each round, traders received two binary signals for free; these were either private or public, depending on the treatment. Then traders decided whether to buy additional private signals at a fixed cost. They could buy up to 10 additional signals. All signals had the following signal quality: $\Pr(s_i = A|\theta = A) = \Pr(s_i = B|\theta = B) = 0.6$.

This information acquisition stage was followed by the trading stage, where all traders saw their signal profile, and traded in a standard continuous double auction for 3 minutes. All other experiments also used a double auction. During this time, traders could buy the assets of others for cash or sell their assets for cash (or not trade at all). At the end of the round, the state of the world as well as their earnings based on the actual asset value were revealed.

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2In fact, the asset paid off 10 in the experiment, but we normalize it to 1 in this paper to ease notation.
Other studies with similar market settings

We obtained data from several asset market experiments with similar features: a binary state/asset value, imperfect signals\(^3\) one-period lived assets (which excludes multi-period “bubble experiments”), and common asset values (otherwise there is no objective asset value). We thank all of the authors who shared their data.

First, we use two treatments from the Deck et al. (2013) study (control and liquidity treatments). They have a double auction set-up very similar to ours, with one asset whose return depended on a binary state of the world. Some parameters differ, in particular, the quality of the signals was \(\Pr(s_i = A|\theta = A) = \Pr(s_i = B|\theta = B) = 2/3\) (compared to 0.6 in our case). Moreover, their experiment had 8 traders per market (whereas we typically had 12) and each trader received exactly one signal (whereas our traders received two and were able to acquire more). From the two treatments we use the data 40 of markets in total.

Second, we use data from Fellner and Theissen (2014)’s experiment where the asset takes value \(L = 100\) or value \(H = 200\) (which we normalised to \(L = 0\) and \(H = 1\)). In each market, 10 traders each get a private signal with precision 0.6 or 0.8, depending on the round and treatment. We use 318 markets from this study.

Third, we use two treatments from Halim et al. (2017) who use a very similar design to Page and Siemroth (2017). In their control treatment, traders have the possibility to acquire private signals before trading, with a signal precision of 0.6. In their fully connected network treatment, traders can also acquire signals but this information is shared publicly with all traders in the network. In all of their treatments, traders receive two public draws for free, but because the vast majority of signals in their control treatment was private, we designate it as a private information treatment. From these two treatments we use the data of 142 markets in total.

Fourth, we use the real money, no manipulation treatment from Su and Wang (2017) which replicates the control treatment of Deck et al. (2013) and therefore uses the same parameters, i.e., also 8 signals for 8 traders with a signal precision equal to 2/3. We use the data of 20 markets from this study.

Table I summarizes all of the important experimental parameters.

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\(^3\)With perfect signals that reveal the asset value, it does not matter whether the market has one or ten signals, since they have the same informational content. The imperfect signal setup, on the other hand, allows us to infer how many signals are used to price the asset, since using more signals implies different information and hence different predicted prices.
Table I Overview of the experimental parameters

<table>
<thead>
<tr>
<th>Data source</th>
<th>Signals</th>
<th>Number markets</th>
<th>Traders per market</th>
<th>Num. signals per market</th>
<th>Signal precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deck et al. (2013)</td>
<td>private</td>
<td>40</td>
<td>8</td>
<td>8</td>
<td>2/3</td>
</tr>
<tr>
<td>Fellner and Theissen (2014)</td>
<td>private</td>
<td>318</td>
<td>10</td>
<td>10</td>
<td>0.6 or 0.8</td>
</tr>
<tr>
<td>Halim et al. (2017)</td>
<td>private</td>
<td>70</td>
<td>8</td>
<td>17.2</td>
<td>0.6</td>
</tr>
<tr>
<td>Halim et al. (2017)</td>
<td>public</td>
<td>72</td>
<td>8</td>
<td>8.2</td>
<td>0.6</td>
</tr>
<tr>
<td>Page and Siemroth (2017)</td>
<td>private</td>
<td>108</td>
<td>12</td>
<td>40.7</td>
<td>0.6</td>
</tr>
<tr>
<td>Page &amp; Siemroth (New)</td>
<td>public</td>
<td>36</td>
<td>12</td>
<td>15</td>
<td>0.6</td>
</tr>
<tr>
<td>Su and Wang (2017)</td>
<td>private</td>
<td>20</td>
<td>8</td>
<td>8</td>
<td>2/3</td>
</tr>
<tr>
<td>Sum</td>
<td></td>
<td>664</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

II. Estimation of the proportion of information reflected in prices

A. Empirical approach

This section present the structural model that allows us to estimate how much information is incorporated in asset prices. The challenge is to derive a method or model that is consistent with two results from the literature mentioned earlier: market prices are well calibrated but do not incorporate all the available information. Taking these two properties into account, it looks as if the market uses only randomly sampled subsets of the available signals to price the asset: Random sampling, because prices “are correct” based on a weak informational criterion (prices are well calibrated), and subsets of information, which explains the underreaction to information. Note that we do not impose underreaction to information in our model, we merely allow for it. Whether and to what degree prices underreact is a parameter to be estimated ($\lambda$ below).

To illustrate our approach first, let us continue the example presented in Section I.A. Given a full information set $s = (A, A, A, A, B)$, if the market only uses a share of $\lambda = 0.4$ of the information, i.e., 2 out of 5 signals, then the possible information subsets are $s' = (A, A)$ and $s'' = (A, B)$, which corresponds to prices $\Pr(A|s') \approx 0.69$ and $\Pr(A|s'') = 0.5$, respectively. If the market uses a larger share of $\lambda = 0.6$ of the information, then the possible subsets are $S' = (A, A, A)$ or $S'' = (A, A, B)$, with corresponding prices of $\Pr(A|S') \approx 0.77$ or $\Pr(A|S'') = 0.6$. Clearly, the possible prices become more extreme as the relative size of the information subset $\lambda$ increases. Given random sampling, we also know the probability that each of these possible subsets are drawn. In particular, $s'$ is more likely than $s''$ since $s$ contains more $A$ than $B$ signals. Thus, our approach allows us to estimate the size of the subset via maximum likelihood, i.e., to estimate which $\lambda$ fits the observed prices best.
B. Benchmark: The market uses all available information to price the asset

All of the experiments whose data we use have a binary state of the world $\theta \in \{A, B\}$, which is randomly drawn by nature, with both states being equally likely (i.e., the prior probability is $1/2$). Traders can hold a riskless asset with return equal to 1 (cash). Moreover, the financial market trades a risky asset that pays off 1 if and only if $\theta = A$ and 0 if and only if $\theta = B$. Each trader $i = 1, 2, \ldots, I$ in the financial market receives or acquires binary signals $j = 1, 2, \ldots, J_i$, denoted $s_{j,i} \in \{A, B\}$, from an i.i.d. distribution $\Pr(s_{j,i}|\theta)$ about the state of the world $\theta$ before trading. For example, in the Page and Siemroth (2017) experiment, we used the binary i.i.d. signal distribution

$$\Pr(s_{j,i} = A|\theta = A) = \Pr(s_{j,i} = B|\theta = B) = 0.6 \ \forall i, \forall j.$$  \hfill (1)

Denote the total number of signals in the market by $N = \sum_{i=1}^{I} J_i$ and the total number of $s_{j,i} = A$ signals in the market by $K = \sum_{i=1}^{I} \sum_{j=1}^{J_i} 1\{s_{j,i} = A\}$, where $1\{\cdot\}$ is the indicator function. To ease notation, we omit the trader subscript from now on and denote all signals in the market by $s_1, s_2, \ldots, s_N$, which are included in set $S_N$.

