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by

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Three essays on portfolio management

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FACULTÉ DES SCIENCES ÉCONOMIQUES

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Neuchâtel, le 26 octobre 2015

La doyenne

Carolina Salva

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“Della critica intelligente e spassionata, io ho sempre approfittato, anzi dirò meglio: mi servì da lezione.”

Vincenzo Vela

Executive Summary

This dissertation is constituted of three distinct chapters. The first two study the information role of sell-side analysts from two specific angles of attack. The first chapter focuses on the investment value of target prices. Based on a sample of more than 590'000 expected return revisions over the 1999-2011 period, I construct tercile portfolios that buy (sell) stocks with the highest (lowest) expected return revisions. The strategy initiated at the end of announcement day and held for a month that is long the highest tercile and short the lowest tercile yields a risk-adjusted performance of 0.48% per month. Similar results are obtained when the expected return revisions are industry or market adjusted. The risk-adjusted return remains significant if the position is initiated five days after the announcement (0.29% per month). Given the high number of target price revisions, I identify ex-ante likely valuable target prices. The risk-adjusted performance of the portfolio based on this subset increases to 0.81%. The downside exposures to SMB and MOM factors are negative and statistically significant at the 1% and 5% level, respectively. I demonstrate that more weight is given to pro cyclical (neutral) stocks when the expected probability of recession is low (high). Finally, we show that the results are not driven by firm specific events, post earnings announcement drift (PEAD), limited investors' attention or illiquid stocks.

In the second chapter I analyze the information conveyed by analysts' research and how it is perceived by investors. I introduce a methodology that disentangles the information conveyed through analysts' target prices according to its availability and scope. The purpose is to investigate if investors correctly interpret analysts' research by analyzing whether there is correspondence between investors' reaction and the type of information conveyed through analysts. The empirical results provide evidence that investors duly process analysts' research and appropriately incorporate this information into prices. Indeed, public information is not associated with any abnormal return, whereas private information is. Moreover, the reaction to firm-specific private information is confined to the firm analyzed, but industry-wide private information is associated with a reaction that spreads to the whole industry. The decomposition also shows

that target prices are based on an equal amount of private and public information, and that private information is mostly firm-specific.

In the last chapter I turn my attention to hedge fund managers, a category of sophisticated users of analysts' research. More specifically, I analyze how the remuneration structure of hedge funds affects the performance to investors to rationalize the persistent abnormal performance of hedge funds. I show that when managers expect to receive a performance fee payment, the commitment to deliver an absolute return, the decreasing returns to scale to which hedge fund strategies are subject, and the performance-linked remuneration combine with the income-maximizing behavior of managers to effectively align the interests of investors and managers. In consequence of the coexistence of these elements, managers have an incentive to control the size of the funds. Therefore, performance-diluting flows do not occur and abnormal performance persists. The model quantitatively reproduces many empirical facts about hedge funds.

Keywords: financial analysts; target price; brokerage; information and market efficiency; asymmetric and private information; hedge fund; incentives; remuneration; persistence

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Introduction

Financial analysts are specialist advisors who gather information on publicly traded companies from several sources, process it, and then communicate their conclusions to investors. On the one hand, analysts base their research on publicly available information such as financial statements, regulatory filings, management guidance, and the like. On the other hand, they employ non-public information gathered by interacting with the management and the other stakeholders of the analyzed companies. They then use their expertise to combine all these pieces of information into a mosaic to infer growth and earnings prospects at different horizons. These estimates serve as input for a valuation model that converts the forecasts into an intrinsic value known as target price. The difference between the target and the market price of securities determines the recommendation (e.g. "buy", "hold", and "sell"). Financial analysts act thus as information intermediaries between the firms covered and the investors. Portfolio managers following semi- or fully-active investment approaches are an example of investors that count on analysts' research to decide their allocation. With their trades, portfolio managers contribute to impound information into prices and foster market efficiency.

Until recently, regulators, academics, and common wisdom conferred an important role upon analysts. As acknowledged by the U.S. Securities and Exchange Commission (SEC), analysts promote "the efficiency of our markets by ferreting out facts and offering valuable insights on companies and industry trends."[1] Finance literature also recognizes analysts' research as informative; see, e.g., Womack (1996) or Asquith, Mikhail and Au (2005). These findings legitimize the considerable efforts made by brokers who produce and distribute equity reports. Recent studies cast however doubts on the role of analysts; see, e.g., Altınkılıç and Hansen (2009) or Altıkılıç, Hansen and Ye (2015). These studies demonstrate that analysts *piggyback* their reports on recent events and news. The investors' reaction that used to be attributed to the release of analysts' reports is in reality due to these contemporaneous events and news. It is thus not clear whether analysts' research is informative for the fund managers and the other investors that exploit

[1] The SEC publication is available at http://www.sec.gov/investor/pubs/analysts.htm.

analysts' investment advices. For this reason, the first two chapters of this dissertation study the information role of sell-side analysts from two specific angles of attack.

The focus of the first chapter is on the investment value of analysts' research. To study the underreaction to analysts' research, academics have extensively relied upon stock recommendations, presumably because of their availability; see, e.g., Jegadeesh, Kim, Krische and Lee (2004) or Barber, Lehavy and Trueman (2007). I use target prices because they offer several advantages with respect to recommendations. More specifically, they are less likely to be contaminated by analysts' subjectivity, broker-specific definitions, and ambiguous mappings with databases. Furthermore, because of their continuous nature, target prices convey more information than categorical variables such as recommendations.

I take the investors' perspective and I construct tercile portfolios based on target price revisions, i.e. the changes in the expected returns implied by target prices. More precisely, I implement a trading strategy that buys (sells) the stocks with the most positive (negative) target price revisions and hold them in the long-run. The analysis of the returns earned by the long-short portfolio shows that target prices have an investment value. In fact, target price revisions do not trigger an immediate and complete price adjustment. Instead, they are associated to a price drift in the same direction as the expected return revision. The long-short portfolios earn positive abnormal returns by capturing this drift. Interestingly, not all the target prices are equally valuable. Using an out-of-sample filtering procedure that exploits the characteristics of analysts, target prices, and analyzed companies, I separate ex-ante the most valuable target prices from the least valuable ones. I find that the investment value is concentrated only among a subset of target prices. A closer analysis of the returns points out that the performance is mostly attributable to market timing skills, not stock picking. Further tests prove that the abnormal performance generated by the long-short portfolios is not due to other known anomalies such as investors' inattention, post-earnings announcement drift, liquidity, or contemporaneous firm-specific events.

The second chapter sheds light on the information role of analysts by directly analyzing the information mix conveyed by analysts. Instead of inferring the informativeness of analysts' research from an investment strategy as in the previous chapter, I decompose the expected return implied by target prices. This approach differs significantly also from the one employed in the literature. The few studies that examine the information conveyed by analysts use the stock returns measured after the publication of the analysts' research; see, e.g., Piotroski and Roulstone (2004) and Liu (2011). These studies implicitly assume that investors correctly interpret analysts' research, even if there is no empirical evidence supporting that. I propose a model that separates the information used by analysts along two dimensions: availability and scope. In the first step, I focus on availability. I split the expected return in two components attributable either to public or private information. In the next step, the model disentangles private information according to its scope, i.e. firm-specific and industry-wide information. By bypassing the market reaction, this methodology permits also to verify if investors correctly interpret the information conveyed by analysts' research.

The empirical analysis shows that the average target price is based on approximately equivalent amounts of private and public information, and that private information is mostly firm-specific. The decomposition also points out that investors duly process analysts' research and appropriately incorporate this information into prices. Indeed, public information is not associated with any abnormal return, whereas private information is. Moreover, the reaction to firm-specific private information is confined to the firm covered, while the industry-wide private information is associated with a reaction that spreads to the whole industry. Finally, I find that investors' reaction varies with firms' characteristics. For instance, the reaction to firm-specific information is stronger for firms with high idiosyncratic volatility, i.e. the firms more affected by this type of information. This behavior mirrors the one of analysts who provide more firm-specific information for high idiosyncratic volatility firms.

Taken as a whole, the first part of this dissertation helps in understanding what information is used by analysts, whether it is valuable to investors, and how investors interpret it. Overall, the results show that analysts' research is informative for investors. Analysts provide them a significant amount of private information that is exploitable to implement profitable investment strategies. The private information included in each single target price is, to a large extent, firm-specific. However, the broad macroeconomic information is repeated each time that a target price is released. As a consequence, the investment value of target prices is attributable to industry factors, even if industry-wide private information is of secondary importance in the formation of target prices.

After having shown that it is possible to earn positive abnormal returns exploiting analysts' research, I turn my attention to sophisticated users of analysts' research, i.e. fund managers. More specifically, in the third chapter I assess whether the remuneration structure of hedge funds managers has an impact on how managers share the gains with individual investors, i.e. the buyers of the funds. I focus on hedge funds because this family of funds, in particular the ones belonging to the equity long/short strategy, extensively relies on analysts' research. The relation between remuneration and performance is not a new topic in the finance literature but it is still debated; see, e.g., Makarov and Plantin (2015). Most of the recent studies are based on the seminal work of Berk and Green (2004). One of the predictions of this model is that investment funds earn zero abnormal return in equilibrium. However, the empirical evidence on hedge funds is inconsistent with this prediction since the abnormal performance of hedge fund persists. Furthermore, fund managers limit the flows to the funds. This contradicts what one expects from rational managers that should let the funds grow to increase their remuneration. With this chapter, I help to bridge the gap between the theoretical predictions of Berk and Green (2004) and the empirical evidence on hedge funds.

I analyze the optimal behavior of managers who receive a performance-based remuneration and have not access to passive benchmarking opportunities. On the one hand, optionality is a typical feature of hedge funds managers' compensation. On the other hand, the investment mandate of hedge funds and the monitoring exerted by investors prevent managers from investing into passive benchmarks. Under these conditions, hedge fund managers have to generate a positive return to maximize their remuneration. As hedge fund strategies are subject to diseconomies of scale, this can be achieved by limiting the size of the fund. Thus, the performance-diluting flows do not occur and the fund keeps outperforming. Therefore, the remuneration structure of hedge funds emerges as an effective way to align the interests of managers and existing investors when no straightforward benchmark is available.

The predictions of the model, in addition to being consistent with the literature, are supported by numerical and empirical analyses. I illustrate through simulation how the model reproduces several stylized facts about hedge funds, such as the level and the persistence of returns, the size of funds, and the attrition rate of the industry. The hedge fund performance around fee revisions is also consistent with the model. In particular, the analysis documents a counterintuitive positive relation between revisions of performance fees and net returns. Altogether, the chapter points out that the performance-linked remuneration of managers plays a central role in explaining the persistence observed in the abnormal returns of hedge funds.

Taken together, I believe that the novel insights provided in this dissertation leaves some space for optimism. A careful analysis of publicly traded companies permits to discover information valuable from an investment perspective. This advocates financial analysts as promoter of market efficiency. Furthermore, individual investors benefit from this information even if the investment is delegated to money managers such as hedge funds managers.

At the same time, this dissertation calls for caution and specialization in the finance profession. My results show that discovering valuable information is not trivial. For instance, about half of the information disclosed by analysts is already known by investors. Moreover, only a subset of target prices has an investment value. It is thus unlikely that individual investors, who have significantly less expertise, can successfully accomplish this task. Also, three empirical findings suggest that using analysts' research is not straightforward. First, the investment value of target prices is heterogeneous. One has to cherry-pick the best research and neglects the poorly informative reports. Second, analysts bundle information with different availability and scope into a single signal. Thus, before being used, the research released by analysts has to be wisely interpreted. Third, analysts publish a noteworthy number of reports. To successfully exploit them, investors have to design strategies that master the transaction costs that will otherwise cancel out the abnormal performance. Individual investors have to be prudent also because managers do not capture the entire surplus only under strict conditions like the absence of passive benchmarks. This condition cannot realize if investors do not duly monitor fund managers.

References

Agarwal, V., N. D. Daniel, and N. Y. Naik, 2009, Role of managerial incentives and discretion in hedge fund performance, *Journal of Finance* 64, 2221-2256.

Altıkılıç, O., R. S. Hansen, and L. Ye, 2015, Can analysts pick stocks for the long-run?, *Journal of Financial Economics, forthcoming*.

Altınkılıç, O., and R. S. Hansen, 2009, On the information role of stock recommendation revisions, *Journal of Accounting and Economics* 48, 17-36.

Asquith, P., M. B. Mikhail, and A. S. Au, 2005, Information content of equity analyst reports, *Journal of Financial Economics* 75, 245-282.

Barber, B. M., R. Lehavy, and B. Trueman, 2007, Comparing the stock recommendation performance of investment banks and independent research firms, *Journal of Financial Economics* 85, 490-517.

Berk, J. B., and R. C. Green, 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269-1295.

Jagannathan, R., A. Malakhov, and D. Novikov, 2010, Do hot hands exist among hedge fund managers? An empirical evaluation, *Journal of Finance* 65, 217-255.

Jegadeesh, N., J. Kim, S. D. Krische, and C. M. C. Lee, 2004, Analyzing the analysts: When do recommendations add value?, *Journal of Finance* 59, 1083-1124.

Liu, M. H., 2011, Analysts' incentives to produce industry-level versus firm-specific information, *Journal of Financial and Quantitative Analysis* 46, 757-784.

Makarov, I., and G. Plantin, 2015, Rewarding trading skills without inducing gambling, *Journal of Finance* 70, 925-962.

Piotroski, J. D., and D. T. Roulstone, 2004, The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices, *Accounting Review* 79, 1119-1151.

Womack, K. L., 1996, Do brokerage analysts' recommendations have investment value?, *Journal of Finance* 51, 137-167.

Chapter 1: The Investment Value of Target Prices

(In collaboration with Michel Dubois and David Ardia)

1.1. Introduction

Previous research shows that sell-side analysts' recommendations, when interpreted correctly, are valuable from an investment perspective; see, e.g., Stickel (1995), Womack (1996), Barber, Lehavy, McNichols and Trueman (2001), Jegadeesh, Kim, Krische and Lee (2004), and Jegadeesh and Kim (2006). The price drift associated to stock recommendations suggests that the profitable holding period lasts beyond the announcement date; see e.g. Ivković and Jegadeesh (2004) or Barber, Lehavy and Trueman (2010). However, Altınkılıç and Hansen (2009), Altınkılıç, Balashov and Hansen (2013) and Altınkılıç, Hansen and Ye (2015) question the real analysts' ability to discover relevant information beyond public news. They show that analysts essentially relay and, perhaps, contribute to amplify the effect of public news. Loh and Stulz (2011) also show that only 12% of recommendation changes have an impact on price or volume when recommendations are issued in isolation.

The question we address in the present paper is whether the information conveyed by target prices is valuable from an investment perspective. Everything else being equal, the short-term stock price reaction surrounding the issuance of target prices is stronger compared to that of stock recommendations and earnings forecasts revisions; see, e.g., Brav and Lehavy (2003), Asquith, Mikhail and Au (2005), and Feldman, Livnat and Zhang (2012). To capture this incremental information, we define the following strategy. As of the end of the day, the stocks for which a target price was released are assigned to tercile portfolios based on the magnitude of the target price revision, i.e. the revision of the expected return implied by the target price. We use terciles to be consistent with the three-tier scale that is commonly used for stock recommendations. The cutoffs of the terciles are obtained from the distribution of the valid target price revisions issued during the last three months. These cutoffs are changing over time to account for time-varying expectations at the market level. A stock enters the tercile portfolio at the end of the announcement day and is held for one-month (twenty-one trading days) or until the broker that assigned the target price issues a revision. The tercile portfolios are value-weighted. To avoid overweighting stocks whose target prices are clustered within a month, a stock only enters the corresponding tercile portfolio if it is not already included in it.

Based on a sample of 735,191 target prices issued over the 1999-2011 period, we compute the corresponding annual expect return (target price divided by the current stock price minus one). The target price revision is the difference between the current and the previous expected return issued on the same stock by the same broker. We also define revisions with respect to the industry and the market. For our sample period, we find that the portfolio long in the highest tercile and short in the lowest target price revision tercile yields 0.45% per month, and 0.48% after adjusting for risk with the Carhart (1997) model. Both are statistically significant at the 1% level. This performance is similar whether based on industry or market adjusted expected return, and does not persist beyond the one-month holding period. Interestingly, we show that the monthly return of a strategy initiated five trading days after the target price release still yields a 0.35% risk-adjusted return for both the absolute and the relative market revisions, suggesting that there is a target price announcement drift.

Given the high number of target price revisions, we then consider only target prices that are likely to be valuable. Building on Loh and Stulz (2011) model, we determine *ex-ante* likely valuable target prices and construct one-month holding period portfolios based on this subset. The risk-adjusted performance increases to 0.80% per month for the long-short portfolio based on likely valuable target prices and is statistically significant at the 1% level. These results are robust both to the model choice and to the critical level that defines likely valuable target prices. Interestingly, most of the extra-performance originates from the long leg, whose return is also statistically significant at the 1% level. At the opposite, the portfolios based on unlikely valuable target price revisions do not outperform, i.e., the extra return is never statistically significant at the 5% level.

The portfolios that we construct based on target price revisions are dynamically managed. Therefore, we examine whether their exposure to risk factors is also time-varying and, more specifically, how they react to downside risk. We find that the downside exposure to *SMB* and *MOM* is negative and statistically significant at the 1% and 5% level, respectively. The negative exposure to *SMB* occurs when large firms outperform small firms. Also, the long-short portfolio turns out to be negatively exposed to the momentum factor when its return is below average. The upside exposure to *MOM* is positive and significant at the 1% level. This indicates that the extra-performance is obtained by timing the exposure to risk factors. Therefore, the strategy avoids the negative payoffs of the momentum and size factors and is mostly neutral to the market. We demonstrate that more weight is given to pro-cyclical (neutral) stocks when the probability of recession is low (high).

Finally, we perform several robustness tests. First, it is possible that our results are driven by firm-specific events that occur in concomitance with target price releases. We find that the strategy based on likely valuable target price revisions driven by information discovery yields a positive and significant risk-adjusted return, while the strategy based on information interpretation does not. Nevertheless, the risk-adjusted returns of the former and the latter are not statistically different at the usual level. Second, we check whether our results are driven by the post earnings announcement drift (PEAD). We find that it is not the case since the portfolios built on target price revisions of stocks with low (high) standardized unexpected earnings (SUE) earn (no) extra-positive return statistically significant at the 1% level. Third, we investigate whether limited investors' attention is a plausible explanation for the price drift that drives the extra-performance. We demonstrate that the performance of portfolios constructed with high and low turnover stocks are not statistically different. Fourth, to examine whether the results are driven by illiquid stocks, we sort firms into two groups according to their liquidity. Our results show that portfolios based on likely valuable target price revisions of illiquid stocks do not outperform those based on liquid stocks. Fifth, the remaining question is whether the long-short strategy based on valuable target price revisions resists transaction costs. Our strategy involves a 130% monthly turnover meaning that transaction costs should be lower than 18 bps for the extra-performance to survive. However, it turns out that strategies involving less rebalancing or being more profitable could survive. For instance, a strategy that reduces the turnover by opening every day a one-month long-short position yields significant net-of-fees monthly returns for transaction costs up to 80 bps.

This paper contributes to the literature in several ways. First, we add to the literature on the investment value of financial analysts' advices by studying the role of target prices. Contrarily to stock recommendations, target prices have been the focus of few studies. We demonstrate that there is not a one-to-one correspondence between target prices and stock recommendations. Closely related to our study, Da and Schaumburg (2011) show that the target price consensus has investment value. We depart from them with respect to both the universe of stocks that we cover and the methodology that we use to derive our results. More importantly, we show that the abnormal risk-adjusted performance originates from the ability of financial analysts to adjust target prices according to the expected probability of recession; i.e., the weight invested in cyclical (neutral) stocks increases when the probability is low (high). Second, we complement previous finding on stock recommendations with target prices. Consistent with Jegadeesh et al. (2004), we find that portfolios based on target prices are tilted toward momentum in good times. However, analysts avoid small and momentum firms and favor value stocks in (expected) bad times. Third, our results show that the rotation strategy from cyclical stocks to neutral stocks drives the positive performance of target prices based portfolios. This finding contradicts Kadan, Madureira, Wang and Zach (2012), who document stock picking ability and no market timing skills. Fourth, we show that target prices can be appropriately filtered ex-ante with the model of Loh and Stulz (2011). However, we find that target prices based on both information discovery and information interpretation are valuable at the one-month horizon.

The remainder of the chapter is organized as follows. In the next section, we provide details on the differences between recommendations and target prices which are related to their informational content, the brokers' rating scales, and the ambiguous translation from the data provider. Section 1.3 describes the construction of target price based portfolios. It also presents how to determine *ex-ante* target prices that are potentially valuable. Section 1.4 presents the performance of portfolios based on target price revisions. Section 1.5 reports the time-varying exposure of these portfolios to risk factors. Section 1.6 examines potential confounding effects that could also explain portfolios performance. Section 1.7 concludes.

1.2. On the informational content of stock recommendations and target prices

The target price obtained from a valuation model reflects the information contained in the earnings forecasts as well as additional material information such as the risk of the investment and the cost of capital. Among analysts' production, stock recommendations are extremely popular. Therefore, it is legitimate to wonder whether the investment value of the target price differs from that of the corresponding recommendation. In the remainder of this section, we discuss how target prices and stock recommendations are connected and what their respective advantages are.

1.2.1. Target prices and recommendations: Why are they different?

The target price is a continuous variable that is translated into the stock recommendation, a categorical variable. The aim of the categorization is to create clusters that investors should consider as similar when making investment decisions. However, this procedure induces a loss of information and creates heterogeneity within clusters. To illustrate this point, consider the following example. On September, 20th, 2011, Carlo Santarelli, a research analyst at Deutsche Bank, issued a "Hold" recommendation for two lodging stocks, Choice Hotel Intl. and Gaylord Entertainment Co.[1] However, their upside potential was different, with a target price expected return of 1.5% and 14.3%, respectively.

Some brokers assign recommendations subjectively. For example, Deutsche Bank does not include any official threshold that stock expected return has to exceed to receive a "Buy" recommendation. As shown in the example, analysts are free to assign identical (different) recommendations to stocks with different (same) investment prospects. The resulting heterogeneity of stocks receiving the same rating translates into biased and predictable market reactions. Consequently, by equally treating the stocks with the same rating, or recommendation change, researchers do not estimate appropriately the market reaction. In a nutshell, the reactions and the expectations based on recommendations are biased, while the ones based on target prices are not.

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[1] The corresponding report is available at http://www.luxesf.com/wp-content/uploads/2011/10/DB-on-lodging-industry.pdf

Subjectivity in the assignment of ratings can be interpreted as a positive feature since it allows the analysts to integrate proprietary "soft" information. If this was the case, recommendations would be more informative that target prices. However, empirical evidence shows the opposite; see Brav and Lehavy (2003). In addition, recommendations are strategically biased because, contrary to earnings forecasts and target prices, their accuracy is hardly gauged; see Lin and McNichols (1998). Subjectivity is not limited to recommendations' rating but also to their definition. In fact, the definitions of the rating scale are brokerage house dependent; see Kadan et al. (2012). Brokers use either an absolute benchmark (e.g., Citigroup), an industry benchmark (e.g., Morgan Stanley), a market benchmark (e.g., UBS), or no explicit benchmark at all (e.g., Deutsche Bank); see Appendix, Table 1.A.1. Therefore, even if equally named, stock recommendations should be interpreted differently. For instance, a "Sell" recommendation from Citigroup means a negative expected return, whereas Raymond James & Associated assigns a "Sell" as soon as the stock is expected to underperform the market. Conversely, recommendations defined similarly can be named differently. For example, the recommendations from Credit Suisse and UBS are defined with respect to a market benchmark but only Credit Suisse uses the appropriate terms "Underperform" and "Outperform". Moreover, brokerage houses change their rating scales over time, making the comparison of recommendations released at different periods awkward. To be more specific, half of the one hundred most active brokers, representing more than 90% of the stock recommendations, changed their rating scale at least once during the 1990-2011 period. Kadan et al. (2012) suggest that investors and researchers should adjust recommendations appropriately but the differences across brokers and the changes of scale within brokers render this task extremely cumbersome.

Since the approval of NASD Rule 2711 in May 2002, the majority of the brokers switched from a five-tier rating system to a three-tier system. Despite that, I/B/E/S still uses a five-tier scale as standard rating system. This may suggest that I/B/E/S recommendations are unambiguous, since the differences that exist across brokerage houses are smoothed by the mapping. However, the mapping is decided by the brokerage houses (not I/B/E/S) and, as a result, the ambiguity remains. Appendix, Table 1.A.1, shows that the I/B/E/S rating is as ambiguous as the brokerage house ratings. For instance, the definition of

"Overweight" assigned by Morgan Stanley is equivalent to "Outperform" with Wells Fargo. However, the "Outperform" of Wells Fargo is mapped as a "Strong Buy" in I/B/E/S, whereas the "Overweight" of Morgan Stanley translates into a "Buy".[2] This heterogeneity poses a serious challenge to archival research using recommendations because there is no one-to-one relation between the rating scale and the expected performance provided by the broker. To summarize, each broker speaks its own language and the translator (I/B/E/S) does not come up with a reliable translation. Target prices naturally circumvent this ambiguity because, for all brokers and time periods, they represent the expected stock price over a defined and common horizon (mostly twelve-month horizon).

1.2.2. Empirical evidence

To illustrate the differences between recommendations and target prices, we obtain target prices and stock recommendations from the I/B/E/S detail database. We match target prices and recommendations released by the same broker, for the same firm, during the three-day window surrounding the announcement of the target price. This procedure results in 136,982 target prices and recommendations over the 1999-2011 period. The upside (downside) potential is the analyst expected return, which is defined as *(TP-P)/P*, where *TP* is the target price and *P* the closing price on the announcement day. For each standard rating on the I/B/E/S rating scale, Figure 1.1 displays the corresponding kernel-based distribution of the analyst expected return.

[Insert Figure 1.1 about here]

Figure 1.1 illustrates empirically that brokerage houses indeed use three-tier rating scales and that the I/B/E/S conversion to a five-notch scale is inappropriate and misleading. As a matter of fact, the distributions of the upside potential of stocks rated as "Buy" and "Strong Buy" are very close since 86.0% of the "Buy" recommendations have an upside potential that overlaps with "Strong Buy" recommendations. Similarly, according to the I/B/E/S rating, the expected performance of a "Sell" should

[2] Even more striking, the definition given by Credit Suisse for the "Outperform" recommendations is stricter than the one given by Wells Fargo. Nevertheless, "Outperform" recommendations of Credit Suisse are mapped with "Buy", i.e. a rating worse than the one received by the looser recommendations of Wells Fargo.

be lower than that of an “Underperform”. However, the downside potential of 58.4% of the “Sell” recommendations overlaps with “Underperform”. Therefore, not combining “Sell” with “Underperform” recommendations, and “Buy” with “Strong Buy” respectively, overestimates the impact of the extreme ratings.

Figure 1 reflects also the heterogeneity of brokers’ rating. For instance, a stock with the upside potential of Gaylord Entertainment (14.3%) has a 66% probability of receiving a “Buy”, 32% of receiving a “Hold”, and 2% of receiving a “Sell”. This happens because there is a significant overlap between the different ratings. When the five-notch rating is merged into a three-notch rating, i.e. “Sell” with “Underperform” and “Buy” with “Strong Buy”, “Hold” recommendations overlap with “Sell” (“Buy”) recommendations 23.1% (36.9%) of the time. There is also a 6% overlap between “Sell” and “Buy” recommendations. To summarize, the above results show that recommendations and target prices do not convey the same information. These differences arise because of three reasons: i) the information lost when target prices are mapped to recommendations, ii) the subjectivity with which brokers define their rating system and iii) the inappropriate mapping of recommendations with the five-tier I/B/E/S rating system. Target prices are not subject to any of these drawbacks. For all these reasons, we argue that target prices are best suited to answer our research question.

1.3. Construction of target price-based portfolios

1.3.1. Data

Target prices and stock prices are obtained from the Institutional Broker Estimate Service (I/B/E/S) and the Center for Research in Security Prices (CRSP) respectively. We rely on the unadjusted version of the databases to avoid the issues related to adjusted data; see Payne and Thomas (2003). We focus on the target prices issued between 1999 and 2011, by identifiable analysts, on US firms.[3] Target prices have to meet the following criteria. First, they must have a twelve-month forecast horizon. This restriction affects a small number of observations since 98% of the target prices have a twelve-month horizon. Second, to

[3] We identify US firms as the ones having a COMPUSTAT currency code of “USD” and a CRSP share code of 10 or 11; see Daniel, Grinblatt, Titman and Wermers (1997) and Wermers (2004).

obtain a meaningful comparison between target prices and stock prices, we only retain the target prices expressed in USD. Third, to ensure that firms are of sufficient interest to investors, we focus on firms followed by at least three analysts. Fourth, we require a valid closing share price above one USD on the announcement date. Appendix, Table 1.A.2, Panel A reports the details of the sample selection and the annual statistics.

Our selection procedure yields a sample of 735,191 target prices, made by 8,732 analysts (655 brokerage houses), on 6,223 US firms that represent 82.4% of the total market capitalization; see Appendix, Table 1.A.2, Panel B. The number of analysts and firms followed remain roughly constant over time while target prices are issued more frequently at the end of the sample period. The fraction of the market capitalization of our sample decreases over time, but still represents more than 75% of the US stock market capitalization at the end of the sample period.

To determine the likelihood of investment value of target prices, we collect additional information from the All-American rankings published yearly by the Institutional Investor magazine. We identify firm-specific events, in addition to I/B/E/S (earnings announcements), from I/B/E/S Guidance (management guidance), SDC (mergers and acquisitions, equity issuance), and LPC Dealscan (syndicated loans). Institutional ownership is computed using data obtained from 13F filings that we download from the EDGAR database.

Table 1.1 describes the size, book-to-market, and momentum characteristics of our sample relative to the NYSE universe.[4]

[Insert Table 1.1 about here]

Overall, analysts tend to follow large and growth firms, but there are important changes over time. For instance, we observe an almost parallel trend toward small and value firms. The trend started when small

[4] The tercile breakpoints are constructed using all the NYSE stocks. Each December, we compute the three variables for all the firms in our sample. Size and book-to-market are computed as in Davis, Fama and French (2000), momentum is the buy-and-hold return from the beginning of January till the end of November. The variables are then used to classify the target prices issued in the following year into terciles. We include in the NYSE universe only the stocks with a CRSP share code equal to 10 or 11.

and value firms were outperforming large and growth firms, respectively, and reverted in 2008 with the financial crisis.[5]

1.3.2. Target price interpretation and portfolio construction

Previous studies show that stock recommendation revisions are more informative than recommendations themselves; see, e.g., Boni and Womack (2006) and Jegadeesh and Kim (2010). Similarly, Feldman et al. (2012) find larger abnormal market-adjusted returns around the revision of target prices. Therefore, we measure the revision of the expected return embedded in target prices in two steps. First, we compute the target price expected return defined as:

$$(1) \quad TPER_{i,b,\tau} = \frac{TP_{i,b,\tau}}{P_{i,\tau}} - 1 ,$$

where $TP_{i,b,\tau}$ denotes the twelve-month target price for firm *i*, issued by broker *b* at date τ, and $P_{i,\tau}$ denotes the closing stock price for firm *i* at τ. If the target price is released between 4:30 PM and 11:59 PM, $P_{i,\tau}$ is replaced by the closing price of the next trading day; see Loh and Stulz (2011). As we retain only target prices with a twelve-month horizon, *TPERs* represent the annual expected returns. Second, we compute the revision of the expected return to measure the new information conveyed by the target price:

$$(2) \quad \Delta TPER_{i,b,\tau} = TPER_{i,b,\tau} - TPER_{i,b,\tau-1} ,$$

where $\tau-1$ is the date of the previous target price from the same brokerage house *b* for firm *i*. $\Delta TPER$ is computed only if $TPER_{i,b,\tau-1}$ is still valid at τ, i.e. if it meets three conditions: i) the end of the forecast horizon is after τ, ii) $TP_{i,b,\tau-1}$ is the most recent target price issued on firm *i* by the brokerage house *b*, and iii) broker *b* did not stop covering firm *i* from $\tau-1$ to τ.

To construct the portfolios we follow Barber et al. (2001). As of the end of day τ, stocks are assigned to tercile portfolios according to the value of $\Delta TPER_{i,b,\tau}$. The cutoffs of the tercile portfolios are based on

[5] There is no clear preference for high or low momentum stocks. In fact, the proportion of past winners and losers varies strongly over time

the distribution of valid $\Delta TPER$ released during the last three months.[6] We use terciles to be consistent with the three-tier recommendation scale. The portfolio consisting of stocks in the highest (lowest) $\Delta TPER$ tercile can be interpreted as a "Buy" ("Sell") portfolio. A stock enters the portfolio at the end of the announcement day and exits the portfolio after a month (21 trading days) or when the broker revises its target price. To avoid cross-correlation problems arising from the inclusion of identical returns, we follow Brav and Lehavy (2003) and keep each stock only once.[7] The composition of each portfolio p being known at the date τ, the value-weighted return for the following trading day, denoted $t_\tau+1$, is computed as in Barber et al. (2001). The return is given by:

$$(3) \quad R_{p,t_\tau+1} = \sum_{i=1}^{n_{p,\tau}} x_{i,t_\tau} R_{i,t_\tau+1} ,$$

where $R_{p,t_\tau+1}$ ($R_{i,t_\tau+1}$) denotes the return of portfolio p (stock i) at $t_\tau+1$, $n_{p,\tau}$ the number of stocks in portfolio p at the date τ, and x_{i,t_τ} is the weight of stock i, computed as the ratio of the market value of firm i to the aggregated market capitalization of the firms in portfolio p. We employ value-weighted portfolios to avoid an overstatement of returns due to bid-ask bounces; see Blume and Stambaugh (1983) and Canina, Michaely, Thaler and Womack (1998). For each portfolio, the daily returns are then compounded over the n_m trading days of the month m to obtain portfolio's p monthly returns:

$$(4) \quad R_{p,m} = \prod_{j=1}^{n_m} \left(1 + R_{p,j}\right) - 1 .$$

This procedure yields a time-series of monthly returns for each tercile portfolio which is evaluated with the Carhart (1997) four-factor model.

[6] Results remain unchanged with a six-month window. Longer windows are less well suited because target prices are revised frequently (every three months on average) and market expectations are changing over time. These results as well as other unreported results are available from the authors upon request.
[7] The cross-correlation problem arises when a stock is selected by several brokers during the holding period. If these multiple entries are considered as different holdings of the portfolio, the correlation between the components of the portfolio increases, as well as the volatility of the whole portfolio. A stock can appear in several distinct portfolios simultaneously. Note that the standard event study methodology does not exclude these stocks either; see, e.g., Womack (1996), Altınkılıç and Hansen (2009), Jegadeesh and Kim (2010), and Loh and Stulz (2011).

We consider two additional measures of the information content of target prices. First, there is evidence that analysts' production is more valuable if considered at the industry level. For instance, Boni and Womack (2006) show that recommendations have more investment value when they are considered within industries. Similarly, Da and Schaumburg (2011) find that rankings of *TPERs* are more informative within industries. For this reason, we also construct portfolios according to the industry-adjusted revision of *TPER*, defined as:

$$(5) \quad \Delta TPER^{IND}_{i,b,\tau} = \Delta TPER_{i,b,\tau} - \Delta\overline{TPER}_{ind(i),\tau} ,$$

where $\overline{TPER}_{ind(i),\tau}$ is the average valid *TPER* of firms operating in the same industry as firm *i*. We compute the average excluding firm *i* to prevent spurious correlations between $\Delta\overline{TPER}_{ind(i),\tau}$ and $\Delta TPER_{i,b,\tau}$ in industries with few firms. We use the 68 GICS industries (6 digits) classification because it matches analysts' industry specialization; see Boni and Womack (2006). We interpret $\Delta TPER^{IND}$ as the revision of the industry-adjusted expected return. We also compute the expected return in excess to the market expected return. In fact, Kadan et al. (2012) show that analysts often issue recommendations based on a market benchmark. Therefore, we construct portfolios according to a variable that measures the revision of the market-adjusted expected return, defined as:

$$(6) \quad \Delta TPER^{MKT}_{i,b,\tau} = \Delta TPER_{i,b,\tau} - \Delta\overline{TPER}_{\tau} ,$$

where $\Delta\overline{TPER}_{\tau}$ is the average of valid *TPERs*. To construct portfolios according to $\Delta TPER^{IND}$ and $\Delta TPER^{MKT}$, we obtain the cutoffs of the tercile portfolios from the distributions of valid $\Delta TPER^{IND}$ and $\Delta TPER^{MKT}$, respectively, and we use the methodology described previously.

