Analyst earnings forecasts, individual investors' expectations and trading volume: An experimental approach

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Abstract

This article examines how analysts' earnings forecasts affect investors' expectations and trading decisions. The results of ten experimentally-controlled double-auction markets show that investors incorporate part of the forecasting information in both their expectations and trading decisions. More precisely, the heterogeneity of investors' expectations can be divided into: *i*) a common heterogeneity, strictly related to analysts' heterogeneous forecasts, monotonically prevents investors from trading, especially when forecasts are pessimistic; and *ii*) an idiosyncratic heterogeneity, independent from analysts' forecasts, affects trades in a concave way. Trading volume also changes with analysts' forecast errors and reacts asymmetrically to the types of analysts' forecasts.

Keywords: analysts' forecasts, investor expectations, trading volume, experimental asset market, earnings announcement.

JEL classification: C91, G12, M41

1. 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 time or required skills to produce their own predictions. Moreover, financial analysts are commonly regarded as experts and therefore their forecasts help gauge the future corporate earnings and financial performance. Prior research has often used analyst earnings forecasts to benchmark unexpected earnings and found 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)

There is however evidence to suggest that analysts' forecasts contain errors and are not efficient, thus questioning the usefulness of analyst recommendations and forecasts in investment decision-making. Forecast errors typically reflect the optimism bias according to which financial analysts overreact to recent earnings announcements (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). On the other hand, 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. It is however worth noting that these errors and inefficiencies are not totally independent since their optimism may cause analysts to underreact to bad news and overreact to good news (Easterwood and Nutt, 1999).

The above contradictory evidence about 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, whereas Brown (1996) shows that investment community does not trust analysts' forecasts very much, but indeed gives an important weight to forecasts based on time-series models. In a very recent contribution, So (2013) shows that investors overweight analysts' fore-

casts since stock prices do not fully reflect predictable components of analyst errors (i.e., investors weight a signal in excess of the optimal Bayesian weights when forming expectations of future earnings). This finding contradicts however 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 mainly characterized by errors and heterogeneity. The first figure has been extensively studied. From an empirical perspective, most studies examining analysts' forecast errors and market behavior show evidence of a significant effect of this factor on stock prices (Abarbanell and Bernard, 1992; Beaver et *al.*, 2008). On the other hand, relatively few papers have studied the relationship between analysts' forecast errors and 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 trading volume from the inverse of the variation in the analysts' forecast errors over five years - a proxy for earnings precision - and this is robust to changes in the measures of trading volume and to the number of analysts' forecasts available for the firms.

The heterogeneity of analysts' forecasts has also been frequently investigated, but generally in connection with 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 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 trading volume still remains significant even after allowing for the effect of forecast revisions. Some studies based on other variables conclude that trading volume tends to increase to the extent that announcements of analysts' earnings forecasts convey more information (Beaver, 1968; Bamber, 1987) or with the precision of the information provided, but decreases 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 the precision of analysts' forecasts, we would have expected its effect on trading volume to take different forms.

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

Despite their significant contributions to the understanding of investors' reactions to earnings announcements, the majority of the previous work faces 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 to heterogeneity. As a result, the impact of each component cannot be separated from that of the others, leading to potentially spurious conclusions. More importantly, since the necessary data concerning investor expectations are in practice not recorded, previous studies have often used analysts' forecasts of annual earnings as a surrogate (Ajinkya et al., 1991). This is questionable because investors and analysts have different motivations and market positions. Heterogeneity of analysts' forecasts does not fully capture investor uncertainty (Abarbanell et al., 1995), and thus its influence on 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 here trading volume instead of stock prices. This allows us to focus on individual expectations since "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). Moreover, theoretical and empirical studies are strongly focused either on forecasts' heterogeneity or on 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 the analysts' forecasts and the other not. They 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 generally refer to analysts' forecasts to formulate their

