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Do Analysts' Exclusions Lead to Better Forecasts?

An Analysis of the Effects of Street Earnings Exclusions on Target Price Forecast Accuracy

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Abstract:

Sell-side analysts regularly make earnings forecasts, stock recommendations, and target price forecasts in their research reports. As part of their earnings forecasts, analysts commonly make "exclusions", which is the process of excluding expense and income items that they believe will not reoccur in future periods. This is done in an attempt to derive an earnings number that is devoid of transitory items that will likely not have earnings impacts in future periods. These earnings are regularly used as inputs into valuation models as part of analysts' target price formation. This thesis explores the effects of exclusions on analysts' target price forecast accuracy on firms listed on the S&P 500 between 2004 and 2013. Using a threefold approach to examine accuracy, we find that exclusions are statistically and economically significant factors that inhibit analysts' ability to accurately forecast target prices. Using an absolute error measure and two accuracy measures observing whether the target price is met or exceeded, we find the size of exclusions to be positively associated with target price forecast error and negatively associated with the target price being met. We also find that analysts' subjective (incremental) exclusions reduce overall forecast accuracy, and accuracy is improved by only excluding objective nonrecurring (special) items. Our findings contribute to the emerging body of research examining target price forecast accuracy and to the ongoing debate regarding non-GAAP earnings exclusions.

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1. Introduction

Since Ball & Brown (1968) documented market reactions to earnings reports, it has long been accepted that accounting information is value relevant to investors. A large body of research has since developed to determine what types of accounting information is valuable to the capital markets. Sell-side analysts hold important positions in the market as intermediaries between companies and investors and as knowledgeable interpreters of accounting information (Asquith et al., 2005). Like accounting information, analysts' reports have been shown to be value relevant for investors. However, analysts' reports have been called a "black box" (Brown et al., 2015) because of the ambiguity of the inputs that help generate their forecasts and recommendations. In their research reports, analysts commonly issue earnings forecasts for future periods, stock recommendations, and stock price targets. While all three areas have received significant attention in academia, earnings have, in recent years, garnered particular criticism.

Sell-side analysts make earnings forecasts, in part, to help investors make investment decisions. In doing so, they attempt to determine an earnings figure that will reliably persist into the future. Thus, they meticulously consider a number of financial statement items that they believe will persist in the future and include them in their forecasts. This also means that they ignore, or *exclude*, items that they believe will not have earnings impacts in future periods. In academia, analysts' adjusted earnings have become known as "street" earnings.

A number of prior studies contend that exclusions are systematically used as tools to inflate earnings and steer the market's attention away from income statement-based GAAP earnings (e.g. Bhattacharya et al., 2003). This has given rise to the debate of whether analysts' adjustments help to determine more value-relevant earnings through higher persistence, or simply constitute earnings management. It is within the context of this debate that prior studies have placed the most focus. However, earnings forecasts are not in themselves a final output, but instead an input into creating a final product (Schipper, 1991). Earnings forecasts have been shown to be direct inputs for valuation that help generate analysts' target prices (e.g. Brown et al., 2015). It is therefore of interest to consider whether exclusions, which directly affect earnings, also affect target price forecasts.

Purpose

Even though there is an implicit relationship between exclusions and target prices through their connection with street earnings, exploring a connection between the exclusions and target price literature is something that has largely been overlooked in prior research. The purpose of this thesis is to bridge this research gap and provide a preliminary exploration into how exclusions affect target price forecasts. More specifically, we aim to analyze how exclusions affect the target price forecast accuracy. We contribute to an emerging body of research (e.g. Asthana, Balsam, & Mishra, 2011; Bilinski, Lyssimachou, & Walker, 2013; Bonini et al. 2010) that explores the determinants of target price forecast accuracy (error)[1].

Investigating a relationship between exclusions and target price forecasts constitutes the primary focus of this thesis. However, this study distinguishes itself from prior research in several additional ways. Firstly, we study a recent time period encompassing an entire business cycle that so far has not been studied in target price accuracy literature. This will allow us to make observations of the exclusions and target price forecasts analysts make in different macroeconomic conditions. Secondly, we employ a research method comprised of a number of studies in the prevailing literature to most aptly control for different determinants of target price forecasting accuracy (error).

Thesis Structure

The remainder of this thesis is organized as follows: section two provides an overview of prior research on street earnings and target prices, highlighting both previous foci as well as the knowledge gap that motivates this study. Section three presents the research method, including the data sample, hypothesis development, and research design inspired by previous literature. Section four presents descriptive results and discusses the findings in relation to prior studies. Section five analyzes the results of the study and further tests for robustness of the data. Section six discusses the main conclusions, implications, and contributions of our study to existing literature. Section seven presents the research limitations and finally, section eight discusses opportunities for future research.

[1] Throughout this study, we reference both "target price forecast accuracy" and "target price forecast error". These terms are essentially used interchangeably to reference how "correct" or accurate analysts are, or how "incorrect" they are (i.e. the size of error in their forecast). These are simply different ways of defining forecast accuracy. When addressing both terms, we use the term, "overall forecast accuracy."

2. Literature Review

This section outlines the previous research conducted in the areas of street earnings and target prices. It provides a comprehensive overview of non-GAAP earnings and the actors that make them, with specific attention placed on sell-side analysts. We then proceed with an overview of recent research into target prices, specifically highlighting analysts' target price forecast accuracy.

2.1 A Shifting Focus

2.1.1 Importance of Earnings

Stock prices are largely based on capital market actors' expectations of a firm's future performance. Using information sources such as a firm's financial statements, investors often derive stock prices through use of valuation models like discounted cash flow and market multiples. Both models require assumptions regarding the firm's future performance. Research has shown that inputs into valuation models often include firms' earnings (Collins, Maydew, & Weiss, 1997; Loh & Mian, 2006).

Financial statements report several different lines of earnings to help users gauge metrics like operational and "bottom line" profitability. Bottom line, or "GAAP" earnings, represents a firm's aggregate earnings for a period after considering all sources of income and deducting all expenses necessary under an accounting regime. This has traditionally been the metric used as an input into valuation multiples like price-to-earnings. Despite the regulation and trustworthiness of GAAP earnings, the value investors place on these earnings has dwindled in the past decades with focus moving up the income statement.