Assuming risk neutral pricing\footnote{This is standard and, among other reasons, can be justified by the fact that a deviation from risk neutral pricing allows risk neutral arbitrageurs to make profits in expectation. In the appendix, we allow for different risk attitudes and show that the estimates for the parameter of interest $\lambda$ remain very close to those derived based on risk neutrality.}, financial market prices perfectly incorporate all available trader information if they equal the expected asset value based on the Bayesian posterior probability of $\theta$ given all signals, i.e., if

$$p^* = \Pr(\theta = A|s_1, s_2, \ldots, s_N) = \frac{\Pr(\theta = A) \cdot \Pr(s_1, s_2, \ldots, s_N|\theta = A)}{\Pr(s_1, s_2, \ldots, s_N)} = \frac{\Pr(\theta = A) \cdot 0.6^K \cdot 0.4^{N-K}}{0.6^K \cdot 0.4^{N-K} + 0.6^{N-K} \cdot 0.4^K}.$$  \hfill (2)

Expression (2) is also the price function of a fully revealing rational expectations equilibrium with risk neutral traders. More recently, several theoretical papers have given a strategic foundation to this “full information” outcome, e.g., Reny and Perry (2006) based on double auctions with private value components or Ostrovsky (2012) in dynamic markets. If market prices follow expression (2), then all private information of traders is incorporated in the prices, i.e., financial market prices are strong-form informationally efficient. It is as if the market observed all private signals and used Bayes’ rule to price the asset. This is the theoretical benchmark and the “ideal” mentioned in the introductory quote.

C. The market uses a subset of the available information to price the asset

The informal description of our formal estimation method is that market prices are set as if the market observes only a randomly drawn (without replacement) subset $S_n \subset S_N$ of all available signals. Hence, formally, the market observes only a number $n \leq N$ of all available signals. The expected value of the asset is equal to the posterior probability of $\theta$ given all signals, because the asset pays off 1 in state $A$ and 0 otherwise.

\footnote{The expected value of the asset is equal to the posterior probability of $\theta$ given all signals, because the asset pays off 1 in state $A$ and 0 otherwise.}
signals with a corresponding number of \( k \leq K \) \( A \)-signals. For a \textit{given} subset of signals \( S_n \), the market price is again the expected asset value based on the posterior probability, except now based on the information subset \( S_n \),

\[
\hat{p} = \Pr(\theta = A|S_n) = \frac{\Pr(\theta = A) \cdot \Pr(S_n|\theta = A)}{\Pr(S_n)} = \frac{0.5 \cdot 0.6^k \cdot 0.4^{n-k}}{0.5 \cdot 0.6^k \cdot 0.4^{n-k} + 0.5 \cdot 0.6^{n-k} \cdot 0.4^k}.
\]

Using (3) and applying the conditional expectation with respect to prices on both sides, we obtain by the law of iterated expectations

\[
\mathbb{E}[\hat{p}|\hat{p}] = \mathbb{E}[\mathbb{E}[1\{\theta = A\}|S_n]|\hat{p}] 
\implies \hat{p} = \mathbb{E}[1\{\theta = A\}|\hat{p}] = \Pr(\theta = A|\hat{p}),
\]
i.e., market prices set by (3) are well calibrated. Consequently, our pricing model can accommodate both underreaction and the calibration of market prices, and allows us to quantify the underreaction.

\section{Estimation}

We can express the subsample size that the market uses as

\[
n = \lceil \lambda N \rceil,
\]

where \( \lambda \in [0, 1] \) is the share of all available signals used and \( \lceil x \rceil \) is the ceiling function which ensures that every \( \lambda \) yields a \( n \in \mathbb{N} \). \( \lambda \) is the main parameter of interest; it tells us how much information—relative to the available signals \( N \) in the entire market—is incorporated in the observed prices.

To estimate \( \lambda \), we first parameterize the error of the pricing model using the subsample (3) in predicting the observed (empirical) prices \( p_m \) for markets \( m = 1, 2, \ldots, M \). This prediction error \( \varepsilon_m \) is

\[
p_m = \hat{p}_m(\lambda, k) + \varepsilon_m \iff \varepsilon_m = p_m - \frac{0.6^k \cdot 0.4^{[\lambda N_m]-k}}{0.6^k \cdot 0.4^{[\lambda N_m]-k} + 0.5 \cdot 0.6^{[\lambda N_m]-k} \cdot 0.4^k},
\]

where \( N_m \) indicates that the number of signals available is market specific (each round in the experiment is one market). As is common in structural estimation, we model the distribution of \( \varepsilon_m \) as normal, i.e., \( \varepsilon_m \sim \mathcal{N}(0, \sigma^2) \), where the standard deviation of the error distribution \( \sigma \) is a (nuisance) parameter to be estimated.

Now we can assign a probability (technically a density) of observing a specific market price \( p_m \) given \( (\lambda, k, \sigma) \), which is

\[
\Pr(p_m|\lambda, k, \sigma) = \phi\left( \frac{\varepsilon_m}{\sigma} \right) / \sigma = \phi\left( \frac{p_m - \hat{p}_m(\lambda, k)}{\sigma} \right) / \sigma,
\]

where \( \phi(x) \) is the standard normal density. Clearly, for a given \( \lambda \) (which determines the total number of signals \( n \)), the observed price \( p_m \) can be generated by the model with several different \( k \) (number of \( A \)-signals), yielding varying errors \( \varepsilon_m \) and corresponding densities. Indeed, the observed price can be generated by all \( k \in \{ \max\{0, [\lambda N_m] - N_m + K_m\}, \min\{[\lambda N_m], K_m\} \} \), where the upper bound ensures that not more than \( n = [\lambda N_m] \) or
more than the \( K_m \) available \( A \)-signals are used, and the lower bound ensures that no more than the \( N_m - K_m \) available \( B \)-signals are used.

Since the market is assumed to draw a subset with \( n = \lceil \lambda N_m \rceil \) out of the \( N_m \) available signals randomly without replacement,

the probability distribution of the samples \((n, k)\) is hypergeometric. Thus, the probability of drawing a specific \( k \) given \( \lambda \) is

\[
    \Pr(k|\lambda) = \frac{{\binom{K_m}{k} \binom{N_m-K_m}{\lceil \lambda N_m \rceil-k}}}{{\binom{N_m}{\lceil \lambda N_m \rceil}}}. \tag{5}
\]

Informally, \((5)\) states that if the full sample has a lot of \( A \)-signals \((K_m \) large), then it is likely that a random subsample also has a lot of \( A \)-signals. So random sampling tends to generate similar fractions of \( A \) to \( B \) signals as in the full information set. Now we can bring the two probabilities of the \( \varepsilon_m \)-realizations and of the \( k \)-realizations together in a single likelihood function. The likelihood of observing market price \( p_m \) given the model is the probability of drawing an information subset with \( k \) \( A \)-signals and an error term \( \varepsilon_m \) such that \( p_m = \hat{p}(\lambda, k) + \varepsilon_m \). Thus,

\[
    \Pr(p_m|\lambda, \sigma) = \min_{\{\lceil \lambda N_m \rceil, K_m\}} \sum_{k=\max\{0,\lceil \lambda N_m \rceil\}} \Pr(p_m|\lambda, k, \sigma) \cdot \Pr(k|\lambda) \\
    = \min_{\{\lceil \lambda N_m \rceil, K_m\}} \sum_{k=\max\{0,\lceil \lambda N_m \rceil\}} \phi \left( \frac{p_m - 0.6^k \times 0.4^{\lceil \lambda N_m \rceil - k}}{\sigma} \right) \cdot \frac{\binom{K_m}{k} \binom{N_m-K_m}{\lceil \lambda N_m \rceil-k}}{\binom{N_m}{\lceil \lambda N_m \rceil}}.
\]

The objective is to find parameters \((\lambda, \sigma)\) that maximize the overall log-likelihood of observing the prices \((p_1, p_2, \ldots, p_M)\) in \( M \) markets,

\[
    (\lambda, \sigma) = \arg \max_{\lambda \in [0.1], \sigma > 0} \sum_{m=1}^{M} \ln \Pr(p_m|\lambda, \sigma).
\]

Since the objective function is not continuous in the parameter \( \lambda \) due to the ceiling function in \( n = \lceil \lambda N_m \rceil \), standard numerical maximization procedures are not applicable. We therefore use a grid optimization for all \( \lambda \in G \) with grid \( G = [0, 1] \cap \{0+0.01 \cdot l\}_{l=0,1,\ldots,100} \), and similarly for \( \sigma \) in 0.01 steps.

