How Do Public Forecasts Affect Price Efficiency and Welfare Allocations? -The Role of Exogenous Disclosure and Endogenous Prices in Empowering Uninformed Traders*

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ABSTRACT

In a laboratory market with half traders endowed with heterogeneous private signals and the other half uninformed, we manipulate the availability of a forecast concerning a forthcoming public signal and the informativeness of this public signal. We find that when the public signal is more informative than individual private signals, price efficiency not only improves following the forecast (short-run effect) but also after the public signal is realized (spillover effect). Public forecasts allow uninformed traders to submit limit orders closer to the fundamental value which exerts competitive pressure on informed traders. The intensified competition in market making results in more informative short-run prices, a source of *endogenous public information* which serves to increase competition among traders even after *exogenous public information* (i.e., earnings forecasts) has lost information value. We also find that uninformed traders make significantly positive profits in both periods after public forecasts and underlying public signals are announced, which suggests that informative public disclosure empowers uninformed traders.

Keywords: public forecast, information aggregation, information asymmetry, price efficiency, investor welfare, experimental market.

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1 Introduction

Public forecasts are ubiquitous. In practice, financial analysts and firm management frequently provide earnings forecasts prior to earnings announcements. Beyer et al. (2010) document that the majority of earnings news is revealed through forecasts before earnings announcements. On average, earnings announcements contain only 8% of total earnings news, while management forecasts contribute 59%, analysts' forecasts contribute 22%, and earnings pre-announcements contribute 11%. Given the prevalence of forecasts and the magnitude of the news contained in them, it is important to understand how earnings forecasts affect capital markets by advancing the timing of earnings news. The immediate effects of forecasts such as reducing information asymmetry and improving market liquidity (i.e., short-run effects) have been well documented in the literature.[1] However, whether such effects persist after the forecasted earnings are announced (i.e., spillover effects) remains unclear.

After earnings are publicly announced, the earnings forecasts contain no additional information because earnings subsumes the information content of its forecasts. If we only consider the information content of ***public information*** itself, earnings forecasts should no longer affect market after the release of earnings. We propose that public forecasts can have sustainable market effects when the role of ***private information*** is considered. In addition to public information, market participants often possess diverse private knowledge about fundamentals. For example, corporate insiders have proprietary information about production, and professional analysts have superior insights about the industry and macroeconomic environment. Market frictions may prevent efficient aggregation of these private information in prices. Public forecasts, by partially revealing the underlying information signal, can significantly affect market participants' trading behavior, and

[1] Archival studies mostly examine these short-run effects of public forecasts that arise due to their information content (e.g., Amiram, Owens, and Rozenbaum 2016; Coller and Yohn 1997). One exception is Rogers, Skinner, and Van Buskirk (2009), who study the change in market uncertainty around management forecasts. See Kothari (2001), Beyer et al. (2010), and Hirst, Koonce, and Venkataraman (2008) for literature reviews on the information role of forecasts by financial analysts and management.

consequently the efficiency of private information aggregation. Economists have been interested in understanding how institutional features such as different auction rules impact price efficiency by affecting bidders' incentives and strategies.[2] We believe that public information is an important element of the market design. Who has the right to receive information and when they receive information are choice variables in designing market rules, and these features of public information environment have potential consequences on trading decisions and market outcomes. Adopting this institutional perspective, we attempt to explore how public forecasts affect market participants' trading behavior and consequently market outcomes in a laboratory market.

A controlled laboratory market offers several advantages for addressing our research questions. First, we directly observe the distribution of private information, which allows us to analyze how prices impound heterogeneous private information and how public forecasts influence this process. Second, we can measure individual investors' beliefs, trading decisions and profits. Such individual-level information is unavailable in archival data but valuable and critical dependent variables that allow us to study how and why public forecasts change the trading behavior of investors with different private information endowments and corresponding consequences on welfare allocations.

A key feature of our laboratory market is the presence of information asymmetry due to unequal access to private information. Specifically, our market contains three groups of traders: (1) informed traders who are endowed with heterogeneous private signals about fundamental value, (2) uninformed traders who do not receive private signals, and (3) a robot liquidity trader that mechanically buys or sells for non-strategic reasons. The individual private signals have independent noise terms. Efficient aggregations of these diverse private signals is the key for achieving price efficiency (Plott and Sunder 1988). However, in the presence of noises injected by exogenous liquidity trading, market will not fully unravel information collectively held by informed traders.

[2] See a review of the use of experimental economics in studying economic institutions in Smith (1982).

Furthermore, uninformed traders can potentially inject noises to this market. Bloomfield, O'Hara, and Saar (2009) find that uninformed traders are irrational contrarian traders and their noise trading harms market efficiency. However, it is unclear whether and how public disclosures change their behavior. Given market frictions that prevent efficient private information aggregation, public information can affect the degree of efficiency in private information aggregation.[3]

In a three-period market, we manipulate the informativeness of a public signal about fundamental value and whether a forecast of this signal is present. For ease of exposition, we refer to the public signal as *earnings* and the public forecast as an *earnings forecast*. Informed traders receive idiosyncratic private signals in the first trading period, and earnings are publicly announced in the third trading period. In the second period, we manipulate whether an earnings forecast is present (*Forecast/No Forecast*). In addition, we manipulate the informativeness of earnings. In the *High Informativeness* condition, earnings is more informative than individual private signal. In the *Low Informativeness* condition, earnings is as informative as individual private signal.[4]

In the *High Informativeness* condition, we find that earnings forecasts improve price efficiency and market liquidity immediately following forecast issuance, and these beneficial effects persist after earnings are announced. Specifically, we observe smaller absolute price errors and smaller bid-ask spreads after earnings forecasts are released, and these results continue to hold even after earnings are realized. These market-level results are explained by individual trading behavior, in particular, market making. We find that earnings forecasts significantly reduce the deviation of bid offers from the fundamental value for both informed and uninformed traders. Earnings forecasts also

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[3] The noise trading introduces market frictions which makes it possible for public information such as financial accounting information to help improve the financial market efficiency. Similarly, public information such as managerial accounting information is useful in improving the efficiency of contracting in a principal-agent relationship when the exogenous noise prevents the principal from fully inferring agents' action by observing outcomes of production (Holmström 1979).

[4] We generate earnings signal by adding an independent and unbiased error term to the fundamental value. A more informative earnings signal has smaller standard deviation in the error term.

enable the uninformed traders to specify limit orders at more informative prices, which potentially exerts further pressure on the informed traders to post more competitive offers. After earnings are announced, ask offers from both informed and uninformed are closer to the fundamental values in the *Forecast* condition. Public forecasts, which result in more informative short-run prices, continue to impact trading behavior after earnings announcements because the short-run prices represent another source of public information that utilized by uninformed traders to compete against informed traders. Uninformed traders make positive profits not only in the period after earnings is announced but also in the period after earnings forecasts are announced, and the robot liquidity trader's losses are also significantly reduced in both of these two periods.

In the *Low Informativeness* condition, forecasts do not have significant effects on uninformed trading after earnings are announced and the spillover effects of public forecasts are not observed. We find evidence that the informed traders seems to use public information inefficiently when forecasts are present. Based on the value estimates elicited from informed traders after earnings announcement when forecasts are present, we find that informed traders underreact to information in prices and overreact to information in earnings. Such an inefficiency in processing public information does not exist among uninformed traders.

By identifying a mechanism through which forecasts affect trading behavior beyond their direct information content, our findings help inform regulators and firm management about the potential consequences of timely disclosure such as forecasts on price efficiency and welfare allocations. In the absence of public disclosure, informed traders exploit the passive liquidity trader as well as uninformed traders. Empowered by public disclosure, uninformed traders can become a potential threat to informed traders. Advancing the timing of informative public disclosure can allow the uninformed to participate in market competition earlier, which results in more informative short-run price, a source of *endogenous public information* that further strengthens the powers of the uninformed. Increases in market competition result in more efficient prices which protect non-strategic liquidity traders.

Our evidence concerning how public disclosure affects uninformed traders has both practical and theoretical implications. Following analytical models (e.g., Grossman and Stiglitz 1980), we define uninformed traders as market participants who have no privileged access to private information and rely solely on public information such as disclosure or market prices. In practice, a large portion of traders can be considered uninformed according to this definition. However, existing research offers limited evidence regarding their trading behavior. Bloomfield, O'Hara, and Saar (2009) first explore the behavior of uninformed traders in a laboratory market. They find that uninformed traders mostly behave as noise traders who trade irrationally. Our findings in the first period confirm their results in that uninformed traders suffer losses without public disclosure. Our new insight is that the role of uninformed traders changes with the introductions of public disclosure. Moreover, uninformed traders are able to learn from prices and use this knowledge in market making. Instead of suffering losses, uninformed traders make positive profits in both periods with informative public disclosure.

Existing experimental studies in finance focus on the ability of markets to aggregate ***private information*** (e.g., Bloomfield 1996a; Plott and Sunder 1988; Lundholm 1991; O'Brien and Srivastava 1991). In contrast, experimental studies in accounting only focuses on how market assimilates ***public information*** (Bloomfield and Wilks 2000; Dietrich et al. 2001). These two streams of literature offer unique insights by studying private and public information independently, but our understanding of markets is incomplete if the interdependency between the public and private information is overlooked. [5] Our findings suggest that the interactions among public and private information can be in both directions. On the one hand, public information affects the use of private

[5] Bloomfield (1996b) examines the interaction between the private information environment and strategic disclosure decisions by managers. His paper offers insights into the strategic disclosure literature by considering the role of private information in markets.

information in trading. On the other hand, private information can hinder the ability of traders to use public information.

