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Three essays in empirical finance

Tristan Roger

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THÈSE

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Introduction

This dissertation studies the behavior of two types of market participants: individual investors and financial analysts. The former are information consumers while the latter provide, through their reports, useful information to the market. Individual investors obtain information from stock prices, newspapers and financial analysts. Ivkovic and Jegadeesh (2004) identify two sources of value that analysts bring to the market. First, they extract useful information for investors from public information. Second, through a careful examination of accounting documents and contacts with firm managers, they acquire information previously unknown to other market participants. As such, their reports and forecasts are of great importance since they render private information public. Analysts' reports are typically composed of three main figures: earnings forecasts, purchase recommendations and target prices.

The first part of this dissertation focuses on the herding behavior of individual investors. Herding behavior corresponds to a mimetic behavior or can result from correlated behavior patterns (correlated trading). This behavior typically arises from payoff externalities, reputational concerns or information externalities (Devenow and Welch, 1996). A general consensus in the literature is that economic agents are relatively prone to herd. Evidence of herding behavior has been found for mutual

funds (Lakonishok, Shleifer, and Vishny, 1992; Grinblatt, Titman, and Wermers, 1995; Chevalier and Ellison, 1999; Wermers, 1999), individual investors (Feng and Seasholes, 2004; Dorn, Huberman, and Sengmueller, 2008; Barber, Odean, and Zhu, 2009; Venezia, Nashikkar, and Shapira, 2011) and financial analysts (Trueman, 1994; Olsen, 1996; Hong, Kubik, and Solomon, 2000; Clement and Tse, 2005).

The first chapter of this dissertation is the first study on herding behavior that focuses on French individual investors. Our empirical analysis relies on a database of nearly 8 million trades accomplished between 1999 and 2006 by 87,373 individual investors. We show that the trading decisions of the investors in our sample are highly correlated. Using the measure of Lakonishok, Shleifer, and Vishny (1992), we find a similar level of herding than what is observed for U.S. individual investors (Barber, Odean, and Zhu, 2009). However, the main contribution of this first chapter is the study of the determinants of individual investors' herding behavior.

Standard measures of herding behavior (such as the measure Lakonishok, Shleifer, and Vishny, 1992) permit to estimate, for a given stock, the level of herding. However, they do not allow for studying herding at the individual level. We introduce a new measure that allows us to track over time the level of herding of a given individual investor. We are then able to investigate the determinants of herding at the investor level and the motivations of individual investors to engage in this behavior. We show that investors' characteristics influence their propensity to herd. We find that the degree of sophistication of an individual investor is negatively related to her propensity to herd. Our results also indicate that, following a bad performance, the trading decisions of individual investors are more correlated with their peers'.

Finally, we intent to provide an answer to a question that remained unaddressed by the literature: is herding profitable? We find that investors trading against the crowd exhibit more extreme returns and poorer risk-adjusted performance than herders. We also observe that investors trading against the crowd, contrary to herders, improve their performance by trading. Although we are not able to provide an explanation to why most investors decrease their performance by trading (Barber and Odean, 2000), this result indicates that our measure is successful in determining who trades against the crowd.

The second part of this dissertation focuses on financial analysts' target prices. A target price corresponds, for a given firm, to the analyst's evaluation of the future stock price (usually 12-month ahead). As pointed out by Bradshaw (2011), in a survey on financial analysts, "the literature [...] suffers from an overemphasis on earnings forecasts relative to other important tasks performed by analysts". In addition to earnings forecasts and recommendations, most analysts now include a target price to their reports. Although this statistic does not attract a lot of attention from institutional investors, it is the most comprehensive one (relatively to earnings forecasts and recommendations). As such, this statistic is potentially the most useful for individual investors.

As a consequence of the investors' great interest for earnings forecasts, researchers have investigated whether financial analysts have the ability to accurately forecast earnings. A large stream of literature has focused on determining whether analysts' earnings forecasts are superior to time-series forecasts (Cragg and Malkiel, 1968; Elton and Gruber, 1972; Barefield and Comiskey, 1975; Brown and Rozeff, 1978;

Fried and Givoly, 1982; Brown, Hagerman, Griffin, and Zmijewski, 1987). Once the superiority of analysts' forecasts was established, the literature investigated whether some analysts were better than others. Stickel (1992) and Sinha, Brown, and Das (1997) showed that financial analysts exhibit differential abilities to issue accurate earnings forecasts.

One of the reasons why target prices have not yet attracted a lot of attention from market participants is that it is unclear whether the information embedded in target prices is reliable. Aside from the potential conflict of interests, we postulate that the lack of confidence in target prices results from the absence of feedback. Contrary to earnings forecasts, the literature has not yet provided a proper framework with which to evaluate the quality of target prices. Without a consensual way to evaluate whether some target prices are superior to others, brokerage firms cannot provide analysts with incentives to issue accurate target prices. Furthermore, the lack of short-term feedback (target price accuracy measures are usually *ex-post* measures: 12 months are typically needed to evaluate the quality of a target price) prevents analysts from improving their ability to issue accurate target prices. As stated by Kahneman (2011): "whether professionals have a chance to develop intuitive expertise depends essentially on the quality and speed of the feedback".

The second chapter of this dissertation intends to provide a comprehensive framework for measuring the quality of analysts target prices. An important contribution of our work is to consider, when evaluating target prices, the issue of forecast predictability. We show that measuring whether a target price is accurate or not is not sufficient to assess its quality. Indeed, the difficulty of issuing an accurate target price

varies across stocks and over time. This predictability issue is a well-known concern in the literature on earnings forecasts (Huberts and Fuller, 1995; DeBondt and Forbes, 1999; Beekers, Stelias, and Thomson, 2004). Jacob, Lys, and Neale (1999) note that “forecasting difficulty is [...] like to differ cross-sectionally” while Hong, Kubik, and Solomon (2000) state that “some firms are more difficult than others to predict accurately”. These differences in predictability prevent, for instance, the direct aggregation of individual forecast accuracies (forecasts issued on different stocks) into a measure of analyst accuracy. To circumvent this issue, researchers employ relative measures of accuracy, that is, the quality of a forecast is determined with respect to other forecasts issued in similar conditions (*i.e.*, forecasts issued on the same firm and during the same period of time). The use of relative measures, however, is not possible when dealing with target prices. Contrary to earnings forecasts where all forecasts issued during a given year predict the same thing (the earnings to be announced at the end of the fiscal year), target prices made on different days forecast different things (the 12-month ahead stock price).

The predictability of a forecast depends on the variability of the predicted variable and on the horizon of the forecast. Evidence of a link between horizon and predictability has been established early in the literature on earnings forecasts (Brown, Richardson, and Schwager, 1987; O’Brien, 1988; Kross, Ro, and Schroeder, 1990; Brown, 1991; Lys and Soo, 1995; Sinha, Brown, and Das, 1997). Dichev and Tang (2009) demonstrate the existence of a relationship between predictability and variability. They show that earnings predictability is negatively related to earnings volatility.

The literature on earnings forecasts use relative measures of accuracy to control

for differences in predictability. The use of relative measures comes from the fact that the data on earnings does not permit to compute a good estimation of the predictability. In the second chapter of this dissertation, we show that, in the case of target prices, it is possible to estimate precisely the predictability (as the number of observations for stock prices is much greater than for earnings). The predictability can be measured as the expected value of the absolute forecast error. Estimating this expected value is actually equivalent to pricing a straddle (a call and a put option with the same strike price). We therefore use methodologies from the option-pricing field to incorporate the predictability in our measure of target price quality. Beyond the issue of predictability, our approach has the following advantages. First, our measure of quality rewards bold accurate forecasts. Second, it is a dynamic measure; our measure allows us to evaluate, at any moment in time, the quality of a target price (one does not need to wait until the end of the forecast horizon to assess the target price quality).

Taking into account the predictability has important consequences on the analysis of target prices. For instance, previous papers (Bradshaw, Brown, and Huang, forthcoming; Bilinski, Lyssimachou, and Walker, 2013) find some evidence that analysts exhibit persistent differential abilities to issue accurate target prices. We show, using a database of 649,471 target prices issued between 2000 and 2010 by 9,367 analysts on 7,268 U.S. stocks, that this result is driven by persistence in volatility and does not hold when predictability is taken into account.

The third chapter of this dissertation studies whether analysts' characteristics - such as the experience, the number of firms followed or the size of the employer - influ-

ence their ability to issue accurate target prices.¹ Bilinski, Lyssimachou, and Walker (2013) find that target price accuracy is positively related to analyst experience and to the number of firms followed. We show in this paper that coverage decisions are heterogeneous with respect to experience. Our results indicate that experienced analysts and inexperienced analysts cover different types of firms. Experienced analysts follow primarily blue chips while inexperienced analysts cover mainly small, young, growth firms. These differences in coverage decisions have important implications on the predictability of analysts' target prices as blue chips' stock returns tend to be less volatile. Because experienced analysts cover mainly blue chips, the stock prices of the firms they cover are more predictable. Therefore, the probability of being accurate is higher for experienced analysts, regardless of their ability. It is thus possible that the results of Bilinski, Lyssimachou, and Walker (2013) are driven by differences in predictability. In order to test the influence of analysts' characteristics on analysts' ability to issue accurate target prices, we use the target price quality measure introduced in the second chapter which incorporates predictability. We obtain that target price quality is positively related to analyst experience and to the number of firms followed but negatively related to employer size. These results confirm that forecasting skills improve with experience (learning by doing) or/and that analysts with low ability do not manage to stay in the profession.

The differences in coverage decisions between experienced and inexperienced analysts have implications beyond the sole topic of target prices. For instance, it sheds a new light on analysts' preferences. We postulate that these coverage differences

¹We built proxies for analysts' characteristics (following the methodology of Clement, 1999) using all the one-year ahead earnings forecasts provided by I/B/E/S for the 1982-2010 period.

between experienced analysts and inexperienced analysts appear because coverage decisions are constrained by brokerage firms. Experienced analysts are assigned (or get to choose) large, mature firms (blue chips) while inexperienced analysts are left with firms that attract less attention from market participants. This type of organization for brokerage firms is not surprising. Indeed, in most business and law firms, inexperienced employees start with small accounts and gradually obtain bigger accounts when they acquire a better knowledge of the job. We detail, in the third chapter, the consequences, in terms of research, of these constraints imposed on coverage decisions.

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Chapter 1

What drives the herding behavior of individual investors?

Forthcoming in *Finance*

Joint work with

Maxime Merli (LaRGE Research Center, EM Strasbourg Business School, University of Strasbourg)

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Abstract

We introduce a new measure of herding that allows for tracking dynamics of individual herding. Using a database of nearly 8 million trades by 87,373 retail investors between 1999 and 2006, we show that individual herding is persistent over time and that past performance and the level of sophistication influence this behavior. We are also able to answer a question that was previously unaddressed in the literature: is herding profitable for investors? Our unique dataset reveals that the investors trading against the crowd tend to exhibit more extreme returns and poorer risk-adjusted performance than the herders.

1.1 Introduction

The herding behavior is defined in a broad way as an investor's imitation of the actions of others. Devenow and Welch (1996) emphasize three reasons for herding.¹ The first reason is payoff externalities (the outcome of an action is increasing in the number of agents undertaking it). For instance, investors tend to trade at the same time to benefit from a deeper liquidity (see Admati and Pfleiderer, 1988; Dow, 2004). The second reason is reputational concerns and issues related to the principal-agent theory (see Scharfstein and Stein, 1990; Rajan, 1994; Graham, 1999). When the performance of a manager is assessed relative to a benchmark (*i.e.*, by using the average performance of other managers, or the performance of a market/industry index), it is quite tempting for her to mimic the benchmark. By doing so, the manager sacrifices the potential to perform better than average but hedges herself against a poor relative performance. It is often said that the manager hides in the herd. Finally, the third explanation for rational herding is informational externalities. In Bikhchandani, Hirshleifer, and Welch (1992) and Welch (1992), investors acquire (noisy) information by observing the actions of the other agents. The externalities may be so strong that an investor can voluntarily decide to ignore her own information. In the most extreme cases, individuals' actions do not carry information anymore because they result only from the imitation of others' actions. In that case, an informational cascade occurs.

Early studies such as Lakonishok, Shleifer, and Vishny (1992) investigate a method

¹Herding can be rational or irrational. Irrational herding is extremely difficult to capture empirically because it is driven by fashion and fads. We therefore do not address this issue in the rest of the paper.

to empirically measure correlated trading across groups of investors. The idea underlying the measure proposed by the authors (the LSV measure, hereafter) is to quantify the buying pressure on a given asset for a homogeneous subgroup (pension funds, mutual funds, individual investors). For the market as a whole, each purchase is balanced by a sale. However, for a given subgroup of investors and a given asset, there can be an excess of purchases or sales, indicating that the investors in the subgroup herd. After the seminal work of Lakonishok, Shleifer, and Vishny (1992), herding among investors has been the subject of a number of empirical studies, which are divided in two categories. The first category primarily addresses institutional investors and the second category addresses individual investors. The present paper belongs to this second stream of the literature.

The mimetic behavior of U.S. mutual funds and institutional investors has been scrutinized (Lakonishok, Shleifer, and Vishny, 1992; Grinblatt, Titman, and Wermers, 1995; Wermers, 1999). Similar studies have been performed outside of the U.S., in particular in Germany (Oehler, 1998; Frey, Herbst, and Walter, 2007), the United Kingdom (Wylie, 2005), Portugal (Loboa and Serra, 2007) and Poland (Voronkova and Bohl, 2005).

In the second category of studies, targeting individual investors, the number of studies is lower. These studies have been performed in the U.S. (Barber, Odean, and Zhu, 2009), Germany (Dorn, Huberman, and Sengmueller, 2008), Israel (Venezia, Nashikkar, and Shapira, 2011) and China (Feng and Seasholes, 2004). All of these studies demonstrate that the trades of individuals are significantly correlated. The herding behavior is clearly stronger for individuals than for fund managers and it

exhibits a strong persistence over time (Barber, Odean, and Zhu, 2009). This behavior is positively and significantly correlated with the volatility of the market returns (Venezia, Nashikkar, and Shapira, 2011). Addressing the drivers of these findings, Barber, Odean, and Zhu (2009) show that psychological biases contribute to the herding behavior. These biases, for instance, lead investors to buy stocks with strong recent performance or with an abnormally high trading volume. In an original way, Feng and Seasholes (2004) demonstrate a positive relationship between the herding behavior of Chinese investors and their trading location.

Despite its popularity, the LSV measure suffers from some drawbacks. In particular, it does not permit for an evaluation of the herding level of a given investor, and thus, fails to evaluate herding persistence over time at the investor level. Furthermore, the drivers of the individual herding behavior cannot be investigated.

A key contribution of this paper is to provide a new measure of herding behavior at the individual level. Our measure (the Individual Herding Measure, denoted IHM hereafter) evaluates the individual herding for a given quarter as the weighted sum of the signed LSV measures of the stocks for which changes in holdings, for the quarter under consideration, occur. This measure allows for tracking dynamics of individual herding and therefore has the potential to highlight sources of individual heterogeneity. We conduct an empirical analysis of the herding behavior of individual investors using a unique database of the trading records of 87,373 investors for the 1999-2006 period. Our results demonstrate a high level of herding and a significant persistence of this behavior over time at the investor level. Our analysis of the individual heterogeneity of the herding behavior shows that a poor past performance

increases the propensity to herd in the next quarter. By using direct and indirect measures of sophistication (derivatives trading or portfolio value, for example), we show that sophisticated investors are less prone to herd after a poor past performance. However, the main contribution of the paper is to show that, contrary to the other individual investors, those trading against the crowd improve their returns by doing so. Unfortunately, this premium is not sufficient to compensate for the higher risk that they bear. Consequently, they perform poorly, compared to the average investor.

This paper is structured as follows. In the first section, we describe the methodological framework and introduce our individual herding measure. In the second section, we present the data used in this article. The third section focuses on the herding behavior measured at the stock level. In the fourth section, we examine the level and the persistence of the herding behavior at the investor level and highlight the factors that impact this behavior. The last section concludes the paper.

1.2 The framework

We first define notations that are common to all measures. We denote by $n_{i,j,t}$, the number of shares (adjusted for splits and corporate actions) of stock j held by investor i at time t . The universe contains J stocks.

1.2.1 Measuring herding at the asset level: the LSV measure and extensions

In Lakonishok, Shleifer, and Vishny (1992), herding is defined as the tendency for traders to accumulate on the same side of the market for a given stock and during a given period. To measure this tendency, we observe the difference between the number of shares held at time t and at time $t - 1$.² If the difference $n_{i,j,t} - n_{i,j,t-1}$ is positive (resp. negative), then it means that investor i increases (resp. decreases) her holdings of asset j during the period $[t - 1; t]$. The investor is said to be on the buy side (resp. sell side). We denote by $b_{i,j,t}$ (resp. $s_{i,j,t}$) a binary variable that takes the value 1 if the investor i increases (resp. decreases) her holdings of stock j between $t - 1$ and t and the value 0 otherwise. For a given asset j , the purchase intensity $p_{j,t}$ is defined as the number of investors that increased their holdings divided by the number of investors that traded the asset. We write

$$p_{j,t} = \frac{\sum_{i=1}^{I_{j,t}} b_{i,j,t}}{\sum_{i=1}^{I_{j,t}} (b_{i,j,t} + s_{i,j,t})} = \frac{1}{I_{j,t}} \sum_{i=1}^{I_{j,t}} b_{i,j,t}, \quad (1.1)$$

where $I_{j,t}$ is the number of active traders over the period $[t - 1; t]$. Notice that the number of traders $I_{j,t}$ varies across stocks and over time. The purchase intensity (thus the LSV measure) is computed for a subgroup of investors only. Formally, the LSV

²We stress the fact that the variations in holdings between $t - 1$ and t correspond to the variations in the number of shares and not in weight because price variations would incur artificial increases or decreases. It is also important to point out that corporate actions such as splits, new issues, etc., must be taken into account.

measure of stock j at time t is written as

$$LSV_{j,t} = |p_{j,t} - p_t| - \underbrace{E[|p_{j,t} - p_t|]}_{AF_{j,t}}, \quad (1.2)$$

where $E[\cdot]$ stands for the expectation, p_t is the purchase intensity across all stocks³ and $AF_{j,t}$ is an adjustment factor given by

$$AF_{j,t} = \sum_{k=0}^{I_{j,t}} \binom{I_{j,t}}{k} (p_t)^k (1 - p_t)^{I_{j,t}-k} \left| \frac{k}{I_{j,t}} - p_t \right|. \quad (1.4)$$

The quantity p_t is subtracted to account for systematic liquidity shocks, that is, when the aggregation of investors on a given side (buy or sell) is not the consequence of herding but rather the reaction to a common shock. The adjustment factor $AF_{j,t}$ makes the LSV measure unbiased in the case of no herding.

As mentioned before, the LSV measure suffers from a few drawbacks and has therefore been exposed to a number of criticisms. The LSV measure does not allow us to observe the intertemporal herding behavior of investors. We are able to follow how investors herd over time on a given asset, but we cannot observe the persistence in herding of a given investor. We address this issue in the following subsection by introducing an investor-specific herding measure. Among the other criticisms

³The purchase intensity across all stocks is computed as

$$p_t = \frac{\sum_{j=1}^J \sum_{i=1}^{I_{j,t}} b_{i,j,t}}{\sum_{j=1}^J I_{j,t}} \quad (1.3)$$

addressed to the measure, Bikhchandani and Sharma (2001) first note that the LSV measure captures both intentional and unintentional (or spurious) herding. According to their definition, an investor is said to herd intentionally if, by observing the other investors' actions, she prevents herself from making an investment she would have made otherwise (or conversely, she undertakes an investment that she would not have undertaken otherwise). In other words, intentional herding corresponds to a deliberate imitation of others' actions. Alternatively, spurious herding occurs when investors with similar preference sets are provided with the same information. Separating these two types of herding is important because the latter is an efficient outcome whereas the former can destabilize markets and increase volatility. A second issue discussed by Bikhchandani and Sharma (2001) is that the LSV measure considers only the number of traders and ignores the amount that is bought or sold. Oehler (1998) and Wermers (1999) propose derived measures that aim to remedy this problem. This issue has important consequences when studying the impact of herding on the market. However, because we adopt a more behavioral approach and focus on the drivers of the herding behavior, this issue does not have important consequences for our results.

Finally, Frey, Herbst, and Walter (2007) show that under the alternative hypothesis of herding, the measure is biased downward. Therefore, because the adjustment factor does not depend on the herding level, the LSV measure is biased downward and this bias increases with the herding level. These authors also prove that the bias declines with the number of active traders $I_{j,t}$. We will see in the empirical results that the level of herding rises when we impose a minimum number of active traders. This observation has crucial consequences for the interpretation of the em-

empirical results. For example, Dorn, Huberman, and Sengmueller (2008) establish a link between differences in opinion (proxied by trading activity) and herding behavior because they observe a very important positive correlation between trading activity and herding. It appears that the properties of the adjustment factor might explain part of the observed correlation. Indeed, the higher the trading activity, the lower the bias and the higher the herding measure. Even if trading activity and herding behavior were independent, a positive correlation would appear.

To remedy this problem, Frey, Herbst, and Walter (2007) propose using square values instead of absolute values in the expression of the LSV measure. Formally, their new measure is defined as

$$FHW_{j,t}^2 = ((p_{j,t} - p_t)^2 - E[(p_{j,t} - p_t)^2]) \frac{I_{j,t}}{I_{j,t} - 1}, \quad (1.5)$$

where the notations are the same as in the previous equations.

For a given time period $[t - 1; t]$ and a universe of J stocks, the average FHW measure is computed as

$$\overline{FHW}_t = \sqrt{\frac{1}{J} \sum_{j=1}^J FHW_{j,t}^2}. \quad (1.6)$$

Monte-Carlo simulations show that this new measure does not suffer from the bias that exists for the LSV measure. Frey, Herbst, and Walter (2007) show that for varying values of the number of active traders and/or for the level of herding, their measure is unbiased and possesses good statistical properties.

However, Bellando (2010) shows that the measure is unbiased only in the particu-

lar setting considered by Frey, Herbst, and Walter (2007). As soon as the probability of no herding is not null or when some asymmetry is introduced, the measure is biased upward. It follows that it is virtually impossible to compute the true value of the herding intensity. Nonetheless, we know that this true value is bounded below by the LSV value and above by the FHW value.

1.2.2 Measuring herding at the investor level: the Investor Herding Measure

We introduce now the new measure called the Investor Herding Measure (IHM hereafter). IHM considers herding only for the stocks currently traded by the investor. To analyze the tendency of individual investors to herd, we first discriminate between buy herding ($p_{j,t} > p_t$) and sell herding ($p_{j,t} < p_t$). In the spirit of Grinblatt, Titman, and Wermers (1995) and Wermers (1999), we define the signed herding measure as⁴

$$SLSV_{j,t} = \begin{cases} LSV_{j,t} & p_{j,t} > p_t \\ -LSV_{j,t} & p_{j,t} < p_t \end{cases} = p_{j,t} - p_t + \begin{cases} -AF_{j,t} & p_{j,t} > p_t \\ +AF_{j,t} & p_{j,t} < p_t \end{cases}. \quad (1.7)$$

⁴As in Grinblatt, Titman, and Wermers (1995), we set the LSV measure equal to 0 if there are less than 10 investors trading the stock.

For a given transaction, there are six possible scenarios

	Purchase	Sale
SLSV > 0	Herding	Anti-Herding
SLSV < 0	Anti-Herding	Herding
SLSV = 0	No Herding	No Herding

The IHM is then defined as

$$IHM_{i,t} = \frac{\sum_{j=1}^J (n_{i,j,t} - n_{i,j,t-1}) \bar{P}_{j,t} SLSV_{jt}}{\sum_{j=1}^J |n_{i,j,t} - n_{i,j,t-1}| \bar{P}_{j,t}}, \quad (1.8)$$

where $\bar{P}_{j,t}$ is the average price of asset j over the period $[t-1; t]$. The value $(n_{i,j,t} - n_{i,j,t-1}) \bar{P}_{j,t}$ is the average value of the transaction made on stock j and the denominator in the formula is the total value of all transactions⁵ made by investor i in the considered period. In this way, we account only for the herding coefficient of the stocks that are traded during the considered period, and we weight them by the size (euros-volume) of the transactions. The IHM measure indicates that investor i is herding if it takes a positive value and that she is going against the herd if the value is negative.

To compare with, Grinblatt, Titman, and Wermers (1995) define the “Fund Herd-

⁵We only observe the number of shares at time t and $t-1$ but not the sequence of transactions during the period under study. Hence, we use the average price to evaluate the value by which the investor increases or decreases her holdings.

ing Measure” as

$$FHM_{i,t} = \sum_{j=1}^J (\omega_{i,j,t} - \omega_{i,j,t-1}) SLSV_{j,t},$$

where $\omega_{i,j,t}$ is the weight of asset j in the portfolio of the i^{th} fund at time t . A potential issue associated with this measure is that an investor can be seen as herding on an asset she does not trade (a transaction in one asset - or a price variation - causes the weights of all the assets in the portfolio to change.).

1.3 Data and descriptive statistics

The primary data for our study consists of a eight-year panel (from 1999 to 2006) of all executed trades and daily portfolio holdings of French individuals at a major European brokerage house. We exclude investments in mutual funds, warrants and options from the database. The total number of stock transactions is slightly below 8 millions. The database contains information on the opening date of the accounts (if ever, closing date), the birth date, the gender and the state of residence of the investors. At the beginning of the sample period, 33,130 investors had open positions. The representative mean investor holds 4.8 stocks worth 19,113 euros and she executes 89 trades over the period. The median investor holds 2.92 stocks worth 5,163 euros and trades 32 times.

In addition to the individual investor database, for each stock in our sample, we obtain daily prices, returns, market capitalization and volumes from Bloomberg

(1,180 stocks) and Eurofidai⁶ (1,311 stocks). Note that, due to missing data, we must ignore a little over one thousand securities that represent only 1.51% of the total number of transactions. Of the 2,491 stocks under consideration, 1,190 stocks are listed on the French market, 1,020 in the U.S., 62 in Great Britain, 35 in Canada, 34 in Netherlands, 31 in Germany, 15 in Italy and 104 somewhere else. As one may expect, the trading volume is not homogeneous across countries. The stocks listed on the French market represent more than 90% of the total volume of trading, while the stocks from U.S. account for less than 1%.

Figure 1.1 below shows the evolution, from January 1999 to December 2006, of the number of investors, the average number of stocks, and the average portfolio value (measured at the beginning of each quarter). To gain a deeper look into the structure of the data, we present in Table 1.1 the distribution of portfolio values conditioned on the number of stocks held, at three points in time.

1.4 Herding behavior at the stock level

1.4.1 Herding and stock characteristics

Table 1.2 provides the average values, on the 1999-2006 period of the semiannually, quarterly and monthly LSV and FHW measures. The first line provides the average value across all stocks of the LSV and FHW measures. The following lines report averages on subsets based on the capitalization (Large, Medium, Small), on the volume of trading (High, Medium, Low) and on the industry classification (based

⁶European Financial Data Institute, www.eurofidai.org

on the Industry Classification Benchmark).

The average value across all stocks of the LSV measure computed on a monthly basis is equal to 0.1263. This means that, for a given stock and during a given month, approximately 13% more investors are “on the same side” than what would be predicted if decisions were randomly taken. Hence, French individual investors exhibit a high degree of herding. These results are consistent with typical findings for U.S. individual investors (Barber, Odean, and Zhu, 2009, find an average of monthly LSV measures on all stocks equal to 0.1279), but slightly higher than the value of 0.064 obtained by Dorn, Huberman, and Sengmueller (2008) for Germany. This result also supports previous findings that individual investors herd more than institutional investors. In the U.S., Lakonishok, Shleifer, and Vishny (1992) provide an average value of 0.02 for institutional investors and Wermers (1999) reports a value of 0.036. More recently, in Israel, Venezia, Nashikkar, and Shapira (2011) obtain an average herding measure of 0.058.

As in Dorn, Huberman, and Sengmueller (2008), our results highlight correlated trading across all horizons and all industries. Concerning the impact of the capitalization, our results, using the LSV measure, confirm the findings of Dorn, Huberman, and Sengmueller (2008) and contrast with those of Barber, Odean, and Zhu (2009) and of previous studies of institutional investors that demonstrate that investors herd more on small firm stocks (Wermers, 1999, for example). In fact, we find that correlated trading is higher for larger capitalizations. However, this result is not robust when using the FHW measure. Indeed, with this last measure, we find that the herding behavior is more pronounced for smaller capitalizations.

Finally, the LSV measure takes a higher value for the stocks ranked in the “high volume of trading” category. Although further investigations are needed, this result could be due to a concentration of purchases in attention-grabbing stocks (Barber and Odean, 2008; Barber, Odean, and Zhu, 2009) or to informational signals. Once again however, this result is not robust when using the FHW measure instead. Considering these findings, it is natural to wonder how the downward bias of the LSV measure (see the previous section) could impact our results. Comparing the level of the two measures (Table 1.2), it is apparent that the values of FHW are sharply higher whatever the category under study. The monthly average value across all stocks of the FHW measure is equal to 21.70%. The herding behavior is estimated as being 1.72 times stronger when this last measure is implemented. Note that this difference is stable when the observation intervals are modified (6 months or 3 months). We can conclude, for monthly observation intervals, that the true value of herding for the French individual investors in our sample is high and takes a value between 12.63% and 21.70%.

1.4.2 Persistence

In this section, we adopt another approach (following the methodology used by Barber, Odean, and Zhu, 2009) to test whether investors’ trading decisions are correlated. We also analyze the persistence, at the stock level, of the herding behavior. The herding behavior is said to be persistent if the autocorrelation of the purchase intensity $p_{j,t}$ is high: a high (respectively low) level of purchase intensity at time t is followed by a high (low) level in the consecutive periods.

For each month, we divide the population of investors into two equally sized random groups. We then calculate the assets' monthly purchase intensity $p_{j,t}^{G_1}$ (respectively, $p_{j,t}^{G_2}$) resulting from the transactions of group 1 (group 2). If the investors' trading decisions are independent, we should observe no correlation between the purchases intensities $p_{j,t}^{G_1}$ and $p_{j,t}^{G_2}$. The transaction records span over 8 years, resulting in a time-series of 96 contemporaneous correlations between purchases intensities. We then compute the average correlation and employ a t-test to check whether the average correlation is significantly different from 0. As explained by Barber, Odean, and Zhu (2009), the null hypothesis of no correlation is similar to the null hypothesis of no herding in the LSV and FHW herding measures. As in the previous analysis, it is not possible to distinguish between spurious and intentional herding. The rejection of the null hypothesis only indicates that trading decisions are correlated, but it does not allow us to verify whether the investors intentionally herd.

Once we show that investors engage into correlated trading, we aim to see if they tend to herd on the same assets over time. A high persistence in the herding behavior would indicate that herding is influenced by characteristics that do not change much over time such as industry classification, index membership and market capitalization. On the contrary, a low persistence might indicate that herding is dynamic and is a direct reaction to new information, new market conditions or new trading strategies.

To measure the persistence of herding, we first compute for each month the correlation between stock purchase intensities at time t and time $t + \tau$ with $\tau = 0, \dots, 36$. Note that $\tau = 0$ corresponds to a test of the null hypothesis of no herding while $\tau > 0$ corresponds to a test of the persistence in herding. For $\tau = 1$, we measure

the correlation between the purchase intensities between month t and the consecutive month. We thus obtain a time series of 95 correlations that we average to obtain the general persistence for a horizon equal to 1. It follows that we have a time-series of 94 correlations for $\tau = 2, \dots$, and a time-series of 60 correlations for $\tau = 36$. We first compute these correlations for the entire set of investors. In a second calculation, we compute this persistence for two random groups of investors (in the fashion of the analysis for contemporaneous correlations which is actually the particular case where $\tau = 0$). That is, we compute the correlation between the purchase intensities obtained from the transactions of group 1 at time t , and the purchases intensities obtained from the transactions of group 2 at time $t + \tau$.