In some experiments or treatments the number of signals is either fixed or relatively small. In these cases, the likelihood-maximizing \( \lambda \) is typically not unique. For example, if the number of signals is fixed at 10, then any \( \lambda \in [0.01, 0.1] \) corresponds to 1 out of 10 signals and has the same likelihood. In these cases, we report the largest estimate of the likelihood-maximizing interval in the results, e.g., \( \max [0.01, 0.1] = 0.1 \) in the example. If a \( \lambda \)-estimate is not unique, then we point this out with a †-symbol in the results table.\footnote{We can derive all of our results with replacement instead, in which case we would use a binomial rather than hypergeometric mass function. We opted for no replacement here, because it tends to be less noisy and the drawn subsets \( S_n \) tend to reflect the information of the full sample \( S_N \) better.}

\footnote{For example, given the fixed number of \( N = 8 \) signals in Deck et al. (2013), any share \( \lambda \in [0.01, 0.12] \) is equivalent, namely \( n = 1 \) signal used by the market (recall the relation of \( \lambda \) and \( n \): \( n = \lceil \lambda N \rceil \)). Similarly, there is a range of \( \lambda \) for \( n = 2 \) signals, \( n = 3 \) and so on as discussed above, and the results report the largest \( \lambda \)-estimate of the interval.}
We determine confidence intervals via the bootstrap percentile method, i.e., we randomly draw rounds to create 1000 samples with the same number of rounds/observations as the full sample. For each bootstrapped sample, we compute the parameters \((\lambda, \sigma)\). The 95% confidence interval is then given by the inner 95% of the 1000 parameter estimates. This percentile bootstrap method has the advantage that the interval can never fall out of the possible interval \(\lambda \in [0, 1]\), while parametric methods based on normal distributions can.

III. Results

A. How much private information is incorporated in prices?

Table II displays the maximum likelihood estimates of \(\lambda\), which represents the share of the full sample of signals used by the market, based on data from various experiments in the literature. The variance of the error distribution \((\sigma)\) is estimated with \(\lambda\) but not displayed in the table as it is a nuisance parameter. We use three measures of the market price, since the double auction typically does not feature uniform prices. In particular, we compute \(\lambda\) based on the mean and median transaction price of every market, and based on the last transaction price to allow for the fact that later transaction prices may converge or improve towards the fundamental value. In this section, we only use treatments with private information and a comparison with public information treatments follows below.

The most striking result in Table II is that the share of signals used, \(\lambda\), is small. Most point estimates based on mean or median prices for \(\lambda\) are below 20%, except those from the Halim et al. (2017) experiment, where the point estimates indicate almost 30% of information is used to price the asset. For every experiment, we can reject the hypothesis that 50% or more information is incorporated in mean or median prices, as none of the confidence intervals of \(\lambda\) include 0.5. Overall, Su and Wang (2017) is the negative extreme in this comparison with the best estimate indicating that observed prices were no better than prices based on the prior distribution, and Halim et al. (2017) is the positive extreme.

The estimates of \(\lambda\) tend to be larger for the last transaction price, increasing for example from 4% to 10% in the Page and Siemroth (2017) experiment or from 20% to 30% in the Fellner and Theissen (2014) experiment. This improvement means that later transaction prices are closer to the full information price and incorporate more of the available information in the market. Convergence or improvement over time is a common finding in the experimental asset market literature, and very early studies already found it for double auctions (e.g., Plott and Sunder, 1982, 1988).

While framing the results in terms of “percentage of information” \(\lambda\) makes the experiments comparable, we can also look at the underlying number of signals to make the estimates comparable. In appendix B, we also run the same estimations for the Page and Siemroth (2017) data on the unaggregated transaction level data with very similar results.

In one of the Page and Siemroth (2017) treatments (29 observations) and in the Halim et al. (2017) private information treatments, two out of many signals in the market were public, so information was “predominantly private” and we classify these markets as private here. All other treatments/experiments used exclusively private signals.

This improvement over time is visible when plotting the absolute differences between the transaction prices and the full information prices over the 180 seconds of trading time. See Figure 4 in Appendix C.
**Table II**: Maximum likelihood estimates of $\lambda$ based on data from the literature

<table>
<thead>
<tr>
<th>Data source</th>
<th>mean price $\lambda$</th>
<th>median price $\lambda$</th>
<th>last price $\lambda$</th>
<th>LL</th>
<th>LL</th>
<th>LL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deck et al. (2013)</td>
<td>0.12†</td>
<td>0.12†</td>
<td>0.12†</td>
<td>9.15</td>
<td>7.93</td>
<td>2.01</td>
</tr>
<tr>
<td>(40 Obs.)</td>
<td>[0.00, 0.25]</td>
<td>[0.00, 0.25]</td>
<td>[0.00, 0.25]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fellner and Theissen (2014)</td>
<td>0.10†</td>
<td>0.20†</td>
<td>0.30†</td>
<td>100.71</td>
<td>91.62</td>
<td>35.46</td>
</tr>
<tr>
<td>(318 Obs.)</td>
<td>[0.10, 0.20]</td>
<td>[0.10, 0.20]</td>
<td>[0.20, 0.30]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Page and Siemroth (2017)</td>
<td>0.01</td>
<td>0.04</td>
<td>0.10</td>
<td>73.09</td>
<td>63.18</td>
<td>40.09</td>
</tr>
<tr>
<td>(108 Obs.)</td>
<td>[0.01, 0.05]</td>
<td>[0.01, 0.07]</td>
<td>[0.05, 0.12]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Su and Wang (2017)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>14.27</td>
<td>13.91</td>
<td>9.15</td>
</tr>
<tr>
<td>(20 Obs.)</td>
<td>[0.00, 0.12]</td>
<td>[0.00, 0.12]</td>
<td>[0.00, 0.25]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Halim et al. (2017)</td>
<td>0.29</td>
<td>0.29</td>
<td>0.30</td>
<td>27.16</td>
<td>25.65</td>
<td>13.93</td>
</tr>
<tr>
<td>(70 Obs.)</td>
<td>[0.12, 0.43]</td>
<td>[0.15, 0.46]</td>
<td>[0.19, 0.46]</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note:* The table displays the maximum likelihood estimates for the share of signals in the market used for pricing the asset ($\lambda$). The variance of the error distribution ($\sigma$) is estimated but not displayed due to lack of space. Estimates are based on the observed mean, median, or last transaction price. LL is the log-likelihood. The 95% confidence intervals below the estimates were determined by non-parametric percentile bootstrap, i.e., the confidence intervals correspond to the inner 95% of bootstrapped parameter estimates. † † estimate is the largest in the likelihood maximizing interval (see II.D for explanation)

more tangible. In the experiment with the most markets (observations), Fellner and Theissen (2014), ten traders each got one signal, so the estimates $\lambda = 0.1$, $\lambda = 0.2$, and $\lambda = 0.3$ indicate that one, two, or three out of the ten available signals are used by the market to price the asset. In Page and Siemroth (2017), each market had a varying number of signals, with an average of 41, so the market effectively used only between one and two pieces of information when dozens were available, and the later transaction prices used around four.

The estimates overall imply that the market does not incorporate all private information into prices, i.e., it is not strong-form informationally efficient. However, the estimates also suggest that markets use some information and improve over the prior price prediction of $p = 0.5$, which does not use any information, since most (but not all) 95% intervals do not include $\lambda = 0$.

**Result 1:** In none of the experiments, more than 50% of private information is incorporated into asset prices. In all but one experiment, mean and median prices incorporate no more than 20% of information.

**Result 2:** In none of the experiments, asset prices are strong-form informationally efficient, i.e., $\lambda$ is significantly different from 1 in all experiments.

**B. Understanding the low estimates of $\lambda$ (Result 1)**

Let us consider the Page and Siemroth (2017) experiment to understand the perhaps surprising finding that the market uses only a small part of the available information to
price the risky asset. The results follow inevitably from the observed prices, which are largely between 0.4 and 0.7 and are displayed in Figure 1a (a histogram of the observed mean prices), whereas the market price should be close to 0 or 1 if all information had been used (see Figure 1b for a histogram of the full information prices). Comparing graphs 1a and 1b, the observed prices do not follow the full information price prediction and they are considerably less extreme, i.e., closer to the (no information) prior price prediction of 0.5. This is underreaction to information.