own expectations. However, they partly correct for forecasting errors and their expectations are less heterogeneous than analyst forecasts. Within this research, one of the explanations is a timing advantage in favor of the investors, since they usually form their expectations about future stock prices after the publication of the financial analysts' forecasts. Next, we find evidence of a significant negative impact of the heterogeneity of analysts' forecasts on trading volume. However, it is important to note that different results are obtained when we take into account the investors' heterogeneous expectations and separate them into two components, as discussed in the previous paragraph: the common heterogeneity part and the idiosyncratic heterogeneity part 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 trading volume. Conversely, the latter part reveals the idiosyncrasies of the individual investors' own sentiments, which have a non-monotonic impact on volume. As for forecasting errors, they are not determined at the beginning of the trading period, but only at the end. So if trading volume is affected by forecasting errors, the errors are those of the previous period, 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 respectively present the experimental design and the proxy measurements. Section 5 reports and discusses the results obtained. Section 6 presents a summary of our observations together with our conclusions.

2. Theoretical basis and derivation of hypotheses

Investor beliefs cannot be directly observable. Therefore, most empirical studies, including for example 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 such as 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 in order to increase the revenues obtained from the analyst's 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 overreaction to good news is not fully offset by overreaction to bad news (De Bondt and Thaler, 1985, 1987, 1990)[2].

Considering analyst's forecasts with systematic and persistent errors, one of the major objectives of this article is to examine how investors respond to such forecasts. 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, since investors, especially experienced ones, are able to detect and correct some of the potential errors in analysts' forecasts, though not all. This 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 becomes useful to explore in which measure the investors attach importance to analysts' forecasts in forming their own expectations. This 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 analysts' 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 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 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 trading volume. We support the negative impact of the heterogeneity of analysts' forecasts by arguing

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[2] Other explanations such as herd behavior (Trueman, 1994), low earnings predictability (Huberts and Fuller, 1995), and analysts' tendency to withhold information in the event of/to avoid unfavorable forecasts (Affleck-Graves, 1990; McNichols and O'Brien, 1997) may also account for analyst bias.

that the investors would have an inclination towards self-protection and would 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 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 is explained by the fact that although they are influenced by analysts' forecasts, investors' expectations may always contain a specific element. This 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 or probability functions (Harris and Raviv, 1993; Kandel and Pearson, 1995). Note that investors' expectations can easily be observed and measured in laboratory experiments.

One way to reconcile the two preceding types of explanations consists in disentangling the part of investors' expectations strictly related to the heterogeneity of analysts' forecasts (hereafter designated as common heterogeneity) from the part associated with investors' own sentiment (hereafter called idiosyncratic heterogeneity). The first fraction should negatively affect trading volume, since 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 – the necessary condition to generate exchanges. Nevertheless, this portion reduces trading when being too high because if expectations are too divergent among investors, they carry a considerable risk of losses, and thus a fear of trading. Accordingly, we propose to test the following hypothesis:

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

Furthermore, if the 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 trading volume and this factor, designated as unexpected earnings. The presence of forecast errors will give investors an incentive to trade in order either to

take advantage of previous erroneous forecasts or to correct them. We therefore hypothesize that:

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

3. 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 Readymade Economic Experiments) software. It comprises ten double-auction markets of which nine markets contain twelve exchange periods and one has six exchange periods. In total, these markets involve 81 undergraduate students with no prior experience in any similar experiment or with market anomalies. Each market is composed of from 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 good understanding of market's rules and participate to 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 consideration[3]. 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.

3.1 Analyst's forecasting process

Every experimental market has six analysts whose forecasts must fall between 60 and 140. The annual earnings are the sum of the mean of all forecasts (expected portion) and a term representing the forecast error (unexpected portion). The forecast error comprises a random term and a tendency term.

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[3] 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. Gain and 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.

The random term is created in order to generate an entirely unpredictable link between the forecast mean and annual earnings. With a zero mean and a standard deviation of 2.16, it is drawn, at the end of each period, from the following values: -3; -2; -1; 0; 1; 2 and 3.

The tendency term represents the optimism, pessimism, or lack of bias in the analysts' forecasts, based on which we establish three types of forecasting information. 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 of zero mean. This means that the forecast average is a noisy but unbiased proxy for annual earnings. In contrast, optimistic forecasts are characterized by systematic negative errors whatever the value of the random term. We thus allow the tendency term to fluctuate from -9 to -6. Therefore, 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, both optimistic and pessimistic forecast means are also noisy and biased. Using these categories of earnings forecasts, the experiment can be divided into three groups of markets: two unbiased forecast markets, four optimistic forecast markets, and four pessimistic forecast markets. In all markets, forecast errors are distinguished from forecast heterogeneity.