2.1.2 A New Type of Earnings

The increasing size and complexity of businesses has made financial reporting similarly complex (Andersson & Hellman, 2007). This has, in turn, made earnings harder to understand due the number of necessary disclosures required by accounting standards. The valuation models investors use to make investment decisions hinge on forecasts of predictable, sustainable earnings that will persist into the future. As a result, capital market actors have begun to exercise scrutiny with accounting earnings, following the logic of Andersson & Hellman (2007) that accounting standards introduce disclosures that sometimes hamper the sustainable nature of core earnings. When forecasting earnings, analysts have thus begun to routinely remove or *exclude* items of transitory nature. The result are earnings that are, in theory, more persistent and better lend to valuation.

Among actors that make these exclusions are sell-side analysts and firm management. A firm's management issues their adjusted earnings, known as "pro forma" earnings, along with typical earnings reports. Tracking services such as the Institutional Brokers' Estimate System (I/B/E/S) collect analysts' forecasts, known as "street earnings", and record both the details of individual analyst reports as well as consensus figures. When earnings are later reported by the firm, I/B/E/S reports "actual" earnings that are then adjusted for the same exclusions made in analysts' forecasts[2]. These, too, are referred to as street earnings. Research commonly refers to managements' and sell-side analysts' earnings as "non-GAAP" earnings[3].

Exhibit 1 ***"Street" vs. GAAP earnings***

"Street" Earnings		**GAAP Earnings**
Consensus Forecast	*I/B/E/S Actual*	*Actual*
Revenue	Revenue	Revenue
– Expenses	– Expenses	– Expenses
+ / – ***Exclusions***	+ / – ***Exclusions***	
*Street Earnings**	*Street Earnings***	*GAAP Earnings****

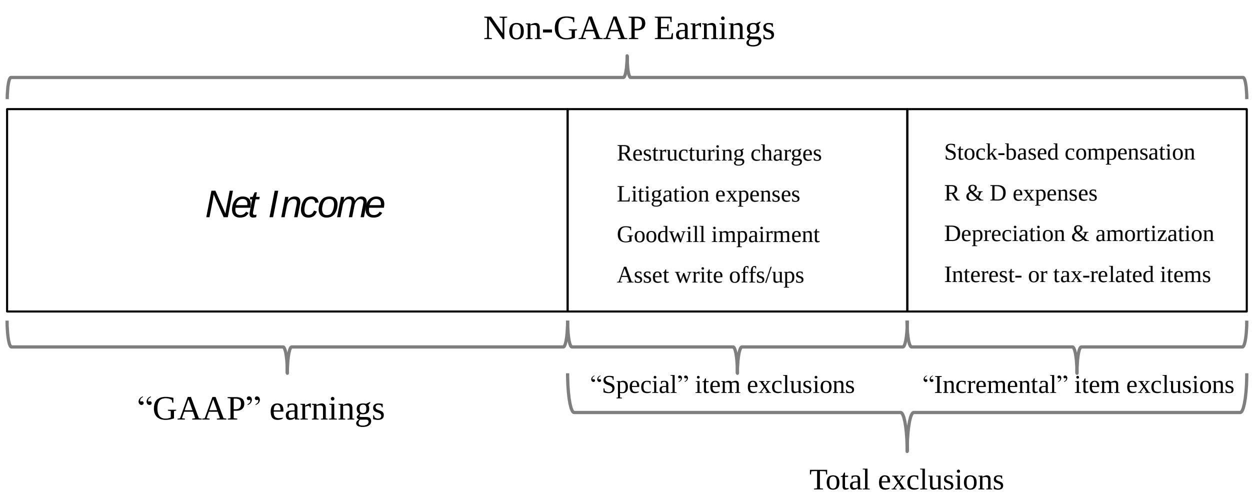
Description: "Street earnings" encompasses both analysts' forecasts and I/B/E/S actual reported earnings. I/B/E/S attempts to match the same exclusions made in analysts' forecasts in accordance with the "majority rule." That is, I/B/E/S makes exclusions based on the majority of what other analysts have excluded in their forecasts. I/B/E/S does not know specifically what items were excluded, but based on the sizes of analysts' exclusions, they are able to reliably deduce what was excluded by the majority of analysts and make similar exclusions to their actual earnings. We refer to these different measures later in the study as *(*EPS_Street*), **(*EPS_Actual*), and ***(*EPS_GAAP*).

Exclusions include both income- and expense-related items, though research indicates that the majority of items that are excluded are expenses or losses (Elliot & Hanna, 1996) and are often comprised of items

[2] That is, I/B/E/S takes GAAP earnings and adjusts it for exclusions made by analysts in their forecasts.
[3] We use "non-GAAP" earnings as an umbrella term to encompass earnings that are adjusted for exclusions. Our study focuses on street earnings, but for this literature review, includes pro forma earnings research and hence uses this term.

such restructuring charges, asset write-downs, merger and acquisition costs, and stock compensation expenses (Bradshaw & Sloan, 2002). Recent studies have attempted to further categorize exclusions according to how transitory they are in nature, classifying them as either “special” or “incremental” exclusions (Christensen et al., 2011). Special-item exclusions are primarily comprised of items that are thought to be objectively (truly) nonrecurring, whereas incremental-item exclusions constitute additional exclusions that are more subjective, and have a higher tendency to reoccur in subsequent periods.

Exhibit 2 ***Examples of Exclusions***



Description: This table presents examples of some, but not all, special and incremental-item exclusions. Non-GAAP Earnings refers to both analysts’ street earnings and managements’ pro forma earnings. Special items are “objectively” defined, or generally accepted by all as nonrecurring. Incremental exclusions are “subjectively” defined, meaning that it is up to the discretion of individual analysts, or management, whether that item will be excluded.

