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Analyst Earnings Forecasts, Individual Investors' Expectations and Trading Volume: An Experimental Approach

I. Introduction

Earnings forecasts are an important source of information for asset valuation and trading in financial markets. Almost all market operators, and particularly investors, rely on analyst earnings forecasts to form their earnings target and make investment decisions. De Bondt and Thaler (1990) explain this dependence by the fact that most investors do not have the time or required skills to produce their own predictions. Moreover, financial analysts are commonly regarded as experts; therefore, their forecasts help gauge future corporate earnings and financial performance. Many prior studies use analyst earnings forecasts to benchmark unexpected earnings, finding that this approach provides a more accurate measure of earnings surprises than time-series econometric models, such as the random walk model (Bamber, 1987; Park and Stice, 2000). Several studies document that analysts' forecasts have economic value for investors and that security prices reflect analyst forecast revisions and recommendation changes (Givoly and Lakonishok, 1984; Lin and McNichols, 1998; Jegadeesh et al., 2004; Frankel et al., 2006; Kirk, 2011).

The experiments were carried out at CIRANO (Center for Inter-university Research and Analysis on Organizations). We are indebted to Claude Montmarquette for his valuable help and to Julie Héroux for technical assistance in conducting this research. Financial support was provided by IRG and CDC Institute for Economic Research (Caisse des Dépôts et Consignations). We particularly thank Isabelle Laudier. Finally, we benefited from helpful comments at the Behavioural Finance Working Group Conference (London, 2013) and the Multinational Finance Society (Rome, 2011). We want to thank the Associate Editor, Sébastien Pouget and two anonymous referees for their fruitful comments.

However, there is evidence that analysts' forecasts contain errors and are not efficient, which raises questions about the usefulness of analyst recommendations and forecasts in investment decision-making. Forecast errors typically reflect the optimism bias (Abarbanell, 1991; Abarbanell and Bernard, 1992; Dreman and Berry, 1995; Brown, 1996). In particular, some studies document that analysts tend to provide optimistic forecasts and recommendations to secure lucrative investment banking relationships (Dechow et al., 2000; Hong and Kubik, 2003). De Bondt and Thaler (1990) find evidence of overreaction in stock analyst forecasts, which contributes to explaining the excess future returns of previously losing firms. However, it is worth noting that these errors and inefficiencies are not totally independent because optimism may cause analysts to underreact to bad news and overreact to good news (Easterwood and Nutt, 1999).

The above contradictory evidence regarding the accuracy of analysts' forecasts gives rise to the question of how individual investors follow analysts' forecasts. This issue has been investigated previously, but the empirical evidence is inconclusive. Dreman and Berry (1995) find that investors continue to rely too much on analysts' forecasts even though forecast errors are large. By contrast, Brown (1996) shows that the investment community does not trust analysts' forecasts very much but gives an important weight to forecasts based on time-series models. In a very recent contribution, So (2013) shows that investors overweight analysts' forecasts because stock prices do not fully reflect the predictable components of analyst errors (*i.e.*, investors weight a signal in excess of the optimal Bayesian weights when forming expectations of future earnings). However, this finding contradicts the evidence reported in Hughes et al. (2008) that investors do not overweight analysts' forecasts.

It is now commonly accepted that the quality of financial analysts' forecasts is primarily characterized by errors and heterogeneity. Financial analysts' errors have been extensively studied. From an empirical perspective, most studies examining analysts' forecast errors and market behavior find evidence that this factor has a significant effect on stock prices (Abarbanell and Bernard, 1992;

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Beaver *et al.*, 2008). Relatively few papers have studied the relationship between analysts' forecast errors and the trading volume. Among these works, Bamber (1987) documents that the greater the magnitude of earnings forecast errors - as measured by the unexpected earnings - the greater the magnitude and duration of the abnormal trading volume reaction. Bildersee *et al.* (1996) find a positive impact on the trading volume from the inverse of the variation in the analysts' forecast errors over five years - a proxy for earnings precision - which is robust to changes in the measures of the trading volume and to the number of analyst forecasts available for the firms.

The heterogeneity of analysts' forecasts has also been frequently investigated but generally in connection with the market trading volume. Ziebart (1990) finds a positive association between changes in abnormal trading activity surrounding earnings announcements and changes in the level of consensus about earnings expectations. This result is consistent with a positive relationship between changes in the dispersion of analysts' forecasts and the trading volume. In a related study, Ajinkya *et al.* (1991) show that the positive relationship between the dispersion in analysts' forecasts of annual earnings per share and the trading volume remains significant even after allowing for the effect of forecast revisions. Some studies based on other variables conclude that the trading volume tends to increase to the extent that the announcements of analysts' earnings forecasts convey more information (Beaver, 1968; Bamber, 1987) or with the precision of the information provided but decrease in proportion to the amount of public and private information already available (Kim and Verrecchia, 1991)¹. By contrast, in a situation where the costs of trade are not negligible, the impact of accurate information is not monotonically positive but can be negative (Barron and Karpoff, 2004). Accordingly, if the heterogeneity of analysts' forecasts is taken as an inverse measure of their precision, we would expect its effect on the trading volume to take different forms.

Despite their significant contributions to the understanding of investors' reactions to earnings announcements, the majority of previous works face several pitfalls. First, the effects of analysts' forecasts have not been clearly dissociated. Neither empirical nor experimental research has explicitly investigated differential trading volume reactions to analysts' forecast errors or heterogeneity. As a result, the impact of each component cannot be separated from that of the others, leading to potentially spurious conclusions. More importantly, because the necessary data concerning investor expectations are not recorded in practice, previous studies have often used analysts' forecasts of annual earnings as a surrogate (Ajinkya *et al.*, 1991). This decision is questionable because investors and analysts have different motivations and market positions. The heterogeneity of analysts' forecasts does not fully capture investor uncertainty (Abarbanell *et al.*, 1995); thus, its influence on the trading volume should be different from the impact produced by the investors' own heterogeneous expectations.

In this experimental study, we investigate how financial analysts' forecasts influence investors' expectations and

trading decisions. In contrast to the majority of previous experimental studies, we consider the trading volume instead of stock prices, which allows us to focus on individual expectations because "an important distinction between price and volume tests is that the former reflects changes in the expectations of the market as a whole while the latter reflects changes in the expectations of individual investors" (Beaver, 1968).

In our experiment, there is no information asymmetry, but the no-trade theorem does not apply to the underlying game.² Divergent interpretations arise because investors form different beliefs based on the same set of information formed by financial analysts' forecasts.³ Under the assumption of a homogeneous structure of information where all investors receive the same information, trading volume can be explained by a dispersion of initial beliefs and/or by idiosyncratic interpretations of information, which is more likely in our experiment (Kandel and Pearson, 1995; Bamber *et al.*, 1999).

Moreover, prior theoretical and empirical studies are strongly focused on either forecasts' heterogeneity or forecast errors. We consider both at the same time but disentangle the two effects on investors' expectations and trading decisions. In this regard, our article contributes to the existing literature in several original ways. First, the use of an experimental approach allows us to discriminate between analysts' forecasts and investors' expectations by measuring them directly. If the results show that they are not exactly the same, investors' expectations should contain two components, one related to analysts' forecasts and the other not related. These components should affect trading in different ways. Second, the extent to which market participants react to analysts' forecasts can be explained in a more precise and accurate way by considering the mean error and heterogeneity of the forecasts separately. The experimental method plays an important role in isolating these two factors because it allows one variable to be manipulated while controlling for the other. In addition, by using the experimental method, we can more usefully focus on informational effects by "minimizing" investor liquidity and speculative desire.