3.2 Conduct of experiments

Recall that there are 9 twelve-period markets and 1 six-period market. All the trading periods last about 6 minutes and take place in the same way with 3 stages.

At 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 pencil and paper in order to note all the information they want. Then they observe these forecasts during 30 seconds before giving their own expectations of earnings. This stage is mandatory, and continues until all the subjects have given their predictions.

The second stage lasts five minutes during which 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 desire to purchase securities at a price equal to or less than *p*, whereas a sell order at price *p* specifies that securities will only be traded at a price equal to or greater than *p*. An order is executed when there exists one or more offers in the opposite direction which satisfy the trading price condition. In addition, subjects can respond to orders displayed in the order book. Neither short selling nor cash balances are al-

lowed 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.

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.

4. Measurements of test parameters

In this study four measures are used as proxies for the divergence of analysts' earnings forecasts. The first two correspond to the standard deviation of analysts' forecasts divided by the mean of the earnings forecasts and the earnings respectively. 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.

First measure of forecast heterogeneity:

$$HetFOR1_t = \left(\sqrt{\frac{1}{n} \sum_{i=1}^{n} (FOR_{i,t} - FOR_t)^2} \right) / FOR_t$$

Second measure of forecast heterogeneity:

$$HetFOR2_t = \left(\sqrt{\frac{1}{n} \sum_{i=1}^{n} (FOR_{i,t} - FOR_t)^2} \right) / RES_t$$

Third measure of forecast heterogeneity:

$$HetFOR3_t = (FOR_{max,t} - FOR_{min,t}) / ((FOR_{max,t} + FOR_{min,t}) / 2)$$

Fourth measure of forecast heterogeneity:

$$HetFOR4_t = (FOR_{max,t} - FOR_{min,t}) / RES_t$$

In the above expressions, *HetFOR1_t*, *HetFOR2_t*, *HetFOR3_t* and *HetFOR4_t* measure the heterogeneity of analysts' forecast for period *t*. $FOR_{i,t}$ stands for the forecast of analyst *i* for period *t*. $FOR_{max,t}$ and $FOR_{min,t}$ are respectively the maximum and minimum forecasts for period *t*. FOR_t is the mean of analysts' forecasts for period *t*. RES_t represents the annual earnings for period *t*, and *n* is the number of analysts.

In spite of the dispersion of the analysts' forecasts, the heterogeneity of the investors' expectations is simply approximated by two measures. These are the standard deviation of all

individual forecasts divided either by their mean or by the announced earnings. This result is explained by the fact that the subjects' expectations are private, and unknown to the other investors, while the analysts' forecasts are publicly revealed and strictly controlled to satisfy predetermined conditions. Accordingly, the two extreme values of investors' expectations should not significantly influence the behavior of the market as a whole.

First measure of expectation heterogeneity:

$$HetEXP1_t = \left(\sqrt{\frac{1}{m} \sum_{i=1}^{m} (EXP_{i,t} - EXP_t)^2} \right) / EXP_t$$

Second measure of expectation heterogeneity:

$$HetEXP2_t = \left(\sqrt{\frac{1}{m} \sum_{i=1}^{m} (EXP_{i,t} - EXP_t)^2} \right) / RES_t$$

where $HetEXP1_t$, and $HetEXP2_t$ measure the heterogeneity of investors' earnings expectations for period t; $EXP_{i,t}$ the earnings expectation announced by investor i for period t; and m the number of investors involved in the market.

We define the common heterogeneity as the part of the investors' expectations which is strictly correlated with the analysts' forecasts, and the idiosyncratic heterogeneity as the part which is specific to the investors alone. 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 part of the heterogeneity of investors' expectations predicted by the heterogeneity of analysts' forecasts, while the idiosyncratic heterogeneity corresponds simply to the unpredicted part of the regression.