Bradshaw & Sloan (2002) argue that there has been an increasing investor focus on non-GAAP rather than GAAP earnings and that this focus has triggered a continually growing difference between GAAP and non-GAAP earnings (i.e. more exclusions are being made). They also argue that this focus has led to a dramatic increase in both the frequency and size of special items. Near the end of the 1990s, they estimate that non-GAAP earnings exceeded GAAP earnings on average by around 20%. Moreover, they find evidence that stock prices have a higher association with non-GAAP earnings rather than GAAP earnings. Their results are evidence that investors are willing to trust analysts’ exclusions and accept modified versions of earnings.

The shifting investor focus has caused concern and garnered heavy criticism by standard setters, regulators, and academia. This is largely due to the fact that exclusions are not made systematically or categorically, but are instead up to the discretion of individual analysts and management. The central critique is that the shifting focus towards non-GAAP earnings allows a fundamentally subjective earnings figure to influence investors (Bradshaw & Sloan, 2002). Critics contend that it enables opportunistic behavior by allowing analysts and management to adjust earnings upward through exclusions. Additionally, critics argue that excluded items have a tendency to show up again in subsequent periods (Doyle, Lundholm, & Soliman, 2003). Exclusions literature is at a crossroads, however. Given the potentially more persistent nature of non-GAAP earnings and facilitation for valuation, there is strong divergence in opinion as to the value relevance of non-GAAP earnings.

2.1.3 Value Relevance or Earnings Management?

The extant literature is generally separated into those that view non-GAAP earnings as value relevant, and those that argue they simply represent a form of earnings management[4]. Proponents of non-GAAP earnings argue that accounting earnings have become a "noisier measure of true economic value" that has become less value relevant (Amir & Liv, 1996; Collins, Maydew, & Weiss, 1997). Moreover, Heflin, Hsu & Jin (2014) contend that analysts' street earnings are in part a response to investors' desire for more valuation-useful information. Advocates maintain that investors are eager for simplified financial statements that are devoid of accounting complexities (Bhattacharya et al., 2003). Non-GAAP earnings have therefore come to, in some capacity, fill a valuation role and attempt to help investors make more informed investment decisions (Bradshaw & Sloan, 2002; Frankel & Roychowdhury, 2005; Baik et al., 2009).

In support of non-GAAP earnings' value relevance, a number of prior studies have attempted to provide evidence that excluded items are nonrecurring in nature. Bhattacharya et al. (2003) test the permanence of pro forma earnings by collecting 1,149 quarterly reports of American firms between 1998 and 2000 and identifying the types of expenses excluded from pro forma earnings. They find that the exclusions results in earnings that are more persistent. Moreover, observing short-window returns at earnings announcement date, they find stock price changes that move with managements' adjustments and conclude that management's pro forma earnings guidance is more informative to investors. In addition to pro forma

[4] This section of the review contains literature that looks at both street and pro forma earnings, and sometimes considers the two interchangeable. It is therefore difficult to distinguish every study into either street or pro forma earnings, but we make references where distinctions have been made. Otherwise, we use the term "non-GAAP" earnings to encompass both.

earnings, Brown & Sivakumar (2003) argue that street earnings deduced by sell-side analysts are more value-relevant than operating earnings taken from financial statements. They run a variety of predictability, valuation, and information content tests and find that pro forma and street earnings have higher predictive power for earnings in future periods and are more correlated with stock price. Complementing the above findings, Heflin, Hsu & Jin (2014) find in settings of high accounting conservatism, street earnings are more likely to differ from GAAP earnings. They contend that conservative settings introduce additional transitory components that make GAAP earnings even less predictive of future earning potential.

The potential value of non-GAAP earnings to investors is acknowledged in the exclusions literature as limiting the information asymmetry between a firm and investors. Critics, on the other hand, argue that informative reporting via non-GAAP earnings is preceded by opportunistic motives (Young, 2014) and succeeded by inability to consistently identify and exclude items that will not recur. Doyle, Lundholm & Soliman (2003) find that analysts' exclusions consistently show up in future periods. They also argue that firms with relatively large exclusions in their pro forma earnings suffer predictably lower future cash flows and lower future stock returns. They conclude that the capital market does not fully appreciate the cash flow implications of the exclusions and are systematically fooled by use of pro forma earnings. Furthermore, numerous studies argue that pro forma earnings merely represent attempts by management to shift focus away from accounting earnings and to artificially inflate income. Bradshaw & Sloan (2002) argue that managers' pro-forma earnings represent a new type of earnings management whereby managers use pro forma reports as an attempt to hide costs and inflate earnings.

In the United States, the controversial nature of non-GAAP earnings has garnered the attention of standard setters and regulators. In a speech, the former Chief Accountant of The Securities and Exchange Commission (SEC), referred to pro forma earnings as companies' desire to show "earnings before the bad stuff" (Turner, 2000). Worried about potential opaqueness that non-GAAP reporting could bring to financial reporting, the SEC issued "Regulation G" in 2003, requiring firms that presented pro forma earnings to, among other requirements, present a reconciliation table of pro forma to GAAP earnings (SEC, 2003). This necessity would bring to light the specific items and amounts that management excluded. Regulation was not limited to management. Based on similar concerns, the SEC issued new regulations to control for sell-side analysts. NASD 2711 and SEC rule 472 were issued to limit potential conflicts of interest. As Bilinski, Lyssimachou & Walker (2013) describe that the regulation "*prohibits members of the NASD and NYSE from tying analyst compensation to the broker's investment banking transactions and from offering favorable research to a firm as an incentive to elicit future investment* *banking business"* (Bilinksi, Lyssimachou, & Walker, 2013, p. 21). A number of studies in the years following SEC regulation show a marked impact in the frequency of firms issuing pro forma reports. Marques (2006) finds a significant decline in the number of firms reporting pro forma earnings following Regulation G. Similarly, Kolev, Marquadt & McVay (2008) corroborate these findings and argue that exclusions were of higher quality following SEC intervention. These findings appear to confirm critics' suspicions of opportunistic reporting.

2.2 Sell-side Analysts' Street Earnings

In addition to the debate underlying non-GAAP earnings, the exclusions literature is further categorized into strands that explore non-GAAP earnings from distinct management and analyst perspectives. The extant literature largely examines the contextual factors of influences and incentives that motivate these actors' exclusion decisions. Research also criticizes their ability to skillfully identify and exclude non-recurring items. As street earnings constitute the focus of this study, the following section will present findings that pertain primarily to sell-side analysts, but will make references to firm management as well.