According to our estimates, 1% to 4% of information (mean and median price estimates from Table II) corresponds to about 1 or 2 signals out of on average 41 signals to price the asset. Consider some simple calculations to understand the low magnitude of the estimated $\lambda$. If the market uses only 1 signal, then the posterior probability of $A$ is $\Pr(\theta = A | s = A) = 0.6$ or $\Pr(\theta = A | s = B) = 0.4$ depending on the signal realization. This is already remarkably close to the market prices between 0.4 and 0.6 that we observe (Figure 1a). If the market uses 2 signals, then the posterior probabilities are $\Pr(\theta = A | s_1 = A, s_2 = A) \approx 0.69$, $\Pr(\theta = A | s_1 = B, s_2 = B) \approx 0.31$, or $\Pr(\theta = A | s_1 = A, s_2 = B) = 0.5$, depending on the signal realization. As more signals are used, the posteriors can become more extreme, but more extreme posteriors imply a larger deviation from the observed prices and therefore do not fit the data as well.

C. Potential cause of informational inefficiency: Private vs public information

In order to understand better why only a small share of information is incorporated in asset prices, we investigate the informational reasons and compare experimental treatments where all of the signals are private and treatments where all of the signals are public. The difference $\lambda_{\text{public}} - \lambda_{\text{private}}$ represents the difficulty of aggregating and incorporating private information. There may be other reasons apart from information asymmetries why not all information is incorporated, such as mistakes in using Bayes’ rule or short sale constraints, in which case we would obtain $\lambda_{\text{public}} \neq 1$. 

Figure 1. Mean transaction prices compared with the full information price predictions.
Table III The effect of private vs public information on $\lambda$

<table>
<thead>
<tr>
<th>Data source</th>
<th>mean price $\lambda$</th>
<th>median price $\lambda$</th>
<th>last price $\lambda$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LL</td>
<td>LL</td>
<td>LL</td>
</tr>
<tr>
<td><strong>Halim et al. (2017)</strong>, Public info (72 Obs.)</td>
<td>1.00†</td>
<td>51.74</td>
<td>1.00†</td>
</tr>
<tr>
<td></td>
<td>[0.70, 1.00]</td>
<td>[0.79, 1.00]</td>
<td>[0.83, 1.00]</td>
</tr>
<tr>
<td>New treatment</td>
<td>0.15†</td>
<td>19.05</td>
<td>0.15†</td>
</tr>
<tr>
<td></td>
<td>[0.05, 0.40]</td>
<td>[0.05, 0.60]</td>
<td>[0.20, 1.00]</td>
</tr>
<tr>
<td><strong>Halim et al. (2017)</strong>, Private info (70 Obs.)</td>
<td>0.29</td>
<td>27.16</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>[0.12, 0.43]</td>
<td>[0.15, 0.46]</td>
<td>[0.19, 0.46]</td>
</tr>
<tr>
<td><strong>Page and Siemroth (2017)</strong>, Private info (108 Obs.)</td>
<td>0.01</td>
<td>73.09</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>[0.01, 0.05]</td>
<td>[0.01, 0.07]</td>
<td>[0.05, 0.12]</td>
</tr>
<tr>
<td>Mean difference public vs private</td>
<td>0.40**</td>
<td>0.42**</td>
<td>0.63***</td>
</tr>
<tr>
<td></td>
<td>[0.01, 0.81]</td>
<td>[0.01, 0.81]</td>
<td>[0.14, 0.92]</td>
</tr>
</tbody>
</table>

**Note:** The table displays the maximum likelihood estimates for the share of signals in the market used for pricing the asset ($\lambda$) and for the standard deviation of the error distribution ($\sigma$). Estimates are based either on the observed mean or median transaction prices. LL is the log-likelihood. The 95% confidence intervals below the estimates were determined by non-parametric percentile bootstrap. The mean difference is determined by bootstrapping the differences in $\lambda$ between the public and private information treatments, giving equal weight to all experiments, and then taking the mean of these differences. **Significant at the 1% level; ** significant at the 5% level; *significant at the 10% level (only displayed for mean differences).

† estimate is the largest in the likelihood maximizing interval (see II.D for explanation)

Halim et al. (2017) ran both private and public information treatments, and the $\lambda$-estimates for both of them, as well as the difference, are displayed in Table III. The share of incorporated information increases from 29% to 100% when information is public rather than private, a difference of 71 percentage points (which is significant at any conventional level). Thus, we cannot reject the hypothesis that the public information treatment of Halim et al. (2017) produced semi-strong informationally efficient prices.

In addition to the private information treatments from Page and Siemroth (2017), we ran additional public information treatments for this study, where (instead of an information acquisition stage) the computer randomly chose 10 or 20 signals to be shown to all traders prior to the double auction trading. The results in Table III show that while the share of information incorporated increases relative to the private information treatments, the number is still very low for mean and median transaction prices at 15%.

However, the estimate based on last transaction prices is 90%, a large improvement which corresponds to about 18 out of 20 signals. Moreover, the last transaction prices are not significantly different from fully informationally efficient prices ($\lambda = 1$). Thus, in our experiment, prices in the public information treatments needed time to move in the right direction. Such an improvement is often found in private information treatments, but

11Figure 5 in Appendix C visualizes this improvement over time, displaying the absolute difference between the transaction prices and the full information price over the 180 seconds of the double auction trading
it is somewhat surprising here, since the trades of others should not reveal any relevant information unlike in private information treatments, as all information was made public before trading. A recent theory explaining underreaction to public information (Ottaviani and Sørensen, 2015) does not seem to be at play here, since it relies on heterogeneous priors while all experiments we use ensured a common prior.

Result 3: In both experiments, late transaction prices are semi-strong form informationally efficient, i.e., $\lambda$ is not significantly different from 1. The mean difference of $\lambda_{\text{public}}$ and $\lambda_{\text{private}}$ over both experiments is large and significant at about 40 percentage points for mean and median transaction prices, and at about 63 percentage points for the last transaction prices. Hence, we have strong evidence that the aggregation of private information is imperfect, as the share of signals that are incorporated in prices is larger in the public information treatments. Since the $\lambda$ estimates are based on experimental data, these differences have a causal interpretation.

Result 4: The share of information incorporated into market prices ($\lambda$) is larger if information is public rather than private.

Overall, the Halim et al. (2017) experiment suggests that information asymmetries are the only obstacle to achieving full informational efficiency, as their public information treatment prices incorporate all information ($\lambda = 1$). Our data also suggests that informational asymmetries play a role, but there are separate non-informational reasons that prevent full informational efficiency, at least for early transaction prices.

Our data with low $\lambda$-estimates for early transactions suggests a temporary underreaction to public information, so that profits in these early transactions are possible in expectation by exploiting the public information to the fullest, while the estimates based on Halim et al. (2017) suggest there is no underreaction and no scope for systematic profits. Hence, the evidence on (initial) underreaction to public information is mixed.

D. Other factors influencing informational efficiency

The previous section established that the share of information incorporated in prices, $\lambda$, is significantly larger if information is public compared to private information. In this section, we conduct further difference tests to illustrate how our method can help identify conditions where more information is incorporated in prices.

First, we test whether $\lambda$ differs in the early three rounds of Page and Siemroth (2017) experiment compared to the last three rounds. Subjects likely have more experience in the last three rounds, having completed at least nine rounds before, which might translate into more efficient prices. However, the estimates in Table IV show that this is not the case: While the point estimate of the difference is up to 6 percentage points, these differences are not statistically different from zero.