Introducing private information in accounting research helps understand the subtle role of public disclosure and its welfare allocation implications. A closely related study by Barron and Qu (2014) examine how the informativeness of public information affects the aggregation of private information and find that when public information is more informative, prices are more efficient even before public information is released. This counterintuitive result on the *ex ante* effect of public information quality is explained by the change in the strategic trading decisions by privately informed traders.[6] The competitive pressure from the uninformed traders who are empowered by public disclosure and prices helps to explain our counterintuitive results on spillover effects of public forecasts. Both papers suggest that we cannot fully understand the market impacts of public disclosure by anchoring exclusively on the information content of public information. The institutional perspective, that is, how public disclosure as a market rule changes the trading decisions, deserves more attention from researchers and regulators.

The remainder of the paper proceeds as follows. Section 2 reviews related literature and discusses our predictions. Section 3 describes our experimental design and procedures. Section 4 reports and analyzes the experimental results. Section 5 concludes the paper and offers suggestions for future research.

[6] The informed traders trade more aggressively before public disclosure in the high quality public information treatment because they anticipate that the forthcoming high quality disclosure erodes their profits. Barron and Qu (2014) find that strategic informed traders execute more trades before public disclosure in high quality treatment. We do not find evidence that forecasts affect trade ratio allocations by informed traders.

2 Market Setup and Predictions

2.1 Market Setup

The disparity in information endowment, or information asymmetry, is an important feature of our markets. Accordingly, the key element of our design is the specification of private information endowment. We endow half traders with heterogeneous private information about fundamental value, the other half do not have private information.

One security is traded in a three-period market. The common prior about security value $\tilde{v}$ is a random variable which is normally distributed with a mean of 500 and a standard deviation of 200. Private information is a signal ($\tilde{s}$) about value, which is

$$\tilde{s} = v + \tilde{\varepsilon}_s \qquad (1)$$

Where $\tilde{\varepsilon}_s \sim \mathbf{N}(0, \sigma_s)$ and σ_s is 50. Four different private signals are generated by adding four independent noise terms to value. Each informed traders receive one private signal. Their private signals are unbiased and have independent noises. Thus, informed traders collectively know much more about the value than each individual.

A second feature of our design is the presence of a robot liquidity trader that mechanically buys or sells for non-strategic reasons. The presence of liquidity trader injects uncertainty to the motives behind trades, which allows rational trades to occur in a market with asymmetrically informed traders.[7] The noise introduced by the robot trader prevents human traders to infer others' information perfectly. Prices, thus, will not fully reveal all traders' information. This makes it possible for public disclosure to play a role in influencing the degree to which prices aggregate private information.

[7] In the absence of robot liquidity trader, a rational trader knows that the only reason others will trade with him/her is to profit from private information; therefore, a rational trader should not trade because trading will only make him/her worse off (Milgrom and Stokey 1982).

2.2 Experimental Manipulations

Our main manipulation is the presence of forecasts. At the beginning of period 1, informed traders receive heterogeneous private signals. At the beginning of period 3, everyone receives a public signal (i.e., earnings announcement). In the *Forecast* condition, everyone also receives an earnings forecast at the beginning of period 2. In the *No Forecast* condition, earnings forecasts are absent.

We also manipulate the informativeness of earnings. This manipulation is motivated by empirical evidence that firms with more informative earnings (proxied by higher earnings response coefficient) are more likely to provide public forecasts (Lennox and Park 2006). This evidence implies that providing forecasts of less informative earnings involves costs that are higher than benefits. Archival research cannot assess the cost and benefit of forecasting low informative earnings due to the absence of such counterfactuals. We exploit the unique advantage of experimental methods by implementing a regime that does not exist in practice to evaluate how cost and benefits of forecasts vary with informativeness of earnings.

We manipulate the informativeness of earnings by varying the noise term in the earnings. Similar to private signals, earnings ($\tilde{e}$) is a noisy but unbiased estimate of the value.

$$\tilde{e} = v + \tilde{\varepsilon}_e \qquad (2)$$

Where $\tilde{\varepsilon}_e \sim \mathbf{N}(0, \sigma_e)$. Earnings is generated by adding noise to the value, and its noise term is independent from the private signals' noise terms. Thus, earnings has additional information beyond all private signals. In the *High Informativeness* condition, σ_e = 20. Earnings are more informative than the individual private signal (σ_s = 50). In the *Low Informativeness* condition, σ_e = 50, the same as the private signal noise σ_s. Earnings are equally informative as individual private signal.

A forecast ($\tilde{f}$) is a noisy but unbiased estimate of the public signal (e).

$$\tilde{f} = e + \tilde{\varepsilon}_f \qquad (3)$$

Where $\tilde{\varepsilon}_f \sim \mathbf{N}(0, \sigma_f)$ and σ_f is 10. The noise term in the forecast is independent from both the public and private signals' noise terms. The noise term in the forecast has a relatively smaller standard deviation. This choice is motivated by archival observations that earnings forecasts are typically close to actual earnings.

2.3 Theoretical Benchmark: Strong Form Market Efficiency

To evaluate the degree of information efficiency, we use a theoretical benchmark based on security's expected value when all available information is aggregated into prices. Specifically, the expected value is a weighted average of all available information where the weight on each signal is proportional to the signal's precision. We measure the degree of price efficiency by comparing observed prices to this theoretical benchmark. The derivations of the theoretical benchmark are elaborated in Appendix A.

There is aggregate uncertainty in our market as the collective information does not fully reveal the fundamental value (Lundholm 1991). It is useful to quantify the change in the aggregate uncertainty over time to see how each information event reduces aggregate uncertainty. To gauge the aggregate uncertainty, we calculate the standard deviation of posterior beliefs given all information available in the economy. Below is a summary of aggregate uncertainty assuming strong form efficiency when forecasts are available with larger numbers indicate greater uncertainty.

	Period 1	**Period 2**	**Period 3**
High Informativeness	24.8	16.6	15.6
Low Informativeness	24.8	22.3	22.2

In period 1, the posterior beliefs are calculated based on the prior and all private signals. Aggregate uncertainty is the same between the *High* and *Low Informativeness* conditions (i.e., standard deviation is 24.8). In period 2, the forecasts provide new information which reduces aggregate uncertainty. The standard deviation drops to 16.6 in the High *Informativeness*, and to 22.3

in the *Low Informativeness* condition. The drop is larger when earnings are more informative. In period 3, earnings announcements further reduce aggregation uncertainty, but the reduction is relatively small because forecasts are very accurate and preempt most of the news in earnings. Specifically, the standard deviation decreases from 16.6 to 15.6 in the *High Informativeness*, and decreases from 22.3 to 22.2 in the *Low Informativeness* condition.

In essence, the presence of forecasts splits total earnings news into two pieces: one is revealed through the forecasts in period 2 and the remainder is revealed through earnings in period 3. To get a measure of the information split, we calculate the percentage of variance reduction due to earnings news that occurs at period 2 and period 3. In the *High Informativeness* condition, 91% of earnings news is revealed in forecasts and 9% left in earnings. This split is similar to the findings in the archival study by Beyer et al. (2010). In the *Low Informativeness* condition, 97% of earnings news is revealed in forecasts and 3% is left in earnings. The residual news in earnings is extremely small both in percentage and absolute terms, which scenario may not exist in practice. We implement this regime to shed light on potential reasons for why it is not observed.

2.4 Hypotheses on Market Effects of Forecasts

The analysis above on the effects of forecasts on changes in aggregate uncertainty suggests that providing forecasts have two effects. First, forecasts allow earnings news to be revealed earlier and reduce uncertainty earlier ("timing effect"). Second, compared to the *No Forecast* condition, the total earnings news is split in two separate news: forecast news and subsequent earnings news ("split effect"). Based on economic theory, the timing effect has the potential to affect how the equilibrium of the trading game plays out, but the split effect should not matter assuming traders are rational Bayesian as whether traders receive the total earnings news all at once or in two pieces makes no difference. [9] Accordingly, our discussions below focus on how the timing effect lead to changes in trading behavior and market outcomes.

2.4.1 The Spillover Effects of Forecasts on Price efficiency

To analyze the effect of public forecasts on private information aggregation, we need to understand the micro-structure of trading which determines how fast private information is impounded into prices.[10] The key concept we rely on is the competition in trading. We draw on intuition from simplified trading models, in particular, the strategic trading model of Kyle (1985). The original Kyle model only has one trader who is perfectly informed about value and enjoys monopoly power of private information. Holden and Subrahmanyam (1992) extend to multiple informed traders to gain insights about market competition. As the number of informed traders increases, market approaches strong form efficiency. Foster and Viswanathan (1996) introduce imperfect private information that are correlated with each other. The uncorrelated portion of private information gives trader some degree of monopoly power because this part is known only to him. This reduces the degree of competition and provides an incentive to trade less aggressively.

Our market has four informed traders who each receives a private signal with noise terms that are independent across traders. As in Foster and Viswanathan (1996), the uncorrelated portion of information in their private signals reduces their incentive to trade aggressively. The public forecasts provide information to all traders, which potential impacts trading incentives for both informed and uninformed. For informed traders, forecasts increases the correlation of their information due to increases in common information, which incentivizes informed traders to trade more aggressively.