Table 1.3 presents contemporaneous and time-series correlations of the purchase intensities. The first row ($\tau = 0$) indicates the contemporaneous correlation of purchase intensities between groups 1 and 2. We observe that the average correlation is very strong (a little over 85%), indicating that the investors' trading decisions are highly correlated. Our correlation is 10 points higher than the correlation found by Barber, Odean, and Zhu (2009). This finding is coherent with the fact that we also obtain slightly higher values for the LSV measure. It follows that by knowing the purchase intensities associated with one group, we are able to explain over 2/3 of the variations in purchase intensities of the second group. The rest of the table presents the correlations between the purchase intensities at time t and time $t + \tau$ where $\tau = 1, \dots, 36$. The persistence between two consecutive months is expressed by an average correlation of 30.27%. The average correlations are all significantly different from zero up to a horizon of $\tau = 15$. In comparison to Barber, Odean, and

Zhu (2009), the correlations are slightly lower (30.27% instead of 46.7% for a horizon of one month) and the persistence fades at a faster rate (the correlation at a 6 month horizon is 9.10% in our study compared to 16.4% in Barber, Odean, and Zhu, 2009).

1.5 Herding behavior at the individual level

1.5.1 First results

We first provide a brief overview of the computed IHM values. Figure 1.2 gives the distribution of the IHM at three time points (first quarter of 2000, 2003 and 2006). Not surprisingly, we observe that most individuals have a positive IHM value. The average IHM value is equal to 0.1003 for the first quarter of 2000, 0.1078 for the first quarter of 2003 and 0.0770 for the first quarter of 2006. Medians are, respectively, 0.0954, 0.0887 and 0.0675.

1.5.2 Persistence

Using the same methodology as the one employed to measure the persistence at the asset level, we check whether there is significant autocorrelation in the investor herding behavior. That is, we verify if a high herding (anti-herding) behavior at a quarter t is followed by high herding (anti-herding) in the subsequent quarters. The presence of a strong autocorrelation would tend to indicate that some investors are more prone to herd, regardless of the time-period considered. The results in Table 1.4 give an average correlation of 12.43% between the IHM values of two consecutive quarters. The correlations appear to be significant for a horizon up to four years

with a minimum of 4.74%. It follows that the herding behavior shows some signs of persistence. However, this persistence is relatively weak and these results call for a deeper investigation of the components of the individual herding behavior.

1.5.3 Herding and investor characteristics

We test here whether the investor's profile determines part of the observed herding behavior. The baseline assumption is that some investors might be more prone to herd than others (regardless of the market conditions or other time-varying variables). We test different characteristics such as gender, sophistication and the wealthiness of individuals.

The gender differences in investment behavior are well-documented. For instance, Barber and Odean (2001) investigate overconfidence by using a "gender approach" and show that men are more overconfident than women, leading them to trade 45% more than women. This behavior consequently hurts portfolio performance and reduces net returns. It follows that it is a natural choice to test whether the herding intensity differs between women and men.

The second attribute we consider is the investor's sophistication. Our hypothesis is that sophisticated investors herd less on average. A number of researchers have documented the role played by sophistication on trading behavior. For instance, the individual differences in the disposition effect - which describes the tendency of investors to more readily sell winning stocks than losers - are significantly related to financial sophistication (Feng and Seasholes, 2005; Dhar and Zhu, 2006). Because sophisticated investors have a better ability to obtain and manage information (or, at

least, they have the impression that they do), the need to rely on others' information is less pronounced.

We proxy sophistication using three different variables. The first proxy is the total number of transactions made by an investor over the sample period. The second proxy is a dummy variable that equals one if the investor is trading warrants in addition to common stocks (and zero otherwise).⁷ The third proxy is the investor average portfolio value. It accounts for the wealth of the individuals. Of course, this variable captures the wealth of individuals only imperfectly, because it neglects assets such as real estate investments.

Table 1.5 reports the average IHM values for the different categories: a) men *versus* women, b) investors who trade warrants *versus* investors who do not, c) investors with less than 100 trades *versus* investors with more than 200 trades d) investors with an average portfolio value below 5,000€ *versus* an average portfolio value above 100,000€.

For each attribute and each quarter, we aim at testing, for each category, whether the average IHMs are equal. Under the null, there is no difference between the average IHMs (*i.e.*, males *vs* females). Because we do not know the theoretical distribution of the difference, we run Monte-Carlo simulations to estimate the p -values. For a given attribute and a given quarter, we compute the average IHM of the two subgroups that we denote as \overline{IHM}_1 and \overline{IHM}_2 . \overline{IHM}_1 (respectively, \overline{IHM}_2) is the average of the n_1 (n_2) IHM values of the investors that belong to the first (second) subgroup. To estimate the empirical distribution of the difference, we randomly divide the pop-

⁷Trading warrants requires familiarity with option-like payoffs.

ulation of investors into two subgroups of size n_1 and n_2 . We compute the average IHM for each subgroup and calculate the absolute value of the difference, which we denote as $|\overline{IHM}_1^* - \overline{IHM}_2^*|$. This step is then repeated 10000 times. The p -value ξ associated with the test of no difference is then equal to

$$\xi = \frac{1}{10000} \sum_{k=1}^{10000} 1_{\{|\overline{IHM}_1 - \overline{IHM}_2| < |\overline{IHM}_{1,k}^* - \overline{IHM}_{2,k}^*|\}}, \quad (1.9)$$

where \overline{IHM}_1 (\overline{IHM}_2) is the average IHM value of the investors that belong to the first (second) subgroup and $\overline{IHM}_{1,k}^*$ ($\overline{IHM}_{2,k}^*$) is the average IHM value associated with the first subgroup of n_1 (n_2) investors obtained by randomly dividing the sample for draw k .

The quarterly results are provided in Table 1.5. It appears that, on average, women herd more than men. The overall average IHM value for men is 0.1051 compared to a value of 0.1094 for women. However, the reported p -values indicate that, for most quarters, the difference is not significant. The results for sophistication reveal that the investors who trade warrants have, on average, a lower herding intensity than the investors who do not. The individuals with a low number of transactions tend to herd more than the investors who trade frequently. For both sophistication attributes, the differences are highly significant. In particular, when considering the number of transactions, we observe a very high magnitude (up to 8 points) difference between the two subgroups' average IHM values. The average IHM value for the subgroup associated with a low number of transactions is 0.1150, whereas the value for the subgroup associated with a high number of transactions is only 0.0870. Finally, we observe differences between the two subgroups when discriminating by the

portfolio's average value. Although these differences are significant for most quarters, their sign varies over the different quarters and prevents us from drawing any clear conclusion.

1.5.4 Relationship between past performance and herding

To go deeper in analysis, we investigate now whether and how investors' past performance can influence herding. To this end, we use the investors' quarterly gross returns, computed from their daily positions. The portfolio returns are estimated using total returns (*i.e.*, dividends are included) calculated using Eurofidai and Bloomberg data. We deliberately ignore the intraday movements and the transactions are evaluated using day closing quotes. The gross quarterly return $R_{i,t}$ for investor i and quarter t is therefore calculated as

$$R_{i,t} = \prod_{\tau=1}^{n_t} \left(1 + \sum_{j=1}^{N_{i\tau}} \omega_{j,\tau} r_{j,\tau} \right) - 1, \quad (1.10)$$

where n_t is the number of days in quarter t ; $N_{i\tau}$ is the number of stocks composing the portfolio of investor i for day τ of quarter t ; $\omega_{j,\tau}$ is the weight of stock j and $r_{j,\tau}$ is its daily return.

In our first analysis, we compute the Spearman rank correlation between investor's IHM and the four moments of the investors' portfolio past returns for each quarter. The results in Table 1.6 indicate that there exists a strong rank correlation between the past average returns and the investors' herding (all but four coefficients are significant at a 1% level). However, the sign of these coefficients varies over time without any clear pattern. The coefficients for the Spearman correlation between the IHM

and the portfolio's standard deviation are all significant and negative. This result means that the less risky investors are those that herd the most. The results for skewness⁸ are less clear because only 20/28 of the coefficients are significant at a 1% level and the sign changes over time.

So far, we are not able to determine precisely how an investor's own past performance influences her herding behavior. However, it appears clear that a relationship exists. We now wish to exploit both the cross-section and the time dimensions of our database. For each quarter, we compute the investors' IHM value, past performance, level of diversification, and portfolio value. We then have unbalanced panel data.⁹ We aim to test the influence of past performances that vary across individuals and over time. We thus run a panel data regression. The results of the Hausman test lead us to reject the null hypothesis of random effects. We therefore choose to include both the investor and the time fixed effects. We estimate the past performances by using the risk-adjusted past return, that is, the return of the portfolio divided by its standard deviation. The formulation of the regression is the following:

$$\begin{aligned}
 IHM_{i,t} = & \gamma_0 IHM_{i,t-1} + \gamma_1 IHM_{i,t-2} + \sum_{\tau=1}^2 \beta_{\tau} RAR_{i,t-\tau} \\
 & + \theta EXP_{i,t} + \alpha_1 IFE_i + \alpha_2 TFE_t + \varepsilon_{i,t},
 \end{aligned} \tag{1.11}$$

⁸Mitton and Vorkink (2007) show that individual investors have a heterogeneous preference for skewness. This heterogeneity helps explain why individual investors are underdiversified.

⁹The panel is unbalanced because investors are excluded from the quarters where they do not trade.

where $IHM_{i,t}$ is the herding value of investor i in quarter t , $RAR_{i,t-\tau}$ is the performance of investor i in the quarter $t-\tau$ and $EXP_{i,t}$ is the investor experience, proxied by the cumulative number of trades made up to quarter t by investor i . IFE_i are the individual fixed effects and TFE_t are the time fixed effects. We include two lags for IHM; more lags would too dramatically reduce the size of our sample. Thus, we consider the observations that correspond only to investors trading three quarters consecutively.

The results are presented in Table 1.7 (IFE and TFE not reported). The lags of the herding measure appear to be significant and negatively correlated with the herding measure. The estimates of the coefficients are -0.0614 for lag 1 and -0.0312 for lag 2. The coefficients for the performance over the preceding quarter and the quarter before that take the negative values -0.0165 and -0.0208 and are significant. This result confirms our hypothesis that poor past performance creates incentives to herd. Additionally, we note that the variable EXP matters as θ is significant and negative. This finding indicates that, as investors acquire experience on the stock market (and therefore knowledge), they tend to rely more on their private information.

In models 2 to 4, we condition the performance RAR to the realization of a sophistication variable. The new variable is equal to the risk-adjusted return if the characteristic is realized and 0 otherwise. The sophistication characteristics are the same as those used in the previous section. We find that trading warrants has an impact on the coefficient of the performance variable. Indeed, the coefficient for RAR_{t-1} is not significantly different from 0 for the investors that trade warrants, while it is negative and highly significant for the others. When considering the second

lag ($t - 2$), both coefficients are negative and significant, but the effect is lower for the sophisticated investors. In Model 3, we use the total number of transactions as the sophistication variable. For the first lag, the performance is significant and negative for investors with fewer than 100 trades while it is not significant for the investors associated with a high number of transactions. For the second lag, although the coefficient is significant and negative for the active investors (over 200 transactions), it is much lower than the coefficients for the investors that do not trade frequently. In Model 4, the sophistication is proxied by the Average Portfolio Value. The results are consistent with Models 3 and 4. We observe that the effect of past performance is weaker for sophisticated investors (*i.e.*, investors with a high Average Portfolio Value).

1.5.5 Payoff externalities

A question that was not yet addressed in the literature is whether there exist some (positive) payoffs externalities for herding. In other words, we want to check whether there is a rational motivation for this behavior that can be expressed in terms of increased performance. At an aggregate level, some concerns are that herding could increase volatility and destabilize markets (see Bikhchandani and Sharma, 2001). However, the literature is nearly non-existent on the consequences of herding on the investors' performance. A simple reason for this dearth of information is the lack of herding measures at the individual level. We remedied this problem by introducing the Individual Herding Measure (IHM).

A preliminary analysis consists in computing the Spearman rank correlation be-

tween the IHM values and the investors' average return, standard deviation, skewness and kurtosis for each quarter. The results in Table 1.8 appear to indicate that a relationship exists between herding and returns. The correlation between the IHM and the average return is significant for nearly all quarters. However, the sign does not remain the same for every quarter. We thus cannot yet determine the relationship between the two variables. The results for the standard deviation are easier to interpret. All of the coefficients are negative and significant at a 1% level indicating that herders hold less risky portfolios. The interpretation of the coefficients for skewness and kurtosis is not straightforward because they change signs and are not all significant.

To extend our analysis on the influence of herding on performance, we build four average investors for whom we compute performance measures. First, we consider an average investor who is representative of the entire population. Her return is calculated as

$$R_t^{AV} = \frac{1}{I_t} \sum_{i=1}^{I_t} R_{i,t}, \quad (1.12)$$

where I_t is the number of investors for quarter t .

We then form, for each quarter, an average investor for each herding category, whom we designate as an anti-herder, an independent trader and a herder. These three average investors correspond, respectively, to investors trading against the crowd (determined by an IHM value below -0.05), investors trading independently of others (defined by $-0.05 \leq IHM \leq 0.05$) and investors engaging in a herding behavior

($IHM > 0.05$).¹⁰ The anti-herder quarterly return R_t^{AH} is estimated to be

$$R_t^{AH} = \frac{1}{I_t^{AH}} \sum_{i=1}^{I_t} R_{i,t} 1_{\{IHM_i < -0.05\}}, \quad (1.13)$$

where I_t is the number of investors who trade at least once during quarter t and I_t^{AH} is the number of investors with IHM values below -0.05 .

The independent trader return R_t^{IT} is computed as

$$R_t^{IT} = \frac{1}{I_t^{IT}} \sum_{i=1}^{I_t} R_{i,t} 1_{\{-0.05 \leq IHM_i \leq 0.05\}}, \quad (1.14)$$

where I_t^{IT} is the number of investors with IHM values between -0.05 and 0.05 .

Finally, the herder return R_t^H is

$$R_t^H = \frac{1}{I_t^H} \sum_{i=1}^{I_t} R_{i,t} 1_{\{IHM_i > 0.05\}}, \quad (1.15)$$

where I_t^H is the number of investors with IHM values above 0.05 .

We follow the approach of Barber and Odean (2000) when choosing the performance measures. First, we compute the own-benchmark abnormal return. For a given quarter, this return is simply the return that would have been obtained by the beginning-of-quarter portfolio if no transactions had been made. For each quarter and each individual, the abnormal return is thus computed as the difference between the realized return (computed from daily returns) and the own-benchmark return. Our second benchmark is the quarterly market-adjusted return. This return is sim-

¹⁰The limit of 0.05 is arbitrarily determined. However, our results do not change if we impose different bounds (in the neighborhood).

ply the difference between the investors' realized return and the market return. Our third benchmark is the intercept obtained from Carhart (1997) four-factor model. The intercept is obtained by estimating the following time-series regression

$$R_{i,t} - R_{f,t} = \alpha + \beta(R_{m,t} - R_{f,t}) + \theta SMB_t + \lambda HML_t + \eta MOM_t + \varepsilon_{i,t}, \quad (1.16)$$

where $R_{f,t}$ is the EURIBOR 3-month rate, $R_{m,t}$ is the quarterly return on the French CAC All-Tradable index¹¹, SMB_t and HML_t are the two additional Fama and French (1993) factors, respectively the quarterly return on a zero-investment size portfolio and the quarterly return on a zero-investment book-to-market portfolio. The last coefficient MOM_t is the momentum factor (Jegadeesh and Titman, 1993), which is the quarterly return on a zero-investment momentum portfolio.¹²

The results for the four average investors (the investor representative of the whole population, the anti-herder, the independent trader and the herder) are presented in Table 1.9. We obtain a negative and significant (as in Barber and Odean, 2000) coefficient of -0.23% for the own-benchmark abnormal return. This result means that the investors would earn an additional 0.23 point by keeping their portfolio unchanged. More interestingly, we observe a clear negative relationship between the own-benchmark abnormal return and the Individual Herding Measure (IHM). It appears that the investors who trade against the crowd dramatically increase their

¹¹This index (also called SBF250) is composed of the 250 largest capitalizations on the French market.

¹²The index and the Carhart (1997) factors are provided by Eurofidai (www.eurofidai.org).

performance by trading contrary to the rest of the population.¹³ This finding suggests that the trades made by anti-herders are motivated by information. The results for the market-adjusted return and the intercept from the Carhart (1997) four-factor model are not significant. This finding is not surprising because the under-diversification and the particularities of the individual investors make these benchmarks unfit. It is worth noting however, that the anti-herders and independent traders hold much more aggressive portfolios than herders. The market betas for these investors are, respectively, 1.3734 and 1.3859 compared to 1.2976 for herders. The tilt toward small stocks is relatively strong for independent traders (the SMB coefficient takes the value 0.5016). Because the probability of trading with the other investors in the sample is lower for smaller capitalizations, the investors who invest mainly in small capitalizations tend to have an IHM value close to zero (because the LSV value of the stocks they trade is zero).

To go one step further in our analysis, we choose another approach that evaluates investors' returns, conditional on their herding behavior, relative to the remainder of the sample. That is, we want to evaluate whether an investor that herds has better performance than the rest of the investors in the sample and, more generally, if there exists a relationship of dependence between performance and herding.

For each quarter, we build a 10×3 contingency table where the quarterly returns are divided into ten deciles and investors are split in three categories (anti-herders, independent traders and herders defined as before). The generic element α_{ij} of the

¹³This result is an indirect proof of the validity of our measure. Indeed, as documented by Barber and Odean (2000), most of the individual investors decrease their performance by trading. The fact that the investors with a negative IHM value increase their performance by trading shows that our measure is successful in determining investors who trades against the crowd.

table is the number of investors in decile i and category j . To test the null hypothesis of independence between herding and returns, we use a χ^2 test. The advantage of this test is that nothing is assumed about the type of relationship between the two variables (returns and IHM); in particular, it does not need to be linear. The component of the chi-square CS_{ij} for decile i and category j is calculated as

$$CS_{ij} = \frac{(\alpha_{ij} - \alpha_{ij}^*)^2}{\alpha_{ij}^*}, \quad (1.17)$$

where α_{ij} is the observed number of investors for decile i and category j and α_{ij}^* is the theoretical number of investors that should be observed under the null hypothesis of independence.

The global chi-square value GCS is simply equal to

$$GCS = \sum_{i=1}^{10} \sum_{j=1}^3 CS_{ij} \rightsquigarrow \chi^2((10-1)(3-1)). \quad (1.18)$$

The chi-square values for the 32 quarters from January 1999 to December 2006 range from 59.90 to 520.64 (unreported). With a critical value of 28.87 for 18 degrees of freedom, these results indicate the existence of a relationship between herding and returns. We then perform the same analysis with Sharpe ratios instead of returns. We obtain chi-square values ranging from 22.56 to 230.90. We then reject the null hypothesis of independence between the IHM and the Sharpe ratios for nearly all quarters.

The limitation of the chi-square test is that while we are able to show that a relationship exists between herding and performance, we do not have any informa-

tion concerning its type. To make this distinction, we build, for each quarter, a new contingency table where the generic element α_{ij} corresponds to the ratio of the observed number of investors for decile i and category j over the theoretical number that would be observed for this decile and this category if the IHM and performance were independent.¹⁴ If the generic element α_{ij} is greater than one, it means that there are more investors for this decile and this category than should be observed if there was independence between herding and performance.

Because we do not know the theoretical distribution of the number of investors for a given decile and a given category, we need to estimate it. The process that is used is similar to the one used for Table 1.5. Each decile (category) contains d_i , $i = 1, \dots, 10$ (c_j , $j = 1, \dots, 3$) investors. For a given quarter, we randomly separate the investors in the sample into ten categories (corresponding to the deciles) of size d_i , $i = 1, \dots, 10$ and in three categories of size c_j , $j = 1, \dots, 3$. We then compute the number of investors \overline{I}_{ij} for each decile and category. We repeat this step 10000 times. The p -value ξ_{ij} associated with the test of no difference between the observed number of investors and the theoretical one is then

$$\xi_{ij} = \frac{1}{10000} \sum_{k=1}^{10000} \mathbf{1}_{\{|I_{ij} - I_{ij}^*| < |\overline{I}_{ijk} - I_{ij}^*|\}}, \quad (1.19)$$

where $\mathbf{1}$ is an indicator function, I_{ij} is the observed number of investors for decile i and category j , I_{ij}^* is the theoretical number of investors that should be observed under the null hypothesis of independence and \overline{I}_{ijk} corresponds to the number of

¹⁴The theoretical number of investors for decile i and category j is equal to the number of investors in decile i times the number of investors in category j divided by the total number of investors.

investors observed at draw k (where the sample is randomly divided).

Table 1.10 shows, for each decile i and category j , the average of the generic elements α_{ij} of the 32 contingency tables computed for each quarter from January 1999 to December 2006. The numbers between parentheses indicate the number of quarters for which the observed number of investors is significantly different than the theoretical number at the 5% level (using p -values computed with Monte-Carlo simulations as explained previously). In addition, we estimate the statistical significance of the coefficients by applying a t-test on the 32 values obtained.

We observe that the anti-herders have a higher probability of exhibiting extreme returns. For the lowest (highest) return decile, this category contains 27% (15%) more investors than it would contain under independence. On the contrary, the values taken for deciles 4 through 8 range from 0.8866 to 0.9255. The result for the herders is completely opposite. We find that the herders are underrepresented in the lowest and highest deciles while there are more investors than would be expected under independence in the intermediate ones. The lowest (highest) decile contains 7% (5.5%) fewer investors than would be observed if the herding behavior had no impact on performance.

The results for Panel B (using Sharpe ratios instead of returns) are even more striking. For the anti-herders, the proportion is 1.1772 for the first decile, and it decreases monotonically to reach 0.9341 by decile 9. This trend appears to indicate that the portfolios of the investors who trade against the crowd perform poorly. The results for the herders show that these investors concentrate in the intermediate deciles.

To conclude, on the one hand, investors who invest against the crowd improve their performance by trading. On the other hand, the portfolios of these same investors exhibit lower Sharpe ratios. One possible explanation for these results is that, by trading against the crowd, they earn a liquidity premium. However, the consequence of this behavior is that they hold stocks that are more risky and that perform relatively poorly (hence the lower Sharpe ratios).

1.6 Conclusion

Most studies focus on stock characteristics to explain the herding behavior of individual or institutional investors. By introducing a new individual measure that allows the herding behavior of a given investor to be evaluated over time, we are able to investigate whether the herding behavior can be explained by some investor attributes. In addition, this is the first study to analyze the relationship between individual performance and herding. Our primary findings are the following. First, by studying a unique sample of 87,373 French individual investors, we demonstrate the importance and the persistence of the herding behavior. Our results confirm, at an individual level, the observation made in previous studies that herding is much more pronounced for individual investors than for institutional ones. Second, we were able to show that sophisticated investors are less prone to herding. Additionally, we found an interesting link between past performance and mimetic behavior. It appears that an adverse performance decreases the incentives to gather information. When faced with negative performance, investors (and, in particular, unsophisticated ones) tend to herd in the next period. Finally, we provide original insights on the relationship

between herding and performance. It appears that the investors who invest against the crowd improve their performance by reallocating their portfolio. However, we also found that these investors exhibit more extreme results and that they have lower Sharpe ratios than the rest of the population.

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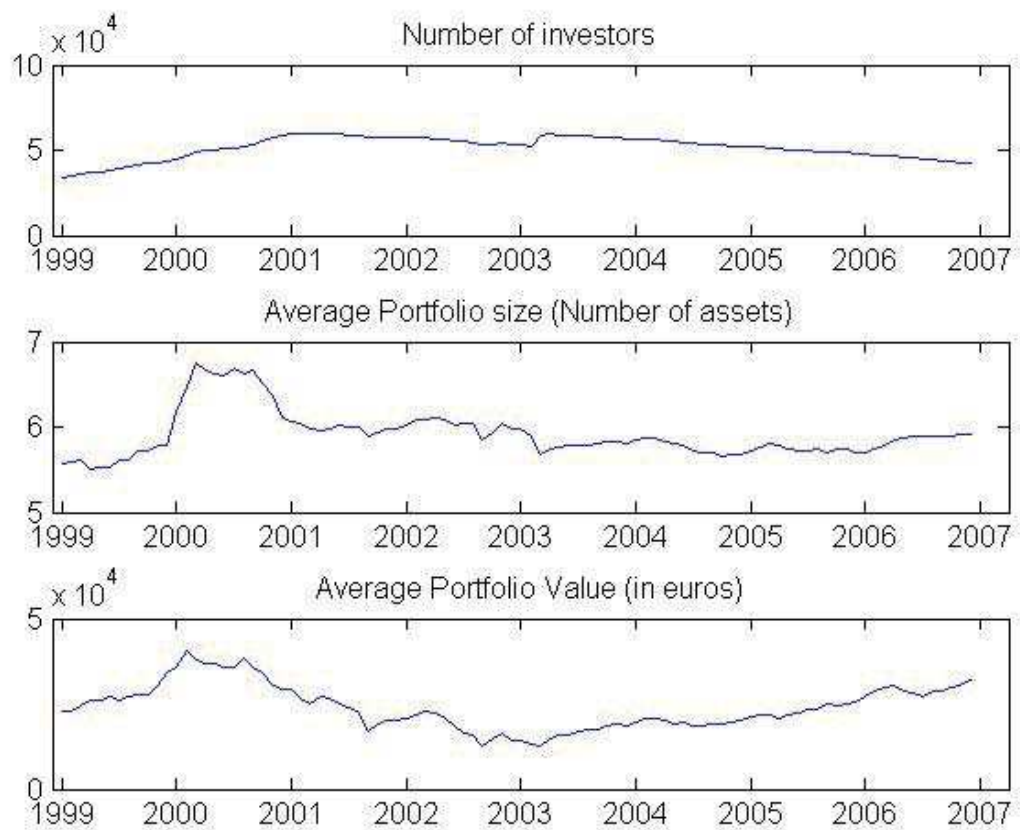
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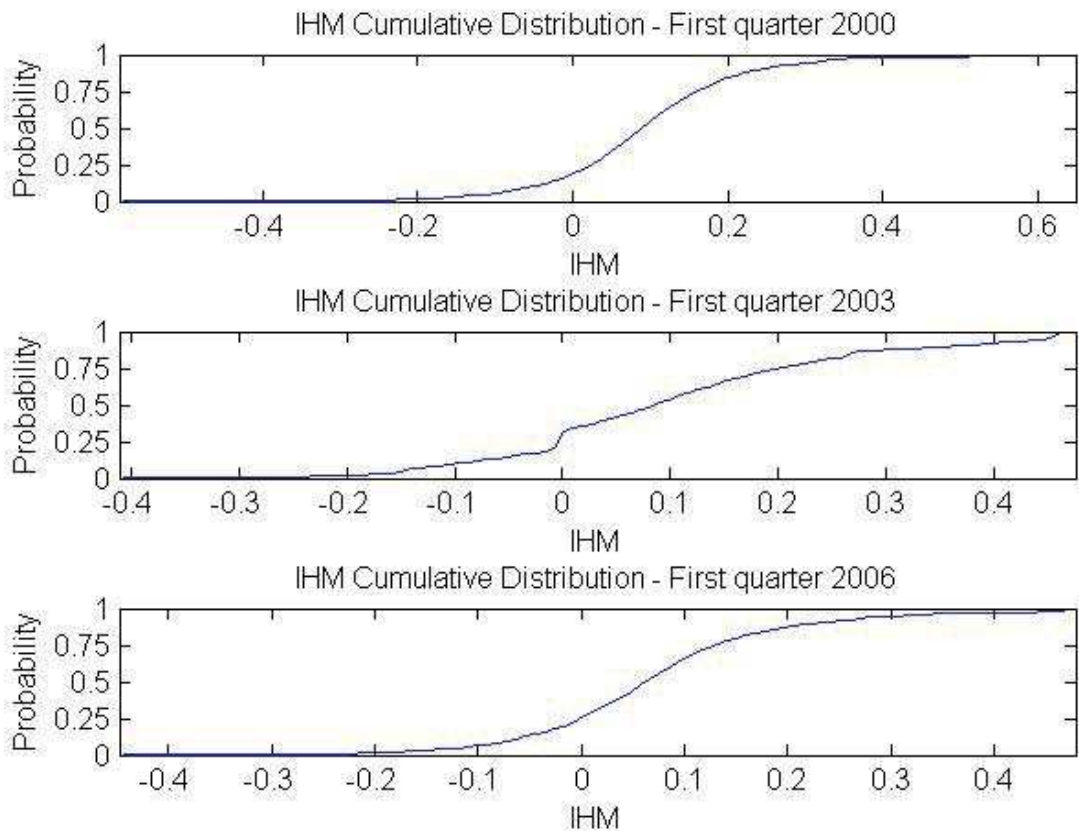
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Figure 1.1
Characteristics of the sample



This figure presents the number of investors, the investors' average number of stocks and their portfolio average value in euros for each quarter of the January 1999 to December 2006 period.

Figure 1.2
The IHM cumulative distribution



This figure presents the cumulative distribution of the IHM at three points in time (First quarter of 2000, 2003 and 2006).

Table 1.1
Descriptive statistics

Portfolio Size	Nb. of Observations	Portfolio Value (€)			
		Mean	25 th percentile	Median	75 th percentile
Panel A: Portfolios as of January 2000					
1	9,109	6,973	740	1,640	3,930
2	6,797	9,717	2,038	3,782	7,755
3	5,321	15,479	3,623	6,265	12,067
4	4,046	19,734	5,366	9,038	16,888
5	3,131	24,223	7,262	12,184	21,318
6-9	7,640	41694	11263	18,797	35,279
10+	7,593	105,255	27,578	48,552	91,609
All	43,637	34,039	3,179	9,317	26,336
Panel B: Portfolios as of January 2003					
1	11,421	2,154	218	502	1,329
2	7,925	3,738	700	1,417	3,115
3	6,087	6,377	1,330	2,532	5,304
4	4,793	7,585	2,040	3,750	7,561
5	3,692	10,275	3,002	5,254	10,061
6-9	9,256	16,380	4,969	8,714	16,297
10+	9,866	44,771	13,471	24,499	46,293
All	53,040	14,341	1,160	4,027	12,572
Panel C: Portfolios as of January 2006					
1	11,221	4,216	381	993	2,487
2	7,349	7,878	1,243	2,769	6,250
3	5,468	11,025	2,456	4,796	10,190
4	4,131	16,214	3,772	7,104	14,428
5	3,344	20,720	5,189	9,537	19,292
6-9	8,073	31,114	8,856	16,137	31,167
10+	8,065	83,783	23,769	44,358	87,414
All	47,651	25,784	1,923	6,831	21,720

The dataset consists of the transaction records of 87373 investors at a major European broker for the period from January 1999 to December 2006. The investors' portfolios are sorted with respect to the number of stocks held at three points in time (January 2000, January 2003 and January 2006). The first (second) column gives the number of stocks in the portfolio (of investors). The four remaining columns indicate the mean, the 25th percentile, the median and the 75th percentile of the portfolio values in euros, conditional on the number of stocks held.