Next, we test whether the share of signals $\lambda$ incorporated into prices changes by how many traders were informed, i.e., acquired extra signals in the Page and Siemroth (2017) experiment. We split the experimental data at the median to divide the sample in markets where many traders were informed in this sense and in markets where few traders were
### Table IV: Difference tests of $\lambda$ based on Page and Siemroth (2017) data

<table>
<thead>
<tr>
<th></th>
<th>mean price $\Delta \lambda$</th>
<th>median price $\Delta \lambda$</th>
<th>last price $\Delta \lambda$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Last 3 rounds vs first 3 rounds</td>
<td>0.02</td>
<td>0</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>$[-0.09, 0.06]$</td>
<td>$[-0.10, 0.07]$</td>
<td>$[-0.18, 0.25]$</td>
</tr>
<tr>
<td>Many informed traders vs few informed traders</td>
<td>$-0.02$</td>
<td>$-0.03$</td>
<td>$0.03$</td>
</tr>
<tr>
<td></td>
<td>$[-0.05, 0.02]$</td>
<td>$[-0.08, 0.02]$</td>
<td>$[-0.11, 0.19]$</td>
</tr>
<tr>
<td>Last transaction price vs first transaction price</td>
<td>0.07***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$[0.02, 0.11]$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: The table displays the average difference of $\lambda$ estimated from two subsamples, estimated from 1000 bootstrap draws. The 95% confidence intervals of the differences were determined by non-parametric percentile bootstrap. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

informed. We find that the share $\lambda$ does not significantly differ by how many traders are informed. Finally, we test whether the share of information incorporated by the last transaction price of every round differs from the information incorporated in the first transaction price. We already found $\lambda$ based on last transaction prices tended to be larger than the estimates based on mean or median transaction prices, so here we specifically test whether more information is aggregated over the course of the trading window. Table IV shows that this is indeed the case. For the Page and Siemroth (2017) experiment, the difference is 7 percentage points, which is significantly different from zero at the 1% level.

Result 5: The share of information incorporated into market prices ($\lambda$) is larger in the last transaction price compared to the first transaction price, and does not differ early vs late rounds of the experiment, nor by how many traders are informed.

### E. Price accuracy and mispricing due to imperfect information aggregation

The posterior probabilities $\Pr(A|s)$ in (2), and thus prices based upon them, are concave in the number of $A$-signals (if $s$ contains more $A$- than $B$-signals) and in the number of $B$-signals (if $s$ contains more $B$- than $A$-signals), see Figure 2 for a plot. For this reason, the mispricing that is due to imperfect information aggregation is not as pronounced as the imperfect information aggregation itself, because the first signals move the posterior a lot more than the last signals.

To quantify the effect of imperfect information aggregation on prices, we define and estimate a measure of “price accuracy” (absence of mispricing) $\psi$ that captures how close the observed prices are to full information prices. This measure differs from $\lambda$, which captures how close the information set consistent with observed market prices is to the full information set.

The price accuracy measure is of interest besides $\lambda$, because price differences due to imperfect information aggregation—more than the shares of information incorporated in
prices—determine the scope for earning profits. As is well known, perfect price accuracy means there are no profits to be made from superior information, so that even a chimpanzee could assemble a portfolio by throwing darts at newspapers [Malkiel, 2003]. However, the more price accuracy $\psi$ decreases below one, the more market prices differ from full information prices, and so more profits can potentially be made with full information. Mispricing, $1 - \psi$, can therefore be viewed as an indirect profitability measure. Moreover, traders should be willing to spend more on additional information the smaller $\psi$.

The straightforward measure of price accuracy $\psi$ is the distance between the the observed price $p_m$ and the prior (no) information price 0.5, relative to the distance between the full information price and the prior information price:

$$\psi_m = \min \left\{ 1, \frac{p_m - 0.5}{\text{Full Information Price}_m - 0.5} \right\}.$$  \hspace{1cm} (6)

The minimum operator ensures that $\psi$ cannot exceed 1 for prices that overreact to information.\footnote{The minimum operator ensures that markets which overreact to information do not compensate for underreaction to information in other markets, which might otherwise yield a perfect score of $\psi = 1$ on average, even if observed prices never actually equal full information prices.} A larger $\psi$ indicates more price accuracy and less mispricing. A value of $\psi = 1$ corresponds to no underreaction. The price accuracy measure $\psi$ can be negative if the observed price and the full information price are on opposite sides of the prior price of 0.5. But empirically $\psi$ is almost always between 0 and 1, so we can compare the magnitudes of price accuracy $\psi$ and the share of incorporated information $\lambda$.\footnote{Several other mispricing measures have been used in the literature, especially when analyzing price bubbles. For example, the relative absolute deviation measure from Stöckl et al. (2010) relates observed prices to the full information prices.}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure2.png}
\caption{Posterior probability \(\Pr(A|s)\) depending on the number of \(A\) minus \(B\)-signals in information set \(s\).}
\end{figure}
Table VOLS estimates of price accuracy $\psi$ based on data from the literature

<table>
<thead>
<tr>
<th>Data source</th>
<th>mean price $\psi$</th>
<th>median price $\psi$</th>
<th>last price $\psi$</th>
<th>LL</th>
<th>LL</th>
<th>LL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td><strong>Private information</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Deck et al. (2013)</td>
<td>0.13</td>
<td>11.92</td>
<td>0.12</td>
<td>10.92</td>
<td>0.24</td>
<td>8.83</td>
</tr>
<tr>
<td>(40 Obs.)</td>
<td>$[-0.05, 0.31]$</td>
<td>$[-0.05, 0.30]$</td>
<td>$[0.04, 0.44]$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fellner and Theissen (2014)</td>
<td>0.45</td>
<td>86.38</td>
<td>0.49</td>
<td>54.03</td>
<td>0.54</td>
<td>9.06</td>
</tr>
<tr>
<td>(318 Obs.)</td>
<td>$[0.38, 0.51]$</td>
<td>$[0.42, 0.56]$</td>
<td>$[0.46, 0.61]$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Page and Siemroth (2017)</td>
<td>0.17</td>
<td>78.13</td>
<td>0.17</td>
<td>64.77</td>
<td>0.30</td>
<td>48.18</td>
</tr>
<tr>
<td>(108 Obs.)</td>
<td>$[0.11, 0.22]$</td>
<td>$[0.10, 0.23]$</td>
<td>$[0.22, 0.36]$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Su and Wang (2017)</td>
<td>0.20</td>
<td>17.21</td>
<td>0.18</td>
<td>16.01</td>
<td>0.20</td>
<td>12.86</td>
</tr>
<tr>
<td>(20 Obs.)</td>
<td>$[0.04, 0.36]$</td>
<td>$[0.01, 0.34]$</td>
<td>$[0.01, 0.38]$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Halim et al. (2017)</td>
<td>0.38</td>
<td>41.25</td>
<td>0.40</td>
<td>40.72</td>
<td>0.44</td>
<td>27.94</td>
</tr>
<tr>
<td>(70 Obs.)</td>
<td>$[0.28, 0.49]$</td>
<td>$[0.29, 0.50]$</td>
<td>$[0.29, 0.56]$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Public information</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Halim et al. (2017)</td>
<td>0.89</td>
<td>105.13</td>
<td>0.90</td>
<td>104.84</td>
<td>0.91</td>
<td>114.75</td>
</tr>
<tr>
<td>(72 Obs.)</td>
<td>$[0.83, 0.93]$</td>
<td>$[0.84, 0.94]$</td>
<td>$[0.85, 0.96]$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>New (Page &amp; Siemroth)</td>
<td>0.34</td>
<td>33.84</td>
<td>0.37</td>
<td>28.64</td>
<td>0.58</td>
<td>25.92</td>
</tr>
<tr>
<td>(36 Obs.)</td>
<td>$[0.23, 0.47]$</td>
<td>$[0.22, 0.52]$</td>
<td>$[0.42, 0.74]$</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: The table displays the OLS estimates for the price accuracy measure $\psi$, see (6). Estimates are based on the observed mean, median, or last transaction price. LL is the log-likelihood. The 95% confidence intervals below the estimates were determined by non-parametric percentile bootstrap.