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[9] Experimentally, we cannot rule out the possibility that human traders may suffer biases and use heuristics in information processing so that the split effect may exist for behavioral reasons. Our study is not designed to study such behavioral biases. We collect subjective beliefs data by asking traders make estimates of the fundamental value and we use these subjective estimates to infer how efficiently they use their information.

[10] Ideally, an analytical model incorporating the feature of our information structure and market mechanism provides clear predictions, but such models are extremely complex, in particular, continuous time double auction is hard to model.

For uninformed traders, public information in forecasts reduces their relative information disadvantage. Consider the case in which public information is much more precise than individual private information so that public information dominates. The correlation of the information among all traders increases. Therefore the number of market participants actively participating in trading increases from four (informed traders only) to eight (both informed and uninformed traders), which leads to more intense competition. In the *High Informativeness* condition, forecasts are more precise than individual private signals. In the *Low Informativeness* condition, forecasts are equally precise as individual private signals. We expect that the competition effects of forecasts are stronger in the *High Informativeness* than in the *Low Informativeness* condition.

The more informative short-run prices represent another important source of public information. After earnings are announced, the total amount of **exogenous** public information is the same whether forecasts are present or not. However, the **endogenous** public information is higher when forecasts are present because more efficient short-run prices provide public information to both informed and uninformed traders. If traders learn information from prices, more informative short-run prices may also lead to an increase in competition among all traders and consequently more efficient prices after earnings are announced. Thus, forecasts can have spillover effects into the period after earnings announcement even though the information value of forecasts are lost.

Our hypotheses above hinge on the following assumptions: (1) the release of earnings forecasts sufficiently increases the correlation of information among informed and uninformed traders, and their competition results in more informative prices and (2) traders rationally infer information from prices and competition further increases even after earnings announcements. Whether traders learn from prices remains a question that awaits evidence. We ask traders to estimate fundamental value after various information events, and these value estimates allow us to infer the degree to which traders extract information from prices.

The measure of competition is rather specific to our trading mechanism, which is different from the Kyle-type model. The most important difference is that our traders can choose whether to make or take market. We expect informed traders play the role of market makers as in Bloomfield, O'Hara, and Saar (2005). However, it is unclear how uninformed traders participate in the market. In a market without public disclosure, Bloomfield, O'Hara, and Saar (2009) show that uninformed traders behave like noise traders and suffer losses by trading irrationally. In our setting, public information such as earnings forecasts or prices may equip the uninformed with the ability to participate and compete in market making. We analyze individual market making behavior to explore this possibility.

3 The Experiment

This section describes our experimental design and the features of our experimental market. A *session* refers to a four-hour laboratory session during which a group of eight subjects trade shares of stock in a market with a single asset, which is referred to as a *security*. Securities are traded one at a time, and we refer to the trading of each security as a *trial*. In each session there are 32 trials (and thus 32 securities).

3.1 Experimental Design

We manipulate two factors in our experiment: (1) the informativeness of the public signal and (2) the presence of a forecast. We adopt a 2 × 2, within-subject design (*Low Informativeness/High Informativeness* × *Forecast/No Forecast*). Each session includes 32 trials, and we rotate the order of our factor manipulations to mitigate an order effect. Table 1 provides a session summary.

[Insert Table 1 here]

We generate 32 securities with independent liquidating values and private signal realizations, and use these securities for all sessions. The liquidating value realizations are independent between the 32 securities. The mean (standard deviation) of the realized liquidating values is 553.31 (182.62), and the values range from 154 to 823. The mean (standard deviation) of the four private signals' noise terms are 4.31 (45.71), 8.47 (53.75), -0.34 (47.47) and 5.72 (50.57).

The public signals' realized noise terms have mean (standard deviation) of 3.59 (45.97) and 2.75 (18.14) in the *Low Informativeness* and *High Informativeness* conditions, respectively. The mean (standard deviation) of the forecasts' noise terms is 1.58 (10.17). We performed statistical tests to verify that the properties of the realized values for each randomly generated parameter are not statistically different from the theoretical distributions.

3.2 Procedures

We conducted our experiments using a computerized continuous double auction market through the Financial Trading System (FTS) software.[11] We conducted eight sessions of market experiments at a computer laboratory in a large state university during the Fall 2014 and Spring 2015 semesters. Eight student subjects (undergraduate and graduate) participated in each session.

Given the complexity of the task for this experiment, we divided the total experiment study into two parts. The first part was a two-hour session devoted to training and practice to familiarize the subjects with the task and trading software. We recruited subjects for training sessions with group sizes of up to 30 individuals. In these training sessions, participants read the instructions and completed quiz questions to test their understanding of the instructions and experimental task. The experimenter then reviewed the instructions and answers to the quiz questions. Subjects practiced trading a minimum of 10 securities under both *Forecast* and *No Forecast* conditions. Subjects' trading profits during the training sessions did not affect their cash compensation; instead, subjects were paid a flat fee of $30 for completing the two-hour training session.[12]

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[11] http://www.ftsweb.com/

[12] Data from the training sessions is not included in any of our analyses.

Trained subjects were invited back to participate in the second part of the study. During these sessions, eight subjects traded 32 securities. Subjects were paid in cash after successfully completing the session based on their trading and value estimating performance, which was measured in a fictitious currency called "experimental dollars" and converted to U.S. dollars at a rate of $1 for every 1000 experimental dollars. Each subject began the session with a base cash payment of $30. Trading profits (losses) increased (decreased) the base cash payment to a minimum payment of $5, which was the guaranteed payment for participating in the session. Additionally, subjects were able to increase their cash payment by making accurate value estimates. At the end of each session, we randomly selected one trial and paid the traders based on the accuracy of the selected estimate. Specifically, subjects earned $10 minus 0.2 times their absolute estimate error, which is the absolute value of the difference between their value estimate and the realized fundamental value. Each session lasted approximately four hours, and the average cash payment was $53.60.

The timeline of events for each trial is summarized in Figure 1.

[Insert Figure 1 here]

At the beginning of each trial, half of the traders receive independent private signals about the security's value. We rotate trader types in each session so that subjects alternate between informed and uninformed approximately every other trial. The rotation allows all subjects experiences being both informed and uninformed. Trading pauses after one minute, and traders make their first estimates of the liquidating value (denoted F_1). In the *Forecast* condition, the experimenter announces a forecast of earnings. After the forecast is announced, traders submit a second estimate of the security's value (denoted F_2), and the second trading period begins. There is no public announcement of a forecast in the *No Forecast* condition; thus, we do not collect F_2 in this condition. After trading again for one minute, the market pauses and the experimenter announces the earnings. Following this announcement, traders make their final estimates of the security's value (denoted F_3), and the third trading period begins. At the conclusion of the third period, the market closes. The security's is liquidated, trading profits are calculated, and subjects receive feedback about their trading performance. The same procedure is repeated for each of the trading of 32 securities.

At the beginning of each trial, traders are endowed with zero shares and zero experimental dollars. Unlimited borrowing and short selling are permitted at zero cost. If traders sell short, their positions in the security become negative. At the end of the trial, if a trader's position is negative, an amount equal to the liquidating value multiplied by the quantity of the short position is deducted from the trader's account. Traders' experimental dollars and stock position carryover from period-to-period in each trial, but they do not carry over from one trial to another.

Trading is organized as a continuous double auction. Traders can make bid and ask offers by submitting limit orders with prices at which they are willing to buy or sell. To simplify the task, the quantity of each order is restricted to be 1. A bid offer specifies the price at which a trader is willing to buy a share, and an ask offer specifies the price at which a trader is willing to sell a share. Traders can submit an unlimited number of limit orders at any time during the trading periods. When there are outstanding orders in the market, traders can accept them by submitting market orders to buy or sell. A transaction occurs when a limit order has been accepted.[13] The robot trader submits a market order to buy or sell a share every 10 seconds, and the choice between buy or sell is randomly determined. All traders are informed about the presence of the robot trader. However, transactions activity in the market are is anonymous, and thus traders are unaware of the identity or type (i.e., informed, uninformed, or robot) of the party they engage in trade with.

[13] If a trader accepts a bid offer, he will sell a share at the highest bid price and the trader who made the corresponding bid offer buys a share; if a trader accepts an ask offer, he will buy a share at the lowest ask price and the trader who made the corresponding ask offer sells a share. All trades are executed at the best available price.

4 Results

We first analyze the price at the aggregate market level, and then the trading and forecasting behavior at the individual level.

4.1 Market-Level Analysis

4.1.1 Absolute Price Errors

We define price error as the difference between a transaction price and the full-information benchmark we derive in Appendix A. The absolute value of the price error is a measure of price efficiency. A smaller absolute price error indicates that market prices are more informationally efficient. Figure 2 plots the evolution of absolute price errors over time. We measure absolute price errors at the transaction level and average the errors over 15-second intervals.[14]

[Insert Figure 2 here]

We observe that absolute price errors decrease throughout the trial, consistent with prices gradually reflecting more information over time. Panel A plots the evolution of absolute price errors in the *High Informativeness* condition, with the solid line showing the *Forecast* treatment and the dotted line showing the *No Forecast* treatment. In all three trading periods, absolute price errors are lower in the *Forecast* treatment than the *No Forecast* treatment. Panel B plots the evolution of absolute price errors in the *Low Informativeness* condition. In all three trading periods, absolute price errors in the *Forecast* treatment are indistinguishable from those in the *No Forecast* treatment.