Since the primary use of analysts' earnings forecasts in security analysis is to provide references for investment decisions, investors would prefer analysts' forecasts to be more accurate than they are. This is why in earlier literature the quality of forecasts is often benchmarked by the actual earnings. Accordingly, we measure the forecast error by the difference between the forecast and actual annual earnings, deflated by the actual earnings. Moreover, in order to be consistent with the previous set of variables, we also use another measure of forecast error by dividing the same difference by the mean forecast.

First measure of forecast error:

$$ErrFOR1_t = (RES_t - FOR_t) / FOR_t$$

Second measure of forecast error:

$$ErrFOR2_t = (RES_t - FOR_t)/RES_t$$

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

First measure of expectation error:

$$ErrEXP1_t = (RES_t - EXP_t)/EXP_t$$

Second measure of expectation error:

$$ErrEXP2_t = (RES_t - EXP_t)/RES_t$$

Trading volume is determined in two ways. The first measure refers to the fraction of shares traded during a period divided by the total number of outstanding shares. The second measure is obtained by dividing the value of the shares traded (i.e., the number of shares traded 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).

First measure of trading volume:

$$VOL1_t = \left(\sum N_{i,t}\right)/N_{m,t}$$

Second measure of trading volume:

$$VOL2_t = \frac{\sum N_{i,t} \times PRICE_{i,t}}{N_{m,t} \times RES_t}$$

where $VOL1_t$ and $VOL2_t$ are the two proxies of trading volume for the period t; $N_{i,t}$ the number of shares traded involving the transaction i during the period t; $N_{m,t}$ the total number of shares outstanding; and $PRICE_{i,t}$ the exchange price for the transaction i in the period t.

Table 1
Summary statistics for primary variables and extracted components of investors' expectations

Primary variables	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^+
Components of investor expectations						
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^+

Table 1 provides summary statistics of the first measures for the primary variables and extracted components of investor expectations used in this article. Data are obtained from running ten double-auction markets 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.

5. Results and interpretations

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

Several remarks should be noted before we present the experimental findings. First, for sake of concision, we report and comment only the results obtained with the first measures of all the variables, because the results with the other measures remain unchanged. . Second, tests indicate that there is no multicolinearity in our regression models as each explanatory variable has a valuable informative content on the dependent variable[4]. Finally, we use the bootstrap procedure in order to improve the performance of the OLS method in estimating the parameters of all the regression models[5]. We are particularly encouraged by the fact that the bootstrap technique is highly suitable in cases where the assumption of normality is not justi-

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[4] Multicolinearity can be identified by calculating, from a multiple regression model, two widely used statistical indicators, "Tolerance" and "Variance Inflation Factor". The results are available upon request to the corresponding author.

[5] 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 then produce a new random sample of the same size as the original sample, with replacement from the observed data points, estimate the regression model in question, and retain the estimates. Because a large number of new samples are created, we are able to generate the "true" empirical sampling distributions, at least approximately, for the estimates, and to determine their upper and lower confidence intervals.

fied, owing for example to a small number of observations. Indeed, we perform 1,500 replications of each initial sample in order to obtain robust estimates of the models' coefficients[6].

5.1 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, and especially to their mean variation. Such verification is not useless since it gives an idea of the effect of analysts' forecasts on investors' expectations. In addition, unlike many previous works which rely 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 thus 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 *(All data)*	Model 2 *(All data)*	Model 3 *(All data)*	Model 4		
				All data	*Optimistic case*	*Pessimistic case*

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[6] In our study the use of the bootstrap procedure does not change the main findings of the article in general, but provides more robust standard deviations and thus accurate significance levels for the estimates. For interested readers, the results of the standard OLS estimations are available under request to the corresponding author.