While $\psi_m$ is the price accuracy for market $m$, we can estimate the average accuracy $\psi$ in an experiment—a linear statistic—via OLS as follows:

$$Y_m = \psi (\text{Full Information Price}_m - 0.5) + \varepsilon_m,$$

with

$$Y_m = \begin{cases} 
\min\{p_m - 0.5, \text{Full Information Price}_m - 0.5\} & \text{if Full Information Price}_m > 0.5, \\
\max\{p_m - 0.5, \text{Full Information Price}_m - 0.5\} & \text{if Full Information Price}_m < 0.5.
\end{cases}$$

Table V displays the estimates for $\psi$. Clearly, for all private information treatments $\psi > \lambda$, that is, observed prices are closer to the ideal of full information prices than the information sets underlying the observed prices are to the ideal full information sets, which reflects the concavity of the posterior discussed above. However, all private information prices to fundamental values. While these measure mispricing from a single fundamental value very well, we want to relate deviations of observed prices from full information prices relative to prior information prices, yielding an index between 0 and 1.
treatments have a price accuracy $\psi$ that is significantly smaller than 1, or in other words, observed prices significantly differ from the full information prices.

Result 6: In all experiments, observed prices underreact to private information ($\psi < 1$).

Considering only private information treatments, the average $\psi$ exceeds the average $\lambda$ by a factor of about 2.6 for mean transaction prices. In other words, while the information incorporated in prices is about 10% over all experiments, the price accuracy is about 26%. Moreover, for median transaction prices $\psi$ exceeds $\lambda$ by a factor of 2.1 and for last transaction prices $\psi$ exceeds $\lambda$ by a factor of 2.1 over all private information treatments. Consequently, the mispricing due to imperfect information aggregation is smaller than the low $\lambda$-estimates may suggest.

Result 7: Over all private information treatments, price accuracy is larger than the share of incorporated information by a factor of more than 2, i.e., $\psi > 2\lambda$.

Finally, and unsurprisingly, there is generally less mispricing/more price accuracy $\psi$ with public information compared to private information, in line with the results based on $\lambda$.

Result 8: Prices are closer to full information prices if information is public rather than private.

Overall, the $\psi$-estimates in the private information treatments—all significantly below 65%—suggest that the mispricing is substantial.

IV. Survey on beliefs among academics

In the more than five decades of debate surrounding the efficient market hypothesis, many academics formed beliefs about how much information is incorporated by financial markets. It was our impression that economists have on average a lot of confidence in the ability of markets to aggregate information. The existing literature on market experiments has seemingly contributed to this perception (Smith, 2007). In order to see whether economists beliefs differ systematically from our experimental estimates, we conducted a survey asking economists to tell us how much information they think is incorporated in financial markets in general (question 1) and in experimental asset markets in particular (question 2, incentivized). We invited all participants from the Econometric Society meetings in 2017 in Australia/Asia, North America, and Europe—which are some of the largest general interest economics conferences on these continents—along with other economists to fill out the survey.

We randomly selected 10 respondents for payment (known to respondents beforehand), which was computed from respondent $i$’s answer to question 2 (denoted $r_i$) with the quadratic scoring rule

$$\text{Payment}(r_i) = 100 - 50\left(\frac{r_i}{100} - \lambda\right)^2$$

with payments ranging from a possible minimum of $53.92^{14}$ to a possible maximum of $100.$

---

14This minimum is computed based on our estimate $\lambda = 0.04$ from the Page and Siemroth (2017) median prices data, which was our main estimate at the time of the survey.
Table VI Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>mean</th>
<th>sd</th>
<th>min</th>
<th>max</th>
<th>count</th>
</tr>
</thead>
<tbody>
<tr>
<td>PercentGeneral</td>
<td>76.95</td>
<td>20.84</td>
<td>0.00</td>
<td>100.00</td>
<td>336</td>
</tr>
<tr>
<td>PercentExperimental</td>
<td>71.46</td>
<td>20.94</td>
<td>0.00</td>
<td>100.00</td>
<td>336</td>
</tr>
<tr>
<td>AcademicFinance</td>
<td>0.14</td>
<td>0.35</td>
<td>0.00</td>
<td>1.00</td>
<td>336</td>
</tr>
<tr>
<td>AcademicEcon</td>
<td>0.83</td>
<td>0.38</td>
<td>0.00</td>
<td>1.00</td>
<td>336</td>
</tr>
<tr>
<td>MethodEmpirical</td>
<td>0.39</td>
<td>0.49</td>
<td>0.00</td>
<td>1.00</td>
<td>336</td>
</tr>
<tr>
<td>MethodExp</td>
<td>0.15</td>
<td>0.36</td>
<td>0.00</td>
<td>1.00</td>
<td>336</td>
</tr>
<tr>
<td>MethodTheory</td>
<td>0.41</td>
<td>0.49</td>
<td>0.00</td>
<td>1.00</td>
<td>336</td>
</tr>
<tr>
<td>Age</td>
<td>36.91</td>
<td>9.17</td>
<td>23.00</td>
<td>74.00</td>
<td>321</td>
</tr>
<tr>
<td>Male</td>
<td>0.81</td>
<td>0.39</td>
<td>0.00</td>
<td>1.00</td>
<td>324</td>
</tr>
<tr>
<td>ContinentEurope</td>
<td>0.61</td>
<td>0.49</td>
<td>0.00</td>
<td>1.00</td>
<td>336</td>
</tr>
<tr>
<td>ContinentNA</td>
<td>0.16</td>
<td>0.37</td>
<td>0.00</td>
<td>1.00</td>
<td>336</td>
</tr>
<tr>
<td>ContinentAsia</td>
<td>0.12</td>
<td>0.33</td>
<td>0.00</td>
<td>1.00</td>
<td>336</td>
</tr>
<tr>
<td>ContinentAus</td>
<td>0.08</td>
<td>0.28</td>
<td>0.00</td>
<td>1.00</td>
<td>336</td>
</tr>
<tr>
<td>EmailProvided</td>
<td>0.69</td>
<td>0.46</td>
<td>0.00</td>
<td>1.00</td>
<td>336</td>
</tr>
</tbody>
</table>

The survey comprised of the following two main questions (secondary questions about demographics etc. and explanations are omitted here but can be found in the complete survey in the appendix).

1. Consider financial markets with risky assets whose payoffs can have different values. Traders in the economy have information, public and private, about the value of these assets. How much of this information would you say is reflected in the price of the assets? Please specify a percentage number between 0 and 100. [variable: PercentGeneral]

2. Now consider a small laboratory financial market with 10-12 traders (see details). How much information do you think is reflected in these asset prices? Please specify a percentage number between 0 and 100. [variable: PercentExperimental]

In the following analysis, we exclude all non-academics, i.e., all that did not respond (a)-(d) to question 3, because we want to compare the beliefs among academics with our estimates. Table [VI] displays the summary statistics from the survey. Overall, we obtained 336 responses from academics, most of which are from economics, and about 14% from finance. The academics are about the same share theorists and empirical researchers, with around 40% each. The mean age is 37 years and 81% of respondents are male. Most respondents live in Europe, followed by North America and Asia. This ranking reflects the fact that the European Econometric Society meeting, shared with the European Economic Association meeting, is the largest of the three conferences.

Academics on average believe that 77% of information is incorporated in financial market prices in general (PercentGeneral), and that 71% of information is incorporated in experimental asset prices (PercentExperimental). The distribution of the beliefs is also displayed in histograms in Figures 3a and 3b.

The correlation between PercentGeneral and PercentExperimental is positive but not perfect at 0.37, and significantly different from zero ($p < 0.0001$). Among only finance
academics, the correlation is slightly higher with 0.42 (significantly different from zero, $p = 0.0035$). Moreover, a t-test shows that academics on average believe that real world financial markets incorporate more information than experimental financial markets ($t = 4.288$, $df = 335$, $p < .0001$).

Result 9: **Survey:** *On average, academics believe that financial markets incorporate more*
Interestingly, although the average belief is significantly larger for real world markets compared to experimental markets, about 32% of academics believe that experimental markets incorporate more information than real world markets (i.e., PercentGeneral; < PercentExperimental; for about 32% of respondents).