Table 2 reports the average price errors in each period for the four treatments.

[Insert Table 2 here]

Forecasts do not have a significant impact on absolute price errors in the *Low Informativeness* condition. In the *High Informativeness* condition, forecasts significantly reduce absolute price error in

[14] The first 15-second interval is omitted because there are many trials where no transactions occur during this time. This occurs because traders must submit limit orders (i.e., bid or ask offers) at the beginning of each trading period; if there are no offers available, no transaction can occur.

both period 2 and period 3. The average absolute price error is 48.17 without a forecast and 25.43 when a forecast is present in period 2 and the difference is statistically significant (p<0.001). The average adjusted absolute price error is 25.81 without a forecast and 17.48 when forecast is present in period 3 and the difference is statistically significant (p=0.003). Overall, the presence of a forecast improves price efficiency when the forthcoming earnings are highly informative about liquidating value but has no impact on price efficiency when earnings have low informativeness.

4.1.2 Bids and Asks

A transaction occurs when a trader accepts an existing offer (i.e., an outstanding limit order) from another trader. To a large extent, the bid and ask offers submitted by traders determine the level of transaction prices. We measure the deviation of bid and ask offers from the full-information benchmark we derive in Appendix A.

We calculate the difference between the best outstanding offer and the full-information benchmark. We measure this deviation for both bid and ask offers at any time during the trial when an offer is outstanding, and we average the deviations over 15-second intervals. Figure 3 plots the deviation of best bid and ask offers from expected value over time. Panel A plots the *High Informativeness* condition and Panel B plots the *Low Informativeness* condition.

[Insert Figure 3 here]

In all treatments, the average best bid offer is lower than the expected value, and the average best ask offer is higher than the expected value. Uncertainty about the liquidating value changes dynamically over time as prices gradually impound private information. Figure 3 shows that the deviation of both best bid and ask offers from expected value gradually decreases over time and converges toward zero. In the *High Informativeness* condition, the presence of a forecast decreases the deviation between best bid offers and expected value, but such an effect does not exist in the *Low Informativeness* condition.

We measure bid-ask spreads as the difference between the best ask offer and the best bid offer at any time during the trial when offers are outstanding, and we average the spreads over 15-second intervals. Table 3 reports the average bid ask spreads the final 15 seconds of the period.[15]

[Insert Table 3 here]

Forecasts do not have a significant impact on the bid-ask spread in the *Low Informativeness* condition. In the *High Informativeness* condition, forecasts significantly reduce the bid-ask spread in period 2 and period 3. The average adjusted bid-ask spreads is 46.68 without a forecast and 32.27 with a forecast in period 2, and the difference is statistically significant (p=0.015). The average adjusted bid-ask spread is 30.70 without a forecast and 24.20 with a forecast, and the difference is statistically significant (p=0.074). Overall, when earnings informativeness is high, the presence of a forecast significantly reduces the bid-ask spread in the period following the forecast, and it further reduces spreads in the period after earnings are announced. In contrast, the presence of a forecast has no impact on information asymmetry when earnings informativeness is low.

4.2 Individual-Level Analysis

We further examine how behavior at the individual level could explain the market-level results discussed above. A controlled laboratory market allows us to measure three variables of theoretical importance that are not observable in archival data. First, we can elicit trader beliefs at various points in time and directly examine how information affects informed and uninformed traders' beliefs. Second, we can observe individual trading behavior, which allows us to study how public disclosure affects trading decisions. In particular, we focus on market making decisions (i.e., bid and ask offers). Third, we observe individual trading profits, which allows us to measure the welfare consequences of public disclosure.

[15] At the beginning of each period, order books are cleared and traders must submit new offers. The bid-ask spread in the first interval tends to increase relative to the end of the previous period because of this restart effect. Bid-ask spreads stabilize over time within each period; therefore, we use the last interval in each period to conduct our tests.

4.2.1 Traders' Value Estimates

Traders were asked to estimate the security's liquidating value at various points in time during each trial. We rely on these value estimates to examine how traders' beliefs are affected by the market's information environment. We define estimate error as the difference between a trader's value estimate and the full-information benchmark derived in Appendix A. The absolute value of the estimate error is a measure of a trader's estimation accuracy. Table 4 reports the average individual absolute estimate errors for the forecasts we collected in all treatments

[Insert Table 4 here]

Table 4, Panel A reports absolute estimate errors for the *Low Informativeness* condition and Panel B for the *High Informativeness* condition. The average absolute estimate errors decreases over time. In period 1, the uninformed traders' absolute estimate errors are significantly greater than the informed traders' in all treatments, suggesting that the informed traders have a significant information advantage over the uninformed. In the *High Informativeness* condition, the presence of an earnings forecast has a significant impact on uninformed traders' value estimates. Specifically, unformed traders' average absolute estimate error is 57.29 without a forecast and 47.39 with an earnings forecast, which is a statistically significant difference (p = 0.014). Thus, uninformed traders have more accurate value estimates in the period before earnings forecasts are announced.

In period 2, when forecasts are available, both informed and uninformed absolute estimate errors decreases. Furthermore, the difference in the average absolute estimate errors between the informed and uninformed traders disappears after the earnings forecast for both *High* and *Low Informativeness* conditions. This suggests that earnings forecasts significantly reduce information asymmetry.

In period 3, both informed and uninformed absolute estimate errors are significantly reduced by the presence of forecasts in the *High Informativeness* condition. Specifically, the average absolute estimate error for informed traders is 13.11 when there is an earnings forecast and 15.70 when there is no forecast, which is a marginally significant difference (p = 0.092). The average absolute estimate error for the uninformed traders is 13.43 with an earnings forecast and 16.58 without forecast, which is a significant difference (p = 0.041). Thus, when earnings informativeness is high, all traders' value estimate accuracy is significantly higher when forecasts are present than when forecasts are absent in the period after earnings are realized.

4.2.2 Trading Behavior

Traders must decide how and when to participate in the market. In our market, they can act as both *market makers* by submitting limit orders (i.e., bid or ask offers) and *market takers* by submitting market orders (i.e., buy or sell offers) in continuous time. We find both informed and uninformed traders more frequently employ limit orders (i.e., market making). To measure traders' choice between market making and market taking, we calculate a *submission rate* similar to Bloomfield, O'Hara, and Saar (2005). This rate is defined as the number of limit orders (i.e., bid or ask offers) a trader submits divided by the sum of her limit and market orders (i.e., buy or sell offers). In untabulated results, the submission rate of both informed and uninformed traders is around 90%, which suggests that both types of traders primarily engage in market-making activities. To measure how trades are executed, we calculate a *take rate*, which is the number of market orders a trader submits divided by the sum of her market orders and *executed* limit orders (i.e., limit orders that are accepted by other traders). In untabulated results, the take rate is similar between informed and uninformed traders, and the average is around 30%. The only exception is that the take rate is higher in the pre-forecast trading period for the informed traders at slightly above 40%. Given the predominance of limit orders over market orders, our analysis focuses on the former.

Table 5 reports the deviation of limit orders from the expected value submitted by trader type in each trading period. Panel A reports results for the *Low Informativeness* condition, and Panel B reports results for the *High Informativeness* condition. The first table in each panel reports the ask deviation and the second table reports the bid deviation.

[Insert Table 5 here]

We include all limit orders submitted by each trader type in each period to calculate the average ask or bid prices and then compare it to the expected value. All ask offers are higher than the expected value consistent with the sellers' incentive to sell at high prices. All bid offers are lower than the expected value consistent with the buyers' incentive to buy at low prices. The deviation from the expected value decreases over time.

In the *High Informativeness* condition, the presence of forecasts has a significant effect on bid deviation in period 2. Both informed and uninformed traders' bids are closer to the expected value in the *Forecast* condition than *No Forecast* condition. The informed bid deviation is -62.53 in the *No Forecast* condition and -43.08 in the *Forecast* condition. The difference is statistically significant (*p=0.027*). The uninformed bid deviation is -66.06 in the *No Forecast* condition and -36.87 in the *Forecast* condition. The difference is statistically significant (*p=0.002*). This suggests that the average bid offers by both informed and uninformed traders are more competitive as they are much closer to the expected value when forecasts are present than when forecasts are absent.

In period 3, the presence of forecasts has a significant effect on ask deviation. Both informed and uninformed traders' ask prices are closer to the expected value in the *Forecast* condition than the *No Forecast* condition. The informed ask deviation is 27.84 in *No Forecast* condition and 16.06 in *Forecast* condition. The difference is statistically significant (*p=0.025*). The uninformed ask deviation is 29.38 in *No Forecast* condition and 17.53 in *Forecast* condition. The difference is statistically significant (*p=0.08*). This suggests that the average ask offers by both informed and uninformed traders are much more competitive.

4.2.3 Learning from Prices

This section examines whether traders use information including their private information and public information such as earnings, forecasts and prices efficiently. If they use available information efficiently, their value estimate error would be unpredictable based on this information. We only find evidence of inefficient use of information for the informed traders in the *Low Informativeness/ Forecast* treatment for their value estimates after earnings announcement (F_3). Our theoretical benchmark analysis suggests that there is very little information (only 3% of earnings news) left in earnings when forecasts are provided in the *Low Informativeness* condition. Human subjects may fail to correctly use this information.