Constant	0.011**	0.148***	0.102***	0.014	0.013	0.020
	(0.004)	(0.023)	(0.016)	(0.008)	(0.015)	(0.014)
Mean variation of analysts' forecasts	0.902***	-	-	0.917***	0.948***	0.889***
	(0.030)			(0.031)	(0.046)	(0.047)
Heterogeneity of analysts' forecasts	-	-0.281**	-	0.047	-0.030	0.094
		(0.135)		(0.050)	(0.095)	(0.072)
Prior mean error of analysts' forecasts	-	-	0.313	-0.215*	-0.044	-0.416**
			(0.309)	(0.106)	(0.266)	(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 in order 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 were 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). 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 is fairly normal because optimistic investors often neglect the previous errors made by analysts. As for the coefficient associated with the mean variation of financial analysts' forecasts, it is lower for pessimistic forecasts than for optimistic forecasts, though both are significant at the 1% level. This 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 news and good news, 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 then involves examining whether they correct the forecasts' errors. Figures 1 to 3 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 respectively. Table 3 also indicates that these inves-

tor errors are not driven by the heterogeneity, but mostly by analysts' forecast biases. The size of the investors' expectation errors in absolute terms is however less than that of the analysts' bias. This is confirmed by investors under-reacting to available forecasting information and partially correcting its errors. The semi-rational expectations model seems to be valid.
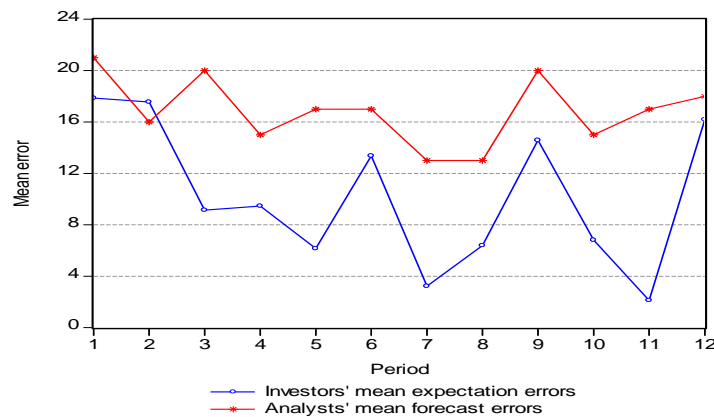
Figure 1
Investors' expectation errors versus financial analysts' forecast errors: all data
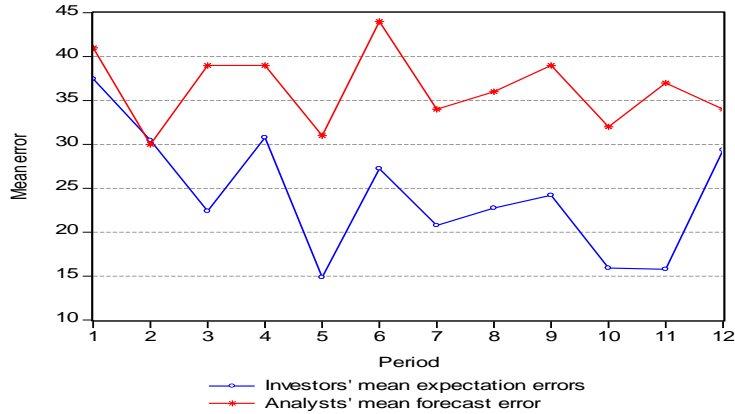
Figure 2
Investors' expectation errors versus financial analysts' forecast errors: optimistic forecasts
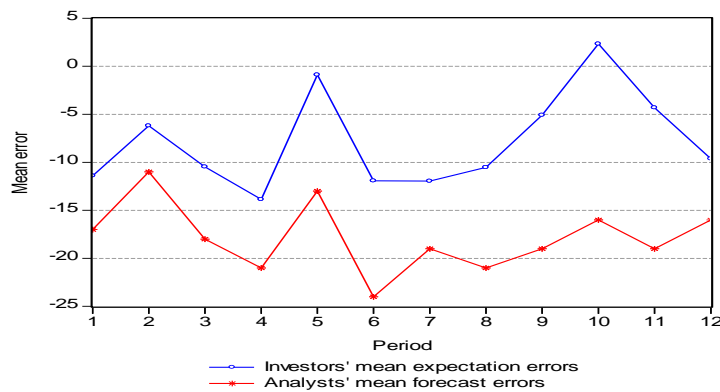
Figure 3
Investors' expectation errors versus financial analysts' forecast errors: pessimistic forecasts