Table 1.2 reports the descriptive statistics of 595,995 target price revisions. The average and median $\Delta TPER$ is 0% with a significant variability both between and within years. For instance, the annual average ranges from -4.5% (2009) to 5.0% (2000). The dynamics of $\Delta TPER$ shows that analysts' forecasts are stickier than market prices and that the analysts revise their target prices with a delay compared to the market. In fact, *TPER* are inversely related to stock market returns, i.e. they are higher when market returns are negative (2000, 2008) and lower when market returns are positive (2003, 2009). The interquartile range varies between 13.5% and 28.5%, showing that there is a large cross-sectional dispersion of $\Delta TPER$ across stocks. Interestingly, the largest interquartile ranges coincide with the years of downturn. The descriptive statistics of $\Delta TPER^{IND}$ and $\Delta TPER^{MKT}$ are similar to the ones of $\Delta TPER$. $\Delta TPER^{IND}$ can be computed only for 594,383 target price announcements because some firms are not assigned to any valid industry or because there are too few observations to compute $\overline{\Delta TPER}_{ind(i),\tau}$. The signals used to construct the portfolios are economically significant; see Appendix, Table 1.A.3. For instance, the average of $\Delta TPER$ is -21.4% (21.5%) in the first (third) tercile portfolio. Similar numbers are obtained for portfolios based on $\Delta TPER^{IND}$ and $\Delta TPER^{MKT}$.

[Insert Table 1.2 about here]

1.3.3. Likely valuable target prices

Given the high number of target prices released (i.e., 230 target prices per day on average), we determine *ex-ante* with a model, which ones are potentially valuable and analyze whether this filter improves the performance of the tercile portfolios. We estimate the parameters of the model as follows. First, we define a dummy variable, *Valuable*, that equals 1 if the target price is valuable *ex-post* and 0 otherwise. A target price is considered to be valuable if the $\Delta TPER$ revision is positive (negative) and the corresponding cumulated abnormal return over the holding period is statistically positive (negative) at the 5% level; see Loh and Stulz (2011).[8] We focus on the cumulated abnormal return in the month (21 trading days) that follows the announcement of the target price. The benchmark is the Carhart (1997) four-factor model. The parameters of the four-factor model are estimated running a daily time-series regression over the estimation window [-150; -1], where day zero is the date at which the target price is announced. To properly identify the factor-exposures and compute the abnormal returns, we require stocks to have at least 120 observations over the estimation window and valid closing prices on the event-day zero and 21.

[8] The results are similar when $\Delta TPER^{IND}$ or $\Delta TPER^{MKT}$ are used to identify likely valuable target prices. In fact, for more than 91% of $\Delta TPER$, $\Delta TPER^{IND}$, and $\Delta TPER^{MKT}$ have the same sign.

The factor-exposures and the abnormal returns are estimated using the dummy variable approach of Salinger (1992).[9]

Second, when at least a target price is released on trading day τ, we identify the target prices released during the last three months skipping the most recent twenty-one trading days. We skip this period because a target price is known to be valuable only after this period. As we aim at predicting *ex-ante* whether a target price is likely valuable, we estimate Probit regressions that relate the dependent variable *Valuable* to the analyst, firm, and target price characteristics as defined in Loh and Stulz (2011). The list and the definition of the explanatory variables are presented in Appendix, Table 1.A.4. As the determinants of valuable target prices can change with the direction of the revision, we separate target price revisions according to their sign and fit two Probit models: one for positive and one for negative $\Delta TPER$. We use the estimated coefficients to predict the likelihood that a target prices released on trading day τ is valuable. These predicted probabilities are compared to the median fitted probability to separate the *most likely valuable* from *least likely valuable* target prices. In the remainder of the paper we refer to them as *likely valuable* and *unlikely valuable*, respectively. Notice that all the variables are known *ex-ante* (i.e. before date τ) so that the prediction is made out-of-sample and it can be implemented in real time.

Having determined likely valuable target prices, we construct portfolios using the methodology detailed previously. We obtain two sets of tercile portfolios, each containing either *likely valuable* or *unlikely valuable* target prices.

1.4. Performance of portfolios

1.4.1. Unconditional portfolios

In this section, we discuss the performance of the portfolios that consider the whole sample of target prices. To investigate the speed at which the information is incorporated into prices, we implement the strategy using different starting dates. We focus on strategies with a one-month holding period that start

[9] To account for potential missing returns in the estimation window, we run a WLS regression with observations weighted by the inverse of the square root of the number of trading days between two valid returns; see Heinkel and Kraus (1988).

either at the end of the announcement day ([+1 ; +21]) or at the beginning of the following two months ([+22 ; +42] and [+43 ; +63], respectively). To verify that the information is not incorporated into prices in the days that immediately follow the announcement, we also compute the monthly return of a strategy that starts investing in a stock five days after the target price release ([+5 ; +21]). Table 1.3 reports both the raw and the risk-adjusted returns of the tercile portfolios for the four holding periods.[10]

[Insert Table 1.3 and Figure 1.2 about here]

Table 1.3, Panel A, reports the raw returns of the portfolios based on $\Delta TPER$. The strategy starting at the announcement date that buys high $\Delta TPER$ stocks and sells low $\Delta TPER$ stocks earns an average 0.44% per month (statistically significant at the 1% level). The price trend is significant and is not concentrated in the few days after the announcement since the [+5; +21] portfolios show that the returns are statistically significant at the 5% level. In Figure 1.2, Panel A, we see that the gap between abnormal returns of the top and bottom portfolios continues to increase over the whole period considered, even if the trend is more pronounced during the first month after the target price announcement. In fact, the economically small returns (below 10bps), and statistically insignificant at the 5% level, of the [+22; +42] and [+43; +63] portfolios demonstrate that this trend is not significant beyond the first month. The results obtained for $\Delta TPER^{IND}$ are similar, the statistical significance being slightly lower. For instance, the risk-adjusted performance of the portfolio based on industry-adjusted target price revisions that start investing five days after the target price release and stops at the end of the month ([+5; +21]) is no longer statistically significant at the 5% level (p-value = 9% for the raw return). Figure 1.2, Panel B, shows that the dynamics of $\Delta TPER^{IND}$ portfolio returns is less clear cut than the one of $\Delta TPER$ portfolios. The top portfolio grows at a lower rate, while the bottom portfolio, after a rapid adjustment in the first ten trading days following the announcement, displays a small reversal. The performance of the portfolios obtained with a ranking based on $\Delta TPER^{MKT}$ is similar to the one obtained for $\Delta TPER$ and confirms that the post target price announcement drift lasts beyond the first days following the announcement.

[10] Standard errors are corrected for heteroskedasticity and autocorrelation using the Newey and West (1987) estimator with six lags. The results do not change qualitatively with twelve lags.

The results for risk-adjusted returns are presented in Table 1.3, Panel B. We observe marginal changes. The long-short strategy initiated at the announcement date earns positive risk-adjusted returns (0.49% per month). Overall, the results indicate that the information contained in expected return revisions is incorporated within the month following the announcement of the target price but is not limited to the first days after the announcement. For this reason, the focus of the rest of the paper is on the performance of these first-month portfolios.[11]

1.4.2. Portfolios performance of likely valuable target prices

We now turn to the portfolios constructed with likely valuable target prices. Out of the 593,872 target prices for which the information is available, 26.3% are valuable. The sample of valuable target prices is slightly tilted toward observations with positive $\Delta TPER$ since 53% of valuable observations have a positive revision of implied expected returns.

Table 1.4, Panel A, reports the risk-adjusted performance of the two sets of portfolios. As expected, the extra-performance of long-short portfolios is limited to the portfolios constructed with *likely valuable* target prices. The risk-adjusted performance is economically large and statistically significant at the 1% level for target price revisions (0.81% per month) as well as for the industry (0.66% per month) and the market (0.87% per month) adjusted target price revisions. The over-performance of the *likely valuable* portfolios comes exclusively from the long leg. Figure 1.3 also illustrates that the high $\Delta TPER$ portfolio shows a clear upward trend over the whole period, whereas the low $\Delta TPER$ portfolio reacts sharply in the few days following the announcement, and then exhibit a reversal. The rightmost columns of Table 1.4 contain the performance of the portfolios constructed with *unlikely valuable* target prices. Regardless of the interpretation of target prices, the performance of portfolio T3 and T1 is never statistically significant at the usual critical levels. Figure 1.3, illustrates that the abnormal performance of *unlikely valuable* portfolios do not show any drift.

[Insert Table 1.4 and Figure 1.3 about here]

[11] Similar portfolios constructed on *TPER* (implied return instead of revision of implied return) generate abnormal returns up to four trading days. Beyond this horizon, no abnormal return is observed.

To verify the robustness of our filtering procedure (identification of likely valuable target prices), we run an OLS regression where the dependent variable is the ratio of the cumulated abnormal returns over the holding period divided by the corresponding standard error (t-stat associated to the one-month CAR), the independent variables being the ones of the Probit model. Table 1.4, Panel B, shows that our results are robust to the methodology.[12] However, a target price can simply be a *false positive*, i.e. the target price is classified as valuable when it is not. To gauge the impact of the Type I error, we determine whether a target price is valuable with a test whose critical value is based on the Gumbel distribution; see Boudt, Croux and Laurent (2011). This procedure strongly decreases the probability of having false discoveries. Table 1.4, Panel C, shows that portfolio performance is only marginally affected by false discoveries.

1.5. Time-varying risk exposures

The long-short strategy based on $\Delta TPER$ being dynamic, the exposure to the factors potentially varies with market and economic conditions. In this section, we analyze the risk exposures of our strategy conditionally on the market movements.

1.5.1. Upside and downside risk

Risk adverse investors care differently about losses and gains. Therefore, investors ask a larger risk premium to hold assets that co-vary strongly with the market during market declines. Ang, Chen and Xing (2006) show that stocks with downside exposure have higher average returns. They also quantify the downside risk premium at approximately 6% per year. Lettau, Maggiori and Weber (2014) find further evidence supporting the existence of a downside risk premium for other asset classes like options, commodities, and currencies. To verify whether the abnormal performance of portfolios based on target prices is attributable to downside risk exposure, we follow Ang et al. (2006) and estimate the upside and downside market betas of our strategies. In addition, we also include conditional exposures to size, value,

[12] We also build portfolios based on target prices that are *likely valuable* with both the Probit and the t-statistic regression. The results are similar.

and momentum factors. Formally, the downside and upside beta, denoted β_F^- and β_F^+ respectively, are defined as:

$$(7) \quad \beta_F^- = \frac{\operatorname{cov}\left(r_p, r_F \mid r_F < \mu_F\right)}{\operatorname{var}\left(r_F \mid r_F < \mu_F\right)}$$

and

$$(8) \quad \beta_F^+ = \frac{\operatorname{cov}\left(r_p, r_F \mid r_F > \mu_F\right)}{\operatorname{var}\left(r_F \mid r_F > \mu_F\right)},$$

where r_p (r_F) denotes the portfolio (risk factor) return, and μ_F the average return of the risk factor *F*. If the abnormal performance of the portfolio is a reward for downside risk exposures, we expect the downside beta to be positive and statistically significant. Note that β_F^- and β_F^+ are *conditional univariate* betas since they are computed conditionally on the magnitude of the factor return and each factor is considered separately. Therefore, these betas cannot be compared to the sensitivities obtained from the Carhart (1997) four-factor model. For this reason, we also estimate *unconditional univariate* betas.

[Insert Table 1.5 about here]

Table 1.5, column 2 to 4, contain the univariate sensitivities to *MKT*, *SMB*, *HML* and *MOM* factors. Both $\Delta TPER$ and $\Delta TPER^{MKT}$ long-short portfolios exhibit *unconditional univariate* negative downside sensitivities to the *SMB* and the *MOM* factors that are statistically significant at the 1% and 5% level respectively. The corresponding upside exposures to the *MOM* factor are positive and statistically significant at 5% and 5.4% level, respectively, while the upside exposures to the *SMB* factor are no longer statistically significant at the usual level. The $\Delta TPER^{IND}$ portfolio shows a negative downside sensitivity to the *SMB* factor and a positive upside sensitivity to the *HML* factor that are statistically significant at 1%. These exposures suggest that the significant abnormal performance is obtained by timing the downside exposures to the *SMB* ($\Delta TPER$, $\Delta TPER^{IND}$ and $\Delta TPER^{MKT}$) and *MOM* ($\Delta TPER$ and $\Delta TPER^{MKT}$) factors, or the upside exposure to *HML* ($\Delta TPER^{IND}$).

1.5.2. Timing of downside exposure

To analyze how the timing of risk-exposures impacts the performance of our strategy, we compute the *multivariate* conditional exposures of the portfolio. Following Ang et al. (2006), we obtain these exposures by running the following regression:

(9) $$r_{p,t} = a_p + \sum_F b_F \times r_{F,t} + \sum_F b_F^- \times r_{F,t}^- + \varepsilon_{p,t},$$

where $r_{F,t}^- = \min\left(r_F, \mu_F\right)$. This model extends Henriksson and Merton (1981) to multiple sources of risk. However, it departs from that model with respect to the sign of $r_{F,t}^-$, which is reversed, and the value of the threshold (average of the factor instead of the risk-free rate). In our model, b_F measures the exposure when the factor return is above its sample mean, and b_F^- measures the marginal change in b_F when *F* is below its sample mean. Therefore, negative b_F^- identifies the timing skills with respect to factor *F*.

The rightmost columns of Table 1.5 report the coefficient obtained by fitting Equation (9). Column 5, labeled "Up", contains the coefficients b_F. The exposure to the momentum factor is the only one statistically significant at the 1% level. This is a positive feature since the strategy is long momentum when its returns are positive. Column 6, reports the "Down" coefficients b_F^-. The exposures to the size and momentum factors decrease significantly when these factors experience downside movements. The resulting downside sensitivities to *SMB* and *MOM* turn out to be negative and statistically significant at the 1% and 5% level, respectively. The analysis highlights also an adverse increase in the downside exposure to the value factor. Finally, the intercept a_p is no longer statistically significant at the usual critical level of 5%. Portfolios based on $\Delta TPER^{IND}$ and $\Delta TPER^{MKT}$ show similar results.

These results confirm that trading strategies based on target price revisions earn positive abnormal returns because they opportunely adjust their exposure to conventional sources of risk. In particular, the strategy avoids the negative payoffs of the momentum and size factors, i.e. the two factors with the largest downside risk. The strategy also shows a neutral exposure to the broad market and an adverse positive exposure to downside movements of the value factor.

1.5.3. Portfolio holding over the business cycle

We analyze whether the market timing ability documented above is achieved by exploiting expected variations of the business cycle. Analysts' forecasts are based on macroeconomic scenarios which are critical to forecast the prospect of specific companies or industries; see e.g. Hugon, Kumar and Lin (2015). For instance, when the economy is expected to slow down, analysts should lower (raise) their expectations on pro-cyclical (counter-cyclical) stocks and vice versa when the economy is expected to expand.

To test this hypothesis, we measure the cyclical exposure of the long-short portfolio; see Goetzmann, Watanabe and Watanabe (2012). We first estimate a regression where the quarterly return of each stock composing the portfolios is the dependent variable and the quarterly market return and the GDP growth rate are the independent variables.[13] The coefficient associated to the growth rate of GDP, β_{GDP}, measures the stock cyclicality. We estimate the cyclical exposure over the 2000-2011 period, i.e. the same time span used to construct the portfolio. By computing a single β_{GDP} for each stock, instead of a time varying exposure, we implicitly assume that the cyclicality of the stock does not change over time. Consistently with Goetzmann et al. (2012), we find a significant cross-sectional dispersion of the cyclical exposure. On average, the β_{GDP} is -0.93 and 90% are in the [-12.5 and 7.9] interval. Stocks are then separated into terciles based on their β_{GDP}. We refer to the stocks in the top tercile (high β_{GDP}) as pro-cyclical stocks, the one in the middle tercile as neutral stocks, and to the ones in the bottom tercile (low β_{GDP}) as counter-cyclical stocks.

The next step consists in computing the daily weights invested in each β_{GDP} tercile. This variable measures how much is invested in procyclical, neutral, and countercyclical stocks. To test whether these

[13] The market return is the value-weighted return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11. The growth rate of GDP is computed from the seasonally adjusted GDP obtained from the US Bureau of Economic Analysis adjusted for inflation using the Consumer Price Index provided by the US Bureau of Labor Statistics.

weights depend on the business cycle expectations, we consider the change in the probability of recession[14] and estimate the following regression:

(10) $w_q = b_0 + b_1 \Delta RecProb_q + \varepsilon_q$,

where w_q is the quarter's q average weight of either procyclical, neutral, or countercyclical stocks. $\Delta RecProb_q$ is the change in the probability of recession from *q-1* to *q*.

[Insert Table 1.6 about here]

The results are presented in Table 1.6. The two leftmost columns contain descriptive statistics on β_{GDP}. The average cyclical exposure is statistically different across the three groups of stocks at the 1% level. The following two columns contain the average weight of pro-cyclical, neutral and counter-cyclical stocks. As we analyze the allocation of a long-short portfolio, the three allocations sum up to zero. The average allocations are not statistically different, i.e. the average allocation is not tilted toward a specific category of stocks. Finally, the coefficients of the regression show that the weight invested in pro-cyclical stocks is higher when the probability of a recession decreases. Symmetrically, the weight invested in neutral stock increases as the probability of recession increases. These results are statistically significant at the 1% level. Note that the weight invested in counter-cyclical stocks does not change over the cycle. Implicitly, the portfolios based on likely valuable target price revisions correspond to a "rotation" strategy based on the expectation of the business cycle.

1.6. Additional tests

1.6.1. Coincident firm-specific events

There is evidence that the usefulness of analyst research stems from two co-existing sources: i) the discovery of private information and ii) the interpretation of public information; see, e.g., Ivković and Jegadeesh (2004), Asquith et al. (2005), and Chen, Cheng and Lo (2010). To isolate analysts' contribution, Altınkılıç and Hansen (2009) and Loh and Stulz (2011) remove the stock recommendations that are issued around firm-specific events. Moreover, recommendations stemming from information

[14] This variables is available at https://research.stlouisfed.org/fred2/series/RECPROUSM156N

interpretation trigger economically larger short-term market reactions than recommendations based on information discovery; see Loh and Stulz (2011). However, there is no evidence of such effect in the mid-term. The interpretation of information, which is based on facts, is likely to trigger a quick reaction, whereas the reaction to information discovery, which is based on hypotheses, is postponed until these hypotheses materialize. Therefore, we examine whether target prices resulting from information discovery and interpretation induce different portfolio returns.

We consider that a target price is based on information interpretation if it is released in the three-day window surrounding a firm-specific event; see Altınkılıç and Hansen (2009) and Loh and Stulz (2011) . Firm-specific events are quarterly earnings announcements, management guidance, mergers and acquisitions, as well as equity and debt issuance (including public bonds and syndicated loans). About 47% of the target prices in our sample are associated with firm-specific events.[15]

In our sample, 27.3% (25.1%) of the information discovery (interpretation) driven target prices are likely valuable. This 2% difference is not economically important. We construct two sets of portfolios. The first set exploits the information content of target price revisions based on information interpretation, whereas the second set uses target price revisions based on information discovery. Table 1.7, Panel A, column 1 and 2, show the risk-adjusted performance obtained for portfolios based on $\Delta TPER$. From an investment perspective, target prices stemming from information discovery (column 2) are economically more valuable that the one based on information interpretation (target price revision around firm-specific events, column 1). However, pairwise tests show that the abnormal performance of the portfolios based on information discovery and that based on information interpretation are not statistically different at the 5% level. Similar results are obtained for $\Delta TPER^{IND}$ and $\Delta TPER^{MKT}$ portfolios. As a consequence, both sources of information contribute to the performance of the *likely valuable* portfolios.

[Insert Table 1.7 about here]

[15] This figure is in line with Altınkılıç and Hansen (2009), who find that about 45% of the recommendation revisions are due to information interpretation. Our figure is slightly higher since we introduce additional firm events related to debt issuance.

1.6.2. Post earnings announcement drift

If analysts react to unexpected earnings, they will revise their target price upward for firms with positive (negative) earnings surprises, increasing the likelihood of these firms to enter the high (low) $\Delta TPER$ portfolio. As a consequence, the performance of our strategy could be driven by the post earnings announcement drift (PEAD).

To test our conjecture, we follow Chordia and Shivakumar (2006). Standardized unexpected earnings (*SUE*) is defined (at the firm level) as the last announced quarterly earnings minus the quarterly earnings four quarters before, scaled by the standard deviation of the unexpected earnings over the preceding eight quarters. A target price is classified as high (low) *SUE* when the most recent *SUE* of firm *i* is above (below) the median of the most recent *SUE*s reported on NYSE stocks.[16] To avoid using stale earnings, we require the most recent earnings announcements to be released no earlier than four months before the announcement of the target price. High and low *SUE* target prices are then separately sorted into tercile portfolios based on $\Delta TPER$.[17] Only *likely valuable* target prices are retained.

Table 1.7, columns 3 and 4, confirm that our results are not driven by PEAD. As a matter of fact, contrarily to the prediction of the PEAD hypothesis, the risk-adjusted performance of high *SUE* portfolios is never significant. The performance of the low $\Delta TPER$ and of the long-short portfolios of low *SUE* target prices earn risk-adjusted returns that are not statistically significant at the 5% level. The difference between the return of high and low *SUE* portfolios is also economically significant. For instance, the monthly risk-adjusted return of the low *SUE* long-short portfolio is about 30 bps higher than that of the high *SUE* long-short portfolio. The difference is more than doubled for high $\Delta TPER$ portfolios. Overall, the performance of our trading strategy is not driven by PEAD.

[16] The NYSE universe is composed by all the NYSE stocks that have a CRSP share code of 10 or 11. Closed end funds and REITs are excluded. Results are qualitatively unchanged if the breakpoints are obtained using the stocks composing the portfolios.
[17] Results reported in Appendix shows that results are unchanged when the portfolios are constructed according to $\Delta TPER^{IND}$ or $\Delta TPER^{MKT}$.

1.6.3. Limited investor attention

Recent literature suggests that *limited investor attention* explains various post-announcements drifts. Limited investor attention refers to the psychological limits that prevent investors to properly deal with all the information at their disposal, especially when facing multiple sources or when performing multiple tasks. For instance, in the theoretical models of Dellavigna and Pollet (2009) and Hirshleifer, Lim and Teoh (2011), the reaction to earnings announcements is incomplete because investors neglect part of the information contained in the latest earnings. The incorporation of the neglected information results in a post-announcement price drift in the direction of the initial adjustment. Loh (2010) studies the link between limited attention and the recommendation drift documented by Womack (1996). He finds that the magnitude of the recommendation drift of low attention stocks is more than double than that of high attention firms. Therefore, analysts' production is likely to act as a stimulus that turns investors' attention toward low attention stocks. Among the various proxies for investor attention proposed in the literature, turnover is likely to be the variable most correlated with attention; see Hou, Xiong and Peng (2009). We classify a target price release either as high or low turnover according to its average daily turnover over the last three months, i.e. over the window [-63;-1].[18] If the outperformance of high $\Delta TPER$ portfolios is due to limited attention, we expect to find higher (lower) outperformance among stocks with low (high) turnover.

Table 1.7, Panel A, columns 5 and 6, display the risk-adjusted returns of portfolios composed with low and high turnover stocks. The high $\Delta TPER$ portfolios, with both high and low turnover, earn significant risk-adjusted returns, even if the performance of the high-attention stocks portfolio is almost double than that of the low-attention portfolio. The low $\Delta TPER$ portfolios do not generate any significant risk-adjusted performance. As a result, only the performance of the high turnover long-short portfolio is significant. Again, in Panel B and C, we report similar results for the tercile portfolios sorted on $\Delta TPER^{IND}$ or

[18] The NYSE universe is defined as the one used for earnings surprises. Results are unchanged if the breakpoints are obtained using the stocks composing the portfolios. The daily turnover is the number of shares traded divided by the total number of shares outstanding obtained from CRSP. To account for the double counting of interdealer trades, we divide the number of shares traded on NASDAQ firms by two. The breakpoint for the two groups is the median average daily turnover for the NYSE stocks and it updated every time that a target price is released.

$\Delta TPER^{MKT}$. As a robustness check, we use analyst coverage to proxy the level of investor attention. Coverage is defined as the number of analysts that issued target prices for a given firm over the last three months. As for turnover, firms are categorized as high or low coverage firms by comparing their coverage to the median of the NYSE universe. Unreported results confirm that investor attention is not the source of the target price announcement drift. In fact, both the low and high coverage long-short portfolios earn significant return. Hence, it is unlikely that the performance of the portfolios constructed according to the information conveyed by target prices is a consequence of limited investors' attention.

1.6.4. Stock liquidity and transaction costs

We test whether the performance of portfolios based on *likely valuable* target prices is driven by a liquidity premium. In that perspective, we partition the sample in two groups according to stock liquidity and measure the performance of the portfolios composed by *likely valuable* target prices. If the extra-return remunerates the holding of illiquid stocks, we expect the performance to be stronger among illiquid stocks. Liquidity is measured by the Amivest liquidity ratio computed over the three months that precede the target price announcement. The breakpoint is the median of the NYSE universe estimated in real time. Table 1.7, Panel A, column 7 and 8, show that the extra-returns are not attributable to a liquidity premium. Panel B and C confirm these results for portfolios constructed with $\Delta TPER^{IND}$ or $\Delta TPER^{MKT}$. These results also hold with alternative proxies of liquidity like the proportion of zero daily stock returns and by size.

Our trading strategy requires a daily rebalancing that implies a significant turnover. For example, the average monthly turnover of the long-only portfolios (T1, T2, and T3) is approximately 130%. Anand, Irvine, Puckett and Venkataraman (2012) find that the execution shortfall for large institutional trades varies between 7 bps and 34 bps over the period 2000-2010, with an average of 25bps. The execution shortfall measures the one-way trading cost and captures the bid-ask spread, the price impact, and the slippage costs. The abnormal returns vanish even for moderate transaction costs, in particular for the portfolio T1, whose gross return is not significantly different from zero. To investigate whether our findings are robust to transaction costs we implement an alternative strategy that exploits the target price announcement drift with a limited turnover. This strategy consists in building one portfolio every day and hold it for twenty-one trading days, without any rebalancing. After a training period of 20 days, we simultaneously hold 21 of such buy-and-hold sub-portfolios. The initial investment in each portfolio is equal and corresponds to 1/21 dollar. By construction, this strategy has a monthly turnover of approximately 100%. When implemented with likely valuable high $\Delta TPER$ announcements, it earns a significant risk-adjusted return of 1.31% (Newey-West standard error of 0.32%). The performance of this strategy cannot be directly compared to the one discussed in Section 4.2 because buy-and-hold strategies involves a higher leverage. Given the transaction costs faced by institutional investors (around 50 bps), the alternative strategy based on the target price announcement drift yields a 0.81% risk-adjusted monthly returns that is statistically significant at the 1% level.

Improving the performance of the strategy based on valuable target prices could be done in several ways. First, long-short position could be constructed daily and held for a month to reduce turnover. Second, as the long leg of the portfolio (T3) captures most of the extra-returns, a future index could be used to the hedge the position. Third, given the abundance of target prices, more stringent filters could be used. This is left for further research.

1.7. Conclusion

We use target price releases to construct investable portfolios. Our analysis highlights several notable results. First, we show that target price and stock recommendation changes do not convey the same information. Second, we find that a strategy that is long the stocks with the highest target price revisions and short the lowest ones has a positive risk-adjusted return for the month that follows the announcement of the target price. Third, this positive return is amplified when only likely valuable target prices are included in the portfolio. Fourth, this extra-performance vanishes as soon as the time-varying exposure of the portfolios is accounted for, showing that target prices incorporate the cyclicality of the underlying stocks. The main message of this paper is that financial analysts altogether adequately interpret the state of the economy and provide appropriate advices. However, we find no evidence that analysts capture valuable firm-specific information.

References

Altınkılıç, O., V. S. Balashov, and R. S. Hansen, 2013, Are analysts' forecasts informative to the general public?, *Management Science* 59, 2550-2565.

Altınkılıç, O., and R. S. Hansen, 2009, On the information role of stock recommendation revisions, *Journal of Accounting and Economics* 48, 17-36.

Anand, A., P. Irvine, A. Puckett, and K. Venkataraman, 2012, Performance of institutional trading desks: An analysis of persistence in trading costs, *Review of Financial Studies* 25, 557-598.

Ang, A., J. Chen, and Y. Xing, 2006, Downside risk, *Review of Financial Studies* 19, 1191-1239.

Asquith, P., M. B. Mikhail, and A. S. Au, 2005, Information content of equity analyst reports, *Journal of Financial Economics* 75, 245-282.

Barber, B., R. Lehavy, M. McNichols, and B. Trueman, 2001, Can investors profit from the prophets? Security analyst recommendations and stock returns, *Journal of Finance* 56, 531-563.

Barber, B. M., R. Lehavy, and B. Trueman, 2010, Ratings changes, ratings levels, and the predictive value of analysts' recommendations, *Financial Management* 39, 533-553.

Blume, M. E., and R. F. Stambaugh, 1983, Biases in computed returns: An application to the size effect, *Journal of Financial Economics* 12, 387-404.

Boni, L., and K. L. Womack, 2006, Analysts, industries, and price momentum, *Journal of Financial and Quantitative Analysis* 41, 85-109.

Boudt, K., C. Croux, and S. Laurent, 2011, Robust estimation of intraweek periodicity in volatility and jump detection, *Journal of Empirical Finance* 18, 353-367.

Brav, A., and R. Lehavy, 2003, An empirical analysis of analysts' target prices: Short-term informativeness and long-term dynamics, *Journal of Finance* 58, 1933-1968.

Canina, L., R. Michaely, R. Thaler, and K. Womack, 1998, Caveat compounder: A warning about using the daily crsp equal-weighted index to compute long-run excess returns, *Journal of Finance* 53, 403-416.

Carhart, M. M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Chen, X., Q. Cheng, and K. Lo, 2010, On the relationship between analyst reports and corporate disclosures: Exploring the roles of information discovery and interpretation, *Journal of Accounting and Economics* 49, 206-226.

Chordia, T., and L. Shivakumar, 2006, Earnings and price momentum, *Journal of Financial Economics* 80, 627-656.

Da, Z., and E. Schaumburg, 2011, Relative valuation and analyst target price forecasts, *Journal of Financial Markets* 14, 161-192.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035-1058.

Davis, J. L., E. F. Fama, and K. R. French, 2000, Characteristics, covariances, and average returns: 1929 to 1997, *Journal of Finance* 55, 389-406.

Dellavigna, S., and J. M. Pollet, 2009, Investor inattention and friday earnings announcements, *Journal of Finance* 64, 709-749.

Feldman, R., J. Livnat, and Y. Zhang, 2012, Analysts' earnings forecast, recommendation and target price revisions, *Journal of Portfolio Management* 38, 120-132.

Goetzmann, W. N., A. Watanabe, and M. Watanabe, 2012, Procyclical stocks earn higher returns, http://ssrn.com/abstract=1570705.

Heinkel, R., and A. Kraus, 1988, Measuring event impacts in thinly traded stocks, *Journal of Financial and Quantitative Analysis* 23, 71-88.

Henriksson, R. D., and R. C. Merton, 1981, On market timing and investment performance. Ii. Statistical procedures for evaluating forecasting skills, *Journal of Business* 54, 513-533.

Hirshleifer, D., S. S. Lim, and S. H. Teoh, 2011, Limited investor attention and stock market misreactions to accounting information, *Review of Asset Pricing Studies* 1, 35-73.

Hou, K., W. Xiong, and L. Peng, 2009, A tale of two anomalies: The implications of investor attention for price and earnings momentum, http://ssrn.com/abstract=976394.

Hugon, A., A. Kumar, and A.-P. Lin, 2015, Analysts, macroeconomic news, and the benefit of in-house economists, *Accounting Review, forthcoming*.

Ivković, Z., and N. Jegadeesh, 2004, The timing and value of forecast and recommendation revisions, *Journal of Financial Economics* 73, 433-463.

Jegadeesh, N., J. Kim, S. D. Krische, and C. M. C. Lee, 2004, Analyzing the analysts: When do recommendations add value?, *Journal of Finance* 59, 1083-1124.

Jegadeesh, N., and W. Kim, 2006, Value of analyst recommendations: International evidence, *Journal of Financial Markets* 9, 274-309.

Jegadeesh, N., and W. Kim, 2010, Do analysts herd? An analysis of recommendations and market reactions, *Review of Financial Studies* 23, 901-937.

Kadan, O., L. Madureira, R. Wang, and T. Zach, 2012, What are analysts really good at?, http://ssrn.com/abstract=1961199.

Lettau, M., M. Maggiori, and M. Weber, 2014, Conditional risk premia in currency markets and other asset classes, *Journal of Financial Economics* 114, 197-225.

Lin, H.-w., and M. F. McNichols, 1998, Underwriting relationships, analysts' earnings forecasts and investment recommendations, *Journal of Accounting and Economics* 25, 101-127.

Loh, R. K., 2010, Investor inattention and the underreaction to stock recommendations, *Financial Management* 39, 1223-1252.

Loh, R. K., and R. M. Stulz, 2011, When are analyst recommendation changes influential?, *Review of Financial Studies* 24, 593-627.

Newey, W. K., and K. D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

Payne, J. L., and W. B. Thomas, 2003, The implications of using stock-split adjusted I/B/E/S data in empirical research, *Accounting Review* 78, 1049-1067.

Salinger, M., 1992, Standard errors in event studies, *Journal of Financial and Quantitative Analysis* 27, 39-53.

Stickel, S. E., 1995, The anatomy of the performance of buy and sell recommendations, *Financial Analysts Journal* 51, 25-39.

Wermers, R., 2004, Is money really 'smart'? New evidence on the relation between mutual fund flows, manager behavior, and performance persistence, http://ssrn.com/abstract=414420.

Womack, K. L., 1996, Do brokerage analysts' recommendations have investment value?, *Journal of Finance* 51, 137-167.

Appendix

Table 1.A.1: Current rating scale of main brokerage houses
This table contains the rating scale, the definition of each rating, and the I/B/E/S translation for ten major brokerage houses presenting 32% of the target prices.

Rating scale	Definition	I/B/E/S mapping
CITIGROUP		
Sell (3)	Sell (3) for negative Expected Total Return (ETR).	5 (Sell)
Neutral (2)	Any covered stock not assigned a Buy or a Sell is a Neutral (2).	3 (Hold)
Buy (1)	Buy (1) ETR of 15% or more or 25% or more for High risk stocks.	1 (Strong buy)
CREDIT SUISSE		
Underperform	The stock's total return is expected to underperform the relevant benchmark by 10-15% or more over the next 12 months.	4 (Underperform)
Neutral	The stock's total return is expected to be in line with the relevant benchmark (range of ±10-15%) over the next 12 months.	3 (Hold)
Outperform	The stock's total return is expected to outperform the relevant benchmark by at least 10-15% (or more, depending on perceived risk) over the next 12 months.	2 (Buy)
DEUTSCHE BANK		
Sell	Based on a current 12-month view of total shareholder return, we recommend that investors sell the stock.	4 (Underperform)
Hold	We take a neutral view on the stock 12-months out and, based on this time horizon, do not recommend either a Buy or Sell.	3 (Hold)
Buy	Based on a current 12-month view of total shareholder return, we recommend that investors buy the stock.	2 (Buy)
GOLDMAN SACHS & CO		
Sell	Buy or Sell on an Investment List is determined by a stock's return potential relative to its coverage group […] Any stock not assigned as	4 (Underperform)
Neutral	a Buy or a Sell on an Investment List is deemed Neutral. […] global guideline of 25%-35% of stocks as Buy and 10%-15% of stocks as	3 (Hold)
Buy	Sell.	2 (Buy)
Remark	On the top of the stock rating, analysts also issue a "coverage view" (cautious, in-line, and attractive).	
JP MORGAN		
Underweight	Over the next six to twelve months, we expect this stock will underperform the average total return of the stocks in the analyst's (or the analyst's team's) coverage universe.	4 (Underperform)
Neutral	Over the next six to twelve months, we expect this stock will perform in line with the average total return of the stocks in the analyst's (or the analyst's team's) coverage universe.	3 (Hold)
Overweight	Over the next six to twelve months, we expect this stock will outperform the average total return of the stocks in the analyst's (or the analyst's team's) coverage universe.	2 (Buy)
MERRILL LYNCH - BANK OF AMERICA		
Underperform	Underperform stocks are the least attractive stocks in a coverage cluster.	4 (Underperform)
Neutral	Neutral stocks are expected to remain flat or increase in value and are less attractive than Buy rated stocks.	3 (Hold)
Buy	Buy stocks are expected to have a total return of at least 10% and are the most attractive stocks in the coverage cluster.	1 (Strong buy)

Table 1.A.1- *Continued*

Rating Scale	Definition	I/B/E/S mapping
MORGAN STANLEY		
Underweight	The stock's total return is expected to exceed the total return of the relevant country MSCI Index or the average total return of the analyst's industry (or industry team's) coverage universe, on a risk-adjusted basis over the next 12-18 months.	4 (Underperform)
Equalweight	The stock's total return is expected to be in line with the total return of the relevant country MSCI Index or the average total return of the analyst's industry (or industry team's) coverage universe, on a risk-adjusted basis over the next 12-18 months.	3 (Hold)
Overweight	The stock's total return is expected to exceed the total return of the relevant country MSCI Index or the average total return of the analyst's industry (or industry team's) coverage universe, on a risk-adjusted basis over the next 12-18 months.	2 (Buy)
Remark	On the top of the stock rating, analysts also issue an "industry view" (no rating, cautious, in-line, and attractive).	
RAYMOND JAMES		
Underperform	Expected to underperform the S&P 500 or its sector over the next six to 12 months and should be sold.	4 (Underperform)
Market perform	Expected to perform generally in line with the S&P 500 over the next 12 months.	3 (Hold)
Outperform	Expected to appreciate and outperform the S&P 500 over the next 12-18 months.	2 (Buy)
Strong buy	Expected to appreciate, produce a total return of at least 15%, and outperform the S&P 500 over the next six to 12 months.	1 (Strong buy)
UBS		
Sell	Forecast Stock Return is more than 6% below the Market Return Assumption.	4 (Underperform)
Neutral	Forecast Stock Return is within +/- 6% of the Market Return Assumption.	3 (Hold)
Buy	Forecast Stock Return is more than 6% above the Market Return Assumption.	2 (Buy)
Remark:	Analyst can also issue a "short-term rating" (three-month expectation) on a two-tier scale (sell and buy), p. 18.	
WELLS FARGO		
Underperform	The stock appears overvalued, and we believe the stock's total return will be below the market over the next 12 months.	5 (Sell)
Market Perform	The stock appears appropriately valued, and we believe the stock's total return will be in line with the market over the next 12 months.	3 (Hold)
Outperform	The stock appears attractively valued, and we believe the stock's total return will exceed that of the market over the next 12 months.	1 (Strong buy)

Table 1.A.2: Sample description

Panel A outlines the sample selection procedure. In Panel B, descriptive statistics are presented. The columns report the number of firms, analysts, brokers and target prices with at least one target price released over the sample period. The last column displays the market capitalization of the firms in our sample with respect to the total market capitalization. The total market capitalization is the market capitalization of all the stocks included in the CRSP universe (NYSE, Amex, Nasdaq, and Arca) measured as of December 31th of each year.