Our estimate error regression in Table 6 reveals that informed traders overreact to the information in earnings. Specifically, their estimate errors are significantly and positively correlated with the information in earnings. On the other hand, they underreact to information in prices. We include the average period 2 price in the regression. Results in Table 6 reveal that informed traders' estimate errors are significantly and negatively correlated with period 2 average price.

[Insert Table 6 here]

In contrast, the uninformed traders' estimate errors are not predictable based on the information available. This evidence suggests that the uninformed can learn from prices more efficiently than the informed traders. The ability to learn from prices is a distinctive feature of human uninformed traders.

4.2.4 Traders' Profits

Our final analysis examines average trading profits by trader type. Table 7 reports the average trading profits for each type in each period for all treatments.

[Insert Table 7 here]

The informed traders make positive profits except in period 3 in the *High Informativeness* condition. The uninformed traders suffer losses in period 1 only. In the *High Informativeness* condition, they make positive profits in period 3 and also in period 2 when forecasts are present. It is surprising that the uninformed traders can make positive profits despite the presence of informed traders who have superior private information. Our analysis of value estimates in Table 4 indicates that the information difference between informed and uninformed traders disappears after earnings forecasts and earnings announcement in the *High Informativeness* condition. Some uninformed traders can have better ability to extract information from prices than some informed traders as indicated by the evidence in Table 6, which allows them to compete away profits earned by the informed traders as indicated by the limit order deviations in Table 5.

The robot liquidity trader suffers losses in each trading period. The earnings forecast significantly reduces the robot trader's losses when earnings informativeness is high. Specifically, in Period 2, the average trading loss by the robot trader is 161.70 in the *No Forecast* condition and reduces to 112.48 in the *Forecast* condition; this difference is statistically significant (p = 0.0972). Similar results continue to hold in the period after earnings are announced (Period 3). Since the robot trader is a price taker, more efficient prices reduce the losses suffered by the robot trader. Consistent with our findings about price efficiency, forecasts improve the robot trader's welfare in both periods after forecasts and earnings are announced.

To gain more insight into the impacts of forecasts on informed and uninformed traders' profits, we break down their profits by the two types of trading activities. Traders can submit limit orders (i.e., bid or ask offers) and trades occur if the offers are taken, or submit market orders by accepting the best outstanding bid or ask offer. Table 8 reports the average trading profits by the two types of activities, Panel A for informed traders and B for uninformed traders.

[Insert Table 8 here]

Table 8, Panel A shows that informed traders' average total profit from limit orders is significantly reduced by the presence of forecasts. In the *High Informativeness* condition, the average total profit from limit orders is 1066.56 in the *No Forecast* treatment and 623.57 in the *Forecast* treatment; this difference is statistically significant (p = 0.0305).

Table 8, Panel B shows that uninformed traders earn some positive profits from executed limit orders. In period 1, the uninformed traders suffer losses from limit orders, but they make money from limit orders in the following two trading periods when public disclosures are available. Earnings forecasts also reduces the profits earned from limit orders by the uninformed traders. Specifically, in the *High Informativeness* condition, the average trading profit by the uninformed traders through limit orders is 185.61 in the *No Forecast* treatment and reduces to 106.19 in the *Forecast* treatment in Period 2; this difference is statistically significant (p = 0.0918).

Furthermore, the difference in the profit through limit orders earned by the informed traders and uninformed traders shrinks dramatically due to the earnings forecasts. In the *No Forecast* condition, the profits earned by informed traders are 289.04, which is higher than the uninformed traders' profits of 185.61 (p = 0.0901). In the *Forecast* condition, the profits earned by the informed traders through limit orders are 100.03, which is not different from the profits earned by the uninformed traders of 106.19 (p = 0.8825).

The presence of the earnings forecast significantly reduces the losses suffered by the uninformed traders through market orders. Specifically, in the *High Informativeness* condition, uninformed traders' average trading losses from market orders is 677.73 in the *No Forecast* treatment and reduces to 343.89 in the *Forecast* treatment. This difference is statistically significant (p = 0.0900).

5 Conclusion

Our paper applies experimental methods to examine whether and how the early release of public news through a forecast has market impacts after the underlying news being forecasted is realized.

We find that when earnings are more informative than individual private information, an earnings forecast not only has the short-run effect of increasing price efficiency, it also generates beneficial spillover effects even after earnings are released. Forecasts that are more informative than individual private information levels the information playing field by empowering the uninformed traders. More informative prices in the short run serve as a source of endogenous public information, which further shrinks the information differences between informed and uninformed traders. The ability to learn from prices enables uninformed traders continue to be a competitive threat to uninformed traders after earnings are announced.

Understanding the market effects of public forecasts has profound implications for managers, regulators, and researchers to assess the overall market impact of disclosure. Our evidence suggests that firms facing greater information asymmetry benefit in the both periods after forecasts and earnings announcements from providing earnings forecasts. This is consistent with findings that firms with higher information asymmetry are more likely to provide earnings forecasts (Coller and Yohn 1997). In addition, our evidence that firms with more informative earnings enjoy greater benefits from providing earnings forecasts is consistent with Lennox and Park (2006), who find that firms with more informative earnings as proxied by higher earnings response coefficient are more likely to provide earnings forecasts. Importantly, our evidence based on individual traders' activities sheds light on the causal effects of public disclosures for investor welfare, which complements archival studies.

We acknowledge that our experimental design imposes some simplifying structural assumptions in order to derive clear predictions. First, forecasts in our experiment are exogenously imposed (i.e., there is no strategic forecasting). Future studies can build on the findings of our study and incorporate strategic disclosure decisions to evaluate the short-run and spillover effect of disclosure. Second, private information is exogenously endowed to traders in our experiment. Relaxing this assumption may lead to opportunities for future research. If traders are allowed to acquire private information, the timing of public disclosure may affect traders' decisions to acquire private information. Third, we assume the earnings forecasts are informative about earnings, and we hold forecast accuracy constant. Future studies can vary forecast accuracy. In practice, the forecast accuracy improves over time as managers gain more information. Thus, managers face the choice of releasing information early with less accuracy or releasing information late with more accuracy. Future studies can examine the trade-off between timing of information disclosure versus accuracy of disclosure.

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Appendix A – Derivations of Full-Information Benchmark

This appendix outlines the derivation of a security's expected value when all available information is aggregated into prices, which we use as a theoretical full-information benchmark. Specifically, the expected value of the security's liquidating value given all available information is a weighted average of all available information where the weight on each signal is proportional to the signal's precision.

In the first trading period, the information set (Ω_1) includes the prior distribution of the security's liquidating value and the four private signals endowed to half of the traders. The precision of the prior is $\frac{1}{200^2}$ and the precision of the private signals is $\frac{1}{50^2}$. Thus, expected liquidating value is specified as follows.

$$\mathbf{E}(\tilde{v}|\Omega_1) = \frac{\frac{1}{200^2}\times 500 + \sum_{i=1}^{4}\frac{1}{50^2}s_i}{\frac{1}{200^2}+\frac{1}{50^2}\times 4} = \frac{1}{65}500 + \sum_{i=1}^{4}\frac{16}{65}s_i \tag{A1}$$

At the beginning of the second trading period, there is no new information in the *No Forecast* condition, and the security's expected value given all available information (Ω_2) is the same as it was in the first trading period. In the *Forecast* condition, the information set includes the prior, the private signals, and the forecast of the public signal. In the *Low Informativeness* condition, the precision of the forecast is $\frac{1}{10^2+50^2}$, and the expected liquidating value is specified below.

$$\mathbf{E_L}(\tilde{v}|\Omega_2) = \frac{\frac{1}{200^2}\times 500 + \sum_{i=1}^{4}\frac{1}{50^2}s_i + \frac{1}{10^2+50^2}f}{\frac{1}{200^2}+\frac{1}{50^2}\times 4 + \frac{1}{10^2+50^2}} = \frac{1}{80.4}500 + \sum_{i=1}^{4}\frac{16}{80.4}s_i + \frac{15.4}{80.4}f \tag{A2}$$

In the *High Informativeness* condition, the precision of the forecast is $\frac{1}{10^2+20^2}$, and the expected liquidating value is specified as follows.

$$\mathbf{E_H}(\tilde{v}|\Omega_2) = \frac{\frac{1}{200^2} \times 500 + \sum_{i=1}^{4} \frac{1}{50^2} s_i + \frac{1}{10^2 + 20^2} f}{\frac{1}{200^2} + \frac{1}{50^2} \times 4 + \frac{1}{10^2 + 20^2}} = \frac{1}{145} 500 + \sum_{i=1}^{4} \frac{16}{145} s_i + \frac{80}{145} f \qquad \text{(A3)}$$

Compared with $\mathbf{E}(\tilde{v}|\Omega_1)$, the prior and private signals receive less weight in $\mathbf{E}(\tilde{v}|\Omega_2)$ because the new information contained in the forecast is more precise and hence receives a greater weight than the other information. Furthermore, the forecast in the *High Informativeness* treatment receives a much greater weight than the other information because of its high information content (i.e., its high precision).