Table 1.2

The LSV and FHW measures

	Semiannually		Quarterly		Monthly	
	LSV	FHW	LSV	FHW	LSV	FHW
All stocks	13.90	22.93	13.10	22.00	12.63	21.70
Market capitalization						
Large capitalization	14.79	22.10	13.97	21.16	13.86	21.28
Medium capitalization	12.42	21.00	11.88	20.48	11.44	20.32
Small capitalization	12.54	22.54	12.09	21.97	12.04	22.16
Volume of trading						
High volume of trading	14.58	21.13	13.68	20.13	13.35	20.16
Medium volume of trading	11.98	20.49	11.56	20.18	11.09	19.90
Low volume of trading	13.29	23.94	12.75	23.16	12.88	23.50
Industry						
Oil & Gas	12.87	20.20	12.77	19.33	12.74	19.75
Basic Materials	14.20	23.33	13.36	22.17	13.67	22.71
Industrials	13.84	23.04	12.81	21.88	12.42	21.47
Consumer Goods	13.78	22.78	13.10	22.15	12.96	22.08
Health Care	13.14	21.93	11.89	20.63	11.86	20.84
Consumer Services	13.79	22.43	13.42	21.96	12.84	21.48
Telecommunications	18.24	27.67	16.33	24.83	14.51	22.50
Utilities	15.68	22.82	14.28	20.49	12.70	18.67
Financials	15.26	24.54	14.17	23.14	13.40	22.54
Technology	13.18	21.75	12.55	21.12	11.90	20.79

The LSV measure for stock j in period t is computed to be $LSV_{jt} = |p_{jt} - p_t| - E[|p_{jt} - p_t|]$, where p_{jt} is the purchase intensity for stock j , p_t is the purchase intensity across all stocks, and $E[|p_{jt} - p_t|]$ is an adjustment factor. With the same notations, the FHW measure for stock j is computed to be $FHW_{jt} = ((p_{jt} - p_t)^2 - E[(p_{jt} - p_t)^2]) \frac{I_{jt}}{(I_{jt} - 1)}$ where I_{jt} is the number of active traders and $E[(p_{jt} - p_t)^2]$ is an adjustment factor. We consider a minimum number of 10 active traders per stock. Stocks with fewer than 10 active traders in period t are excluded from the analysis for this period. The average semiannual, quarterly and monthly LSV and FHW measures are calculated for all stocks over the 1999-2006 period. The LSV and FHW measures are calculated for 3 levels of capitalization ("Market capitalization"). Large (small) capitalizations correspond to the 30 % top (bottom) capitalizations. The medium category contains the remaining observations. The LSV and FHW measures are computed for 3 levels of trading volume in euros ("Volume of trading"). High trading volume (low trading volume) corresponds to the 30 % top (bottom) volume. The medium category contains the remaining observations. The herding measures of the different industries ("Industry") are the average herding measures of the stocks that belong to the industry (using the Industry Classification Benchmark, ICB). The results are expressed in percentages.

Table 1.3

Mean contemporaneous and time-series correlation of purchase intensities by individual investors

Horizon (τ)	Correlation of % buys in month t with % buys in months $t+L$		t-Statistics	
	Whole set of investors	Group 1 with group 2	Whole set of investors	Group 1 with group 2
0	100.00	85.09	n.a.	2330.93***
1	30.27	31.59	22.64***	215.61***
2	19.51	19.82	16.31***	148.91***
3	15.11	14.49	13.74***	118.87***
4	10.95	10.88	10.52***	89.85***
5	11.22	11.14	10.77***	90.53***
6	9.10	8.21	8.94***	71.03***
7	6.48	5.88	6.61***	53.10***
8	6.09	6.52	6.98***	64.20***
9	3.96	3.39	4.00***	29.47***
10	2.74	2.52	2.76***	22.32***
11	3.66	3.55	3.47***	29.91***
12	5.44	5.49	4.97***	43.35***
13	2.96	1.83	2.79***	15.80***
14	1.85	1.66	1.96*	14.88***
15	2.56	0.58	2.60**	5.13***
16	1.29	0.19	1.21	1.58
17	1.95	0.56	1.76*	4.32***
18	2.12	1.97	1.88*	14.95***
19	2.17	2.07	2.47**	18.32***
20	1.42	2.68	1.25	19.69***
21	0.43	-0.45	0.38	-3.37***
22	1.62	1.72	1.40	13.42***
23	2.68	3.24	2.73***	26.06***
24	3.18	2.86	3.07***	21.89***
25	1.34	1.45	1.33	11.37***
26	1.02	-1.14	1.02	-9.09***
27	-0.72	-1.31	-0.72	-9.58***
28	-2.12	-2.55	-1.76*	-16.88***
29	-3.31	-3.68	-2.95***	-28.01***
30	-1.50	-1.15	-1.40	-8.56***
31	-0.18	-0.45	-0.17	-3.18***
32	0.25	-0.97	0.22	-6.66***
33	-0.49	-1.11	-0.44	-8.29***
34	-1.84	-1.56	-1.92*	-12.64***
35	-0.67	0.51	-0.57	3.40***
36	-0.19	0.41	-0.17	2.99***

The results are based on trades data from a large European brokerage house for the January 1999 to December 2006 period. For each stock in each month, we compute the proportion of all trades that are purchases. The second column of the table represents the correlations between the purchase intensities at month t and month $t + \tau$ with $\tau = 1, \dots, 36$. The third column gives the correlations between the purchase intensities by group 1 at time t with the purchase intensities by group 2 at time $t + \tau$. The first element of this column is the mean contemporaneous correlation across groups. T-statistics are based on the mean and the standard deviation of the calculated correlations. The results are expressed in percentages.

Table 1.4

Mean contemporaneous and time-series correlation of individual investors' herding measure

Horizon (τ)	Correlation of % buys in month t with % buys in months $t + \tau$	t-Statistics
	Whole set of investors	Whole set of investors
0	100.00	n.a.
1	12.43	12.19***
2	11.22	12.80***
3	10.23	12.73***
4	10.96	12.62***
5	9.71	16.79***
6	8.68	13.91***
7	7.98	12.49***
8	7.51	10.38***
9	7.13	9.75***
10	6.94	9.82***
11	6.73	9.21***
12	5.90	8.59***
13	5.36	9.08***
14	4.74	7.08***
15	4.74	7.13***
16	5.59	4.98***

The results are based on IHM values computed from trades data from a large European brokerage house for the January 1999 to December 2006 period. The second column of the table represents the correlations between the IHM values at quarter t and quarter $t + \tau$ with $\tau=0, \dots, 16$. The t-statistics are based on the mean and the standard deviation of the calculated correlations.

Table 1.5

The Individual Herding Measure (IHM) and investors' attributes

		Gender			Warrants			Number of transactions			Average Portfolio Value		
		Male	Female	P-value	Yes	No	P-value	< 100	> 200	P-value	< 5000	> 100000	P-value
1999	Q1	0.1097	0.1094	0.9216	0.1135	0.1086	0.0566	0.1071	0.1134	0.0026	0.1058	0.1183	0.0000
	Q2	0.1263	0.1188	0.0066	0.1166	0.1273	0.0000	0.1331	0.1077	0.0000	0.1351	0.1186	0.0000
	Q3	0.1574	0.1590	0.5294	0.1408	0.1621	0.0000	0.1719	0.1309	0.0000	0.1763	0.1361	0.0000
	Q4	0.1332	0.1373	0.0742	0.1269	0.1358	0.0000	0.1393	0.1240	0.0000	0.1342	0.1456	0.0000
2000	Q1	0.1011	0.0972	0.0370	0.1040	0.0994	0.0099	0.1032	0.0978	0.0008	0.1040	0.1006	0.0371
	Q2	0.1336	0.1384	0.0343	0.1299	0.1358	0.0046	0.1349	0.1330	0.2826	0.1225	0.1518	0.0000
	Q3	0.1499	0.1569	0.0029	0.1229	0.1581	0.0000	0.1677	0.1170	0.0000	0.1531	0.1573	0.0424
	Q4	0.1233	0.1290	0.0072	0.1158	0.1265	0.0000	0.1309	0.1076	0.0000	0.1200	0.1242	0.0280
2001	Q1	0.1132	0.1214	0.0002	0.1073	0.1165	0.0001	0.1187	0.1016	0.0000	0.0988	0.1138	0.0000
	Q2	0.1100	0.1135	0.1486	0.1035	0.1124	0.0003	0.1174	0.0913	0.0000	0.0969	0.1219	0.0000
	Q3	0.0875	0.0888	0.5852	0.0837	0.0887	0.0298	0.0941	0.0698	0.0000	0.0763	0.0884	0.0000
	Q4	0.1093	0.1142	0.0623	0.1016	0.1123	0.0000	0.1184	0.0882	0.0000	0.0927	0.1072	0.0000
2002	Q1	0.1566	0.1569	0.9114	0.1465	0.1590	0.0000	0.1617	0.1401	0.0000	0.1256	0.1662	0.0000
	Q2	0.1129	0.1190	0.0204	0.1162	0.1136	0.3396	0.1154	0.1024	0.0000	0.0791	0.1163	0.0000
	Q3	0.0799	0.0823	0.2552	0.0767	0.0812	0.0477	0.0828	0.0673	0.0000	0.0603	0.0825	0.0000
	Q4	0.0953	0.1010	0.0291	0.0857	0.0988	0.0000	0.1087	0.0704	0.0000	0.0898	0.0768	0.0000
2003	Q1	0.1062	0.1143	0.0053	0.0974	0.1102	0.0000	0.1168	0.0885	0.0000	0.1055	0.1130	0.0033
	Q2	0.1225	0.1432	0.0000	0.0982	0.1328	0.0000	0.1503	0.0771	0.0000	0.1158	0.0915	0.0000
	Q3	0.0812	0.0927	0.0001	0.0732	0.0858	0.0000	0.0932	0.0663	0.0000	0.0687	0.0791	0.0000
	Q4	0.0599	0.0613	0.5366	0.0506	0.0624	0.0000	0.0673	0.0483	0.0000	0.0502	0.0542	0.0656
2004	Q1	0.0608	0.0640	0.1471	0.0533	0.0633	0.0000	0.0687	0.0495	0.0000	0.0567	0.0552	0.4841
	Q2	0.0906	0.1005	0.0005	0.0822	0.0950	0.0000	0.1017	0.0745	0.0000	0.0858	0.0811	0.0869
	Q3	0.1328	0.1410	0.0157	0.1026	0.1417	0.0000	0.1641	0.0853	0.0000	0.1450	0.0847	0.0000
	Q4	0.0982	0.0992	0.7272	0.0896	0.1006	0.0000	0.1104	0.0764	0.0000	0.0967	0.0689	0.0000
2005	Q1	0.0723	0.0785	0.0100	0.0731	0.0736	0.8490	0.0774	0.0646	0.0000	0.0549	0.0668	0.0000
	Q2	0.1126	0.1158	0.2837	0.1084	0.1145	0.0395	0.1302	0.0827	0.0000	0.1101	0.0906	0.0000
	Q3	0.1093	0.1144	0.0708	0.0929	0.1142	0.0000	0.1253	0.0850	0.0000	0.0998	0.0894	0.0002
	Q4	0.0993	0.1046	0.0479	0.0905	0.1025	0.0000	0.1142	0.0748	0.0000	0.1114	0.0787	0.0000
2006	Q1	0.0764	0.0794	0.1589	0.0682	0.0789	0.0000	0.0854	0.0589	0.0000	0.0771	0.0577	0.0000
	Q2	0.0786	0.0852	0.0059	0.0672	0.0827	0.0000	0.0965	0.0511	0.0000	0.0866	0.0611	0.0000
	Q3	0.0839	0.0849	0.7015	0.0767	0.0858	0.0010	0.0889	0.0729	0.0000	0.0640	0.0841	0.0000
	Q4	0.0793	0.0793	0.9763	0.0766	0.0799	0.1499	0.0859	0.0657	0.0000	0.0740	0.0677	0.0040

This table reports the average IHM values using various subsamples of investors. Four characteristics are considered: the gender, whether the investor trades warrants during the sample period, the total number of transactions and the average portfolio value. For each characteristic and each quarter, we compare the average IHM values of the two subsamples of investors. The reported p-values (computed with Monte-Carlo simulations) correspond to the test of no difference between the average IHM values of the two subsamples of investors.

Table 1.6

Correlation between investors's portfolio past returns and herding behavior

		Spearman correlation with IHM			
		Average Return	Standard Deviation	Skewness	Kurtosis
2000	Q1	-0.1388***	-0.0896***	0.0235***	-0.0197***
	Q2	-0.1138***	-0.2387***	0.1085***	0.0054
	Q3	0.0582***	-0.1320***	-0.0049	-0.0331***
	Q4	0.0203***	-0.1458***	-0.0265***	0.0187***
2001	Q1	0.1269***	-0.1659***	-0.0265***	0.0015
	Q2	0.1231***	-0.1447***	-0.0293***	0.0232***
	Q3	-0.0288***	-0.0615***	-0.0261***	-0.0119*
	Q4	0.0657***	-0.1061***	-0.0352***	0.0826***
2002	Q1	0.0040	-0.0996***	0.0067	-0.0785***
	Q2	-0.0108*	-0.0552***	0.0327***	0.0094
	Q3	0.0281***	-0.0882***	-0.0188***	-0.0378***
	Q4	0.0649***	-0.1033***	-0.0051	-0.0518***
2003	Q1	-0.0087	-0.1450***	-0.0252***	-0.0654***
	Q2	0.1011***	-0.2723***	0.0139**	-0.0386***
	Q3	-0.1097***	-0.1938***	-0.1117***	0.0178**
	Q4	0.0361***	-0.0884***	0.0141**	0.0130*
2004	Q1	0.0256***	-0.1425***	0.0129*	0.0122*
	Q2	-0.0293***	-0.0851***	0.0150**	-0.0241***
	Q3	0.0621***	-0.1209***	-0.1453***	0.0131*
	Q4	0.0446***	-0.0933***	-0.0513***	-0.0033
2005	Q1	-0.0342***	-0.0686***	-0.0321***	-0.0253***
	Q2	0.0206***	-0.1005***	0.0556***	0.0301***
	Q3	-0.0928***	-0.1228***	-0.0327***	-0.0080
	Q4	-0.0739***	-0.0756***	-0.0393***	-0.0231***
2006	Q1	-0.0027	-0.1170***	-0.0340***	0.0112*
	Q2	-0.0873***	-0.1333***	-0.0263***	-0.0260***
	Q3	0.0990***	-0.1624***	-0.0543***	-0.0847***
	Q4	0.0799***	-0.0923***	0.0028	-0.0460***

The quarterly returns are based on the investors' daily portfolios from January 1999 to December 2006. This table presents the coefficients of the Spearman correlation between investors' IHM and, respectively, the previous quarter portfolios' average return, standard deviation, skewness and kurtosis. *** corresponds to a p-value of 0.01, ** to a p-value of 0.05 and * to a p-value of 0.1.

Table 1.7
Influence of past performance on herding behavior

Explanatory Variable	Model 1	Model 2	Model 3	Model 4
	Coefficients	Coefficients	Coefficients	Coefficients
$(IHM)_{t-1}$	-0.0614*** (-33.2600)	-0.0614*** (-33.2800)	-0.0617*** (-33.4100)	-0.0614*** (-33.2800)
$(IHM)_{t-2}$	-0.0312*** (-16.9000)	-0.0311*** (-16.8700)	-0.0310*** (-16.8100)	-0.0312*** (-16.8900)
$(RAR)_{t-1}$	-0.0165*** (-6.3300)			
$(RAR)_{t-2}$	-0.0208*** (-8.0800)			
$(RAR)_{t-1} (WRT = 1)$		0.0020 (0.5300)		
$(RAR)_{t-1} (WRT = 0)$		-0.0239*** (-8.4600)		
$(RAR)_{t-2} (WRT = 1)$		-0.0150*** (-4.0200)		
$(RAR)_{t-2} (WRT = 0)$		-0.0234*** (-8.3700)		
$(RAR)_{t-1} (NT < 100)$			-0.0363*** (-10.2100)	
$(RAR)_{t-1} (100 \leq NT \leq 200)$			-0.0247*** (-6.1500)	
$(RAR)_{t-1} (NT > 200)$			0.0016 (0.5000)	
$(RAR)_{t-2} (NT < 100)$			-0.0356*** (-10.1400)	
$(RAR)_{t-2} (100 \leq NT \leq 200)$			-0.0231*** (-5.8300)	
$(RAR)_{t-2} (NT > 200)$			-0.0099*** (-3.0900)	
$(RAR)_{t-1} (APV < 5000)$				-0.0144*** (-2.6200)
$(RAR)_{t-1} (5000 \leq APV \leq 100000)$				-0.0192*** (-6.9200)
$(RAR)_{t-1} (APV > 100000)$				-0.0004 (-0.0800)
$(RAR)_{t-2} (APV < 5000)$				-0.0243*** (-4.5300)
$(RAR)_{t-2} (5000 \leq APV \leq 100000)$				-0.0215*** (-7.8300)
$(RAR)_{t-2} (APV > 100000)$				-0.0123** (-2.2400)
$(Experience)_t$	-0.0187*** (-5.7200)	-0.0189*** (-5.7600)	-0.0190*** (-5.7900)	-0.0190*** (-5.8100)
Number of Observations	332154	332154	332154	332154
R-squared	0.2466	0.2467	0.2469	0.2466

This table presents the results of the panel regression estimated by $IHM_{i,t} = \gamma_0 IHM_{i,t-1} + \gamma_1 IHM_{i,t-2} + \sum_{\tau=1}^2 \beta_\tau RAR_{i,t-\tau} + \theta EXP_{i,t} + \alpha_1 IFE_i + \alpha_2 TFE_t + \varepsilon_{i,t}$. The independent variable is the Investor Herding Measure (IHM) for quarter t . We include two lagged values of the IHM (quarters $t-1$ and $t-2$) to account for autocorrelation. RAR_t is the investor's portfolio Risk Adjusted Return for quarter t , defined as the ratio of the average return to the standard deviation. WRT is a dummy variable that takes the value 1 if the investor trades warrants at any moment during the sample period and 0 otherwise. NT is the investor's total number of transactions and APV is the investor's average portfolio value. $Experience_t$ represents the number of transactions accomplished by the investor up to quarter t . Models 1 to 4 incorporate individual- and time-fixed effects. Returns are winsorized at the 1st and 99th percentiles. Coefficients are standardized.

Table 1.8

Correlation between investors's portfolio contemporary returns and herding behavior

		Spearman correlation with IHM			
		Average Return	Standard Deviation	Skewness	Kurtosis
1999	Q1	0.0426***	-0.0228***	-0.0041	-0.0136*
	Q2	0.0338***	0.0574***	0.0043	-0.0040
	Q3	-0.0026	0.0555***	0.0330***	-0.1112***
	Q4	0.0399***	0.0211***	0.0045	-0.0262***
2000	Q1	-0.0910***	-0.0628***	0.0388***	0.0324***
	Q2	0.1421***	-0.1835***	-0.0574***	-0.1102***
	Q3	-0.0298***	-0.0979***	0.0441***	0.0691***
	Q4	0.1007***	-0.1111***	-0.0289***	0.0089
2001	Q1	0.0411***	-0.1038***	-0.0028	-0.0677***
	Q2	-0.0444***	-0.1142***	-0.0722***	-0.0827***
	Q3	0.0105*	-0.0595***	-0.0322***	0.0270***
	Q4	-0.0961***	-0.1089***	-0.0212***	-0.0153**
2002	Q1	0.0322***	-0.0831***	-0.0648***	-0.1073***
	Q2	-0.0164***	-0.0160**	-0.0189***	-0.0020
	Q3	0.0647***	-0.1072***	0.0216***	-0.0435***
	Q4	-0.0468***	-0.0680***	-0.0112*	-0.0196***
2003	Q1	-0.0481***	-0.1023***	-0.0419***	-0.0521***
	Q2	-0.1517***	-0.2037***	-0.0892***	-0.0190***
	Q3	-0.0069	-0.1688***	0.0237***	-0.0365***
	Q4	0.0219***	-0.0811***	-0.0014	0.0088
2004	Q1	0.0139**	-0.0907***	-0.0649***	0.0387***
	Q2	0.0669***	-0.0654***	-0.0110	0.0121*
	Q3	0.1045***	-0.1522***	0.0001	-0.0386***
	Q4	-0.0333***	-0.1009***	-0.0192***	-0.0796***
2005	Q1	0.0063	-0.0537***	-0.0113	0.0168**
	Q2	-0.0496***	-0.1310***	0.0074	-0.0441***
	Q3	-0.1339***	-0.1474***	0.0051	0.0365***
	Q4	0.0395***	-0.1161***	0.0223***	-0.0337***
2006	Q1	-0.0231***	-0.0921***	0.0067	-0.0129*
	Q2	0.0605***	-0.1272***	-0.0279***	-0.0334***
	Q3	0.0814***	-0.1153***	-0.0180**	-0.0656***
	Q4	0.0016	-0.0840***	0.0088	-0.0422***

Quarterly returns are based on the investors' daily portfolios from January 1999 to December 2006. This table presents the coefficients of the Spearman correlation between investors' IHM and, respectively, the portfolios' contemporary average return, standard deviation, skewness and kurtosis. *** corresponds to a p-value of 0.01, ** to a p-value of 0.05 and * to a p-value of 0.1.

Table 1.9
Panel regression of individual herding and performance

	Excess Return	$R_{mt} - R_{ft}$	HML_t	SMB_t	MOM_t	Adjusted R^2
Panel A: Average investor						
Own-benchmark abnormal return	-0.0023*** (-2.7867)					
Market-adjusted return	0.0054 (0.4592)					
Carhart four-factor	0.0004 (0.0400)	1.3274*** (10.6648)	-0.0678 (-0.3915)	0.4287* (1.9444)	-0.1780 (-1.4301)	0.9144
Panel B: Average anti-herder ($IHM < -0.05$)						
Own-benchmark abnormal return	0.0069*** (5.8519)					
Market-adjusted return	0.0034 (0.2641)					
Carhart four-factor	-0.0026 (-0.2217)	1.3734*** (10.0789)	-0.0383 (-0.2020)	0.4099 (1.6982)	-0.1670 (-1.2251)	0.9030
Panel C: Average independent trader ($-0.05 \leq IHM \leq 0.05$)						
Own-benchmark abnormal return	0.0008 (1.4912)					
Market-adjusted return	0.0069 (0.5293)					
Carhart four-factor	-0.0008 (-0.0657)	1.3859*** (9.6000)	-0.0912 (-0.4545)	0.5016* (1.9616)	-0.1423 (-0.9858)	0.8907
Panel D: Average herder ($IHM > 0.05$)						
Own-benchmark abnormal return	-0.0051*** (-4.1973)					
Market-adjusted return	0.0049 (0.4431)					
Carhart four-factor	0.0008 (0.0859)	1.2976*** (11.2751)	-0.0574 (-0.3584)	0.3927* (1.9264)	-0.1831 (-1.5910)	0.9239

Quarterly returns are based on the investors' daily portfolios from January 1999 to December 2006. Panel A corresponds to the average investor who is representative of the entire population. Panel B corresponds to the anti-herders ($IHM < -0.05$), Panel C to the independent traders ($-0.05 \leq IHM \leq 0.05$) and Panel D to the herders ($IHM > 0.05$). The own-benchmark abnormal return is the result of the difference between the realized return and the return of the beginning-of-quarter portfolio. The market-adjusted return corresponds to the investor's realized return minus the return of the market (SBF 250) for the same period. The p-values are computed using the t-statistics based on the 32 observations of the time-series. The Carhart four-factor model is a regression of the individual investor excess return (using the EURIBOR 3-month rate) on the market excess return $R_{mt} - R_{ft}$, a zero-investment size portfolio (SMB_t), a zero-investment book-to-market portfolio (HMB_t) and a zero-investment momentum portfolio (MOM_t). The quarterly returns are winsorized at the 1st and 99th percentiles. *** corresponds to a p-value of 0.01, ** to a p-value of 0.05 and * to a p-value of 0.1.

Table 1.10

The influence of herding behavior on investors' portfolio performance

Panel A: Investors sorted on return										
	Lowest Returns	2	3	4	5	6	7	8	9	Highest Returns
Anti-herder ($IHM < -0.05$)	1.2709*** (28)	1.0729*** (14)	1.0064 (2)	0.9255*** (10)	0.9066*** (15)	0.8878*** (18)	0.8866*** (18)	0.9153*** (15)	0.9848 (8)	1.1476*** (21)
Independent trader ($-0.05 \leq IHM \leq 0.05$)	1.0457 (21)	1.0315* (16)	0.9914 (11)	0.9720** (10)	0.9683*** (8)	0.9660*** (7)	0.9641*** (12)	0.9825 (8)	1.0286 (16)	1.0503* (23)
Herder ($IHM > 0.05$)	0.9330*** (24)	0.9768*** (17)	1.0057 (10)	1.0278*** (15)	1.0331*** (19)	1.0362*** (22)	1.0385*** (20)	1.0200*** (16)	0.9850 (14)	0.9445*** (22)
Panel B: Investors sorted on Sharpe ratio										
	Lowest Sharpe Ratio	2	3	4	5	6	7	8	9	Highest Sharpe ratio
Anti-herders ($IHM < -0.05$)	1.1772*** (20)	1.0691*** (11)	1.0401** (8)	0.9946 (6)	0.9678** (5)	0.9585*** (4)	0.9499*** (9)	0.9473*** (7)	0.9341*** (15)	0.9657 (17)
Independent traders ($-0.05 \leq IHM \leq 0.05$)	1.0284 (18)	1.0213 (12)	0.9986 (9)	0.9820** (6)	0.9911 (4)	0.9873 (4)	0.9850 (8)	0.9758* (10)	1.0125 (14)	1.0184 (19)
Herders ($IHM > 0.05$)	0.9623*** (23)	0.9796** (18)	0.9929 (12)	1.0091* (7)	1.0127*** (11)	1.0138*** (5)	1.0165*** (9)	1.0164*** (14)	1.0046 (14)	0.9925 (18)

Quarterly returns are based on investors' daily portfolios from January 1999 to December 2006. Investors are sorted into deciles on quarterly return (Panel A) and Sharpe ratio (Panel B). Decile 1 corresponds to the lowest returns (respectively Sharpe ratios) while Decile 10 contains investors with the highest ones. Investors are separated into three categories: Anti-herders ($IHM < -0.05$), Independent traders ($-0.05 \leq IHM \leq 0.05$) and Herders ($IHM > 0.05$). We compute, for each intersection of a performance decile and a herding category the ratio of the number of investors on the theoretical number under independence between herding and performance. *** corresponds to a p-value of 0.01, ** to a p-value of 0.05 and * to a p-value of 0.1. P-values are computed using the t-statistics based on the 32 observations of the time-series. The values in brackets correspond to the number of quarters for which the difference between the realized number of investors and the theoretical one is significant (with a significance level of 5 % and using Monte-Carlo simulations to assess the significance). Quarterly returns are winsorised at the 1st and 99th percentiles.

Chapter 2

The (lack of) forecasting quality of financial analysts' target prices

Joint work with

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Abstract

We show, in this paper, that measuring the accuracy of a target price is not sufficient to assess its quality, because the forecast predictability (which depends on the stock return volatility and on the forecast horizon) is likely to vary across stocks and over time. We argue that the evidence of time persistent differences in analysts' target price accuracy, obtained in previous studies, cannot be interpreted as a proof of persistent differential abilities. We demonstrate this claim by showing that the persistence in accuracy remains when replacing the empirical target prices by naïve forecasts. Our analysis indicates that the persistence in accuracy is driven by persistence in stock return volatility.

We introduce a measure of target price quality that considers both the forecast inaccuracy and the forecast predictability. Using elements from option-pricing theory, we provide a simple solution to the issue of estimating target price predictability. Our empirical analysis reveals that, when forecast predictability is taken into account, financial analysts do not exhibit significant persistent differential abilities to forecast future stock prices.

2.1 Introduction

Professional investors, [...], fail a basic test of skill: persistent achievement.

Daniel Kahneman (2011)

We show, in this paper, that measuring the accuracy of a target price is not sufficient to assess its quality, because the forecast predictability (*i.e.* the difficulty of issuing an accurate forecast) is likely to vary across stocks and over time. The importance of the predictability, when assessing the quality of a forecast, is a well-known concern in the literature on earnings forecasts (Huberts and Fuller, 1995; DeBondt and Forbes, 1999; Beckers, Steliaros, and Thomson, 2004). For instance, Jacob, Lys, and Neale (1999) note that “forecasting difficulty is [...] like to differ cross-sectionally”. Similarly, Hong, Kubik, and Solomon (2000) state that “some firms are more difficult than others to predict accurately”. The existing literature on target prices ignores this issue and considers that a target price is better than another if it is more accurate. We show that omitting the issue of predictability (which is a function of the volatility and of the forecast horizon) prevents from evaluating correctly the ability of financial analysts to issue accurate target prices. Furthermore, we show that the controls for the differences in volatility often used in multivariate analysis, are not well-adapted as the relationship between volatility and target price accuracy is nonlinear. We intend, in this paper, to provide a comprehensive framework to evaluate the quality of target prices. The contributions of our new measure of quality are the following: (1) it accounts for differences in predictability (*i.e.* differences in stock return volatility and forecast horizon); (2) it takes into account forecast boldness (*i.e.* how far the analyst’s target price is from the current price); and, (3) it

is a dynamic measure (the forecast quality can be evaluated at any moment in time).¹ When taking into account differences in predictability across target prices, we show that analysts do not exhibit persistent differential abilities. Our results contrast with previous studies (Bradshaw, Brown, and Huang, forthcoming; Bilinski, Lyssimachou, and Walker, 2013).

Analysts play a key role in financial markets. Ivkovic and Jegadeesh (2004) identify two sources of value that analysts bring to the market. First, they extract useful information for investors from public information. Second, through a careful examination of accounting documents and contacts with firm managers, they acquire information previously unknown to other market participants. As such, their reports and forecasts are of great importance since they render private information public. Analysts' reports are typically composed of three main figures: earnings forecasts, purchase recommendations and target prices. Though the latter seems to be of greatest interest to investors (as it gives a precise indication as to whether a stock is under- or overvalued), it has also received the least attention from academics. However, a few articles point out the important role of target prices both for individual investors and practitioners. For instance, Brav and Lehavy (2003) and Asquith, Mikhail, and Au (2005) report significant market reaction to target price revisions, even after controlling for recommendations and earnings forecast revisions. Lawrence, Ryan, and Sun (2012) analyze the web traffic of a leading website of analyst report information and find that target prices are the type of analyst information for which the investors' demand is greatest.

¹Forecast quality/accuracy is usually evaluated *ex-post*.

The main practice for earnings forecasts is to consider that a forecast is accurate if the absolute error is small (*i.e.*, the announced earnings value is close to the forecast). The measures traditionally used to estimate the accuracy of target prices are defined similarly, that is, a target price is considered to be accurate if the stock price at the end of the forecast horizon is close to the target price. The accuracy (or conversely the inaccuracy) is then used to assess the quality of the forecast. We argue, in this article, that the accuracy in itself is not sufficient to evaluate the quality of a forecast as it does not take into account the difficulty of making a correct forecast. Indeed, the difficulty of forecasting a target price is not the same for all stocks. In particular, two factors influence the difficulty of the analyst's task: the stock return volatility and the forecast horizon.² The higher the volatility, the higher the expected value of the absolute forecast error is. Similarly, the higher the horizon, the more difficult it is to forecast the future stock price. Thus, for a given absolute forecast error, it is logical to consider a forecast made on a more volatile stock and/or with a longer horizon to be of higher quality than a forecast made on a less volatile stock and/or with a shorter horizon.

A simple way to measure the difficulty of forecasting a target price is to estimate the expected value of the absolute error $E_t [|S_T - \Phi_{t,T}|]$ where $\Phi_{t,T}$ is the target price issued at time t with horizon $T - t$ and S_T is the stock price at the end of the horizon. The expected value of the absolute error is an increasing function of the stock return

²The predictability of a forecast depends on the variability of the predicted variable and on the horizon of the forecast. Evidence of a link between horizon and predictability has been established early in the literature on earnings forecasts (Brown, Richardson, and Schwager, 1987; O'Brien, 1988; Kross, Ro, and Schroeder, 1990; Brown, 1991; Lys and Soo, 1995; Sinha, Brown, and Das, 1997). Dichev and Tang (2009) demonstrate the existence of a relationship between predictability and variability. They show that earnings predictability is negatively related to earnings volatility.

volatility and the length of the forecast horizon. We can then define the quality as the abnormal absolute forecast error, denoted $E_t [|S_T - \Phi_{t,T}|] - |S_T - \Phi_{t,T}|$ where $E_t [|S_T - \Phi_{t,T}|]$ measures the difficulty of the forecast and $|S_T - \Phi_{t,T}|$ measures the inaccuracy.