Panel A: Sample selection	
Description	Observations
All unique target prices released between 1999 and 2011	923,566
Less	
target prices issued by non-identifiable analysts	-699
firms not matched with CRSP	-19,476
target prices for non-US firms	-147,123
target prices without 12-month forecast horizon	-15,790
target prices not labeled in USD	-399
target prices for firms followed by less than three analysts	-1,364
observations with missing stock prices at announcement	-1,228
observations with stock prices less than one dollar	-2,296
Final sample	735,191

Panel B: Number of observations					
Year	Number of firms followed	Number of analysts	Number of brokers	Number of target prices	% of total market cap
1999	2,823	2,545	156	24,532	85.5
2000	3,342	3,157	195	37,754	87.4
2001	3,233	3,546	169	44,256	87.5
2002	3,119	3,322	175	50,237	87.2
2003	3,126	2,704	236	51,357	85.8
2004	3,248	2,755	260	54,460	84.0
2005	3,358	2,802	259	55,820	81.7
2006	3,381	2,767	251	57,472	80.8
2007	3,389	2,729	244	60,801	78.9
2008	3,269	2,690	251	73,546	81.4
2009	2,967	2,614	268	70,468	77.4
2010	2,985	2,972	292	73,702	76.7
2011	2,976	3,037	275	80,786	76.8
All years	6,223	8,732	655	735,191	82.4

Table 1.A.3: Revision of target price expected return by tercile portfolio

This table displays the descriptive statistics of the changes in expected return based on $\Delta TPER$ (Panel A), $\Delta TPER^{IND}$ (Panel B) and $\Delta TPER^{MKT}$ (Panel C), respectively.

	T1 (lowest)						T2						T3 (highest)					
Year	N	Mean	Std Dev	Q1	Median	Q3	N	Mean	Std Dev	Q1	Median	Q3	N	Mean	Std Dev	Q1	Median	Q3
Panel A: $\Delta TPER$																		
1999	3,773	-23.8	46.2	-26.7	-15.2	-8.9	3,541	1.9	3.8	-1.2	1.8	4.9	3,475	26.2	24.2	12.7	19.4	31.3
2000	8,861	-30.1	39.3	-34.0	-19.2	-11.6	8,275	1.5	4.8	-2.2	1.4	5.3	8,559	44.8	126.0	16.3	25.9	47.3
2001	10,651	-45.5	41.4	-44.7	-24.5	-15.0	10,615	-1.1	4.8	-4.6	-1.0	2.6	10,235	36.7	79.9	12.0	19.8	37.6
2002	13,394	-31.4	60.5	-33.5	-18.3	-10.9	13,112	0.7	4.9	-2.8	0.5	3.6	13,457	33.9	55.8	11.6	20.0	36.5
2003	12,934	-26.4	46.3	-28.3	-17.0	-11.3	14,269	-2.1	3.4	-4.5	-2.0	0.4	13,758	15.2	29.3	5.7	9.7	17.3
2004	15,502	-14.4	14.5	-17.2	-10.2	-6.5	15,056	0.3	2.8	-1.7	0.3	2.3	14,336	16.0	15.9	7.4	11.4	18.9
2005	15,333	-14.5	18.2	-16.8	-10.2	-6.6	15,029	0.0	2.6	-1.9	0.0	1.8	15,510	13.8	17.2	6.4	10.0	16.5
2006	16,433	-14.9	14.6	-17.7	-10.8	-7.0	15,774	-0.2	2.8	-2.2	-0.2	1.8	15,253	14.6	15.7	6.3	10.4	17.7
2007	16,763	-14.2	15.7	-16.6	-10.2	-6.5	16,673	0.0	2.6	-1.9	-0.1	1.8	17,999	14.4	15.9	6.4	10.1	16.9
2008	21,564	-21.2	25.6	-24.5	-13.9	-8.2	19,577	2.4	4.6	-1.0	2.0	5.3	22,076	32.5	37.4	13.3	21.5	37.0
2009	19,073	-31.9	38.9	-35.6	-20.6	-13.4	21,711	-2.0	4.3	-5.1	-1.7	1.3	19,818	19.2	25.3	7.7	12.6	21.5
2010	22,363	-15.0	15.0	-18.0	-10.9	-7.0	20,963	0.4	3.1	-1.9	0.2	2.5	19,571	15.5	14.7	7.7	11.9	18.9
2011	23,438	-14.8	18.5	-17.6	-10.3	-6.4	22,823	0.8	3.5	-1.7	0.6	2.7	24,401	17.7	20.7	7.2	12.4	21.1
All	200,082	-21.4	63.5	-23.3	-13.4	-8.0	197,418	0.1	3.9	-2.4	0.0	2.4	198,448	21.5	41.9	8.0	13.5	23.6

Table 1.A.3 - *Continued*

	T1 (lowest)						T2						T3 (highest)					
Year	N	Mean	Std Dev	Q1	Median	Q3	N	Mean	Std Dev	Q1	Median	Q3	N	Mean	Std Dev	Q1	Median	Q3
Panel B: $\Delta TPER^{IND}$																		
1999	3,417	-22.1	27.7	-26.0	-15.2	-9.3	3,169	1.2	4.0	-2.0	1.0	4.2	2,887	24.5	23.1	12.0	18.4	29.2
2000	8,737	-34.0	40.4	-38.6	-22.9	-14.5	8,229	-0.7	4.9	-4.5	-0.7	3.2	8,541	39.3	124.0	13.2	22.0	40.5
2001	10,421	-47.1	44.3	-47.7	-25.5	-14.9	10,663	-0.2	5.5	-3.9	0.2	4.0	10,416	37.8	78.3	13.7	21.6	38.8
2002	13,833	-29.9	59.2	-32.5	-17.1	-9.3	12,997	1.9	4.9	-1.3	2.0	5.5	13,126	37.4	56.4	14.4	23.1	41.2
2003	12,912	-21.6	45.6	-23.4	-12.8	-7.3	14,227	1.0	3.9	-1.3	1.3	3.9	13,813	20.8	30.0	10.1	14.9	23.9
2004	15,948	-14.1	14.8	-16.9	-10.0	-6.2	15,065	0.6	2.9	-1.4	0.5	2.7	13,881	15.8	15.4	7.6	11.5	18.8
2005	15,378	-14.3	18.5	-16.6	-10.0	-6.4	15,040	0.2	2.5	-1.7	0.2	2.1	15,452	14.1	17.6	6.6	10.2	16.8
2006	16,265	-15.0	14.6	-17.8	-10.9	-7.1	15,729	-0.2	2.7	-2.2	-0.2	1.8	15,454	14.3	15.3	6.5	10.2	17.1
2007	17,156	-13.8	15.5	-16.0	-9.8	-6.2	16,747	0.2	2.4	-1.6	0.3	2.1	17,520	14.6	15.7	6.7	10.2	16.9
2008	22,044	-24.7	25.9	-28.7	-17.4	-11.3	19,471	-0.4	4.2	-3.6	-0.6	2.5	21,678	27.9	35.5	10.6	17.7	31.3
2009	18,583	-27.8	38.6	-31.8	-17.2	-9.0	21,612	0.3	5.0	-2.5	1.0	4.1	20,400	22.4	24.5	11.1	16.2	25.2
2010	22,356	-14.7	14.6	-17.8	-10.7	-6.7	20,902	0.6	3.2	-1.7	0.5	2.8	19,631	15.5	14.7	7.9	11.8	18.8
2011	24,329	-15.1	18.3	-18.1	-10.7	-6.4	22,751	0.3	3.0	-1.6	0.5	2.5	23,566	16.7	19.8	7.4	11.5	19.2
All	201,379	-21.1	63.1	-23.2	-13.1	-7.7	196,602	0.3	3.8	-2.1	0.4	2.9	196,365	21.7	41.2	8.7	13.9	23.7
Panel C: $\Delta TPER^{MKT}$																		
1999	3,936	-22.3	45.3	-25.2	-13.8	-7.8	3,555	3.1	4.0	-0.1	2.9	6.2	3,298	27.8	24.5	14.5	21.0	33.1
2000	9,063	-33.4	39.1	-37.8	-23.1	-15.0	8,225	-1.3	5.4	-5.1	-1.3	2.8	8,407	41.8	126.6	13.8	23.3	43.9
2001	10,222	-46.5	46.4	-46.6	-25.8	-15.5	10,564	-1.0	6.0	-4.8	-0.3	3.2	10,715	36.3	78.1	12.4	20.3	37.2
2002	14,016	-27.8	59.2	-30.1	-15.2	-7.4	12,832	3.3	5.1	0.3	3.6	7.0	13,115	37.1	56.1	15.4	23.0	39.1
2003	13,152	-20.4	45.7	-21.8	-11.5	-6.0	13,952	2.1	3.7	-0.2	2.3	4.8	13,857	19.7	29.1	10.3	14.5	21.8
2004	16,117	-13.9	14.2	-16.7	-10.0	-6.1	14,992	0.4	3.1	-1.6	0.4	2.7	13,785	16.0	15.8	7.7	11.6	19.1
2005	15,431	-14.2	18.1	-16.4	-10.0	-6.3	14,943	0.2	2.5	-1.7	0.2	2.1	15,498	14.0	17.2	6.6	10.2	16.6
2006	16,327	-14.9	14.6	-17.7	-10.9	-7.0	15,555	-0.3	2.7	-2.2	-0.3	1.7	15,578	14.2	15.3	6.3	10.0	17.0
2007	17,205	-13.9	15.5	-16.2	-9.9	-6.3	16,741	0.2	2.4	-1.6	0.3	2.1	17,489	14.6	15.7	6.7	10.2	16.9
2008	22,106	-24.5	25.5	-28.2	-17.4	-11.5	19,472	-0.9	4.2	-4.0	-1.0	2.1	21,639	28.4	36.5	10.3	17.6	32.2
2009	18,547	-27.8	38.9	-32.0	-17.2	-8.6	21,521	0.5	5.2	-2.5	1.2	4.3	20,534	22.0	24.5	10.9	15.9	24.6
2010	22,538	-14.5	14.8	-17.5	-10.5	-6.5	20,781	0.6	3.3	-1.6	0.5	2.9	19,578	15.5	14.7	7.9	11.8	18.9
2011	24,482	-15.0	18.2	-17.9	-10.7	-6.4	22,580	0.3	3.1	-1.7	0.4	2.5	23,600	16.8	20.0	7.3	11.5	19.3
All	203,142	-20.7	63.0	-22.8	-12.8	-7.4	195,713	0.4	4.1	-2.0	0.5	3.1	197,093	21.7	41.6	8.7	13.9	23.6

Table 1.A.4: Variable definitions

Variable	Definition
Analyst characteristics	
Star analyst	Dummy variable equal to one for analysts ranked as All-American (top three or runner-up team) in the annual poll of the Institutional Investor magazine, and zero otherwise.
Analyst experience	Years elapsed since the first earnings forecast, recommendation, or target price. We compute both the global and the firm-specific experience.
Valuable before	Dummy variable equal to one if the analysts issued at least a valuable target price over the previous 12 months, and zero otherwise.
Target price characteristics	
Away from consensus	Dummy variable equal to one if the absolute deviation from the consensus of the new target price increases with respect to the previous target price issued on the same stock and brokerage house, and zero otherwise. Consensus is the average valid target prices outstanding.
$\Delta TPER$	Revision of the target price expected return.
Conc. earnings forecast	Dummy variable equal to one if there is an earnings forecast issued by the same analyst within a three-day window around the target price release, and zero otherwise.
Information discovery	Dummy variable equal to one if the target price is not released in the three-day window surrounding a firm-specific event (earnings' releases, management guidance, mergers and acquisitions, syndicated loans, and equity issuance), and zero otherwise.
Firm characteristics	
Book-to-market	Log of book-to-market, computed as in Davis et al. (2000).
Firm's size	Log of market capitalization, computed as in Davis et al. (2000).
Momentum	Buy-and-hold return for the prior eleven months period skipping the most recent month.
Guidance intensity	Number of guidance issued during the last three months.
Analysts following	Number of brokerage houses with valid target prices outstanding.
Institutional ownership	Log of percent of the firm owned by 13F institutions in the most recent quarter-end.
Turnover	Log of three-month average daily shares traded divided by total shares outstanding.
Dispersion	Standard deviation of $\Delta TPER$.
Idiosyncratic volatility	Idiosyncratic volatility of daily returns, computed over the window [-150; -1] adjusted for infrequent trading.

Table 1.1: Descriptive statistics

This table describes the sample of target prices in terms of market capitalization, book-to-market, and momentum. For each year, we report the percentage of target prices based on size, book-to-market, and momentum tercile. The variables are measured at the end of the year preceding the announcement of the target price. The tercile breakpoints are constructed using NYSE stocks with a CRSP share code of 10 or 11.

	% of observations by market capitalization tercile			% of observations by book-to-market tercile			% of observations by momentum tercile		
Year	Small	Medium	Large	Low	Medium	High	Low	Medium	High
1999	17.1	26.7	56.0	59.0	26.6	14.3	28.3	20.7	50.8
2000	21.6	27.4	50.9	55.0	28.2	16.7	43.0	20.6	36.3
2001	22.2	31.5	46.2	55.4	30.8	13.6	50.4	22.1	27.3
2002	26.7	28.0	45.2	45.5	32.1	22.2	50.1	24.3	25.4
2003	25.6	28.8	45.5	52.2	30.3	17.4	25.5	29.1	45.2
2004	29.3	28.6	41.9	49.3	30.0	20.5	38.8	23.0	38.1
2005	32.2	28.5	39.1	48.5	30.9	20.4	36.8	21.4	41.7
2006	34.2	27.5	38.2	45.7	30.7	23.4	45.2	24.6	30.1
2007	34.9	26.6	38.4	44.6	29.1	26.1	40.1	19.8	40.0
2008	35.0	27.6	37.2	40.1	29.7	30.1	44.6	31.1	24.1
2009	29.8	28.3	41.8	46.7	29.7	23.4	32.4	28.6	38.8
2010	28.9	27.8	43.2	47.4	28.2	24.2	37.8	20.4	41.7
2011	28.5	29.7	41.7	43.9	29.7	26.3	37.6	30.2	32.1
All Years	29.2	28.3	42.4	47.5	29.8	22.5	39.4	24.9	35.6

Table 1.2: Descriptive statistics of target price revisions

This table contains the descriptive statistics of the target price revisions by year. $\Delta TPER$ measures the target price revision with respect to the previous target price issued by the same analysts for the same firm. $\Delta TPER^{IND}$ ($\Delta TPER^{MKT}$) adjusts $\Delta TPER$ for the average $\Delta TPER$ at the industry (market) level. For further details, refer to the text.

	$\Delta TPER$						$\Delta TPER^{IND}$						$\Delta TPER^{MKT}$					
Year	N	Mean	Std Dev	Q1	Median	Q3	N	Mean	Std Dev	Q1	Median	Q3	N	Mean	Std Dev	Q1	Median	Q3
1999	10,836	0.7	36.8	-9.5	1.2	12.2	9,510	-0.1	28.3	-10.4	0.1	10.8	10,836	1.4	36.8	-9.1	1.9	13.0
2000	25,695	5.0	82.4	-12.2	1.2	16.3	25,507	1.3	81.4	-15.1	-0.9	13.3	25,695	1.5	82.2	-16.0	-1.9	13.4
2001	31,501	-3.8	51.4	-15.3	-1.2	11.5	31,500	-3.1	51.6	-14.8	0.2	13.6	31,501	-3.1	51.4	-15.2	-0.0	12.8
2002	39,963	1.1	54.8	-11.0	0.5	12.4	39,956	2.5	55.0	-10.4	1.6	14.2	39,963	3.5	54.6	-8.8	3.1	15.1
2003	40,961	-4.0	35.4	-10.6	-1.7	5.8	40,952	0.6	35.4	-7.0	1.6	10.3	40,961	0.8	35.0	-5.9	2.6	10.5
2004	44,894	0.2	17.6	-6.8	-0.0	7.0	44,894	0.1	17.4	-6.9	0.0	6.9	44,894	0.1	17.4	-7.0	-0.2	6.9
2005	45,872	-0.2	18.6	-6.7	0.0	6.5	45,870	0.0	18.9	-6.5	0.2	6.7	45,872	0.0	18.6	-6.4	0.2	6.7
2006	47,460	-0.5	17.3	-7.3	-0.5	6.2	47,448	-0.6	17.2	-7.4	-0.4	6.2	47,460	-0.6	17.2	-7.4	-0.5	6.1
2007	51,435	0.4	17.6	-6.3	0.2	6.9	51,423	0.4	17.3	-6.3	0.4	6.9	51,435	0.4	17.4	-6.3	0.3	6.8
2008	63,217	4.9	34.9	-8.6	2.1	14.7	63,193	0.8	33.9	-12.0	-0.7	11.1	63,217	0.9	34.2	-12.2	-1.1	10.8
2009	60,602	-4.5	33.4	-12.4	-1.5	7.6	60,595	-0.9	32.8	-9.0	1.5	11.2	60,602	-0.9	32.8	-8.7	1.8	11.1
2010	62,897	-0.4	17.5	-7.6	-0.3	7.1	62,889	-0.2	17.3	-7.4	-0.0	7.3	62,897	-0.2	17.3	-7.4	-0.1	7.3
2011	70,662	1.5	21.0	-6.4	0.7	8.3	70,646	0.5	20.5	-7.1	0.3	7.5	70,662	0.5	20.6	-7.1	0.2	7.4
All	595,995	0.0	47.4	-8.4	-0.0	8.4	594,383	0.1	47.1	-8.3	0.3	8.8	595,995	0.3	47.2	-8.2	0.4	8.9

Table 1.3: Performance of tercile portfolios

This table contains the returns of the unconditional tercile portfolios constructed according to the revisions of the expected return derived from target prices ($\Delta TPER$), the industry-adjusted revisions ($\Delta TPER^{IND}$), and the market-adjusted revisions ($\Delta TPER^{MKT}$). We also include the return of a zero-investment portfolio that buys portfolio T3 and sells portfolio T1. The table shows the raw returns (Panel A) as well as the risk-adjusted returns obtained from the Carhart (1997) four-factor model (Panel B). Figures in brackets represent the Newey and West (1987) heteroskedasticity and autocorrelation consistent estimates of the standard error with six lags. One and two asterisks denote statistical significance at the 5% and 1% significance level.

	$\Delta TPER$				$\Delta TPER^{IND}$				$\Delta TPER^{MKT}$			
	[+1 ; +21]	[+22 ; +42]	[+43 ; +63]	[+5 ; +21]	[+1 ; +21]	[+22 ; +42]	[+43 ; +63]	[+5 ; +21]	[+1 ; +21]	[+22 ; +42]	[+43 ; +63]	[+5 ; +21]
Panel A: Raw returns												
T1 (lowest)	-0.075	0.080	0.041	0.020	-0.077	0.075	0.063	0.050	-0.103	0.115	0.069	-0.013
	[0.478]	[0.511]	[0.524]	[0.467]	[0.490]	[0.518]	[0.511]	[0.473]	[0.480]	[0.492]	[0.521]	[0.474]
T2	0.166	0.171	0.281	0.233	0.174	0.213	0.252	0.227	0.203	0.173	0.257	0.300
	[0.428]	[0.446]	[0.458]	[0.431]	[0.440]	[0.452]	[0.450]	[0.444]	[0.430]	[0.461]	[0.457]	[0.428]
T3 (highest)	0.368	0.190	0.017	0.308	0.362	0.230	0.053	0.311	0.346	0.171	0.033	0.284
	[0.510]	[0.555]	[0.552]	[0.518]	[0.500]	[0.535]	[0.565]	[0.509]	[0.498]	[0.547]	[0.556]	[0.511]
T3 –T1	0.444**	0.110	-0.023	0.289*	0.440**	0.155	-0.010	0.261	0.450**	0.056	-0.036	0.297*
	[0.126]	[0.125]	[0.122]	[0.140]	[0.164]	[0.184]	[0.135]	[0.153]	[0.125]	[0.138]	[0.136]	[0.148]
Panel B: Four-factor intercept												
T1 (lowest)	-0.217**	-0.038	-0.078	-0.119	-0.193*	-0.019	-0.016	-0.062	-0.238**	-0.011	-0.062	-0.143
	[0.078]	[0.064]	[0.104]	[0.093]	[0.081]	[0.081]	[0.106]	[0.094]	[0.076]	[0.066]	[0.111]	[0.091]
T2	-0.016	0.005	0.100	0.047	0.003	0.051	0.074	0.059	0.031	0.011	0.084	0.119
	[0.045]	[0.062]	[0.097]	[0.057]	[0.055]	[0.077]	[0.093]	[0.066]	[0.046]	[0.072]	[0.099]	[0.065]
T3 (highest)	0.271	0.069	-0.067	0.234	0.246	0.085	-0.064	0.204	0.248*	0.036	-0.047	0.200
	[0.144]	[0.140]	[0.088]	[0.163]	[0.135]	[0.145]	[0.103]	[0.155]	[0.123]	[0.143]	[0.097]	[0.150]
T3 –T1	0.487**	0.107	0.011	0.353*	0.438**	0.105	-0.048	0.266	0.486**	0.047	0.015	0.343*
	[0.148]	[0.128]	[0.127]	[0.161]	[0.141]	[0.145]	[0.145]	[0.138]	[0.146]	[0.135]	[0.143]	[0.168]

Table 1.4: Performance of tercile portfolios conditioned on predicted investment value

This table contains the returns of tercile portfolios that control for the likelihood that a target price announcement is valuable. In Panel A (B), portfolios are constructed with the Probit model (OLS regression). In Panel C, we control for the false discovery. The portfolios are constructed according to the revisions of the expected return implied by target price ($\Delta TPER$), the industry-adjusted revisions ($\Delta TPER^{IND}$), and the market-adjusted revisions ($\Delta TPER^{MKT}$), conditional on the likelihood that a target price is valuable. Stocks are held for the period [+1; +21]. We also include the return of a zero-investment portfolio that buys T3 and sells T1. The table shows the performance obtained with the Carhart (1997) four-factor model. The figures in brackets represent the Newey and West (1987) heteroskedasticity and autocorrelation consistent estimates of the standard error with six lags. One and two asterisks denote statistical significance at the 5% and 1% significance level, respectively.

	Likely valuable			Unlikely valuable		
	$\Delta TPER$	$\Delta TPER^{IND}$	$\Delta TPER^{MKT}$	$\Delta TPER$	$\Delta TPER^{IND}$	$\Delta TPER^{MKT}$
Panel A: Probit regression						
T1 (lowest)	-0.086	0.062	-0.161	-0.117	-0.027	-0.129
	[0.139]	[0.127]	[0.132]	[0.172]	[0.160]	[0.163]
T2	0.381**	0.372**	0.470**	0.004	0.015	-0.027
	[0.112]	[0.130]	[0.136]	[0.121]	[0.133]	[0.116]
T3 (highest)	0.720**	0.719**	0.702**	0.141	0.229	0.052
	[0.250]	[0.228]	[0.208]	[0.182]	[0.224]	[0.212]
T3 –T1	0.807**	0.657**	0.863**	0.258	0.257	0.181
	[0.233]	[0.230]	[0.231]	[0.219]	[0.219]	[0.255]
Panel B: OLS regression						
T1 (lowest)	-0.197	-0.161	-0.183	0.039	0.075	-0.037
	[0.183]	[0.208]	[0.169]	[0.177]	[0.170]	[0.188]
T2	0.312*	0.357*	0.375**	0.038	0.007	0.074
	[0.126]	[0.151]	[0.142]	[0.097]	[0.110]	[0.114]
T3 (highest)	0.634**	0.604**	0.622**	0.264	0.367	0.222
	[0.239]	[0.222]	[0.217]	[0.183]	[0.196]	[0.193]
T3 –T1	0.831**	0.764**	0.805**	0.225	0.292	0.260
	[0.203]	[0.226]	[0.197]	[0.201]	[0.201]	[0.241]
Panel C: Controlling for false discoveries in Probit regression						
T1 (lowest)	-0.001	0.023	-0.084	0.143	0.108	0.135
	[0.175]	[0.206]	[0.179]	[0.155]	[0.163]	[0.156]
T2	0.166	0.303*	0.369**	0.190	0.099	0.055
	[0.100]	[0.117]	[0.120]	[0.139]	[0.143]	[0.120]
T3 (highest)	0.708*	0.601**	0.692**	0.209	0.433	0.244
	[0.294]	[0.202]	[0.219]	[0.198]	[0.256]	[0.213]
T3 –T1	0.708*	0.578*	0.776**	0.066	0.324	0.109
	[0.272]	[0.238]	[0.256]	[0.182]	[0.219]	[0.199]

Table 1.5: Risk exposures of the long-short portfolios

This table contains the risk exposure of the long-short portfolios based on *likely valuable* target prices. Column 1 displays the risk exposures obtained with the Carhart (1997) four-factor model. Columns 2 to 4 show the corresponding univariate exposure. The exposure obtained using all the periods are reported in Columns 2. Column 3 (4) shows the exposure obtained considering the periods during which the factor returns are above (below) their sample average. Columns 5 and 6 report the multivariate conditional exposure. The figures reported in Column 5 represent the exposure of the portfolio when the factor returns are above their sample average. The figures in Column 6 are the change in exposure when the risk factor return is below its sample average. One and two asterisks denote statistical significance at the 5% and 1% significance level, respectively.

	Carhart (1997) four-factor	Univariate exposures			Multivariate exposures	
		All	Up	Down	Up	Down
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Long-short portfolio based on $\Delta TPER$ ranking						
MKT	-0.024	-0.047	-0.072	-0.046	-0.197	0.312
	[0.077]	[0.058]	[0.120]	[0.148]	[0.187]	[0.318]
SMB	-0.121	-0.165*	-0.111	-0.625**	-0.044	-0.517**
	[0.124]	[0.073]	[0.116]	[0.162]	[0.174]	[0.194]
HML	0.085	0.139	0.061	0.153	-0.235	0.689*
	[0.135]	[0.077]	[0.183]	[0.124]	[0.164]	[0.272]
MOM	-0.026	-0.033	0.179	-0.181*	0.385**	-0.653*
	[0.089]	[0.044]	[0.093]	[0.076]	[0.135]	[0.265]
Intercept	0.807**	-	-	-	0.310	
	[0.233]	-	-	-	[0.387]	
Panel B: Long-short portfolio based on $\Delta TPER^{IND}$ ranking						
MKT	-0.042	-0.057	-0.117	-0.086	-0.154	0.224
	[0.070]	[0.047]	[0.106]	[0.114]	[0.163]	[0.280]
SMB	-0.050	-0.117	0.057	-0.518**	0.098	-0.534**
	[0.108]	[0.060]	[0.093]	[0.133]	[0.142]	[0.181]
HML	0.135	0.163**	0.362**	0.064	0.076	0.130
	[0.071]	[0.062]	[0.134]	[0.111]	[0.101]	[0.269]
MOM	-0.018	-0.017	0.127	-0.097	0.144	-0.260
	[0.057]	[0.036]	[0.069]	[0.068]	[0.110]	[0.189]
Intercept	0.657**	-	-	-	0.079	
	[0.230]	-	-	-	[0.345]	
Panel C: Long-short portfolio based on $\Delta TPER^{MKT}$ ranking						
MKT	-0.024	-0.049	0.002	-0.105	-0.108	0.172
	[0.072]	[0.055]	[0.119]	[0.138]	[0.197]	[0.328]
SMB	-0.125	-0.166*	-0.127	-0.622**	-0.072	-0.441*
	[0.125]	[0.070]	[0.113]	[0.151]	[0.155]	[0.169]
HML	0.080	0.134	0.119	0.086	-0.169	0.526*
	[0.117]	[0.073]	[0.174]	[0.120]	[0.161]	[0.217]
MOM	-0.022	-0.029	0.186*	-0.175*	0.356*	-0.591*
	[0.090]	[0.043]	[0.091]	[0.071]	[0.141]	[0.274]
Intercept	0.863**	-	-	-	0.119	
	[0.231]	-	-	-	[0.429]	

Table 1.6: Macroeconomic expectations and the portfolio composition
This table presents the average exposure to GDP growth and its standard deviation, the weights invested in pro-cyclical, neutral, and counter-cyclical stocks (columns 1 to 4). The last two columns are the coefficient and the R-square of a regression where the dependent variable is the weight invested in pro-cyclical, neutral and counter-cyclical stocks. One and two asterisks denote statistical significance at the 5% and 1% significance level, respectively.

	β_{GDP}		Weight (%)			
	Mean	Std Dev	Mean	Std Dev	b_1	Adj R^2
Panel A: Long-short portfolio based on $\Delta TPER$ ranking						
High β_{GDP} (pro-cyclical stocks)	5.526	0.212	0.568	1.000	-0.002** [0.001]	0.149
Medium β_{GDP}	-0.583	0.010	0.713	1.259	0.002** [0.001]	0.146
Low β_{GDP} (counter-cyclical stocks)	-8.846	0.374	-1.281	1.351	-0.000 [0.001]	-0.016
Panel B: Long-short portfolio based on $\Delta TPER^{IND}$ ranking						
High β_{GDP} (pro-cyclical stocks)	5.476	0.199	-1.483	0.976	-0.002** [0.001]	0.149
Medium β_{GDP}	-0.581	0.010	1.278	1.346	0.002* [0.001]	0.096
Low β_{GDP} (counter-cyclical stocks)	-8.937	0.400	0.205	1.096	-0.000 [0.001]	-0.019
Panel C: Long-short portfolio based on $\Delta TPER^{MKT}$ ranking						
High β_{GDP} (pro-cyclical stocks)	5.515	0.208	0.298	0.938	-0.002** [0.001]	0.184
Medium β_{GDP}	-0.579	0.010	1.071	1.223	0.002** [0.001]	0.123
Low β_{GDP} (counter-cyclical stocks)	-8.869	0.385	-1.369	1.300	-0.000 [0.001]	-0.021

Table 1.7: Alternative explanations

This table contains the returns of *likely valuable* tercile portfolios (*ΔTPER)* conditional on an additional variable. The additional variables are i) whether the target prices stem from information interpretation (all target prices issued in a three-day window around a firm-specific event, i.e. earnings' releases, management guidance, mergers and acquisition, syndicated loans, and equity issuance) or from information discovery (all the other target prices); ii) Standardized Unexpected Earnings (*SUE*), defined as the last announced quarterly earnings less the quarterly earnings four quarters before, scaled by the standard deviation of the unexpected earnings over the preceding height quarters; iii) the level of investors inattention, measured by the average daily number of shares traded divided by the total number of shares outstanding over the last three months; and iv) liquidity, measured by the Amivest liquidity ratio computed over the three months preceding the target price release. One and two asterisks denote statistical significance at the 5% and 1% significance level, respectively.

	Firm-specific events		Earning momentum		Investor inattention		Liquidity	
	Yes	No	High SUE	Low SUE	Low turnover	High turnover	Illiquid stocks	Liquid stocks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: $\Delta TPER^{IND}$				
T1 (lowest)	-0.095	-0.244	-0.332	0.027	0.186	-0.126	0.395	-0.089
	[0.251]	[0.146]	[0.232]	[0.154]	[0.289]	[0.176]	[0.277]	[0.142]
T2	0.619**	0.176	0.148	0.488**	0.390*	0.226	0.745**	0.376**
	[0.200]	[0.141]	[0.142]	[0.145]	[0.149]	[0.167]	[0.234]	[0.113]
T3 (highest)	0.394	0.663*	0.362	1.014**	0.478*	0.747*	1.210**	0.701**
	[0.241]	[0.271]	[0.305]	[0.294]	[0.223]	[0.326]	[0.343]	[0.252]
T3 –T1	0.489	0.907**	0.694	0.987**	0.292	0.873**	0.816*	0.790**
	[0.260]	[0.285]	[0.356]	[0.272]	[0.282]	[0.323]	[0.323]	[0.244]
				Panel B: $\Delta TPER^{IND}$				
T1 (lowest)	-0.075	-0.087	-0.227	0.140	0.096	-0.124	0.406	0.070
	[0.273]	[0.163]	[0.256]	[0.167]	[0.297]	[0.175]	[0.250]	[0.129]
T2	0.478**	0.201	0.368*	0.351*	0.299*	0.382*	0.770**	0.366**
	[0.181]	[0.142]	[0.148]	[0.153]	[0.145]	[0.184]	[0.213]	[0.132]
T3 (highest)	0.490*	0.726**	0.437	1.026**	0.385	0.801*	1.282**	0.699**
	[0.231]	[0.253]	[0.273]	[0.302]	[0.196]	[0.327]	[0.284]	[0.231]
T3 –T1	0.565*	0.813**	0.664	0.886**	0.290	0.925**	0.875**	0.629*
	[0.242]	[0.270]	[0.338]	[0.302]	[0.263]	[0.347]	[0.245]	[0.241]
				Panel C: $\Delta TPER^{MKT}$				
T1 (lowest)	-0.230	-0.298	-0.328	-0.097	0.034	-0.185	0.378	-0.168
	[0.260]	[0.157]	[0.239]	[0.152]	[0.323]	[0.178]	[0.231]	[0.134]
T2	0.588**	0.254	0.253	0.560**	0.523**	0.322	0.866**	0.464**
	[0.191]	[0.144]	[0.172]	[0.172]	[0.170]	[0.187]	[0.247]	[0.137]
T3 (highest)	0.507*	0.754**	0.361	0.957**	0.402*	0.743*	1.202**	0.683**
	[0.244]	[0.222]	[0.260]	[0.257]	[0.175]	[0.303]	[0.303]	[0.210]
T3 –T1	0.738*	1.052**	0.689*	1.054**	0.368	0.929**	0.825**	0.851**
	[0.294]	[0.269]	[0.342]	[0.277]	[0.303]	[0.319]	[0.300]	[0.238]

Figure 1.1: Density of target price implied expected return by recommendation

The figure plots the kernel-based density of the implied expected return by recommendation rating. I/B/E/S recommendations (recorded with their scale) are matched with target prices if they are issued by the same broker, for the same firm, in the three days surrounding the recommendation issuance.