At the beginning of third trading period, the public signal is realized. The information set (Ω_3) includes the prior, the private signals, and the public signal. The forecast is redundant information once the public signal is announced because the forecast is a noisy signal of the public signal and there is no new information in the forecast after considering the information in the public signal. In the *Low Informativeness* condition, the precision of the public signal is the same as the precision of the private signals; therefore, the weights on each private signal and the public signal are the same in deriving expected liquidating value.

$$\mathbf{E_L}(\tilde{v}|\Omega_3) = \frac{\frac{1}{200^2} \times 500 + \sum_{i=1}^{4} \frac{1}{50^2} s_i + \frac{1}{50^2} e}{\frac{1}{200^2} + \frac{1}{50^2} \times 4 + \frac{1}{50^2}} = \frac{500}{81} + \sum_{i=1}^{4} \frac{16}{81} s_i + \frac{16}{81} e \qquad \text{(A4)}$$

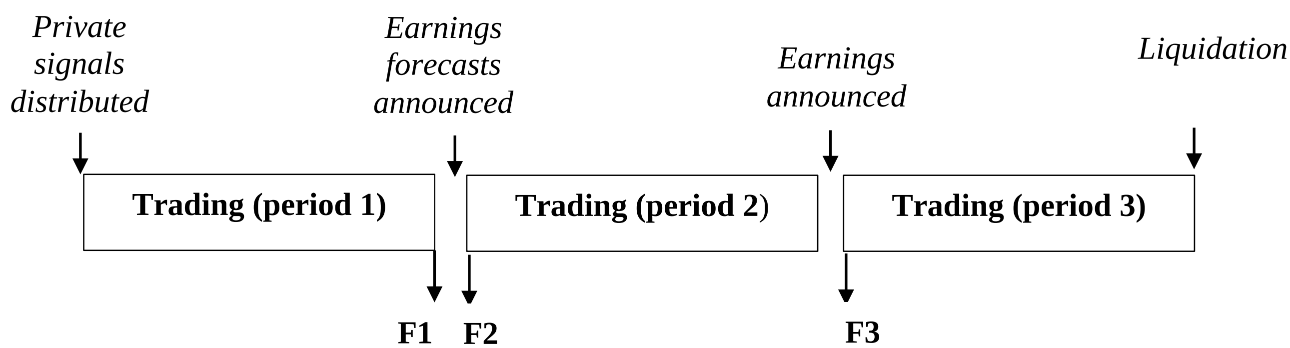
In the *High Informativeness* condition, the precision of the public signal is higher, so the weight on the public signal is greater than the weight on other information.

$$\mathbf{E_H}(\tilde{v}|\Omega_3) = \frac{\frac{1}{200^2} \times 500 + \sum_{i=1}^{4} \frac{1}{50^2} s_i + \frac{1}{20^2} e}{\frac{1}{200^2} + \frac{1}{50^2} \times 4 + \frac{1}{20^2}} = \frac{500}{165} + \sum_{i=1}^{4} \frac{16}{165} s_i + \frac{100}{165} e \qquad \text{(A5)}$$

Figure 1 – Experimental Timelines

This figure illustrates the timeline of events for trading a security in the *High Informativeness*/*Forecast* condition. The only difference of the *No Forecast* condition from the *Forecast* condition is that the forecast of public signal is not available. There are three one-minute trading periods. At the start of the trading, private information is distributed. At the end of the first trading period, traders make the initial forecasts of the value (F_1 and F_1'). After they submit their forecasts, the experimenter announces an earnings forecasts in the *Forecast* treatment. After the announcement, traders make the second forecasts of the value (F_2). In the *No Forecast* treatment, traders do not make this second forecasts of value. Then the second period begins. At the end of the second trading period, the experimenter announces earnings and traders make the third forecasts of the value (F_3 and F_3'). Then the third trading period begins. At the end of the third trading period, the true value is realized and trading profits are calculated.

A. Forecast condition



B. No Forecast condition

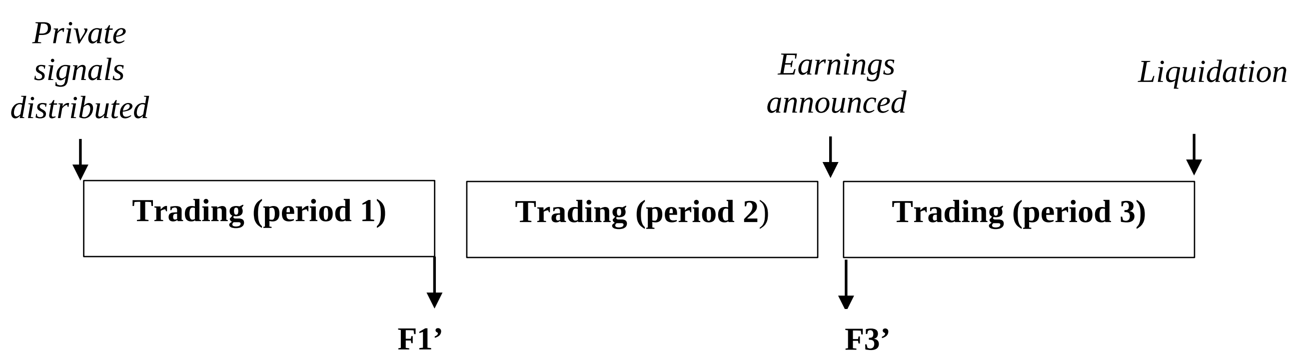
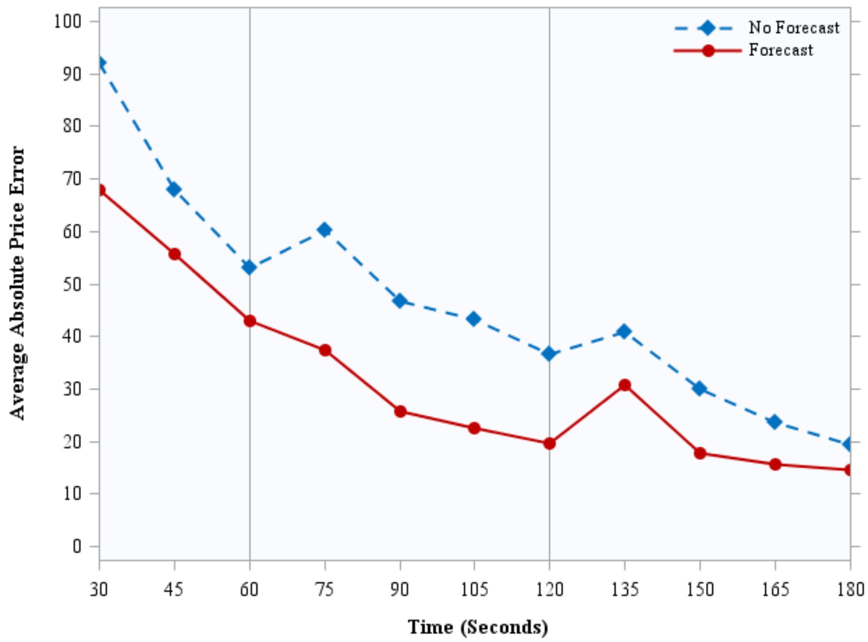


Figure 2 – Absolute Price Errors

This figure plots the evolution of average absolute price errors over time. We define price error as the difference between a transaction price and the full-information benchmark derived in Appendix A. There are three 60-second trading periods: (1) Pre-Forecast, (2) Post-Forecast, and (3) Post-Earnings. We measure absolute price errors at the transaction level and average the errors over 15-second intervals.

Panel A: High Informativeness



Panel B: Low Informativeness

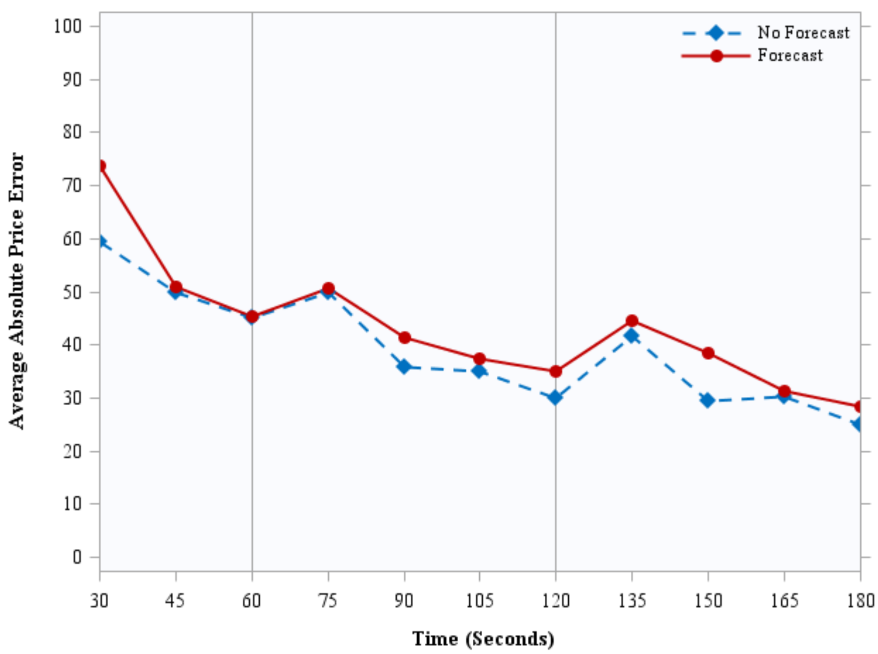
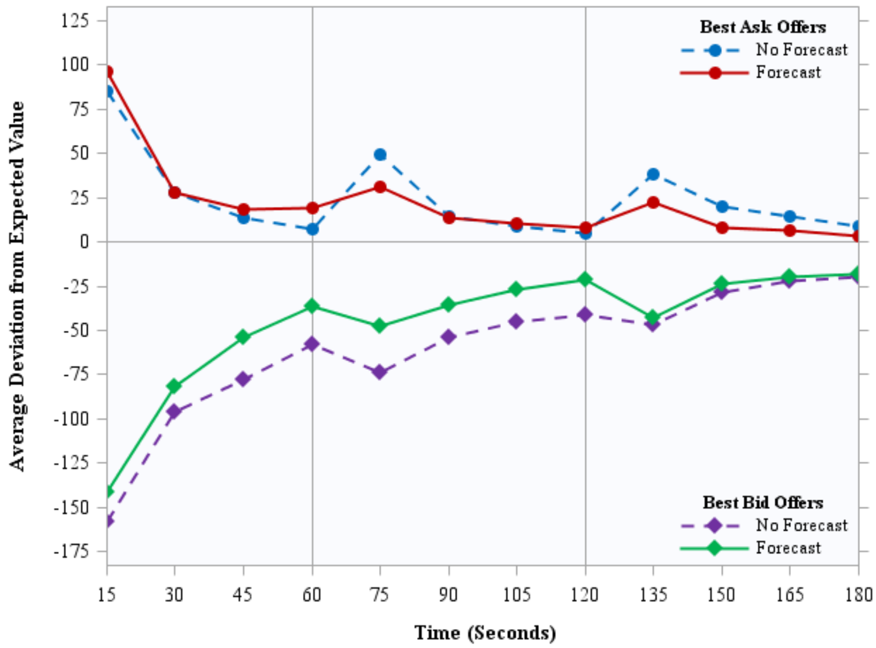