Our main findings, drawn from nine 12-period and one 6-period double-auction markets in a laboratory, indicate that investors partly correct for analysts' forecast errors, and their expectations are less heterogeneous than analysts' forecasts. Within this research, one explanation is a timing advantage in favor of investors because they usually form their expectations about future stock prices after the publication of the financial analysts' forecasts. Next, we find evidence that the heterogeneity of analysts' forecasts has a significant negative impact on the trading volume. However, it is important to note that different results are obtained when we take into account investors' heterogeneous expectations and separate them into two components, as discussed in the previous paragraph: the common heterogeneity and idiosyncratic heterogeneity of investors' expectations. The former arises from the fact that the expectations of individual investors reflect the heterogeneity of analysts' forecasts. This part has a negative effect on the trading volume. Conversely, the

latter part reveals the idiosyncrasies of the individual investors' own sentiments. According to our results, this part has a non-monotonic impact on volume. Trading volume increases when investors' expectations become heterogeneous, but decreases when this heterogeneity exceeds a certain threshold. As for forecasting errors, they are not determined at the beginning of the trading period, but rather only at the end. Therefore, if the trading volume is affected by forecasting errors, the errors are those of the previous period, which are already known when investors trade, not the current ones. The results show that in the presence of significant divergences in analysts' forecasts, previous forecasting errors do not result in major changes in trading.

The remainder of this article is organized as follows. Section 2 describes the theoretical bases and derives hypotheses for testing. Sections 3 and 4 present the experimental design and proxy measurements, respectively. Section 5 reports and discusses the obtained results. Section 6 presents a summary of our observations and our conclusions.

■ II. Theoretical basis and derivation of hypotheses

Investor beliefs cannot be directly observed. Therefore, most empirical studies, including Givoly and Lakonishok (1984) and Previts *et al.* (1994), consider analysts' earnings forecasts to be a reasonable proxy for investor beliefs. Nevertheless, based on data from various markets, the majority of them show evidence of biases in analysts' forecasts. For instance, papers by Richardson *et al.* (1999) and Easterwood and Nutt (1999) establish that these forecasts are rather optimistic. Potential explanations of this optimism primarily include economic incentives and cognitive bias. Indeed, incentives come from the fact that financial analysts may develop commercial relationships with firms for which they conduct research and give investment recommendations and tend to inflate corporate earnings to increase the revenues obtained from their work (e.g., Dugar and Nathan, 1995; Michaely and Womack, 1999; Dechow *et al.*, 2000). According to the behavioral hypothesis, there is an asymmetry in the analysts' reaction: they systematically overreact to information, and, moreover, overreactions to good news are not fully offset by overreactions to bad news (De Bondt and Thaler, 1985, 1987, 1990)⁴.

One of the major objectives of this article is to examine how investors respond to forecasts with systematic and persistent errors. Under the naive expectations model, investors closely follow analysts' forecasts even though they are likely to contain biases. Under the rational expectations model, investors reappraise analysts' forecasts when forming their own expectations. In practice, these simplified models seem to lack credibility because investors, especially experienced ones, are able to detect and correct some, though not all, of the potential errors in analysts' forecasts, which amounts to saying that investors may neither completely follow analysts' recommendations nor totally reject them when making up their own minds. In

this case, experimental research is useful for exploring to which measures in analyst forecasts investors attach importance when forming their own expectations, which leads us to the following research hypothesis:

■ **Hypothesis 1 (H1):** *Investors follow analysts' forecasts in formulating their own expectations.*

The above hypothesis will be mainly tested for two aspects of forecasts: heterogeneity and errors. If investors follow analysts' forecasts, their expectations should be dispersed and biased when the forecasts are.

If H1 cannot be rejected, *i.e.*, if investors do incorporate some part of the financial analysts' forecasts into their own expectations, we then investigate the question of how they trade. Previous theoretical research suggests that the trading volume is increasingly linked to investors' differential interpretations of information (Harris and Raviv, 1993; Kandel and Pearson, 1995), divergent prior expectations (Karpoff, 1986), and changes in heterogeneity (Ziebart, 1990; Barron, 1995; Bamber *et al.*, 1997, 1999). Other works, including Holthausen and Verrecchia (1990) and Kim and Verrecchia (1991), show that the trading volume increases with the precision of the announcement. If we take the heterogeneity of financial analysts' forecasts as an inverse proxy for this precision, then it should negatively affect the trading volume. We support the negative impact of the heterogeneity of analysts' forecasts by arguing that investors would have an inclination towards self-protection and not trade away assets in the face of a clear dispersion in analysts' forecasts. Accordingly, the following hypothesis is examined in this study:

■ **Hypothesis 2 (H2):** *There is an inverse relationship between the trading volume and the heterogeneity of analysts' forecasts.*

By considering financial analysts' forecasts as the only source of forecasting information, empirical studies logically assume that the incentive for investors to trade strongly depends on the changing patterns of these forecasts. However, given the possibility of measuring investor expectations, motivations for trades may prove to be more complicated. This argument is explained by the fact that although they are influenced by analysts' forecasts, investors' expectations may always contain a specific element, which is at least partly related to their differing interpretations of public information (in this case, analysts' forecasts and earnings announcement) due to many factors, such as using different models and probability functions (Harris and Raviv, 1993; Kandel and Pearson, 1995). Note that investors' expectations can be easily observed and measured in laboratory experiments.

One way to reconcile the two types of explanations is to disentangle the part of investors' expectations strictly related to the heterogeneity of analysts' forecasts (hereafter called common heterogeneity) from the part associated with investors' own sentiments (hereafter called idiosyncratic heterogeneity).⁵ The first fraction should negatively affect the trading volume because it is positively correlated with the dispersion in analysts' forecasts. The second one is assumed to have a concave effect, *i.e.*, it positively alters trades when it is not too large because it

ensures opposite trading orders – a necessary condition for generating exchanges. Nevertheless, this portion reduces trading when it is too high because if expectations are too divergent among investors, they carry considerable risk of losses and, consequently, fear about trading. It should be specified that as the investors can see the entire order book, they could infer the heterogeneity of expectations from the order book. To some extent, the concave effect may come from a counterparty risk (*i.e.*, no opposite order in the order book). Accordingly, we propose to test the following hypothesis:

■ **Hypothesis 3 (H3):** *There is a concave relationship between the trading volume and the idiosyncratic heterogeneity of investors' expectations.*

Furthermore, if traders take into account financial analysts' forecasts in their trading decisions, the volume of trades should also reflect forecast errors. Bamber (1987) shows a positive relationship between the trading volume and this factor, designated as unexpected earnings. The presence of forecast errors will give investors an incentive to trade to either take advantage of previous erroneous forecasts or correct them. Therefore, we hypothesize the following:

■ **Hypothesis 4 (H4):** *There is a positive relationship between the trading volume and the magnitude of previous errors contained in analysts' forecasts.*