An important issue here is to find a way to estimate the expected value of the absolute forecast $E_t [|S_T - \Phi_{t,T}|]$. However, option-pricing theory provides us with all the necessary elements to estimate the expected value of the absolute forecast error. First, we note that the absolute forecast error $|S_T - \Phi_{t,T}|$ corresponds to the final payoff of a straddle with a strike price equal to $\Phi_{t,T}$, that is, a portfolio containing a call option and a put option on the same underlying stock; the two options are characterized by the same strike price $\Phi_{t,T}$ and the same maturity $T - t$. Second, we note that the price of the straddle at time t corresponds to the discounted expected value of the final payoff. It follows that, when issuing a target price, an analyst acts as if she shorts a straddle. Selling a straddle implies that she receives up front the discounted expected value of the absolute forecast error $E_t [|S_T - \Phi_{t,T}|]$. She will then pay the realized absolute forecast error $|S_T - \Phi_{t,T}|$ at the end of the horizon.

The contributions of our approach are the following. First, our approach permits to account for differences in volatility. Second, it allows us to consider forecasts with different horizons. Third, we account for the boldness of the forecasts. Fourth, we are able to measure the quality of a forecast at any moment in time: the quality of a target price at time $t + \tau$, $\tau \in [0; T]$ is simply the price of the straddle at time t capitalized until time $t + \tau$ minus the price of the straddle at time $t + \tau$.³ In other

³The quality of the target price at time $t + \tau$ is equal to $E_t [|S_T - \Phi_{t,T}|] - E_{t+\tau} [|S_T - \Phi_{t,T}|]$.

words, we use the price at time $t + \tau$ to “mark-to-market” the quality. This last feature is particularly important as it provides a simple and consistent solution to the issue of measuring, when a revision occurs, the quality of the initial target price .

In the second part of the paper, we conduct an empirical analysis based upon our measure which investigates whether financial analysts exhibit skills in forecasting future prices. Kahneman (2011) exposes two basic conditions for the possible existence of expertise skills: (1) an environment that is sufficiently regular to be predictable; and (2) an opportunity to learn the regularities through prolonged practice. Although the second condition is met, the first condition is not likely to be fulfilled. Indeed, one can hardly define the stock market as a regular environment. Even without assuming any kind of market efficiency, predicting stock prices at a 12-month or longer horizon is an extremely difficult task.

Furthermore, as stated by Kahneman (2011), “whether professionals have a chance to develop intuitive expertise depends essentially on the quality and speed of the feedback”. In the case of target prices with 12-month or longer horizon, the use of *ex-post* measures implies that the speed of the feedback is drastically low. Taking into account these different elements, we therefore expect financial analysts not to demonstrate any significant skill in forecasting future stock prices.

Using a dataset similar to ours, Bradshaw, Brown, and Huang (forthcoming) find statistically significant (albeit economically weak) evidence that financial analysts are able to consistently forecast accurate target prices.⁴ We show in this paper that this persistence is mechanically induced by the persistence in volatility. Analysts tend to

⁴Although their results are statistically significant, their analysis shows that evidence of persistent differential abilities is rather limited.

issue target prices for a small pool of stocks. This pool of stocks is relatively stable over time, meaning that the analysts cover the same stocks for several periods. We show that, because the magnitude of the absolute forecast error is highly correlated with stock return volatility, analysts who cover a pool of stocks with low volatility exhibit low persistent absolute forecast errors. We provide empirical evidence for this causality. Our results indicate that a significant persistence in accuracy remains when considering naïve forecasts. When taking into account differences in volatility, that is, when considering the quality of the forecasts rather than the accuracy, we show that the persistence in correctly forecasting future stock prices disappears (the relation is no more statistically significant). Our findings are robust to a number of changes such as restricting the sample to experienced financial analysts, or restricting the validity of target prices to a shorter period of time.

This paper is structured as follows. In section 2, we present the data used in our study. In section 3, we discuss the importance of target price predictability and we show why target price accuracy cannot be used to measure the ability of financial analysts to forecast future stock prices. In section 4, we introduce our measure of target price quality. Section 5 reports the empirical results and the last section concludes.

2.2 Data and descriptive statistics

Our primary dataset consists of a total of 686,863 target prices made by 10,137 analysts (620 brokers) on 7,646 U.S. stocks for the 2000-2010 period. The provider for the target prices is I/B/E/S. For each forecast, we have the code of the analyst (and

the broker code) who issues the forecast, the issue date, the horizon in months (usually 6 or 12 months), and the target price. We remove from the database the forecasts for which the stock price is not available on the issue date (20,766 forecasts), or is less than one dollar (2,044 forecasts). We also delete from the database the forecasts for which the ratio of the target price over the stock price is in the bottom one percent of the distribution (7,468 forecasts) and the forecasts for which this ratio is higher than four (2,313 forecasts). Finally, we discard the observations for which the price history is too short to compute an acceptable estimation of the historical volatility⁵ (4,801 forecasts). After deleting these 37,392 observations, 770 analysts are removed from the database as they are left with no forecasts. Our final sample consists of 649,471 target prices made by 9,367 analysts (583 brokers) on 7,268 stocks.

Our secondary dataset consists of the prices, capitalization levels and volumes of trading for the 7,268 stocks considered. This second dataset comes from CRSP. Target prices and stock prices are adjusted for splits and corporate actions.

Table 2.1 reports for each year the number of forecasts, number of active analysts, the average, median and maximum number of active analysts per stock, and the average, median and maximum number of stocks covered per analyst. We observe that the number of forecasts per year more than doubles over the sample period while the number of active analysts remains roughly constant. It appears that the inclusion of a target price in analysts' reports is an increasingly popular practice. An analyst typically covers 4 different stocks at the beginning of the sample period; this number increases to 7 in the last years. Conversely, the number of analysts covering a given

⁵We delete the observations for which there are less than 2 months of price history prior to the forecast.

stock increases over the sample period from 4 to 6.

On average, the analysts in our sample revise their forecasts approximately every 6 months (137 trading days). The target prices in our sample are on average 23% higher than the current stock price.⁶ This statistic is similar to what can be observed for other periods and/or countries. For instance, Brav and Lehavy (2003) find that target prices on U.S. stocks for the 1997-1999 period are on average 28% higher than the current price while Kerl (2011) reports an implicit return of 18.07% for German stocks for the 2002-2004 period. Finally, it appears that the analysts in our sample are mainly optimistic about stock prices with only 13% of the target prices forecasted below the concurrent price.

2.3 Target price accuracy

2.3.1 Definition and shortcomings

Similarly to earnings forecasts, the most popular measure of target price accuracy is the absolute forecast error. It is defined as

$$|TPERROR|_t = \frac{|S_T - \Phi_{t,T}|}{S_t}, \quad (2.1)$$

where $\Phi_{t,T}$ is the value of a target price issued at time t with horizon T , S_T is the stock price at the end of the forecast horizon and S_t is the stock price at the time the forecast was issued.

⁶The annualized return for the S&P 500 Composite index for the same period is -1.21% .

Despite its wide use in the literature, this measure of accuracy has a number of drawbacks and is not well suited to evaluate whether a forecast is better than another or whether an analyst is better than her peers at issuing accurate target prices. The main drawbacks of the absolute forecast error are: (1) it does not reward bold accurate forecasts; (2) the *ex-post* approach implies a low feedback speed (the accuracy can be evaluated only at the end of the target price horizon, usually 12 months); (3) it does not permit a clean treatment of target price revisions; and, (4) it does not account for stock price predictability (*i.e.*, the difficulty of issuing an accurate target price).

This section studies the issue of target price revisions and stock price predictability.

2.3.2 Stock price predictability

The stock price (un)predictability corresponds to the difficulty of issuing an accurate target price. This difficulty is a function of both the stock return volatility and the target price horizon. As a consequence, there exists a mechanical relationship between accuracy and stock return volatility.⁷ We provide here both empirical and theoretical evidence that target price accuracy is mechanically influenced by stock return volatility. Furthermore, we show that this relationship is nonlinear.

Existence of a relationship between volatility and accuracy

Each year, we assign target prices to five quintiles with respect to the volatility of the underlying stock. For each quintile, we report the average accuracy of the target prices in the quintile. Table 2.2 provides the average accuracy per quintile for

⁷We do not consider here the issue of target price horizon as most studies consider only target prices with a 12-month horizon.

the 2000-2010 period. Panel A reports the results using actual target prices. Panel B provides the average accuracy using naïve forecasts. Naïve forecasts are defined as the stock price at the issued date capitalized by the risk-free rate. We report results using naïve forecasts in order to eliminate the possibility that the relationship between accuracy and stock return volatility ensues entirely from financial analysts being particularly good at forecasting stock prices for high volatility firms. Our findings indicate a strong monotonic relationship between stock return volatility and target price accuracy. This result holds both for actual data and naïve forecasts.

Nonlinearity of the relationship

We now show that the relationship between stock return volatility and target price accuracy is nonlinear. In order to demonstrate this nonlinearity, we perform the following regression

$$|TPERROR|_{jt} = \alpha + \sum_{k=1}^{10} \beta_k \mathbf{1}_{jt}^k \sigma_{jt} + \epsilon_{jt}, \quad (2.2)$$

where $|TPERROR|_{jt}$ is the absolute forecast error of a target price on firm j issued by any analyst at time t , σ_{jt} is the stock return volatility of stock j measured at time t and $\mathbf{1}_{jt}^k$ is an indicator that takes the value 1 if the stock return volatility σ_{jt} belongs to the k -th volatility decile and 0 otherwise.

The idea underlying this regression is the following one. In case of perfect linearity, all the coefficients β_k will take the same value. On the contrary, if the relationship between accuracy and volatility is nonlinear, we will find differences in the values taken by the coefficients β_k . For instance, if the coefficient β_k decreases (increases)

with k , the relationship between volatility and accuracy will be concave (convex). Table 2.3 reports the results of the regression. The coefficient β_k increases with k , indicating that the relationship between volatility and accuracy is nonlinear and convex.

We now provide theoretical evidence of the nonlinearity of the relationship between volatility and accuracy. Assuming, as it is common in the financial literature, that stock prices can be modeled as a Geometric Brownian Motion, we have

$$\log(S_T) \sim \mathcal{N} \left(\log(S_t) + \left(\mu - \frac{1}{2} \sigma^2 \right) (T - t), \sigma^2 (T - t) \right), \quad (2.3)$$

where μ is the drift and σ is the volatility.

The probability that the stock price ends up inside an interval $[b_l; b_u]$ at the end of a determined horizon is equal to

$$\begin{aligned} \Pr [\log(b_l) < \log(S_T) < \log(b_u)] &= \Pr \left[\frac{\log(b_l/S_t) - (\mu - \frac{1}{2} \sigma^2)(T-t)}{\sigma \sqrt{T-t}} < z < \frac{\log(b_u/S_t) - (\mu - \frac{1}{2} \sigma^2)(T-t)}{\sigma \sqrt{T-t}} \right] \\ &= \Pr [b_l^* < z < b_u^*] \\ &= G(b_u^*) - G(b_l^*), \end{aligned} \quad (2.4)$$

where b_l^* and b_u^* are defined by

$$b_l^* = \frac{\log(b_l/S_t) - (\mu - \frac{1}{2} \sigma^2)(T-t)}{\sigma \sqrt{T-t}} \text{ and } b_u^* = \frac{\log(b_u/S_t) - (\mu - \frac{1}{2} \sigma^2)(T-t)}{\sigma \sqrt{T-t}}, \quad (2.5)$$

G is the cumulative distribution function of a standard normal distribution and z is

a standard Gaussian variable.

The probability for the stock price to end up inside a given interval at the end of a determined horizon is a nonlinear function of both the volatility and the horizon. It follows, by extension, that the expected value of the absolute forecast error is a nonlinear function of both the stock return volatility and the target price horizon.

The nonlinearity of the relationship between volatility and accuracy implies that it is not possible to introduce, in multivariate analyses, the volatility as a control variable. It follows that a new framework of evaluation is needed for measuring the ability of financial analysts to issue accurate target prices.

2.3.3 The issue of target price revisions

Target prices are generally issued with a 12-month horizon. However, in practice, analysts often revise their forecasts before the end of this horizon. Bonini, Zanetti, Bianchini, and Salvi (2010) provide an interesting insight on the issue of computing an *ex-post* measure of accuracy when forecast revisions occur. When a target price is revised, the two possible approaches to address the problem are:

(1) to consider the revised target price as a new forecast and to estimate the global accuracy on the two overlapping periods; and,

(2) to assess the accuracy of the first forecast by adjusting the time horizon and to consider the revision as a new forecast.

To illustrate the two approaches, we use two well-known stocks. Assume that an analyst issues the 2nd of July 2012 (date t), a 12-month target price of \$50 on Facebook, with the current price at date t being \$30.77. One month later, the analyst

becomes convinced the stock price is overvalued. She revises her forecast and sets a new 12-month target price at \$10 (while the current stock price is \$20.04). If we consider the first approach, we now have two forecasts on Facebook; the first one is at \$50 starting at the beginning of July 2012, and the second one is at \$20 starting at the beginning of August 2012. As noted by Bonini, Zanetti, Bianchini, and Salvi (2010), there are a number of problems associated with this approach. Mainly, there is no obvious economic meaning in considering two opposite forecasts. (One forecast is higher than the stock price and the revised one is lower.) Indeed, if the stock price of Facebook decreases, the analyst is considered simultaneously inaccurate (on the first target price) and accurate (on the second target price).

What happens if we follow the second approach? Two successive forecasts are considered: first, a 1-month forecast with a target price of \$50, and second, a 12-month forecast with a \$20 target price. This second approach also has obvious drawbacks. Let us consider a second example to illustrate them. Suppose an analyst issues a 12-month target price of \$800 on Apple, the current stock price being \$592.52. In doing so, she translates her optimistic expectations about Apple's future sales. One month later, the analyst learns that Apple is about to reveal the Ipad mini and the Iphone 5. She then anticipates that the launch of these two new products will boost Apple's stock price. Consequently, she revises her forecast at \$1000. According to the second approach of target price revisions, the accuracy of the first target price is measured by considering the first forecast as a 1-month target price of \$800. In other words, this assumption means that the analyst expected an annualized return of 351% (while it was only an annualized return of 35% when issued with a 12-month

horizon)!

These two simple examples show that dealing smoothly with revisions is not so easy. We show, in the next section, that it is possible to remedy the problem by using the expected value of the absolute forecast error to estimate the (in)accuracy at the time the revision occurs.

2.4 A measure of forecasting quality

2.4.1 Definition

The *ex-post* absolute forecast error is equal to $|S_T - \Phi_{t,T}|$ and corresponds to the inaccuracy of the target price. In order to measure the quality of a target price, we should take into account the difficulty of the forecast, which is a function of the stock return volatility and the length of the forecast horizon. For a given stock price of $S_t^A = S_t^B$ and a target price of $\Phi_{t,T}$, the expected value of the absolute forecast error $E_t [|S_T^A - \Phi_{t,T}|]$ on stock A will be higher than the expected value of the absolute forecast error $E_t [|S_T^B - \Phi_{t,T}|]$ on stock B if the volatility of stock A is higher than the volatility of stock B. Similarly, if a target price is issued with a longer horizon, the expected value of the absolute forecast error will be higher than the expected value of the absolute forecast error of the target price issued with a smaller horizon.

The quality of a target price corresponds to the balance between the forecast difficulty (or predictability) and the forecast inaccuracy. We therefore define the quality of a target price $\Phi_{t,T}$ so that it is equal to $E_t [|S_T - \Phi_{t,T}|] - |S_T - \Phi_{t,T}|$. The absolute forecast error $|S_T - \Phi_{t,T}|$ corresponds to the final payoff of a straddle on the

stock with a strike price equal to $\Phi_{t,T}$, that is, a portfolio containing a call option and a put option on the same underlying stock; the two options are characterized by the same strike price and the same maturity. A possible way to estimate the expected value of the forecast error, denoted as $E_t[|S_T - \Phi_{t,T}|]$, is to consider the price of the straddle at time t capitalized until time T . In other words, we consider that the absolute forecast error $|S_T - \Phi_{t,T}|$ is the penalty that should be paid by the analyst for forecasting $\Phi_{t,T}$ in place of S_T . The price of the straddle corresponds to the reward associated with the difficulty of forecasting the target price. When an analyst issues a target price of $\Phi_{t,T}$ at time t , it is equivalent to her short-selling a straddle with a strike price $\Phi_{t,T}$, cashing in the value of the straddle, investing it in the risk-free asset, and waiting until the end of the horizon T . The value of the straddle at the end of the horizon T is equal to $|S_T - \Phi_{t,T}|$. Therefore, the liquidation value of the straddle at any time $t + \tau$ is a good way to measure the inaccuracy of a target price. Consequently, we define the quality of a target price at any time $t + \tau$ as follows.

Definition 1 *The quality $\gamma_{t,t+\tau}$ at time $t + \tau$, $\tau \in [0; T - t]$ of a target price $\Phi_{t,T}$, issued at time t with an horizon equal to $T - t$, on a stock S , is denoted $\gamma_{t,t+\tau}$ and is defined as*

$$\begin{aligned} \gamma_{t,t+\tau} &= E_t[|S_T - \Phi_{t,T}|] - E_{t+\tau}[|S_T - \Phi_{t,T}|] \\ &= (C_t + P_t) e^{r\tau} - (C_{t+\tau} + P_{t+\tau}), \end{aligned} \tag{2.6}$$

where C_t (P_t) is the price at time t of a call (put) option on the stock S with maturity date T and strike price $\Phi_{t,T}$.

Before going further, we consider two special cases: $\tau = 0$ and $\tau = T - t$. The first case corresponds to the issue date while the second case corresponds to the *ex-post* version of the measure. At the time the target price is issued ($\tau = 0$), we have $\gamma_{t,t} = 0$. This result translates the idea that at the time of the issue, one does not know the quality of the forecast. At the end of the horizon ($\tau = T - t$), we have $\gamma_{t,T} = (C_t + P_t) e^{r(T-t)} - |S_T - \Phi_{t,T}|$. As mentioned before, the absolute forecast error $|S_T - \Phi_{t,T}|$ is the penalty paid by the analyst for not having issued a perfect forecast. So our approach is economically sound because shorting the straddle at date t leads to an amount $(C_t + P_t) e^{r(T-t)}$ at time T . As a consequence, $\gamma_{t,T}$ is the amount obtained after the liquidation of the position. This amount is maximum if the forecast is perfect ($\Phi_{t,T} = S_T$) and is equal to $\gamma_{t,T} = (C_t + P_t) e^{r(T-t)}$.

As we need to compare the quality of forecasts made on stocks with different price levels, we require the measure of quality to be homogeneous of degree one (we do not want the stock price level to influence the measure of quality). This means that we assume the stock price to be equal to 1 at the time the target price is issued. We write $S_t = 1$. We adjust the target price $\Phi_{t,T}$ accordingly.

If we assume a geometric Brownian motion for the stock price, the *ex-post* quality of a target price issued at time t can be calculated according to the Black and Scholes (1973) model⁸ as

⁸For simplicity's sake, we choose to compute the value of the straddle using Black and Scholes (1973) model. However, our measure of forecasting quality could be extended to more complex models of option pricing.

$$\begin{aligned}
 \gamma_{t,T} &= e^{r(T-t)} [N(d_{1,t}) - N(-d_{1,t}) - \Phi_{t,T} e^{-r(T-t)} (N(d_{2,t}) - N(-d_{2,t}))] - |S_T - \Phi_{t,T}| \\
 &= e^{r(T-t)} [2N(d_{1,t}) - 1] - \Phi_{t,T} [2N(d_{2,t}) - 1] - |S_T - \Phi_{t,T}|,
 \end{aligned} \tag{2.7}$$

with

$$\begin{aligned}
 d_{1,t} &= \frac{\ln\left(\frac{1}{\Phi_{t,T}}\right) + \left(r + \frac{1}{2}\sigma_t^2\right)(T-t)}{\sigma_t\sqrt{T-t}} \\
 d_{2,t} &= d_{1,t} - \sigma_t\sqrt{(T-t)},
 \end{aligned} \tag{2.8}$$

where $N()$ is the cumulative distribution function of a standard Gaussian random variable, t is the time at which the forecast is issued, and σ_t is the stock return volatility estimated at time t . Remember the assumption $S_t = 1$ which explains the way $d_{1,t}$ is written.

It follows from the previous definition that the *ex-post* quality $\gamma_{t,T}$ is a continuous function of the target price $\Phi_{t,T}$. When the analyst issues the target price, she “receives” the value of the call and the value of the put. At the end of the horizon, there are three possible scenarios. If the stock price is below the target price (the strike price), the value of the call is null and the put is exercised. (The analyst has to pay the difference between the target and the current stock price.) The quality of the forecast is therefore equal to $(C_t + P_t) e^{r(T-t)} - (\Phi_{t,T} - S_T)$. If the stock price is higher than the strike price, we have the opposite situation. The put is worth zero and the call is exercised. The quality of the forecast is $(C_t + P_t) e^{r(T-t)} - (S_T - \Phi_{t,T})$.

Finally, if the target price and the stock price coincide perfectly, both the call and put are worth zero and the analyst does not have to repay anything. The quality of the forecast is then equal to the initial value of the straddle capitalized at the risk-free rate $(C_t + P_t) e^{r(T-t)}$.

Our approach implies that we do not distinguish between under- and over-achievement. If we consider two forecasts $\Phi_{t,T}^1 = S_t - \Delta$ and $\Phi_{t,T}^2 = S_t + \Delta$, we should obtain the same forecasting quality if, at the end of the horizon, we have $|S_T - \Phi_{t,T}^1| = |S_T - \Phi_{t,T}^2|$. However, because $\ln(\frac{S_t}{S_t + \Delta}) \neq -\ln(\frac{S_t}{S_t - \Delta})$, this is not the case. In order to solve this issue, we apply a simple transformation (see Appendix A).

2.4.2 Properties

Our measure is composed of two components: the reward for forecasting a target price (*i.e.*, the difficulty) and the penalty for not being accurate (*i.e.*, the inaccuracy). The reward must meet two requirements. It needs to increase with the stock return volatility σ_t and it needs to be positively linked with the length of the forecast horizon $T - t$ (*e.g.* the task of forecasting a 24-month target price is more difficult than the task of forecasting a 12-month target price).

Proposition 2 *For a given final stock price S_T and a given target price $\Phi_{t,T}$, the quality $\gamma_{t,T}$ of a target price is an increasing function of the length of the horizon.*

Proposition 3 *For a given final stock price S_T and a given target price $\Phi_{t,T}$, the quality $\gamma_{t,T}$ of a target price is an increasing function of the volatility.*

The proofs for these two propositions can be found in Appendix B.

2.4.3 Target price revisions

In practice, analysts often revise the target prices before the end of the horizon. We consider the initial forecast and the revision as two separate forecasts. Once a revision occurs at time $t + \tau$, the first forecast is no longer valid. However, we need to compute the forecasting quality over the period $]t; t + \tau]$. It follows from the previous definitions that the value at time $t + \tau$ of the absolute forecast error $|S_T - \Phi_{t,T}|$ is simply equal to the value of the straddle. In other words, the analyst buys back the straddle she shorted. We then consider the revised forecast as if the analyst shorts a new straddle with a strike price equal to the new target price and a reset maturity (forecast horizon).

For a given stock, the forecasting quality FQ of the target prices of an analyst over a given period is equal to the sum of the qualities of the different forecasts over this period. When a revision occurs at time $t + \tau$, the forecasting quality FQ over a period $]t; t + \tau + \tau']$ is defined as follows.

Definition 4 *Let us consider a target price Φ_{t,T_1-t}^1 with a horizon of $T_1 - t$ issued at time t and a revision equal to $\Phi_{t+\tau,T_2-(t+\tau)}^2$ with a horizon of $T_2 - (t + \tau)$ occurring at time $t + \tau$ with $t < t + \tau < t + \tau + \tau'$. For the period $]t; t + \tau + \tau']$, the forecasting quality $FQ_{t,t+\tau+\tau'}$ of the analyst on this stock is defined as*

$$\begin{aligned}
 FQ_{t,t+\tau+\tau'} &= \gamma \left(\Phi_{t,T_1-t}^1, \sigma_t, T_1 - t \right)_{t,t+\tau} \\
 &\quad + \gamma \left(\Phi_{t+\tau,T_2-(t+\tau)}^2, \sigma_{t+\tau}, T_2 - (t + \tau) \right)_{t+\tau,t+\tau+\tau'}. \quad (2.9)
 \end{aligned}$$

Remark 5 *Note that the volatility is set constant for a given forecast. That is, once a*

target price is set, we use the stock volatility at the time of the forecast to estimate the value of the straddle. This same volatility is used until a new target price (revision) is issued. If the volatility was not set constant during the target price horizon, an increase in volatility will lower the forecasting quality of an analyst, even though the stock price moves toward her target price. With this methodology, we distinguish between the forecasts made on stocks with different volatilities (cross-section) but the variations over time do not influence the quality of the forecast (time-series).

2.4.4 Illustration of the new measure

To gain a clear understanding of how the quality is computed, in Figure 2.1, we present an example of three target prices made on a stock by a given analyst. In this example, the risk-free rate is equal to 0. The first forecast is made at time t_1 and is equal to 45 (while the stock price is equal to 35.76). The second forecast (first revision) is made at time t_2 with a target price set at 30 (while the stock price is equal to 31.88). Finally, at time t_2 , the analyst revises her forecast and announces a target price of 33 (while the stock price is equal to 49.34).⁹

At time t_1 , we consider that the analyst shorts a straddle with a strike price equal to 45. The price of the straddle¹⁰ is computed with a 6-month historical volatility of $\sigma_{t_1} = 0.3905$ and is equal to 0.4091. The price of this straddle is used to evaluate the difficulty of the forecast. The forecasting quality FQ of the analyst over the period $]t_1; t_2]$ is then equal to the value of the straddle at time t_1 (*i.e.*, the difficulty) minus

⁹Every forecast has a 12-month horizon.

¹⁰Remember that the stock price is normalized to 1.

the value of the straddle at time t_2 (*i.e.*, the inaccuracy). The price of the straddle at time t_2 is computed using the same volatility as the one used to compute the price of the straddle at t_1 ($\sigma_{t_1} = 0.3905$). The straddle at time t_2 is worth 0.4249. As a result, the forecasting quality for the period $]t_1; t_2]$ is equal to $FQ_{t_1, t_2} = \gamma_{t_1, t_2} = -0.0158$. As can be seen in Figure 2.1, the forecasting quality for the period $]t_2; t_3]$ is equal to $FQ_{t_2, t_3} = \gamma_{t_2, t_3} = -0.2901$. It follows that the forecasting quality for the period $]t_1; t_3]$ is equal to $FQ_{t_1, t_3} = \gamma_{t_1, t_2} + \gamma_{t_2, t_3} = -0.3059$.

We see that for the period $]t_1; t_2]$, the sensitivity of the quality measure to the stock price (the delta of the quality) is positive (because the stock price is below the target price). The forecasting quality increases when the stock price increases (*i.e.*, gets closer to the target price) and decreases otherwise. The delta of the forecasting quality becomes negative for the period $]t_2; t_3]$ as the target price is below the stock price. Because the target prices are not too far from the stock price, the sensitivity to the horizon is positive.

To illustrate the influence of the volatility on target prices' quality, we assume in the previous example that the volatility is multiplied by 1.2 (everything else being equal). Figure 2.2 shows the quality computed using the real volatility (solid line) and the quality computed with a volatility set 20% higher (dashed line). Because the sensitivity of our measure to the volatility is positive, it appears on the graph that the quality is higher when the volatility is higher.

2.5 Empirical analysis

The main objective of this paper is to determine whether financial analysts exhibit genuine skills in forecasting future stock prices. Observing a positive forecasting quality is not sufficient to conclude to the existence of a forecasting ability. This positive forecasting quality can be the result of skill, luck or simply the fact that by being overly optimistic, the quality increases when the market rises. A first analysis of the existence of forecasting skills is to check whether analysts exhibit persistent forecasting quality. As stated by Kahneman (2011): “the diagnostic for the existence of any skill is the consistency of individual differences in achievement”. We will thus consider an analyst to be skilled if she manages to consistently beat the other analysts. Our analysis can be broken down into two parts. First, we investigate whether the differential forecasting abilities found in previous studies may be mechanically induced by the persistence in volatility. Second, we evaluate if the forecasting quality is still persistent after controlling for volatility.

2.5.1 Persistence in accuracy and volatility of stock returns

We show in this section that the persistence in accuracy found in previous studies is mechanically caused by persistence in volatility. Analysts covering less volatile stocks automatically obtain, when using classical measures, a higher forecasting accuracy. The persistence in volatility and the fact that analysts tend to cover the same pool of stocks over time imply that the analysts covering stocks with low volatility exhibit a persistent forecasting accuracy. Therefore, the persistence in accuracy is not a proof of the existence of differential forecasting abilities. In order to evaluate the existence

of forecasting skills, we need to demonstrate the existence of persistence in forecasting quality.

Persistence in accuracy using empirical data

In this section, we test for the persistence in accuracy when the absolute forecast error is chosen as the measure of accuracy.¹¹ For a given target price, the absolute forecast error $|TPERROR|$ is defined as

$$|TPERROR|_t = \frac{|S_T - \Phi_{t,T}|}{S_t}, \quad (2.10)$$

where $\Phi_{t,T}$ is the value of a target price issued at time t with horizon T , S_T is the stock price at the end of the forecast horizon and S_t is the stock price at the time the forecast was issued.

We then define the individual analyst performance as in Bradshaw, Brown, and Huang (forthcoming). For a given period $]t; t + 1]$, the individual analyst performance is defined as the mean of the absolute forecast errors of all the target prices issued by the analyst within this period $]t; t + 1]$. It is important to note that because the absolute forecast error is an *ex-post* measure, the individual analyst performance can only be measured 12 months after the end of the period $]t; t + 1]$. We are also interested in the volatility of the stocks for which the analyst issues target prices. We define the forecast underlying volatility as the stock return volatility for the 6 months preceding the target price issue date. We then define the analyst forecast underlying

¹¹In order to be able to compare the different absolute forecast errors, we only keep the target prices with a 12-month horizon.

volatility as the mean of the forecast underlying volatilities of all the target prices issued during the period under consideration.

The methodology employed by Bradshaw, Brown, and Huang (forthcoming) consists of assigning analysts to five quintiles with respect to their individual performance over the measurement period $]t; t + 1]$. The persistence is then measured by estimating their individual performance over the test period $]t + \tau + 1; t + \tau + 2]$ conditional on their ranking over the measurement period. A lag of $\tau = 12$ months is added between the measurement period and the test period because the absolute forecast error is an *ex-post* measure of accuracy (the individual performance over the period $]t; t + 1]$ is computed at time $t + \tau + 1$). This lag insures that the measurement period and the test period do not overlap. We therefore avoid mechanically inducing a positive relation between the current and subsequent performance. Financial analysts exhibit a persistent accuracy if the most (least) accurate analysts over the measurement period $]t; t + 1]$ are ranked in the highest (lowest) quintile for the test period $]t + \tau + 1; t + \tau + 2]$ and if the difference of accuracy between quintiles 1 and 5 is statistically different from zero.

Table 2.4 presents the results using the target prices in our sample. As our database is similar to the one of Bradshaw, Brown, and Huang (forthcoming), it is not surprising that we obtain the same results. Table 2.4 indicates that analysts with a lower average absolute forecast error in the measurement period do have a lower average absolute forecast error in the test period. When the individual analyst performance is computed using a quarterly frequency, the analysts in the first quintile (last) exhibit an absolute forecast error of 0.1551 (0.9693) in the measurement period

and 0.3322 (0.5779) in the test period. We observe, however, that the analyst forecast underlying volatility is lower in the first quintile than in the last one. The analyst forecast underlying volatility increases with the quintiles both in the measurement period and in the test period. This result indicates that if we observe a persistence in accuracy, as measured by the absolute forecast error, we also observe a persistence in volatility.

Persistence in accuracy using naïve forecasts

We observe in the previous results both a persistence in accuracy and a persistence in volatility. Here, we want to check whether the persistence in volatility could cause the observed persistence in accuracy. In order to do so, we replace the target prices in our data with naïve forecasts. We build our naïve forecasts so that the implied stock return $(\Phi_{t,T} - S_t) / S_t$ of a 12-month horizon target price is equal to the 12-month risk free rate. As the target prices result from a mechanical rule, the analysts cannot exhibit differential abilities in forecasting stock prices. If, when using naïve forecasts, we observe a persistence in accuracy, we can conclude that the persistence in volatility drives the persistence in accuracy. Such a result would indicate that the accuracy is not the right measure to estimate the ability of financial analysts to forecast future stock prices.