Table 3
Impact of analysts' forecasts on errors in investors' expectations

Explanatory variables	Model 1 *(All data)*	Model 2 *(All data)*	Model 3		
			All data	*Optimistic case*	*Pessimistic case*
Constant	0.030***	0.009**	0.004	-0.007	-0.005
	(0.004)	(0.004)	(0.005)	(0.009)	(0.006)
Heterogeneity of analysts' forecasts	-0.011	-	0.036	-0.002	0.011
	(0.033)		(0.028)	(0.042)	(0.045)
Mean error of analysts' forecasts	-	0.469***	0.486***	0.673***	0.732***
		(0.086)	(0.087)	(0.168)	(0.135)
R^2	0.14%	31.43%	33.02%	39.76%	43.58%
Adjusted R^2	-1.11%	30.57%	31.33%	35.74%	39.82%

Notes: 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 in order 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 were replicated 1,500 times. *, ** and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% levels respectively.

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), whatever the type of market (i.e., all data, optimistic forecasts, and pessimistic forecasts). However, the associated coefficient is notably less than unity. These findings thus 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 can be explained by the fact that investors are likely to be able to detect an optimistic bias more easily than a pessimistic one. This explanation seems to be in line with Chen et *al.* (2002)'s prediction according to which market behavior reflects agents' optimism better than pessimism. Moreover, it is commonly accepted that investors have a natural inclination to self-protection. When recognizing a bias of optimism, especially strong bias, investors tend to reprocess the information and form less heterogeneous expectations to avoid the risk of big losses. Overall, this reaction leads to a lowering of the heterogeneity of investors' expectations.

Table 4
Impact of analysts' forecasts on heterogeneity of investors' expectations

Explanatory variables	Model 1 (All data)	Model 2 (All data)	Model 3 All data	Optimistic case	Pessimistic case
Constant	0.018***	0.041***	0.018***	0.036***	0.016**
	(0.002)	(0.004)	(0.004)	(0.008)	(0.007)
Heterogeneity of analysts' forecasts	0.174***	-	0.174***	0.281***	0.131***
	(0.029)		(0.029)	(0.060)	(0.044)
Mean absolute error of analysts' forecasts	-	-0.077	0.003	-0.431**	0.084
		(0.078)	(0.065)	(0.168)	(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 in order 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 were replicated 1,500 times. *, ** and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% levels respectively.

5.2 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 of trades. Thus, we first relate trading volume to the heterogeneity of financial analysts' forecasts. Results are reported in Table 5. Overall, our experiment indicates that 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, because of increased risk aversion. This conclusion is consistent with earlier studies which consider the heterogeneity of analysts' forecasts as a proxy for market uncertainty or imprecision in the public information (Ziebart, 1990; Barron, 1995; Bamber et *al.*, 1997). Moreover, a segment of the investment community, namely "sophisticated investors", may recognize specific bias in analysts' forecasts and do not consider such information as a very relevant reference for their own expectations which directly affect their trading decisions.

Table 5
Impact of the heterogeneity of analysts' forecasts on trading volume

Explanatory variables	All data	Optimistic case	Pessimistic case
Constant	0.358***	0.293***	0.416***
	(0.025)	(0.046)	(0.021)
Heterogeneity of analysts' forecasts	-0.758***	0.132	-1.236***
	(0.165)	(0.303)	(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 in order 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 were replicated 1,500 times. *, ** and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% levels respectively.

To our knowledge, no previous empirical work has detected such a negative relationship, perhaps because the analysts' earnings forecasts were not sufficiently divergent owing 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.

Regarding 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), it is closely related to the results displayed in Table 4. That is, since they more easily recognize optimistic errors, the 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. On the other hand, a too high level of heterogeneity in financial analyst's pessimistic forecasts makes investors doubtful about the future of the firm's profitability and leads 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 trading volume (Doukas et *al.*, 2006).