■ III. Experimental design

Our experiment was carried out at the Centre for Interuniversity Research and Analysis on Organizations (CIRANO) in Montreal, using the "Z-Tree" (Zurich Toolbox for Ready-made Economic Experiments) software. Our experiment comprises 10 sessions, of which nine contain twelve rounds and one has six rounds. Each round consists in two stages, prediction and exchange. In total, the experiment involves 81 undergraduate students with no prior experience in similar experiments or with market anomalies. Each cohort is composed of seven to nine subjects. The subjects receive written instructions, which are orally explained before all experimental sessions start. In addition, they have to successfully answer all the control questions testing their understanding of market rules and participate in some trial sessions before playing. Each subject begins with an initial allocation of 2,000 EMU (Experimental Money Units) and 20 shares of a single stock. Their experimental gains are the sum of the gains from each trading period. These periodical gains depend on the accuracy of participants' earnings expectations as well as the performance of their trades normalized by the stock fundamental value of the period under consideration⁶. If these gains are positive, they are converted into Canadian dollars (CAD), to which we add an appearance bonus of 10 CAD. Our statistics show that, on average, subjects participating in a complete two-hour session receive a reward of 25 CAD.

iii.1. AnAlYst's ForEcASting procEss

Every session has six analysts whose forecasts must fall between 60 and 140. The annual earnings are the

sum of the mean of all the forecasts (expected portion) and a term representing the forecast error (unexpected portion). The forecast error, which corresponds to the difference between the annual earnings and the forecast, thus comprises a random term and a tendency term. Each analyst forecast contains two parts: one expected part corresponding to the tendency term and one randomly generated corresponding to the random term. To some extent, analysts may be considered as robots, because analysts' forecasts are automatically generated.

The random term is created to generate an entirely unpredictable link between the forecast mean and annual earnings. With a mean of zero and standard deviation of 2.16, at the end of each period, it is drawn from the following values: -3; -2; -1; 0; 1; 2 and 3. On the other hand, the tendency term represents the optimism, pessimism, or lack of bias in the analysts' forecasts, upon which we establish three types of forecasting information. This allows for three treatments in the experiment.

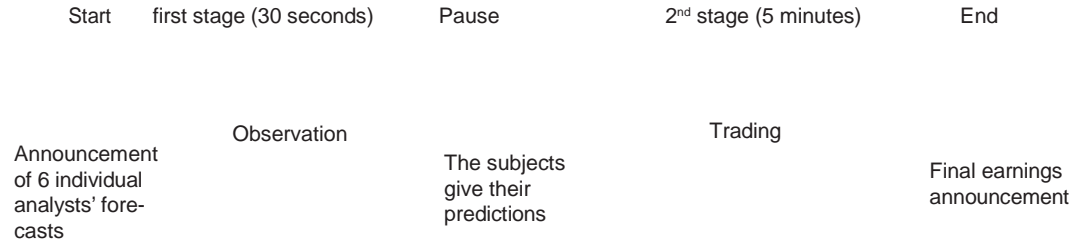
In the case of unbiased forecasts, the tendency term is 0; thus, the annual earnings represent the sum of the forecast mean and the random term with a mean of zero, which means that the forecast average is a noisy but unbiased proxy for annual earnings. In contrast, optimistic forecasts are characterized by systematic negative errors, regardless of the value of the random term. Thus, we allow the tendency term to fluctuate from -9 to -6. Forecast errors are constrained between -12 and -3. In the same way, the tendency term for pessimistic forecasts takes values from 6 to 9 so that all forecast errors are positive without exception, *i.e.*, they vary from 3 to 12. Thus, the optimistic and pessimistic forecast means are both noisy and biased. Using these categories of earnings forecasts, the experiment contains 3 treatments: two sessions run under the unbiased forecast treatment, four sessions run under the optimistic forecast treatment, and four sessions run under the pessimistic forecast treatment. In all rounds, forecast errors are distinguished from forecast heterogeneity.

Note that within our experiment design, subjects do not know how analysts' forecasts are determined. However, analysts' forecasts were constructed in such a way that their mean error is always negative or positive, *i.e.*, they have a tendency (optimism or pessimism). Subjects are expected to learn about this tendency error and to formulate more homogeneous anticipations. Accordingly, this learning effect would reduce their mean anticipation error.

iii.2. conduct OF ExpErimEnts

Recall that there are 9 twelve-period sessions and 1 six-period session which runs under the unbiased forecast treatment. All the trading periods last approximately 6 minutes and take place in the same way with 2 stages. According to figure 1, in the first stage, the period starts with the release of six individual analysts' annual earnings forecasts for the recent year without their predetermined means and standard deviations. The participants are given a pencil and paper to note any information. Then, they observe these forecasts for 30 seconds before giving their own expectations of earnings. This stage is

Figure 1. time-line of one round



Notes: nine sessions of the experiment contain twelve periods and one has six periods. All rounds follow the same time-line.

mandatory and continues until all the subjects have given their predictions.

The second stage lasts five minutes. The participants can trade securities by introducing limit buy or sell orders, each of which is characterized by a price and a quantity. A buy

order at price p means that traders want to purchase securities at a price equal to or less than p , whereas a sell order at price p means that securities will only be traded at a price equal to or greater than p . An order is executed when one or more offers in the opposite direction satisfy the trading price condition. In addition, subjects can respond to orders displayed in the order book. Neither short selling nor cash balances are allowed in our experiment. Rounds are independent so that unexecuted orders from the previous period do not appear in the order book for the next period. There is no initial price at the beginning of the stage.

At the end of each round, we determine the annual earnings by adding the drawn values of the random term and the tendency term to the mean of all forecasts for the period. Then, the final annual earnings are announced to the participants. Assuming that the entire amount of annual earnings is distributed to investors as dividends, the level of earnings can be taken as the fundamental value of the equity.

■ IV. Measurements of test parameters

In this study, four measures are used as proxies for the divergence of analysts' earnings forecasts. The main corresponds to the standard deviation of analysts' forecasts divided by the mean of the earnings forecasts.⁷

$$HetFOR_t = \sqrt{\frac{1}{n} \sum_{i=1}^n (FOR_{i,t} - FOR_t)^2} / FOR_t$$

$FOR_{i,t}$ stands for the forecast of analyst i for period t . FOR_t is the mean of analysts' forecasts for period t .

In spirit of the dispersion of analysts' forecasts, the heterogeneity of the investors' expectations is simply approximated by the standard deviation of all individual forecasts divided by their mean.⁸

$$HetEXP_t = \sqrt{\frac{1}{m} \sum_{i=1}^m (EXP_{i,t} - EXP_t)^2} / EXP_t$$

$EXP_{i,t}$ measures the earnings expectation announced by investor i for period t , and m is the number of investors involved in the market.

We define the common heterogeneity as the part of investors' expectations that is strictly correlated with analysts' forecasts and the idiosyncratic heterogeneity as the part that is specific to the investors. We obtain these components by regressing the heterogeneity of the investors' expectations on the heterogeneity of the analysts' forecasts. The common heterogeneity corresponds to the heterogeneity of investors' expectations predicted by the heterogeneity of analysts' forecasts, whereas the idiosyncratic heterogeneity simply corresponds to the unpredicted part of the regression.