Figure 3 – Deviation of Best Bid and Ask Offers from Expected Value

This figure plots the deviation of average best bid and ask offers from expected value over time. There are three 60-second trading periods: (1) Pre-Forecast, (2) Post-Forecast, and (3) Post-Earnings. We calculate the difference between the best outstanding offers and the full-information benchmark we derive in Appendix A. This deviation is measured for both bid and ask offers at any time during the trial when an offer is outstanding, and we average the deviations over 15-second intervals.

Panel A: High Informativeness



Panel B: Low Informativeness

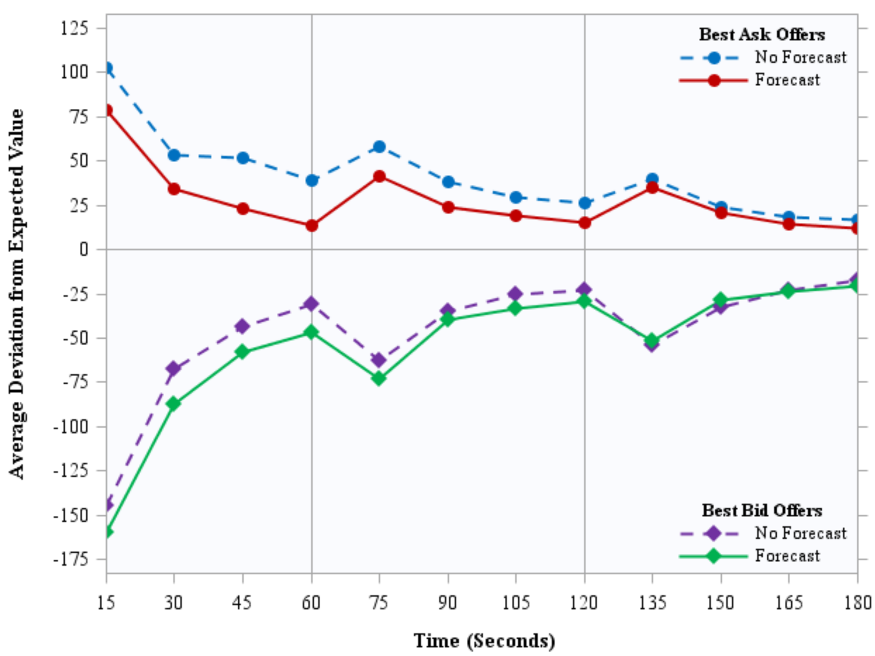


Table 1 – Experimental Market Design

This table summarizes the experimental market design and displays the rotation of our factor manipulations by session and trial. We adopt a 2 × 2, within-subjects design that manipulates earning informativeness (*High* or *Low Informativeness*) and the presence of earnings forecasts (*Forecast* or *No Forecast*). We conducted eight experimental sessions. Each session includes 32 trials, and subjects trade a single security during each trial.

Sessions	Trials 1-8	Trials 9-16	Trials 17-24	Trials 25-32
1 & 8	*Low / Forecast*	*Low / No Forecast*	*High / Forecast*	*High / No Forecast*
2 & 7	*Low / No Forecast*	*Low / Forecast*	*High / No Forecast*	*High / Forecast*
3 & 6	*High / Forecast*	*High / No Forecast*	*Low / Forecast*	*Low / No Forecast*
4 & 5	*High / No Forecast*	*High / Forecast*	*Low / No Forecast*	*Low / Forecast*

Table 2 – Absolute Price Errors

This table reports the mean (standard deviation) of absolute price errors over time for each of our treatments. We define price error as the difference between a transaction price and the full-information benchmark derived in Appendix A. We measure absolute price errors at the transaction level and average the errors over each 60-second trading period. We test for differences in absolute price errors between the *Forecast* and *No Forecast* treatments for both *Low* and *High Informativeness* of earnings. Tests of differences are based on a mixed model ANCOVA analysis with the stocks' expected value and trial number as covariates and a random effect for session. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively, based on one-tailed *t*-tests.

Period	Low Informativeness			High Informativeness		
	No Forecast	**Forecast**	**Diff.**	**No Forecast**	**Forecast**	**Diff.**
1	64.23 (35.49)	68.39 (38.41)	-4.16 (t = -0.71)	76.69 (51.86)	68.63 (38.94)	8.06 (t = 1.38)
2	41.72 (23.23)	38.36 (19.64)	3.36 (t = 0.86)	48.17 (36.23)	25.43 (14.00)	22.74 *** (t = 5.55)
3	33.80 (23.33)	32.12 (17.68)	1.68 (t = 0.61)	25.81 (20.17)	17.48 (9.39)	8.33 *** (t = 3.01)

Table 3 – Bid-Ask Spreads

This table reports the mean (standard deviation) of bid-ask spreads over time for each of our treatments. We measure bid-ask spreads as the difference between the best ask offer and the best bid offer at any time during the trial when offers are outstanding, and we average the spreads over 15-second intervals; however, we restrict the analysis to the final 15 seconds of the period. We test for differences in bid-ask spreads between the *Forecast* and *No Forecast* treatments for both *Low* and *High Informativeness* of earnings. Tests of differences are based on a mixed model ANCOVA analysis with the stocks' expected value and trial number as covariates and a random effect for session. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively, based on one-tailed t-tests.

Period	Low Informativeness			High Informativeness		
	No Forecast	**Forecast**	**Diff.**	**No Forecast**	**Forecast**	**Diff.**
1	74.41 (48.46)	63.46 (37.27)	10.95 (t = 1.58)	67.23 (51.26)	60.50 (40.33)	6.73 (t = 0.97)
2	50.96 (40.56)	44.34 (29.48)	6.62 (t = 1.26)	46.68 (42.91)	32.27 (23.47)	14.41 ** (t = 2.57)
3	37.62 (23.51)	35.01 (23.27)	2.61 (t = 0.75)	30.70 (24.10)	24.20 (16.91)	6.50 * (t = 1.85)

Table 4 – Absolute Individual Estimate Errors by Trader Type

This table reports the mean (standard deviation) of individual absolute estimate errors by informed and uninformed traders. We calculate absolute estimate errors as the absolute value of difference between traders' value estimates and the full-information benchmark derived in Appendix A. We test for differences in traders' absolute estimate errors between the *Forecast* and *No Forecast* treatments for the first and third value estimates. Traders do not submit the second value estimate in the *No Forecast* treatment; thus, we report only descriptive statistics. We also test for differences in absolute estimate errors between trader type (*Informed* or *Uninformed*) by earnings informativeness for each value estimate. Tests of differences are based on a mixed model ANCOVA analysis with the stocks' expected value and trial number as covariates and a random effect for session. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively, based on one-tailed *t*-tests.