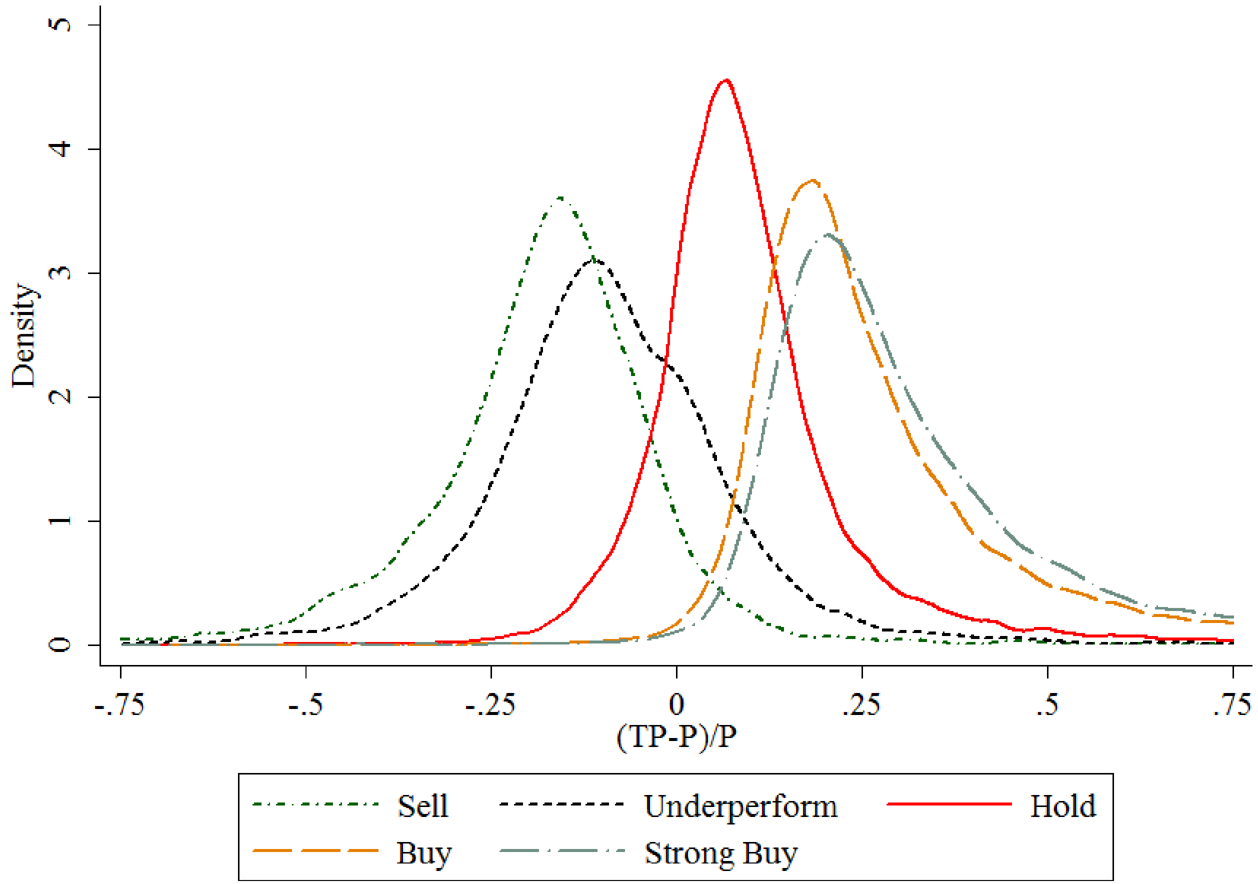


Figure 1.2: Performance of top and bottom target prices portfolios at different investment horizons

The figures represent the abnormal return for the 63 trading days subsequent to the announcement of a target prices for top and bottom tercile portfolios ranked on the basis of $\Delta TPER$, $\Delta TPER^{IND}$, and $\Delta TPER^{MKT}$, three alternative measures of the information content of target prices. Abnormal returns are computed using the Carhart (1997) four-factor model.

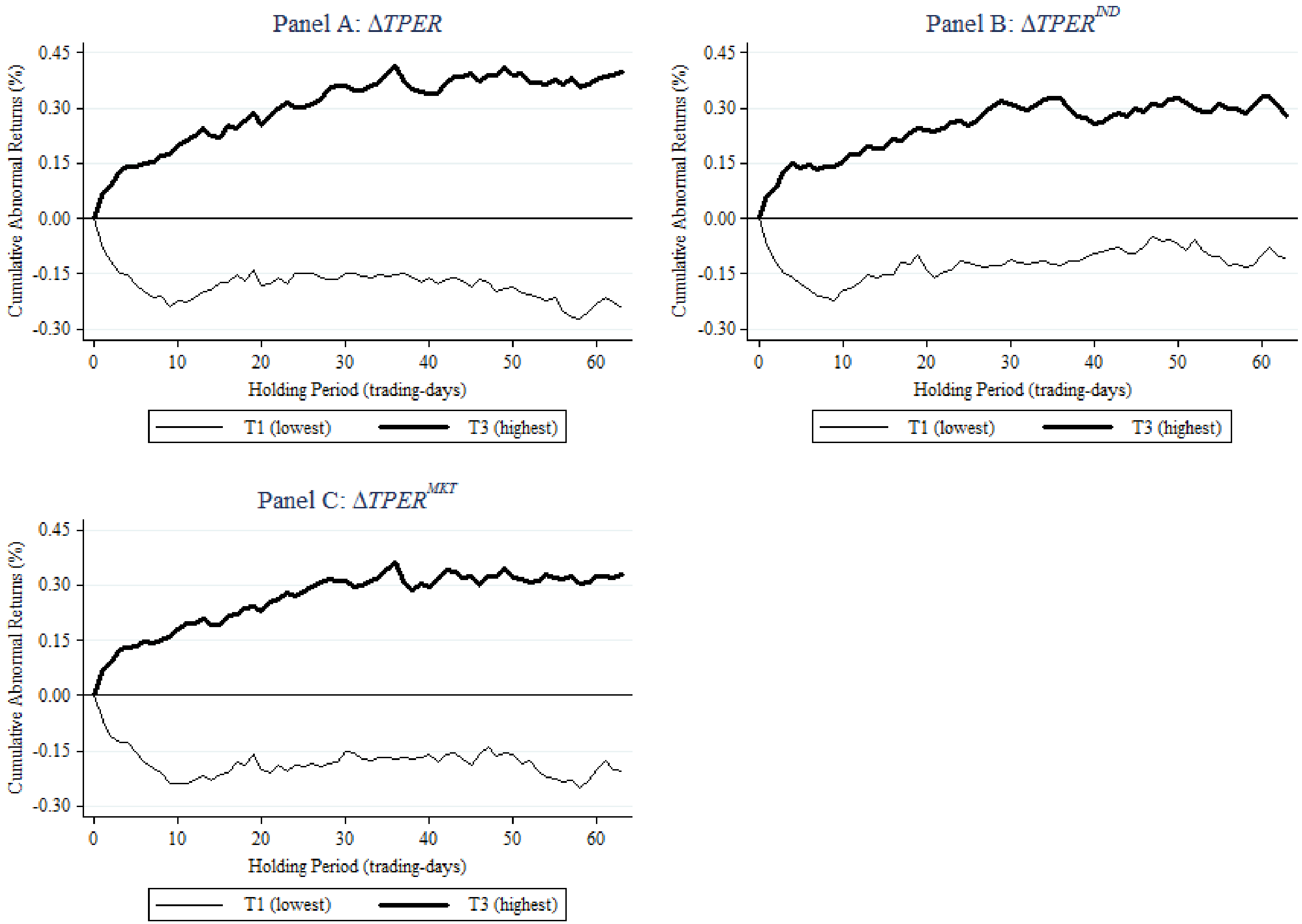


Figure 1.3: Performance of top and bottom portfolios conditioned on the predicted investment value

The figures represent the abnormal return for the 63 trading days subsequent to the announcement of a target prices for top and bottom tercile portfolios constructed on the basis of either $\Delta TPER$, $\Delta TPER^{IND}$, or $\Delta TPER^{MKT}$ and the likelihood that a target price is valuable. Abnormal returns are computed using the Carhart (1997) four-factor model.

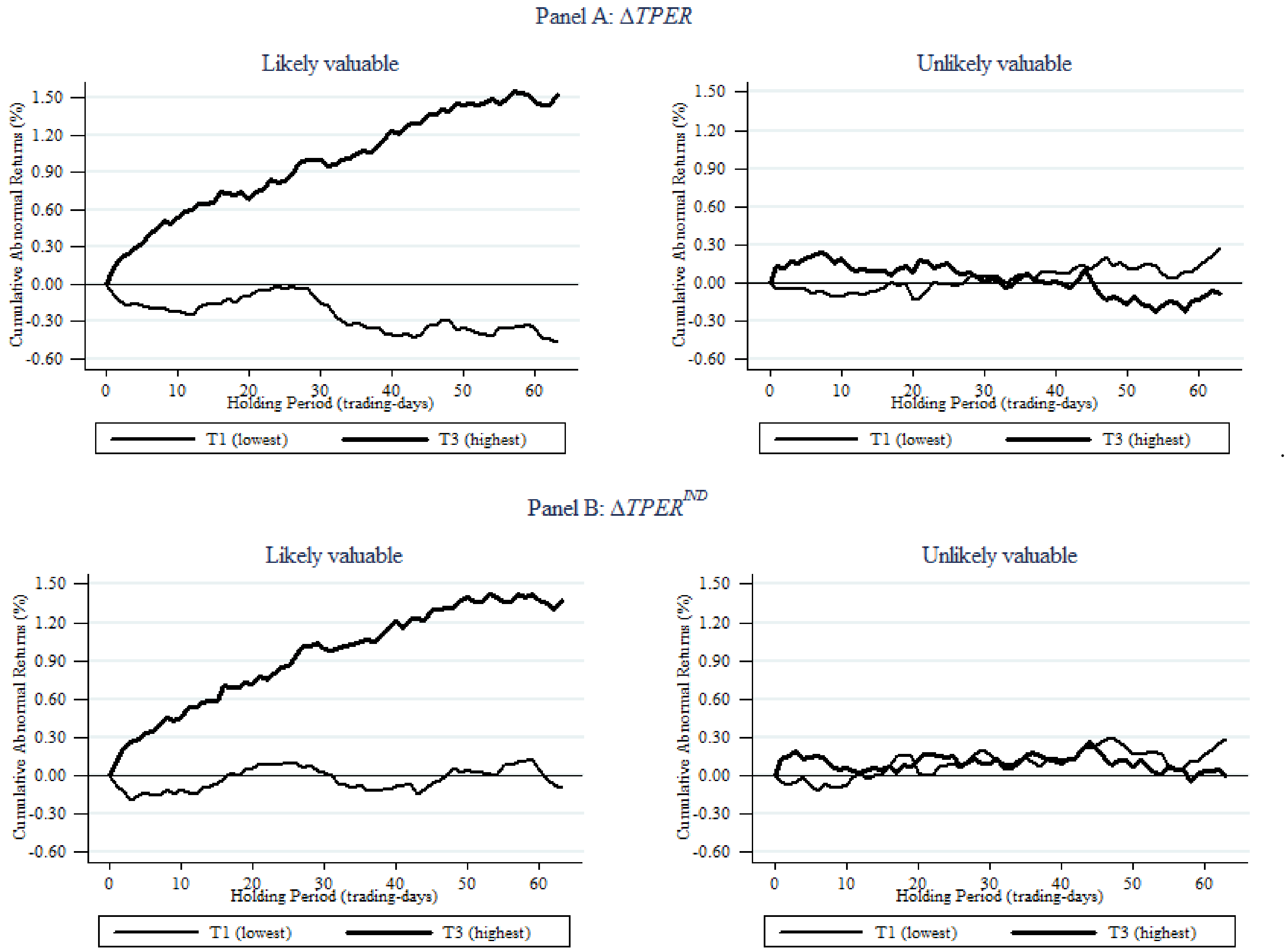
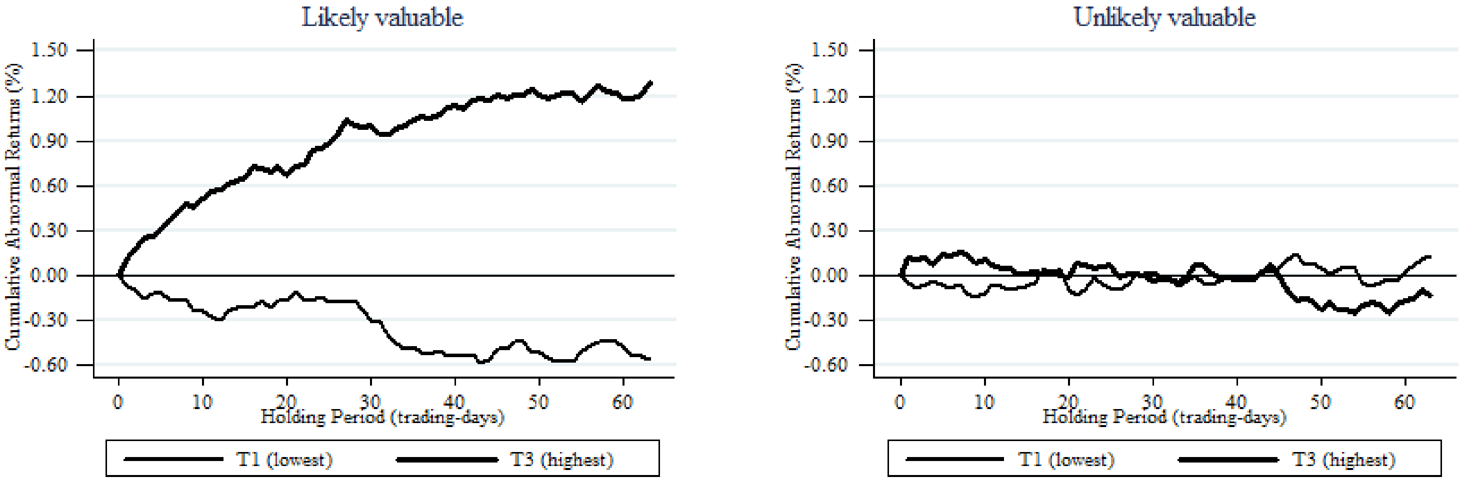


Figure 1.3 - *Continued*

Panel C: $\Delta TPER^{MKT}$



Chapter 2: Do Investors Correctly Interpret Analysts' Production?

2.1. Introduction

Several studies exploit the market reaction to infer the informativeness of analysts' research; see, e.g., Piotroski and Roulstone (2004), Chan and Hameed (2006), Liu (2011). These studies implicitly assume that investors correctly interpret the information conveyed through analysts' research, which is based on a mixture of information with different availability and scope. Availability specifies whether information is public (common to brokers and investors) or not; see, e.g., Barron, Kim, Lim and Stevens (1998). Scope states whether the information concerns only one firm or a group of firms; see e.g. Hugon, Kumar and Lin (2015). Analysts bundle public and private information into a single figure (e.g. an earnings forecast, a target price, or a recommendation) and there is no straightforward procedure to separate it.

In this paper, I disentangle the information conveyed through target prices into three components (public, private industry-wide, and private firm-specific), which permits to verify whether investors correctly interpret this information. Only in this case it is possible to exploit investors' reaction to infer the information conveyed through analysts' research. Secondarily, my methodology allows analyzing the information bundled in target prices. The finance literature has not yet reached a consensus on the information mix employed by analysts. I tackle the question by decomposing the information conveyed through target prices without relying on investors' reaction.

In my analysis, I first focus on the availability of information. I split the expected return implied by target prices in two components attributable either to public or private information. More precisely, I assume that the market is in equilibrium when no information flows to the market, i.e. when no target price is released, so that the CAPM holds. I thus plug into the CAPM an expected equity risk premium based on public information to measure the expected return attributable to public information. I use expectations on the value of the S&P500 Index obtained from the Livingston Survey. This survey is considered as public information because it is freely available from the Philadelphia Federal Bank Reserve and it is often reported in major newspapers and Internet newswires. The design of the survey allows constructing an expected market returns with a horizon that matches the one of target prices, i.e. twelve months. I attribute the difference between the returns implied by target prices and the CAPM public expected return to private information.

According to my decomposition, analysts bundle in target prices, on average, equivalent amounts of public and private information. However, the amount of private information employed is more dispersed than the amount of public information. Univariate and multivariate analysis show that investors correctly interpret the availability of the information conveyed through target prices. As public information is already known, investors react only to private information and generate an economically and statistically significant abnormal return. This reaction is not confined to the period immediately following the target price announcement since it lasts beyond the first month. The relation between public information and abnormal return is neither statistically nor economically significant.

After having separated public from private information, I focus on the scope of information. Following the literature, I consider that analysts use firm-specific, industry-wide, and market-wide information; see, e.g., Asquith, Mikhail and Au (2005). I assume that market-wide information is only public. This reflects the fact that economists that work for brokers often publicly disclose their forecasts (e.g. research notes, Livingston Survey, Bloomberg GDP Survey). Firm-specific and industry-wide information can be both public and private. For instance, the information disclosed by companies through management guidance and conference calls is shared by all the brokers, whereas other information, such as the one collected by analyzing the environment of the firm, is specific to each broker. I separate the firm-specific and the industry-wide component of private information using accounting identities. I limit this analysis to private information because public information, regardless of its scope, is already reflected into prices.

I find that private information is, to a large extent, firm-specific. This finding is consistent with Mikhail, Walther and Willis (1997), Park and Stice (2000), Forbes, Huijgen and Plantinga (2006), and Liu (2011). If investors correctly interpret the information conveyed through target prices, the reaction to firm-specific private information is confined to the stock covered while the reaction to industry-wide private information spreads to the whole industry. My results are consistent with this hypothesis. The firm-specific private information is associated with the abnormal return of the firm, whereas the industry-wide private information is associated with abnormal returns only at the industry level.

I investigate if firm characteristics affect the relation between investors' reaction and information conveyed through analysts' research. Investors are likely to demand more information of the type that is more relevant to value the firm; see Liu (2011). Therefore, investors expect more firm-specific (industry-wide) information when the company has a large idiosyncratic volatility (industry sensitivity). This should be reflected both in analysts' production and investors' reaction. I find that analysts use more firm-specific (industry-wide) private information to forecast target prices of firms with high idiosyncratic risk (industry exposure). The result is strong for the firm-specific private information, while the economic significance is weak for the industry-wide private information. However, also the market reaction changes with the firm characteristics. The reaction to the same amount of firm-specific (industry-wide) private information is indeed stronger for firms with high idiosyncratic volatility (industry sensitivity). Again, the result is more pronounced for firm-specific information. Furthermore, the results are not driven by the misclassification of the public information that is announced with firm-specific events.

Finally, I explore the robustness of my main findings. First, I analyze if the results are affected by the choice of the market expected return. I use the expected return implied by target prices instead of a direct forecast to estimate the market expected return. This alternative market expected return does not affect significantly the results. Second, the estimated stock sensitivities can be affected by firm-specific events. I thus measure the sensitivities excluding the three trading-days surrounding quarterly earnings announcements, management guidance, mergers and acquisitions, equity issuance and the release of target prices. The findings show that misestimated firm sensitivities are not driving the baseline results. Third, in industries with few firms, stock returns and industry returns are correlated by construction. I verify whether this spurious correlation affects the baseline results by constructing a value-weighted industry index that excludes the firm itself. Again, the conclusions remain unchanged. Fourth, I test whether the results are driven by brokers that do not have a specialized economic research department. I repeat the analysis using only the target prices issued by brokers participating at least once to the Bloomberg GDP survey to retain only brokers that have a specialized macroeconomic research department. The exclusion of brokers not participating to the Bloomberg GDP survey does not affect the conclusions.

This paper contributes to the literature examining the informativeness of analysts' research. By documenting that investors correctly interpret the information bundled in target prices, I corroborate the methodology and the conclusions of studies that rely on investors' reaction. Moreover, my results support the studies documenting that analysts use both public and private information and they produce mainly firm-specific private information; see, e.g., Mikhail et al. (1997), Park and Stice (2000), and Forbes et al. (2006). This conclusion seems at odds with the recent studies showing that analysts essentially relay and amplify important public news; see, e.g., Altınkılıç and Hansen (2009), Loh and Stulz (2011), and Altınkılıç, Balashov and Hansen (2013).

My work differs from the existing literature analyzing the market reaction because I *decompose* the return implied by target prices into returns attributable to different types of information. The approach used so far in the literature consists in *classifying* analysts' research according to a given criterion. For instance, Stickel (1995) sorts recommendations according to analysts' reputation, Loh and Mian (2006) use the analyst earnings forecast accuracy, whereas Kecskés, Michaely and Womack (2015) separate recommendation changes accompanied by earnings forecast revisions from the other recommendations. As analysts' production stems from a mixture of different types of information, I argue that the decomposition of information bundled into analysts' research is more appropriate than a mere classification. For instance, analysts can reach earnings forecast accuracy by correctly gauging industry-wide trends, firm-specific factors, or both. The decomposition of analysts' research preserves these details, while the classification loses them. Also, as analysts use a mix of information, recommendation revisions are often driven by several factors, not exclusively by earnings forecast revisions. The decomposition of the information conveyed by analysts identifies the factors that lead to the change in analysts' opinion. The decomposition of the information conveyed through analysts' research is possible because I use target prices whose implied return is a continuous variable. In addition to permit this decomposition, target prices have several advantages with respect to other outputs produced by analysts. Because of their continuous nature, target prices convey more detailed information than categorical variables such as recommendations. Furthermore, they are less likely to be contaminated by analysts' subjectivity, broker-specific definitions, and ambiguous mappings with databases.

Studies close to mine include Liu (2011), Bonsall, Bozanic and Fischer (2013), and Kecskés et al. (2015). Even if I share several results with Liu (2011), the purpose and the methodology of the two studies are different. My goal is to verify whether there is correspondence between the information conveyed through analysts' research and the market reaction, while Liu (2011) analyzes how the information used by analysts varies with firm characteristics. We both show that analysts mainly use firm-specific information and that the production of such information increases with the idiosyncratic risk of firms. I reach this conclusion by directly analyzing the analysts' production, while Liu (2011) relies on the market reaction. However, Liu (2011) is likely to overestimate the amount of firm-specific information produced for firms with high idiosyncratic risk since I find that the relation between the market reaction and firm-specific private information strengthens with the level of idiosyncratic volatility. Bonsall et al. (2013) separate individual management earnings guidance into a firm-specific and a macroeconomic component and find that management guidance contains macroeconomic information. My work differs because I use target prices issued by equity analysts instead of management earnings guidance. In addition, I employ a different methodology. Bonsall et al. (2013) investigate whether guidance convey news on a selected set of macroeconomic indicators. My approach is more flexible. First, I consider the industry level instead of the global economy. This allows taking into account industry-specific factors, which can hardly be included in a global model. Second, I do not determine the industry-specific factors ex-ante. As I focus on the expected returns implied by target prices, all the essential industry-wide factors are aggregated into an industry abnormal return. Third, Bonsall et al. (2013) categorize information according to its scope. I take into account also the availability of the information. As public information is already reflected into prices, I categorize only private information according to its scope. Kecskés et al. (2015) distinguish the recommendation changes based on earnings forecast revisions from the ones based on revisions of discount rates. They find that earnings-based recommendation changes are more informative than discount rate-based recommendation changes because the former are characterized by harder information, greater verifiability, and shorter forecast horizons. This is close to the present work since both studies focus on the information that serves as input for the valuation model used by analysts. However, my classification of information differs from Kecskés et al. (2015) since I consider the availability and the scope of information. Furthermore, I use target prices instead of recommendations.

The remainder of the chapter is organized as follows. Section 2.2 presents the literature review and the hypotheses development. Section 2.3 introduces the methodology that disentangles the information conveyed through target prices. Section 2.4 describes the data and the empirical design. Section 2.5 presents the main results and the additional robustness checks. Finally, Section 2.6 concludes.

2.2. Related literature and hypotheses development

2.2.1. Related literature

There is consensus on the fact that analysts' research is based on both public and private information; see, e.g., Barron et al. (1998). The private information is used because of its innovative nature, whereas the public information complements the private information set possessed by the analysts; see Kim and Verrecchia (1997). However, the average analyst assigns an excessive weight to the private information he possesses; see Chen and Jiang (2006). This overweighting is related to incentives and depends on the signal that has to be sent. In fact, analysts tend to overweight (underweight) private information when issuing positive (negative) forecasts.

The focus of another strand of literature is on the scope, instead of the availability, of the information contained in analysts' forecasts. Economic intuition, anecdotal evidence provided by analysts, and academic studies confirm that analysts' forecasts contain firm-specific, industry-wide, as well as market-wide information. For instance, Gilson, Healy, Noe and Palepu (2001) find that, after conglomerates breakups, industry-specialized analysts improve their forecasting accuracy more than non-specialists. This suggests that the forecasts of industry-specialized analysts benefit from intra-industry commonalities. Similarly, Hugon et al. (2015) show that the earnings forecasts error is lower for analysts that have access to in-house macroeconomic research. Moreover, the earnings forecast error is negatively related to the accuracy of the macroeconomic forecast. Thus, broad information (industry- and market-wide) is likely to be embedded in analysts' forecasts. Taking a different perspective, Hann, Ogneva and Sapriza (2012) find that the earnings forecasts of analysts strongly covary with the macroeconomics forecasts made by macroeconomist. This is interpreted as evidence that the two sets of forecasts contain common macroeconomic information.

Other authors exploit the investors' reaction around analysts' releases to identify the scope of the information contained in analysts' forecast. The earliest studies suggest that analysts mainly rely on firm-specific information; see Mikhail et al. (1997), Park and Stice (2000), and Forbes et al. (2006). In contrast, Piotroski and Roulstone (2004) and Chan and Hameed (2006) exploit the synchronicity between stock returns and market- or industry-indices to show that analysts mainly rely on broad information. Gilson et al. (2001) and Boni and Womack (2006) corroborate the view that analysts' edge lies in the industry- and market-expertise. Recent research on the topic presents a more balanced view. For instance, Liu (2011) decomposes the abnormal return around recommendation revisions into a firm-specific, an industry-wide, and a market-wide component. He finds that the information mix used by analysts varies to accommodate the demand of investors. For instance, firms with high idiosyncratic risk are more affected by firm-specific private information. Therefore, investors demand more private information for these firms. For stocks with large industry sensitivity, whose value is more affected by industry-wide information, investors demand more industry-wide private information. Consistently, analysts include more firm-specific (industry-wide) information in researches covering firms with high idiosyncratic (systematic) risk. This behavior is similar to the one highlighted by Crawford, Roulstone and So (2012) where analysts select the information mix used to differentiate their research from that of competitors. As a consequence, the amount of firm-specific information in analysts forecast is negatively related to the coverage of the stock analyzed. Using a return decomposition similar to Liu (2011), Muslu, Rebello and Xu (2014) show that analysts use a broader spectrum of information. In particular, analysts rely also on coverage-specific information, i.e. information common to the companies followed by a given analyst. The spillovers of coverage-specific information to other stocks covered by the same analyst are as important as the spillovers of industry- and market-wide information.

These studies infer the availability and the scope of the information used by analysts by examining the market reaction around the releases of analysts' research. I argue that this is a potential drawback since this market based reaction measures *how investors perceive* the information conveyed through analysts' research, which assumes that investors correctly interpret the information contained in analysts' research. For this reason, in the present paper, I study the investors' reaction to the information bundled in analysts' research.

2.2.2. Hypotheses development

To investigate whether investors correctly interpret the information bundled into target prices, I verify whether there is a correspondence between the information conveyed through analysts' research and the investors' reaction. First, I analyze whether investors duly understand the *availability* of information used by analysts. Thus, assuming semi-strong efficient markets, I posit the first testable hypothesis as follows:

Hypothesis 1: *The investors' reaction to target prices is (not) related to the amount of private (public) information they convey.*

Second, I analyze whether investors duly understand the *scope* of the information conveyed through target prices. Firm-specific and industry-wide private information should trigger a different reaction. The firm-specific private information is mute about the value of stocks other than the one covered. The reaction to this information should remain confined to the covered stock and, as long as the stock has a small weight in the industry index, the firm-specific private information should not be associated with any reaction at the industry level. At the opposite, the industry-wide private information is informative about the whole industry. The reaction to this information should spread to all the stocks belonging to the industry. The second testable hypothesis is:

Hypothesis 2: *The investors' reaction at the stock (industry) level increases with the amount of firm-specific (industry-wide) private information.*

Third, I investigate whether firm characteristics affect the investors' ability to interpret the information conveyed through target prices. Liu (2011) finds that the information mix used by analysts varies with firm's characteristics to meet investors' demand. I take a different stance and I analyze if the intensity of investors' reaction varies with firm characteristics. For instance, investors can react more strongly to firm-specific (industry-wide) private information when this type of information is more relevant to value the firm, i.e. for firms with high idiosyncratic volatility (industry sensitivity). Notice that this hypothesis can coexist with the one of Liu (2011). The fact that analysts modify the production of information according to the characteristics of the firms and investors' demand does not prevent investors from reacting differently. If firm's characteristics affect the investor's reaction, the relation between the scope of the information contained in target prices and the reaction of investors strengthens with the idiosyncratic volatility and the industry sensitivity, more precisely:

Hypothesis 3: *The relation between investors' reaction at the stock (industry) level and the firm-specific (industry-wide) private information strengthens with idiosyncratic volatility (industry sensitivity).*

2.3. Analysts' information environment and investors' perception

2.3.1. Analysts' information environment

In this section, I describe the information used by analysts and how it is bundled into target prices. The framework I employ is well established in the literature. It shares several features with Barron et al. (1998). Bonsall et al. (2013) use a similar setting to analyze the information conveyed through management guidance. Let denote by $TP_{i,b}$ the target price issued by broker b for stock i at date t. For clarity, I omit the time index t. The target price is the forecasted value of the i's stock at a future date, for the sake of simplicity say in twelve months. The forecast is based both on public and private information; see Barron et al. (1998). The private information is represented by $Z_{i,b}$. This component is innovative and idiosyncratic to each broker. By definition, public information is common to all the analysts and the investors. If markets are efficient in the semi-strong form, the stock prices reflect the public information and are expected to grow at the equilibrium rate of return. The public component of the target price corresponds thus to the current stock's price P_i compounded at the required annual rate of return μ_i, and the target price is

(1) $$TP_{i,b} = P_i\left(1+\mu_i\right) + Z_{i,b}\,.$$

Regardless of its availability, the information can either be firm-specific, industry- or market-wide. The decomposition of public information according to its scope is uninteresting because this information is already reflected into prices. On the contrary, the decomposition of private information is more appealing. Following Liu (2011), I separate the innovative information $Z_{i,b}$ into a firm-specific $z_{i,b}$ and an industry-wide component $z_{I,b}$:

(2) $$Z_{i,b} = S_i z_{I,b} + z_{i,b}\,,$$

where S_i is the sensitivity of the value of stock i to the industry's value and $z_{i,b}$ is independent from $z_{I,b}$. I consider that the industry private component $z_{I,b}$ is common to all the analysts working for a given broker. This reflects the collaborative organization of brokers in which the economic research department provides macroeconomic scenarios used by all the analysts; see, e.g., Hugon et al. (2015). I assume that the market-wide information is exclusively public. This reflects the fact that economists working for brokerage houses often disclose their forecasts through research notes and surveys. The firm-specific private information $z_{i,b}$ is labeled with the broker's subscript b even if it is produced by an analyst. Labeling it as broker- or analyst-specific is equivalent since, within each brokerage firm, each stock is followed only by one analyst; see Hong and Kacperczyk (2010).

Figure 2.1, Panel A, illustrates how the information possessed by analysts flows to the market. The top of the figure shows that analysts combine public, private industry-wide, and private firm-specific information to form the target price $TP_{i,b}$. Analysts disclose only the target price, not the details of the information bundled into it. Therefore, as illustrated in the rest of the figure, investors have to interpret this information before trading. Investors first separate the information conveyed through target prices and then react consequently. The reaction to target prices depends on the information bundled into them. Public information is already reflected into prices and does not trigger any reaction. Private firm-specific information is associated to a reaction that remains confined to the firm, while the reaction to industry-wide information spreads to the whole industry. In the next Section, I focus on how investors decompose the information, whereas the investors' reaction is formalized by the testable hypotheses.

[Insert Figure 2.1 about here]

2.3.2. Disentangling the information conveyed through target prices

At a first stage, investors have to identify the availability of information, i.e. to separate the private component of target prices from the public one. In that perspective, I assume that the market is in equilibrium when no private information flows to the market and that the CAPM holds when investors have full information. The required rate of return for the *i*th stock is thus:

(3) $$\mu_i = r + \beta_i^M \left(\mu_M - r \right),$$

where r is the risk-free rate, β_i^M the sensitivity of security's i return to the return of the market, and μ_M the public expected market return.[1] The expected return implied by target prices differs from the required rate of return because of the private information conveyed through target prices. I thus add to Equation (3) two terms that account for that. First, I express the industry-wide private information $z_{I,b}$ by accommodating a broker-specific industry risk premium. Second, I include a firm-specific excess return $\alpha_{i,b}$ to account for the firm-specific component $z_{i,b}$. The expected return implied by the target price is expressed as:

(4) $$\mu_{i,b} = \frac{TP_{i,b} - P_i}{P_i} = \frac{z_{i,b}}{P_i} + \frac{S_i z_{I,b}}{P_i} + \mu_i = \alpha_{i,b} + \beta_i^I \mu_{I,b} + \mu_i,$$

where $\alpha_{i,b} = z_{i,b} / P_i$ is the expected firm-specific abnormal return, β_i^I the sensitivity of security i return to the return of the industry, and $\mu_{I,b}$ the expected return of the industry implied by the industry-wide private information. The expected return of security i attributable to the industry-wide private information is

[1] The CAPM is selected for the sake of simplicity, but the model can be adapted to any other asset pricing model.

$\beta_i^I \mu_{I,b} = S_i z_{I,b} / P_i$ and, to ensure that it is independent from μ_M, $\mu_{I,b}$ is orthogonalized relative to the public expected market return μ_M.

Figure 2.1, Panel B, illustrates the relation between the current stock price P_i and the target price TP_i. The difference between P_i and TP_i is decomposed in three components attributable to 1) the public information, 2) the industry-wide private information, and 3) the firm-specific private information. In the absence of private information, current price P_i is expected to grow at the required rate of return μ_i and to reach the public expected future value $P_i(1+ \mu_i)$ represented at the bottom on the right-hand side. The industry-wide private information implies an incremental expected return $\beta_i^I \mu_{I,b}$. The firm-specific private information implies an additional expected return $\alpha_{i,b}$. Public and private information sums up to $TP_{i,b}$ and implies the expected return expressed in Equation (4).

So far, I simply translated the target price into an expected return. By itself, this manipulation does not allow disentangling the different types of information bundled into it. However, the return expected by an agent who has no access to private information can be easily computed using Equation (3). μ_i is in fact the public expected return for stock i, i.e. the expected return formed only with public information. The difference between the public expected return and the one implied by the target price is:

(5) $$\Delta\mu_{i,b} = \mu_{i,b} - \mu_i = \alpha_{i,b} + \beta_i^I \mu_{I,b} = \frac{z_{i,b}}{P_i} + \frac{S_i z_{I,b}}{P_i}$$

and reflects all the private information, both firm-specific and industry-wide, used by the broker to forecast the value of the stock.

I further decompose private information into an industry-wide and a firm-specific component. In that perspective, I assume that brokers calibrate their industry views against the market. Under this condition, the sum of the firm-specific abnormal performance weighted by its industry relative market capitalization is zero:

(6) $$\sum_{i=1}^{N_{I,b}} x_i^I \alpha_{i,b} = 0 ,$$

where $N_{I,b}$ is the number of stocks belonging to industry I followed by broker b and x_i^I the market capitalization of the ith stock relative to the total market capitalization of the industry. The proof of Equation (6) is in the Appendix.

The sum of the expected return attributable to private information across the firms belonging to an industry and followed by a broker, weighted by the stock's relative industry capitalization x_i^I, is:

$$(7) \qquad \sum_{i=1}^{N_{I,b}} x_i^I \left(\Delta\mu_{i,b}\right) = \sum_{b=1}^{N_{I,b}} x_i^I \left(\alpha_{i,b} + \beta_i^I \mu_{I,b}\right) = \sum_{b=1}^{N_{I,b}} x_i^I \alpha_{i,b} + \mu_{I,b} \sum_{b=1}^{N_{I,b}} x_i^I \beta_i^I = \mu_{I,b} \sum_{b=1}^{N_{I,b}} x_i^I \beta_i^I \,.$$

Notice that this is not a weighted average. In fact, the sum of the weights is smaller than one because the sum is over the $N_{I,b}$ stocks followed by the broker and x_i^I is the weight of stock i in the industry, not in the universe of stocks followed by the broker. As $\Delta\mu_{i,b}$, x_i^I, and β_i^I are known, from Equation (7) it is possible to infer the return attributable to industry-wide private information:

$$(8) \qquad \mu_{I,b} = \sum_{i=1}^{N_{I,b}} x_i^I \left(\Delta\mu_{i,b}\right) \Big/ \sum_{b=1}^{N_{I,b}} x_i^I \beta_i^I$$

and the return attributable to firm-specific private information:

$$(9) \qquad \alpha_{i,b} = \Delta\mu_{i,b} - \beta_i^I \mu_{I,b} \,.$$

2.4. Data and empirical methodology

2.4.1. Sample construction

Target prices and stock prices are obtained from the Institutional Broker Estimate Service (I/B/E/S) and the Center for Research in Security Prices (CRSP), respectively. I rely on the unadjusted version of the databases to avoid the issues related to adjusted data; see Payne and Thomas (2003). I focus on the target prices issued between 1999 and 2012 by identifiable analysts on US firms. Target prices have to meet the following criteria. First, they must have a twelve-month forecast horizon. This restriction affects a small number of observations since 98% of the target prices have a twelve-month horizon. Second, to obtain a meaningful comparison between target prices and stock prices, I only retain the target prices expressed in USD. Third, to ensure that firms are of sufficient interest to investors, I focus only on firms followed by at least three analysts. Fourth, I require a valid closing share price above one USD on the announcement date. Table 2.A.1 in Appendix reports the details of the sample selection and the annual statistics. The selection procedure yields a sample of 811,620 target prices, made by 9,072 analysts (686 brokerage houses), on 6,357 US firms that represent 79% of the total market capitalization. The number of analysts and firms followed remain roughly constant over time, but target prices are issued more frequently at the end of the sample period. The fraction of the market capitalization of my sample decreases over time, but still represents more than 70% of the US stock market capitalization at the end of the sample period.

To control for analysts' characteristics, I collect additional information from the All-American rankings published yearly by the Institutional Investor magazine. I identify firm-specific events from I/B/E/S (earnings announcements), I/B/E/S Guidance (management guidance), SDC (mergers and acquisitions, equity issuance), and LPC Dealscan (syndicated loans). Institutional ownership is computed using data obtained from 13F filings that I download from the EDGAR database. The risk-free rate *r* is the one-year T-bill rate obtained from the Board of Governors of the Federal Reserve System.