Accordingly, we measure the forecast error by the difference between the actual annual earnings and the forecast, deflated by the mean forecast.⁹

$$ErrFOR_t = (RES_t - FOR_t) / FOR_t$$

The mean error of investors' expectations is determined in the same way, but the numerator refers to their difference from the annual earnings.

$$ErrEXP_t = (RES_t - EXP_t) / EXP_t$$

The trading volume is measured by the fraction of shares traded during a round divided by the total number of outstanding shares.

$$VOL_t = (\sum N_{i,t}) / N_{m,t}$$

$N_{i,t}$ is the number of traded shares involving the transaction i during the period t , $N_{m,t}$ is the total number of outstanding shares.¹⁰

Table 1 provides summary statistics of the primary variables and extracted components of investor expecta-

table 1. summary statistics for primary variables and extracted components of investors' expectations

<i>Primary variables</i>	Mean	Std. dev	Max.	Min.	Range	JB
Heterogeneity of analysts' forecasts	0.108	0.075	0.296	0.023	0.141	16.16 ⁺
Mean of analysts' forecast errors	-0.099	0.989	0.877	-8.962	0.153	30.87 ⁺
Heterogeneity of investors' expectations	0.037	0.024	0.134	0.007	0.024	30.42 ⁺
Mean of investors' expectation errors ($\times 10^5$)	0.111	1.000	4.208	-1.885	0.869	30.67 ⁺
Trading volume	0.276	0.138	0.767	0.028	0.167	11.59 ⁺
<i>Components of investor expectations</i>						
Common heterogeneity of investors' expectations	0.037	0.014	0.073	0.022	0.026	16.11 ⁺
Idiosyncratic heterogeneity of investors' expectations ($\times 10^{-5}$)	0.111	1.000	4.208	-1.885	0.869	30.67 ⁺
Squared idiosyncratic heterogeneity of investors' expectations	0.989	2.656	17.711	0.000	0.601	30.67 ⁺

Notes: This table reports summary statistics for primary variables, computed from our experiment data: mean (Mean), standard deviation (Std. dev.), maximum (Max.), minimum (Min.), and interquartile 75-25 (Range). Primary variables refer to the first measures of all the variables we describe in this section. To obtain the components of investors' expectations, we regress the heterogeneity of investors' expectations on the heterogeneity of analysts' forecasts and retain the common heterogeneity of investors' expectations (i.e., the portion of the heterogeneity of investors' expectations explained by the heterogeneity of analysts' forecasts) and the idiosyncratic heterogeneity of investors' expectations (i.e., the residuals of this regression). JB refers to the empirical statistics of the Jarque-Bera test for normality. (*) indicates normality is rejected at the 1% level.

tions used in this article. The data are obtained from ten rounds, as explained in Section 3. The non-normality of all the variables considered, as indicated by the Jarque-Bera tests, fully justifies our decision to combine the OLS estimation with a bootstrap procedure.

■ V. Results and interpretations

Expectation formulation, judgment making, and decision-making are distinct steps in an investor's response to information, although they may overlap. Accordingly, we begin with an analysis of investors' earnings expectations to gain insights concerning their ability to perform precise judgments. Then, we discuss the findings as regards the effects of heterogeneity and errors in analysts' earnings forecasts on the trading volume.

Several remarks should be noted before we present the experimental findings. First, for the sake of concision, we report and comment only on the results obtained with the main measures of all the variables because the results with the other measures remain unchanged. Second, tests indicate that there is no multicollinearity in our regression models; each explanatory variable has a valuable informative content with regard to the dependent variable.¹¹ Finally, we use the bootstrap procedure to improve the performance of the OLS method in estimating the parameters of all the regression models.¹² We are particularly encouraged by the fact that the bootstrap technique is highly suitable in cases where the assumption of normality is not justified, owing, for example, to a small number of observations. Indeed, we perform 1,500 replications of each initial sample to obtain robust estimates of the models' coefficients.¹³

v.1.inFluEncE of AnAlYstS' ForEcAstS on invEstors' ExpEcTAtions

Before examining the impact of the heterogeneity and errors of analysts' forecasts on investors' expectations, we first investigate whether investors revise their expectations with respect to analysts' forecasts, especially their mean variation. Such verification is not useless because it gives an idea of the effect of analysts' forecasts on investors' expectations. Also, unlike many previous works relying on forecast revisions during the same period, the mean variation here corresponds to the difference between the mean forecasts for two consecutive periods.

Table 2 shows that investors change their own expectations mainly on the basis of changes in analysts' forecasts. The adjusted R^2 is fairly high (92.31%) when the mean variation of analysts' forecasts is the only explanatory variable. This finding is consistent with the evidence reported in Ziebart (1990), according to which variations in analysts' forecasts seem to be a good proxy for changes in aggregate investors' beliefs and reflect the earnings surprises at the time of the announcements. This coefficient, significant at the 1% level, is less than unity, meaning that investors do partially incorporate financial analysts' forecasts into their expectations. Other variables, such as the heterogeneity or prior mean error of analysts' forecasts, explain only a small fraction of the mean variation of investors' expectations (i.e., Models 2 and 3 of Table 2). However, only the coefficient related to the dispersion of analysts' forecasts is significant and negative for all data. Accordingly, investors should become less confident in the forecasting information published and have less incentive to change their own expectations when this factor increases in size.

table 2. impact of analysts' forecasts on the variation of investors' expectations

Explanatory variables	Model 1	Model 2	Model 3	All data	Model 4	
	(All data)	(All data)	(All data)		Optimistic case	Pessimistic case
Constant	0.011** (0.004)	0.148*** (0.023)	0.102*** (0.016)	0.014 (0.008)	0.013 (0.015)	0.020 (0.014)
Mean variation of analysts' forecasts	0.902*** (0.030)	-	-	0.917*** (0.031)	0.948*** (0.046)	0.889*** (0.047)
Heterogeneity of analysts' forecasts	-	-0.281** (0.135)	-	0.047 (0.050)	-0.030 (0.095)	0.094 (0.072)
Prior mean error of analysts' forecasts	-	-	0.313 (0.309)	-0.215* (0.106)	-0.044 (0.266)	-0.416** (0.184)
R ²	92.41%	4.31%	0.61%	92.85%	94.41%	93.65%
Adjusted R ²	92.31%	3.11%	-0.63%	92.57%	93.84%	92.99%

Notes: The dependent variable represents the mean variation of investors' expectations. It is measured by the relative difference between the means observed for two consecutive periods. The heterogeneity of analysts' forecasts is measured by the standard error of analysts' forecasts, divided by the mean of the analysts' forecasts. The variation of analysts' forecasts is measured by the relative difference between the means observed in two consecutive periods. The mean error of analysts' forecasts is measured by the difference between the annual results and the mean analysts' forecast, reported to the mean analysts' forecast. Except for Models 1 and 3, mean variation and mean error variables are calculated in absolute values. All the regression models are estimated using the OLS method incorporating the bootstrap method to correct for the departure from normality. The bootstrap standard errors of the estimates are reported in parentheses. The initial samples of 82 observations for all data and 33 observations for both optimistic and pessimistic cases are replicated 1,500 times. *, ** and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% levels, respectively.