2.2.1 Analysts' Influences and Expertise

Analysts' reports are a decidedly vague area of research. Prior literature has attempted to penetrate the "black box" of sell-side analysts' decision processes and incentives that underlie the formation of street earnings and exclusion decisions. Critics argue that analysts have incentives that bias forecasts upwardly. Baik et al. (2009) explore the economic incentives that influence analysts' earnings forecasts. They argue that analysts are economically incentivized to promote "glamour stocks" (i.e. overvalued stocks) and that analysts are more likely to exclude expenses or include non-recurring income in their forecasts that bias and upwardly adjust their earnings. They argue that this is, in part, due to prior findings that "buy" recommendations[5] generate higher trading activity for a firm and analysts' compensation has been linked to trade activity. Moreover, Brown et al. (2015) find in their surveys with sell-side analysts that generating underwriting business is a specific and important determinant of their compensation. Finally, Hong & Kubik (2003) argue that for analysts who cover firms underwritten by their bank, optimistic forecasts play an important role in advancing the analysts' careers. They find evidence that brokerage houses reward optimistic analyst reports that promote stocks.

[5] "Buy" recommendations, according to Baik et al. (2009) are the result of optimistic earnings forecasts that translate into higher target prices which drive the recommendations they make of "buy", "sell", or "hold".

Christensen et al. (2011) argue that managers are able to actively influence analysts' own street earnings exclusion decisions via their pro forma earnings reports. They observe that analysts are more likely to make exclusions if management has made exclusions, and that analysts are less likely to exclude these items if management has not. In a similar vein, observing a Swedish sample, Andersson & Hellman (2007) find that when analysts are given pro forma reports where pro forma earnings are higher than GAAP earnings, analysts tend to make higher earnings forecasts themselves.

Although exclusions literature has been critical of analysts, research argues that analysts earnestly attempt to add a layer of informational value and predictability to firms' future earnings (Barth, Gow, & Taylor, 2012). In addition to a number of studies providing evidence of street earnings value relevance, research argues that analysts possess expertise in differentiating persisting items from non-recurring. Observing analysts' specific treatment of individual items, Gu & Chen (2004) document that analysts' appear to have expertise in identifying and excluding items that are non-recurring. They focus on the specific exclusion decisions analysts make and contrast this with the items they include. They find that included items have a higher predictive power for future earnings than excluded and that, consistent with prior studies, street earnings are of higher quality that GAAP earnings.

Analysts' earnings forecasts are not only important for investors, but are often the most important criteria that analysts are measured and evaluated by (Loh & Mian, 2006). However, earnings forecasts are not the only important aspect of analyst' reports. Schipper (1991) argues that earnings forecasts are *"not a final product but rather an input into generating a final product"*. Similarly, Brown et al. (2015) find that analysts themselves argue that the purpose of issuing accurate earnings is to use them as inputs into valuation models that support stock recommendations. The debate regarding exclusions should therefore not end with earnings, but should extend to analyzing the effects for the final output.

2.3 Target Prices

In addition to earnings, analysts also forecast stock "target prices" which are the price levels analysts believe a stock will reach within the forecast period. Target price estimations have, like street earnings, been shown to be value-relevant for investors. This underscores their importance to the capital markets and, like earnings, warrants a closer understanding of their determinants. Target prices constitute a relatively new body of research, where studies are broadly separated into three categories: market impact, derivation, and accuracy (Bradshaw, Brown, & Huang, 2013). This section outlines the most prominent studies within the topic and sheds light on the findings most relevant for this study.

2.3.1 Market Impact

Target prices were first documented to have stock price impacts by Liu, Smith & Syed (1990), where they found that stock price movements shifted with the direction of the target price. They found that notable reactions were correlated with target price forecasts that were significantly different from the price at forecast date. Brav & Lehavy (2003) document a similarly significant market reaction to the information contained in analyst's target prices. They also find a stronger market reaction to price target revisions than that of an equal percentage change in earnings forecasts. Recognizing the market impact of target prices, trading strategies have even been developed around target price forecasts. Studying target prices between 1985 and 1996, Barber et al. (2001) find that going long in stocks with the highest target price forecasts, relative to price at forecast date, and going short in stocks with the lowest, or most negative target price forecast, yielded an abnormal return of over 4%. These studies highlight the value relevance and importance of target prices to the capital markets.

2.3.2 Derivation

Target prices are fundamentally analyst-specific assessments of future value (Asquith et al., 2005; Bradshaw et al., 2014), but how the prices are derived is part of the "black box". A number of studies have attempted to determine the method used in target price formation by using street earnings as inputs into a variety of valuation models. Bradshaw (2004) considers four different types of valuation models to attempt to "backout" the most likely method used to determine stock price, given the analysts' forecast earnings as inputs, using both present value and multiple methods. His results are inconclusive, though he finds that relative valuation is slightly more consistent with the target prices. Asquith, Mikhail & Au (2005) conduct a similar study, using different models. The results are likewise inconclusive, though they find no difference in consistency of accuracy depending on the type of valuation model. Brown et al. (2015) attempt to resolve this issue by questioning analysts directly. They find in their survey of 365 analysts that price-to-earnings ratios (P/E) or price-to-earnings to growth (PEG) models are the most frequently used methods for valuation.

2.3.3 Accuracy

Like earnings, target price forecasts have been subject to heavy criticism in the extant literature. The most common criticisms of target prices are that they are consistently optimistic and inaccurate. Brav & Lehavy (2003) observe a 12-month ahead target price that was, on average, 28% higher than the current market value. In a similar study using data between 2000 and 2009, Bradshaw, Huang & Tan (2014) observe price targets of about 24% higher than market prices at forecast date. These target premiums are in essence what the analysts believe the firms will return (Brav & Lehavy, 2003). However, actual returns across these two samples from 1997 to 2009 were closer to 8% (Bradshaw et al., 2014). These findings are corroborated by Bradshaw et al. (2012) that find implied target price-based returns exceed actual returns by 15%. They argue that this optimism has led to critics viewing target prices merely as tools for marketing.