As can be seen in Table 2.5, the accuracy is persistent even though the target prices in the sample are naïve forecasts. The average absolute forecast errors range from 13.17% to 76.14% for the measurement period. In the test period, we observe a significant difference of 14.24% between the first and the last quintiles. This result

indicates that the analysts that were the most (least) accurate in the measurement period are still the most (least) accurate in the test period. We also observe a strong persistence in volatility. Given that we considered naïve forecasts, we can conclude that the persistence in accuracy is mainly driven by the persistence in volatility.

Test of persistence in forecasting quality

We have shown that measuring the persistence in accuracy does not allow us to make any inference on the existence of differential forecasting abilities. In order to solve this issue, we conduct the same analysis as before using our measure of forecasting quality instead of accuracy. As our measure of quality take into account the differences in volatility, a significant persistence would imply that financial analysts possess differential abilities to forecast target prices. In order to allow for a direct comparison with the previous results, we use the *ex-post* version of our measure. The individual analyst performance is here defined as the mean of the *ex-post* quality of all the target prices issued by the analyst within the considered period.

For this measure, we only take into account the target prices with a 12-month horizon. The quality of the forecasts is computed at the end of the 12-month horizon. The revisions are considered as new independent forecasts. As defined in equation (2.7), the *ex-post* quality at time T of a target price issued at time t with horizon T

is equal to

$$\begin{aligned}
\gamma_{t,T} &= E_t [|S_T - \Phi_{t,T}|] - |S_T - \Phi_{t,T}| \\
&= e^{r(T-t)} [N(d_{1,t}) - N(-d_{1,t})] - \Phi_{t,T} [N(d_{2,t}) - N(-d_{2,t})] \\
&\quad - |S_T - \Phi_{t,T}|,
\end{aligned} \tag{2.11}$$

where $S_t = 1$ and $\Phi_{t,T}$ is the target price issued at time t .

The results in Table 2.6 show that when controlling for differences in volatility, the persistence vanishes. In the measurement period, the analysts in the first quintile (*i.e.*, best performance) exhibit an average forecasting quality of 0.3536 while the analysts in the last quintile (*i.e.*, worst performance) exhibit an average forecasting quality of -0.2487 . This difference in forecasting quality between the first and the last quintile is no more significant in the test period. We obtain this result both for quarterly and semiannual periods.

2.5.2 The absence of forecasting skills

Persistence in forecasting quality over the short run

The main limitation of the *ex-post* measure of quality used in the previous subsection is that it is necessary to introduce a 12-month lag between the measurement period and the test period. A second limitation is that the forecasting quality is measured using the stock price at the end of the 12-month horizon. However, in practice, when a revision occurs the first forecast becomes inactive and only the revision is taken into account. The measure of forecasting quality FQ defined in equation

(2.9) permits to overcome these drawbacks. For a given stock and a given analyst, the forecasting quality over the period $]t; t + 1]$ can be measured using only information over this same period. This feature allows us to evaluate the persistence over the short-run, *e.g.* we set the measurement period on $]t; t + 1]$ and the test period on $]t + 1; t + 2]$. Another advantage is that this measure allows us to test for the persistence using smaller frequencies.

When using the forecasting quality measure FQ , we need to restrict the sample period to the 2001-2010 period. Indeed, for 2000, we do not observe the target prices issued in 1999 which could still be active. Therefore, we do not have the full portfolio of target prices for the first year of the sample. These unobserved target prices could influence the forecasting quality of the analysts.

The results in Table 2.7 show that, even over the short run, there is no persistence in forecasting quality. For all the three frequencies, we do not observe any significant difference, in the test period, between the forecasting quality in the first quintile and the forecasting quality in the last quintile.

Robustness check: the impact of learning

One reason why we might not observe any persistence in the forecasting quality is that financial analysts learn over time and subsequently improve their forecasting quality. If the experience influences the forecasting quality, young inexperienced analysts will be ranked in the lower quintiles when they enter the sample period. They will then gradually move toward the highest quintiles as they learn and acquire experience. These agents would therefore add noise to our analysis of the persistence

in forecasting quality.

We run the same analysis as above on a restricted sample containing only analysts with at least two years of experience. We compute, at time t , the experience of an analyst by observing the time $t - \tau$ at which she issued her first target price; the experience is then simply equal to $t - (t - \tau) = \tau$. We restrict the sample period to 2003-2010 in order to have enough observations for the first period.

The results presented in Table 2.8 show that a potential learning process cannot explain the absence of persistence in forecasting quality. When restricting the sample to analysts with at least two years of experience, we still do not observe any significant difference between the first and last quintiles in the test period.

Robustness check: slow adjustment of target prices

Dechow and You (2013) assume that financial analysts might be slow at adjusting their target prices. One of the reasons for this slow adjustment is that target prices are usually embedded in analysts' reports. Because writing a report is a long, difficult task, financial analysts may not adjust their target prices as often as they should. For example, if the analyst changes her opinion about the future price of a stock one month after her initial forecast, she might have to wait for the next report publication to revise her target price. This feature might cause the analysts to appear less skilled than they actually are.

In order to test this hypothesis, we restrict the validity of the target prices to a shorter period of time (*e.g.* one month). That is, for a given stock and a given target price, we compute the forecasting quality only for the first month following the

issue date. In other words, we consider the forecasts to be inactive after one month. We then compute the analysts' average performance using these short-validity target prices.

We conduct the same analysis as before to test for the existence of differential abilities. The results (unreported) we obtain, using 1 month, 3 months and 6 months for the validity of the target prices, do not indicate any changes in the persistence of forecasting quality. We still observe no differential forecasting abilities.

2.5.3 Scoring

An alternative way to check whether some analysts consistently outperform (or underperform) their colleagues is to compute the average relative performance over the sample period. The methodology is the following. Each month, we compute the average analyst performance using our measure of forecasting quality FQ . We then rank the analysts in five quintiles. The score of the analyst is equal to $(\text{quintile}-1)/4$. Thus, the best analysts receive a score of 1 while the worst analysts receive a score of 0. The analysts ranked in the intermediate quintiles obtain a score of 0.25, 0.5 or 0.75. As the 2001-2010 period contains 120 months, we have, for each analyst, up to 120 monthly scores. In order to be able to compare the different scores, we remove the analysts with less than 24 monthly scores (less than 2 years of activity). The total number of analysts in the restricted sample is 5,481. Finally, we compute, for each analyst, the average of her monthly scores. An analyst who always ranks with the 20% best analysts will then have an average score equal to 1. An analyst who oscillates between the first quintile and the second quintile will have an average score

between 0.75 and 1, and so on.

Figure 2.3 shows the average score of all the financial analysts for whom we were able to compute at least 24 monthly scores. We observe that only one analyst has a score higher than 0.75 and none have a score below 0.25. The average score is concentrated around the value 0.5. The solid curve corresponds to a Gaussian distribution. We observe that the distribution of the average score is a close fit with the Gaussian distribution. This additional result confirms our previous findings that financial analysts do not exhibit differential abilities when forecasting target prices.

2.6 Conclusion

This article sets a new framework for evaluating the forecasting quality of target prices made by financial analysts. We show that measuring target price accuracy is not sufficient to evaluate the quality of target prices. Differences in volatility lead to different degrees of difficulty (predictability) when forecasting future stock prices. These differences of difficulty must be incorporated when evaluating the forecasting ability of financial analysts. Our measure of target price quality is defined as the difference between the target price predictability (the expected value of the absolute forecast error estimated at the issue date) and the target price inaccuracy (the realized absolute forecast error). By using option-pricing theory, we are able to estimate the expected value of the absolute forecast error. We are then able to evaluate forecast predictability. The contributions of our measure are the following. First, our measure accounts for differences in volatility. Second, it allows us to consider forecasts with different horizons. Third, we account for the boldness of the forecasts. Fourth, our

measure is a dynamic measure, meaning that we are able to measure the quality of a forecast at any moment in time. As a consequence of this last feature, our measure also provides a simple and consistent solution to the issue of measuring the quality of a target price when a revision occurs. In the empirical part of our study, we show that, when taking into account the issue of the predictability, financial analysts do not exhibit persistent differential abilities. Our measure of quality is designed for evaluating the quality of target prices. However, this measure could also be used to evaluate the quality of other types of forecasts (exchange rates, for instance). A very challenging objective for the future is to adapt our measure so that it can be used to evaluate the quality of earnings forecasts. In its current state, the literature on earnings forecast employs relative measures of accuracy to control for differences in predictability. An important contribution would therefore be to introduce a methodology that permits a precise estimation of forecast predictability. However, the feasibility of such a measure is unclear as, contrary to target prices, the earnings forecast process is highly discontinuous.

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Appendix A

Consider two forecasts $\Phi_{t,T}^1 = S_t - \Delta$ and $\Phi_{t,T}^2 = S_t + \Delta$. As we do not distinguish between under- and over-achievement, we should have $|S_T - \Phi_{t,T}^1| = |S_T - \Phi_{t,T}^2| \implies \gamma_{t,T}^1 = \gamma_{t,T}^2$. However, because $\ln(\frac{S_t}{S_t+\Delta}) \neq -\ln(\frac{S_t}{S_t-\Delta})$, we have $[C_t(\Phi_{t,T}^1) + P_t(\Phi_{t,T}^1)] e^{r(T-t)} < [C_t(\Phi_{t,T}^2) + P_t(\Phi_{t,T}^2)] e^{r(T-t)}$ and, therefore, we have $\gamma_{t,T}^1 < \gamma_{t,T}^2$. Even though the absolute deviation of the target price from the stock price S_t is the same for target price A and target price B and the absolute forecast errors are the same at the end of the horizon, we do not obtain the same quality for the two forecasts. We apply a simple transformation to correct this.

As we do not distinguish between under- and over-achievement, the quality of the forecast depends only on the size of the deviation of the stock price from the target price. We therefore adopt the following convention. When a target price is below the stock price, we consider the symmetric of the price with respect to the target price. That is, we set the target price equal to 1 and consider the stock price to be equal to $1 + |S_t - \Phi_{t,T}|$. However, when there is a positive drift $\mu = r > 0$, the probability of reaching a target price of $\Phi_{t,T} = S_t - \Delta'$ is lower than the one of reaching a target price of $\Phi_{t,T} = S_t + \Delta'$. Therefore, we need to consider the symmetric of the price with respect to the discounted target price. The consequence of defining the stock price as a function of the discounted target price is that the risk-free rate in the Black-Scholes model is equal to 0.

Definition 6 We consider the function f which measures the discounted deviation

of the stock price from the target price. We write

$$f(S_{t+\tau}, \Phi_{t,T}, r) = 1 + |S_{t+\tau} - \Phi_{t,T} e^{-r(T-t-\tau)}| \quad (2.12)$$

The quality of a target price issued at time t with horizon $T - t$ writes

$$\begin{aligned} \gamma_{t,T} &= (C_t + P_t) e^{r(T-t)} - |f(S_T, \Phi_{t,T}, r) - 1| \\ &= e^{r(T-t)} (f(S_t, \Phi_{t,T}, r) [N(d_{1,t}) - N(-d_{1,t})] - [N(d_{2,t}) - N(-d_{2,t})]) \\ &\quad - |f(S_T, \Phi_{t,T}, r) - 1| \end{aligned} \quad (2.13)$$

with

$$\begin{aligned} d_{1,t} &= \frac{\ln(f(S_t, \Phi_{t,T}, r)) + (\frac{1}{2}\sigma_t^2)(T-t)}{\sigma_t\sqrt{T-t}} \\ d_{2,t} &= d_{1,t} - \sigma_t\sqrt{(T-t)} \end{aligned}$$

$N()$ is the Gaussian cumulative distribution function. t is the time at which the forecast was issued, C_t is the value of the call option at time t , P_t is the value of the put option at time t , σ_t is the stock return volatility estimated at time t , r is the risk-free rate and $T - t$ is the horizon of the target price.

Appendix B

Proposition 7 For a given final stock price S_T and a given target price $\Phi_{t,T}$, the quality $\gamma_{t,T}$ of a target price is an increasing function of the length of the horizon

$T - t$.

Proof. For a given final stock price S_T and a given target price $\Phi_{t,T}$, the sensitivity of the quality $\gamma_{t,T}$ to the horizon $T - t$ writes

$$\frac{\partial \gamma_{t,T}}{\partial (T - t)} = \left[\frac{\partial C_t}{\partial (T - t)} + \frac{\partial P_t}{\partial (T - t)} \right] e^{r(T-t)} + r e^{r(T-t)} (C_t + P_t). \quad (2.14)$$

The sensitivity of a straddle to the maturity $T - t$ writes

$$\begin{aligned} \frac{\partial C_t}{\partial (T - t)} + \frac{\partial P_t}{\partial (T - t)} &= S_t N'(d_{1,t}) \frac{\partial d_{1,t}}{\partial (T - t)} \\ &\quad - e^{-r(T-t)} \Phi_{t,T} N(d_{2,t}) \frac{\partial d_{2,t}}{\partial (T - t)} \\ &\quad + S_t N'(-d_{1,t}) \frac{\partial d_{1,t}}{\partial (T - t)} \\ &\quad + e^{-r(T-t)} \Phi_{t,T} N'(d_{2,t}) \frac{\partial d_{2,t}}{\partial (T - t)} \\ &= \frac{\sigma}{\sqrt{T - t}} S_t N'(d_{1,t}) \\ &\quad + r \Phi_{t,T} e^{-r(T-t)} [N(d_{2,t}) - N(-d_{2,t})] \end{aligned} \quad (2.15)$$

with $N'(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$.

The sensitivity of a call option to the maturity $T - t$ is always positive. The sensitivity of a put option to the maturity $T - t$ is also positive except when the option is deep in the money. The transformation we apply (see Appendix A) implies that the put option is never in the money. Thus, the sensitivity of the straddle to the

horizon $T - t$ is always positive. We then have

$$\frac{\partial \gamma_{t,T}}{\partial (T-t)} = \left[\frac{\partial C_t}{\partial (T-t)} + \frac{\partial P_t}{\partial (T-t)} \right] e^{r(T-t)} + r e^{r(T-t)} (C_t + P_t) > 0. \quad (2.16)$$

■

Proposition 8 For a given final stock price S_T and a given target price $\Phi_{t,T}$, the quality $\gamma_{t,T}$ of a target price is an increasing function of the volatility.

Proof. For a given final stock price S_T and a given target price $\Phi_{t,T}$, the sensitivity of the quality $\gamma_{t,T}$ to the volatility σ_t writes

$$\begin{aligned} \frac{\partial \gamma_{t,T}}{\partial \sigma_t} &= \left[\frac{\partial C_t}{\partial \sigma_t} + \frac{\partial P_t}{\partial \sigma_t} \right] e^{r(T-t)} \\ &= 2e^{r(T-t)} S_t \sqrt{(T-t)} N'(d_{1,t}) > 0 \end{aligned} \quad (2.17)$$

with $N'(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$. ■

Figure 2.1
An illustration of the properties of the forecasting quality

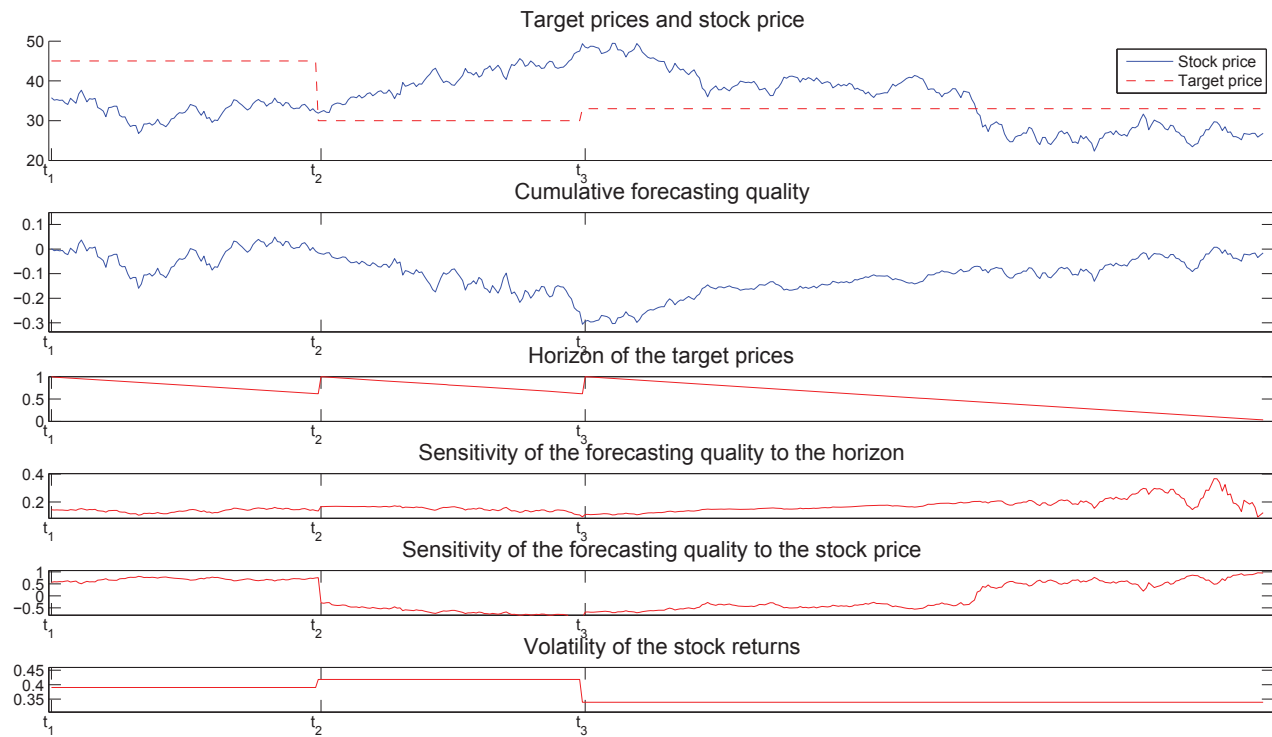
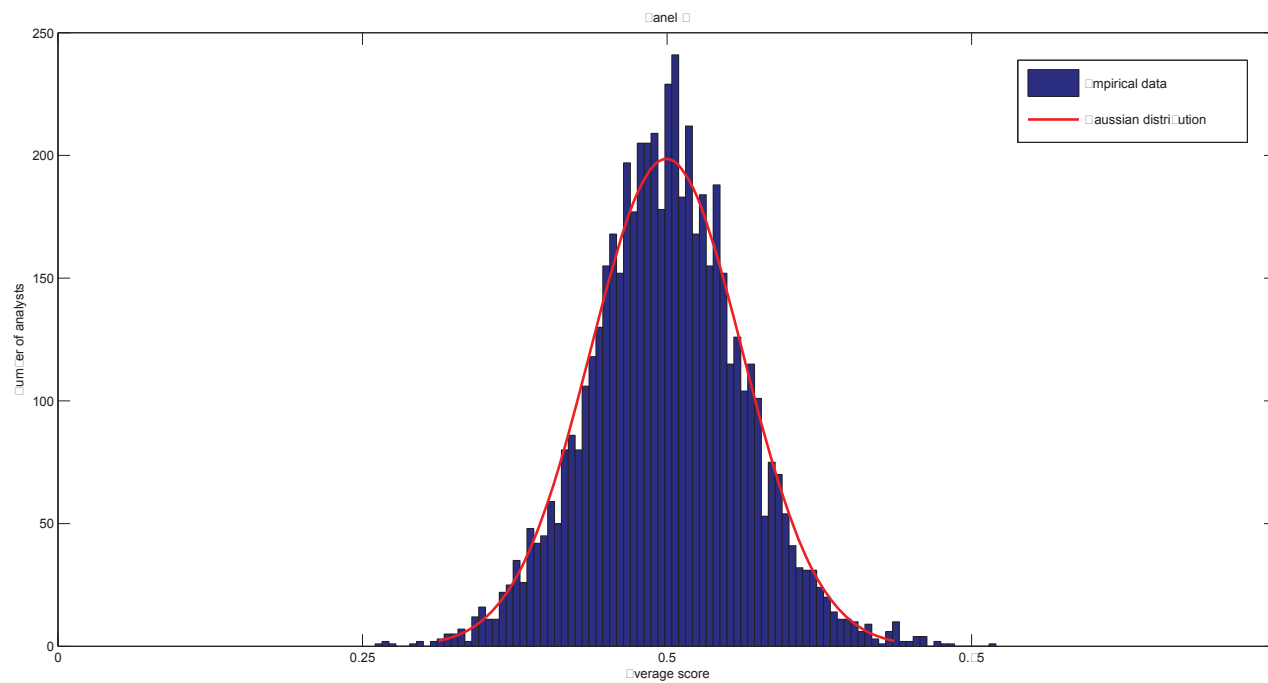


Figure 2.2
The influence of stock return volatility on forecasting quality



Figure 2.3

Average score of the financial analysts' forecasting quality over the 2001-2010 period



This figure presents the histogram of the average score of 5,481 analysts over the 2001-2010 period. We include an analyst in the sample only if we can compute at least 24 monthly average forecasting qualities. Each month, the analysts are ranked in five quintiles with respect to their average forecasting quality. The monthly score is then computed as $(\text{quintile}-1)/4$. The average score corresponds to the mean of the monthly scores over the sample period.

Table 2.1
Descriptive statistics

	Number of forecasts	Number of active analysts	Number of analysts covering a stock			Number of stocks covered per analyst		
			Mean	Median	Max	Mean	Median	Max
2000	36,825	-	-	-	-	-	-	-
2001	44,178	4,466	6.30	4.00	50.00	6.38	4.00	213.00
2002	48,756	4,611	7.10	5.00	50.00	6.31	4.00	183.00
2003	51,263	4,342	7.22	5.00	55.00	6.61	4.00	102.00
2004	54,863	3,773	6.54	4.00	44.00	7.16	5.00	64.00
2005	56,291	3,731	6.67	5.00	51.00	7.72	6.00	76.00
2006	59,952	3,800	6.82	5.00	45.00	7.97	6.00	87.00
2007	65,377	3,768	7.00	5.00	46.00	8.42	7.00	100.00
2008	77,281	3,829	7.53	6.00	46.00	8.59	7.00	92.00
2009	75,275	3,833	8.00	6.00	50.00	8.48	7.00	81.00
2010	79,410	3,908	8.69	6.00	59.00	8.47	7.00	79.00

The sample consists in a total of 649,471 target prices made by 9,367 analysts (583 brokers) on 7,268 U.S. stocks for the 2000-2010 period. The first column indicates the number of target prices issued each year. The second column shows the number of active analysts. The three following columns report the average, median and maximum number of active analysts per stock. The remaining columns indicate the average, median and maximum number of stocks covered per analyst. The statistics for 2000 are not reported as the target prices issued in 1999 and still active in 2000 cannot be observed.

Table 2.2
Relationship between volatility and target price accuracy

Panel A: Accuracy computed using actual target prices											
Years	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
1 (Low volatility)	0.2813	0.2522	0.2431	0.1994	0.1759	0.1656	0.1698	0.2852	0.4712	0.2265	0.1796
2	0.3821	0.3549	0.3154	0.2558	0.2331	0.2153	0.2197	0.3824	0.5458	0.3091	0.2385
3	0.5274	0.5210	0.4161	0.3193	0.2903	0.2661	0.2865	0.4692	0.5538	0.3844	0.3015
4	0.7947	0.7711	0.5742	0.3953	0.3698	0.3351	0.3654	0.5624	0.6064	0.4952	0.3760
5 (High volatility)	1.2803	1.1467	0.8577	0.6502	0.5284	0.5075	0.4958	0.7327	0.7671	0.7782	0.5092
Diff (5-1)	0.9989	0.8946	0.6146	0.4508	0.3525	0.3419	0.3260	0.4475	0.2959	0.5517	0.3296
Mean t-test	104.0171***	109.6470***	71.6153***	62.3884***	76.3825***	67.8006***	61.2385***	94.0024***	45.3043***	68.8016***	85.0555***
Panel B: Accuracy computed using naïve forecasts											
Years	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
1 (Low volatility)	0.2534	0.1908	0.1903	0.2213	0.1648	0.1508	0.1590	0.2450	0.3328	0.2365	0.1927
2	0.3210	0.2499	0.2484	0.2898	0.2370	0.2039	0.2058	0.3239	0.4038	0.3201	0.2408
3	0.3963	0.3513	0.3211	0.3545	0.2885	0.2493	0.2600	0.3927	0.4216	0.4052	0.2859
4	0.5342	0.4659	0.4468	0.4200	0.3333	0.3104	0.3210	0.4554	0.4975	0.5374	0.3526
5 (High volatility)	0.6954	0.6052	0.7336	0.6852	0.3729	0.4319	0.4017	0.5264	0.6874	0.8857	0.4160
Diff (5-1)	0.4420	0.4144	0.5433	0.4639	0.2081	0.2811	0.2427	0.2814	0.3546	0.6492	0.2233
Mean t-test	83.8646***	99.4626***	59.7663***	57.8992***	54.8949***	57.6214***	49.7714***	84.4185***	54.5609***	72.9812***	64.2128***

Each year, the target prices in the sample are assigned to five quintiles with respect to the 6-month historical volatility of the underlying stock estimated at the issue date. The table reports, for each year and each quintile, the average target price accuracy. Panel A reports the average accuracy using the actual target prices from our sample. Panel B reports the average accuracy using naïve forecasts (each target price is replaced by a forecast that is equal to the price at the issued date capitalized by the risk-free rate). The statistical significance of the difference across top and bottom quintiles is computed using a t-test. ***/**/* represent significance at the 0.01, 0.05 and 0.1 level.

Table 2.3

Nonlinear relationship between volatility and accuracy

k -th decile = $\mathbf{1}_{jt}^k \sigma_{jt}$	Accuracy (Absolute forecast error)			
	Coefficient (β_k)	Standard error	t-statistic	p-value
1st decile (Low volatility)	0.2311***	0.060756	3.80	0.000
2nd decile	0.4129***	0.045587	9.06	0.000
3rd decile	0.4824***	0.038026	12.69	0.000
4th decile	0.5361***	0.032872	16.31	0.000
5th decile	0.5850***	0.028770	20.33	0.000
6th decile	0.5979***	0.025255	23.67	0.000
7th decile	0.5990***	0.022002	27.22	0.000
8th decile	0.6059***	0.018644	32.50	0.000
9th decile	0.6136***	0.015021	40.85	0.000
10th decile (High volatility)	0.6395***	0.010952	58.39	0.000
Number of observations		604,677		
R-squared		0.1893		

This table shows the coefficient estimates (Coefficients) from the following OLS regression: $|TPERROR|_{jt} = \alpha + \sum_{k=1}^{10} \beta_k \mathbf{1}_{jt}^k \sigma_{jt} + \epsilon_{jt}$, where $|TPERROR|_{jt}$ is the absolute forecast error of a target price on firm j issued by any analyst at time t , σ_{jt} is the stock return volatility of stock j measured at time t and $\mathbf{1}_{jt}^k$ is an indicator that takes the value 1 if the stock return volatility σ_{jt} belongs to the k -th volatility decile and 0 otherwise. We denote the variable $\mathbf{1}_{jt}^k \sigma_{jt}$ as the k -th decile. ***/**/* correspond to 1%/5%/10% significance levels. P-values are computed using robust standard errors.

Table 2.4

Test of forecasting ability using the absolute forecast error

Panel A: Quarterly period								
Performance quintile (ranked at time t)	Time t		Time $t + \tau + 1$			Time $t + \tau + 3$		
	TPERROR	Volatility	Nb obs	TPERROR	Volatility	Nb obs	TPERROR	Volatility
1 (Best)	0.1551	0.3870	11,083	0.3322	0.3720	9,470	0.3355	0.3743
2	0.2847	0.4364	11,079	0.3654	0.4161	9,465	0.3677	0.4142
3	0.4026	0.4919	11,085	0.4108	0.4673	9,471	0.4039	0.4552
4	0.5627	0.5720	11,079	0.4838	0.5284	9,465	0.4609	0.5073
5 (Worst)	0.9693	0.6850	11,083	0.5779	0.5973	9,470	0.5386	0.5638
Diff (5-1)	0.8143	0.2980		0.2456	0.2253		0.2031	0.1895
Mean t-test	17.7540***	11.0277***		12.5456***	12.6069***		15.5653***	14.7648***
Panel B: Semiannual period								
Performance quintile (ranked at time t)	Time t		Time $t + \tau + 1$			Time $t + \tau + 3$		
	TPERROR	Volatility	Nb obs	TPERROR	Volatility	Nb obs	TPERROR	Volatility
1 (Best)	0.1713	0.3747	6,258	0.3266	0.3653	4,629	0.3306	0.3784
2	0.2992	0.4291	6,260	0.3672	0.4102	4,625	0.3613	0.4082
3	0.4128	0.4924	6,256	0.4116	0.4648	4,628	0.3983	0.4452
4	0.5662	0.5729	6,260	0.4847	0.5217	4,625	0.4426	0.4973
5 (Worst)	0.9559	0.6876	6,258	0.5758	0.5897	4,629	0.5170	0.5440
Diff (5-1)	0.7847	0.3128		0.2491	0.2244		0.1864	0.1656
Mean t-test	12.6568***	8.1821***		10.5185***	10.6874***		19.0406***	10.4888***

This table presents the analysts' performance at time $t + \tau + 1$ and $t + \tau + 3$ conditional on their performance at time t . τ is a 12-month lag which insures independence in prices (the measurement and the test periods are not overlapping). The measurement periods are quarterly (Panel A) and semiannual (Panel B). For period t , we measure the analyst performance as the average of the absolute forecast errors on all the target prices issued within this period. We rank the analysts in 5 quintiles based on their performance during the measurement period and obtain the corresponding performance in the test periods. We also report the analyst forecast underlying volatility computed as the average of the 6-month historical volatilities on all the target prices issued by the analyst within the considered period. Conditional on the ranking made at time t , we report both the average of the absolute forecast errors and the analyst forecast underlying volatility at time $t + \tau + 1$ and $t + \tau + 3$. The statistical significance of the difference across top and bottom quintiles is computed using a t-test. ***/**/* represent significance at the 0.01, 0.05 and 0.1 level.

Table 2.5
Persistence in accuracy using naïve forecasts

Panel A: Quarterly period								
Performance quintile (ranked at time t)	Time t		Time $t + \tau + 1$			Time $t + \tau + 3$		
	TPERROR	Volatility	Nb obs	TPERROR	Volatility	Nb obs	TPERROR	Volatility
1 (Best)	0.1317	0.4044	11,083	0.3057	0.3845	9,470	0.3170	0.3873
2	0.2422	0.4445	11,079	0.3254	0.4199	9,465	0.3336	0.4163
3	0.3357	0.4988	11,085	0.3564	0.4678	9,471	0.3612	0.4561
4	0.4550	0.5673	11,079	0.3975	0.5219	9,465	0.3910	0.5022
5 (Worst)	0.7614	0.6573	11,083	0.4481	0.5870	9,470	0.4195	0.5531
Diff (5-1)	0.6297	0.2529		0.1424	0.2025		0.1025	0.1658
Mean t-test	16.3544***	9.9624***		6.9959***	11.8540***		7.1992***	14.1030***

Panel B: Semiannual period								
Performance quintile (ranked at time t)	Time t		Time $t + \tau + 1$			Time $t + \tau + 3$		
	TPERROR	Volatility	Nb obs	TPERROR	Volatility	Nb obs	TPERROR	Volatility
1 (Best)	0.1465	0.3908	6,258	0.3033	0.3756	4,629	0.3221	0.3874
2	0.2554	0.4386	6,260	0.3319	0.4180	4,625	0.3381	0.4142
3	0.3434	0.4944	6,256	0.3603	0.4609	4,628	0.3570	0.4474
4	0.4567	0.5720	6,260	0.3964	0.5192	4,625	0.3938	0.4953
5 (Worst)	0.7507	0.6609	6,258	0.4475	0.5779	4,629	0.4115	0.5288
Diff (5-1)	0.6042	0.2701		0.1442	0.2022		0.0893	0.1414
Mean t-test	12.2240***	7.3593***		6.2430***	9.4990***		5.3543***	10.4273***

This table presents the analysts' performance at time $t + \tau + 1$ and $t + \tau + 3$ conditional on their performance at time t . τ is a 12-month lag which insures independence in prices (the measurement and the test periods are not overlapping). The measurement periods are quarterly (Panel A) and semiannual (Panel B). For period t , we measure the analyst performance as the average of the absolute forecast errors on all the target prices issued within this period. This analysis uses naïve forecasts instead of the real target prices. That is, the analysts systematically issue target prices with an implied return equal to the risk-free interest rate. We rank the analysts in 5 quintiles based on their performance during the measurement period and obtain the corresponding performance in the test periods. We also report the analyst forecast underlying volatility computed as the average of the 6-month historical volatilities on all the target prices issued by the analyst within the considered period. Conditional on the ranking made at time t , we report both the average of the absolute forecast errors and the analyst forecast underlying volatility at time $t + \tau + 1$ and $t + \tau + 3$. The statistical significance of the difference across top and bottom quintiles is computed using a t-test. ***/**/* represent significance at the 0.01, 0.05 and 0.1 level.