The estimation of Model 4 in Table 2 indicates that investors continue to rely heavily on the mean variation of analysts' forecasts to form their expectations. They further revise their expectations downwards with respect to the prior mean error of analysts' forecasts in the event of a significant negative coefficient (at the 10% level).¹⁴ When optimistic and pessimistic data are considered separately, we do not observe large differences in the estimates, except for the fact that the prior mean error variable becomes insignificant in the case of optimistic data. This finding is fairly normal because optimistic investors often neglect the previous errors made by analysts. The coefficient associated with the mean variation of financial analysts' forecasts is lower for pessimistic forecasts than for optimistic forecasts, although both are significant at the 1% level. This finding indicates that investors incorporate financial analysts' pessimistic forecasts less readily than optimistic ones. Thus, the difference in adjustment speed may be the origin of the investors' asymmetric reaction to bad and good news, as documented in previous studies.

If investors alter their expectations on the basis of the variation of analysts' forecasts in an incomplete fashion, as presented in Table 2, another issue of interest involves examining whether they correct the forecasts' errors. Figures 2 to 4 show that investors' expectations are biased in the same direction as analysts' forecasts, regardless of the type of forecasts considered. More precisely, investors' expectations make negative (positive) errors when analysts provide optimistic (pessimistic) forecasts. Moreover, Figures 2 to 4 show that subjects do not improve their ability to correct the systematic errors they make when

forming their forecasts across the rounds. This confirms the results found by Dinh and Gajewski (2005) about market efficiency. They found that prices deviate systematically from the fundamental value whatever the period.

As explained in the experiment design, the annual earnings are the sum of the mean of all the forecasts (expected portion showing optimism or pessimism) and a term representing the forecast error (unexpected portion). After some learning, rational investors are expected to be at least aware of the expected portion of the result. Here, we observe a decrease in the investors' mean error, but this is not significant at the 5% level. Thus, the theory of perfect rationality cannot be validated.

Table 3 also indicates that these investor errors are not driven by heterogeneity but rather mostly by analysts' forecast biases. However, the size of investors' expectation errors in absolute terms is less than that of the analysts' bias, which is confirmed by investors under-reacting to available forecasting information and partially correcting its errors. The semi-rational expectation model seems to be valid.

Table 4 reports the results related to the impact of the dispersion and errors in the analysts' forecasts on investors' heterogeneous expectations. The latter are found to be strongly and significantly related to the heterogeneity of the analysts' forecasts (at the 1% level), regardless of the type of market (*i.e.*, all data, optimistic forecasts, and pessimistic forecasts). However, the associated coefficient is notably less than unity. These findings support H1. Further analysis shows that the link between the heterogeneity of investors' expectations and the absolute mean error is controversial. In fact, the

associated coefficient is significant at the 5% level in the case of optimistic forecasts, which implies that a higher absolute mean error among analysts' forecasts reduces the level of investors' heterogeneous expectations. This finding seems to be in line with the prediction of Chen et al. (2002) that market behavior reflects agents' optimism better than pessimism. Moreover, it is commonly accepted that investors have a natural inclination to self-protect. When recognizing a bias toward optimism, especially a strong bias, investors tend to reprocess the information and form less heterogeneous expectations to avoid the risk of large losses. Overall, this reaction leads to a lowering of the heterogeneity of investors' expectations.

It is clear that in our experiments, investors have heterogeneous posterior beliefs despite the same public information contained in analysts' forecasts, thus sug-

gesting that they have heterogeneous priors. The fact that investors' posterior beliefs are less dispersed than analysts' forecasts confirms that investors' reaction is not in line with perfect rationality, but semi-rationality.

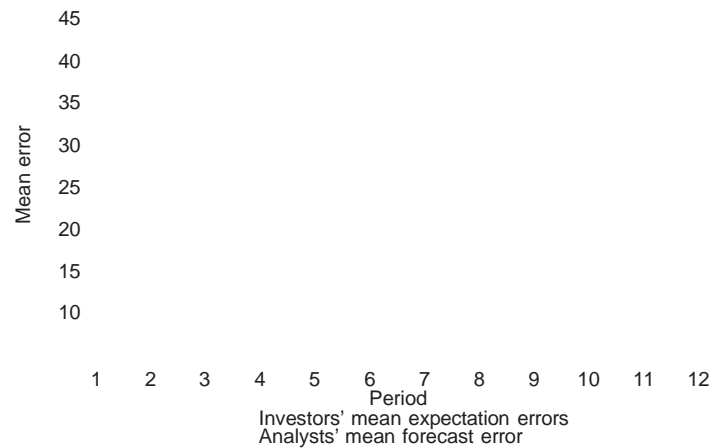
v.2. impAct of AnAlysts' ForEcAsts on trADing volume

The preceding section shows that investors make the same types of errors as analysts but do not amplify these errors when formulating their own expectations. We now examine how investors refer to financial analysts' forecasts to make their decisions about trades. Thus, we first relate the trading volume to the heterogeneity of financial analysts' forecasts. The results are reported in Table 5. Overall, our experiment indicates that the trading volume is negatively and significantly influenced by the heterogeneity of analysts' forecasts, except in the case of optimistic forecasts. Thus, H2 cannot be rejected. The more heterogeneous the analysts' forecasts, the lower the willingness to trade. This conclusion is consistent with earlier studies that consider the heterogeneity of analysts' forecasts as a proxy for market uncertainty or imprecision in public information (Ziebart, 1990; Barron, 1995; Bamber et al., 1997). Moreover, a segment of the investment community, "sophisticated investors", may recognize a specific bias in analysts' forecasts and do not consider such information as a very relevant reference for their own expectations that directly affect their trading decisions.

To the best of our knowledge, no previous empirical work has detected such a negative relationship, perhaps because the analysts' earnings forecasts were not sufficiently divergent due to their extraction from the same source of information (e.g., I/B/E/S). Additionally, most empirical studies experience some difficulties in identifying the origin of trades. As a matter of fact, trades may arise either from liquidity shocks or from private information, which is voluntarily excluded in our experiment.

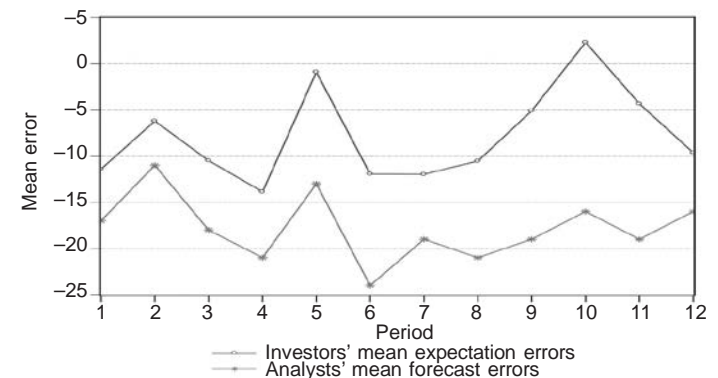
The asymmetry of trading volume reactions to analysts' heterogeneous forecasts (*i.e.*, a significant negative impact of the heterogeneity of analysts' forecasts on trades in the case of pessimistic forecasts and insignificant effects in the case of optimistic forecasts) is closely related to the results displayed in Table 4. That is, because they more

Figure 2. investors' expectation errors versus financial analysts' forecast errors: all data



Note: the mean error is calculated in absolute value.