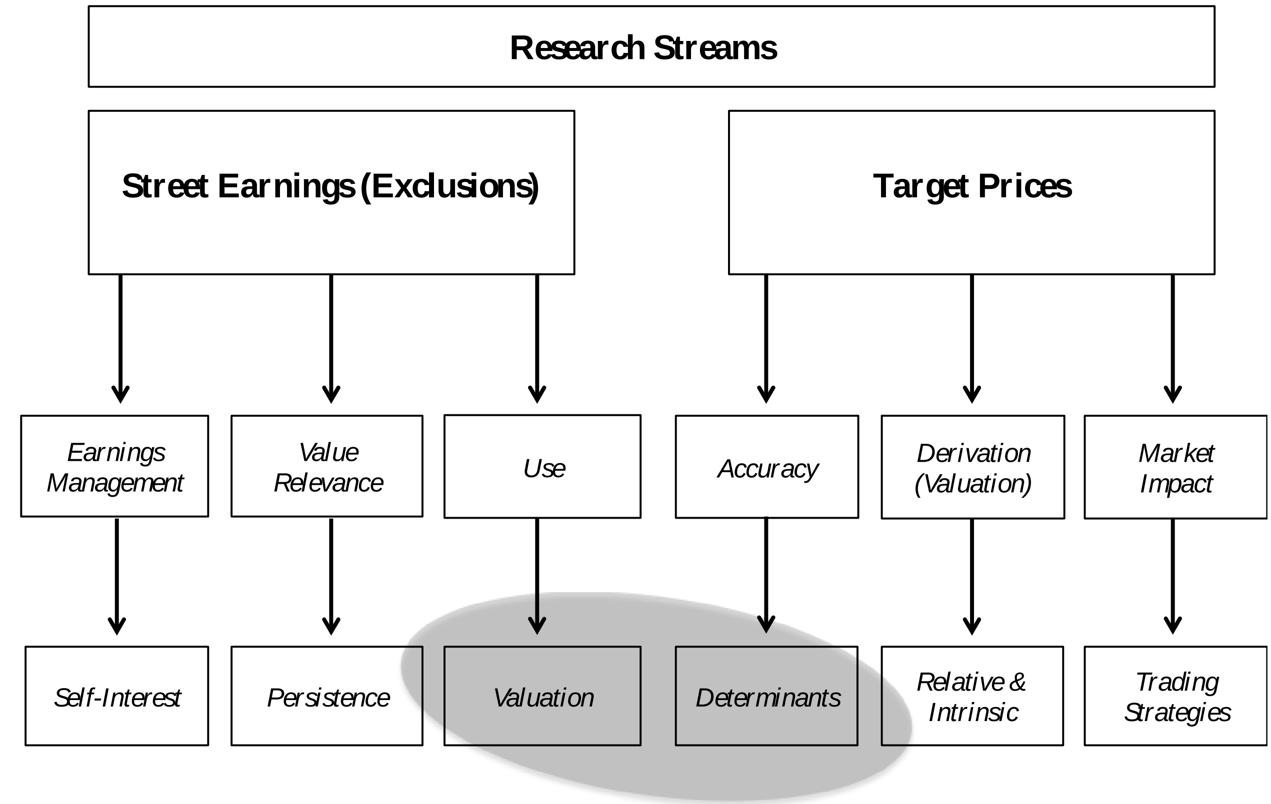
While the effects of analysts' recommendations on stock returns and target price derivations have been researched extensively, target price accuracy has received limited attention by research. Bonini et al. (2010) states that determinants of analysts' ability to accurately set target prices remain essentially unexplored by research. However, a trend has recently emerged in target price literature that attempts to link target price accuracy to its specific determinants (Bradshaw et al., 2014). Loh & Mian (2006) find that earnings have implications for target prices. They analyze the accuracy of both earnings and target prices and find that analysts who exhibit an ability to consistently forecast earnings correctly give consistently better recommendations. They argue that this is potentially because higher quality inputs (i.e. more accurate earnings) lead to more accurate target prices.

External factors have also been attributed to affecting target price forecast accuracy. Asthana, Balsam & Mishra (2011) find that information technology has had a positive impact on accuracy. They find that the growing availability of information and the ease with which it is attained has increased analysts' forecast accuracy. Bilinski, Lyssimachou & Walker (2013) study target price accuracy in an international context with the goal of identifying how different institutional and regulatory environments might affect accuracy. They find significant differences in accuracy and attribute higher forecast error to higher regulatory pressure. They argue that countries with strong enforcement of accounting standards prevents managers from engaging in income-smoothing activities which results in more volatile, less predictable earnings.

2.4 Research Gap

While these studies do not represent all of target price accuracy determinants so far identified, they constitute some of the findings in an emerging body of research that attempt to understand how target price forecasts are affected by certain factors. Given the demonstrable value relevance of target prices to the capital markets, closer attention to this relatively immature stream of literature is warranted. At the same time, the ongoing debate concerning street earnings highlights the importance of understanding the effects of exclusions and how they influence all parts of analysts' reports, rather than just earnings. Prior research has largely focused on the contextual factors underlying exclusions and has so far been limited in its extension to target prices, despite the tacit relationship between them. We bridge the gap between these research streams by investigating the relationship between exclusions and target prices.

Exhibit 3 ***Research Focus***



Description: This diagram shows the research gap we fill. We attempt to bridge the gap between exclusions and target price studies by observing how exclusions affect overall target price forecast accuracy.

3. Research Design

3.1 Hypothesis Development

Given the relationship that exists between earnings and target prices that has been documented by prior research, the assumptions that determine earnings are implicitly transferred to target prices. Therefore, it is plausible that a link between analysts' exclusions and target prices exists, whereby exclusions affect the target price. Consider the following three scenarios: a scenario without exclusions, a second scenario with expense exclusions and a third scenario with income exclusions.