Table 6
Impact of prior forecast errors on trading volume

Explanatory variables	Model 1 (All data)	Model 2 (All data)	Model 3 All data	Model 3 Optimistic case	Model 3 Pessimistic case
Constant	0.222^{***}	0.211^{***}	0.169^{***}	0.191^{**}	0.253^{***}
	(0.021)	(0.025)	(0.027)	(0.081)	(0.077)
Mean absolute forecast variation	0.512^{***}	-	0.473^{***}	0.614^{**}	0.371^{**}
	(0.130)		(0.126)	(0.245)	(0.171)
Mean absolute prior forecast error	-	1.493^{***}	1.209^{**}	0.820	-0.138
		(0.532)	(0.468)	(1.318)	(0.990)
R^2	16.15%	7.52%	20.99%	21.98%	12.15%
Adjusted R^2	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 in order 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 were replicated 1,500 times. *, ** and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% levels respectively.

In our experiment, all the exchange periods are independent, but the same asset is used. In other words, each 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 investigated this link and report the results in Table 6. The evidence suggests that the magnitude of analysts' forecast errors exerts a significant impact on 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 thanks to the presence of the 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 bigger and the impact of forecast errors becomes insignificant. It also appears that trading volume is an increasing function of variations in analysts' forecasts, whichever the regression model. Since 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 in order to adjust their asset holdings.

5.3 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 trading volume in the presence of analysts' forecasts. Indeed, the disagreement between the investors might be the most important determinant of trading volume since trades require opposite orders. Moreover, given the fact that 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: a common heterogeneity which is strongly correlated with the disagreement in analysts' forecasts, and an 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 trading volume in different ways.

As expected, Panel A of Table 7 indicates a negative relationship between 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 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 the investors' heterogeneous expectations positively influences trades, both for all data and for pessimistic forecasts. In this regard, Karpoff (1986) obtained similar results in explaining trading volume by differences in the prior expectations of investors.

Consistently, Panel B exhibits a positive impact of the idiosyncratic heterogeneity, the unique explanatory variable for trading volume. We also conduct a further analysis by performing a multiple regression in which 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 trading volume and the idiosyncratic component of investors' expectations. In other words, trading volume tends to increase when investors' expectations become heterogeneous, but decreases when this heterogeneity goes beyond a certain threshold. We thus validate H3 for the all-data and pessimistic forecast cases. This

result seems to be consistent with the finding by Hales (2009), using a series of laboratory markets, according to which participants have a tendency to trade aggressively when they fail to see the value implicit 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.

Table 7
Impact of heterogeneity in investors' expectations on trading volume

Panel A				
Explanatory variables		All data	Optimistic case	Pessimistic case
Constant		0.417^{***}	0.292^{***}	0.501^{***}
		(0.038)	(0.074)	(0.032)
Common heterogeneity of investors' expectations		-3.810^{***}	0.382	-5.791^{***}
		(0.875)	(1.706)	(0.742)
Idiosyncratic heterogeneity of investors' expectations		0.029^{**}	-0.002	0.027^{*}
		(0.013)	(0.019)	(0.015)
R^2		20.35%	0.10%	60.73%
Adjusted R^2		18.52%	-5.95%	58.35%
Panel B				
Models	Explanatory variables	All data	Optimistic case	Pessimistic case
Model 1	Constant	0.277^{***}	0.305^{***}	0.301^{***}
		(0.014)	(0.026)	(0.023)
	Idiosyncratic heterogeneity of investors' expectations	0.029^{*}	-0.000	0.062^{*}
		(0.016)	(0.023)	(0.032)
	R^2	4.40%	0.00%	15.53%
	Adjusted R^2	3.32%	-2.94%	13.04%
Model 2	Constant	0.295^{***}	0.309^{***}	0.346^{***}
		(0.015)	(0.027)	(0.021)
	Idiosyncratic heterogeneity of investors' expectations	0.057^{***}	0.018	0.030^{*}
		(0.015)	(0.050)	(0.017)
	Idiosyncratic heterogeneity of investors' expectations squared	-0.018^{**}	-0.006	-0.069^{***}
		(0.009)	(0.031)	(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 in order 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 were replicated 1,500 times. *, ** and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% levels respectively.