Figure 3. investors' expectation errors versus financial analysts' forecast errors: optimistic forecasts

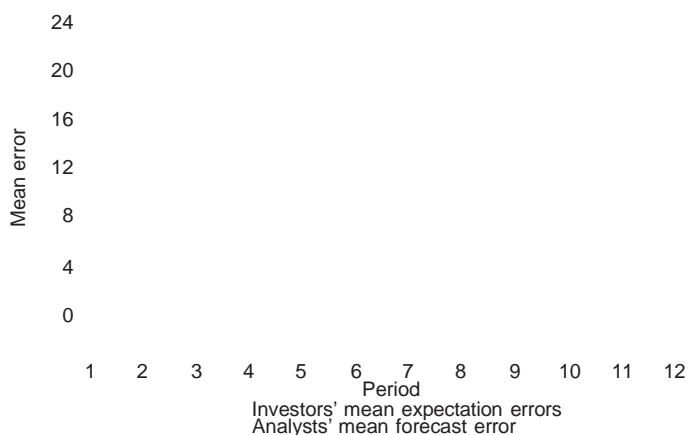


Note: the mean error is calculated in absolute value.

easily recognize optimistic errors, investors might be less confident in publicly available optimistic forecasts and might not lower their trading activity when they see too much heterogeneity in these forecasts. They refer instead to their own expectations. By contrast, a very high level of heterogeneity in financial analysts' pessimistic forecasts will make investors doubtful about the future of the firm's profitability and lead them to reduce their trading volume. One should note that the asymmetry of investors' reactions to analysts' optimistic and pessimistic forecasts has been confirmed by certain earlier studies focusing on changes in both equity returns and the trading volume (Doukas et al., 2006).

In our experiment, all the exchange periods are independent, but the same asset is used. In other words, each

Figure 4. investors' expectation errors versus financial analysts' forecast errors: pessimistic forecasts



Note: the mean error is calculated in absolute value.

period can be considered as a trading year for the same asset and the investors' trading decisions are assumed to reflect the forecasts' errors - a proxy for the unexpected portion of the annual earnings. We also investigate this link and report the results in Table 6. The evidence suggests that the magnitude of analysts' forecast errors exerts a significant impact on the trading volume at the 1% and 5% levels for Model 2 and Model 3, respectively, when all data are used but an insignificant impact when optimistic and pessimistic forecasts are considered separately. This result can be explained as follows. Forecast errors may represent uncertainty or imprecise

information. At a reasonable level, they create trading opportunities for market operators who try to correct or speculate on these errors and trade more aggressively. This is the case of the all-data model where the mean error is low due to the presence of unbiased forecasts. However, large errors might prevent risk-averse investors from trading. Thus, when the optimistic and pessimistic forecasts are examined separately, the mean error is larger and the impact of forecast errors becomes insignificant. It also appears that the trading volume is an increasing function of variations in analysts' forecasts, regardless of the regression model. Because forecast variations tend to reflect the common consensus of analysts' opinions about changes in corporate earnings (*i.e.*, the market's overall trend), investors tend to follow analysts and are more willing to trade to adjust their asset holdings.

v.3. impact of investors' Expectations on trading volume in the presence of Analysts' ForEcAsTs

Although analysts' forecasts constitute a source of public information in our experiment (*i.e.*, they are revealed to all the subjects), investors' expectations are completely private. This setting offers us the possibility of examining separately how investors' expectations influence the trading volume in the presence of analysts' forecasts. Indeed, the disagreement between investors might be the most important determinant of the trading volume because trades require opposite orders. Moreover, given the perfect correlation coefficient between heterogeneous expectations and analysts' forecasts (0.59, significant at the 5% level), we think that the heterogeneity of investors' expectations may contain two components: common heterogeneity, which is strongly correlated with the

table 3. impact of analysts' forecasts on errors in investors' expectations

Explanatory variables	Model 1	Model 2	All data	Model 3	
	(All data)	(All data)		Optimistic case	Pessimistic case
Constant	0.030*** (0.004)	0.009** (0.004)	0.004 (0.005)	-0.007 (0.009)	-0.005 (0.006)
Heterogeneity of analysts' forecasts	-0.011 (0.033)		0.036 (0.028)	-0.002 (0.042)	0.011 (0.045)
Mean error of analysts' forecasts	-	0.469*** (0.086)	0.486*** (0.087)	0.673*** (0.168)	0.732*** (0.135)
R ²	0.14%	31.43%	33.02%	39.76%	43.58%
Adjusted R ²	1.11%	30.57%	31.33%	38.74%	39.82%

Note: The dependent variable represents the mean error of investors' expectations. It is measured by the relative difference between the annual results and the mean investors' expectation divided by the mean investors' expectation. The heterogeneity of analysts' forecasts is measured by the standard error of analysts' forecasts divided by the mean of the analysts' forecasts. The mean error of analysts' forecasts is measured by the difference between the annual results and the mean analysts' forecast, reported to the mean analysts' forecast. Except for Model 2, the mean error variable is calculated in absolute values. All the regression models are estimated by using the OLS method incorporating the bootstrap method to correct for the departure from normality. The bootstrap standard errors of the estimates are reported in parentheses. The initial samples of 82 observations for all data and 33 observations for both optimistic and pessimistic cases are replicated 1,500 times. *, ** and *** indicate that the coefficients are statistically significant at the 10%, 5% and 1% levels, respectively.

table 4. impact of analysts' forecasts on heterogeneity of investors' expectations

Explanatory variables	Model 1	Model 2	All data	Model 3	
	(All data)	(All data)		Optimistic case	Pessimistic case
Constant	0.018*** (0.002)	0.041*** (0.004)	0.018*** (0.004)	0.036*** (0.008)	0.016** (0.007)
Heterogeneity of analysts' forecasts	0.174*** (0.029)	-	0.174*** (0.029)	0.281*** (0.060)	0.131*** (0.044)
Mean absolute error of analysts' forecasts	-	-0.077 (0.078)	0.003 (0.065)	-0.431** (0.168)	0.084 (0.112)
R ²	34.55%	0.79%	34.55%	53.64%	33.62%
Adjusted R ²	33.74%	-0.45%	32.90%	50.55%	29.19%

Notes: The dependent variable, the heterogeneity of investors' expectations, represents the standard error of investors' expectations divided by the mean of the investors' expectations. The heterogeneity of analysts' forecasts is measured by the standard error of analysts' forecasts reported to the mean of the analysts' forecasts. The mean error of the analysts' forecasts is measured by the difference between the annual results and the mean analysts' forecast divided by the mean analysts' forecast. All the regression models are estimated by using the OLS method incorporating the bootstrap method to correct for the departure from normality. The bootstrap standard errors of the estimates are reported in parentheses. The initial samples of 82 observations for all data and 33 observations for both optimistic and pessimistic cases are replicated 1,500 times. *, ** and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% levels, respectively.

table 5. impact of the heterogeneity of analysts' forecasts on trading volume

Explanatory variables	All data	Optimistic case	Pessimistic case
Constant	0.358*** (0.025)	0.293*** (0.046)	0.416*** (0.021)
Heterogeneity of analysts' forecasts	-0.758*** (0.165)	0.132 (0.303)	-1.236*** (0.146)
R ²	17.13%	0.035%	63.53%
Adjusted R ²	16.19%	-2.58%	62.45%

Notes: the dependent variable represents the number of shares traded divided by the total number of outstanding shares. The heterogeneity of analysts' forecasts is measured by their standard error reported to the mean of analysts' forecasts. Other proxies for the heterogeneity have been used, and confirm these results. All the regression models are estimated by using the OLS method incorporating the bootstrap method to correct for the departure from normality. The bootstrap standard errors of the estimates are reported in parentheses. The initial samples of 90 observations for all data and 36 observations for both optimistic and pessimistic cases are replicated 1,500 times. *, ** and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% levels, respectively.

disagreement in analysts' forecasts, and idiosyncratic heterogeneity, which is independent from analysts' forecasts. The first element corresponds to the predicted value from the regression of investors' heterogeneous expectations on analysts' heterogeneous forecasts. The second element is the estimated residual series from this regression. These components are likely to affect the trading volume in different ways.