Table 2.6
Test of forecasting ability using the *ex-post* measure of forecasting quality

Panel A: Quarterly period								
Performance quintile (ranked at time t)	Time t		Time $t + \tau + 1$			Time $t + \tau + 3$		
	<i>Ex-post</i> quality	Volatility	Nb obs	<i>Ex-post</i> quality	Volatility	Nb obs	<i>Ex-post</i> quality	Volatility
1 (Best)	0.3536	0.6222	11,082	0.0716	0.4967	9,469	0.0662	0.4862
2	0.1700	0.5000	11,079	0.0637	0.4470	9,463	0.0536	0.4360
3	0.0819	0.4588	11,082	0.0585	0.4385	9,472	0.0565	0.4278
4	-0.0122	0.4647	11,079	0.0578	0.4634	9,463	0.0598	0.4514
5 (Worst)	-0.2487	0.5148	11,082	0.0651	0.5231	9,469	0.0676	0.5012
Diff (5-1)	-0.6023	-0.1075		-0.0065	0.0264		0.0013	0.0151
Mean t-test	-20.2776***	-6.3892***		-0.9256	1.7703*		0.1979	1.2910
Panel B: Semiannual period								
Performance quintile (ranked at time t)	Time t		Time $t + \tau + 1$			Time $t + \tau + 3$		
	<i>Ex-post</i> quality	Volatility	Nb obs	<i>Ex-post</i> quality	Volatility	Nb obs	<i>Ex-post</i> quality	Volatility
1 (Best)	0.3268	0.6095	6,257	0.0651	0.4905	4,629	0.0646	0.4726
2	0.1560	0.4961	6,260	0.0614	0.4402	4,624	0.0618	0.4321
3	0.0762	0.4613	6,254	0.0551	0.4358	4,629	0.0604	0.4297
4	-0.0086	0.4660	6,260	0.0577	0.4585	4,624	0.0650	0.4435
5 (Worst)	-0.2292	0.5131	6,257	0.0633	0.5149	4,629	0.0747	0.4835
Diff (5-1)	-0.5561	-0.0963		-0.0018	0.0244		0.0101	0.0109
Mean t-test	-14.5024***	-4.1288***		-0.2123	1.2637		1.1673	0.6948

This table presents the analysts' performance at time $t + \tau + 1$ and $t + \tau + 3$ conditional on their performance at time t . τ is a 12-month lag which insures independence in prices (the measurement and the test periods are not overlapping). The *ex-post* quality is measured as the expected value of the absolute forecast error estimated at the time the forecast is issued minus the realized absolute forecast error measured at the end of the 12-month horizon. In this set-up, we consider a revision as a new and independent forecast. The measurement periods are quarterly (Panel A) and semiannual (Panel B). For period t , we measure the analyst performance as the average of *ex-post* qualities on all the target prices issued within this period. We then rank the analysts in 5 quintiles. We also report the analyst forecast underlying volatility computed as the average of the 6-month historical volatilities on all the target prices issued by the analyst within the considered period. Conditional on the ranking made at time t , we report both the average quality of the forecasts and the analyst forecast underlying volatility at time $t + \tau + 1$ and $t + \tau + 3$. The statistical significance of the difference across top and bottom quintiles is computed using a t-test. ***/**/* represent significance at the 0.01, 0.05 and 0.1 level.

Table 2.7

Test of forecasting ability using the forecasting quality measure

Panel A: Monthly period					
Performance quintile (ranked at time t)	Time t	Time $t + 1$		Time $t + 3$	
	Quality (FQ)	Nb obs	Quality (FQ)	Nb obs	Quality (FQ)
1 (Best)	0.0732	72,104	0.0061	67,388	0.0071
2	0.0261	72,113	0.0068	67,394	0.0073
3	0.0076	72,093	0.0058	67,369	0.0065
4	-0.0114	72,113	0.0055	67,395	0.0059
5 (Worst)	-0.0654	72,104	0.0032	67,388	0.0044
Diff (5-1)	-0.1386		-0.0029		-0.0027
Mean t-test	-31.7852***		-0.9546		-1.1829
Panel B: Quarterly period					
Performance quintile (ranked at time t)	Time t	Time $t + 1$		Time $t + 3$	
	Quality (FQ)	Nb obs	Quality (FQ)	Nb obs	Quality (FQ)
1 (Best)	0.1312	21,684	0.0207	17,429	0.0227
2	0.0551	21,687	0.0200	17,435	0.0189
3	0.0211	21,680	0.0188	17,427	0.0181
4	-0.0135	21,687	0.0196	17,435	0.0188
5 (Worst)	-0.1043	21,684	0.0149	17,429	0.0223
Diff (5-1)	-0.2355		-0.0059		-0.0004
Mean t-test	-17.0704***		-0.5806		-0.0694
Panel C: Semiannual period					
Performance quintile (ranked at time t)	Time t	Time $t + 1$		Time $t + 3$	
	Quality (FQ)	Nb obs	Quality (FQ)	Nb obs	Quality (FQ)
1 (Best)	0.1904	9,251	0.0414	6,296	0.0402
2	0.0853	9,249	0.0387	6,295	0.0358
3	0.0395	9,250	0.0334	6,293	0.0317
4	-0.0071	9,249	0.0306	6,295	0.0339
5 (Worst)	-0.1326	9,251	0.0223	6,296	0.0390
Diff (5-1)	-0.3230		-0.0191		-0.0012
Mean t-test	-12.6962***		-1.3708		-0.1745

This table presents the analysts' performance at time $t + 1$ and $t + 3$ conditional on their performance at time t . For the period considered, we measure the performance of an analyst as the average of the forecasting quality (computed with our new measure FQ) across all stocks covered. The measurement periods are monthly (Panel A), quarterly (Panel B) and semiannual (Panel C). We rank the analysts in 5 quintiles. In order to be included in the analysis, an analyst must have an active target price for at least 80 percent of the days in the sample period. Conditional on the ranking made at time t , we report the average forecasting quality at time $t + 1$ and $t + 3$. The statistical significance of the difference across top and bottom quintiles is computed using a t-test. ***/**/* represent significance at the 0.01, 0.05 and 0.1 level.

Table 2.8

The influence of the experience on the persistence of the forecasting quality

Panel A: Monthly period					
Performance quintile (ranked at time t)	Time t	Time $t + 1$		Time $t + 3$	
	Quality (FQ)	Nb obs	Quality (FQ)	Nb obs	Quality (FQ)
1 (Best)	0.0612	15,878	0.0053	13,428	0.0052
2	0.0212	15,879	0.0051	13,423	0.0042
3	0.0058	15,869	0.0054	13,428	0.0056
4	-0.0098	15,879	0.0044	13,423	0.0050
5 (Worst)	-0.0560	15,878	0.0048	13,428	0.0044
Diff (5-1)	-0.1173		-0.0006		-0.0008
Mean t-test	-28.9400***		-0.6208		-1.1953
Panel B: Quarterly period					
Performance quintile (ranked at time t)	Time t	Time $t + 1$		Time $t + 3$	
	Quality (FQ)	Nb obs	Quality (FQ)	Nb obs	Quality (FQ)
1 (Best)	0.1136	4,246	0.0155	3,533	0.0133
2	0.0451	4,241	0.0167	3,528	0.0150
3	0.0168	4,245	0.0134	3,533	0.0136
4	-0.0124	4,241	0.0128	3,528	0.0161
5 (Worst)	-0.0953	4,246	0.0147	3,533	0.0128
Diff (5-1)	-0.2090		-0.0008		-0.0005
Mean t-test	-14.9959***		-0.3498		-0.2169
Panel C: Semiannual period					
Performance quintile (ranked at time t)	Time t	Time $t + 1$		Time $t + 3$	
	Quality (FQ)	Nb obs	Quality (FQ)	Nb obs	Quality (FQ)
1 (Best)	0.1602	1,761	0.0293	1,277	0.0205
2	0.0678	1,763	0.0267	1,277	0.0305
3	0.0246	1,764	0.0249	1,275	0.0289
4	-0.0173	1,763	0.0299	1,277	0.0224
5 (Worst)	-0.1426	1,761	0.0267	1,277	0.0245
Diff (5-1)	-0.3028		-0.0026		0.0040
Mean t-test	-10.4057***		-0.5724		1.0912

We restrict the sample to the analysts who have at least two years of experience. The sample period is 2003-2010. This table presents the analysts' performance at time $t + 1$ and $t + 3$ conditional on their performance at time t . For the period considered, we measure the performance of an analyst as the average of the forecasting quality (computed with our new measure FQ) across all stocks covered. The measurement periods are monthly (Panel A), quarterly (Panel B) and semiannual (Panel C). At time t , we measure the average forecasting quality on all the target prices that are issued during this period of time. We then rank the analysts in 5 quintiles. In order to be included in the analysis, an analyst must have an active target price for at least 80 percent of the sample period length. Conditional on the ranking made at time t , we report the average forecasting quality at time $t + 1$ and $t + 3$. The statistical significance of the difference across top and bottom quintiles is computed using a t-test. ***/**/* represent significance at the 0.01, 0.05 and 0.1 level.

Chapter 3

Analyst experience, differences in coverage decisions and target price quality

Joint work (in progress) with

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Abstract

In this paper, we show that experienced financial analysts tend to cover different firms than inexperienced analysts. Experienced analysts tend to follow blue chips (*i.e.*, large, international, mature firms) while inexperienced analysts focus on small, young, growth-oriented firms. These differences in coverage decisions imply that inexperienced analysts issue target prices on firms for which stock returns are more volatile, and thus less predictable. As a consequence, the accuracy measure of target prices fails to evaluate differences in ability and skill between experienced and inexperienced analysts. When taking into account these differences in coverage decisions, we still find that experienced analysts do a better job at forecasting stock prices. Our results on the influence of analysts' characteristics on target price quality are statistically significant but economically weak.

3.1 Introduction

Studies on the determinants of forecast accuracy have investigated the influence of analysts' characteristics on their forecasting ability (Mikhail, Walther, and Willis, 1997; Jacob, Lys, and Neale, 1999; Clement, 1999). The main characteristics considered in these studies are the analysts' ability, the forecasting task complexity and the resources available to the analysts. These three characteristics are proxied, respectively, by the analysts' experience, the number of firms or industries followed and the employer size. This article investigates whether these same characteristics have an influence on coverage decisions. Using a large database of analysts' forecasts, we show that experienced analysts and inexperienced analysts do not follow the same type of firms. More generally, the greater the experience gap between two analysts, the less correlated their coverage decisions are. Our analysis of the profile of the firms covered by experienced analysts and inexperienced analysts indicates that experienced analysts tend to focus on "blue chips"¹ while inexperienced analysts cover mainly young, small, growth firms. Taking into account this differential coverage, we study whether the ability of financial analysts to accurately issue target prices is associated with the combination of their experience, the number of firms followed and employer size. In line with the findings on earnings forecasts (Clement, 1999), we obtain that experienced analysts issue better target prices. However, contrary to what is obtained for earnings forecasts, we find that the ability of financial analysts

¹Firms referred to as "blue chips" are usually characterized by a large market capitalization, a proven record of financial strength, a capacity to produce earnings and a limited amount of debt. They are established, well-known companies considered to be stable and mature, and leader in their industry.

to issue accurate target prices is positively related to the number of firms followed and negatively related to employer size. We point out that our results are statistically significant but economically weak.

Our first analysis studies whether differences in coverage decisions between analysts can be explained by differences in experience. In this preliminary test, we do not seek to determine the respective profiles of firms covered by experienced and inexperienced analysts. Rather, we aim to show that experienced analysts and inexperienced analysts cover different sets of firms. This analysis is done by computing, for each possible pair of analysts, their degree of joint coverage. The degree of joint coverage is obtained by considering the number of firms covered by both analysts while controlling for the total number of firms covered by each analyst composing the pair. We show that the degree of joint coverage is higher when analysts have similar levels of experience. We also find that the degree of joint coverage between two analysts increases with their average experience. This result suggests that experienced analysts tend to cover firms with higher analyst coverage.

In our second analysis, we aim at determining the profiles of firms covered respectively by experienced analysts and inexperienced analysts. We consider an extensive set of variables which cover both financial characteristics and fundamentals. We use a Principal Component Analysis to summarize these different characteristics into a single measure. Our measure, called the “Blue Chip Index” (BCI), is the first principal component of a Principal Component Analysis on the following variables: (1) Capitalization; (2) Book-to-market ratio; (3) Free cash flow scaled by average total assets; (4) External financing scaled by average total assets; (5) Institutional ownership

(the fraction of outstanding shares owned by institutional investors); (6) Ownership breadth; (7) Asset growth (average over the past five years); (8) Sales growth (average over the past five years); (9) Accruals (as calculated in Richardson, Sloan, Soliman, and Tuna, 2006); (10) Analyst coverage (number of analysts issuing earnings forecasts for a given firm); (11) Stock return volatility; and, (12) Bid-ask spread. Our measure (BCI) is positively related to the level of capitalization, the number of analysts covering the firm, the level of ownership breadth and the size of the free cash flows, and negatively related to the amount of external financing, the asset growth rate, the sales growth rate, the size of the bid-ask spread and the stock return volatility. On average, our measure takes a high value for firms with the following characteristics: firms that are large and liquid, that attract a lot of attention from market participants, that generate cash and rely only moderately on external financing. These firms have a large investor base, a low rate of growth and their returns are not too volatile. A large positive value for BCI indicates that the firm is a “blue chip” while a negative value corresponds to a young, small, growth firm.

We use a multivariate regression to investigate the link between our BCI measure and analysts characteristics. Our results indicate that the firms covered by experienced analysts and analysts working for large brokerage firms take higher BCI values. We also find a positive association between the number of firms covered by analysts and the BCI value of the firms they covered.

Blue chips have typically a lower stock return volatility. Because target price accuracy is mechanically influenced by volatility (As shown by Roger and Fontaine, 2013), the fact that experienced analysts cover mainly blue chips induces a bias in

the analysis of the impact of experience on target price accuracy. In our analysis, we control for firm-year differences and use the measure of Roger and Fontaine (2013) which takes into account the impact of volatility when evaluating the quality of target prices. Hence, we neutralize the impact of the differential coverage. Our results show that experienced analysts do issue better target prices. However, the influence of experience on target prices' quality is economically small.

Financial analysts specialize by industry. However, within industries, the common assumptions made in the literature are that analysts share similar preferences (about the profile of firms to cover) and that these preferences are stable over the analysts' life.² The literature on analysts' preferences focuses mainly on the link between analyst coverage (the number of analysts covering a firm) and firm characteristics. For instance, Bhushan (1989) shows that analyst coverage is positively associated with firm size and institutional ownership. O'Brien and Bushan (1990) find that a decrease in a firm's stock return volatility leads to an increase in the number of analysts following the firm. Barth, Kasznik, and McNichols (2001) show that analyst coverage is higher for firms with high intangible assets. Finally, Lang, Lins, and Miller (2004) find that analyst coverage is lowered by potential firms' incentives to withhold or manipulate information. The article of McNichols and O'Brien (1997) stands out as they focus on analysts' behavior rather than on analyst coverage. Their findings indicate that analysts tend to issue forecasts on firms for which they have favorable views and choose not to cover firms for which they are pessimistic about the firms' future performance.

²We point out that these assumptions are never clearly stated in the literature. However, the approaches that are usually followed in the different articles imply that such assumptions are made.

We believe our results on the relationship between coverage decisions and experience to shed a new light on analysts' preferences. In particular, these results lead us to question whether the existence of a link between analyst coverage and a firm characteristic expresses analysts' preference for this characteristic. Our reasoning is the following. The fact that experienced analysts cover a different type of firms than inexperienced analysts has potentially two explanations. The simplest one is that the preferences of analysts evolve with their experience. The second explanation, which seems more probable, is that preferences are stable but coverage decisions are constrained. Preferences are stable over the analysts' life but their coverage decisions are constrained by the brokerage firm and these constraints evolve with experience (and with their position in the hierarchy). Inside a brokerage firm, analysts specialize by industry. If all the analysts within an industry share similar preferences, they would all cover the same limited pool of firms. This situation is of course not efficient for the brokerage firm as the revenues resulting from analyst coverage increase with the number of firms covered. It follows that the brokerage firm has incentives to constrain the number of analysts covering each firm.³ The brokerage firm thus faces a matching problem. Assuming that experienced analysts have priority over inexperienced analysts, the former choose which firms to cover according to their preferences. As the firms that match inexperienced analysts' preferences are already taken by experienced analysts, inexperienced analysts are assigned to the remaining firms in the industry. As a result of this matching mechanism, analysts gradually move towards the firms that correspond to their preferences as they gain experience.

³It is probable that a relationship between the maximum number of analysts covering a firm and the potential revenues associated with this firm exists.

If analysts share similar experiences but their coverage decisions are constrained by the brokerage firm, the link between analyst coverage and firm characteristics may be driven not only by analysts' preferences but also by brokerage firms' preferences. For instance, the findings of Bhushan (1989) showing that analyst coverage is positively associated with firm size might also be explained by brokerage firms assigning more analysts to large firms (because potential revenues are higher for large firms). It follows that analyst coverage should be interpreted with respect to both analysts' preferences and brokerage firms' incentives.

This paper is structured as follows. In section 2, we describe the different analysts' characteristics considered in the article and introduce their proxy. We outline our hypotheses on the impact of these characteristics on coverage decisions. In section 3, we present the data used in our study. Section 4 focuses on the link between experience and coverage decisions. In section 5, we study the relationship between analysts' characteristics and target price quality. The last section concludes the paper.

3.2 Analysts' characteristics

The analysts' characteristics considered in this article are, as in Clement (1999), the experience (a proxy for analyst ability), the number of firms followed (a proxy for forecasting task complexity) and the employer size (a proxy for the level of resources available to the analyst). In this section, we present our hypotheses on the influence of these variables on the type of firms covered by analysts. We then explain the methodology used to compute proxies for analyst ability, task complexity and resources available.

3.2.1 Hypotheses for analyst ability (experience)

Our hypothesis is that experienced analysts cover mainly large, international, mature firms. We propose two explanations to why experienced analysts would tend to cover blue chips.

The first explanation is that the coverage is motivated by brokerage firms' incentives. Blue chips are of special interest for brokerage firms as these firms generate the most trading and investment banking (IPOs, underwriting activity...) fees. However, these firms are also the ones for which competition is fiercest. Because financial analysts participate in the reputation of the brokerage firm, it seems reasonable to assume that these brokerage firms assign their best analysts to blue chips. Experience is often seen as a proxy for analyst's ability. Experienced analysts are, by definition, individuals who managed to stay in the profession. Clement (1999) points out that, because the analyst labor market functions as a tournament⁴, the best analysts stay in the profession while the worst ones are forced out. It is therefore a safe assumption that experienced analysts are, on average, individuals who are good at doing their job. A second reason why experienced analysts would be more skillful is that skills and knowledge improve over time (learning-by-doing). Finally, because the analyst's work also includes contacts with companies' managers, brokerage firms have incentives to select analysts who have a long term relationship with the executives of the covered company.

The second explanation to why blue chips are covered by experienced analysts

⁴This is the way brokerage firms and clients evaluate analysts. Also, the Institutional Investor ranking uses a tournament-like process to nominate All-star analysts.

is that experienced analysts have a larger discretion, with respect to inexperienced analysts, regarding which firms to cover and that analysts have an intrinsic preference for blue chips. Assuming that experienced analysts are higher up in the hierarchy, they have priority when choosing which firms to cover (either because they are already covering them, or because they get priority when choosing) while young inexperienced analysts are left with the remaining firms. There are some incentives to cover blue chips. First, researching a young, growth firm may result in a waste of the analyst's time and resources if the firm ends up disappearing or if it is acquired by a larger firm. In this sense, researching a blue chip guarantees the acquired knowledge (superior information) to be useful for a longer period of time. Second, large, mature firms attract more attention. The reports written on firms of this type have a larger potential client base and typically generate more revenues than reports written on small, growth firms⁵.

3.2.2 Hypotheses for task complexity (number of firms followed)

Our hypothesis is that analysts following blue chips cover a small number of firms. This hypothesis is motivated by the different nature of the work done when covering blue chips compared to covering small, young, growth firms. Blue chips have several business activities, located in different countries and often related to different industries. Their structure is much more complex than that of small, growth firms and

⁵The profits of sell-side analysts arise mainly from the brokerage house's investment banking fees and trading fees.

thus their coverage is more time demanding. We therefore expect analysts covering blue chips to focus on a limited number of firms.

3.2.3 Hypotheses for resources (employer size)

Large brokerage firms have a competitive advantage when concluding investment banking deals with large companies.⁶ Therefore, it might be a successful strategy for smaller brokerage firms to target smaller, younger companies. We therefore expect smaller brokerage firms to specialize in growth, young firms where they are not at a disadvantage with regards to the main investment banks.

3.2.4 Proxies for analysts' characteristics

The study of the influence of analysts' characteristics on their forecasting behavior is a difficult task because standard databases such as I/B/E/S do not provide information, other than an identifying code, about analysts. However, some characteristics can be extracted from the data. Clement (1999) provides a methodology to build proxies for analysts' experience, employer size as well as the number of firms followed. Although our article studies target prices, we choose to follow the methodology of Clement (1999) and to construct analysts' characteristics proxies using earnings forecasts. We use earnings rather than target prices to compute proxies because (1) forecasting earnings is the core activity of financial analysts (they cover more stocks than the ones for which they issue target prices); (2) financial analysts only recently started to issue target prices (*i.e.*, they start issuing target prices on stocks they have

⁶For instance, Facebook IPO's lead underwriters were Morgan Stanley, JP Morgan and Goldman Sachs.

been covering for many years); and, (3) the data on target prices is left-censored (the number of observations is very small before 2000).

When building proxies for experience and the number of firms followed, we exclude earnings forecasts that are issued less than 30 days or more than one year before the end of the fiscal year. As stated by Clement (1999), an analyst who only issues forecasts more than a year before the end of the fiscal year is not likely to be following the company closely. In the same way, an analyst who only issues forecasts in the month preceding the end of the fiscal year is likely to build her forecasts upon the forecasts of other analysts rather than by carefully investigating the company.

The general experience $GEXP_{it}$ is calculated as the number of years through year t for which analyst i supplied at least one forecast. When computing the proxy for experience, we also take into account the firms for which the analysts do not issue target prices. Indeed, analysts might issue target prices only for a limited number of stocks. Not considering the other firms that they cover can bias the estimation of the experience level. In other words, when calculating the experience proxies, we only care about earnings forecasts and not about target prices. We use as the proxy for the forecasting task complexity, the number of firms (NF_{it}) covered by analyst i during year t .

Finally, we define the employer size (ES_{it}) as the number of analysts employed in year t by the broker for which analyst i works during year t . We assume, as in Stickel (1995) and Clement (1999), that two level of resources can be distinguished. On one hand, large employers provide analysts with important resources. On the other hand, smaller brokerage firms provide analysts with more limited resources. We define a

dummy (DES_{it}) that takes the value 1 if analyst i is employed by a broker that belongs to the top size decile and 0 otherwise.⁷

3.3 Data

Our primary dataset consists of a total of 686,863 target prices made by 10,137 analysts (620 brokers) on 7,646 U.S. stocks for the 2000-2010 period. The provider for the target prices is I/B/E/S. For each forecast, we have the code of the analyst (and the broker code) who issues the forecast, the issue date, the horizon in months (usually 6 or 12 months), and the target price. We remove from the database the forecasts for which the stock price is not available on the issue date (20,766 forecasts), or is less than one dollar (2,044 forecasts). We also delete from the database the forecasts for which the ratio of the target price over the stock price is in the bottom one percent of the distribution (7,468 forecasts) and the forecasts for which this ratio is higher than four (2,313 forecasts). Finally, we discard the observations for which the price history is too short to compute an acceptable estimation of the historical volatility⁸ (4,801 forecasts). After deleting these 37,392 observations, 770 analysts are removed from the database as they are left with no forecasts. Our final sample consists of 649,471 target prices made by 9,367 analysts (583 brokers) on 7,268 stocks.

Our secondary dataset consists of all the one-year ahead earnings forecasts for the 1982-2010 period. The data on earnings forecasts is used to compute proxies for

⁷About 50% of the analysts are employees of the top size decile brokers.

⁸We delete the observations for which there are less than 2 months of price history prior to the forecast.

analysts' experience. Following Clement (1999), we only keep the earnings forecasts issued between 365 and 30 days before the end of the fiscal year to compute proxies for experience and task complexity (but we keep all the forecasts to calculate the employer size variable).

Our third dataset contains daily stock prices, market capitalizations and bid-ask spreads for the 7,268 stocks considered. This third dataset comes from CRSP. Target prices and stock prices are adjusted for splits and corporate actions.

Finally, we obtain fundamental data from Compustat Xpressfeed. Each fiscal year, we compute accruals, asset growth, sales growth and external financing. Data on institutional ownership is obtained through Thomson Financial Institutional Holdings.

Table 3.1 reports for each year the number of target prices issued, the number of active analysts, the average, median and maximum number of active analysts per stock, and the average, median and maximum number of stocks covered per analyst. We observe that the number of forecasts per year more than doubles over the sample period while the number of active analysts remains roughly constant. It appears that the inclusion of a target price in analysts' reports is an increasingly popular practice. An analyst typically covers 4 different stocks at the beginning of the sample period; this number increases to 7 in the last years. Conversely, the number of analysts covering a given stock increases over the sample period from 4 to 6.

On average, the analysts in our sample revise their forecasts approximately every 6 months (137 trading days). The target prices in our sample are on average 23% higher than the current stock price.⁹ This statistic is similar to what can be observed

⁹The annualized return for the S&P 500 Composite index for the same period is -1.21% .

for other periods and/or countries. For instance, Brav and Lehavy (2003) find that target prices on U.S. stocks for the 1997-1999 period are on average 28% higher than the current price while Kerl (2011) reports an implicit return of 18.07% for German stocks for the 2002-2004 period. Finally, it appears that the analysts in our sample are mainly optimistic about stock prices with only 13% of the target prices below the concurrent price.

The average (median) level of experience of the analysts in our sample is 7.15 years (6 years). The 5th percentile is equal to 1 year while the 95th percentile is 18 years. The average (median) number of firms followed is 16.20 (15). The 5th percentile is equal to 5 firms while the 95th percentile is 28 firms.

3.4 Experience and coverage decisions

3.4.1 Joint coverage

Our first analysis consists in checking whether experienced analysts and inexperienced analysts cover the same firms. For each possible pair of analysts, we compute their degree of joint coverage. This degree of joint coverage corresponds to the degree to which two analysts cover the same firms. It is a function of the number of firms jointly covered by the two analysts and of the number of firms covered by each analyst composing the pair.

Methodology

Our methodology to compute the degree of joint coverage is the following. For a given year, there are M firms covered by at least one analyst and N analysts covering at least one firm. First, let us consider the case where analysts choose randomly which stocks to cover. An analyst A_i (A_j) chooses to cover a subset S_i (S_j) of m_i (m_j) firms with $\max(m_i, m_j) \leq M$. As stocks are randomly chosen, the number (denoted m_{ij}) of elements in the intersection $S_i \cap S_j$, is the number of firms jointly covered by the two analysts A_i and A_j . m_{ij} is a random variable following a hypergeometric distribution with parameters (M, m_i, m_j) , denoted $H(M, m_i, m_j)$.¹⁰

Our methodology is the following. For a year t , we define the coverage matrix C as

$$C_t = \begin{bmatrix} c_{11t} & \dots & \dots & \dots & c_{1Nt} \\ \dots & \dots & & & \dots \\ c_{i1t} & & c_{ijt} & & c_{iNt} \\ \dots & & & \dots & \dots \\ c_{M1t} & \dots & \dots & \dots & c_{MNt} \end{bmatrix}, \quad (3.1)$$

where M is the number of firms covered during year t , N is the number of active analysts and c_{ijt} is a binary variable that takes the value 1 if analyst i covers firm j during year t .

The number of firms jointly covered by a pair of analysts is obtained by the multiplication of the transposed of the coverage matrix C^T by the coverage matrix

¹⁰In the set of M firms, there are m_i firms followed by analyst i . If analyst j draws m_j firms among the M existing ones, the number m_{ij} of firms drawn by analyst j in the subset of m_i firms follows $H(M, m_i, m_j)$.

C. The joint coverage matrix JC is a symmetric matrix of size (N, N) , written as

$$\begin{aligned}
 JC_t &= C_t^T \times C_t \\
 &= \begin{bmatrix} n_{11t} & \dots & \dots & \dots & n_{1Nt} \\ \dots & \dots & & & \dots \\ n_{i1t} & & n_{ijt} & & n_{iNt} \\ \dots & & & \dots & \dots \\ n_{N1t} & \dots & \dots & \dots & n_{NNt} \end{bmatrix}, \tag{3.2}
 \end{aligned}$$

where n_{iit} is number of different firms covered by analyst i . For $i \neq j$, n_{ijt} is the number of firms covered simultaneously by analysts i and j .

Obviously, the number of firms jointly covered by two analysts depends on the number of firms covered by each analyst and on the total number of firms in the universe.¹¹ The probability for an analyst j to cover the same firms as another analyst i increases with the number of firms she covers and with the number of firms covered by the other analyst i . This probability decreases with the total number of firms in the universe. In order to compare the joint coverage of a pair of analysts with the joint coverage of another pair of analysts, we need to control for the number of firms covered by the analysts in each pair. Similarly, if we want to compare joint coverages at different points in time, we need to control for the total number of firms in the universe. We therefore define the matrix SJC of standardized joint coverage

¹¹For a given year, we estimate this number by the number of firms covered by at least one analyst.

where the elements are defined as

$$sjc_{ijt} = \frac{n_{ijt} - E(n_{ijt})}{\sqrt{V(n_{ijt})}}, \quad (3.3)$$

where $E(n_{ijt})$ and $V(n_{ijt})$ are the expected value and the variance of joint coverage under the random choice assumption.¹²

We provide below a numerical example to illustrate our methodology.