I obtain public forecasts of macroeconomic variables from the Livingstone Survey. Maintained by the Federal Reserve Bank of Philadelphia since 1990, the Livingston Survey is conducted twice a year in June and December. The survey summarizes the forecasts of approximately 50 economists – from industry, government, banking, and academia – about 18 different variables describing national output, prices, unemployment, and other macroeconomic data.[2]

Table 2.1 describes the size, book-to-market, and momentum characteristics of our sample relative to the NYSE universe. Overall, analysts tend to follow large and growth firms, but there are important changes over time. For instance, there is an almost parallel trend toward small and value firms. The trend started when small and value firms were outperforming large and growth firms, respectively, and reverted after the financial crisis (2008 onwards).

[Insert Table 2.1 about here]

[2] See Croushore (1997) and Federal Reserve Bank of Philadelphia (2014) for a detailed description of the Livingston Survey.

2.4.2. Decomposing the target prices

I measure the expected return forecasted by broker b for firm i at date t as $\mu_{i,b}=(TP_{i,b}-P_i)/P_i$, where P_i denotes the closing stock price for firm i at date t. If the target price is issued on non-trading days or between 4:30 PM and 11:59 PM, P_i is replaced by the closing stock price on the first following trading day; see Loh and Stulz (2011).

The public expected market return μ_M is based on the S&P500 Index. I obtain its publicly available expected return from the Livingston Survey. Each release of the survey contains forecasts for three horizons: the end of the month in which the survey is taken (month-end forecast), the end of the month that is six months beyond the survey date, and the end of the month that is twelve months beyond the survey date (twelve-month-ahead forecast). For each horizon, the survey's participants report, among other, the expected level of the S&P500 Index. I compute the twelve-month public expected market return by comparing the median twelve-month-ahead forecast to the median month-end forecast. As the survey is published semiannually, I update the expected market return twice a year.

I compute the sensitivity of security's i return to the return of the market and the industry index in two steps. First, I orthogonalize the industry return with respect to the market return by running the following regression:

$$(10) \qquad R_{I,t} - r_t = a_I + b_I^M \left(R_{M,t} - r_t \right) + \varepsilon_{I,t} \, ,$$

where $R_{I,t}$ and $R_{M,t}$ are the realized return of industry index I and of the market in day t. Respectively, to be consistent with the public expected market return, I use the S&P500 as market index. I retain the GICS six-digit industry classification because the resulting 68 industries match analysts' specialization; see Boni and Womack (2006). Second, I estimate the following regression over the 250 trading-days preceding the target-price announcement:

$$(11) \qquad R_{i,t} - r_t = a_i + b_i^M \left(R_{M,t} - r_t \right) + b_i^I \left(a_I + \varepsilon_{I,t} \right) + \varepsilon_{i,t} \, ,$$

where $R_{i,t}$ is the realized return of stock i in day t, and α_I as well as $\varepsilon_{I,t}$ are obtained from Equation (10). b_i^M and b_i^I are the estimates for the stock's sensitivities β_i^M and β_i^I, respectively. To account for potential missing returns, I estimate Equation (11) running a WLS regression with observations weighted by the inverse of the square root of the number of trading days between two valid returns; see Heinkel and Kraus (1988). For each regression, at least 150 daily returns are required. If the market sensitivity b_i^M is estimated with bias, also the decomposition of the expected returns is biased. For instance, if b_i^M is upward biased, the amount of public (private) information is overestimated (underestimated). By construction, the true average market sensitivity, when weighted by the stock market capitalization, has to be one. In my sample, the average market sensitivity is 1.01 and it is not statistically different from one. This result suggests that the bias of b_i^M is not a concern for my results. I winsorize the components of the expected returns at 1% in each tail to reduce the effect of outliers and measurement error of b_i^M and b_i^I.

The separation of information according to its scope is meaningful only for brokers whose coverage group is diversified within each industry. A lack of diversification can indicate that the broker has a positive outlook for the few firms followed. To identify the diversified brokers, I follow Sonney (2009). For each broker, I compute the broker-industry-year concentration ratio based on the Herfindahl Index, defined as:

(12) $$HI_{b,I,y} = \sum_{i=1}^{N_{I,b}} \left(\frac{N_{b,i,y}}{N_{b,I,y}} \right)^2 ,$$

where $N_{b,i,y}$ is the number of target prices issued by broker b in year y for firm i, and $N_{b,I,y}$ is the number of target prices issued by broker b in year y for firms operating in industry I. $HI_{b,I,y}$ equals one if the broker follows only one firm in the industry I. The more the efforts of the broker are spread among the firms belonging to the industry, the lower is $HI_{b,I,y}$. I consider that a broker is sufficiently diversified if $HI_{b,I,y}$ is below 0.9.

Table 2.2 contains descriptive statistics of the components of the firm expected return. Panel A reports the decomposition of information according to availability. The decomposition is available only for the stocks whose b_i^M and b_i^I can be estimated. As a consequence, the information conveyed through 798,960 target prices, out of 811,620, is separated into a public and a private component. I find that, on average, target prices are based on an almost equal amount of public (10%) and private information (10.3%). Even if statistically significant, the difference between these two values is not economically important. The amount of private information, $\Delta\mu_{i,b}$, displays a greater dispersion both over time and in the cross-section. The standard deviation is 21.5%, almost four times the one of public information (5.5%). Notice however that, μ_M being constant within each semester, the variance of the public information arises mainly from the stock sensitivities b_i^M. Table 2.2, Panel B, displays the decomposition of the private information into the industry-wide and the firm-specific private information. Approximately 6% of the target prices are excluded from the analysis because of the filter based on the Herfindahl Index. Consistently with Liu (2011), I find that the firm-specific private information is the most important whereas the industry-wide private information plays a secondary role.

[Insert Table 2.2 about here]

2.4.3. Empirical design

To test Hypotheses 1 and 2, I sort target prices into quintiles by the amount of information they convey. This is measured either by μ_i (public information), $\Delta\mu_{i,b}$ (private information), $\alpha_{i,b}$ (firm-specific private information), or $\mu_{I,b}$ (industry-wide private information). The bottom quintile (Q1) contains the target prices conveying the less information and the top quintile (Q5) contains the target prices conveying the most information. I then measure the average abnormal returns associated with the target prices included in each quintile. The abnormal return is defined as the buy and hold return in excess of the CAPM equilibrium return:

$$(13) \qquad BHAR_{i,(\tau_1,\tau_2)} = \prod_{\tau=\tau_1}^{\tau_2}\left(1+R_{i,\tau}\right) - \prod_{\tau=\tau_1}^{\tau_2}\left(1+r_\tau + b_i^M\left(R_{M,\tau}-r_\tau\right)\right).$$

When the quintiles are sorted by $\mu_{I,b}$, I compute the cumulative buy and hold abnormal return at the industry level $BHAR_I$. I study the buy and hold abnormal return in the long-term and I consider three different periods starting the day after the announcement, i.e. I set $\tau_1=1$, where day $\tau=0$ is the target price date. The periods last respectively one, two, and three months ($\tau_2=21, 42, 63$). According to Hypotheses 1 and 2, I expect the average *BHAR* to increase across information-based quintiles, except when they are sorted by the public information μ_i. In the latter case, I expect the average *BHAR* to be the same in all the quintiles. I verify whether the difference between the average return in the top and the bottom quintile (Q5-Q1) is different from zero.

I test the first two hypotheses also in a multivariate setting. On that perspective, I regress *BHAR* on the amount of information conveyed through the target price and a set of control variables. Formally, the model is:

$$(14) \qquad BHAR_{i,(\tau_1,\tau_2)}^{t,b} = \gamma_{ind(i),t} + \eta Info_{i,t,b} + \boldsymbol{\varphi}\mathbf{X}_{i,t,b} + \varepsilon_{i,(\tau_1,\tau_2)}^{t,b}$$

The dependent variable $BHAR_{i,(\tau_1,\tau_2)}^{t,b}$ is the buy and hold abnormal return of stock *i* in the period following date *t* in which the broker *b* released a target price for firm *i*. The explanatory variable $Info_{i,t,b}$ is either μ_i, $\Delta\mu_{i,b}$, $\alpha_{i,b}$, or $\mu_{I,b}$ computed using the target price issued on date *t* by broker *b*. The dependent variable is replaced by the industry *BHAR* when the explanatory variable is $\mu_{I,b}$. The coefficient of interest η measures the relation between the abnormal return and the information conveyed through target prices. The control variables **X**, known to correlate with the abnormal return around analyst announcements, are taken from Loh and Stulz (2011) and are defined in the Appendix (Table 2.A.2). In addition, I account for industry cyclicality by including quarter-industry fixed effects $\gamma_{ind(i),t}$. I allow the error term to be correlated within industries and I correct the standard errors as in Petersen (2009). I expect η to be positive and significant when the explanatory variable $Info_{i,t,b}$ is $\Delta\mu_{i,b}$, $\alpha_{i,b}$, or $\mu_{I,b}$. η should be zero when *BHAR* is regressed on public information μ_i.[3]

To test Hypothesis 3, I sort target prices into terciles based on the characteristics of the firm covered. The firm characteristics considered are the idiosyncratic volatility and the absolute value of the industry sensitivity. I then fit Equation (14) using only the target prices for the stocks belonging to a given

[3] The results are robust to different specifications of Equation (14). First, to ensure that the measurement error of *Info* does not affects the results, I replace *Info* by dummy variables that take the value of 1 if the target price is in a given information-based quintile and zero otherwise. This corresponds to measure the average reaction associated with target prices conveying similar amount of information, after controlling for the effect of the other independent variables. Second, I separately account for time-invariant industry heterogeneity and time-specific effects by including two sets of dummy variables controlling for industry and quarter fixed effects. In both cases the results remain unchanged.

characteristic-based tercile. According to Hypothesis 3, the reaction is expected to be stronger among stocks in the top characteristic-based tercile, i.e. stocks with high idiosyncratic volatility or industry sensitivity. Therefore, I expect the coefficient η to increase across the characteristic-based terciles.

2.5. Results

2.5.1. Baseline results

I start by investigating the relation between the public information μ_i and *BHAR*. According to Hypothesis 1, these two variables should not be correlated. Table 2.3, Panel A, contains the average *BHAR* by quintile when target prices are sorted by the level of public information. The relation between *BHAR* and μ_i is negative in the first month following the target price announcement. Beyond the first month there is a positive relation between public information and investors' reaction. The difference between top and bottom information-based quintiles is economically small (-24 bps for one month and 36 bps for three months) and not statistically significant. Furthermore, *BHAR* does not increase monotonically with the quintiles of μ_i. Table 2.4 contains the multivariate results. Columns (1) to (3) of Panel A tabulate the coefficients obtained by regressing *BHAR* on public information. This analysis confirms the lack of relation between public information and *BHAR*. In fact, for all the windows considered, the coefficient η is not statistically significant. Therefore, the empirical evidence suggests that the public information embedded in target prices is not associated with an investors' reaction.

[Insert Tables 2.3 and 2.4 about here]

The results are different when I consider the private information $\Delta\mu_{i,b}$. Table 2.3, Panel B, displays the average *BHAR* obtained by sorting target prices according to private information. The relation between private information and *BHAR* is positive and the difference between top and bottom information-based quintiles is both economically and statistically significant. For instance, in the month following the announcement, the average *BHAR* of the top quintile is 1.06% higher than the one of the bottom quintile. When the horizon is extended, this difference increases up to reaching 1.45% (for three months). Regardless of the horizon considered, the reaction associated with private information is significantly higher than the one associated with the public information and, except for the three months horizon, *BHAR* increases monotonically with the amount of private information conveyed through target prices. Moreover, the difference between top and bottom information-based quintiles measured in the first month after the target price release is smaller than the one obtained with longer horizons (p-value = 1.9%). This indicates that investors' reaction associated with target prices does not last only the month following the announcement, but it persists for longer. The multivariate analysis confirms these results. Columns (4) to (6) of Table 2.4, Panel A, display the coefficients obtained for the regression of private information. Regardless of the windows considered, there is a statistically significant relation between abnormal returns and private information. As in the univariate analysis, the coefficient η is significantly smaller in the short term (p-value = 2.1%). All in all, consistently with Hypothesis 1, private (public) information is (not) related to the stock abnormal return in the months that follow the release of target prices.

I test Hypothesis 2 by first focusing on firm-specific private information. Table 2.3, Panel C, contains the univariate results. As expected, there is a positive relation between the amount of information and investors' reaction. The difference between top and bottom information-based quintiles is significantly smaller in the first month (p-value = 0.8%). The multivariate analysis is displayed in Columns (1) to (3) of Table 2.4, Panel B. The firm-specific private information remains significantly related to *BHAR* also after controlling for the variables known to correlate with abnormal returns. The coefficients are similar to the ones obtained for private information. Again, the magnitude of η increases with the length of the window considered (p-value = 3.5%). The relation between industry-wide private information and industry *BHAR* is similar. Table 2.3, Panel D, shows that the reaction strengthens across the information-based quintiles. However, the reaction is not as strong as the one observed for firm-specific private information, especially in the short term. The conclusions drawn from the multivariate analysis are the same; see Columns (4) to (6) of Table 2.4, Panel B. All the coefficients are significant, even if smaller than the ones obtained for firm-specific private information. The relation between industry-wide private information and industry abnormal reaction increases with the horizon considered only in the univariate analysis. Other unreported results confirm that industry-wide private information is not associated with firm abnormal return.[4] Overall, the results are consistent with the hypothesis that investors correctly interpret the scope of private information. The reaction to firm-specific private information is confined to the firm covered, whereas industry-wide private information is associated with an industry *BHAR* but not with firm abnormal return.

Table 2.5 shows the tests corresponding to Hypothesis 3. Columns (1) to (3) report the results for the test of the impact of idiosyncratic volatility on the relation between firm-specific private information and firm abnormal return. Regardless of the level of idiosyncratic volatility, there is a positive relation between information and abnormal returns. The coefficients η associated with $\alpha_{i,b}$ are positive and significant for the three idiosyncratic volatility groups. Consistently with Hypothesis 3, the level of idiosyncratic risk does affect the investors' reaction. The magnitude of η is higher among high idiosyncratic risk firms (0.031) than among low idiosyncratic risk firms (0.019). The difference between these two groups of firms is economically and statistically significant (p-value < 1%). This confirms that investors react more strongly to firm-specific private information when this information is more likely to affect the firms' value.

The remaining columns of Table 2.5 display the results obtained for the tests of the effect of industry sensitivity on the relation between investors' reaction and industry-wide private information. The coefficient associated to $\mu_{I,b}$ is significant for the three groups of firms and its magnitude increases with the level of industry sensitivity of the firm. The difference between the coefficients obtained for the firms with high and low industry sensitivity is weakly significant (p-value = 8%). These results indicate that industry sensitivity has only a minor impact on investors' behavior. This is consistent with the results of Liu (2011), who finds stronger results when he sorts stocks by risk. Unreported results show that the conclusions are unchanged if I analyze the abnormal returns at longer horizons (two and three months after the release).

[Insert Table 2.5 about here]

[4] These results as well as other unreported results are available from the author upon request.

2.5.2. Misclassification of the information conveyed after firm-specific events

We cannot exclude that prices do not react immediately and completely when firm-specific events occur and significant amounts of public information suddenly flow to the market. In this case, the baseline results discussed in the previous section overstate the reaction to private information. In fact, if there is an incomplete reaction to public information, the model classifies the public information not yet reflected into prices as private. For instance, assume that a firm discloses a positive outlook for the forthcoming years. If the market ignores part of this public information, the current stock price P_i is lower than its equilibrium level. As a consequence, the expected future value of the stock $P_i(1+ \mu_i)$ is underestimated, while the private component of the target price $Z_{i,b}$ is overestimated. Therefore, the reaction to public information – that occurs with a delay – is associated to the misclassified information and the relation between private information and abnormal returns is overstated.

In the baseline model I control for this potential misclassification of information with the control *Information discovery*, a variable that identifies the target prices that are not released in the three-day window surrounding firm-specific events. This approach is flawed since it tries to capture with a single control variable the effect of firm-specific events, which can be both positive and negative depending on the information disclosed. The coefficient associated to this variable turns out to be rarely significant, probably because it measures the average effect. To better assess whether the results are driven by this misclassified information, I repeat the analysis excluding all the target prices released immediately after firm-specific events. These target prices, in addition to be the observations for which information is more likely to be misclassified, are obtained by interpreting and relaying public information; see, e.g., Altınkılıç and Hansen (2009) and Altıkılıç, Hansen and Ye (2015). I classify a target price as released immediately after a firm-specific event if it is announced in a five-day window that starts on the day of the firm-specific event.[5] Firm-specific events are quarterly earnings announcements, management guidance, mergers and acquisitions, as well as equity and debt issuance (including public bonds and syndicated loans).

[5] Results are unchanged if shorter (three-day) and longer (ten-day) windows are used and if the windows are extended to include the day that precedes the firm-specific event.

The exclusion of the target prices announced in concomitance to firm-specific events reduces the size of the sample of approximately 45% but has a small impact on the decomposition of the information conveyed by target prices. The descriptive statistics of μ_i, $\Delta\mu_{i,b}$, $\alpha_{i,b}$, and $\mu_{I,b}$ are in fact unchanged with respect to those of the baseline approach. Table 2.6 displays the results obtained by estimating Equation (14) using only the subsample of target prices not released immediately after firm-specific events. The model differs from that of the baseline analysis only because the control variable *Information discovery* is excluded. The coefficients obtained are neither qualitatively nor quantitatively different from the baseline results. The results are unchanged also when the sample is split into characteristic-based tercile. Therefore, the results are not driven by misclassified public information. Furthermore, these results suggest that the information role of analysts is not limited to the interpretation of public information since analysts are able to discover valuable private information also when firms do not disclose any public information.

[Insert Table 2.6 about here]

2.5.3. Additional tests

2.5.3.1. Alternative public market expected return

I repeat the analysis using the expected return of the S&P500 Index constructed with analysts' expectations. The main difference with respect to the public expected market return obtained from the Livingston Survey consists in the fact that μ_M is revised daily instead of semiannually. I estimate μ_M by averaging the expected returns implied by target prices ($\mu_{i,b}$) of all the stocks composing the index. In each trading day, all the valid target prices are used for the computation.[6] Each $\mu_{i,b}$ is weighted by the market capitalization of stock *i* in the S&P500. If several brokers issue target prices on the same stock, the $\mu_{i,b}$ are first averaged across brokers.

[6]A target price is valid if: (1) the end of the forecast horizon is after the date at which μ_M is computed, (2) it is the most recent target price issued on firm *i* by the brokerage house *b*, and (3) the broker did not stop covering firm *i* between the release date and the date at which μ_M is computed. The results are unchanged when the expected market return is estimated using only the target prices issued recently (in the last one, three, and six months).

Analysts are systematically more optimistic than the participants to the Livingston Survey. Both the average and the median expected market return μ_M are approximately the double (17.6% and 15.5% vs 8.1% and 7.3%, respectively). As a consequence, the decomposition of the $\mu_{i,b}$ finds that the average target prices is almost exclusively composed by public information (19.3%). Furthermore, the dispersion of the private information $\Delta\mu_{i,b}$ is unchanged (21.1%), indicating a significant dispersion of the amount of private information conveyed by target prices. The leftmost columns of Table 2.7 report the estimated coefficient η obtained from Equation (14).[7] Panel A of Table 2.7 reports the coefficients obtained by regressing the abnormal returns on the different components of target prices. When the industry-wide private information is the explanatory variable, the dependent variable is the industry abnormal return. In the other cases, the dependent variable is the firm abnormal return measured at different horizon. The results reported in Table 2.7 are qualitatively similar to the ones reported in Table 2.4. The only noticeable difference is that the public information is significantly related to investors' reaction in the two months after the target price release. Panel B and C of Table 2.7 contain the coefficients obtained by regressing abnormal returns on the expected return attributable to firm-specific and industry-wide private information, respectively. In Panel B firms are sorted into terciles by the idiosyncratic volatility. In Panel C firms are sorted by industry sensitivity. The only difference arises for the industry-wide private information. The coefficient obtained for high industry sensitivity stock is significantly higher than the one of low industry sensitivity. Hence, the reaction to firm-specific private information increases with the idiosyncratic volatility of firms and the reaction to industry-wide private information increases with the industry sensitivity.

[Insert Table 2.7 about here]

2.5.3.2. Stocks' sensitivity estimation

In the baseline analysis, the market and industry sensitivities are estimated using the returns of the 250 trading-days preceding the target-price announcement. Firm-specific events that affect the stock's return,

[7] For the sake of space, nor the loadings on the control variables neither the univariate analysis are reported.

and consequently the estimated sensitivities, occur over this period. To gauge the impact of such events on the estimated values of b_i^M and b_i^I, I fit Equation (11) by excluding the three trading-days around firm-specific events (quarterly earnings announcements, management guidance, mergers and acquisitions, equity issuance) and the release of target prices. Again, I require at least 150 daily returns in the estimation window. I then use these sensitivities to disentangle the information bundled into target prices and I repeat the analyses.

The exclusion of these trading-days reduces the number of firms to 667,759. These market sensitivities are generally lower than the one found in the baseline test but their weighted average remains close to one (0.99 on average). As a consequence, the expected return attributable to public information is slightly lower than the one presented in the baseline results (9.5%) and the expected return attributable to firm-specific private information increases marginally (9.4%). Columns (4) to (6) of Table 2.7 report the results of the multivariate analysis. The exclusion of observations around firm-specific events does not change either qualitatively or quantitatively the results. In fact, all the coefficients obtained are very close to the one presented in the baseline results, even if they are generally slightly higher. Therefore, the results are not affected firm-specific events.

2.5.3.3. Correlation in small industries

The baseline results show that the firm-specific private information is associated with the stock's abnormal return measured after the releases of target prices. Similarly, the industry-wide private information is associated with an abnormal return at the industry level. In industries composed by few firms, the firm and the industry abnormal returns are correlated. To verify whether this spurious correlation drives the results discussed above, I follow Durnev, Morck and Yeung (2004). For each firm, I construct an industry index that excludes the firm in question. As a consequence, the sensitivity of industries to the market b_I^M is not anymore common to all the stocks belonging to the same industry. This comes at a price because the accounting identities exploited in Section 2.3.2 to disentangle the components of target prices do not hold anymore. For instance, the expected industry return is not anymore common to all the firms, because each firm has a different industry index. The different methodology of index computation affects the results mainly through the stock's sensitivities b_i^M and b_i^I.

The coefficients obtained with the modified industry indices are presented in Columns (7) to (9) of Table 2.7. The coefficients are similar to the ones of the baseline tests in terms of sign, significance, and magnitude. Therefore, the results from the baseline model are not due to a spurious correlation between firm and industry returns.

2.5.3.4. Brokers' organization

When I introduce the theoretical framework that allows disentangling information according to availability and scope, I assume that analysts produce only firm-specific private information, whereas the broad information is produced at the broker level and shared by all the analysts. This assumption is supported by the collaborative organization of brokers, in which analysts do not produce research in isolation but they leverage in-house expertise; see, e.g., Bradshaw (2012). In the empirical part, I collect target prices from all the brokers, without verifying whether they are organized in a collaborative way or not. I verify whether the broker's organization affects the results by retaining only the target prices issued by brokers with a specialized economic research department. This guarantees that all the target prices released by a given broker are based on the same economic scenario. I identify the brokers with a specialized economic research department as the one participating at least once to the Bloomberg GDP survey; see Hugon et al. (2015). Since only the economists that are deemed as credible by Bloomberg participate to the survey, this procedure is likely to identify a subset of brokers that truly have an economic research department.

Out of the 686 brokers that report to I/B/E/S, only 123 participate to the Bloomberg survey. The sample shrinks to 502,117 target prices issued by 6,407 analysts on 5,687 firms (78.0% of the total market capitalization). Thus, this filter excludes mainly brokers that follow small firms and release few target prices. Despite this smaller sample, the results remain unchanged. The average market sensitivities, both over the whole sample and year by year, are similar to the ones obtained for the entire sample. Columns

(10) to (12) of Table 2.7, reports the results of the multivariate analysis. The magnitude of the coefficients of interest remains unchanged with respect to the baseline results.

2.6. Conclusions

I propose a model that disentangles the information bundled in target prices and I use it to verify which type of information is used by analysts and whether it is correctly interpreted by investors. The analysis highlights several notable results. First, my results confirm that analysts use both public and private information to predict future prospects of firms. Moreover, private information is mainly firm-specific, not industry-wide. Second, I find that investors correctly interpret the information produced by analysts. Public information is not associated with abnormal returns, but private information is. In addition, the reaction to firm-specific private information is confined to the stock covered and the reaction to industry-wide private information spreads to the whole industry. Third, I find that the investors' reaction to the same information varies with the characteristics of the firm covered. More specifically, the strength of the reaction to firm-specific (industry-wide) private information increases with the idiosyncratic volatility (industry sensitivity) of the firm.

In the paper, I consider a simple version of the methodology. For instance, I assume that the CAPM holds when no private information flows to the market and that private information is either firm-specific or industry-wide. The methodology can be extended in several ways and these two assumptions can be easily relaxed. The CAPM can be replaced by any asset pricing model. Also, one can consider any other classification of private information. For instance, it is possible to consider the existence of private market-wide information or even coverage-specific information as in Muslu et al. (2014).

References

Altıkılıç, O., R. S. Hansen, and L. Ye, 2015, Can analysts pick stocks for the long-run?, *Journal of Financial Economics, forthcoming*.

Altınkılıç, O., V. S. Balashov, and R. S. Hansen, 2013, Are analysts' forecasts informative to the general public?, *Management Science* 59, 2550-2565.

Altınkılıç, O., and R. S. Hansen, 2009, On the information role of stock recommendation revisions, *Journal of Accounting and Economics* 48, 17-36.

Asquith, P., M. B. Mikhail, and A. S. Au, 2005, Information content of equity analyst reports, *Journal of Financial Economics* 75, 245-282.

Barron, O. E., O. Kim, S. C. Lim, and D. E. Stevens, 1998, Using analysts' forecasts to measure properties of analysts' information environment, *Accounting Review* 73, 421-433.

Boni, L., and K. L. Womack, 2006, Analysts, industries, and price momentum, *Journal of Financial and Quantitative Analysis* 41, 85-109.

Bonsall, S. B., Z. Bozanic, and P. E. Fischer, 2013, What do management earnings forecasts convey about the macroeconomy?, *Journal of Accounting Research* 51, 225-266.

Bradshaw, M. T., 2012, Discussion of "analysts' industry expertise", *Journal of Accounting and Economics* 54, 121-131.

Chan, K., and A. Hameed, 2006, Stock price synchronicity and analyst coverage in emerging markets, *Journal of Financial Economics* 80, 115-147.

Chen, Q., and W. Jiang, 2006, Analysts' weighting of private and public information, *Review of Financial Studies* 19, 319-355.

Crawford, S. S., D. T. Roulstone, and E. C. So, 2012, Analyst initiations of coverage and stock return synchronicity, *Accounting Review* 87, 1527-1553.

Croushore, D., 1997, The Livingston Survey: Still useful after all these years, *Business Review* (March/April), Federal Reserve Bank of Philadelphia.

Durnev, A., R. Morck, and B. Yeung, 2004, Value-enhancing capital budgeting and firm-specific stock return variation, *Journal of Finance* 59, 65-105.

Federal Reserve Bank of Philadelphia, 2014, Livingston Survey documentation, https://www.philadelphiafed.org/research-and-data/real-time-center/livingston-survey/livingston-documentation.pdf.

Forbes, W., C. Huijgen, and A. Plantinga, 2006, Using analysts' earnings forecasts for country/industry-based asset allocation, *Managerial Finance* 32, 317-336.

Gilson, S. C., P. M. Healy, C. F. Noe, and K. G. Palepu, 2001, Analyst specialization and conglomerate stock breakups, *Journal of Accounting Research* 39, 565-582.

Hann, R. N., M. Ogneva, and H. Sapriza, 2012, Forecasting the macroeconomy: Analysts versus economists, http://ssrn.com/abstract=2194179.

Heinkel, R., and A. Kraus, 1988, Measuring event impacts in thinly traded stocks, *Journal of Financial and Quantitative Analysis* 23, 71-88.

Hong, H., and M. Kacperczyk, 2010, Competition and bias, *Quarterly Journal of Economics* 125, 1683-1725.

Hugon, A., A. Kumar, and A.-P. Lin, 2015, Analysts, macroeconomic news, and the benefit of in-house economists, *Accounting Review, forthcoming*.

Kecskés, A., R. Michaely, and K. Womack, 2015, Do earnings estimates add value to sell-side analysts' investment recommendations?, http://ssrn.com/abstract=1478451.

Kim, O., and R. E. Verrecchia, 1997, Pre-announcement and event-period private information, *Journal of Accounting and Economics* 24, 395-419.

Liu, M. H., 2011, Analysts' incentives to produce industry-level versus firm-specific information, *Journal of Financial and Quantitative Analysis* 46, 757-784.

Loh, R. K., and G. M. Mian, 2006, Do accurate earnings forecasts facilitate superior investment recommendations?, *Journal of Financial Economics* 80, 455-483.

Loh, R. K., and R. M. Stulz, 2011, When are analyst recommendation changes influential?, *Review of Financial Studies* 24, 593-627.

Mikhail, M. B., B. R. Walther, and R. H. Willis, 1997, Do security analysts improve their performance with experience?, *Journal of Accounting Research* 35, 131-157.

Muslu, V., M. Rebello, and Y. Xu, 2014, Sell-side analyst research and stock comovement, *Journal of Accounting Research* 52, 911-954.

Park, C., and E. Stice, 2000, Analyst forecasting ability and the stock price reaction to forecast revisions, *Review of Accounting Studies* 5, 259-272.

Payne, J. L., and W. B. Thomas, 2003, The implications of using stock-split adjusted I/B/E/S data in empirical research, *Accounting Review* 78, 1049-1067.

Petersen, M. A., 2009, Estimating standard errors in finance panel data sets: Comparing approaches, *Review of Financial Studies* 22, 435-480.

Piotroski, J. D., and D. T. Roulstone, 2004, The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices, *Accounting Review* 79, 1119-1151.

Sonney, F., 2009, Financial analysts' performance: Sector versus country specialization, *Review of Financial Studies* 22, 2087-2131.

Stickel, S. E., 1995, The anatomy of the performance of buy and sell recommendations, *Financial Analysts Journal* 51, 25-39.

Appendix: Brokers' view calibration and average expected firm-specific abnormal return

In this appendix I prove that, if brokers calibrate their industry views against the market, the sum of the firm-specific abnormal performance, weighted by the industry relative capitalization, is zero, i.e. $\sum_{i=1}^{N_{I,b}} x_i^I \alpha_{i,b} = 0$.

The expected market return is the weighted average of the non-orthogonalized industry return:

$$\text{(A.1)} \qquad \mu_M = \sum_I x_I \mu_{I,b}^* = \sum_I x_I \left(r + \beta_I^M \left(\mu_M - r \right) + \mu_{I,b} \right) = \mu_M + \sum_I x_I \mu_{I,b} ,$$

where β_I^M is the sensitivity of industry I to the market return and x_I is the market capitalization of industry I relative to the market capitalization of the entire market. It follows thus that $\Sigma x_I \mu_{I,b}=0$. The expected non-orthogonalized industry return is the average expected return of the stocks composing the industry, weighted by their capitalization:

$$\text{(A.2)} \qquad \begin{aligned} \mu_{I,b}^* &= \sum_{i=1}^{N_I} x_i^I \mu_{i,b} = \sum_{i=1}^{N_I} x_i^I \left(\alpha_{i,b} + \beta_i^I \mu_{I,b} + \mu_i \right) = \sum_{i=1}^{N_I} x_i^I \left(\alpha_{i,b} + \beta_i^I \mu_{I,b} + r + \beta_i^M \left(\mu_M - r \right) \right) \\ &= r \underbrace{\sum_{i=1}^{N_I} x_i^I}_{1} + \mu_{I,b} \underbrace{\sum_{i=1}^{N_I} x_i^I \beta_i^I}_{1} + \left(\mu_M - r \right) \underbrace{\sum_{i=1}^{N_I} x_i^I \beta_i^M}_{\beta_I^M} + \sum_{i=1}^{N_I} x_i^I \alpha_{i,b} = \mu_{I,b}^* + \sum_{i=1}^{N_I} x_i^I \alpha_{i,b} \end{aligned} ,$$

where N_I is the number of stocks composing industry I and x_i^I is the market capitalization of stock i relative to the market capitalization of the industry. The equality holds only if $\Sigma x_i^I \alpha_{I,b}=0$. If this is true at the industry level, it is true also at the market level. The average $\alpha_{i,b}$ can be decomposed in two components: one that is due to the stocks followed and another due to the other stocks. As $\alpha_{i,b}$ is equal to zero for the stocks not followed, we can write:

$$\text{(A.3)} \qquad \sum_{i=1}^{N_I} x_i^I \alpha_{i,b} = \underbrace{\sum_{i=1}^{N_{I,b}} x_i^I \alpha_{i,b}}_{\text{stocks followed}} + \underbrace{\sum_{i=N_{I,b}+1}^{N_I} x_i^I \alpha_{i,b}}_{\text{stocks not followed}} = \sum_{i=1}^{N_{I,b}} x_i^I \alpha_{i,b} + 0 \sum_{i=N_{I,b}}^{N_I} x_i^I = \sum_{i=1}^{N_{I,b}} x_i^I \alpha_{i,b} = 0 ,$$

where $N_{I,b}$ is the number of stocks belonging to industry I followed by broker b. It follows that $\sum_{i=1}^{N_{I,b}} x_i^I \alpha_{i,b} = 0$.

Table 2.A.1: Sample description

Panel A outlines the sample selection procedure and Panel B contains the descriptive statistics. The columns report the number of firms, analysts, brokers and target prices with at least one target price released over the sample period. The last column displays the market capitalization of the firms in our sample with respect to the total market capitalization. The total market capitalization is the market capitalization of all the stocks included in the CRSP universe (NYSE, Amex, NASDAQ, and Arca) measured as of December 31th of each year.

Panel A: Sample selection

Description	Observations
All unique target prices released between 1999 and 2012 by identifiable analysts	1,022,622
Less	
firms not matched with CRSP	-22,201
target prices for non-US firms	-166,473
target prices without 12-month forecast horizon	-16,703
target prices not labeled in USD	-444
target prices for firms followed by less than three analysts	-1,365
observations with missing stock prices at announcement	-1,297
observations with stock prices less than one dollar	-2,519
Final sample	811,620

Panel B: Number of observations

Year	Number of firms	Number of analysts	Number of brokers	Number of target prices	% of total market cap
1999	2,825	2,546	157	24,560	81.6
2000	3,342	3,157	195	37,769	85.6
2001	3,233	3,548	169	44,251	86.1
2002	3,119	3,323	175	50,233	85.0
2003	3,126	2,705	236	51,357	83.6
2004	3,251	2,755	260	54,463	81.6
2005	3,361	2,803	259	55,830	79.3
2006	3,384	2,767	251	57,481	78.0
2007	3,391	2,730	244	60,804	75.7
2008	3,269	2,690	251	73,547	76.2
2009	2,968	2,613	268	70,476	74.0
2010	2,987	2,971	292	73,709	73.3
2011	2,978	3,033	276	80,719	73.8
2012	2,859	2,897	260	76,421	72.6
All years	6,357	9,072	686	811,620	79.0

Table 2.A.2: Control variables for multivariate analysis

Variable	Definition
Analyst characteristics	
Star analyst	Dummy variable equal to one for analysts ranked as All-American (top three or runner-up team) in the annual polls in the Institutional Investor magazine, and zero otherwise.
Analyst experience	Years elapsed since the first earnings forecast, recommendation, or target price.
Target price characteristics	
Leader-follower ratio	Ratio of the gap sum of the previous two target prices over the gap sum of the next two target prices.
Conc. earnings forecast	Dummy variable equal to one if there is an earnings forecast issued by the same analyst within a three-day window around the target price release, and zero otherwise.
Information discovery	Dummy variable equal to one if the target price is not released in a three-day window surrounding a firm-specific event (earnings' releases, management guidance, mergers and acquisitions, and equity issuance), and zero otherwise.
FD regulation	Dummy variable equal to one if the target price is released after the fair disclosure regulation, and zero otherwise.
Settlement	Dummy variable equal to one if the target price is released after the global settlement, and zero otherwise.
Firm characteristics	
Guidance intensity	Number of guidance issued during the last three months.
Analysts following	Number of brokerage houses with valid target prices outstanding.
Analysts activity	Number of target prices for the firm issued in the last three months.
Institutional ownership	Percent of the firm owned by 13F institutions in the most recent quarter-end.
Turnover	Three-month average daily percentage of shares traded divided by total shares outstanding.

Table 2.1: Descriptive statistics

This table describes the sample of target prices in terms of market capitalization, book-to-market, and momentum. For each year, I report the percentage of target prices based on size, book-to-market, and momentum tercile. The variables are measured at the end of the year preceding the announcement of the target price. The tercile breakpoints are constructed using NYSE stocks with a CRSP share code of 10 or 11.