Panel A: Low Informativeness

Value Estimate	Informed			Uninformed			Differences (Informed-Uninformed)	
	No Forecast	Forecast	Diff.	No Forecast	Forecast	Diff.	No Forecast	Forecast
1	37.68 (37.47)	42.09 (38.62)	-4.41 (t = -1.11)	53.75 (57.11)	58.13 (52.16)	-4.38 (t = -1.11)	16.07 *** (t = 4.06)	16.04 *** (t = 4.05)
2		28.54 (28.61)			32.17 (28.13)			3.63 (t = 1.63)
3	27.86 (26.42)	28.58 (23.14)	-0.72 (t = -0.39)	33.66 (29.89)	32.42 (23.54)	1.24 (t = 0.67)	5.80 *** (t = 3.12)	3.84 ** (t = 2.07)

Panel B: High Informativeness

Value Estimate	Informed			Uninformed			Differences (Informed-Uninformed)	
	No Forecast	Forecast	Diff.	No Forecast	Forecast	Diff.	No Forecast	Forecast
1	39.18 (39.02)	37.51 (56.38)	1.67 (t = 0.42)	57.29 (52.26)	47.39 (43.62)	9.90 ** (t = 2.47)	18.11 *** (t = 4.52)	9.88 ** (t = 2.47)
2		17.23 (17.96)			19.21 (19.89)			1.98 (t = 1.23)
3	15.70 (17.67)	13.11 (18.06)	2.59 * (t = 1.68)	16.58 (17.83)	13.43 (16.73)	3.15 ** (t = 2.05)	0.88 (t = 0.58)	0.32 (t = 0.21)

Table 5 – Deviation of Limit Orders from Expected Value by Trader Types

This table reports the mean (standard deviation) of the deviation of limit orders from the expected value by informed and uninformed traders. We include all bid and ask offers submitted by each group. We test for differences between the *Forecast* and *No Forecast* treatments in each of the three trading periods for the informed and uninformed traders separately; these tests are performed separately for each public signal informativeness condition (*Low* in Panel A and *High* in Panel B). ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively, based on one-tailed *t*-tests.

Panel A1: Low Informativeness – ASKS

PERIOD	INFORMED			UNINFORMED		
	No Forecast	Forecast	Diff	No Forecast	Forecast	Diff
1	72.27	59.22	13.05	82.57	58.05	24.52
	(47.23)	(83.53)	(t=1.08)	(102.6)	(110.4)	(t=1.3)
2	43.07	28.27	14.80*	50.66	33.25	17.41*
	(53.07)	(43.48)	(t=1.73)	(52.88)	(47.94)	(t=1.94)
3	31.64	24.9	6.74	26.71	30.99	-4.27
	(42.19)	(38.91)	(t=0.94)	(54.43)	(47.12)	(t=-0.47)

Panel A2: Low Informativeness – BIDS

PERIOD	INFORMED			UNINFORMED		
	No Forecast	Forecast	Diff	No Forecast	Forecast	Diff
1	-95.57	-97.81	2.24	-96.41	-111.90	15.49
	(80.60)	(79.93)	(t=0.16)	(117.3)	(112.7)	(t=0.76)
2	-48.64	-54.84	6.2	-52.69	-56.52	3.83
	(61.62)	(36.12)	(t=0.69)	(71.97)	(50.44)	(t=0.35)
3	-36.76	-41.67	4.91	-38.75	-44.61	5.86
	(39.92)	(51.94)	(t=0.60)	(40.45)	(47.15)	(t=0.75)

Panel B1: High Informativeness – ASKS

PERIOD	INFORMED			UNINFORMED		
	No Forecast	Forecast	Diff	No Forecast	Forecast	Diff
1	58.72	68.36	-9.64	62.54	65.66	-3.12
	(74.98)	(63.19)	(t=-0.78)	(116.4)	(106.3)	(t=-0.16)
2	31.73	25.88	5.85	32.28	31.99	0.29
	(53.52)	(25.23)	(t=0.79)	(71.47)	(29.24)	(t=0.03)
3	27.84	16.06	11.78**	29.38	17.53	11.85*
	(37.06)	(18.96)	(t=2.26)	(48.64)	(25.03)	(t=1.73)

Panel B2: High Informativeness – BIDS

PERIOD	INFORMED			UNINFORMED		
	No Forecast	Forecast	Diff	No Forecast	Forecast	Diff
1	-92.42	-89.62	-2.81	-123.60	-103.00	-20.60
	(95.16)	(61.68)	(t=-0.2)	(99.20)	(95.13)	(t=-1.18)
2	-62.53	-43.08	-19.46**	-66.06	-36.87	-29.19***
	(61.84)	(31.36)	(t=-2.24)	(65.86)	(32.28)	(t=-3.16)
3	-30.23	-36.34	6.1	-36.09	-29.88	-6.21
	(58.41)	(33.76)	(t=0.72)	(29.56)	(21.81)	(t=-1.35)

Table 6 – Regression Analysis on Estimate Errors (F_3) in *Forecast* Condition

This table reports the results of regression analysis on traders' value estimate errors when earnings forecasts are present. The dependent variables are the traders' value estimate after earnings announcement (F_3) minus the expected value. The independent variable includes the earnings announcement, the average transaction price in trading period 2. In addition, private signals are included as the independent variable for the informed traders. If individuals use available information efficiently in making value estimates, we cannot predict their estimate errors using any information available. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

	Low Informativeness		**High Informativeness**	
Independent variables	**Informed**	**Uninformed**	**Informed**	**Uninformed**
Private	-0.025 (*t* =-0.92)		-0.009 (*t* =-0.75)	
Earnings	0.139 *** (*t* =3.68)	0.065 (*t* =1.60)	-0.115 (*t* =-0.19)	0.113 (*t* =1.55)
Price_period2	-0.098** (t=-2.23)	-0.037 (*t* =-0.84)	0.011 (*t* =0.22)	-0.111 (*t* =-1.53)
Intercept	19.31 *** (*t* =3.95)	16.6*** (*t* =2.94)	18.41*** (*t* =3.14)	12.15*** (*t* =4.12)
Number of Observations	256	256	256	256
R square	0.07	0.05	0.01	0.02

Table 7 – Trading Profits by Trader Types

This table reports the mean trading profits by trader type and period. We test the difference between trading profits in the *No Forecast* and *Forecast* conditions; these tests are performed for each combination of trader type (*Informed*, *Uninformed*, or *Robot*) and public signal informativeness (*Low* or *High*). Tests of differences are based on a mixed model ANCOVA analysis with the stocks' expected value and trial number as covariates and a random effect for session. We also perform *t*-tests to determine whether mean trading profits in each trader type/period/treatment combination are statistically different from zero. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively, based on one-tailed *t*-tests.

Trader Type	Period	Low Informativeness			High Informativeness		
		No Forecast	Forecast	Difference	No Forecast	Forecast	Difference
Informed	1	592.51 ***	581.02 ***	11.49	975.25 ***	615.55 ***	359.70
	2	182.21 ***	126.05 ***	56.16	156.01 **	57.11 **	98.90
	3	115.97 ***	82.40 ***	33.57	39.24	27.43	11.81
	Total	887.07 ***	788.18 ***	98.89	1,168.06 ***	699.24 ***	468.82
Uninformed	1	-318.53 ***	-306.71 ***	-11.82	-725.03 **	-327.29 **	-397.74
	2	-6.02	36.83	-42.85	8.12	56.46 **	-48.34
	3	6.66	19.35	-12.69	79.30 ***	53.55 **	25.75
	Total	-317.79 **	-240.95 **	-76.84	-626.28***	-219.00***	-407.28
Robot	1	-273.98 ***	-283.89 ***	9.91	-261.55 ***	-288.26 ***	26.71
	2	-176.28 ***	-162.87 ***	-13.41	-161.70 ***	-112.68 ***	-49.02 *
	3	-119.01 ***	-100.47 ***	-18.54	-118.53 ***	-79.29 ***	-39.24 **
	Total	-569.27 ***	-547.23 ***	-22.04	-541.78 ***	-480.24 ***	-61.54

Table 8 – Trading Profits by Limit and Market Orders

This table reports the mean trading profits for informed and uninformed traders by their trading activity. There are two ways to trade. One is by submitting market orders which accept existing bid or ask offers posted by other traders. The other is by posting limit orders such as bid or ask offers and wait for other traders to accept them. We separately report the profits from market offers orders and executed limit orders. We test the difference between trading profits in the *No Forecast* and *Forecast* conditions; these tests are performed for each combination of trader type (*Informed*, *Uninformed*, or *Robot*) and public signal informativeness condition (*Low* or *High*). Tests of differences are based on a mixed model ANCOVA analysis with the stocks' expected value and trial number as covariates and a random effect for session. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively, based on one-tailed t-tests.

Panel A: Informed Traders

Activity	Period	Low Informativeness			High Informativeness		
		No Forecast	Forecast	Diff.	No Forecast	Forecast	Diff.
Limit orders	1	532.12	414.06	118.06	660.86	471.22	189.64
	2	258.47	185.72	72.75	289.04	100.03	189.01 ***
	3	163.25	106.63	56.62	123.10	57.48	65.62
	Total	944.70	704.74	239.96	1,066.56	623.57	442.99 **
Market orders	1	62.34	178.09	-115.75	341.03	159.27	181.76
	2	-81.10	-76.38	-4.72	-144.50	-54.02	-90.48
	3	-59.82	-34.69	-25.13	-97.11	-34.96	-62.15
	Total	-57.64	84.76	-142.40	103.11	78.11	25.00

Panel B: Uninformed Traders

Activity	Period	Low Informativeness			High Informativeness		
		No Forecast	Forecast	Diff.	No Forecast	Forecast	Diff.
Limit orders	1	-7.21	-133.92	126.71	-321.78	-83.08	-238.70
	2	75.03	107.34	-32.31	185.61	106.19	79.42 *
	3	69.94	77.85	-7.91	183.33	93.75	89.58 **
	Total	134.43	52.52	81.91	51.45	114.15	-62.70
Market orders	1	-406.77	-221.37	-185.40	-504.45	-301.17	-203.28
	2	-111.80	-83.82	-27.98	-219.09	-60.85	-158.24 **
	3	-82.91	-83.20	0.29	-113.59	-58.06	-55.53
	Total	-459.40	-302.93	-156.47	-677.73	-343.89	-333.84 *