Next, we want to address the question whether the beliefs of academics systematically differ from the experimental estimates. Clearly, the average belief is considerably larger than the largest estimate of private information incorporated from the data (λ = 0.3), and this difference is significant at any level (t = 36.28, df = 335, p < .0001). Moreover, only 4% of academics believe that experimental markets incorporate 30% of information or less.

Result 10: Survey: Average beliefs about how much information is incorporated in experimental asset markets far exceed the estimated share of incorporated private information. Only 4% of respondents have beliefs equal or less than the maximum estimate of λ = 0.3.

Thus, these results suggest that economists overestimate the share of private information that is incorporated in experimental asset markets. This might have important implications for the interpretation of academic policy advice, as financial market prices may not be as informed as often believed. Consequently, regulations and policies that depend on market information, such as contingent capital with market triggers (e.g., Flannery 2016), may be less effective than previously thought.

Finally, we run a multiple regression using the demographic responses to explain the responses PercentGeneral and PercentExperimental. The reference category in Table VII is female, Europe, finance, and empirical, and all the coefficients are relative to this group. Interestingly, experimentalists are more pessimistic about the ability of experimental markets to incorporate information than empirical researchers (at the 10% level). Economists on average do not hold significantly different beliefs from finance researchers, neither regarding financial markets in general nor regarding experimental markets.

Result 11: Survey: Economists on average do not hold significantly different beliefs from finance researchers.

\[^{15}\text{The average belief is also significantly different from the maximal price accuracy estimate (based on private information treatments), } \psi = 0.54, \text{ at any level } (t = 15.28, df = 335, p < .0001).\]
Table VII OLS regression explaining the survey responses.

<table>
<thead>
<tr>
<th></th>
<th>PercentGeneral</th>
<th>PercentExperimental</th>
</tr>
</thead>
<tbody>
<tr>
<td>AcademicEcon</td>
<td>-2.421</td>
<td>5.917</td>
</tr>
<tr>
<td></td>
<td>(3.253)</td>
<td>(3.810)</td>
</tr>
<tr>
<td>MethodExp</td>
<td>-0.520</td>
<td>-7.814*</td>
</tr>
<tr>
<td></td>
<td>(3.385)</td>
<td>(3.203)</td>
</tr>
<tr>
<td>MethodTheory</td>
<td>-0.441</td>
<td>-4.452</td>
</tr>
<tr>
<td></td>
<td>(2.723)</td>
<td>(2.751)</td>
</tr>
<tr>
<td>Constant</td>
<td>82.80***</td>
<td>63.78***</td>
</tr>
<tr>
<td></td>
<td>(6.204)</td>
<td>(7.343)</td>
</tr>
<tr>
<td>Demographic controls</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

V. Concluding remarks

In this paper, we present a new maximum-likelihood method to estimate how much information is incorporated in binary experimental asset markets, and use it with data from several different experiments from the literature. Our most important finding is that surprisingly little private information is reflected in prices—for most experiments less than 30%. Our private information estimates about how much information is incorporated are considerably smaller than the beliefs of most economists that participated in our incentivized survey, which indicates that economists might overestimate the ability of financial markets to aggregate private information. However, we also show that markets are very successful in incorporating public information into prices, and late transaction prices are statistically not distinguishable from full information prices. Thus, our estimates indicate that experimental markets may be semi-strong informationally efficient, but not even close to strong-form efficient.

A common observation is that strong-form informationally efficient markets imply that traders cannot systematically earn risk-adjusted profits relative to the market. However, the inverse need not be true. Our finding of not strong-form informationally efficient markets does not necessarily imply that systematic profits can be made. Our results state that markets are not perfectly efficient based on the strongest of criteria—the combined information of decentrally distributed private signals—but exploiting this inefficiency for profit might require more information than any single trader has access to. This is in contrast to the weaker criteria of semi-strong or weak informational efficiency, where the information needed to exploit an inefficiency is public. Thus, our findings of a small share of private information being integrated in prices are not necessarily in conflict with the many empirical findings that it is hard to systematically earn risk-adjusted profits.
REFERENCES


Asparouhova, Elena, Peter Bossaerts, and Wenhao Yang, 2017, Costly information acquisition in decentralized markets: An experiment Working paper.


Goeree, Jacob K, and Jingjing Zhang, 2015, Inefficient markets Working paper.


Kirchler, Michael, 2009, Underreaction to fundamental information and asymmetry in mispricing between bullish and bearish markets. an experimental study, *Journal of Economic Dynamics and Control* 33, 491–506.


## Appendix A. Other risk preferences

### Model and estimation

In the main part we model “the market” as being risk neutral, but it might be informative to ask whether our results about how much information the market uses—represented by parameter $\lambda$—is affected by this modeling choice. For example, a “risk averse market” would require a risk premium to hold all the available assets, thus there would be deviations from risk neutral prices based not on information but on risk preferences. Thus, in this section we allow for other risk preferences.

We first ask whether our results change when allowing for risk averse preferences. We parameterize risk aversion with the commonly used CARA utility function

$$u(W) = -\exp\{-aW\},$$

where $a > 0$ is the coefficient of absolute risk aversion and $W \geq 0$ is the wealth level. Parameter $a$ is estimated in addition to $\lambda$ and the nuisance parameter $\sigma$ (SD of the error distribution). However, it turns out that allowing for risk aversion does not change our results: For any grid over $a > 0$, we get a corner solution close to $a = 0$, and risk neutrality actually fits the data better. This is because average prices in our experiment were above 0.5 (the average asset value), i.e., there was a “negative” risk premium (see Figure 1a for the distribution).

Thus, we next derive a pricing model based on risk loving preferences. Again, we use an exponential utility function

$$u(W) = \exp\{rW\},$$

where $r > 0$ indicates the strength of risk lovingness and $W \geq 0$ is the wealth level. Let the probability of state $A$ given the signals $S_n$ be $\alpha := \Pr(\theta = A|S_n)$; this is the state where the asset pays off 1. Moreover, let the (fixed) supply of assets in the market be $X > 0$.

The market price $\tilde{p}$ is the one at which the risk loving representative agent is just willing to hold all assets compared to not holding any. At a higher price the representative agent is not willing to hold any assets, and at a lower price he is even more willing to hold all assets. A representative trader is indifferent between not holding any assets and holding all assets.
Table VIII: Maximum likelihood estimates for the signal-subsample share $\lambda$, the SD of the error distribution $\sigma$, and the risk seeking parameter $r$ for the Page and Siemroth (2017) data.

<table>
<thead>
<tr>
<th></th>
<th>$\lambda$</th>
<th>$\sigma$</th>
<th>$r$</th>
<th>LL</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean transaction prices</td>
<td>0.01</td>
<td>0.06</td>
<td>0.14</td>
<td>100.18</td>
</tr>
<tr>
<td>median transaction prices</td>
<td>0.02</td>
<td>0.06</td>
<td>0.21</td>
<td>97.21</td>
</tr>
<tr>
<td>last transaction prices</td>
<td>0.10</td>
<td>0.08</td>
<td>0.07</td>
<td>42.51</td>
</tr>
</tbody>
</table>

Note: The table displays the maximum likelihood estimates for the share of signals in the market used for pricing the asset ($\lambda$), for the standard deviation of the error distribution ($\sigma$), and for risk lovingness parameter $r$. Estimates are based on the observed mean, median transaction, and last transaction prices. LL is the log-likelihood.

\[
\exp(rW) = \alpha \exp(r((1 - \tilde{p})X + W)) + (1 - \alpha) \exp(r(W - X\tilde{p}))
\]
\[
\iff \exp(rW) = \exp(-rX\tilde{p})[\alpha \exp(rX + rW) + (1 - \alpha) \exp(rW)]
\]
\[
\iff \tilde{p} = -\frac{1}{rX} \ln \left( \frac{1}{\alpha \exp(rX) + (1 - \alpha)} \right).
\]

As is well known, there are no wealth effects with exponential utility, so $\tilde{p}$ does not depend on $W$. The price of the risky asset $\tilde{p}$ is increasing in risk lovingness $r$. Moreover, it can be shown that $\tilde{p} \to \alpha$ (the risk neutral price) as $r \to 0$, so the risk neutral model considered in the main part is the limiting case of this augmented model.