Example 9 Consider the situation where the total number of firms is $M = 5$ and the number of analysts is $N = 4$. We have the following coverage matrix C

$$C = \begin{bmatrix} 1 & 1 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 \end{bmatrix}. \quad (3.5)$$

¹²The first two moments of the hypergeometric distribution are given by

$$\begin{aligned} E(n_{ij}) &= \frac{n_i n_j}{M} \\ V(n_{ij}) &= \frac{n_i n_j (M - n_i) (M - n_j)}{M^2 (M - 1)}. \end{aligned} \quad (3.4)$$

The joint coverage is obtained by calculating the product $JC = C^T \times C$ and we have

$$JC = \begin{bmatrix} 2 & 1 & 0 & 1 \\ 1 & 2 & 1 & 2 \\ 0 & 1 & 3 & 3 \\ 1 & 2 & 3 & 4 \end{bmatrix}. \quad (3.6)$$

The elements on the diagonal represent the number of firms covered by each analyst. The two first analysts cover two firms each, the third analyst covers three firms and the fourth analyst covers four firms in the sample. The joint coverage is expressed by the elements that are outside the diagonal. We have $JC_{34} = 3$, which means that analyst 3 and analyst 4 cover three stocks in common (these two analysts jointly cover the last three firms as can be seen on matrix C). Obviously, because the last analyst covers four firms (the highest number) in the sample, his joint coverage with the other analysts is higher. In order to control for these differences in the number of firms covered per analyst, we consider the standardized joint coverage matrix SJC , which is equal to

$$SJC = \begin{bmatrix} & 0.3333 & -2.0000 & -1.2247 \\ 0.3333 & & -0.3333 & 0.8165 \\ -2.0000 & -0.3333 & & 1.2247 \\ -1.2247 & 0.8165 & 1.2247 & \end{bmatrix}. \quad (3.7)$$

Note that we leave the diagonal empty: we do not compute the standardized joint coverage of an analyst with himself as the number of firms covered by an analyst

does not follow a hypergeometric distribution (it is a constant). We observe that the standardized joint coverages of the pairs (1;2), (2;4) and (3;4) are positive. These positive values mean that the joint coverage is higher than what should be observed if coverage decisions were independent. On the contrary, the joint coverages of (1;3), (1;4), (2;3), (2;4) are below what should be expected under independence.

We want to analyze whether differences in experience between analysts influence their degree of joint coverage. We part, each year, the population of analysts in five groups. The first group is composed of the analysts with the most experience (at least 16 years of experience). The second group is characterized by a level of experience between 12 years and 16 years (8 years to 12 years for the third group; 4 years to 8 years for the fourth group). Finally, the fifth group of analysts is composed of the inexperienced analysts (between 0 and 4 years).

In order to measure the degree of joint coverage between two groups of analysts, we introduce the Intergroup Joint Coverage (IJC) measure. The Intergroup Joint Coverage between a group of analysts \mathcal{K} and a group of analysts \mathcal{L} is defined as

$$IJC_{\mathcal{K}\mathcal{L}t} = \begin{cases} \left(\sum_{k \in \mathcal{K}} \sum_{l \in \mathcal{L}} s_j c_{klt} \right) / (KL) & \text{if } \mathcal{K} \neq \mathcal{L} \\ \left(\sum_{\substack{k, l \in \mathcal{K} \\ k \neq l}} s_j c_{klt} \right) / ((K - 1) K) & \text{if } \mathcal{K} = \mathcal{L} \end{cases}, \quad (3.8)$$

where $K = Card(\mathcal{K})$ is the number of analysts in group \mathcal{K} and $L = Card(\mathcal{L})$ is the number of analysts in group \mathcal{L} .

When $\mathcal{K} \neq \mathcal{L}$, IJC measures the degree of joint coverage between analysts in

group \mathcal{K} and analysts in group \mathcal{L} . When $\mathcal{K} = \mathcal{L}$, IJC measures the degree of joint coverage between the different analysts composing group \mathcal{K} .

We define the Global Level of Joint Coverage (GLJC) as

$$GLJC_t = \left(\sum_{i=1}^N \sum_{j=i+1}^N s_j c_{ijt} \right) / \left(\frac{N^2 - N}{2} \right), \quad (3.9)$$

where N is the number of active analysts during year t .

$GLJC$ is simply the average of $s_j c_{ij}$. It measures the global degree of correlation between the analysts' coverage decisions for a year t . If coverage decisions were random, we would have $GLJC = 0$. However, because coverage decisions are clustered (few firms gather most of the analyst coverage), $GLJC$ takes positive values.

Finally, we define a measure of Intergroup Excess Joint Coverage ($IEJC$) as the difference between IJC and $GLJC$. It writes

$$IEJC_{\mathcal{K}\mathcal{L}t} = IJC_{\mathcal{K}\mathcal{L}t} - GLJC_t. \quad (3.10)$$

$IEJC$ takes a positive (negative) value if the coverage decisions of the analysts of group \mathcal{K} and analysts of group \mathcal{L} are more (less) correlated than what is typically observed in the rest of the population.

Results

If analysts with similar levels of experience tend to follow the same firms, we expect to obtain that $IEJC_{\mathcal{K}\mathcal{K}} > IEJC_{\mathcal{K}\mathcal{L}}$ and we expect the Intergroup Excess Joint Coverage $IEJC_{\mathcal{K}\mathcal{L}}^t$ to become smaller when the experience gap between groups \mathcal{K}

and \mathcal{L} increases. Table 3.2 provides the Intergroup Excess Joint Coverages between the five groups defined above. The highest value (0.0727) for *IEJC* is obtained for the analysts of the group 1 with themselves. The intensity of the joint coverage diminishes monotonically as the experience gap increases. The Intergroup Excess Joint Coverage is not significantly different from zero between group 1 and group 4. It becomes negative between the most experienced analysts and the least experienced analysts. This negative value means that the coverage decisions of the most experienced analysts and the least experienced analysts are less correlated than what is typically observed in the whole population. We find that the Intergroup Excess Joint Coverage decreases when the difference in experience between two groups increases. This is true for all groups except for group 4 (analysts in group 4 have a higher degree of joint coverage with analysts of group 3 than with themselves). The Intergroup Excess Joint Coverage appears to decrease with the average level of experience of the two groups. In particular, inexperienced analysts have globally a low degree of joint coverage with the rest of their peers (and with themselves). A plausible explanation for this lower degree of joint coverage is that inexperienced analysts cover only few firms (as it can be observed in the table) and these firms have, on average, low analyst coverage. They follow firms that do not attract a lot of attention and that are covered only by analysts with low experience. In other words, the universe of firms covered by the first four groups is different from the universe of firms covered by analysts who just started working.

We conduct a second analysis to describe the role of experience on coverage decisions. For a given pair of analysts, we want to understand how the difference in

experience levels between the two analysts influences the degree of joint coverage. Also, we want to check how the average level of experience of the two analysts composing the pair impacts this joint coverage (The results reported in Table 3.2 seem to indicate that a positive relationship exists between the level of experience and the degree of joint coverage). We introduce the following variables: (1) the Pair Experience Differential, defined as $PED_{ijt} = |GEXP_{it} - GEXP_{jt}|$; and, (2) the Pair Average Experience, defined as $PAE_{ijt} = (GEXP_{it} + GEXP_{jt}) / 2$. We adopt the following specification to measure the relationship between joint coverage and experience

$$sjc_{ijt} = \alpha + \beta_1 PED_{ijt} + \beta_2 PAE_{ijt} + \beta_3 n_{it} + \beta_4 n_{jt} + year_t \text{ effects} + \epsilon_{ijt}, \quad (3.11)$$

where n_i (n_j) is the number of firms covered by analyst i (respectively j) during year t and $year_t \text{ effects}$ is a set of dummies for each year of the sample.

With this specification, we can consider the joint effects of both the difference in experience between two analysts and the average level of experience of the analysts composing the pair. However, it is not possible to incorporate in the regression the joint coverage between all the different pairs of analysts as the number of observations is too large. Indeed, for each year, we have $(N_t^2 - N_t) / 2$ different pairs of analysts. This represents an average of 4,854,305 pairs each year. Thus, we reduce the number of observations by drawing randomly 500,000 observations each year. The final sample consists of 5,500,000 observations.

We provide the results of the regression in Table 3.3. As expected, the coefficients associated with the Pair Experience Differential (PED) variable is negative and significant, indicating that there is a higher degree of joint coverage when analysts have

similar levels of experience. The coefficient of the Pair Average Experience (PAE) variable is positive and significant: the correlation between the coverage decisions of two analysts is higher when both analysts are experienced. We also observe that the degree of joint coverage increases with the number of firms followed by analysts.¹³ We note however that the R-squared of the regression is quite small. This low fraction of explained variance finds its source in the high number of observations and in the fact that, for a given level of Pair Experience Differential, there are a multitude of different realizations for the joint coverage variable (there are more than 5 millions different realizations for the standardized joint coverage variable while there are only 30 realizations for the Pair Experience Differential variable and 59 realizations for the Pair Average Experience variable).

3.4.2 Experience and sector coverage

We showed in the previous subsection that experience has an influence on coverage decisions. A possible explanation for this feature is that experienced analysts do not cover the same sectors as inexperienced analysts. We provide, in Table 3.4, some descriptive statistics on the proportion of target prices per sector with respect to the experience. We first note that target prices are extremely popular among the firms of the technology sector. At the beginning of our sample period (which corresponds to the Internet bubble), the target prices issued on technology stocks represent as much as one quarter of all the target prices issued. Although this proportion decreases over time, it remains the sector with the most target prices in 2010. With respect to the

¹³Note that, theoretically, we should obtain the same coefficient for n_{it} and n_{jt} . The difference comes from the fact that we drew randomly 500,000 observations each year.

analysts' experience, we observe some important differences in the proportion of target prices per sector. For instance, analysts with the least experience issue a higher proportion of target prices in the technology sector than experienced analysts. The difference in percentages between inexperienced and experienced analysts is as high as 8 points in 2003. On the contrary, experienced analysts issue a higher proportion of target prices on firms from the Consumer Services sector than inexperienced analysts. We also note that these differences in proportions are not stable over time. Overall, the differences in proportions appear too small to explain our previous findings. However, we will need to control for these differences in our subsequent tests.

3.4.3 Experience and firm characteristics

We demonstrated that experienced analysts and inexperienced analysts do not cover the same firms. We now aim to characterize the profile of the firms covered, respectively, by experienced analysts and inexperienced analysts.

Univariate analysis

We characterize the profile of each firm using the following variables: (1) Capitalization; (2) Book-to-market ratio; (3) Free cash flow scaled by average total assets; (4) External financing scaled by average total assets; (5) Institutional ownership (the fraction of outstanding shares owned by institutional investors); (6) Ownership breadth; (7) Asset growth (average over the past five years); (8) Sales growth (average over the past five years); (9) Accruals (as calculated in Richardson, Sloan, Soliman, and Tuna, 2006); (10) Analyst coverage (number of analysts issuing earnings forecasts for

a given firm); (11) Stock return volatility; and, (12) Bid-ask spread. We provide a complete description of these variables in the Appendix.

We first proceed to univariate tests. Each year, we assign analysts to five quintiles with respect to their general experience *GEXP*. We then report, for different quintiles, the average values of the characteristics listed above for the firms covered by the analysts. The results in Table 3.5 allow us to detail what drives the differences in coverage decisions. These different characteristics establish a dichotomy between blue chips (large, international, mature firms) and growth, young, small firms. Experienced analysts cover firms that are characterized by a large capitalization, a high institutional ownership, a high ownership breadth, a high level of free cash flows, a high analyst coverage but a low asset growth, a low sales growth, a low level of external financing, low accruals, low bid-ask spread and low stock return volatility.

Blue Chip Index

Our findings (reported in Table 3.5) indicate that the profile of the firms covered by the different analysts is linked to their experience. Our exploratory analysis shows that experienced analysts cover firms that are larger and more mature. So far, we have explored the relationship between analyst's experience and each of the firm characteristics separately. We turn to Principal Component Analysis (PCA hereafter) to determine a measure of firms' profile. This methodology permits to characterize the common factors across firms. Our assumption is that one of these factors, if not the most important factor, is a proxy for firm maturity. The purpose of PCA is to reduce the dimensionality of the data space. In the smaller space, interpreting the

data is easier. Formally, PCA is a change of basis which permits to locate firms on a meaningful system of coordinates.¹⁴ The first principal component is the linear combination of the initial variables that maximizes the variance of the projection of the observations on these principal components (*i.e.*, so that it accounts for as much of the variability in the data as possible). The second component is the linear combination of the different variables which maximized the variance under the condition that it is orthogonal to the first component, and so on. If the different variables are perfectly correlated, the first component would explain 100% of the variance. On the contrary, if the different variables are uncorrelated, each component would explain the same amount of the variance (one divided by the number of variables).

In our analysis, an individual is a firm-year while the variables are the ones used in the univariate tests (see Appendix for a full description). The first eigenvalue is 2.7425; it implies that $2.7425/12 = 22.85\%$ of the total variation in the firm characteristics can be explained by a single common factor. The second component explains about 20.37% of the total variation. Figure 3.1 shows how the different variables contribute to the first and the second components. Along the first axis, we have, on one side, the variables that characterize blue chips (Capitalization, Analyst coverage, Ownership breadth and Free cash flow) while we have, on the other side, the variables that characterized small, young, growth firms (External financing, Stock return volatility, Asset growth, Sales growth and Bid-ask spread). Note that the contribution of the variables Accruals, Book-to-market and Institutional ownership is too small to be taken into account. Our measure, called the Blue Chip Index (BCI),

¹⁴Our PCA is performed on the correlation matrix due to the heterogeneity of the variables.

is defined as the projection of the firms on the first component of the PCA. As an illustration of our methodology, Table 3.6 provides the year and the name of the firm for the 50 observations with the highest BCI values and the 50 observations with the lowest BCI values. Not surprisingly, we find Dow Jones components like Microsoft, Intel, Pfizer and Johnson & Johnson among the firms with the highest BCI values.

We adopt the following specification to measure the relationship between analysts' experience and the BCI of the firms they cover

$$BCI_{ijt} = \alpha + \beta_1 GEXP_{it} + \beta_2 NF_{it} + \beta_3 DES_{it} + year_t \text{ effects} + industry_{jt} \text{ effects} + \epsilon_{ijt}, \quad (3.12)$$

where BCI_{ijt} is the Blue Chip Index value of firm j covered by analyst i for year t , $GEXP_{it}$ is the general experience of analyst i for year t , NF_{it} is the number of firms covered by analyst i during year t , DES_{it} is a dummy variable that takes the value 1 if analyst i 's employer is in the top decile size, $year_t \text{ effects}$ is a set of dummies for each year of the sample and $industry_{jt} \text{ effects}$ is a set of dummies for each industry.¹⁵

The coefficient of interest for us is β_1 which measures whether experienced analysts cover mainly blue chips firms. We include year effects in the regression specification in order to control for potential time-varying factors that would influence the BCI value of the firms covered. Because analysts typically specialize in a couple of industries and because the level of analysts' experience influences the choice of the industries she covers, we include industry effects. The inclusion of industry effects allows us to

¹⁵Note that for a given analyst, we only consider the firms she covers.

control for differences of BCI between the different industries and therefore guarantees that the industries covered do not have an impact on the relationship between analyst's experience and BCI. Table 3.7 reports the results of the regression. The coefficient for *GEXP* is positive and significant. This result suggests that experienced analysts cover firms with higher BCI values. The coefficient for *NF* is significant and takes the value -0.0089 . This means that analysts who cover a large number of firms follow young, growth firms. This result seems logical. Blue chips tend to have a complex organization. Thus, covering a blue chip takes more time than covering a young, growth firm. Covering blue chips constrains the capacity of the analyst to cover a large number of different firms. Finally, analysts who work for a large employer tend to cover firms that are large, more international and more mature. The coefficient for *DES* is positive and significant. This is in line with our hypothesis that smaller brokerage firms specialize in growth, young firms where the competition with large investment banks is lower.

3.5 Target prices quality and analysts' characteristics

In this section, we study the relationship between analysts' characteristics and their ability to forecast future stock prices. Given our previous results, we design our empirical analysis to account for differences in the type of firms covered by experienced analysts and inexperienced analysts.

3.5.1 Measuring target price quality

The most popular measure of accuracy in the target prices literature is the absolute forecast error; it is equal to the ex-post deviation between the realized stock price and the target price, scaled by the stock price at the issue date. Formally, the accuracy measure is defined as

$$|TPERROR|_t = \frac{|S_T - \Phi_{t,T}|}{S_t}, \quad (3.13)$$

where $\Phi_{t,T}$ is the value of a target price issued at time t with horizon T , S_T is the stock price at the end of the forecast horizon and S_t is the stock price at the time the forecast was issued.

Despite its wide use in the literature, this measure of accuracy has a number of drawbacks and is not well suited to evaluate whether a forecast is better than another or whether an analyst is better than her peers. Roger and Fontaine (2013) raise a major concern regarding its use for evaluating the ability of financial analysts to issue accurate target prices. They show that there exists a mechanical relationship between the accuracy of a target price and the volatility of the underlying stock. This mechanical relationship implies that target prices issued on volatile stocks have lower accuracy, regardless of the ability of the analyst issuing the forecasts. Furthermore, the relationship between accuracy and volatility is nonlinear. It follows that adding volatility as a control in regressions does not permit to circumvent the issue. Our previous findings indicate that the type of firms covered depends on the analysts' characteristics. In particular, experienced analysts tend to cover firms that are less volatile than the firms covered by inexperienced analysts. These differences in coverage could drive the relationships between accuracy and analysts' characteristics and

mask whether some analysts are better than others. In order to analyze the influence of analysts characteristics on their ability to issue accurate target prices, we thus choose to use the measure of target price quality of Roger and Fontaine (2013) which accounts for both the target price accuracy and the target price predictability (*i.e.*, the volatility and the horizon).

The idea behind the measure is that the mechanical relationship between accuracy and volatility reflects a more general link between accuracy and predictability. The difficulty of issuing a target price is not the same for all stocks (in other words, predictability varies across stocks) and can be estimated by taking the expected value of the absolute forecast error $E_t [|S_T - \Phi_{t,T}|]$. The *ex-post* measure of quality $\gamma_{t,T}$ of Roger and Fontaine (2013) is defined as the abnormal absolute forecast error $E_t [|S_T - \Phi_{t,T}|] - |S_T - \Phi_{t,T}|$. They show that it is possible, by applying option-pricing theory, to obtain a good estimation of the expected value of the absolute forecast error at the time the target price is issued. The use of option-pricing theory also permits to circumvent several technical drawbacks of the accuracy measure: (1) we are able to measure the quality of a target price at any date rather than *ex-post* only; (2) it controls for differences in volatility; (3) it accounts for the horizon of the forecast; (4) it rewards bold and timid forecasts differently; and, (5) it permits a clean treatment of target price revisions.

3.5.2 Results

The literature on earnings forecasts evidences that forecast accuracy is positively associated with experience (Mikhail, Walther, and Willis, 1997; Clement, 1999), neg-

atively associated with the number of firms followed (Clement, 1999) and positively related to the size of the brokerage firm where the analysts is employed (Clement, 1999; Jacob, Lys, and Neale, 1999). We expect to find the same kind of relationships between target price quality and analysts' characteristics. Although Bilinski, Lyssimachou, and Walker (2013) find a positive association between accuracy and experience, it is unclear whether this result will hold when taking into account both the differences in coverage decisions and the predictability of target prices.

The empirical specification of our multivariate regression is

$$\gamma_{ijt} = \alpha + \beta_1 GEXP_{it} + \beta_2 NF_{it} + \beta_3 DES_{it} + \text{firm-year}_{jt} \text{ effects} + \epsilon_{ijt}, \quad (3.14)$$

where γ_{ijt} is the *ex-post* quality (as defined in Roger and Fontaine, 2013) of a target price issued by analyst i on firm j at time t with horizon T , $GEXP_{it}$ is the general experience of analyst i for year t , NF_{it} is the number of firms covered by analyst i during year t , DES_{it} is a dummy variable that takes the value 1 if analyst i 's employer is in the top decile size, and *firm-year_{jt} effects* is a set of dummies for each year and each firm of the sample.

Results from the estimation are reported in Table 3.8. As predicted, the coefficient for GEXP is positive and significant. This coefficient takes the value 0.0003. An analyst who has fifteen years of experience (the 90th percentile value) will have an expected quality that is 0.0042 greater than an analyst who has one year of experience (the 10th percentile value). Although the coefficient is statistically significant, it is economically weak (the standard deviation of the quality is equal to 0.3855). The coefficient for NF_{it} is significant and takes the value 0.0002. This means that an

analyst who covers 24 firms (the 90th percentile value) will have an expected quality that is 0.0033 greater than an analyst who covers only five firms (the 10th percentile value). Finally, the coefficient for DES_{it} is negative and significant. This result indicates that the target price quality of analysts working for large brokerage firms is 0.0119 smaller than analysts working for other brokerage firms. The results for the task complexity (number of firms followed) and the resources available (employer size) are surprising and not in line with what can be observed for earnings forecasts. However, the strength of the relationship between analysts' characteristics and target price quality appears weak (although statistically significant).

3.6 Conclusion and discussion

Using a large database of target prices, we show that experienced analysts and inexperienced analysts do not follow the same type of firms. Experienced analysts tend to cover blue chips while inexperienced analysts cover mainly small, young, growth firms. Controlling for differences in coverage decisions, we analyze the influence of analysts' experience, the number of firms they follow and employer size on the ability of financial analysts to issue accurate target prices. In line with previous results on earnings forecasts, we find that experienced analysts issue better target prices. However, and contrary to what is obtained for earnings forecasts, we find that the quality of target prices increases with the number of firms followed and decreases with the employer size. We stress out that, although our results are statistically significant, the economic impact of analysts' characteristics on forecasting ability appears weak.

The empirical evidence that experience influences coverage decisions has impor-

tant consequences for the study of analysts' forecasting activity. We discuss below the possible implications of such differences in coverage decisions.

The fact that inexperienced analysts cover a different type of firms than their more experienced colleagues shed a new light on some results previously obtained in the literature. For instance, Hong, Kubik, and Solomon (2000) indicate that their forecast accuracy measure is likely to be impacted by the number of analysts covering a firm and the number of firms covered by the analyst. They warn against the fact that analysts who cover few firms are more likely to obtain extreme values of forecast accuracy. Similarly, analysts who cover thinly followed firms are more likely to be in the extremes. Inexperienced analysts follow fewer companies than their older colleagues and they tend to cover firms that are thinly followed. As a consequence, they are much more likely to obtain extreme values of forecast accuracies than experienced analysts.

These differences in coverage decisions may also have consequences for the study of analysts' career outcomes. In Hong, Kubik, and Solomon (2000), an analyst faces a positive career outcome if she transfers to a larger brokerage firm and faces a negative career outcome if she moves to a smaller firm or if she gets fired. This assumption may hold for experienced analysts but not for inexperienced analysts. Indeed, if the negative career outcomes are the same for both types of analysts, the positive career outcomes might differ. Rather than moving to a larger brokerage firm, an inexperienced analyst may be promoted by getting assigned to blue chips (while staying at the same brokerage firm). If this is the case, overlooking the issue of differences in coverage decisions related to experience would lead to conclude that

inexperienced analysts are less likely to get promoted.

Firm-specific experience, defined as the number of years for which an analyst made forecasts for a specific firm, is often seen as a good proxy for analyst ability (some researchers even argue that firm-specific experience should be used instead of general experience). We discuss here, in light of the results on differential coverage obtained in this paper, whether firm-specific experience does necessarily measure analyst ability. Let us assume that analysts start their career by covering small, young, growth firms (*i.e.*, firms that do not attract a lot of attention from market participants) and that the most successful analysts are gradually assigned to blue chip firms. It would follow that the firm-specific experience needs to be interpreted with respect to the profile of the firms covered. While a high-level of firm-specific experience associated with a blue chip may be linked to analyst ability (or success), a similar level of firm-specific experience for a small, growth firm might indicate that the analyst is not skilled enough to get assigned to blue chips. Obviously, because the firm-specific experience is highly correlated with the general experience (by construction, the general experience is at least equal to the firm-specific experience), the unconditional relationship between firm-specific experience and analyst ability is expected to be positive. Indeed, in order to have a high level of firm-specific experience for a given firm, an analyst needs to have at least the same level of general experience, which biases the sample of analysts with high firm-specific experience towards high ability analysts (analysts that manage to stay in the profession for a long time). However, a low level of firm-specific experience is not necessarily informative. It can mean either that the analyst just entered the profession (and therefore has a lower ability) or that

she just got assigned to different firms (which can be a sign of ability if these firms are large, international, mature firms). It follows that firm-specific experience should always be interpreted with regards to the level of general experience.

These differences in coverage decisions may also explain another finding of Hong, Kubik, and Solomon (2000). Their results indicate that experienced analysts issue more timely forecasts and proceed to less frequent revisions. In theory, an analyst should adjust her earnings forecast as soon as she receives new information leading to changes in her evaluation of the future earnings. However, this is not the case in practice; analysts revise their forecast only a couple of times during the fiscal year. There are two reasons why revising forecast frequently may not be the best strategy. The first reason is the benefit cost ratio associated with a revision. Each time an analyst decides to revise her forecast, she needs to provide written motivation of her reasons to do so. It follows that revising a forecast is a time-demanding action. Thus, the analyst has some incentives to delay her revision until the discrepancy between her initial forecast and her new evaluation is large enough. The second reason is reputation. An analyst who would revise her forecasts very frequently would appear as uncertain (lacking of confidence) about her evaluation of the future earnings. The optimal strategy for revising forecasts is therefore a trade-off between accuracy and low frequency of revisions. We could formalize the analyst's choice as follows. A revision occurs as soon as the distance between the initial forecast and the current estimation is higher than a predetermined value. This rule of thumb implies that an analyst revises more often her forecasts on a firm with high volatile earnings. Because inexperienced analysts cover young, growth firms with volatile

earnings, they tend to revise their forecasts more frequently.¹⁶ Indeed, high earnings volatility increases the probability that the distance between the initial forecast and the current estimation exceeds the predetermined threshold. A similar logic could apply to provide an explanation to the fact that inexperienced analysts issue their final forecasts later during the fiscal year than experienced analysts (who issue more timely forecasts).

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¹⁶This revision process can be compared to the adjustment mechanism of a dynamic hedging strategy. Given potential transaction costs, a hedging strategy on a volatile price process needs to be adjusted often in order to keep the risk acceptable.

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Appendix

Variable	Description
Capitalization	Market capitalization of common equity (in billions of dollars).
Book-to-market ratio	Book-to-market ratio, calculated as the ratio of the book value to the market value of common equity.
Free cash flow	Free cash flow scaled by average total assets.
External financing	External financing scaled by average total assets.
Institutional ownership	Fraction of outstanding shares owned by institutional investors.
Ownership breadth	Ratio of the number of institutional investors who hold a long position in the stock to the total number of institutional investors covered in the Thomson database for that quarter.
Asset growth	Average asset growth over the past five years.
Sales growth	Average sales growth over the past five years.
Accruals	Total accrual as calculated in Richardson, Sloan, Soliman, and Tuna (2006).
Analyst coverage	Number of analysts issuing earnings forecasts for a given firm.
Stock return volatility	6-month historical stock return volatility.
Bid-ask spread	Bid-ask spread divided by bid-ask midpoint.

Figure 3.1
Projection of firms' characteristics variables on the two first components of the PCA

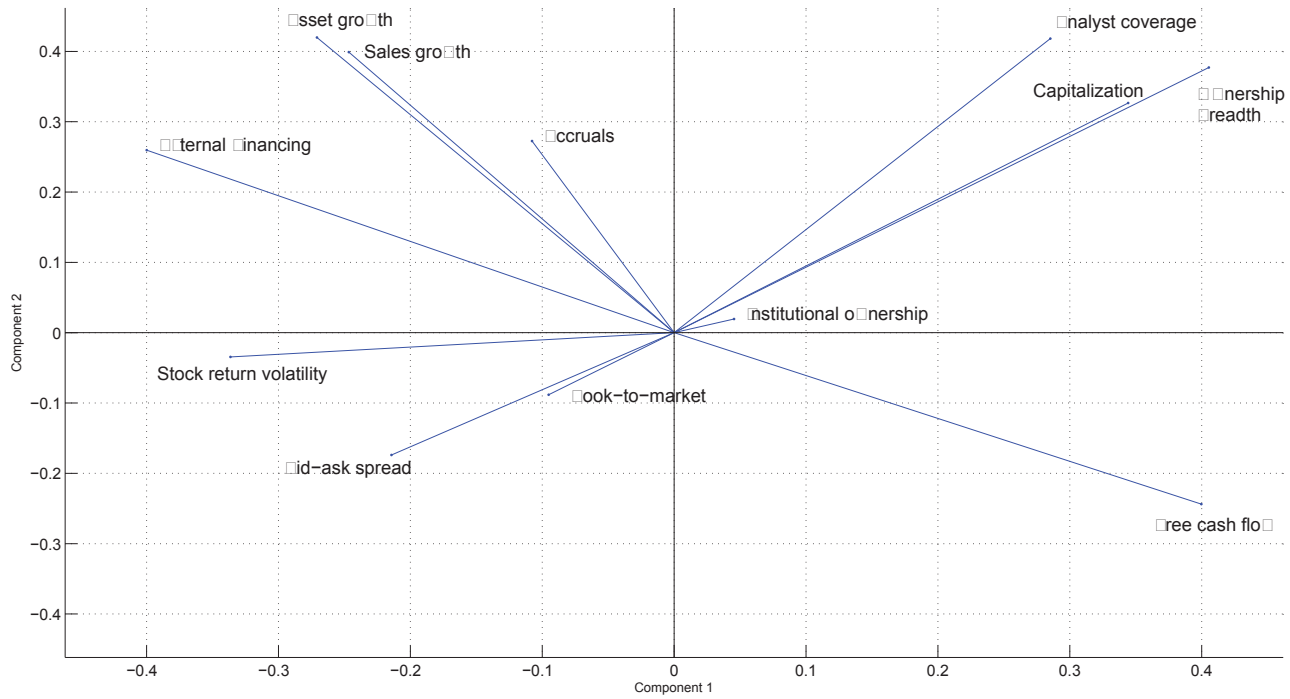


Table 3.1
Descriptive statistics

	Number of forecasts	Number of active analysts	Number of analysts covering a stock			Number of stocks covered per analyst		
			Mean	Median	Max	Mean	Median	Max
2000	36,825	-	-	-	-	-	-	-
2001	44,178	4,466	6.30	4.00	50.00	6.38	4.00	213.00
2002	48,756	4,611	7.10	5.00	50.00	6.31	4.00	183.00
2003	51,263	4,342	7.22	5.00	55.00	6.61	4.00	102.00
2004	54,863	3,773	6.54	4.00	44.00	7.16	5.00	64.00
2005	56,291	3,731	6.67	5.00	51.00	7.72	6.00	76.00
2006	59,952	3,800	6.82	5.00	45.00	7.97	6.00	87.00
2007	65,377	3,768	7.00	5.00	46.00	8.42	7.00	100.00
2008	77,281	3,829	7.53	6.00	46.00	8.59	7.00	92.00
2009	75,275	3,833	8.00	6.00	50.00	8.48	7.00	81.00
2010	79,410	3,908	8.69	6.00	59.00	8.47	7.00	79.00

The sample consists in a total of 649,471 target prices made by 9,367 analysts (583 brokers) on 7,268 U.S. stocks for the 2000-2010 period. The first column indicates the number of target prices issued each year. The second column shows the number of active analysts. The three following columns report the average, median and maximum number of active analysts per stock. The remaining columns indicate the average, median and maximum number of stocks covered per analyst. The statistics for 2000 are not reported as the target prices issued in 1999 and still active in 2000 cannot be observed.

Table 3.2
Experience and joint coverage

	Intergroup Excess Joint Coverage (<i>IEJC</i>)				
	Group 1 (High experience)	Group 2	Group 3	Group 4	Group 5 (Low experience)
Group 1 (High experience)	0.0727***	0.0651***	0.0485***	0.0137	-0.0260**
Group 2		0.0793***	0.0568***	0.0256	-0.0205**
Group 3			0.0594***	0.0354***	-0.0104
Group 4				0.0247	-0.0091
Group 5 (Low experience)					-0.0129
Average number of firms covered	9.9385	9.7565	9.5924	8.3651	4.7172

This table presents the Intergroup Excess Joint Coverages (*IEJC*) between five different groups of analysts. The first group is composed of the most experienced analysts (at least 16 years of experience). The second group is characterized by a level of experience between 12 years and 16 years. The third group is characterized by a level of experience between 8 years and 12 years. The fourth group is characterized by a level of experience between 4 years and 8 years. The fifth group of analysts is composed of the inexperienced analysts (between 0 and 4 years). Intergroup Excess Joint Coverage is positive (negative) if the degree of joint coverage between the two groups is higher (lower) than what is observed in the whole population. ***/**/* indicate that the Intergroup Excess Joint Coverage is different from zero at the 1%/5%/10% significance levels.