	% of observations by market capitalization tercile			% of observations by book-to-market tercile			% of observations by momentum tercile		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
1999	17.0	26.4	56.6	58.8	26.7	14.6	28.2	20.2	51.6
2000	21.5	27.0	51.5	54.7	28.2	17.2	42.8	20.5	36.7
2001	22.2	31.0	46.8	54.7	31.2	14.1	49.9	22.4	27.8
2002	26.7	26.9	46.5	45.1	32.1	22.8	49.5	24.9	25.6
2003	25.6	27.6	46.8	51.3	30.9	17.8	25.4	29.1	45.5
2004	29.2	26.7	44.1	48.5	29.9	21.6	39.0	22.4	38.6
2005	31.2	26.5	42.2	47.3	31.6	21.1	36.6	21.1	42.3
2006	32.7	26.9	40.4	44.4	31.6	24.1	46.4	23.7	29.9
2007	32.3	26.4	41.3	41.6	31.2	27.2	39.2	19.4	41.4
2008	30.9	28.5	40.7	39.7	32.0	28.3	40.8	30.0	29.2
2009	25.8	28.8	45.4	45.6	31.3	23.0	35.9	28.6	35.6
2010	25.9	28.0	46.0	46.9	29.8	23.2	37.7	20.7	41.7
2011	25.4	29.5	45.1	44.6	30.5	24.9	35.9	29.4	34.7
2012	24.2	28.4	47.4	43.7	30.8	25.5	40.2	26.1	33.7
All	27.0	27.9	45.1	46.5	30.8	22.7	39.2	24.7	36.1

Table 2.2: Descriptive statistics of the types of information

This table contains the descriptive statistics of the different types of information conveyed through target prices. In Panel A I decompose the information according to availability. In Panel B I decompose the private information into a firm-specific and an industry-wide component.

Panel A: Decomposition of information by availability

		Public information μ_i					Private information $\Delta\mu_{i,b}$				
Year	N	Mean	Std Dev	D1	Median	D10	Mean	Std Dev	D1	Median	D10
1999	22,379	2.9	1.2	2.3	2.3	4.7	26.0	20.1	3.3	22.6	61.7
2000	36,906	4.8	2.8	2.3	3.8	9.0	29.2	22.5	2.8	25.5	63.6
2001	43,942	9.7	6.8	2.3	7.3	22.1	21.2	23.8	-6.7	17.0	63.6
2002	49,940	11.0	5.8	4.2	9.8	21.2	16.8	23.3	-10.2	12.4	60.0
2003	47,730	12.8	5.4	5.9	12.2	21.8	4.0	19.5	-21.3	1.9	28.5
2004	54,100	11.9	5.2	5.7	11.1	19.9	4.3	17.8	-17.2	2.7	25.8
2005	55,010	8.3	3.3	4.3	8.0	12.8	7.3	17.2	-12.6	5.7	28.2
2006	56,471	7.3	2.8	3.8	7.0	11.1	8.1	17.4	-11.6	6.3	29.6
2007	60,255	6.0	2.3	3.2	5.7	9.1	9.5	17.3	-9.7	7.6	30.8
2008	72,838	7.4	2.7	4.1	7.1	10.8	17.8	24.5	-11.7	13.5	63.6
2009	70,134	17.0	5.4	9.3	17.8	22.6	0.2	21.5	-23.8	-2.8	27.9
2010	73,194	12.6	4.9	6.4	12.2	19.7	4.8	18.2	-17.4	3.0	27.0
2011	80,174	8.5	3.2	4.8	8.0	12.8	10.6	19.5	-10.9	7.6	37.2
2012	75,887	12.5	4.2	7.3	12.4	17.9	5.3	19.0	-15.8	2.6	29.6
All	798,960	10.0	5.5	3.6	8.8	18.5	10.3	21.5	-15.1	7.0	41.6

Panel B: Decomposition of private information by scope

		Firm-specific private information $\alpha_{i,b}$					Industry-wide private information $\mu_{I,b}$				
Year	N	Mean	Std Dev	D1	Median	D10	Mean	Std Dev	D1	Median	D10
1999	20,149	22.4	20.5	-1.3	19.8	58.5	2.3	3.1	0.0	1.0	8.8
2000	34,200	25.1	22.8	-2.2	22.1	59.4	2.4	3.2	0.0	1.0	9.5
2001	41,040	18.0	23.4	-10.3	14.3	59.4	1.9	2.9	-0.0	0.6	7.4
2002	47,092	14.0	22.6	-12.9	10.2	55.6	1.5	2.8	-0.1	0.4	6.0
2003	44,402	3.3	18.6	-20.6	1.6	26.3	0.3	1.9	-1.7	0.0	1.6
2004	50,307	3.6	16.9	-16.7	2.1	23.8	0.3	1.7	-1.1	0.0	1.4
2005	51,288	6.1	16.5	-12.7	4.6	26.1	0.6	1.9	-0.5	0.1	2.1
2006	52,684	6.8	16.7	-12.0	5.0	27.3	0.7	2.1	-0.4	0.1	2.7
2007	56,175	7.9	16.6	-10.4	6.0	28.3	0.9	2.2	-0.3	0.2	3.1
2008	68,786	13.6	24.0	-16.5	9.7	58.1	2.2	3.4	-0.2	0.6	9.5
2009	66,218	-0.2	20.9	-25.1	-2.6	26.6	0.3	2.6	-2.2	-0.0	2.7
2010	68,979	3.8	17.4	-17.3	2.2	25.0	0.6	2.2	-1.2	0.0	2.6
2011	76,105	8.3	18.7	-12.4	5.6	33.5	1.3	2.8	-0.5	0.2	5.5
2012	72,016	4.0	18.2	-16.7	1.5	26.9	0.7	2.4	-1.2	0.1	3.4
All	749,441	8.3	20.6	-16.0	5.4	38.1	1.0	2.6	-0.8	0.1	4.4

Table 2.3: Types of information and abnormal return: univariate analysis

This table provides summary statistics on the abnormal return after the release of target prices. Target prices are sorted into quintiles according to either public information (Panel A), private information (Panel B), firm-specific private information (Panel C), or industry-wide private information (Panel D). I then measure the average and the standard error (within parentheses) of the abnormal returns. In Panels A, B, and C the abnormal return is measured by the stock buy and hold return in excess of the ones predicted by the CAPM. In Panel D the abnormal return is measured at the industry level. One and two asterisks, reported only for Q5-Q1, denote statistical significance at the 5% and 1% significance level, respectively.

	Q1 (lowest)	Q2	Q3	Q4	Q5 (highest)	Q5-Q1
Panel A: Relation between public information and abnormal return						
$BHAR_{i,(1,21)}$	0.820	0.429	0.580	0.633	0.578	-0.242
	(0.136)	(0.112)	(0.078)	(0.101)	(0.171)	(0.230)
$BHAR_{i,(1,42)}$	1.256	0.805	0.940	1.005	1.417	0.161
	(0.251)	(0.206)	(0.170)	(0.194)	(0.324)	(0.446)
$BHAR_{i,(1,63)}$	1.763	1.071	1.129	1.096	2.128	0.365
	(0.398)	(0.262)	(0.232)	(0.273)	(0.487)	(0.680)
Panel B: Relation between private information and abnormal return						
$BHAR_{i,(1,21)}$	0.107	0.335	0.595	0.832	1.171	1.064**
	(0.115)	(0.060)	(0.069)	(0.090)	(0.181)	(0.160)
$BHAR_{i,(1,42)}$	0.569	0.662	1.014	1.343	1.832	1.262**
	(0.218)	(0.126)	(0.127)	(0.156)	(0.346)	(0.333)
$BHAR_{i,(1,63)}$	0.917	0.894	1.245	1.757	2.367	1.450**
	(0.337)	(0.176)	(0.171)	(0.219)	(0.452)	(0.456)
Panel C: Relation between firm-specific private information and abnormal return						
$BHAR_{i,(1,21)}$	0.136	0.329	0.521	0.804	1.144	1.008**
	(0.123)	(0.058)	(0.073)	(0.092)	(0.184)	(0.162)
$BHAR_{i,(1,42)}$	0.577	0.671	0.871	1.298	1.822	1.245**
	(0.221)	(0.124)	(0.134)	(0.156)	(0.357)	(0.330)
$BHAR_{i,(1,63)}$	0.954	0.867	1.068	1.737	2.316	1.362**
	(0.342)	(0.174)	(0.179)	(0.221)	(0.463)	(0.449)
Panel D: Relation between industry-wide private information and industry abnormal return						
$BHAR_{I,(1,21)}$	0.992	0.787	1.066	1.266	1.352	0.360**
	(0.083)	(0.083)	(0.077)	(0.101)	(0.112)	(0.096)
$BHAR_{I,(1,42)}$	1.995	1.559	2.086	2.446	2.674	0.679**
	(0.154)	(0.157)	(0.167)	(0.217)	(0.250)	(0.197)
$BHAR_{I,(1,63)}$	2.999	2.392	3.167	3.663	4.099	1.099**
	(0.228)	(0.216)	(0.256)	(0.322)	(0.347)	(0.273)

Table 2.4: Types of information and abnormal return: multivariate analysis

This table provides a multivariate analysis of the relation between the information conveyed by target prices and *BHAR*. First, the information conveyed by target prices is separated according to its availability and scope. Then, the different sorts of information are used to explain the *BHAR* at different horizons. In Panel A information is separated according to its availability. More precisely, in columns (1) to (3), the explanatory variable is the level of public information and in columns (4) to (6) the level of private information. In Panel B private information is separated according to its scope. In columns (1) to (3), the explanatory variable is the level of firm-specific private information and in columns (4) to (6) the level of industry-wide private information. The standard errors (in parentheses) are adjusted for heteroskedasticity and within-industry clustering. All specifications include control variables and quarter-industry fixed effects. One and two asterisks denote statistical significance at the 5% and 1% significance level, respectively.

Panel A: Availability of information and abnormal return						
	$BHAR_{i,(1,21)}$	$BHAR_{i,(1,42)}$	$BHAR_{i,(1,63)}$	$BHAR_{i,(1,21)}$	$BHAR_{i,(1,42)}$	$BHAR_{i,(1,63)}$
	(1)	(2)	(3)	(4)	(5)	(6)
μ_i	0.001	0.011	-0.012			
	(0.013)	(0.023)	(0.032)			
$\Delta\mu_{i,b}$				0.027**	0.036**	0.039**
				(0.002)	(0.003)	(0.004)
Star analyst	-0.049	0.095	0.194	0.038	0.211	0.322
	(0.125)	(0.189)	(0.227)	(0.125)	(0.189)	(0.227)
Analyst experience	-0.001	-0.002	-0.005	-0.004	-0.005	-0.008
	(0.004)	(0.005)	(0.006)	(0.004)	(0.005)	(0.006)
Leader-Follower Ratio	0.005**	0.005**	0.004*	0.004**	0.005**	0.004*
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Conc. earnings forecast	0.264**	0.408**	0.395**	0.235**	0.372**	0.358**
	(0.054)	(0.072)	(0.088)	(0.054)	(0.072)	(0.088)
Info discovery	-0.064	0.054	0.101	-0.106	-0.001	0.041
	(0.089)	(0.107)	(0.115)	(0.089)	(0.106)	(0.116)
FD regulation	-1.652*	-3.133*	-2.317	-1.483*	-2.957*	-2.212
	(0.748)	(1.349)	(1.359)	(0.734)	(1.342)	(1.360)
Settlement	-0.100	0.621	0.444	0.300	1.204*	1.012
	(0.341)	(0.597)	(0.699)	(0.335)	(0.591)	(0.693)
Guidance intensity	0.026	0.035	0.036	0.036*	0.049	0.051
	(0.017)	(0.027)	(0.036)	(0.017)	(0.027)	(0.037)
Analysts following	-0.007*	-0.011*	-0.012*	-0.005	-0.007	-0.008
	(0.003)	(0.004)	(0.006)	(0.003)	(0.004)	(0.006)
Analyst activity	0.016	0.013	0.009	0.016	0.012	0.010
	(0.010)	(0.016)	(0.021)	(0.011)	(0.016)	(0.021)
Institutional ownership	0.000	0.001	0.002	0.001	0.002	0.003
	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)
Turnover	-0.135*	-0.223**	-0.283*	-0.134*	-0.212*	-0.293*
	(0.053)	(0.083)	(0.125)	(0.053)	(0.083)	(0.123)
N	779,288	778,217	776,548	779,288	778,217	776,548
R-squared	0.04	0.07	0.12	0.05	0.07	0.12

Table 2.4 - *Continued*

Panel B: Scope of information and abnormal return						
	$BHAR_{i,(1,21)}$	$BHAR_{i,(1,42)}$	$BHAR_{i,(1,63)}$	$BHAR_{I,(1,21)}$	$BHAR_{I,(1,42)}$	$BHAR_{I,(1,63)}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\alpha_{i,b}$	0.025**	0.034**	0.038**			
	(0.002)	(0.003)	(0.004)			
$\mu_{I,b}$				0.021**	0.024**	0.025**
				(0.003)	(0.003)	(0.003)
Star analyst	-0.000	0.148	0.252	-0.006	0.025	0.042
	(0.125)	(0.190)	(0.227)	(0.050)	(0.054)	(0.057)
Analyst experience	-0.001	-0.002	-0.007	-0.001	-0.001	-0.001
	(0.004)	(0.005)	(0.006)	(0.001)	(0.002)	(0.002)
Leader-Follower Ratio	0.004**	0.004**	0.003	0.001*	0.001**	0.001
	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)
Conc. earnings forecast	0.228**	0.361**	0.358**	0.101**	0.182**	0.217**
	(0.056)	(0.075)	(0.090)	(0.031)	(0.035)	(0.037)
Info discovery	-0.110	0.020	0.069	0.079	0.138	0.097
	(0.093)	(0.111)	(0.120)	(0.067)	(0.077)	(0.075)
FD regulation	-1.633*	-2.968*	-2.164	-2.010*	-2.324	-1.148
	(0.786)	(1.371)	(1.363)	(0.976)	(1.468)	(1.590)
Settlement	0.237	1.013	0.810	-0.053	-0.496	-1.562*
	(0.355)	(0.604)	(0.699)	(0.400)	(0.628)	(0.757)
Guidance intensity	0.037*	0.049	0.049	0.005	0.006	-0.007
	(0.017)	(0.028)	(0.037)	(0.005)	(0.007)	(0.007)
Analysts following	-0.004	-0.006	-0.008	0.000	0.001	0.000
	(0.003)	(0.004)	(0.006)	(0.001)	(0.002)	(0.002)
Analyst activity	0.018	0.014	0.014	-0.002	-0.006	-0.005
	(0.011)	(0.016)	(0.021)	(0.005)	(0.007)	(0.008)
Institutional ownership	0.001	0.002	0.004	0.000	0.000	-0.000
	(0.001)	(0.002)	(0.003)	(0.000)	(0.000)	(0.000)
Turnover	-0.138*	-0.239**	-0.320*	0.010	0.012	0.014
	(0.054)	(0.085)	(0.126)	(0.013)	(0.016)	(0.019)
N	732,772	731,739	730,157	732,772	731,739	730,157
R-squared	0.05	0.07	0.12	0.17	0.35	0.53

Table 2.5: Firm characteristics and investors' reaction

This table contains the results obtained by sorting firms into characteristic-based terciles. In columns (1) to (3) firms are sorted into terciles by idiosyncratic volatility. For each tercile, I regress *BHAR* on the firm-specific private information ($\alpha_{i,b}$). In columns (4) to (6) firms are sorted by the absolute value of industry exposure. For each tercile, I regress industry *BHAR* on the industry-wide private information ($\mu_{I,b}$).All specifications include a set of control variables and quarter-industry fixed effects. The standard errors (in parentheses) are adjusted for heteroskedasticity and within-industry clustering. One and two asterisks denote statistical significance at the 5% and 1% significance level, respectively.

	Level of idiosyncratic volatility			Level of industry sensitivity		
	Low	Medium	High	Low	Medium	High
	(1)	(2)	(3)	(4)	(5)	(6)
	$BHAR_{i,(1,21)}$			$BHAR_{I,(1,21)}$		
$\alpha_{i,b}$	0.019**	0.019**	0.031**			
	(0.002)	(0.002)	(0.002)			
$\mu_{I,b}$				0.016**	0.019**	0.024**
				(0.004)	(0.004)	(0.004)
Star analyst	0.034	0.060	-0.199	-0.012	-0.023	0.027
	(0.090)	(0.171)	(0.409)	(0.078)	(0.062)	(0.075)
Analyst experience	-0.002	0.001	-0.008	-0.002	0.001	-0.001
	(0.003)	(0.005)	(0.009)	(0.002)	(0.002)	(0.003)
Leader-Follower Ratio	0.003**	0.004**	0.005*	0.000	0.000	0.003**
	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)
Conc. earnings forecast	0.188**	0.208**	0.292*	0.044	0.126**	0.126**
	(0.047)	(0.066)	(0.123)	(0.034)	(0.039)	(0.047)
Info discovery	-0.226**	-0.006	-0.104	0.061	0.014	0.165
	(0.077)	(0.111)	(0.196)	(0.069)	(0.080)	(0.092)
FD regulation	-0.534	0.425	-1.475*	-0.862	-1.767*	-1.941
	(1.074)	(0.852)	(0.749)	(0.738)	(0.856)	(1.029)
Settlement	0.105	-0.613	0.035	-0.473	-0.093	-0.218
	(0.400)	(0.359)	(0.411)	(0.325)	(0.354)	(0.406)
Guidance intensity	0.010	-0.021	0.113**	0.005	-0.001	0.016
	(0.018)	(0.026)	(0.042)	(0.007)	(0.008)	(0.011)
Analysts following	-0.003	-0.005	-0.008	-0.001	-0.003	0.003
	(0.003)	(0.004)	(0.007)	(0.002)	(0.002)	(0.002)
Analyst activity	-0.007	0.013	0.062*	0.005	0.008	-0.012
	(0.009)	(0.015)	(0.026)	(0.006)	(0.006)	(0.007)
Institutional ownership	0.002	0.001	0.002	0.001	-0.000	0.000
	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)	(0.001)
Turnover	-0.097	-0.117	-0.167*	-0.040	0.034	0.021
	(0.106)	(0.099)	(0.075)	(0.023)	(0.023)	(0.020)
N	244,307	244,255	244,210	244,277	244,258	244,237
R-squared	0.04	0.07	0.06	0.24	0.17	0.18

Table 2.6: Misclassification of the information conveyed after firm-specific events

This table provides a multivariate analysis of the relation between *BHAR* and the information conveyed by the target prices not issued immediately after firm-specific events. First, the information conveyed by target prices is separated according to its availability and scope. Then, the different sorts of information are used to explain the *BHAR* at different horizons. In Panel A information is separated according to its availability. More precisely, in columns (1) to (3), the explanatory variable is the level of public information and in columns (4) to (6) the level of private information. In Panel B private information is separated according to its scope. In columns (1) to (3), the explanatory variable is the level of firm-specific private information and in columns (4) to (6) the level of industry-wide private information. The standard errors (in parentheses) are adjusted for heteroskedasticity and within-industry clustering. All specifications include control variables and quarter-industry fixed effects. One and two asterisks denote statistical significance at the 5% and 1% significance level, respectively.

Panel A: Availability of information and abnormal return						
	$BHAR_{i,(1,21)}$	$BHAR_{i,(1,42)}$	$BHAR_{i,(1,63)}$	$BHAR_{i,(1,21)}$	$BHAR_{i,(1,42)}$	$BHAR_{i,(1,63)}$
	(1)	(2)	(3)	(4)	(5)	(6)
μ_i	0.026	0.048	0.018			
	(0.014)	(0.025)	(0.032)			
$\Delta\mu_{i,b}$				0.028**	0.037**	0.039**
				(0.002)	(0.003)	(0.004)
Star analyst	0.012	0.275	0.372	0.086	0.368	0.480
	(0.180)	(0.272)	(0.321)	(0.181)	(0.274)	(0.323)
Analyst experience	-0.000	-0.003	-0.010	-0.003	-0.007	-0.014
	(0.005)	(0.007)	(0.009)	(0.005)	(0.007)	(0.009)
Leader-Follower Ratio	0.010**	0.010**	0.010*	0.010**	0.010**	0.010*
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)
Conc. earnings forecast	0.215**	0.401**	0.443**	0.171**	0.347**	0.389**
	(0.063)	(0.084)	(0.101)	(0.063)	(0.084)	(0.101)
FD regulation	-1.197*	-2.439*	-1.876	-0.974	-2.151*	-1.722
	(0.588)	(1.011)	(1.123)	(0.586)	(1.018)	(1.133)
Settlement	-0.282	-0.270	-0.009	0.232	0.480	0.692
	(0.298)	(0.499)	(0.619)	(0.296)	(0.495)	(0.614)
Guidance intensity	0.035	0.072*	0.055	0.045*	0.084*	0.070
	(0.023)	(0.037)	(0.046)	(0.023)	(0.037)	(0.046)
Analysts following	-0.004	-0.007	-0.010	-0.002	-0.003	-0.006
	(0.004)	(0.005)	(0.007)	(0.004)	(0.005)	(0.007)
Analyst activity	0.012	0.009	0.003	0.011	0.007	0.002
	(0.013)	(0.020)	(0.024)	(0.013)	(0.020)	(0.024)
Institutional ownership	0.002	0.002	0.003	0.003	0.004	0.005
	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)
Turnover	-0.140*	-0.312**	-0.370**	-0.117	-0.260**	-0.354**
	(0.064)	(0.095)	(0.130)	(0.062)	(0.094)	(0.129)
N	423,073	422,324	421,222	423,073	422,324	421,222
R-squared	0.05	0.08	0.16	0.05	0.08	0.12

Table 2.6 - *Continued*

Panel B: Scope of information and abnormal return						
	$BHAR_{i,(1,21)}$	$BHAR_{i,(1,42)}$	$BHAR_{i,(1,63)}$	$BHAR_{I,(1,21)}$	$BHAR_{I,(1,42)}$	$BHAR_{I,(1,63)}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\alpha_{i,b}$	0.026**	0.035**	0.037**			
	(0.002)	(0.004)	(0.004)			
$\mu_{I,b}$				0.019**	0.026**	0.027**
				(0.003)	(0.004)	(0.004)
Star analyst	0.028	0.263	0.368	0.016	0.139	0.135
	(0.179)	(0.275)	(0.325)	(0.075)	(0.082)	(0.091)
Analyst experience	0.001	-0.004	-0.012	-0.001	-0.001	-0.002
	(0.005)	(0.007)	(0.009)	(0.002)	(0.003)	(0.003)
Leader-Follower Ratio	0.010**	0.009**	0.010*	0.001	0.002*	0.001
	(0.003)	(0.003)	(0.005)	(0.001)	(0.001)	(0.001)
Conc. earnings forecast	0.159*	0.321**	0.371**	0.098**	0.160**	0.219**
	(0.065)	(0.087)	(0.102)	(0.034)	(0.043)	(0.045)
Info discovery	-1.161	-2.269*	-1.751	-1.662	-1.673	-1.041
	(0.624)	(1.031)	(1.125)	(0.896)	(1.331)	(1.538)
FD regulation	0.165	0.320	0.535	-0.144	-0.994	-1.816*
	(0.312)	(0.505)	(0.619)	(0.367)	(0.579)	(0.737)
Settlement	0.040	0.080*	0.062	0.006	0.009	-0.003
	(0.023)	(0.037)	(0.047)	(0.007)	(0.010)	(0.010)
Guidance intensity	-0.001	-0.001	-0.006	0.001	0.001	0.001
	(0.004)	(0.005)	(0.007)	(0.002)	(0.002)	(0.003)
Analysts following	0.013	0.009	0.007	-0.008	-0.011	-0.009
	(0.013)	(0.021)	(0.025)	(0.006)	(0.010)	(0.011)
Analyst activity	0.003*	0.004	0.005	-0.000	-0.000	-0.001
	(0.001)	(0.002)	(0.003)	(0.000)	(0.000)	(0.000)
Institutional ownership	-0.116	-0.278**	-0.375**	0.017	0.014	0.013
	(0.065)	(0.098)	(0.135)	(0.016)	(0.021)	(0.023)
Turnover	0.026**	0.035**	0.037**	0.019**	0.026**	0.027**
	(0.002)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
N	397,756	397,035	395,993	397,756	397,035	395,993
R-squared	0.04	0.06	0.11	0.16	0.20	0.24

Table 2.7: Additional tests

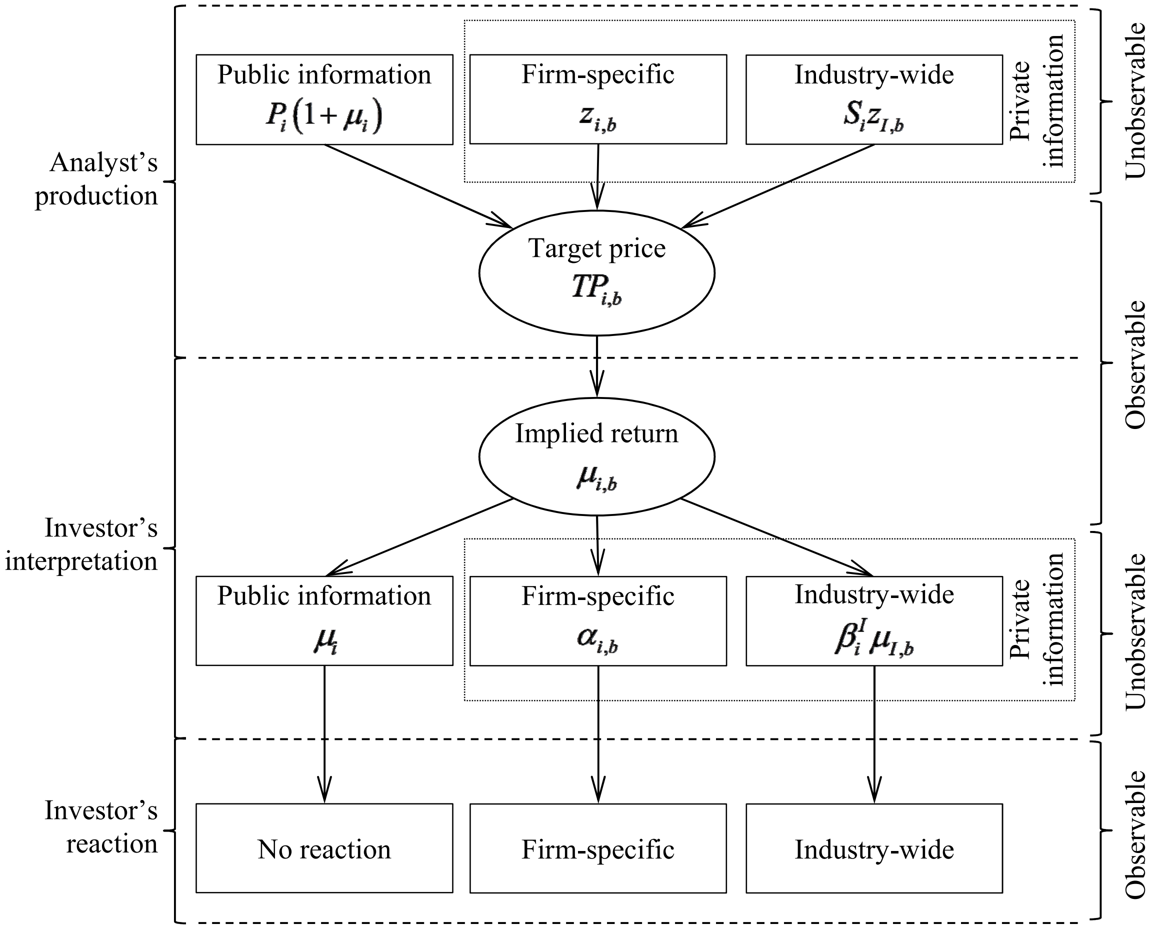
This table provides the results of the robustness analysis. Columns (1) to (3) contain the results obtained by using public market returns inferred from analysts' target prices. The results in columns (4) to (6) are obtained using industry and market sensitivities estimated excluding firm-specific events. Columns (7) to (9) display the results obtained by using industry indices that exclude the firm in question to prevent spurious correlation between stock and industry returns. Columns (10) to (12) contain the results obtained by using target prices issued only by brokers that participate at least once to the Bloomberg GDP survey. The figures reported are the coefficients of interest η obtained by regressing the *BHAR* on the type of information and on the set of control variables and quarter-industry fixed effects. Each coefficient is obtained from one different regression. For the sake of space, the coefficients associated with control variables are not reported. Panel A shows the association between information and abnormal returns at various horizons. In Panel B and C firms are sorted into terciles by idiosyncratic volatility and industry sensitivity, respectively.

	Alternative market expected return			Stocks' sensitivity estimation			Correlation in small industries			Broker organization		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Investors' reaction												
	$BHAR_{.,(1,21)}$	$BHAR_{.,(1,42)}$	$BHAR_{.,(1,63)}$	$BHAR_{.,(1,21)}$	$BHAR_{.,(1,42)}$	$BHAR_{.,(1,63)}$	$BHAR_{.,(1,21)}$	$BHAR_{.,(1,42)}$	$BHAR_{.,(1,63)}$	$BHAR_{.,(1,21)}$	$BHAR_{.,(1,42)}$	$BHAR_{.,(1,63)}$
μ_i	0.011	0.031*	0.018	0.001	0.007	-0.009	0.001	0.010	-0.013	0.013	0.038	0.029
	(0.007)	(0.012)	(0.016)	(0.013)	(0.022)	(0.032)	(0.013)	(0.023)	(0.032)	(0.014)	(0.025)	(0.036)
$\Delta\mu_{i,b}$	0.026**	0.034**	0.037**	0.028**	0.038**	0.040**	0.027**	0.036**	0.039**	0.026**	0.035**	0.038**
	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)
$\alpha_{i,b}$	0.024**	0.031**	0.034**	0.028**	0.038**	0.041**	0.025**	0.034**	0.038**	0.025**	0.034**	0.037**
	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)	(0.002)	(0.004)	(0.004)
$\mu_{I,b}$	0.021**	0.026**	0.025**	0.026**	0.031**	0.030**	0.010**	0.014**	0.017**	0.021**	0.026**	0.026**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)
Panel B: Investors' reaction conditional on idiosyncratic volatility												
	Level of idiosyncratic volatility											
	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
$\alpha_{i,b}$	0.018**	0.018**	0.030**	0.021**	0.024**	0.032**	0.018**	0.019**	0.029**	0.019**	0.020**	0.029**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Panel C: Investors' reaction conditional on industry sensitivity												
	Level of industry sensitivity											
	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
$\mu_{I,b}$	0.012**	0.018**	0.025**	0.017**	0.028**	0.029**	0.005**	0.015**	0.020**	0.017**	0.019**	0.026**
	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.007)	(0.002)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)

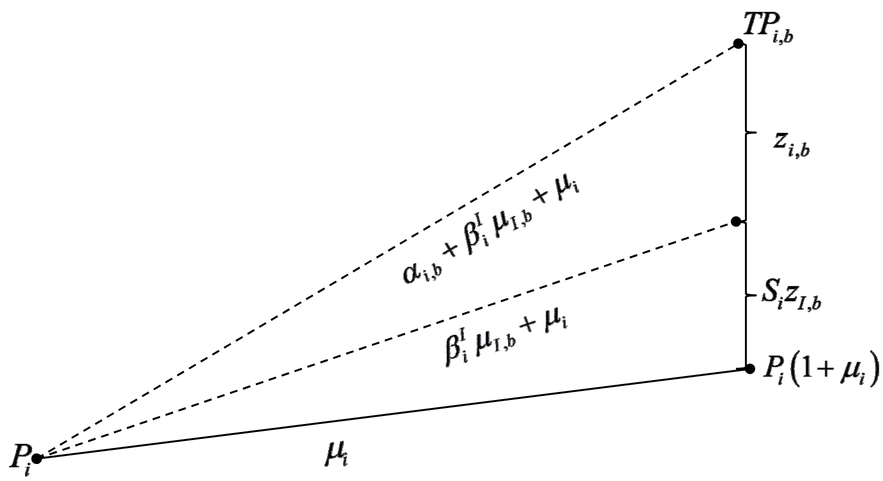
Figure 2.1: Graphical representation

This figure represents graphically the rationale behind the decomposition of the information conveyed through target prices. Panel A displays how the information flows from analysts to investors and its predicted impact on markets. Panel B represents the relation between the components of the return implied by target prices, the information possessed by analysts, and the target price

Panel A: Information flow



Panel B: Return implied by target prices and types of information



Chapter 3: The Role of Remuneration Structures in Hedge Fund Performance

(In collaboration with Istvan Nagy)

3.1. Introduction

Allocation to hedge funds responds to past performance and is negatively related to future returns. Those are the main conclusions of the literature analyzing the relation between flows and performance in the hedge fund industry; see Fung, Hsieh, Naik and Ramadorai (2008) or Ramadorai (2013). Those results indicate that hedge fund investors chase past hedge fund returns and that hedge funds are subject to diseconomies of scale. In the framework of Berk and Green (2004), the coexistence of these conditions leads to the absence of performance persistence and to zero abnormal returns. There is however strong evidence of persistence in the abnormal performance generated by hedge funds; see Kosowski, Naik and Teo (2007) and Jagannathan, Malakhov and Novikov (2010). In light of these results, the behavior of hedge fund managers, who limit the size of their funds by closing them to new investments or by forcing investors to redeem, presents a puzzle. Why do managers restrict the access to their funds, leaving money on the table, instead of expanding them to capture the rents going forward?

In this paper, we propose a model that explains the persistence of hedge fund abnormal performance and that rationalizes the behavior of hedge fund managers. The model connects performance, fund size, and managers' remuneration within a global framework. We show how the absence of true passive indexing opportunities and the presence of performance-linked remuneration are sufficient to explain the persistence of hedge fund abnormal returns when managers expect to receive a performance fee payment. In this framework, managers restrict the size of their funds to maximize their remuneration.

The investment objectives of managers, together with the monitoring exerted by investors, prevent managers from employing passive indexing. As the strategies exploited by hedge funds are subject to diseconomies of scales, the performance fee makes the remuneration of managers concave in fund size. Therefore, managers face a trade-off between expanding the fund to cash in more management fees and limiting the size of the fund to preserve the performance and consequently collect more performance fees.

There is thus an optimal size at which managers maximize their remuneration. We show that managers, as long as they expect to receive a performance fee payment, are better off by limiting the size of the fund and refusing new investments. At this optimal size, the abnormal return to investors is positive. As managers refuse the performance-diluting flows, the abnormal performance of hedge funds persists. Managers below the high watermark or remunerated only by a management fee do not face this trade-off and let the fund grow, thereby negatively impacting the performance. Therefore, when passive indexing is not an option, the performance fee effectively aligns managers' and investors' interests. However, the incentive fee loses its incentive alignment effect when managers do not expect to receive a performance fee payment.

We use a numerical analysis to verify whether the model can reproduce the performance persistence observed in the data. The model reproduces several empirical facts about hedge funds. It matches the observed estimates of net return, size, persistence, and attrition. Though, the flows obtained from the model are not as responsive to past performance as observed in empirical studies. We also analyze the validity of our model by testing its indirect implications on a sample of hedge fund fee revisions. The empirical findings are consistent with the model. Relative to their peers, the funds that revise the performance fee upward experience a statistically and economically significant improvement of performance, and vice-versa for downward revisions. This is consistent with the fact that performance fees participate in aligning the interests of managers and investors. The findings for increases of management fees are also consistent with the model. Indeed, the returns of these funds drop significantly more than the ones of similar funds. Altogether, we illustrate that the performance-linked remuneration of managers plays a central role in explaining the persistence observed in the abnormal returns of hedge funds.

This paper contributes to two strands of research. First, by rationalizing the persistent abnormal performance of hedge funds, we add to the literature on the determinants of hedge fund performance. While most existing studies focus on risk exposures or managerial ability, we examine fund characteristics. We provide support to the idea that hedge fund abnormal performance and persistence are possible because of the limited size of the funds.

Second, we complement the literature on remuneration in the money management industry. The peculiar remuneration schemes of hedge funds have been the subject of many studies and that, consistently with financial theory, generally conclude that performance-linked remuneration is associated with higher returns; see Ackermann, McEnally and Ravenscraft (1999), Goetzmann, Ingersoll and Ross (2003), and Agarwal, Daniel and Naik (2009). Our model pinpoints the mechanisms that transform the performance-linked remuneration into persistence and abnormal performance. The model also highlights which are the conditions necessary to put these mechanisms at work. Furthermore, we balance the view that option-like remuneration gives adverse risk taking incentives; see, e. g, Grinblatt and Titman (1989). In fact, when funds are above the high watermark, the performance fee leads to persistent abnormal returns.

Our work is closely related to Glode and Green (2011), who rationalize the performance persistence in hedge funds using potential information spillovers. Their model assumes that the investors of a fund are sufficiently informed about its strategy to be able to replicate it. By contrast, and consistently with the opacity of hedge funds, our model does not require investors to be well informed about the strategy of the fund. Indeed, investors infer expected returns from past performance. In our model, the persistent performance is the consequence of the absence of passive indexing opportunities and of the performance fee agreed in the remuneration contract. For this reason, our model departs also from Makarov and Plantin (2015), who assume that managers implement information-less strategies to manipulate investors' perception of their skills.[1]

The remainder of the chapter is organized as follows. Section 3.2 presents the theoretical framework. In Section 3.3 we derive the model's predictions in terms of size, returns, flows, and persistence, and we use simulations to appraise the quantitative properties of the model. Section 3.4 empirically tests the model. Section 3.5 summarizes and concludes. Proofs and technical developments are in the Appendix.