Since $\alpha = \alpha(\lambda, k) = \frac{0.6^k \cdot 0.4^{[\lambda N_m] - k}}{0.6^k \cdot 0.4^{[\lambda N_m] - k} + 0.6^{[\lambda N_m] - k} \cdot 0.4^k}$ (see (3)), we obtain the model price prediction
\[
\tilde{p}_m(\lambda, k, r) = -\frac{1}{rX} \ln \left( \frac{1}{\alpha(\lambda, k) \exp(rX) + (1 - \alpha(\lambda, k))} \right).
\]

The remaining steps are very similar to the risk neutral case. The likelihood of observing market price $p_m$ given the model is

\[
\Pr(p_m|\lambda, r, \sigma) = \min\{\lambda N_m, K_m\} \sum_{k = \max\{0, [\lambda N_m]\}}^{N_m - K_m} \phi \left( \frac{p_m - \tilde{p}_m(\lambda, k, r)}{\sigma} \right) / \sigma \cdot \left( \frac{K_m}{N_m - K_m} \right) \left( \frac{K_m}{[\lambda N_m] - k} \right). \]

Finally, we determine the parameters $(\lambda, r, \sigma)$ that maximize the log-likelihood function:

\[
(\lambda, r, \sigma) = \arg \max_{\lambda \in [0,1], r > 0, \sigma > 0} \sum_{m=1}^{M} \ln \Pr(p_m|\lambda, r, \sigma).
\]

In the estimation, we use the average (per trader) number of assets rather than the total number of assets for $X$. This makes $X$ invariant to the number of traders in the market, which varied in the Page and Siemroth (2017) experiment.
Results

We estimate the parameters for the Page and Siemroth (2017) data, but the conclusions are similar for the other studies as well. Based on the augmented model allowing for risk loving preferences (see Table VIII), the market uses only 1% of the private information (based on mean transaction prices), 2% (based on median transaction prices) or 10% (last transaction price). These estimates are almost identical to the risk neutral model in Table II. Thus, our main finding that the market uses little private information in pricing the asset is robust to allowing for different risk preferences.

Appendix B. Estimates based on transaction prices

Rather than using aggregated measures like mean or median transaction prices and estimating the parameters on the market level, we can also run our analysis on the transaction level, so that each transaction price is a data point. This step increases the number of data points by a factor of about 36 for the Page and Siemroth (2017) data.

The Page and Siemroth (2017)-experiment included 3 different treatments: First, a standard treatment with an endowment of 4 assets and 4 cash units for each trader each round, where the initial 2 signals were private. Second, an endowment treatment where each trader had a 50% probability to get twice the endowment, also with the initial two draws being private. And third, an initial draws treatment where the two free initial draws were public rather than private, with endowments as in the standard treatment. Note that the third treatment is different from the public information treatments we ran for this paper (results discussed in section III.C), where all signals were public.

Table IX shows the transaction level estimates and the aggregated median price estimates for comparison. Overall, the transaction level λ-estimates are very similar to those based on the aggregated data, with a maximum difference of two percentage points. The estimated share of information incorporated by transaction prices is 5%, compared to the 4% for median transaction prices reported in Table II.

Appendix C. Asset mispricing over time

Appendix D. Complete survey questionnaire
Table IX: Maximum likelihood estimates for the share of used information $\lambda$ and $\sigma$ based on transaction prices

<table>
<thead>
<tr>
<th></th>
<th>$\lambda$</th>
<th>$\sigma$</th>
<th>LL</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Transaction price estimates</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>all treatments</td>
<td>0.05</td>
<td>0.10</td>
<td>1593.92</td>
</tr>
<tr>
<td>(3952 Obs.)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>standard treat.</td>
<td>0.02</td>
<td>0.11</td>
<td>761.52</td>
</tr>
<tr>
<td>(1583 Obs.)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>endowment treat.</td>
<td>0.05</td>
<td>0.10</td>
<td>515.36</td>
</tr>
<tr>
<td>(1404 Obs.)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>initial draws treat.</td>
<td>0.11</td>
<td>0.08</td>
<td>423.02</td>
</tr>
<tr>
<td>(965 Obs.)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Median price estimates</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>all treatments</td>
<td>0.04</td>
<td>0.08</td>
<td>63.18</td>
</tr>
<tr>
<td>(108 Obs.)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>standard treat.</td>
<td>0.02</td>
<td>0.09</td>
<td>27.44</td>
</tr>
<tr>
<td>(45 Obs.)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>endowment treat.</td>
<td>0.03</td>
<td>0.07</td>
<td>22.21</td>
</tr>
<tr>
<td>(34 Obs.)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>initial draws treat.</td>
<td>0.09</td>
<td>0.06</td>
<td>19.63</td>
</tr>
<tr>
<td>(29 Obs.)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: The table displays the maximum likelihood estimates for the share of signals in the market used for pricing the asset ($\lambda$) and for the standard deviation of the error distribution ($\sigma$). Estimates are based on the observed transaction prices (upper panel) and on the median transaction price (aggregated). LL is the log-likelihood.
Figure 4. Absolute difference between transaction prices and the full information price (2) over time based on the Page and Siemroth (2017) data. The graph is smoothed via polynomial smoothing.
Figure 5. Absolute difference between transaction prices and the full information price over time based on data from the new public information treatments. The graph is smoothed via polynomial smoothing.
Information and financial asset prices

Thank you for participating. This one-page survey typically takes less than 5 minutes to complete. The study is conducted by Lionel Page (Queensland University of Technology) and Christoph Siemroth (University of Essex) as part of a research project that quantifies the amount of information that is incorporated in financial asset prices. If you have any questions about this survey, please do not hesitate to contact us at lionel.page@qut.edu.au or christoph.siemroth@essex.ac.uk.

All questions after the second are optional, but responses are appreciated.

This survey is anonymous, unless you enter your email address at the end of the survey (optional). We will randomly draw 10 respondents that provided their email address and award them a payment of up to $100 each. The payment is larger the closer the answer to question 2 is to the correct number. We use a quadratic scoring rule with the empirical number to determine payments. The expected payment is maximized by reporting the true belief. We will contact the winners by September 2017. We will not use the email address to contact you for any other purpose.

Please press the "submit" button at the end when you are satisfied with your answers. Thank you.

* Required

1. Consider financial markets with risky assets whose payoffs can have different values. Traders in the economy have information, public and private, about the value of these assets. How much of this information would you say is reflected in the price of the assets? Please specify a percentage number between 0 and 100. *
2. Now consider a small laboratory financial market with 10-12 traders (see details). How much information do you think is reflected in these asset prices? Please specify a percentage number between 0 and 100.

Details: Consider a laboratory market with 10-12 traders and an asset that pays off 10 or 0 in the near future. Both payoffs are equally likely in general. Information in the financial market is represented by signals which indicate whether the payoff is 10 or 0. A signal is correct with a probability of 0.6---i.e., it indicates payoff 10 if the payoff is indeed 10 in 60% of the cases---and incorrect with a probability 0.4. Traders may receive multiple independently drawn signals. Asset prices that incorporate 100% of the information equal the expected asset value given the signals of all the traders in the market. Asset prices that incorporate less than 100% of the information equal the expected asset value given a subset of all the signals.

3. Which category describes your career best?

Mark only one oval.

- Academic/finance
- Academic/economics
- Academic/business (non finance)
- Academic/other
- Professional/finance
- Professional/business (non finance)
- Professional/public sector
- Professional/other
- Student
- No answer

4. If academic, which research methodology do you typically use?

Mark only one oval.

- Empirical analysis
- Experiments
- Theory
- Other

5. What is your age?
6. Are you...
*Mark only one oval.*
- Female
- Male
- No answer

7. On which continent do you currently live?
*Mark only one oval.*
- Europe
- North America
- South America
- Africa
- Asia
- Australia
- No answer

8. Is there anything else you want to tell us? Perhaps why you picked your numbers in questions 1 and 2?

9. Provide your email address if you want to qualify for the payment (optional, see above)