Table 3.3
Multivariate analysis: Joint coverage and experience

	Standardized joint coverage			
	Coefficient	Standard error	t-statistic	p-value
Pair Experience Differential (<i>PED</i>)	-0.0054***	0.000240	-22.46	0.000
Pair Average Experience (<i>PAE</i>)	0.0076***	0.000374	20.43	0.000
Number of firms followed by analyst <i>i</i>	0.0019***	0.000148	12.71	0.000
Number of firms followed by analyst <i>j</i>	0.0020***	0.000149	13.25	0.000
Year dummies		Yes		
Number of observations		5,500,000		
R-squared		0.0015		

This table shows the coefficient estimates (Coefficients) from the following OLS regression: $sjc_{ijt} = \alpha + \beta_1 PED_{ijt} + \beta_2 PAE_{ijt} + \beta_3 n_{it} + \beta_4 n_{jt} + year_t \text{ effects} + \epsilon_{ijt}$, where sjc_{ijt} is the standardized joint coverage between analysts i and j for year t , PED_{ijt} is the absolute value of the difference between the level of experience of analyst i and the level of experience of analyst j , PAE_{ijt} is the average level of experience of the pair of analysts i and j , n_{it} (n_{jt}) is the number of firms covered by analyst i (respectively j) during year t and $year_t \text{ effects}$ is a set of dummies for each year of the sample. ***/**/* correspond to 1%/5%/10% significance levels. P-values are computed using robust standard errors.

Table 3.4
Proportion of forecasts (target prices) per sector

Panel A: Proportion of forecasts per sector (all analysts)											
SIG Sectors	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Finance	0.1439	0.1527	0.1626	0.1890	0.1832	0.1887	0.1837	0.1860	0.1828	0.1682	0.1602
Health	0.1011	0.1041	0.1133	0.1172	0.1095	0.1194	0.1098	0.1079	0.0978	0.1030	0.1009
Consumer non-durables	0.0381	0.0362	0.0374	0.0383	0.0363	0.0389	0.0417	0.0431	0.0398	0.0501	0.0463
Consumer services	0.1874	0.1840	0.1875	0.1708	0.1757	0.1597	0.1614	0.1519	0.1490	0.1453	0.1527
Consumer durables	0.0249	0.0230	0.0279	0.0303	0.0274	0.0306	0.0287	0.0229	0.0205	0.0186	0.0221
Energy	0.0755	0.0760	0.0638	0.0650	0.0809	0.0880	0.0762	0.0902	0.1155	0.1041	0.1080
Transportation	0.0195	0.0180	0.0176	0.0217	0.0232	0.0224	0.0261	0.0295	0.0263	0.0295	0.0319
Technology	0.2517	0.2638	0.2402	0.2076	0.2141	0.2006	0.2091	0.1969	0.1965	0.1891	0.1866
Basic industries	0.0442	0.0360	0.0387	0.0489	0.0466	0.0508	0.0561	0.0555	0.0547	0.0623	0.0611
Capital goods	0.0506	0.0498	0.0566	0.0609	0.0591	0.0603	0.0690	0.0759	0.0780	0.0860	0.0862
Public utilities	0.0631	0.0563	0.0544	0.0503	0.0440	0.0405	0.0381	0.0402	0.0392	0.0437	0.0440

Panel B: Difference of the proportions of forecasts per sector between low experience and high experience analysts											
SIG Sectors	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Finance	0.0650	0.0603	0.0535	0.0304	0.0290	0.0400	0.0539	0.0090	-0.0023	-0.0166	-0.0275
Health	-0.0288	0.0199	0.0088	0.0164	0.0239	0.0345	0.0366	0.0288	0.0360	0.0259	0.0315
Consumer non-durables	-0.0221	-0.0163	-0.0148	-0.0284	-0.0084	0.0103	0.0031	0.0076	0.0023	0.0069	0.0054
Consumer services	0.0114	-0.0309	-0.0522	-0.0766	-0.0400	-0.0237	-0.0316	-0.0410	-0.0213	-0.0134	-0.0330
Consumer durables	-0.0133	-0.0143	-0.0088	-0.0021	0.0014	-0.0008	-0.0063	-0.0015	-0.0109	-0.0079	-0.0028
Energy	0.0353	0.0083	0.0279	0.0280	-0.0075	-0.0291	-0.0027	0.0375	0.0453	0.0339	0.0366
Transportation	-0.0008	-0.0008	-0.0106	-0.0013	-0.0058	-0.0062	-0.0114	0.0079	0.0210	0.0127	0.0193
Technology	0.0563	0.0431	0.0616	0.0859	0.0630	0.0353	0.0385	0.0168	-0.0122	-0.0151	-0.0159
Basic industries	-0.0494	-0.0391	-0.0377	-0.0136	-0.0256	-0.0355	-0.0491	-0.0285	-0.0310	-0.0282	-0.0248
Capital goods	-0.0117	-0.0095	-0.0212	-0.0260	-0.0124	-0.0158	-0.0272	-0.0274	-0.0043	0.0203	0.0232
Public utilities	-0.0421	-0.0207	-0.0066	-0.0126	-0.0177	-0.0090	-0.0039	-0.0093	-0.0226	-0.0187	-0.0120

This table provides, for each year of the 2000-2010 period, the proportion of target prices issued for each sector. We define 11 different sectors with respect to the SIG (Sector Industry Group) classification provided by I/B/E/S. Each year, we assign, with respect to their experience (GEXP), the analysts to five quintiles. Panel B provides the difference of the proportions of forecasts per sector between the first quintile (inexperienced analysts) and the fifth quintile (high experience analysts).

Table 3.5
Experience and firm characteristics

Panel A: Capitalization (in billions of dollars)											
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Quintile 1 (Low experience)	10.0219	7.5959	7.8234	7.0737	6.2186	6.6503	7.5951	8.3945	6.7724	7.2611	9.2102
Quintile 3	12.6125	9.6389	7.6874	8.3234	9.5545	10.1233	10.8323	12.5050	9.8305	8.7595	10.3386
Quintile 5 (High experience)	15.4122	11.4323	10.4372	9.8322	10.6347	10.1736	11.5971	13.6057	11.1543	9.3420	11.6554
Panel B: Book-to-market											
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Quintile 1 (Low experience)	0.4385	0.5140	0.5803	0.5065	0.4155	0.4104	0.4243	0.4510	0.6265	0.7934	0.5480
Quintile 3	0.4433	0.5360	0.5574	0.5177	0.4123	0.3948	0.3886	0.4274	0.6404	0.7835	0.5591
Quintile 5 (High experience)	0.4624	0.5106	0.5353	0.5276	0.4380	0.4040	0.4019	0.4616	0.6791	0.8087	0.5759
Panel C: Asset growth (average over the past five years)											
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Quintile 1 (Low experience)	0.3158	0.3737	0.3150	0.2691	0.2491	0.2216	0.1784	0.1817	0.2039	0.2009	0.1803
Quintile 3	0.3038	0.3523	0.3282	0.2846	0.2446	0.2219	0.1757	0.1737	0.1928	0.1854	0.1662
Quintile 5 (High experience)	0.2384	0.2654	0.2510	0.2204	0.2012	0.1895	0.1620	0.1494	0.1658	0.1702	0.1509
Panel D: Sales growth (average over the past five years)											
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Quintile 1 (Low experience)	0.2552	0.2957	0.2657	0.2156	0.1899	0.1815	0.1653	0.1732	0.1982	0.1990	0.1618
Quintile 3	0.2537	0.2871	0.2692	0.2345	0.1907	0.1793	0.1580	0.1588	0.1840	0.1854	0.1526
Quintile 5 (High experience)	0.2032	0.2313	0.2155	0.1793	0.1619	0.1678	0.1497	0.1447	0.1618	0.1692	0.1392
Panel E: External financing scaled by average total assets											
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Quintile 1 (Low experience)	0.1691	0.1707	0.0701	0.0330	0.0447	0.0583	0.0508	0.0560	0.0613	0.0264	0.0089
Quintile 3	0.1349	0.1577	0.0749	0.0304	0.0229	0.0433	0.0367	0.0363	0.0317	0.0077	-0.0008
Quintile 5 (High experience)	0.0702	0.0830	0.0500	0.0139	0.0021	0.0175	0.0118	0.0107	0.0200	0.0054	-0.0117
Panel F: Institutional ownership (fraction of outstanding shared)											
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Quintile 1 (Low experience)	0.5505	0.5907	0.6199	0.6296	0.6503	0.6752	0.7064	0.7349	0.7729	0.7262	0.7228
Quintile 3	0.5503	0.5756	0.6249	0.6499	0.6765	0.6953	0.7215	0.7526	0.7743	0.7379	0.7312
Quintile 5 (High experience)	0.5856	0.6106	0.6326	0.6658	0.6821	0.7002	0.7368	0.7678	0.7845	0.7413	0.7347
Panel G: Ownership breadth											
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Quintile 1 (Low experience)	0.1108	0.1089	0.1207	0.1088	0.0964	0.0923	0.0890	0.0841	0.0834	0.0859	0.0940
Quintile 3	0.1172	0.1208	0.1212	0.1197	0.1187	0.1110	0.1083	0.1055	0.1049	0.1007	0.1030
Quintile 5 (High experience)	0.1483	0.1350	0.1386	0.1342	0.1322	0.1181	0.1145	0.1115	0.1084	0.1043	0.1075

Table 3.5 (Continued)

	Panel H: Accruals (calculated as in Richardson, Sloan, Soliman and Tuna, 2006)										
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Quintile 1 (Low experience)	0.1650	0.1956	0.1033	0.0433	0.0495	0.1094	0.1032	0.0985	0.0862	0.0400	0.0253
Quintile 3	0.1311	0.2050	0.1044	0.0506	0.0512	0.1032	0.0944	0.0880	0.0727	0.0234	0.0170
Quintile 5 (High experience)	0.0849	0.1291	0.0802	0.0431	0.0433	0.0802	0.0822	0.0661	0.0588	0.0244	0.0174
	Panel I: Free cash flow scaled by average total assets										
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Quintile 1 (Low experience)	-0.1110	-0.0970	-0.0441	-0.0199	-0.0175	-0.0362	-0.0299	-0.0364	-0.0284	-0.0104	0.0140
Quintile 3	-0.1029	-0.0975	-0.0448	-0.0110	0.0039	-0.0210	-0.0174	-0.0182	-0.0092	0.0068	0.0192
Quintile 5 (High experience)	-0.0467	-0.0411	-0.0259	0.0049	0.0183	-0.0027	-0.0013	-0.0007	-0.0048	0.0092	0.0303
	Panel J: Analyst coverage (Number of analysts)										
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Quintile 1 (Low experience)	13.9991	13.6173	14.6555	14.2127	13.5507	12.9555	13.0934	13.1215	13.8009	15.3138	16.9309
Quintile 3	14.6601	15.4064	15.2522	14.9689	15.2388	15.4390	15.0124	15.2732	15.3982	16.4715	17.7310
Quintile 5 (High experience)	15.4380	15.4668	15.0176	15.4634	15.6193	15.1459	14.8578	14.5976	14.9671	15.7892	17.4266
	Panel K: 6-month historical stock return volatility										
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Quintile 1 (Low experience)	0.7295	0.6508	0.5506	0.4453	0.3749	0.3428	0.3547	0.3607	0.6236	0.7434	0.4087
Quintile 3	0.6823	0.7045	0.5802	0.4390	0.3614	0.3408	0.3541	0.3459	0.5870	0.7236	0.3926
Quintile 5 (High experience)	0.6196	0.6131	0.5122	0.4214	0.3202	0.3096	0.3232	0.3180	0.5626	0.7246	0.3805
	Panel L: Bid ask spread										
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Quintile 1 (Low experience)	0.0125	0.0085	0.0074	0.0038	0.0021	0.0020	0.0017	0.0022	0.0043	0.0024	0.0013
Quintile 3	0.0131	0.0088	0.0077	0.0036	0.0017	0.0016	0.0015	0.0018	0.0033	0.0024	0.0013
Quintile 5 (High experience)	0.0138	0.0090	0.0074	0.0036	0.0016	0.0017	0.0014	0.0017	0.0034	0.0024	0.0013

Analysts are assigned to five quintiles with respect to their general experience (*GEXP*). The different firm characteristics are: (1) the capitalization; (2) the book-to-market ratio; (3) the free cash flow scaled by average total assets; (4) the external financing scaled by average total assets; (5) the institutional ownership (measured as the fraction of outstanding shares owned by institutional investors); (6) the ownership breadth; (7) the asset growth rate (average over the past five years); (8) the sales growth rate (average over the past five years); (9) the level of accruals (as calculated in Richardson, Sloan, Soliman and Tuna, 2006); (10) the analyst coverage (number of analysts issuing EPS forecasts for a given firm); (11) the 6-month historical stock return volatility; and, (12) the bid-ask spread.

Table 3.6 Firms-years with the highest and the lowest degrees of maturity

Firm-year with highest scores		Firm-year with lowest scores	
Firm-year	Degree of maturity	Firm-year	Degree of maturity
INTEL CORP (2000)	12.6909	R H DONNELLEY CORP (2003)	-6.0307
MICROSOFT CORP (2007)	12.6284	ENCORE MEDICAL CORP (2005)	-6.0320
MICROSOFT CORP (2006)	12.4193	CREE RESEARCH INC (2001)	-6.0995
CISCO SYSTEMS INC (2000)	11.6855	M G I PHARMA INC (2005)	-6.2053
MICROSOFT CORP (2000)	11.5085	CELERITEK INC (2001)	-6.2071
MICROSOFT CORP (2008)	11.3425	WINSTAR COMMUNICATIONS INC (2001)	-6.2722
MICROSOFT CORP (2005)	11.1387	ATLAS PIPELINE PARTNERS L P (2009)	-6.2992
MICROSOFT CORP (2004)	11.0327	LIVEWIRE MOBILE INC (2001)	-6.3421
MICROSOFT CORP (2003)	10.6746	KRAUSES FURNITURE INC (2000)	-6.3461
MICROSOFT CORP (2001)	10.6702	N T E L O S INC (2001)	-6.3552
MICROSOFT CORP (2002)	10.3810	FLOTEK INDUSTRIES INC (2009)	-6.4056
PFIZER INC (2004)	10.1553	FUELCELL ENERGY INC (2002)	-6.4404
MICROSOFT CORP (2010)	9.9800	S D L INC (2001)	-6.4439
PFIZER INC (2003)	9.8998	NETWORK PERIPHERALS INC (2001)	-6.4661
PFIZER INC (2001)	9.8652	INAMED CORP (2000)	-6.5373
MICROSOFT CORP (2009)	9.2742	C T C COMMUNICATIONS GROUP INC (2001)	-6.6238
JOHNSON & JOHNSON (2005)	8.8281	DRYSHIPS INC (2009)	-6.6911
INTEL CORP (2005)	8.7683	EDGE PETROLEUM CORP DEL (2008)	-6.7432
PFIZER INC (2002)	8.7629	P C GROUP INC (2008)	-6.7566
JOHNSON & JOHNSON (2006)	8.6651	MIDCOAST ENERGY RESOURCES INC (2001)	-6.7753
INTEL CORP (2004)	8.5916	MCMORAN EXPLORATION CO (2008)	-6.8263
ORACLE SYSTEMS CORP (2000)	8.4798	MOVIE GALLERY INC (2006)	-6.8419
INTERNATIONAL BUSINESS MACHS CO (2000)	8.4263	DELTA PETROLEUM CORP (2009)	-6.8564
INTEL CORP (2003)	8.3915	CEPHALON INC (2000)	-6.8623
JOHNSON & JOHNSON (2002)	8.3558	CYTOGEN CORP (2004)	-6.8832
PFIZER INC (2000)	8.3205	NEWPORT CORP (2001)	-6.8905
JOHNSON & JOHNSON (2004)	8.2577	COR THERAPEUTICS INC (2001)	-6.8910
A T & T INC (2007)	8.2373	ODETICS INC (2002)	-6.9627
JOHNSON & JOHNSON (2003)	8.2176	T X C O RESOURCES INC (2009)	-7.0357
CISCO SYSTEMS INC (2006)	8.2119	ALLIED WASTE INDUSTRIES INC (2000)	-7.0696
MERCK & CO INC NEW (2000)	8.1834	SILICON STORAGE TECHNOLOGY INC (2001)	-7.1016
INTERNATIONAL BUSINESS MACHS CO (2010)	8.1826	ANAREN MICROWAVE INC (2001)	-7.1452
INTEL CORP (2001)	8.1567	EMCORE CORP (2001)	-7.1652
PFIZER INC (2007)	8.0892	ATLAS ENERGY L P (2009)	-7.2329
INTEL CORP (2006)	8.0714	AUTHENTIDATE HOLDING CORP (2005)	-7.3091
PFIZER INC (2005)	8.0394	COMTECH TELECOMMUNICATIONS CORP (2001)	-7.5640
JOHNSON & JOHNSON (2001)	7.9944	N T L INC (2001)	-7.6098
JOHNSON & JOHNSON (2010)	7.9927	EXCEL MARITIME CARRIERS LTD (2006)	-7.7005
APPLE COMPUTER INC (2010)	7.9795	ATLAS ENERGY INC (2008)	-7.7382
INTEL CORP (2007)	7.9713	APPLIED MICRO CIRCUITS CORP (2001)	-7.9006
MERCK & CO INC NEW (2001)	7.9261	ENCYYSIVE PHARMACEUTICALS INC (2008)	-7.9251
INTERNATIONAL BUSINESS MACHS CO (2001)	7.8968	MILLENNIUM PHARMACEUTICALS INC (2001)	-8.0619
PROCTER & GAMBLE CO (2006)	7.8965	HANGER ORTHOPEDIC GROUP INC (2000)	-8.0697
PFIZER INC (2006)	7.8961	ATLAS PIPELINE PARTNERS L P (2008)	-8.0836
PROCTER & GAMBLE CO (2010)	7.8671	ENZON INC (2001)	-8.1188
PROCTER & GAMBLE CO (2007)	7.8381	EMULEX CORP NEW (2000)	-8.1548
JOHNSON & JOHNSON (2008)	7.8028	RURAL CELLULAR CORP (2001)	-8.2124
CISCO SYSTEMS INC (2005)	7.7962	PSINET INC (2000)	-8.6630
JOHNSON & JOHNSON (2007)	7.7680	PHOTON DYNAMICS INC (2001)	-9.9450
INTEL CORP (2002)	7.7574	RADIO ONE INC (2008)	-12.0359

This table provides the name and year of the 50 observations (firm-year) with the highest degree of maturity and the 50 observations with the lowest degree of maturity. The degree of maturity is computed using the first component from a Principal Component Analysis performed on the following firm characteristics: (1) Capitalization; (2) Book-to-market ratio; (3) Free cash flow scaled by average total assets; (4) External financing scaled by average total assets; (5) Institutional ownership (the fraction of outstanding shares owned by institutional investors); (6) Ownership breadth; (7) Asset growth (average over the past five years); (8) Sales growth (average over the past five years); (9) Accruals (as calculated in Richardson, Sloan, Soliman and Tuna, 2006); (10) Analyst coverage (number of analysts issuing EPS forecasts for a given firm); (11) Stock return volatility; and, (12) Bid-ask spread. The sample period is 2000-2010.

Table 3.7 Multivariate analysis: analysts' characteristics and firms covered

	Blue Chip Index (BCI) of firms covered			
	Coefficient	Standard error	t-statistic	p-value
General Experience (<i>GEXP</i>)	0.0159***	0.002947	5.41	0.000
Number of firms followed (<i>NF</i>)	-0.0089***	0.002139	-4.16	0.000
Dummy Employer size (<i>DES</i>)	0.3458***	0.027448	12.60	0.000
Year dummies		Yes		
Industry dummies		Yes		
Number of observations		143,189		
R-squared		0.2289		

This table shows the coefficient estimates (Coefficients) from the following OLS regression: $BCI_{ijt} = \alpha + \beta_1 GEXP_{it} + \beta_2 NF_{it} + \beta_3 DES_{it} + year_t \text{ effects} + industry_j \text{ effects} + \epsilon_{ijt}$, where $GEXP_{it}$ is the general experience, NF_{it} is the number of firms covered by analyst i during year t , DES_{it} is a dummy variable that takes the value 1 if analyst i 's employer is in the top decile size, $year_t \text{ effects}$ is a set of dummies for each year of the sample and $industry_j \text{ effects}$ is a set of dummies for each industry. ***/**/* correspond to 1%/5%/10% significance levels. P-values are computed from robust analyst-clustered standard errors.

Table 3.8 Multivariate analysis: Target price quality and analysts' characteristics

	Target price quality			
	Coefficient	Standard error	t-statistic	p-value
General Experience (<i>GEXP</i>)	0.0003***	0.000107	2.65	0.008
Number of firms followed (<i>NF</i>)	0.0002***	0.000062	2.82	0.005
Employer size dummy (<i>DES</i>)	-0.0119***	0.001100	-10.81	0.000
Firm-year dummies		Yes		
Number of observations		600,295		
Adj R-squared		0.3673		

This table shows the coefficient estimates (Coefficients) from the following OLS regression: $\gamma_{ijt} = \alpha + \beta_1 GEXP_{it} + \beta_2 NF_{it} + \beta_3 DES_{it} + firm - year_t \text{ effects} + \epsilon_{ijt}$, where $GEXP_{it}$ is the general experience, NF_{it} is the number of firms covered by analyst i during year t , DES_{it} is a dummy variable that takes the value 1 if analyst i 's employer is in the top decile size, $firm-year_t \text{ effects}$ is a set of dummies for each firm and each year of the sample. ***/**/* correspond to 1%/5%/10% significance levels. P-values are computed from robust analyst-clustered standard errors.

Conclusion

The contributions of this PhD dissertation are both methodological and empirical. In the first chapter of this dissertation, we study the herding behavior of individual investors. The main methodological contribution of this chapter is to introduce a measure of herding at the individual level. Using traditional measures of herding behavior, we are able to observe, for a given stock, whether there is an abnormal concentration of investors on either the buy side or the sell side. However, these measures of herding do not allow us to track the herding behavior of a given investor over time. The Individual Herding Measure (IHM) defined in this first chapter fills this gap. This first chapter is the first study on herding behavior focusing on French individual investors. We show that the level of herding behavior for French individual investors is similar to the level observed for individual investors in the U.S. and slightly greater than the level observed for German investors. This chapter contains several empirical results. First, we find that the level of sophistication is inversely related to the level of herding. Second, we establish that adverse past performance increases the propensity to engage into correlated trading. Finally, we show that individual investors do not benefit from herding. Individuals trading against the crowd typically exhibit more extreme returns and lower Sharpe ratios than the rest

of the population. The main limitation of this chapter is that, although we are able to observe how trading is correlated, we do not have any information regarding how individual investors observe their peers' actions. In this regard, our use of the term "herding behavior" should be interpreted in the sense of Devenow and Welch (1996) ("Behavior patterns that are correlated across individuals") rather than in the sense of Bikhchandani and Sharma (2001) ("Actions that were not considered are undertaken because others are doing so and *vice versa*").

The second chapter of this PhD dissertation deals with financial analysts' target prices. This chapter consists in both a theoretical contribution and an empirical analysis. Building on existing evidence from the literature on earnings forecasts that forecast predictability needs to be taken into account when assessing forecast quality, we provide a comprehensive framework for evaluating the quality of target prices. It is common practice in the literature on target prices to consider a target price to be superior to another if it is more accurate. We show, in this second chapter, that the accuracy in itself is not sufficient to assess the quality of a target price as the target price predictability varies across stocks and over time. We show that omitting the issue of predictability (which is a function of the volatility and the forecast horizon) prevents from evaluating correctly the ability of financial analysts to issue accurate target prices. The contributions of our new measure of target price quality are the following: (1) it accounts for differences in predictability (*i.e.* differences in stock return volatility and forecast horizon); (2) it takes into account forecast boldness (*i.e.* how far the analyst's target price is from the current price); and, (3) it can be used both *ex-post* and within a dynamic setting (*i.e.* it is possible to measure the target

price quality at any moment in time). Our empirical analysis focuses on the impact of omitting target price predictability when studying whether financial analysts exhibit persistent differential abilities. We show that the persistent differential abilities found in previous studies can be explained by the fact that the authors use the absolute forecast error as a measure of quality and because there exists a strong non-linear relationship between target price accuracy and stock return volatility. When using our measure of quality, which accounts for differences in predictability, we no longer observe that analysts exhibit persistent differential abilities. A current limitation of our work is that we do not fully exploit the dynamic character of our measure. We restricted most of our analysis to the *ex-post* version of our measure in order to compare our results to previous findings of the literature (which uses solely *ex-post* measures). This dynamic feature can prove useful to both academics and practitioners. For the latter, our measure of quality could be used to generate performance feedbacks at a high frequency.

The third chapter of this dissertation studies the influence of analysts' characteristics such as analyst ability (experience), task complexity (number of firms followed) and resources available (employer size) on target price quality. We first show that these analysts' characteristics have a strong impact on coverage decisions. Our results indicate that experienced analysts cover mainly blue chips while inexperienced analysts focus on young, small, growth firms. These differences in the type of firms covered have important implications in terms of forecasts predictability. Because the stock return volatility of blue chips is typically lower than the volatility of young, small, growth firms, the predictability of target prices issued by experienced analysts

will be higher than the predictability of forecasts made by inexperienced analysts. It follows that it is necessary to consider both the accuracy and the predictability of target prices when evaluating the influence of analysts' characteristics on their ability to issue accurate target prices. We find a positive and statistically significant relationship between the level of experience and the target price quality. However, we note that, although our results are statistically significant, the economic impact of analysts' characteristics on target price quality is very weak.

I briefly conclude by discussing the directions I plan to take for my future research. Note that some of the topics I plan to study were already broached in the conclusion of the third chapter.

The first point in my agenda is to reproduce, using earnings forecasts instead of target prices, the results of the third chapter on the influence of experience on coverage decisions. However, because target prices are often issued in conjunction with earnings forecasts, I do not expect the results to differ much.

Although the research on financial analysts is pretty extensive, our knowledge of how and why analysts choose to cover certain firms is rather limited. Notably, we know little about analysts' preferences for the firms they cover. I intend to study further the way analysts make their coverage decisions, taking into account their personal preferences, incentives, career concerns and the constraints imposed upon them by brokerage firms.

The findings of the third chapter suggest studying the organization of brokerage firms in order to better understand analysts' coverage decisions. The first question to address is whether coverage decisions are homogeneous when considered at the

level of brokerage firms. I plan to study how brokerage firms' characteristics (size, reputation, location...) impact the coverage decisions of their employees. Another direction is to analyze analysts' career concerns within brokerage firms (with the baseline assumption that the most successful analysts are offered to cover blue chips).

The contribution of the second chapter of this dissertation is mainly methodological. My agenda for future research is to build upon this framework and study the determinants of target price quality. Because the ability of financial analysts to issue accurate target prices is closely linked with market efficiency, obtaining a better understanding of how analysts build their (accurate) forecasts is crucial. Another direction for research is to study analysts' motivations when revising target prices. I plan on answering the following questions. When do analysts revise their target prices? Why do they revise them? Do analysts improve their performance by revising often?

A very challenging objective for the future is to adapt the framework of the second chapter to earnings forecasts. In its current state, the literature on earnings forecast employs relative measures of accuracy to control for differences in predictability. An important contribution would therefore be to introduce a methodology that permits a precise estimation of forecast predictability. However, the feasibility of such a measure is unclear as, contrary to target prices, the earnings forecast process is highly discontinuous.

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Abstract: *This dissertation is made of three distinct chapters. In the first chapter, we introduce a new measure of herding that allows for tracking dynamics of individual herding. Using a database of nearly 8 million trades executed between 1999 and 2006 by 87,373 individual investors, we show that individual herding is persistent over time and that past performance and the level of sophistication influence this behavior. We are also able to answer a question that was previously unaddressed in the literature: is herding profitable for investors? Our unique dataset reveals that the investors trading against the crowd tend to exhibit more extreme returns and poorer risk-adjusted performance than the herders. In the second chapter, we show that measuring the accuracy of a target price is not sufficient to assess its quality, because the forecast predictability (which depends on the stock return volatility and on the forecast horizon) is likely to vary across stocks and over time. We argue that the evidence of time persistent differences in analysts' target price accuracy, obtained in previous studies, cannot be interpreted as a proof of persistent differential abilities. Our analysis indicates that the persistence in accuracy is driven by persistence in stock return volatility. We introduce a measure of target price quality that considers both the forecast inaccuracy and the forecast predictability. Using elements from option-pricing theory, we provide a simple solution to the issue of estimating target price predictability. Our empirical analysis reveals that, when forecast predictability is taken into account, financial analysts do not exhibit significant persistent differential abilities to forecast future stock prices. In the third chapter, we show that experienced financial analysts tend to cover different firms than inexperienced analysts. Experienced analysts tend to follow blue chips (i.e., large, international, mature firms) while inexperienced analysts focus on small, young, growth-oriented firms. These differences in coverage decisions imply that inexperienced analysts issue target prices on firms for which stock returns are more volatile, and thus less predictable. As a consequence, the accuracy measure of target prices fails to evaluate differences in ability between experienced and inexperienced analysts. When taking into account these differences in coverage decisions, we still find that experienced analysts do a better job at forecasting stock prices. Our results on the influence of analysts' characteristics on target price quality are statistically significant but economically weak.*

Key words: *Herding, Individual investors, Financial analysts, Target prices, Forecasting quality, Coverage decisions*

Résumé : *Cette thèse de doctorat comporte trois chapitres distincts. Dans le premier chapitre, nous étudions le comportement moutonnier d'investisseurs individuels français. Notre analyse empirique repose sur une base de données de presque 8 millions de transactions réalisées entre 1999 et 2006 par 87 373 investisseurs individuels français. Nous montrons que le comportement moutonnier persiste dans le temps et que la performance passée ainsi que le niveau de sophistication influencent ce comportement. Nous tentons également d'apporter une réponse à une question très peu abordée dans la littérature : adopter un comportement moutonnier est-il profitable pour l'investisseur individuel ? Notre analyse empirique indique que les investisseurs contrariants obtiennent des rendements plus extrêmes (positifs ou négatifs) que les investisseurs moutonniers. Dans le second chapitre, nous montrons que mesurer la précision d'une prévision du prix futur d'une action n'est pas suffisant pour évaluer la qualité de cette prévision car la prévisibilité des prix est susceptible d'évoluer dans le temps et dépend du titre considéré. Nous montrons que la persistance dans les différences individuelles de précision des prévisions d'analystes, mis en avant dans la littérature, ne constitue pas une preuve de différences de compétences entre analystes. Cette persistance est, en réalité, causée par une persistance de la volatilité de la rentabilité des titres. Nous introduisons une mesure de qualité des prévisions qui incorpore à la fois l'erreur de prévision et la prévisibilité du prix. La théorie des options nous fournit les éléments nécessaires à l'estimation de cette prévisibilité. Lorsque celle-ci est prise en compte, il n'y a plus de différences de compétences entre analystes. Dans le troisième chapitre, nous montrons que les analystes expérimentés et inexpérimentés ne couvrent pas le même type d'entreprises. Les analystes expérimentés couvrent des entreprises de type « blue chips » tandis que les analystes inexpérimentés couvrent des entreprises petites, jeunes et en croissance. Ces différences de couvertures impliquent que les analystes inexpérimentés émettent des prévisions de prix sur des entreprises dont les rendements sont plus volatils et donc moins prévisibles. En conséquence, la précision des prévisions n'est pas une bonne mesure pour évaluer si les analystes expérimentés sont meilleurs ou moins compétents que les analystes inexpérimentés. Lorsque ces différences de couvertures sont prises en compte, nous obtenons que les analystes expérimentés émettent néanmoins de meilleures prévisions. Bien que statistiquement significatif, l'impact économique de l'expérience des analystes est faible.*

Mots-clés : *Comportement moutonnier, Investisseurs individuels, Analystes financiers, Prévisions de prix des actions, Qualité de prévision, Décisions de couverture*