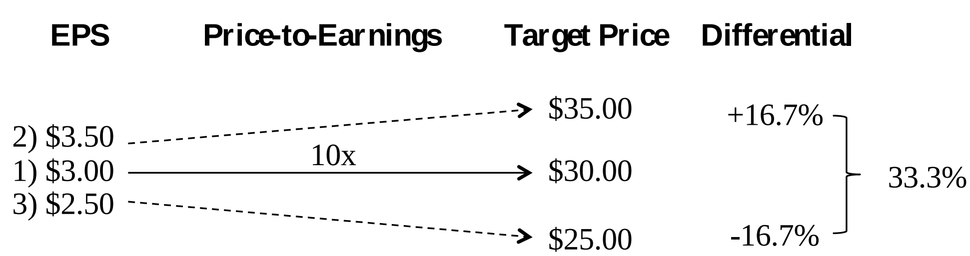
Exhibit 4 ***Differing Scenarios Dependent on Exclusion Decision***

	1) No Exclusions	**2) Expense Exclusion**	**3) Income Exclusion**
Revenue	10,000,000	10,000,000	10,000,000
Expenses	(7,000,000)	(7,000,000)	(7,000,000)
Excluded Item	-	(500,000)	500,000
Earnings	3,000,000	3,500,000	2,500,000
Shares outstanding	1,000,000	1,000,000	1,000,000
Earnings Per Share	$3.00	$3.50	$2.50

Description: This table demonstrates how different exclusions decisions affect earnings per share depending on the exclusion decision. Scenario two demonstrates how excluding 500,000 of expenses increases earnings by 500,000, while scenario three shows how excluding 500,000 of income decreases earnings by 500,000.

Excluding 500,000 of expenses, i.e. increasing total income by 500,000, leads to a small positive change in EPS while excluding 500,000 of income, i.e. decreasing total income by 500,000 leads to a small negative decrease in EPS. There can hence be significant effects for target prices when using relative valuation:

Exhibit 5 ***The Effect of Exclusion Decisions***



Excluding 7%[6] of expenses or 5%[7] of income can lead to drastically different target price forecasts. While the above scenarios are simplified versions of reality and assume a large amount of exclusions per share (as compared with Doyle, Lundholm, & Soliman's (2003) findings of a quarterly average of $0.03 per share), they shed light on the issue that exclusion decisions are fundamental components of target prices that can cause substantial differences in target prices depending on the analyst's exclusion decision. Although exclusions constitute, on average, a relatively small amount in monetary terms, the potential effects are exacerbated in contexts with larger price-to-earnings or similar ratios[8]. Therefore, we formulate the following hypothesis that will constitute the primary focus of this study:

The size of exclusions is negatively associated with analysts' overall target price forecast accuracy.

We posit that exclusions impede analysts' abilities to make accurate target price forecasts. To explore this hypothesis, we must first develop an understanding of what accuracy is for target prices. Unlike earnings-per-share forecasts that are simply measured relative to how close forecasts are to the result, target price accuracy is more ambiguous. When an analyst issues a target price forecast for a 12-month period, it is not explicit whether this represents the analyst's opinion of the specific price at the end of the forecast date, or whether it simply represents a price that the share will reach at some point. With this in mind, we employ a multifaceted approach to measuring accuracy largely inspired by prior research that will allow us to explore differing definitions of target price forecast accuracy. We will elaborate on our approach in section 3.2.1.

The connection between exclusions and target prices is not explicit in prior literature and this thesis constitutes (to our knowledge) the first attempt to link these two research streams. Prior studies will serve as a blueprint for how we will investigate the relationship. The following section details our research method and how we will proceed.

[6] (500,000/7,000,000) = 7.1%
[7] (500,000/10,000,000) = 5.0%
[8] For example, Amazon's twelve months trailing November 2012, price-to-earnings ratio was 2,766 (Elmer-DeWitt, 2012). Given this enormous price-to-earnings, exclusions of just one cent can thus have tremendous impacts for valuation.

3.2 Research Method

3.2.1 Model Development

To investigate our hypothesis, we employ cross-sectional analysis that attempts to identify and control for the factors that research has shown to affect overall target price forecast accuracy with the addition of exclusions as a potential determinant. Prior research has debated the definition of target price forecast accuracy. The definition of accurate target prices is not necessarily confined to measuring how close the forecast is to the actual price at the period end date. Instead, research argues that target prices might reflect analysts' opinions of where the stock price will be at some time during the period, or at period end. Asquith, Mikhail & Au (2005) were among the first to conduct a study of target price forecast accuracy and defined accuracy simply as whether target prices met or exceeded analyst forecasts at the end of the forecast period. Subsequent studies such as Bradshaw et al. (2012) and Bonini et al. (2010) however, criticized this measure, instead contending that target price forecasts are predictions of prices that will be met at some time *within* a period rather than simply at the end of the forecast period. This thesis will consider this twofold approach of accuracy and, in addition, a third measure that aims to capture the difference between the target price forecast and the resulting price consistent with Bradshaw et al. (2012) and Bilinski, Lyssimachou & Walker (2013). See Exhibit 9 for an extensive list of variables used for this study.

We use ordinary least squares (OLS) regression for analyzing forecast error and include yearly dummies to account for annual fluctuations in our dependent variable that is not due to any of our explanatory variables. Because our data includes a time-series component, it could potentially be analyzed as panel data but our study assumes that analysts make exclusions and target price forecasts independent of prior periods. Therefore serial correlation is not considered a major issue and OLS regression has been selected for this paper. Secondly, we employ logistic regressions for our binary dependent variables. We also present a model controlling for fixed effects in the robustness chapter[9].