As expected, Panel A of Table 7 indicates a negative relationship between the trading volume and the common heterogeneity of investors' expectations for all data and for pessimistic forecasts. This result is totally consistent with our previous finding that the heterogeneity of analysts' forecasts negatively influences the trading volume. The insignificant impact observed for optimistic forecasts also confirms our preceding results, showing that these forecasts are not strictly followed by investors, especially

when they are strongly divergent or erroneous. Panel A also indicates that the idiosyncratic portion of investors' heterogeneous expectations positively influences trades for all data and for pessimistic forecasts. In this regard, Karpoff (1986) obtained similar results in explaining the trading volume by differences in the prior expectations of investors.

Consistently, Panel B shows a positive impact for idiosyncratic heterogeneity, the unique explanatory variable for the trading volume. We conduct a further analysis by performing a multiple regression in which the trading volume is explained by both the idiosyncratic heterogeneity and the squared idiosyncratic heterogeneity. The results show that the coefficients associated with these explanatory variables are respectively positive and negative, suggesting a concave relationship between the trading volume and the idiosyncratic component of investors'

table 6. impact of prior forecast errors on trading volume

Explanatory variables	Model 1	Model 2	Model 3		
	<i>(All data)</i>	<i>(All data)</i>	<i>All data</i>	<i>Optimistic case</i>	<i>Pessimistic case</i>
Constant	0.222*** (0.021)	0.211*** (0.025)	0.169*** (0.027)	0.191** (0.081)	0.253*** (0.077)
Mean absolute forecast variation	0.512*** (0.130)	-	0.473*** (0.126)	0.614** (0.245)	0.371** (0.171)
Mean absolute prior forecast error	-	1.493*** (0.532)	1.209** (0.468)	0.820 (1.318)	-0.138 (0.990)
R2	16.15%	7.52%	20.99%	21.98%	12.15%
Adjusted R2	15.10%	6.37%	18.99%	16.78%	6.29%

Notes: the dependent variable represents the number of shares traded divided by the total number of outstanding shares. The mean variation of analysts' forecasts is measured by the relative difference between the means observed in two consecutive periods. The mean error of analysts' forecasts is measured by the difference between the annual results and the mean analysts' forecast, reported to the mean analysts' forecast. All the regression models were estimated by using the OLS method incorporating the bootstrap method to correct for the departure from normality. The bootstrap standard errors of the estimates are reported in parentheses. The initial samples of 82 observations for all data and 33 observations for both optimistic and pessimistic cases are replicated 1,500 times. *, ** and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% levels, respectively.

expectations. In other words, the trading volume tends to increase when investors' expectations become heterogeneous but decrease when this heterogeneity exceeds a certain threshold. Thus, we validate H3 for the all-data and pessimistic forecast cases. This result is consistent with the experiment done by Dinh and Gajewski (2015) who prove the existence of a concave relation between trading volume and the dispersion of investors' beliefs. This result seems to be consistent with Hales (2009), who, using a series of laboratory markets, found that participants have a tendency to trade aggressively when they fail to see the implicit value in the actions of other participants. However, this tendency is dramatically reduced when participants are prompted to estimate pre-trade disagreement among them or when they trade in more transparent markets. As a matter of fact, the design of the experiment allows for the entire transparency of the market. The investors follow the order book and can infer heterogeneity from the order book, with a counterparty risk.

Our analysis also allows us to determine the dominant factor driving changes in the trading volume. Table 8 reports the results from regression models that relate the trading volume to four explanatory variables: common heterogeneity, idiosyncratic heterogeneity, absolute mean forecast variation, and absolute prior mean error. We do not consider the heterogeneity of analysts' forecasts because it can be reasonably represented by the common heterogeneity of investors' expectations. The evidence from the all-data model reveals that the trading volume is jointly driven by all the factors under consideration; the common heterogeneity of investors' expectations is the most important determinant, although they do not all affect the trading volume in the same way. Investors engage in increased trading activity with respect to the absolute values of the variation of the analysts' mean forecast and mean prior forecast error when they have

divergent expectations. In addition, the existence of forecast disagreements between financial analysts prevents investors from trading because investors are self-protective when there is a high level of uncertainty in the information about earnings. The coefficient associated with the idiosyncratic component of the heterogeneity of investors' expectations is positive and significant at the 5% level, which indicates the case in which the investor-specific expectation dispersion is not too high. Finally, there is evidence of asymmetry between the roles of optimistic and pessimistic forecasts in the market's behavior. On the one hand, the trading volume is positively driven by the absolute mean variation in analysts' optimistic forecasts. On the other hand, it decreases significantly with the common heterogeneity of investors' expectations when financial analysts' forecasts are pessimistic. This finding confirms our previous results showing that individual optimistic forecasts are not strictly followed by investors, especially when they are too divergent or too erroneous. Overall, H4 is validated for the all-data. The results differ from several previous studies reporting that the trading volume is positively and significantly linked both to forecast dispersion and to errors (Karpoff, 1986; Ziebart, 1990). The similar effects of these variables can be explained by the high real correlation between them (*i.e.*, higher errors in analysts' forecasts often accompany greater heterogeneity for forecasts). Because forecast errors and heterogeneity are controlled in our study and different types of forecasts are considered separately, the evidence supporting the dissimilar influences of these factors (*i.e.*, smaller effect of analysts' forecast errors on the volume) is strengthened.

To summarize the above results, the tests enable us to conclude that financial market anomalies arise not only from the inaccurate use of available information by investors but also from imperfect information, including analysts' forecasts. The imperfections in analysts' forecasts

table 7. impact of heterogeneity in investors' expectations on trading volume

Panel A		All data	Optimistic case	Pessimistic case
Explanatory variables				
Constant		0.417*** (0.038)	0.292*** (0.074)	0.501*** (0.032)
Common heterogeneity of investors' expectations		-3.810*** (0.875)	0.382 (1.706)	-5.791*** (0.742)
Idiosyncratic heterogeneity of investors' expectations		0.029** (0.013)	-0.002 (0.019)	0.027* (0.015)
R ²		20.35%	0.10%	60.73%
Adjusted R ²		18.52%	-5.95%	58.35%
Panel B		All data	Optimistic case	Pessimistic case
Models	Explanatory variables			
Model 1	Constant	0.277*** (0.014)	0.305*** (0.026)	0.301*** (0.023)
	Idiosyncratic heterogeneity of investors' expectations	0.029* (0.016)	-0.000 (0.023)	0.062* (0.032)
	R ²	4.40%	0.00%	15.53%
	Adjusted R ²	3.32%	-2.94%	13.04%
Model 2	Constant	0.295*** (0.015)	0.309*** (0.027)	0.346*** (0.021)
	Idiosyncratic heterogeneity of investors' expectations	0.057*** (0.015)	0.018 (0.050)	0.030* (0.017)
	Idiosyncratic heterogeneity of investors' expectations squared	-0.018** (0.009)	-0.006 (0.031)	-0.069*** (0.014)
	R ²	12.77%	0.62%	45.09%
	Adjusted R ²	10.77%	-5.40%	41.77%