[1] By information-less strategies we encompass all the strategies that are not based on information edges, such as shorting deep out-of-the-money put options and "smart beta" strategies.

3.2. The model

3.2.1. Background

Berk and Green (2004) propose a model of active management that explains why investors keep investing into mutual funds, even if these funds deliver no abnormal performance. The model is built on two main assumptions. First, investors behave rationally, i.e. they supply capital competitively to funds that have positive expected abnormal returns. Second, the investment strategies exploited by managers are subject to diseconomies of scale. The managers, who want to maximize their remuneration, expand their funds as much as possible, regardless of the fee structure applied. In this context, this behavior of managers leads to a lack of performance persistence and zero abnormal return in equilibrium.

Several studies provide evidence that the hypotheses of Berk and Green (2004) are also valid for the hedge fund industry. Investors' flows chase the best past performers and deteriorate the subsequent performance of funds, suggesting that hedge funds face capacity constraints.[2] Despite that, there is little support for the predictions of the Berk and Green (2004) model in the hedge fund research. The literature reached in fact the consensus that hedge funds deliver abnormal returns which persist over long horizons, even if the length of the persistence horizon is still debated.[3] Moreover, hedge fund managers adopt other behaviors that are inconsistent with Berk and Green (2004). Indeed, managers voluntarily limit the size of the funds by closing it to new investments, by discretionarily refusing subscriptions, or even by forcing investors to redeem.[4] The model of Berk and Green (2004) seems thus inappropriate for the hedge fund industry.

Glode and Green (2011) propose an explanation of hedge funds' persistent outperformance based on information spillovers. The fundamental assumption is that investors become informed about the

[2] Fung et al. (2008) and Ramadorai (2013), among others, pinpoint the relation between past performance and flows. Getmansky (2012) and Ramadorai (2013) find that hedge funds are subject to diseconomies of scale.

[3] Agarwal and Naik (2000), and Boyson (2008) find performance persistence up to one quarter. Baquero, ter Horst and Verbeek (2005), Malkiel and Saha (2005), as well as Kosowski et al. (2007) report evidence of persistence for periods reaching one year. Persistence at longer horizons is also documented; see Jagannathan et al. (2010) (3 years), Ammann, Huber and Schmid (2013) (3 years), and Aggarwal and Jorion (2010) (5 years).

[4] Voluntary closures to new investments are discussed by Bali, Gokcan and Liang (2007) and Getmansky, Lo and Mei (2004). For forced redemptions, see, e. g., Jones, S., Brevan Howard to return $2bn to investors, The Financial Times, 09/20/2011. http://www.ft.com/intl/cms/s/0/c8f7f736-e373-11e0-8f47-00144feabdc0.html#axzz1Z8NyNDbM.

proprietary strategy of the hedge fund in which they invest. Therefore, they could leave the fund to divulgate or copycat the strategy, thereby hurting the fund's profitability. To prevent these information spillovers from happening, managers reward investors at a higher than minimal rate, thereby reducing the incentive to disclose the proprietary strategy. This proposition might be true for some funds in some investment strategies, but the fact that hedge funds are known for their opacity casts doubt on the central hypothesis of their model. Moreover, Glode and Green (2011) do not explicitly address the reasons behind voluntary closures and forced redemptions.

In the rest of this section, we show that performance persistence and the need to control the size of the fund arise from the coexistence of two peculiarities of hedge funds: (1) the performance-linked remuneration and (2) the commitment to deliver an absolute return, i.e. a positive return regardless of market conditions.

3.2.2. General set-up

We assume that managers invest the assets of their funds only in proprietary strategies, i.e. managers do not employ passive indexing. The typical mandate of hedge funds is to deliver an absolute return, which implies being uncorrelated with the market; see Fung and Hsieh (1997). Therefore, a passive investment in a benchmark is inconsistent with the investment objective of hedge funds; see Agarwal and Naik (2004) or Lhabitant (2006, p. 25). This does not mean that hedge funds do not invest at all in indexes, but only that they do it accordingly to a strategy. Moreover, the fee charged by hedge funds as well as the high managerial discretion of hedge funds give investors an incentive to continuously monitor the funds they are invested in. If managers use some kind of passive benchmark or if they deviate too importantly from their contractually agreed upon investment style, investors tend to terminate the contract; see Baquero and Verbeek (2009) or Lhabitant (2006, p. 576). The monitoring of the investors also prevents managers from extensively employing information-less strategies. The absence of passive indexing opportunities is also consistent with other well known facts about hedge funds. For instance, liquidity restrictions such as lockups, redemption frequency, and notice periods exist because hedge funds employ illiquid strategies that cannot be unloaded instantaneously. Investments in a passive benchmark would make such restrictions unnecessary; see Agarwal et al. (2009). Passive benchmarking is also inconsistent with closures to new investments. If hedge funds used passive indexing, they could invest any additional performance-diluting inflow into it, without closing the fund. Notice that the absence of passive indexing opportunities and information-less strategies is a major difference with respect to Berk and Green (2004) and Makarov and Plantin (2015). This difference is supported by the empirical evidence about the different use of indexing in the mutual funds and hedge funds industries[5] and by the fact that sophisticated investors using dynamic risk analytics are able to detect exposures to information-less strategies; see Lo (2008).

For the remaining assumptions, we follow Berk and Green (2004). Managers differ in their ability to generate returns and in the strategy they implement. Hedge funds are thus imperfect substitutes to each other and compete monopolistically. As funds exploit finite investment opportunities and face decreasing returns to scale, the gross return before fees available to pay out investors diminishes with the amount invested in the fund. Let $R_t=\alpha+\varepsilon_t$ be the return of the strategy, gross of all costs and fees, α the ability of managers and ε_t an error term normally distributed with mean zero and variance σ^2. R_t does not depend on the size of the fund, but the variable costs incurred by implementing the strategy, e.g. price impact of trades and execution costs, are increasing and convex in the amount of assets under management (AUM). These costs are denoted $C(q_t)$, where q_t is the amount invested into the strategy. We assume that $C(0)=0$, $C'(0)>0$, and $C''(0)>0$, for all $q_t>0$ and, as a special case, the cost function is assumed to be quadratic, i.e. $C\left(q_t\right)=aq_t^2$ with $a>0$.

The typical hedge fund management remuneration has two components: (1) the management fee and (2) the performance fee. The management fee is expressed as a fixed percentage *mf* of the AUM. The performance fee is specified as a fraction *pf* of the performance generated by the fund. Managers receive the performance fee only if the AUM of the fund, after the payment of the management fee, is above the

[5] For instance, Amihud and Goyenko (2013) investigate US mutual funds and find averages R^2 above 0.9. In a similar analysis on hedge funds, Bollen (2013) finds average R^2 around 0.4. This suggests that, contrarily to the mutual fund industry, indexing is not a common practice for hedge funds.

high watermark. The high watermark in period t is the highest level that the AUM has attained up to time t, taking into account subscriptions and redemptions. The high watermark is compounded at the hurdle rate, if any. We express the high watermark as the return that funds have to beat in order to start collecting incentive fees and we denote it $h_t \geq 0$. For the funds that are above the high watermark, or that apply only the hurdle rate provision, h_t is equal to the hurdle rate. The more the fund is below its high watermark, the higher the h_t is. The level of the management and performance fees is the result of a negotiation between managers and investors. On the one side, managers would like to set the management fee at a level that allows them to extract all the rent. On the other side, investors would like to arrange a lower management fee in exchange for the introduction of a performance fee. Because of the prevailing imperfect competition, investors have some bargaining power that prevents managers from extracting all the rent; see Pastor and Stambaugh (2012). The fee level is contractually agreed and thus managers cannot unilaterally revise it. Managers are indifferent to the origin of the fee (management or performance fee) since they are only interested in the total remuneration, defined as:

$$(1) \qquad Remun_{t+1} = \begin{cases} q_t mf + \left[q_t \left(R_{t+1} - h_{t+1} - mf \right) - C\left(q_t \right) \right] pf & \text{if } q_t \left(R_{t+1} - h_{t+1} - mf \right) - C\left(q_t \right) > 0 \\ q_t mf & \text{otherwise} \end{cases} .$$

The objective of managers is to maximize their expected remuneration. They can do it by choosing either the optimal level of fees or the optimal size of the fund. The revision of fees involves time demanding renegotiations that cannot be implemented immediately. Therefore, managers set the size of the fund at the quantity that allows them to maximize the remuneration. At each period, if the fund size is below its optimal size, managers accept new subscription. If the fund size is above its optimum, managers refuse new investments and eventually force investors to redeem.

Investors supply capital to funds competitively. They redeem from the worst performing funds to reinvest into the best performing funds, as long as their expected return is positive. For the sake of simplicity, we consider the payoff of the fund, i.e. the performance in monetary (rather than relative) terms. This payoff is:

$$(2) \qquad TP_{t+1} = \begin{cases} \left(q_t\left(R_{t+1} - h_{t+1} - mf\right) - C\left(q_t\right)\right)\left(1 - pf\right) + q_t h_{t+1} & \text{if } q_t\left(R_{t+1} - h_{t+1} - mf\right) - C\left(q_t\right) > 0 \\ q_t\left(R_{t+1} - mf\right) - C\left(q_t\right) & \text{otherwise} \end{cases}.$$

Managers and investors have to select the optimal size of the fund and the optimal allocation ex-ante. Their decisions are thus based on expected remunerations and expected payoffs. As the AUMs are observable and the cost functions are common knowledge, market participants need to form expectations of R_t. We denote by $\phi_t=E(R_{t+1}|R_1, \ldots, R_t)$ the expected return gross of all fees and costs. Market participants update this expectation as Bayesians:

$$(3) \qquad \phi_t = \frac{\frac{1}{\eta^2} + \frac{t-1}{\sigma^2}}{\frac{1}{\eta^2} + \frac{t}{\sigma^2}} \phi_{t-1} + \frac{\frac{1}{\sigma^2}}{\frac{1}{\eta^2} + \frac{t}{\sigma^2}} R_t \,,$$

where η is the standard deviation of the prior. Market participants do not observe the gross return R_t, but they infer it from the return net of all costs and fees $r_t=TP_t/q_{t-1}$.

The timing convention of the model is the following. Funds start period t with an AUM of q_{t-1} and expected gross return ϕ_{t-1}. Managers implement their strategies and, at the end of the period, the net return r_t is observable. Market participants then infer R_t and calculate ϕ_t. According to this expectation investors reallocate their resources, and managers decide whether to accept the flows. The size of the fund in the following period q_t depends thus on the value of ϕ_t. If the expected net return of a fund is negative, investors leave the fund and managers shut down the fund. If the expected net return is positive the final decision on the size of the fund belongs to the managers. For that reason, in the next section we focus on the optimal behavior of managers.

3.2.3. Maximizing remuneration without passive indexing opportunities

To emphasize the role of the performance fee in the absence of costless passive benchmarks, we first focus on the case in which the performance fee is nil (pf=0). This corresponds to the traditional fee structure of mutual funds, where managers are solely remunerated by a management fee. In this context, the remuneration of managers is maximized when the size of the fund satisfies the following condition (see Appendix for all the proofs):

$$(4) \qquad \phi_t - mf = \frac{C\left(q_t^{MF}\right)}{q_t^{MF}},$$

where q_t^{MF} is the optimal size for managers remunerated only with a management fee. At the optimal size, the expected return net of management fee is equal to the average cost. Therefore, investors have an expected net payoff of zero. As illustrated by Panel A of Figure 3.1, the remuneration is linearly related to the size of the fund. As a consequence, the managers let the fund grow and the diseconomies of scale erode the performance, until reaching the participation constraint of investors, i.e. a null marginal expected payoff. This result holds regardless of the level of *mf*. The bargaining power of investors affects the size of the funds and managers' remuneration, but not the return to investors. Thus, in a setup with only the management fee, the absence of a costless passive benchmark is not sufficient to align the interests of investors and managers.

[Insert Figure 3.1 about here]

When managers expect to receive a performance fee, their behavior is different. In fact, the remuneration reaches its maximum when:

$$(5) \qquad C'\left(q_t^{PF}\right) = \phi_t - h_{t+1} - mf + \frac{mf}{pf},$$

where q_t^{PF} is the optimal AUM for a fund whose fee structure includes a performance fee. This different behavior is caused by the performance-linked remuneration that managers expect to receive. Thanks to the performance fee, the managers' remuneration becomes concave in the level of AUM. As shown by Panel B of Figure 3.1 the remuneration reaches its maximum at q_t^{PF} and, at that size, the expected net performance is positive. Therefore, the interests of investors and managers are aligned: the managers maximize their remuneration while the performance for investors is positive. Moreover, as the performance is positive, the supply of new money by investors is also positive. This implies that, to maximize their remuneration, managers have to control the size of the fund. As there are no performance-diluting flows, the returns persist. This is consistent with what is observed in the industry, i.e. performance persisting over long horizons and restrictions of funds' size. Thus, when managers expect to receive a performance fee and there is no costless passive benchmark opportunity, the payment of a performance fee is an efficient mean for aligning the interests of investors and managers.

The optimal size of the fund is negatively related to the performance fee and positively related to the management fee. The higher is *mf*, the lower is the relative importance of the performance fee with respect to the total remuneration of the manager. The manager has thus fewer incentives to protect the performance of the fund by restricting its size. Equation (5) additionally allows gauging the impact of the high watermark and the hurdle rate provisions. Both provisions result in a higher *h*, and thus in a smaller optimal fund size. The rationale for this behavior is straightforward: by limiting the size of the fund managers decrease the total cost $C(q_t)$, which in turn increases the expected net return and consequently the remuneration. This rationale is the same as the one that pushes managers to take more risk when there is a high watermark; see e.g. Goetzmann et al. (2003). In fact, by increasing the risk, the managers increase the expected return and consequently their expected remuneration. Our model cannot predict risk taking because we consider that the gross returns of the strategy are identically and independently distributed through time.[6]

The fund managers considered in our theoretical framework so far expect to receive a performance-linked remuneration, i.e. they expect to be above the high watermark. Theoretical works indicate that the option-like remuneration have perverse incentives when the funds are below the high watermark; see e.g. Hodder and Jackwerth (2007) and Panageas and Westerfield (2009). Managers who do not expect to receive a performance fee face a problem identical to the one of the managers who are remunerated only with a management fee. In this case, even if a performance fee is agreed in the remuneration contract, there is no alignment of interests and managers maximize their remuneration by increasing the size of the fund. This is consistent with Agarwal et al. (2009) who find that the performance is explained by the pay-

[6] Instead of reducing the size of the fund, managers may indeed prefer to increase risk because with this alternative they do not forgo any management fee payment.

performance *sensitivity*, not by the *level* of the performance fee. The investors, who recognize the misalignment of interests, stop to allocate to managers expected to be below the high watermark. Thus, to maximize their remuneration, managers have two alternatives. The first one is to increase the risk of the fund to increase the likelihood of reaching the high watermark. The second one is to close the existing funds to start a new one. In this way, managers reset the high watermark and are thus closer to collecting the incentive fee, but they forgo the management fees on the closed fund.[7]

The conclusion that the performance fee aligns the interests of investors and managers is thus in line with the common view that option-like remunerations encourage risk taking behavior. In fact, interests are efficiently aligned only when the fund is expected to be above the high watermark. The performance fee loses its incentive alignment effect when managers do not expect to receive a performance fee payment. In that case managers have perverse incentives such as taking more risk or closing the fund.

3.3. Numerical analysis

In this section we conduct a simulation analysis. Our objective is twofold: a) we evaluate the predictions of the model more in depth, and b) we examine the ability of the model to quantitatively capture empirical facts about hedge funds. In a first stage we develop the predictions of the model. We then describe the methodology used for the simulation and, finally, we discuss the results.

3.3.1. Size, performance, and flows without passive indexing opportunities

In the previous section we proved that, in the absence of a costless passive benchmark, the presence of a performance fee affects managers' behavior. We now examine that in depth by deriving the predictions of the model in terms of fund size, return to investors, fund flows, and performance persistence. To highlight the role of the performance fee, we derive our predictions with respect to managers remunerated only with a management fee.

[7] As argued by Lan, Wang and Yang (2013) a similar outcome can be obtained by resetting the high watermark without closing the fund.

Because of diseconomies of scale, the performance-size relation is concave. The performance fee, which transfers a fraction of the return generated to managers, makes the remuneration concave in the amount of assets managed. Therefore, there is a finite quantity q_t^{PF} that maximizes the remuneration. Moreover, the curvature of the size-remuneration relation depends on the level of *pf*. The higher it is, the more curved is the relation, and the smaller is the optimal size of the fund. This leads to our first hypothesis:

Hypothesis 1. *The size of the fund is always smaller if the manager charges a performance fee and it decreases with the level of the performance fee.*

This result has a direct impact on the return to investors. As the remuneration is maximized without reaching the participation constraint of investors and funds are subject to diseconomies of scale, the performance fee results in a higher expected return to investors. Thus, we posit our second hypothesis as follow:

Hypothesis 2. *The expected net return to investors is always higher if the manager charges a performance fee.*

If the realized return is different from its expected value, the updating of ϕ_t leads to a new optimal size. The unexpected gross return, i.e. the difference between the realized and the expected gross return, determines the direction of the flow (inflow or outflow). From hypothesis 1 we know that, for a given expected gross return, the size of the fund is smaller if managers charge a performance fee. Similarly, for a given unexpected gross return, the change in AUM is lower when the remuneration contract contains a performance fee. Therefore, our third hypothesis is:

Hypothesis 3. *The relative change in AUM is, in absolute terms, always lower if the manager charges a performance fee.*

The incentive to limit the size of the fund arises from the income maximizing behavior of managers. Nevertheless, this behavior safeguards the performance. As the change in AUM is lower, there are fewer flows that would drive away the performance. Consequently, the return of the fund is more persistent when there is a performance fee.[8] Therefore, our last hypothesis is:

Hypothesis 4. *The performance is more persistent if the manager charges a performance fee.*

3.3.2. Simulation

Following Glode and Green (2011), we simulate a cross section of 20,000 funds. We consider two periods (three dates). At the initial date, all the funds have identical expected gross return and AUM. For each fund, we draw the gross return for the first period, which is $R_1=\alpha+\varepsilon_1$. The true value of α is unknown, but market participants have a prior that is normally distributed with mean ϕ_0 and variance η^2. ε_1 is normally distributed with mean zero and variance σ^2. Investors observe r_1, the net return realized in the first period, they infer R_1 and calculate the updated expected profitability for the following period ϕ_1 according to Equation (3). Investors decide whether to reinvest for the following period. They are ready to invest as long as the expected return is positive, i.e. when the performance fee aligns their interest with the ones of the managers. Managers accept inflows until reaching the size that maximizes their remuneration. Managers also decide whether to shut down the fund. Common wisdom suggests that management fees are used to cover the fixed costs. We assume that managers close the fund when the expected remuneration is equal or smaller to the fixed costs, i.e. when they do not expect to receive a performance fee because they are below the high watermark. We then draw the second-period gross return for the funds that continue operations and we compute the realized net return.

With this simulation procedure we obtain a simulated cross section composed by all the first-period funds and by the surviving second-period funds. Using this simulated sample, we compute the average AUM, net return, flows (the change in AUM not attributable to return), the persistence coefficient of Jagannathan et al. (2010), and the attrition rate. We compare these artificial moments to the empirical

[8] Following Jagannathan et al. (2010) we identify persistence by analyzing the relation between the returns of two subsequent periods. Performance is persistent if this relation is significant and positive.

estimates of past studies.[9] To calibrate the model, we begin by fixing *h*=0 and by setting the parameters that can be inferred directly from the descriptive statistics provided in Agarwal et al. (2009). We then chose the parameters α, σ, and η through trial and error to approximate the empirical estimates of Agarwal et al. (2009) and Jagannathan et al. (2010).[10] Table 3.1 displays the parameter values used for the numerical analysis. The values are in line with the ones of Glode and Green (2011), who run a simulation similar to ours.

[Insert Table 3.1 about here]

The empirical estimates and the simulated moments are presented in Table 3.2. Our model fits the empirical moments with a fair precision. All the simulated point estimates are within one standard deviation from their empirical counterpart. The simulated average size is 178.4 $M, less than 1% higher than the estimate reported in Jagannathan et al. (2010) for the period 1996 to 2002. The net return in our artificial cross-section is just 50 bps higher than the average return provided by Agarwal et al. (2009). The persistence coefficient in our cross-section is 0.41 and is also close to the subsample coefficient of 0.38 reported by Jagannathan et al. (2010). The attrition rate of the simulated sample is 14.1%, in line with the yearly values reported by Jagannathan et al. (2010) (between 8.1% and 16.2%) and the overall average of 12.6%. *Flows* is the only variable for which we obtain a simulated average that, even if statistically undistinguishable, differs from its empirical counterpart. In fact, in our cross-section, flows are about the half of the flows measured by Agarwal et al. (2009). Other studies suggest however that flows are lower. For instance, Fung et al. (2008) find flows between 10% and 30%, depending on the managers' ability. In our model, flows can be increased by lowering the diseconomies of scale, at the cost of a higher net return. Table 3.2 displays also the artificial moments obtained by setting *pf*=0. The differences with respect of the results discussed above are exclusively due to the removal of the performance fee. In fact, to keep

[9] The goal of the numerical analysis is to approximate empirical moments of past studies, not to approximate the full empirical distribution. This implies that the simulated single funds do not necessarily match with existing hedge funds, but the moments of the artificial cross-section match with the moments of the cross-section of existing hedge funds. We thank an anonymous referee for pointing this out.

[10] The sample of Agarwal et al. (2009) covers the years from 1994 to 2002. Jagannathan et al. (2010) provide estimates for several sub-periods. We chose to approximate the estimates of the period from 1996 to 2002, the one that overlap the most with the study of Agarwal et al. (2009).

managerial ability constant, we employ the gross returns drawn for the previous simulation. By removing the performance fee, both the returns of the funds and the persistence drop dramatically. As expected, the size of the fund and the flows are higher when there is no performance fee.

[Insert Table 3.2 about here]

This numerical exercise also allows us to analyze the consequences of the performance fee on AUM, return, flows, and persistence more in depth. In that perspective, we simulate several cross sections of funds, each with a different level of performance fee. The other parameters take the values reported in Table 3.1 and are common to all the cross sections. Each cross section is composed by 20,000 artificial funds whose differences are exclusively driven by the realized returns. The gross returns of the funds are drawn only once and used for all the levels of performance fee. Differences across the cross sections are thus attributable only to the different incentives given by the performance fee. Notice that the universe of artificial funds cannot be compared to the universe of real hedge funds. In fact, the former universe is composed by funds that differ only in terms of performance fee level and realized return, while, in reality, hedge funds differ also with respect to other characteristics such as management fee, managerial ability, and diseconomies-of-scale costs.

Figure 3.2 plots the average size, return, flow and persistence coefficient obtained for each level of performance fee. Panel A illustrates that the optimal AUM of the fund decrease monotonically with the level of performance fee. The marginal effect that performance fees have on size decreases quickly. Low levels of performance fee already result in significantly smaller funds. The net return is concave with respect to the level of the performance fee; see Panel B. On the one side, the performance fee is beneficial because it leads to a smaller fund and, because of diseconomies of scale, to a higher return before fees. On the other side, the higher the performance fee, the higher is the share of payoff that is transferred to the managers and the lower the return after fees. Therefore, for given levels of ϕ_t, h_{t+1}, and mf, investors can determine the optimal pf that maximizes the net return. For the parameter values we used, the net return is maximized when the performance fee is around 10%, i.e. less than the average performance fee of 16.3% reported by Agarwal et al. (2009). This difference can be attributable to the bargaining power of managers. Panel C confirms that the evolution of flows is similar to the one of size. Indeed, to prevent funds from growing, managers who negotiated high *pf* have to limit the flows. The lower *pf*, the smaller the incentive to restrict the size of the manager and thus the higher the flows. Panel D illustrates that the coefficient measuring the performance persistence is weakly related to the level of the performance fee when *pf* is above 10%. There are however two points to notice. First, the inclusion of performance fee leads to a strong increase of persistence. In fact, the performance of funds that do not charge a management fee does not persist at all. Second, even if the level of *pf* affects the degree of persistence only marginally, it affects the level at which performance persists. Indeed, the performance of funds with low *pf* persists at a lower level than the one of funds having a higher performance fee. When we compare the plots of Figure 3.2 to the figures obtained with *pf*=0 (rightmost column of Table 3.2) we see that the impact of performance fees, regardless of their level, is significant and in the predicted direction. The size of the fund and the flows are always higher when there is no performance fee. On the contrary, returns and persistence are higher when the remuneration contract includes a performance fee.

[Insert Figure 3.2 about here]

3.4. Empirical analysis

In this section we test the predictions of the model using a sample of hedge funds. The ideal test would consist in verifying whether hedge fund returns and characteristics converge toward the optimal levels predicted by the model. This test however is not feasible since the expected gross return ϕ_t is not observable. Nevertheless, we can analyze the consequences of revisions of the observable parameters *mf* and *pf*. Within our framework, these fee revisions can happen after changes in the relative bargaining power of investors and managers or as a consequence of strong updates of ϕ_t. The levels of *mf* and *pf* are the outcomes of negotiations between managers and investors. A sufficient change of the relative bargaining power between the two parties leads to a renegotiation of the remuneration contracts. Also, the initial fees are fixed when the expected gross return is equal to ϕ_0. As time passes and the expectation are updated, ϕ_t can deviate significantly from ϕ_0 and the two parties can renegotiate the fees.[11] To test our model, we focus on the impact that fee revisions have on net returns. There are several reasons to focus on returns instead of other variables such as size or flows. First, performance is the variable of most interest for both investors and academics. Second, funds report their returns regularly, but several funds disclose their AUM less frequently; see Patton, Ramadorai and Streatfield (2015). Third, flows are calculated from the reported returns and AUM using specific assumptions on the timing of the arrival of new investments. As a consequence, in addition to the biases introduced by these assumptions, flows inherit all the biases of returns and AUM; see Ramadorai (2013).

To obtain our testable hypotheses, we derive the equation of the expected return with respect to the level of management and performance fee. This gives the following marginal effects of fee revisions:

$$\frac{\partial E\left(r_{t+1}^{PF}\right)}{\partial mf} = \frac{pf^2 - 1}{2pf} \tag{6}$$

$$\frac{\partial E\left(r_{t+1}^{PF}\right)}{\partial pf} = \frac{1}{2}\left(\frac{mf}{pf^2} + mf + h_{t+1} - \phi_t\right). \tag{7}$$

Since the performance fee lies in the]0,1[interval, $\partial E\left(r_{t+1}^{PF}\right) / \partial mf$ has a negative sign. Our first testable hypothesis is thus that there is a negative relation between revisions of management fee and variations of returns. The sign of $\partial E\left(r_{t+1}^{PF}\right) / \partial pf$ depends on the magnitude of ϕ_t with respect to $mf / pf^2 + h_{t+1} + mf$. When the manager starts to receive an incentive fee, $\partial E\left(r_{t+1}^{PF}\right) / \partial pf$ is positive and it remains positive for all realistic fee levels.[12] Thus, our second hypothesis is that there is a positive relation between revisions of performance fee and variation of returns. Moreover, because of the effect on h_{t+1}, we expect the effect to be stronger for funds with a hurdle rate and weaker for the funds subject to economies of scale. In the rest of this section we test whether these two hypotheses are empirically verified.

[11] Notice that this does not mean that fund revising the fees are good or bad performers. It simply implies that the realized gross return R_t departs strongly from its expected value ϕ_{t-1}.

[12] For instance, for a fund with the traditional 2/20 fee structure $\partial E\left(r_{t+1}^{PF}\right) / \partial pf$ turns negative when the expected gross return net of h_{t+1} exceeds 50%, which seems not realistic for a large cross section of funds.

3.4.1. Data

The data are from the Hedge Fund Research (HFR). This database contains a static snapshot of the characteristics of each fund, including the remuneration terms along with tables reporting the entire time-series of returns. We obtain a time-series of fund characteristics by combining 83 different HFR updates released between January 2005 and November 2011. We follow a procedure similar to the one used by Patton et al. (2015) but, instead of focusing on the different versions of the returns time-series, we collect the snapshots of funds' characteristics. We retain the funds reporting in USD, net of fees, that report their size regularly and their remuneration and redemption terms at least once. We end up with a sample of 5,680 funds, out of which 2,823 are alive in 2011, while 2,857 stopped reporting during our sample period.

Even if we do not rely on any "graveyard" database, our dataset is not subject to survivorship bias. Since we construct our dataset by merging several monthly updates of HFR, all the funds that appear in at least one of these updates are retained in our sample. Our results can, however, be prone to backfilling bias. Nevertheless, funds tend to revise their fees when they reach a certain degree of seniority. Since we focus on the performance around the fee revision, the probability that we base our calculations on backfilled track records is low.

To identify fee revisions, we analyze the time-series of fund characteristics. For each revision, we verify whether it is due to reporting errors. We consider two types of errors. The first consists in a revision that is changed back to the original value in the following release of the database. The second type occurs when the fund revises its terms several times in a row. In this case, we retain only the latest revision. We identify 435 fee revisions. To isolate the effect of revisions of management and performance fees, we drop the observations in which two terms of the remuneration contract are changed simultaneously. Moreover, we require that funds revising their fees report at least the 24 returns around the revision. This results in a sample of 393 revisions implemented by 390 funds. Increases of management fee are the most frequent revision (59% of the events), followed by decreases of management fee (25%). Revisions of performance fee are less frequent: 9% of the events are upward revisions of performance fee, and 7% decreases.

Among the funds revising their fees, 255 are alive in 2011. These 255 funds implemented 262 fee revisions (72.2% of the total number of revisions). These numbers are interesting for two reasons. First, they suggest that there is a relation between the revision of fees and likelihood of reporting to databases. Second, they show that fee revisions are not a rare event among living funds because fee changes concern more than 9% of the funds alive at the end of our sample period.

3.4.2. Methodology

To test our hypotheses, we use a difference-in-differences analysis. For any revision date t, the treatment group is composed of the funds that experienced a fee revision at date t, while the control group consists of all the funds that are alive at that date which never experienced any fee revision and which follow the same investment style as the treated fund. Since Gibson and Gyger (2007) find evidence of strategy misreporting and opportunism, we identify investment styles using a clustering algorithm.[13] For each type of fee revision,[14] we estimate the following difference-in-differences regression:

$$(8) \qquad \begin{aligned} r_{t,j} = {} & a_0 + a_1 DTreat_j + a_2 DAfter_t + a_3 DTreat_j \times DAfter_t \\ & + a_4 Control_{t,j} + a_5 Strat_{i,t} + a_6 Quarter_t + \varepsilon_{t,j} \end{aligned}$$

where $r_{t,j}$ is the net return of fund j at time t. *DTreat* equals one if the fund is in the treatment group (fee revision) and zero otherwise. *DAfter* is a dummy variable that is equal to one if t is after the fee increase and zero otherwise. Following the literature, we introduce *Control*, a set of variables controlling for capacity constraints, performance persistence, incentives, and liquidity. The variables are defined in Table 3.A.2 in Appendix. We also account for time-invariant strategy heterogeneity by including strategy fixed effects *Strat* as well as time-specific effects by including quarter fixed effects *Quarter*. For the revisions of performance fees, in which we also want to measure the marginal effect of hurdle rates and economies of

[13] At any revision date, the funds reporting their returns over the preceding twelve months are clustered into five categories using a PAM algorithm with a dissimilarity measure based on rank correlation of returns. The optimal number of categories has been selected by maximizing the silhouette width; see Kaufman and Rousseeuw (2008). When dealing with hedge funds returns, the PAM—Partitioning Around Medoids—algorithm has several advantages over the more common k-mean algorithm; see Gibson and Gyger (2007).

[14] By "type of fee revision" we mean the combination of fees and direction of revision. We thus have four types of revisions: increases of management fee, decreases of management fee, increases of performance fee, and decreases of performance fee.

scale, we include additional interaction terms. These variables are obtained by multiplying *DTreat*, *DAfter*, and *DTreat* × *DAfter* with *HR* and *Scale*. *HR* equals one if the fund's remuneration contract includes a hurdle rate provision and zero otherwise. *Scale* equals one if the fund faces economies of scale and zero otherwise. To identify the managers facing capacity constraints, we regress the growth rate of returns on the growth rate of the AUM of the funds during the period preceding the fee revision. A fund is subject to economies of scale if the relation between the two growth rates is positive.

The difference-in-differences approach controls for the fluctuations of returns that are observed at the strategy and industry level. We need to account for that because these variations, which are due to changes in the economic environment, are independent from fee revisions. The difference-in-difference estimators properly measure the effect of fee revision only if the dependent variable complies with the "parallel trend" assumption. This assumption states that, in the absence of treatment, the average change in the dependent variable would have been the same for the treatment and the control groups. Even if this assumption cannot be formally tested, we check whether the net return of treated and matched funds follow the same trend prior to the revisions of fees. To verify this, we compute the mean and median of the average growth rate of net return over the year that precede the fee revision for both treated and control funds. For all the types of fee revision, the *t*-tests and the Wilcoxon signed-rank tests suggest that the growth rates are indistinguishable across treated and control funds in the pre-event period (p-values above 20%). This indicates that the parallel trend assumption holds in our setting.

The potential selection bias in the sample of funds revising fees is another issue that needs to be considered. Table 3.3 shows the characteristics of the treatment group relative to the control group. The funds revising their fees differ from their peers along several dimensions, even if the results are heterogeneous across types of fee revision. Funds revising their remuneration term have an initial fee level that is significantly different from their peers. This result is consistent with Agarwal and Ray (2012). What is novel is that funds that revise the management fee do not simply align it with the ones of the competitors. The new fee level is in fact significantly different from the strategy average. Funds that increase their management fee are the ones that show more differences with respect to their peers. These funds generated higher performance in the twelve months preceding the revision, are older, larger, and initially charge a significantly higher performance fee. For the other type of fee revisions, the differences are less clear cut. For example, the funds that decrease their performance fee are different from the control group only with respect to the level of the performance fee.

[Insert Table 3.3 about here]

Table 3.3 suggests thus that the selection bias is a treat to the reliability of our empirical design. The coefficients obtained from Equation (8) can be biased if the residual of the regression are correlated to the unobserved determinants of fee revisions. For that reason, we apply a Heckman (1979) two-stage procedure. We first estimate a Probit regression to capture the determinants of fee revisions. The inverse Mills ratio of this first-stage Probit is then used as explanatory variable in the difference-in-differences regression. A condition to generate credible estimates with the Heckman (1979) procedure is the "exclusion restriction". This condition states that there must be at least one variable that appears with a significant coefficient in the selection equation, but does not appear in the equation of interest. To identify variables complying with the exclusion restriction, we follow Agarwal and Ray (2012). They find that the difference between the fee level of a given fund and the average fee at the strategy level is the main determinant of fee revisions. This can be read also in Table 3.3, which displays significant differences of the initial fees across treated and control funds. The difference between the fee of a given fund and the average at the strategy level is unlikely to affect the performance. In fact, performance is not significantly affected by the fee level itself, but by the level of managerial incentives; see Agarwal et al. (2009). We thus use the difference between the fee level of a given fund and the average fee for the strategy as explanatory variable in the first-stage regression. We also include other variables that explain the propensity of revising fees; see Agarwal and Ray (2012). These variables are the average return during the year preceding the fee revision, the size of the fund, and the total redemption period. The treatment and control groups are the same as in the difference-in-difference analysis. The variables are measured at each fee revision, and the first-stage regression is estimated separately for each type of fee revision. Table 3.4 displays the results of the Probit regression. The coefficients of the exclusion restrictions are statistically significant and have the expected sign. Funds with fees below the strategy average level tend to increase their fees, and vice-versa. The likelihood of increasing the fees is significantly higher for funds that generated high returns in the past. Moreover, large funds are more likely to revise their management fee.

[Insert Table 3.4 about here]

3.4.3. The effect of fee revisions on net returns

To estimate Equation (8) we consider the 36 months surrounding the fee revisions.[15] We are interested in the change of performance after the fee revisions, which is captured by the coefficient a_3. This coefficient is expected to be positive for decreases of management fee and increases of performance fee, and negative for increases of management fee and decreases of performance fee. Table 3.5 presents the results, both including and excluding the control variables in the regression.