Our model will consist of three different dependent variables to capture different aspects of accuracy. First, in line with Bradshaw et al. (2012), Bonini et al. (2010), and Bilinksi, Lyssimachou & Walker (2013),the absolute target price forecast error (***aTPE***) will be used to document the absolute difference

[9] Panel data is generally used for data with a time-series component, i.e. data that takes place across years. However, as explained, we believe that analysts make forecasts and exclusions that are uncorrelated and independent of prior periods. We present a fixed-effects model in the robustness chapter to solve the problem of unobserved fixed effects.

between the forecast price and actual price. This captures the percentage error in the forecasts, or, how "incorrect" analysts were at the end of the 12-month forecast, P_{12}, scaled by stock price at the forecast issue date, P_s (Bilinski, Lyssimachou, & Walker, 2013).

$$aTPE = \frac{|TP - P_{12}|}{P_s}$$

Secondly, consistent with Asquith, Mikhail & Au (2005), Bradshaw et al. (2012), Bonini et al. (2010), and Bilinski, Lyssimachou & Walker (2013), we employ two measures of accuracy that indicate how often target prices are met. (***TP_Met_End***) will be a binary indicator variable for stocks that have met or exceeded the target price forecast at the forecast period end date, taking the value of one if met, zero if not. (***TP_Met_Any)*** will be another binary indicator variable that will allow an observation of how many target prices were achieved at some point during the 12-month period. For these accuracy measures, we employ a logistic regression model. This choice enables us to investigate the linear relationship with our independent variables even though the dependent variables are binary. Consistent with Bilinski, Lyssimachou & Walker (2013), we define the dependent variables as follows:

for (***TP_Met_Any***):

$$\text{for } {}^{TP}/_{P_s} - 1 > 0 \colon TP\_Met\_Any = 1 \text{ if } TP - P \leq 0 \mid 12 - \text{month forecast horizon,}$$
$$TP\_Met\_Any = 0 \text{ otherwise}$$
$$\text{for } {}^{TP}/_{P_s} - 1 \leq 0 \colon TP\_Met\_Any = 1 \text{ if } TP - P \geq 0 \mid 12 - \text{month forecast horizon,}$$
$$TP\_Met\_Any = 0 \text{ otherwise}$$

for (***TP_Met_End***):

$$\text{for } {}^{TP}/_{P_s} - 1 > 0 \colon TP\_Met\_End = 1 \text{ if } TP - P \leq 0 \mid 12 - \text{month forecast period end,}$$
$$TP\_Met\_End = 0 \text{ otherwise}$$
$$\text{for } {}^{TP}/_{P_s} - 1 \leq 0 \colon TP\_Met\_End = 1 \text{ if } TP - P \geq 0 \mid 12 - \text{month forecast period end,}$$
$$TP\_Met\_End = 0 \text{ otherwise}$$

Exhibit 6 *Dependent Variables*

Description: This graph provides a visual demonstration of our dependent variables. If the target price is met sometime during the forecast (***TP_Met_Any***), the indicator is 1, 0 otherwise. If target price is met at period end (***TP_Met_End***), the indicator is 1, 0 otherwise. (***aTPE***) is used to measure how far away the target price is from the actual price regardless of whether the target price is above or below the actual price.

First and foremost, this thesis extends prior research by attempting to identify an additional determinant of target price accuracy – exclusions. We hypothesize that the size of exclusions are negatively associated with target price forecast accuracy. In the context of our multifaceted definition of target price forecast accuracy, this means that we expect the size of exclusions to be positively associated with forecast error (***aTPE***). We also believe that the size of exclusions will be negatively associated with the target price being met (***TP_Met_Any***) and (***TP_Met_End***). We specify exclusions on an absolute basis to view the effect of size and maintain consistency with the dependent variables. It will also allow an analysis of how the overall size of exclusions has affected accuracy, regardless of sign. Exclusions (***aEXCL***) are specified as the absolute difference between I/B/E/S actual earnings and Compustat GAAP earnings, divided by share price at quarter close, P_t. To facilitate cross-sectional analysts, (***aEXCL***) is scaled by stock price.

$$aEXCL = \frac{|EPS\_Actual - EPS\_GAAP|}{P_t}$$

Prior research identifies a number of factors that have been shown to be influential factors for analyst forecast error, including analyst- and brokerage house-specific, institutional and regulatory factors, and firm-specific factors. As we make exclusive use of consensus forecasts of firms on the S&P 500, we cannot control for several analyst-specific and institutional factors[10]. We therefore focus on attempting to provide a holistic model that controls for firm-specific and some analyst-related determinants[11] of target price forecast accuracy identified in prior research (e.g. Asquith et al., 2005; Bradshaw et al., 2012; Bonini et al., 2010; and Bilinski et al., 2013). The next section will detail the control variables we use in this study. See Exhibit 9 for a list of the variables, our expectations, and how they are specified.

Control Variables

Literature consistently identifies the "implicit return" (***Imp_Ret)*** of the target price as being an important determinant of target price forecast accuracy (error) (Bradshaw, Brown, and Huang, 2013; Bilinski et al., 2011; Bonini et al., 2011). Implicit return (***Imp_Ret***) is specified as target price divided by price at forecast issue date, P_s, minus 1. Implicit return is sometimes referred to as an analyst's "optimism" and is fundamentally a prediction of what the stock will return. These studies find that implicit return is often positively related with forecast error and negatively related with the target price being met. This is due to the fact that the higher the implied return, the lower the likelihood the target price is met, and the higher the likelihood of overall inaccurcay. Consistent with prior research, we expect that higher optimism is associated with higher forecast error and lower likelihood that the target price will be met or exceeded.

$$Imp\_Ret = {}^{TP}\!/_{P_s} - 1$$

Extant literature also finds a connection between earnings forecasts and concurrent target price forecasts. Gleason, Johnson & Li (2014) contend that higher quality earnings (more accurate earnings forecasts) lead to better stock valuations (more accurate target price forecasts). The same sentiment is corroborated by Loh & Mian (2006). Thus, we control for absolute earnings forecast error (***aEFE)*** as a control variable with the expectation that earnings forecast error is negatively related to accuracy and positively related to error. The consensus earnings forecast is used. To facilitate cross-sectional analysis, (***aEFE***) is scaled by stock price at quarter close.

$$aEFE = \frac{|EPS\_Street - EPS\_Actual|}{P_t}$$

[10] We discuss these factors in our limitations, under "omitted variables."
[11] By "analyst-related", we are not referring to the individual analyst-specific variables that we cannot control for, but rather variables related to consensus forecasts.