Notes: the dependent variable represents the number of traded stocks divided by the total number of available stocks. To run regressions in Panel A, we first regress the heterogeneity of investor expectations on the heterogeneity of analysts' forecasts, and save the common heterogeneity of investors' expectations (i.e., the portion of the heterogeneity of investor expectations explained by the heterogeneity of analysts' forecasts) and the idiosyncratic heterogeneity of investor expectations (i.e., the residuals of this regression). Panel B also controls for the potential of nonlinear relationships that may exist between trading volume and the idiosyncratic heterogeneity of investor expectations. All the regression models are estimated by using the OLS method incorporating the bootstrap method to correct for the departure from normality. The bootstrap standard errors of the estimates are reported in parentheses. The initial samples of 90 observations for all data and 36 observations for both optimistic and pessimistic cases are replicated 1,500 times. *, ** and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% levels, respectively.

are partially incorporated into investors' expectations and affect the trading volume. Although the dispersion in analysts' forecasts plays no role in our experiment's earnings-determination process, it does also influence trading decisions. These observations are consistent with the assessment that investors are not entirely rational. However, analysts' forecasts always appear to be useful, despite their errors, because investors do derive their expectations from them when making investment decisions.

■ VI. Conclusion

This article examines the impacts of analysts' earnings forecasts on investors' expectations and the trading volume. The two main attributes of analysts' earnings forecasts, that is, errors and heterogeneity, are analyzed. From ten

experimentally controlled double-auction markets, we find that when formulating their expectations, investors partially incorporate the analysts' forecast errors and heterogeneity. As for the trading volume, it is negatively driven by the heterogeneity of the analysts' forecasts but positively affected by the size of the forecast errors. These results are typically not symmetric between optimistic and pessimistic forecasts. Our results also indicate that analysts' forecasts are not an unbiased proxy for the beliefs of market agents because the effect of investors' heterogeneous expectations on the trading volume differs from that of analysts' heterogeneous forecasts. More precisely, by dividing the dispersion of investors' expectations into two components, we provide evidence that the fraction related to the heterogeneity of the analysts' forecasts negatively affects the trading volume, and the fraction that reflects individual heterogeneity among

table 8. impact of analysts' forecasts and investors' expectations on trading volume

Explanatory variables	All data	Optimistic case	Pessimistic case
Constant	0.260*** (0.038)	0.175** (0.084)	0.425*** (0.051)
Idiosyncratic heterogeneity of investors' expectations	0.028** (0.013)	0.010 (0.027)	0.019 (0.020)
Common heterogeneity of investors' expectations	-0.598*** (0.174)	0.131 (0.382)	-1.187*** (0.156)
Absolute mean variation of analysts' forecasts	0.330** (0.138)	0.624** (0.265)	0.031 (0.167)
Absolute prior mean error of analysts' forecasts	1.030** (0.454)	0.834 (1.756)	-0.147 (0.617)
R ²	34.04%	22.92%	68.86%
Adjusted R ²	30.61%	11.91%	64.41%

Notes: the dependent variable represents the number of traded stocks over the total number of available stocks. To run these regressions, we first regress the heterogeneity of investor expectations on the heterogeneity of analysts' forecasts, and save the common heterogeneity of investors' expectations (i.e., the portion of the heterogeneity of investor expectations explained by the heterogeneity of analyst forecast) and the idiosyncratic heterogeneity of investor expectations (i.e., the residuals of this regression). The mean variation of the analysts' forecasts is measured by the relative difference between means observed in two consecutive periods. The mean error of analysts' forecasts is measured by the difference between the annual results and the mean analysts' forecast divided by the mean analysts' forecast. All the regression models are estimated by using the OLS method incorporating the bootstrap method to correct for the departure from normality. The bootstrap standard errors of the estimates are reported in parentheses. The initial samples of 82 observations for all data and 33 observations for both optimistic and pessimistic cases are replicated 1,500 times. *, ** and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% levels, respectively.

investors generates trades but in a non-monotonic way. This fraction increases trading when it is not too large but prevents investors from trading beyond a certain threshold.

Future research can extend our study by examining how the asset markets respond to analysts' forecasts when this information is not freely available to investors. In such a case, the degree to which investors follow analysts' forecasts must be investigated with respect to the number of investors who purchase forecasts and the price they agree to pay. Future research should also consider the impact of the level of heterogeneous forecasts on annual earnings determination, which is not the case in our study. □

1 Gillette *et al.* (1999) obtain similar findings in the context of an experimental market with no transaction costs.

2 The theorem of no trade does not apply since there is no asymmetric information in our environment. However, in our experiment with symmetric information, differences in risk aversion or differences of opinion could generate trades.

3 There could be also non-informational explanations to changes of trading volume like portfolio rebalancing, liquidity shocks or transaction costs. If the agents have different risk preferences, risk-sharing also can create incentive to trade.

4 Other explanations, such as herd behavior, low earnings predictability, and analysts' tendency to withhold information in the event of/to avoid unfavorable forecasts, may also account for analyst bias.

5 To some extent, idiosyncratic heterogeneity takes into account investors' beliefs about others' sentiment. When idiosyncratic heterogeneity decreases, this effect is stronger. We thank an anonymous referee about this point.

6 The gain or loss from one buy is calculated by multiplying the number of purchased shares by the difference between the security fundamental value and the buy price. A gain or loss of one sell is equal to the number of sold shares, multiplied by the difference between the price and the fundamental value. By assumption, the earnings are entirely distributed to the participants as dividends at the end of each period. We can consider that the fundamental stock value is equal to the whole amount of the earnings.

7 The second reports the standard deviation of analysts' forecasts to the final earnings. The other two measures correspond to the difference between the highest and lowest forecasts, reported to either the mean of these two forecasts or the final earnings. The alternative measures of variables just cited here have been used as robustness checks. They do not change significantly the results of the paper.

8 We have also considered the standard deviation of expectations divided by the final announced earnings.

9 In earlier literature, the quality of forecasts is often benchmarked by actual earnings. We have also used this measure for the mean error of analysts' forecasts as well as for the mean error of subjects' expectations.

10 We have also used another measure of trading volume by dividing the value of the traded shares (i.e., the number of traded shares multiplied by the associated price) by the firm's accounting value (i.e., the number of outstanding shares multiplied by the stock's fundamental value or the announced earnings).

11 Multicollinearity can be identified by calculating two widely used statistical indicators from a multiple regression model, "Tolerance" and "Variance Inflation Factor".

12 This procedure consists of making statistical inferences on the basis of a resampling distribution. Assuming that our sample data are reasonably representative of the population, we produce a new random sample of the same size as the original sample, with replacements from the observed data points; estimate the regression model in question; and retain the estimates. Because a large number of news samples are recreated, we are able to generate the "true" empirical sampling distributions, at least approximately, for the estimates and determine their upper and lower confidence intervals.

13 In our study, the use of the bootstrap procedure does not change the main findings of the article in general but rather provides more robust standard deviations and thus accurate significance levels for the estimates.

14 This result holds because mean errors are measured in absolute value for Model 4.

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