Explanatory variables	All data	Optimistic case	Pessimistic case
Constant	0.260***	0.175**	0.425***
	(0.038)	(0.084)	(0.051)
Idiosyncratic heterogeneity of investors' expectations	0.028**	0.010	0.019
	(0.013)	(0.027)	(0.020)
Common heterogeneity of investors' expectations	-0.598***	0.131	-1.187***
	(0.174)	(0.382)	(0.156)
Absolute mean variation of analysts' forecasts	0.330**	0.624**	0.031
	(0.138)	(0.265)	(0.167)
Absolute prior mean error of analysts' forecasts	1.030**	0.834	-0.147
	(0.454)	(1.756)	(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 in order 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 were replicated 1,500 times. *, ** and *** indicate that the coefficients are statistically significant at the 10%, 5%, and 1% levels respectively.

Our analysis also allows us to determine the dominant driving factor of changes in trading volume. Table 8 reports the results from regression models that relate 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 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 trading volume in the same way. The investors engage in increasing 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. At the same time, the existence of forecast disagreements between financial analysts prevents the investors from trading, since investors have a self-protective behavior 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, 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 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 and optimistic forecast cases, while H4 holds only for all data. The results thus differ from several previous studies reporting that 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 a greater heterogeneity of forecasts). Since 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 volume) is strengthened.

To sum up 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 are partially incorporated into investors' expectations and affect 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 and then make investment decisions.

6. Conclusion

This article examines the impacts of analysts' earnings forecasts on investors' expectations and trading volume. Two main attributes of analysts' earnings forecasts, the errors and heterogeneity, are analyzed. We find, from ten experimentally-controlled double-auction markets, that, when formulating their expectations, the 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 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 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 trading volume, while the fraction that only reflects individual heterogeneity among investors generates trades, but in a non-monotonic way. It increases trading when it is not too large, but prevents the investors from trading beyond a certain threshold.

Future research can extend our study in 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.

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Appendix

You are invited to participate to this game. Please read these instructions carefully. Then, you will be asked to answer to some questions of comprehension and to participate to some trial periods before playing the game.

This game allows you to earn money on the basis of your performance. During the game, you will trade a number of units of a single stock. Each participant makes individual decisions on a computer. Communication between participants is not allowed. If you break any of the game's rules you will forfeit the right to any earnings.

You take part in a twelve-period market. All periods have the same exchange rules, but different information about the value of the stock. The periods are independent. Each period lasts about 6 minutes, at the beginning of which all of you receive 20 shares of the stock and 2,000 fictitious currency units. You are then given a number of professional forecasts concerning the stock's value. You will have 30 seconds to examine these forecasts without making any trades. Following this interval, you will be asked to estimate the true value of the stock. This estimation is mandatory. You can then sell your shares or purchase the shares of others. To do this you announce the quantity you wish to trade and the desired price. A purchase price p means that you will purchase shares only at a price equal to or less than p. Conversely, a sell price p indicates that you wish to sell shares at a price equal to or higher than p. You earn money when you sell a share for more than its true value or buy a share for less than its true value. In the opposite case, you lose money.

Note that the number of shares that you can sell cannot, at any time, exceed the number you possess. Similarly, the amount of your purchase may not exceed the money you have. After every trade you make, your money and the quantity of stock you own are recalculated. Your offer to buy or to sell will be executed as soon as there are reciprocal offers to sell or buy that satisfy your price. You can also accept any number of propositions made by other persons. All offers to buy or sell appear in a window on your computer. Offers that are not executed in the course of one period are no longer valid in the next period.

At the end of each period you are told the true value of the stock. We then calculate your gain or loss. Recall that you gain money when you sell a share for more than its true value or

buy a share for less than its true value. In the opposite case, you lose money. The amount of the gain (loss) is the sum of the gains (losses) in each trade, calculated by multiplying the number of traded shares by the gain (loss) per share. The gain (loss) for the whole session is the sum of the gains (losses) for all the periods in which you took part. Your real cash earnings will be determined by converting the money you gain (zero it you make a loss) over of the course of the session, plus a bonus for the accuracy of your estimate of the stock's value, plus an appearance fee of 10 Canadian dollars. The formula is as follows:

Real cash winnings = [Max (0 ; (Total Gains and Losses from trades + Bonus for stock value estimate))] * Conversion Rate + 10 CAD

The conversion rate is set such that the average winnings will be 25 CAD for two hour session.