[Insert Table 3.5 about here]

The coefficients obtained for increases of management fees, increases of performance fee, and decrease of performance fee are significant at all the conventional significance levels. In all the cases, the signs of the coefficients are as expected. Increases of the management fee result in a decrease of returns. The coefficient of the difference-in-differences estimator is -0.39, which is economically significant. On a monthly basis, in the period immediately following the increase of management fee, the return of the fee revising funds drop by 39 basis points with respect to a peer that does not revise her fee. The effect associated to revisions of performance fee is even stronger. Increases of performance fee lead to a better performance. For these funds, the average change in performance fee is 1.21% larger than the one of funds not revising their fee. Decreases of performance fee are associated with a lower performance. Indeed, the funds decreasing their performance fee experience a drop in performance that is 64 basis points larger than the one of their peers. All the results discussed are robust to the inclusion of variables that have been shown to be related to hedge fund returns. Only the significance is slightly reduced. The results obtained for performance fee are economically large and deserve some attention. Intuitively, fees are a drag on the

[15] Results are robust to different lengths of the period surrounding the fee revisions (12 and 24 months).

performance of the funds. An increase in fee should thus be associated with decrease in performance, and vice-versa for increases of fees. However, we observe the contrary. These results can be rationalized in our theoretical framework. The increases of the performance fee result in a better alignment of the interests of managers and investors and better performance. On the contrary, decreases of performance fee lead to a worst alignment of interests and thus worse returns.

In the regressions for the revisions of performance fee we also control for the effect of the hurdle rate and of economies of scale. The coefficients associated to the variable that controls the effect of the hurdle rate is never significant, indicating that the marginal effect for funds that apply the hurdle rate provision is not strong. The variable related to economies of scale show that, consistently with our model, the positive relationship between revision of fees and performance is concentrated among the funds that do not face economies of scale.

In a nutshell, for three types of fee revision out of four, we obtain coefficients that are significant and consistent with the predictions drawn from our model. As expected, we find negative coefficients for increases of management fee and decreases of performance fee. On their side, increases of the performance fee are associated to increases of performance. These coefficients are both statistically and economically significant.

3.5. Conclusion

In this paper, we propose an explanation to the persistent outperformance of hedge funds. The commitment to deliver an absolute return coupled with a performance fee gives managers an incentive to limit the size of their funds. In this way, the funds do not grow excessively and the performance is not diluted by additional flows. As a consequence, consistently with the interests of the existing investors, the performance remains strong and persists over time. With respect to the models already present in the literature, we take into account the fact that managers' remuneration is not linearly related to fund size, and that there are no passive indexing opportunities. Our study provides a theoretical framework to appraise the recent developments made in the literature on remuneration contracts in the hedge fund industry and the impact of these contracts on performance. In particular, it provides an insight on the relation between fees, performance, and flows. The predictions of our model reproduce empirical facts observed in the literature, i.e. outperformance, persistence, and inflow refusal.

A numerical analysis shows that our model quantitatively captures empirical facts on hedge funds. In particular, it reproduces the performance level, the funds' size, and the attrition rate empirically estimated by existing studies. Moreover, an empirical analysis of the behavior of returns around fee revisions provides additional evidence consistent with our model. Using a difference-in-differences analysis we show that the performance fee is not a simple drag on performance. In fact, for funds facing diseconomies of scale, increases of the performance fee are associated with an improvement of the net return for investors, and vice-versa for decreases of performance fee. This result indicates that the performance fee aligns the interests of managers and investors efficiently.

References

Ackermann, C., R. McEnally, and D. Ravenscraft, 1999, The performance of hedge funds: Risk, return, and incentives, *Journal of Finance* 54, 833-874.

Agarwal, V., N. D. Daniel, and N. Y. Naik, 2009, Role of managerial incentives and discretion in hedge fund performance, *Journal of Finance* 64, 2221-2256.

Agarwal, V., and N. Y. Naik, 2000, Multi-period performance persistence analysis of hedge funds, *Journal of Financial and Quantitative Analysis* 35, 327-342.

Agarwal, V., and N. Y. Naik, 2004, Risks and portfolio decisions involving hedge funds, *Review of Financial Studies* 17, 63-98.

Agarwal, V., and S. Ray, 2012, Determinants and implications of fee changes in the hedge fund industry, http://ssrn.com/paper=1784545.

Aggarwal, R. K., and P. Jorion, 2010, The performance of emerging hedge funds and managers, *Journal of Financial Economics* 96, 238-256.

Amihud, Y., and R. Goyenko, 2013, Mutual fund's R^2 as predictor of performance, *Review of Financial Studies* 26, 667-694.

Ammann, M., O. Huber, and M. Schmid, 2013, Hedge fund characteristics and performance persistence, *European Financial Management* 19, 209-250.

Bali, T. G., S. Gokcan, and B. Liang, 2007, Value at risk and the cross-section of hedge fund returns, *Journal of Banking and Finance* 31, 1135-1166.

Baquero, G., J. ter Horst, and M. Verbeek, 2005, Survival, look-ahead bias and the performance of hedge funds, *Journal of Financial and Quantitative Analysis* 40, 493-517.

Baquero, G., and M. Verbeek, 2009, A portrait of hedge fund investors: Flows, performance and smart money, http://ssrn.com/paper=773384.

Berk, J. B., and R. C. Green, 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269-1295.

Bollen, N. P. B., 2013, Zero-R^2 hedge funds and market neutrality, *Journal of Financial and Quantitative Analysis* 48, 519-547.

Boyson, N. M., 2008, Do hedge funds exhibit performance persistence: A new approach, *Financial Analysts Journal* 64, 27-44.

Fung, W. H., and D. A. Hsieh, 1997, Empirical characteristics of dynamic trading strategies: The case of hedge funds, *Review of Financial Studies* 10, 275-302.

Fung, W. H., D. A. Hsieh, N. Y. Naik, and T. Ramadorai, 2008, Hedge funds: Performance, risk and capital formation, *Journal of Finance* 63, 1777-1803.

Getmansky, M., 2012, The life cycle of hedge funds: Fund flows, size, competition, and performance, *Quarterly Journal of Finance* 2, 1-53.

Getmansky, M., A. W. Lo, and S. X. Mei, 2004, Sifting through the wreckage: Lessons from recent hedge-fund liquidations, *Journal of Investment Management* 2, 6–38.

Gibson, R., and S. Gyger, 2007, The style consistency of hedge funds, *European Financial Management* 13, 287-308.

Glode, V., and R. C. Green, 2011, Information spillovers and performance persistence for hedge funds, *Journal of Financial Economics* 101, 1-17.

Goetzmann, W. N., J. Ingersoll, and S. A. Ross, 2003, High-water marks and hedge fund management contracts, *Journal of Finance* 58, 1685-1717.

Grinblatt, M., and S. Titman, 1989, Adverse risk incentives and the design of performance-based contracts, *Management Science* 35, 807-822.

Heckman, J. J., 1979, Sample selection bias as a specification error, *Econometrica* 47, 153-161.

Hodder, J. E., and J. C. Jackwerth, 2007, Incentive contracts and hedge fund management, *Journal of Financial and Quantitative Analysis* 42, 811-826.

Jagannathan, R., A. Malakhov, and D. Novikov, 2010, Do hot hands exist among hedge fund managers? An empirical evaluation, *Journal of Finance* 65, 217-255.

Kaufman, L., and P. J. Rousseeuw, 2008, *Finding groups in data: An introduction to cluster analysis* (John Wiley & Sons, Inc., Hoboken, NJ, USA).

Kosowski, R., N. Y. Naik, and M. Teo, 2007, Do hedge funds deliver alpha? A bayesian and bootstrap analysis, *Journal of Financial Economics* 84, 229-264.

Lan, Y., N. Wang, and J. Yang, 2013, The economics of hedge funds, *Journal of Financial Economics* 110, 300-323.

Lhabitant, F.-S., 2006, *Handbook of hedge funds* (John Wiley & Sons, Inc., Chichester, West Sussex, UK).

Lo, A. W., 2008, *Hedge funds: An analytic perspective* (Princeton University Press, Princeton, NJ).

Makarov, I., and G. Plantin, 2015, Rewarding trading skills without inducing gambling, *Journal of Finance* 70, 925-962.

Malkiel, B. G., and A. Saha, 2005, Hedge funds: Risk and return, *Financial Analysts Journal* 61, 80-88.

Panageas, S., and M. M. Westerfield, 2009, High-water marks: High risk appetites? Convex compensation, long horizons, and portfolio choice, *Journal of Finance* 64, 1-36.

Pastor, L., and R. F. Stambaugh, 2012, On the size of the active management industry, *Journal of Political Economy* 120, 740-781.

Patton, A. J., T. Ramadorai, and M. Streatfield, 2015, Change you can believe in? Hedge fund data revisions, *Journal of Finance* 70, 963-999.

Ramadorai, T., 2013, Capacity constraints, investor information, and hedge fund returns, *Journal of Financial Economics* 107, 401-416.

Appendix

Table 3.A.1: Important notation

R_t	Return of the strategy gross of all costs and fees in period t
α	Manager's ability
σ	Standard deviation of R_t
q_t	Assets under management at date t. The optimal level is denoted by a superscript (*MF* in the absence of the performance fee, *PF* otherwise)
$C(q_t)=a(q_t)^2$	Variable investment costs faced by managing a fund of size q_t
a	Diseconomy-of-scale cost
mf	Management fee level
pf	Performance fee level
h_t	Return that the manager has to beat in order to receive a performance fee payment, it accounts for both the high watermark and the hurdle rate.
$Remun_t$	Total remuneration of the manager received in period t
TP_t	Total payoff to investors for period t
$\phi_t=E(R_{t+1}\|R_1, \ldots, R_t)$	Expectation, formed at date t, on the return gross of all costs and fees for period $t+1$
η	Standard deviation of the prior over managerial ability α
$r_t = \frac{TP_t}{q_{t-1}}$	Net return for period t

Table 3.A.2: Definitions of the variables

This table contains the definition of the variables used in the empirical part of the paper.

Variable	Definition
Variables used only in the Probit selection equations	
mf distance	Difference between the management fee of a fund and the average management fee of funds belonging to the same strategy
pf distance	Difference between the performance fee of a fund and the average performance fee of funds belonging to the same strategy
Return past 12 M	Average return during the preceding twelve months
Control variables for difference-in-differences analysis	
Age	Number of months since inception of the fund
Size	Size of the fund measured as the natural logarithm of the AUM
Tot redemption	Sum of redemption frequency and notice period, expressed in days
mf	Management fee level
pf	Performance fee level
r_{t-1}	Lagged net return
$Flow_{t-1}$	Lagged investor flow, calculated as the change in AUM net of return, scaled by the AUM
Scale	Indicator variable that equals one if the fund is subject to economies of scale, and zero otherwise
HR	Indicator variable that equals one if the fund has a hurdle rate provision, and zero otherwise

Model solution and proofs

General set up

The remuneration of the manager is:

(A.1) $$Remun_{t+1}=\begin{cases} q_t mf+\left[q_t\left(1+R_{t+1}\right)-C\left(q_t\right)-H_{t+1}-q_t mf\right]pf & \text{if } q_t\left(1+R_{t+1}\right)-C\left(q_t\right)-H_{t+1}-q_t mf>0 \\ q_t mf & \text{otherwise} \end{cases},$$

where H_t is the relevant high watermark level. The performance fee is thus paid only if the month's end AUM, before any redemption or subscription but after the deduction of the management fee, is above the high watermark. The high watermark level H_t takes in account also the eventual hurdle rate hr_t. The high watermark level can be recursively defined as follow:

(A.2) $$\begin{aligned} H_1 &= q_0\left(1+hr_1\right) \\ H_2 &= \max\left(q_1, H_1\right)\left(1+hr_2\right) \\ H_3 &= \max\left(q_2, H_2\right)\left(1+hr_3\right) \\ &\dots \\ H_{t+1} &= \max\left(q_t, H_t\right)\left(1+hr_{t+1}\right), \text{ with } H_0 = q_0 . \end{aligned}$$

This definition can accommodate also funds that do not apply a high watermark provision. The high watermark is more conveniently expressed as the minimum return that the fund has to generate in order to start collecting incentive fees:

(A.3) $$h_{t+1}=\frac{H_{t+1}}{q_t}-1 .$$

This minimum return is equal to the hurdle rate when the fund is above the high watermark and its magnitude increases when the fund is below the high watermark.

The manager remuneration can thus be rewritten as:

(A.4) $$Remun_{t+1}=\begin{cases} q_t mf+\left[q_t\left(R_{t+1}-h_{t+1}-mf\right)-C\left(q_t\right)\right]pf & \textit{if } q_t\left(R_{t+1}-h_{t+1}-mf\right)-C\left(q_t\right)>0 \\ q_t mf & \textit{otherwise} \end{cases}.$$

Similarly, the total payoff of the fund is:

(A.5) $$TP_{t+1}=\begin{cases} \left(q_t\left(R_{t+1}-h_{t+1}-mf\right)-C\left(q_t\right)\right)\left(1-pf\right)+q_t h_{t+1} & \textit{if } q_t\left(R_{t+1}-h_{t+1}-mf\right)-C\left(q_t\right)>0 \\ q_t\left(R_{t+1}-mf\right)-C\left(q_t\right) & \textit{otherwise} \end{cases}.$$

Solution of the model without performance fee

If pf=0, the problem of the managers is:

(A.6)
$$\begin{aligned} \max_{q_t} \quad & Remun_{t+1} = q_t mf \\ s.t. \quad & E\left(TP_{t+1}\right) = q_t\left(\phi_t - mf\right) - C\left(q_t\right) \geq 0 \\ & F \leq q_t mf \\ & q_t \geq 0 \end{aligned},$$

where F is the fix cost of operating the fund at each period.

As the remuneration is strictly increasing with q_t and the payoff is strictly decreasing with q_t, the remuneration is maximized when the expected payoff to the investors is zero. Let q_t^{MF} be the optimal size of a fund that cannot passively invest in a benchmark and that is remunerated only by a management fee. The remuneration is maximized when:

(A.7)
$$q_t^{MF}\phi_t - C\left(q_t^{MF}\right) - q_t^{MF} mf = 0$$

$$\phi_t - mf = \frac{C\left(q_t^{MF}\right)}{q_t^{MF}}.$$

Solution of the model with performance fee

If pf>0 we have to distinguish two cases. The first one is when the investor expects to pay a performance fee, i.e. when $\phi_t > mf + h_{t+1} + C\left(q_t\right)/q_t$. The second case to consider is when investors do not expect to pay a performance fee.

When $\phi_t > mf + h_{t+1} + C\left(q_t\right)/q_t$, the expectations of Equations (A.4) and (A.5) can be written as follow:

(A.8)
$$E\left(Remun_{t+1}\right) = q_t mf + \left[q_t\left(\phi_t - h_{t+1} - mf\right) - C\left(q_t\right)\right]pf,$$

(A.9)
$$E\left(TP_{t+1}\right) = \left[q_t\left(\phi_t - h_{t+1} - mf\right) - C\left(q_t\right)\right]\left(1 - pf\right) + q_t h_{t+1}.$$

To maximize the remuneration, managers solve the following problem:

(A.10) $$\max_{q_t} \; E\left(Remun_{t+1}\right) = q_t mf + \left[q_t\left(\phi_t - h_{t+1} - mf\right) - C\left(q_t\right)\right] pf$$
$$\begin{aligned} s.t. \quad & E\left(TP_{t+1}\right) = \left[q_t\left(\phi_t - h_{t+1} - mf\right) - C\left(q_t\right)\right]\left(1 - pf\right) + q_t h_{t+1} > 0 \\ & F \leq q_t mf + \left[q_t\left(\phi_t - h_{t+1} - mf\right) - C\left(q_t\right)\right] pf \\ & q_t \geq 0 \end{aligned}$$
.

The first order condition is:

(A.11) $$mf + \left(\phi_t - h_{t+1} - C'\left(q_t\right) - mf\right) pf = 0,$$

and the solution of the problem is:

(A.12) $$C'\left(q_t^{PF}\right) = \phi_t - h_{t+1} - mf + \frac{mf}{pf},$$

where q_t^{PF} is the optimal size of a fund that cannot passively invest in a benchmark and that is remunerated by a management and a performance fee.

In the second case $\phi_t \leq mf + h_{t+1} + C\left(q_t\right)/q_t$ and investors do not expect to pay a performance fee. The problem of the manager is thus the following:

(A.13) $$\max_{q_t} \; E\left(Remun_{t+1}\right) = q_t mf$$
$$\begin{aligned} s.t. \quad & E\left(TP_{t+1}\right) = q_t\left(\phi_t - mf\right) - C\left(q_t\right) > 0 \\ & F \leq q_t mf \\ & q_t \geq 0 \end{aligned}$$
.

This problem is the same as the one faced by the manager that is remunerated only by a management fee; see (A.6). Therefore, the manager has an incentive to increase the size of the fund until reaching the point that satisfies $C\left(q_t^{MF}\right)/q_t^{MF} = \phi_t - mf$. However, investors recognize that interests are misaligned and do not allocate to the fund if $\phi_t \leq mf + h_{t+1} + C\left(q_t\right)/q_t$.

Proof of hypothesis 1

If $C(q_t)=a(q_t)^2$, the optimal size when *pf=0* is:

(A.14) $$\frac{C\left(q_t^{MF}\right)}{q_t^{MF}}=\frac{a\left(q_t^{MF}\right)^2}{q_t^{MF}}=\phi_t-mf\Rightarrow q_t^{MF}=\frac{\phi_t-mf}{a}.$$

With performance fee, the optimal size is:

(A.15) $$C'\left(q_t^{PF}\right)=2aq_t^{PF}=\phi_t-h_{t+1}-mf+\frac{mf}{pf}\Rightarrow q_t^{PF}=\frac{\phi_t-h_{t+1}-mf+\frac{mf}{pf}}{2a}.$$

The size of the fund that employs the performance fee is larger only when:

(A.16) $$q_t^{PF}>q_t^{MF}\Rightarrow\frac{\phi_t-h_{t+1}-mf+\frac{mf}{pf}}{2a}>\frac{\phi_t-mf}{a}\Rightarrow\frac{mf}{pf}>\phi_t-h_{t+1}-mf\Rightarrow\phi_t<mf-h_{t+1}+\frac{mf}{pf}.$$

However, for this range of ϕ_t we have $E\left(TP_{t+1}^{PF}\right)<0$. This solution is not feasible because it violates the first constraint of the managers' problem. Thus, q_t^{PF} is always smaller then q_t^{MF}.

Proof of hypothesis 2

Taking the expectation of the net return $E\left(r_{t+1}\right)=E\left(TP_{t+1}\right)/q_t$ and the optimal quantities of Equations (A.14) and (A.15) we have:

(A.17) $$E\left(r_{t+1}^{MF}\right)=\phi_t-\frac{C(q_t^{MF})}{q_t^{MF}}-mf=\phi_t-\left(\phi_t-mf\right)-mf=0,$$

(A.18) $$E\left(r_{t+1}^{PF}\right)=h_{t+1}+\left(\phi_t-h_{t+1}-\frac{C\left(q_t^{PF}\right)}{q_t^{PF}}-mf\right)(1-pf)=h_{t+1}+\frac{1-pf}{2}\left(\phi_t-h_{t+1}-mf-\frac{mf}{pf}\right).$$

To satisfy the investors participation constraint $\phi_t>mf-h+mf/pf$. Thus, $E\left(r_{t+1}^{PF}\right)$ is positive and larger than $E\left(r_{t+1}^{MF}\right)$.

The expected return is negatively related to the level of management fee. In fact, the derivative of (A.18) with respect to *mf* is:

(A.19) $$\frac{\partial E\left(r_{t+1}^{PF}\right)}{\partial mf}=\frac{pf^{2}-1}{2pf}.$$

Since the performance fee lies in the]0,1[interval, $\partial E\left(r_{t+1}^{PF}\right)/\partial mf$ has a negative sign. The marginal effect of the performance fee on the expected return is:

(A.20) $$\frac{\partial E\left(r_{t+1}^{PF}\right)}{\partial pf}=\frac{1}{2}\left(\frac{mf}{pf^{2}}+mf+h_{t+1}-\phi_{t}\right).$$

$\partial E\left(r_{t+1}^{PF}\right)/\partial pf$ has a positive sign as long as $\phi_{t}<mf+h+mf/pf^{2}$. Therefore, the marginal effect of the performance fee is positive when the manager start to receive a performance fee payment and it remains positive for all the conventional levels of *mf* and *pf*.

Proof of hypothesis 3

Let the realized gross return be different from the expected value, for instance $R_{t+1}=\lambda\phi_{t}$. The expected gross return for the following period is:

(A.21) $$\phi_{t+1}=\frac{\frac{1}{\eta^{2}}+\frac{t}{\sigma^{2}}}{\frac{1}{\eta^{2}}+\frac{t+1}{\sigma^{2}}}\phi_{t}+\frac{\frac{1}{\sigma^{2}}}{\frac{1}{\eta^{2}}+\frac{t+1}{\sigma^{2}}}R_{t+1}=\theta_{t+1}\phi_{t}+\left(1-\theta_{t+1}\right)R_{t+1}=\left[\left(1-\theta_{t+1}\right)\lambda+\theta_{t+1}\right]\phi_{t}.$$

The optimal quantity for the following period is thus:

(A.22) $$q_{t+1}^{MF}=\frac{\phi_{t+1}-mf}{a}=\frac{\left[\left(1-\theta_{t+1}\right)\lambda+\theta_{t+1}\right]\phi_{t}-mf}{a},$$

(A.23) $$q_{t+1}^{PF}=\frac{\phi_{t+1}-mf+\frac{mf}{pf}}{2a}=\frac{\left[\left(1-\theta\right)\lambda+\theta\right]\phi_{t}-h_{t+1}-mf+\frac{mf}{pf}}{2a}.$$

The change in AUM is:

(A.24) $$\Delta q_{t+1}^{MF} = \frac{q_{t+1}^{MF} - q_t^{MF}}{q_t^{MF}} = \frac{(1-\theta_{t+1})(\lambda-1)\phi_t}{\phi_t - mf},$$

(A.25) $$\Delta q_{t+1}^{PF} = \frac{q_{t+1}^{PF} - q_t^{PF}}{q_t^{PF}} = \frac{(1-\theta_{t+1})(\lambda-1)\phi_t}{\phi_t - h - mf + \frac{mf}{pf}}.$$

Let consider the right-hand side of Equations (A.24) and (A.25). The numerator is the same, but the denominator is larger when managers charge a performance fee. The change in AUM is thus smaller when managers charge a performance fee.

Proof of hypothesis 4

If the realized gross return is $R_{t+1} = \lambda\phi_t$, the realized net return when the performance fee is charged is:

(A.26) $$r_{t+1}^{PF} = \begin{cases} \left(\phi_t(2\lambda-1) - h_{t+1} - mf - \frac{mf}{pf}\right)\frac{1-pf}{2} + h_{t+1} & if\, \phi_t(2\lambda-1) - h_{t+1} - mf - \frac{mf}{pf} > 0 \\ \left(\phi_t(2\lambda-1) + h_{t+1} - mf - \frac{mf}{pf}\right)\frac{1}{2} & otherwise \end{cases}.$$

The expected return for the following period if managers charge only a management fee is:

(A.27) $$E\left(r_{t+2}^{MF}\right) = 0.$$

Therefore, without performance fee, there is no relation between r_{t+1}^{MF} and $E\left(r_{t+2}^{MF}\right)$. There is thus no performance persistence.

If managers charge a performance fee, the return surprise realized is:

(A.28) $$rs_{t+1}^{PF} = r_{t+1}^{PF} - E\left(r_{t+1}^{PF}\right) = \phi_t(\lambda-1)(1-pf).$$

The expected return for the following period is:

(A.29) $$\begin{aligned} E\left(r_{t+2}^{PF}\right) &= h_{t+2} + \left(\phi_{t+1} - h_{t+2} - mf - \frac{mf}{pf}\right)\frac{1-pf}{2} \\ &= h_{t+2} + \left(\left[(1-\theta_{t+1})\lambda + \theta_{t+1}\right]\phi_t + h_{t+2} - mf - \frac{mf}{pf}\right)\frac{1-pf}{2}. \end{aligned}$$

Readjusting (A.29) and plugging in (A.28) we obtain:

(A.30) $$E\left(r_{t+2}^{PF}\right)=\frac{1+\theta_{t+1}}{2}E\left(r_{t+1}^{PF}\right)+\frac{1-\theta_{t+1}}{2}r_{t+1}^{PF}-\left(1-pf\right)h_{t+2}.$$

As $0 \le \theta_{t+1} \le 1$, the expected return in one period is positively related to the realized return of the previous period.

Table 3.1: Parameter values

This table lists the parameter values used for the simulation. All the parameters but a, σ, and η are inferred from the figures reported in Agarwal, Daniel and Naik (2009). The other parameters are determined through trial and error to approximate the empirical moments from Jagannathan, Malakhov and Novikov (2010) and Agarwal et al. (2009).

	Symbol	Value
Diseconomy-of-scale cost	a	0.0014
Initial expected gross return	ϕ_0	0.377
Standard deviation of idiosyncratic noise	σ	0.08
Standard deviation of perceived managerial ability	η	0.20
Management fee	mf	0.012
Performance fee	pf	0.163
Initial minimum return to collect performance fees	h_0	0

Table 3.2: Empirical estimates and simulated moments

This table compares the moments reported in Jagannathan et al. (2010) and Agarwal et al. (2009) with the moments obtained from our simulation. To compute the simulated moments, we generate a cross-section of 20,000 funds over two periods accordingly to our model. The parameters employed for the simulation are displayed in Table 3.1. Size is in USD million. The persistence is measured as in Jagannathan et al. (2010).

		Simulation	
	Data	pf=0.163	pf=0
Average size (in \$M)	176.8	178.4	271.8
Average net return	12.2%	12.7%	-0.1%
Average flow	60.6%	31.1%	125.1%
Persistence coefficient	0.38	0.41	0.01
Attrition rate	12.6%	14.1%	40.9%

Table 3.3: Descriptive statistics

This table shows summary statistics about our sample. Figures are displayed separately for each type of fee revision. Treatment is the sample composed of funds revising their fees. Control designates the respective control group. Variables are defined in Table 3.A.2. The equality of means is tested using two-tailed Student's t-tests. Standard deviations are reported in brackets. One, two, and three asterisks denote statistical significance at the 10%, 5%, and 1% significance level, respectively.

	Management fee increases			Management fee decreases			Performance fee increases			Performance fee decreases		
	Treatment (i)	Control (ii)	Diff (i)-(ii)	Treatment (iii)	Control (iv)	Diff (iii)-(iv)	Treatment (v)	Control (vi)	Diff (v)-(vi)	Treatment (vii)	Control (viii)	Diff (vii)-(viii)
Return past 12 M (%)	1.37	0.92	0.45***	0.69	0.83	-0.14	1.12	0.79	0.32	0.80	0.80	-0.00
	[1.68]	[1.41]	[0.11]	[1.45]	[1.61]	[0.15]	[1.63]	[1.50]	[0.33]	[1.63]	[1.72]	[0.27]
Age (Months)	86.68	70.17	16.51***	89.44	73.37	16.08**	95.00	72.81	22.19	92.50	72.62	19.88*
	[52.44]	[50.40]	[3.44]	[63.42]	[52.05]	[6.38]	[65.68]	[51.90]	[13.14]	[61.99]	[51.68]	[10.34]
Size (log AUM $M)	4.54	4.17	0.37***	4.63	4.14	0.49**	3.71	4.11	-0.40	4.32	4.14	0.19
	[1.68]	[1.75]	[0.11]	[1.88]	[1.77]	[0.19]	[1.60]	[1.79]	[0.32]	[2.39]	[1.76]	[0.40]
Tot redemption (days)	132.10	125.80	6.32	109.00	123.00	-14.00*	98.32	122.00	-23.64**	147.60	124.90	22.70
	[94.46]	[96.36]	[6.19]	[81.00]	[95.06]	[8.15]	[46.59]	[94.09]	[9.34]	[130.30]	[95.17]	[21.73]
Management fee (%)	1.22	1.59	-0.37***	3.06	1.62	1.44***	1.34	1.62	-0.28**	1.47	1.61	-0.14
	[0.97]	[1.84]	[0.06]	[4.48]	[1.86]	[0.45]	[0.59]	[1.94]	[0.12]	[0.61]	[1.87]	[0.10]
Performance fee (%)	18.81	14.69	4.12***	16.34	14.86	1.48*	9.80	14.96	-5.16***	20.64	14.77	5.87***
	[4.37]	[7.53]	[0.29]	[7.49]	[7.54]	[0.75]	[8.17]	[7.45]	[1.63]	[6.35]	[7.49]	[1.06]
Management fee after revision (%)	2.25	1.59	0.66***	1.26	1.61	-0.36***	-	-	-	-	-	-
	[3.18]	[1.84]	[0.21]	[0.62]	[1.86]	[0.06]	-	-	-	-	-	-
Performance fee after revision (%)	-	-	-	-	-	-	17.50	14.96	2.54	11.71	14.77	-3.06**
	-	-	-	-	-	-	[7.64]	[7.45]	[1.53]	[8.15]	[7.48]	[1.36]

Table 3.4: Determinants of fee revisions

This table presents the results from the Probit selection equations. The dependent variable is a dummy that equals one if the fund revises its remuneration terms and zero otherwise. The variables are defined in Table 3.A.2. All estimations include quarter time effects. Standard deviations are reported in brackets. One, two, and three asterisks denote statistical significance at the 10%, 5%, and 1% significance level, respectively.

	Management fee		Performance fee	
	Increase	Decrease	Increase	Decrease
mf distance	-0.350***	0.035***	-0.140	-0.027
	[0.038]	[0.007]	[0.135]	[0.043]
pf distance	0.003	0.003	-0.044***	0.072***
	[0.004]	[0.006]	[0.009]	[0.009]
Return past 12 M	0.052***	-0.023	0.084**	0.005
	[0.011]	[0.023]	[0.038]	[0.035]
Size	0.058***	0.052***	-0.026	0.028
	[0.012]	[0.018]	[0.036]	[0.030]
Tot redemption	0.000*	-0.000	-0.001	0.001
	[0.000]	[0.000]	[0.001]	[0.001]
Intercept	-3.365***	-3.271***	-3.016***	-3.499***
	[0.127]	[0.185]	[0.337]	[0.380]
N	230,920	85,448	24,359	37,427
Chi-square	110.91	54.47	328.56	171.70
p-value chi-square	0.000	0.000	0.000	0.000
Pseudo. R-square	0.068	0.041	0.140	0.104

Table 3.5: Impact of fee revisions on net return

This table reports the results of difference-in-differences regressions describing the relation between net returns and fee revisions. The dependent variable is the net return of the fund. The control variables are regressors that have been shown to forecast hedge fund returns and are defined in Table 3.A.2. All estimations include quarter time effects. Standard errors clustered at the fund level are reported in brackets. One, two, and three asterisks denote statistical significance at the 10%, 5%, and 1% significance level, respectively.

	Management fee				Performance fee			
	Increase		Decrease		Increase		Decrease	
DTreat	0.442***	0.271***	-0.061	-0.041	-0.629***	-0.696***	0.410	0.346*
	[0.085]	[0.069]	[0.126]	[0.104]	[0.241]	[0.240]	[0.255]	[0.198]
Dafter	-0.301***	-0.230***	-0.212***	-0.158***	-0.116***	-0.078***	-0.236***	-0.232**
	[0.010]	[0.009]	[0.012]	[0.010]	[0.021]	[0.017]	[0.021]	[0.018]
DTreat x *DAfter*	-0.389***	-0.636***	0.102	0.076	1.208***	0.694**	-0.641**	-0.422*
	[0.115]	[0.112]	[0.171]	[0.146]	[0.343]	[0.281]	[0.293]	[0.256]
Dtreat x *HR*	-	-	-	-	0.372	0.605	-0.154	0.010
	-	-	-	-	[0.633]	[0.442]	[0.233]	[0.208]
Dafter x *HR*	-	-	-	-	-0.118***	0.014	-0.077**	-0.009
	-	-	-	-	[0.040]	[0.034]	[0.035]	[0.030]
DTreat x *Dafter* x *HR*	-	-	-	-	1.076	0.776	0.874	0.587
	-	-	-	-	[0.691]	[0.584]	[0.460]	[0.383]
DTreat x *Scale*	-	-	-	-	1.186***	0.961**	-0.579**	-0.536**
	-	-	-	-	[0.430]	[0.387]	[0.278]	[0.225]
Dafter x *Scale*	-	-	-	-	-0.063**	-0.068***	-0.049*	-0.046**
	-	-	-	-	[0.028]	[0.024]	[0.027]	[0.022]
DTreat x *DAfter* x *Scale*	-	-	-	-	-1.771***	-1.367***	0.725*	0.719**
	-	-	-	-	[0.586]	[0.489]	[0.409]	[0.355]
Inverse Mills ratio	-	-0.868***	-	0.343	-	-1.092***	-	0.197***
	-	[0.068]	-	[0.083]	-	[0.057]	-	[0.029]
Control variables	NO	YES	NO	YES	NO	YES	NO	YES
N	8,345,778	8,326,828	3,078,616	3,081,475	878,555	876,753	1,351,877	1,349,129
Adjusted R-square	0.141	0.160	0.129	0.152	0.151	0.171	0.157	0.178

Figure 3.1: Optimal size

The graphs display the relation between size, remuneration, and payoff when it is not possible to benchmark passively. The graphs are obtained using a=0.0014, ϕ_t=0.377, and mf=0.012. Furthermore, for Panel B we set pf=0.163 and h_{t+1}=0.

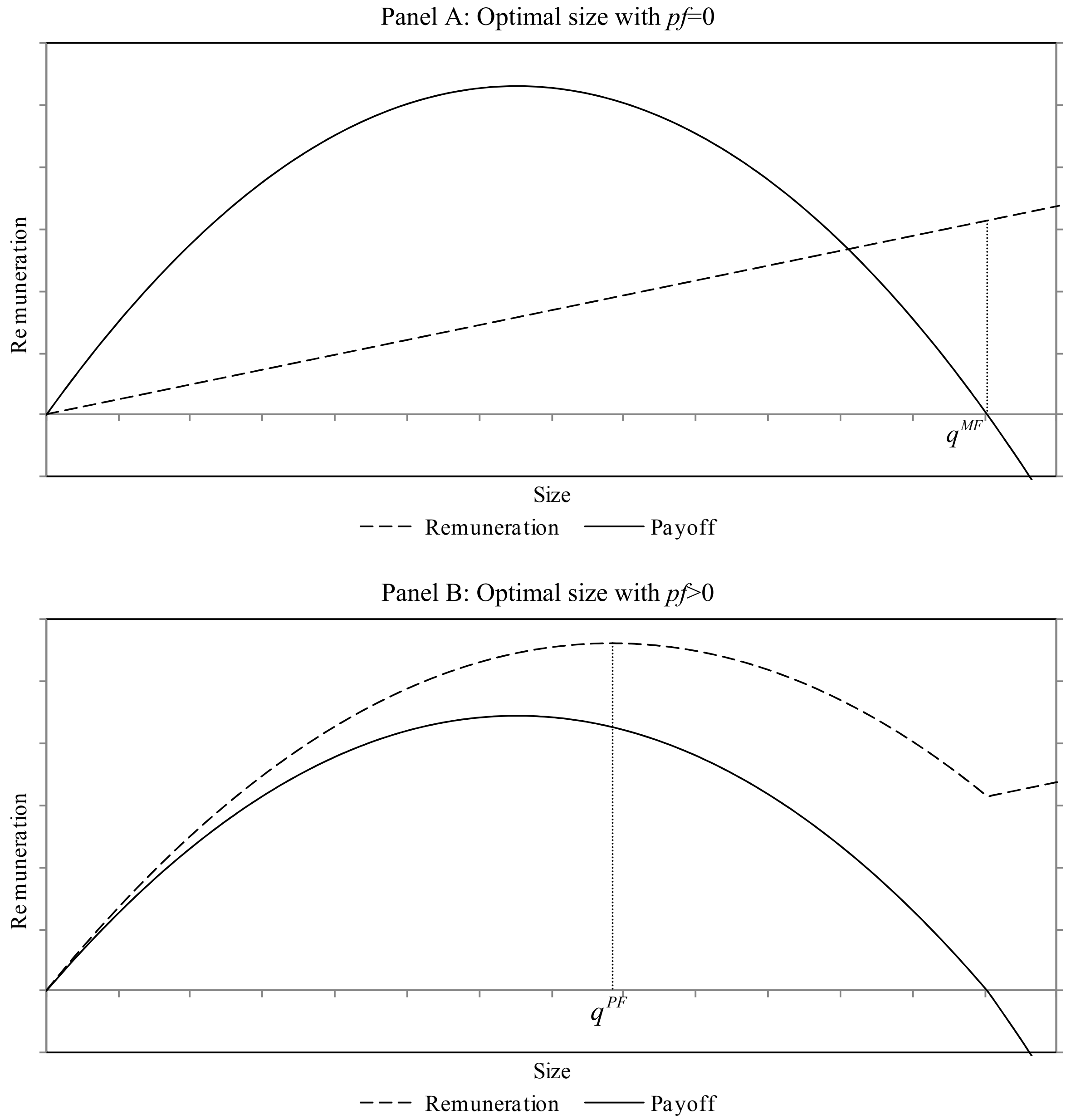


Figure 3.2: Impact of performance fee on fund characteristics

The graphs display the size, returns, flows, and persistence as predicted by the model for various levels of performance fee (*pf*). The graphs are obtained by simulating a cross-section of 20’000 funds over two periods accordingly to our model. Size is measured in \$M, net return is the average return across the two periods, flows are expressed as percentage of AUM, and the persistence coefficient is obtained by regressing the performance of one period on the performance of the previous period; see Jagannathan et al. (2010) The parameters employed for the simulation are a=0.0014, ϕ_t=0.377, σ=0.08, μ=0.2, h_0=0, and mf=0.012.