The number of analysts covering the firm (***Coverage***) has been positively correlated with forecast accuracy, the intuition being that more analysts' following the firm should lead to a more accurate target price due to analysts competing on quality amongst each other. We expect (***Coverage***) to be negatively related to error and positively related to accuracy. The difference between their respective forecasts, however, have been evidenced to have a negative relationship with accuracy, consistent with the idea that higher disagreement leads to higher likelihood of error. This is specified in the model as dispersion (***DISP***), which is the standard deviation of the consensus forecast. Our expectations for (***DISP***) is in line with previous research.

Bilinski, Lyssimachou & Walker (2013) argue that a firm's size and liquidity are important determinants of accuracy. This is corroborated by Bonini et al. (2010) who argue that larger and more liquid firms should be associated with higher forecast accuracy, due to the existence and prevalence of historical information and more stable stock prices. Market value of equity (***LMV)*** and trading volume (***LVOL)*** are hence used as measures that we expect to have positive associations with accuracy and negative relations with forecast error. To facilitate cross sectional analysis, we use the logs of both market value of equity and trading volume. Bonini et al. (2010) also argue that market-to-book (***MB***) is another important determinant of target price forecast error. They argue that accuracy should be smaller for firms with higher market-to-book ratios due to the higher intangible value component. To their surprise, they find that analysts can better capture the price drivers for these companies with high market-to-book ratios and can forecast more accurately. Bradshaw et al. (2014) support this finding by noting that analysts are less optimistic for stocks with high market-to-book ratios. They posit that analysts generally understand when firms have are viewed as overvalued and account for this in their target price setting. They argue that this leads to less optimistic target prices that are more likely to be met. Given these results, we expect that higher market-to-book ratio (***MB***) will be positively associated with TP being met, and negatively related with (***aTPE)***.

Risk factors have been positively associated with target prices being reached or exceeded. In line with option pricing theory, Bilinski, Lyssimachou & Walker (2013) argue that the more volatile a security is, the more likely the target price will be met or exceeded during the forecast period, yet this can simultaneously cause greater forecast error at the period end date. It is unclear, however, how volatility will be related to accuracy at forecast period end. Research argues that the prior quarter's stock price volatility is positively related to the price being met. This is considered using the coefficient of variation (***COV***) and is specified as the price on a trading day divided by the mean stock price for the quarter. We also employ the yearly company beta (***Beta***) obtained from CRSP to capture volatility over a longer time period as a supplementary measure, in line with Bradshaw et al. (2012). We expect volatility to be positively related with the target price being met at some point and absolute target price forecast error (in line with Bilinski et al., 2013). We have no expectations for ***(TP_Met_End***).

Bonini et al. (2010) argue that firms with negative earnings in prior periods are negatively associated with forecast accuracy because of the difficulty of predicting future earnings. An indicator variable ***(Neg_GPS)*** is thus used to control for previous losses, taking the value of one if a firm experienced negative earnings in the quarter prior to the forecast being made. In line with Bonini et al. (2010), we expect (***Neg_GPS***) to be positively related to forecast error and negatively related to the target price being met.

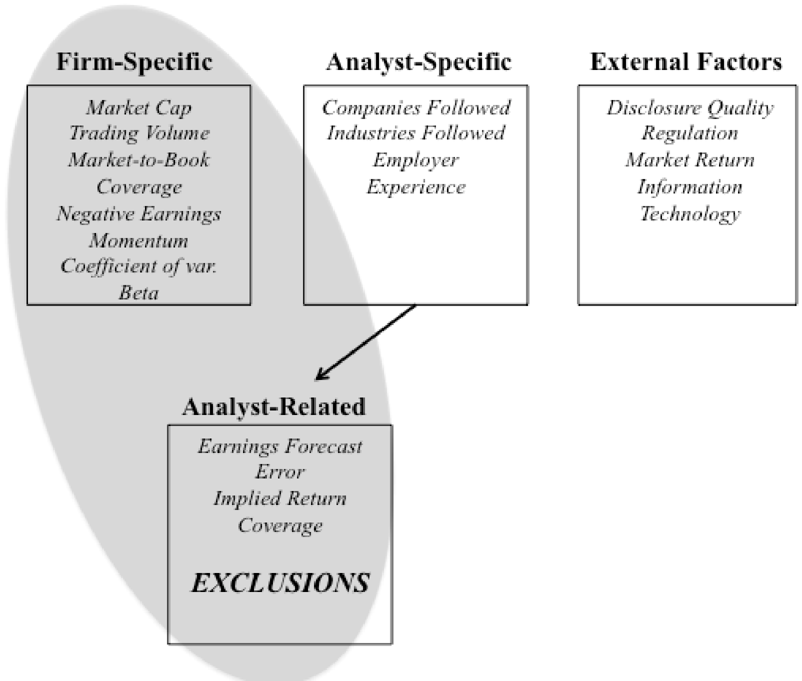
Bonini et al. (2010) argue that positive momentum of the overall market increases the likelihood that target prices are met or exceeded. However, competing research posits that positive market returns can also be reason for analyst optimism and therefore higher forecast error (Bradshaw, Brown, & Huang, 2013). Thus, we have no expectations, but market returns (***Mark_Ret)*** in the quarter leading up to the forecast are considered. Similarly, momentum of individual firms' stock prices has also been positively associated with accuracy. Like market returns, previous research argue that a stock's positive (negative) movement increases the likelihood that optimistic (pessimistic) forecasts are met, though it is unclear how forecast error will be affected. The stock return momentum (***MOM***) in the prior quarter is hence controlled for. Our expectations are limited but a positive relation with target prices being met is anticipated.

Finally, several indicator (dummy) variables are used. These include the different industries (***IND***) and each year over the ten-year observation period (***Year***). We have limited expectations to how these variables will affect the analysis, but we believe they will absorb the industry-specific and year-specific effects from our explanatory variables.

To test our hypothesis, we employ the following model:

$$\begin{aligned} Accuracy\ Measure \\ = \ & \beta_0 + \beta_1 aEXCL_i + \beta_2 aEFE_i + \beta_3 Neg\_GPS_i + \beta_4 Imp\_Ret_i + \beta_5 LMV_i + \beta_6 MB_i \\ & + \beta_7 LVOL_i + \beta_8 COV_i + \beta_9 Beta_i + \beta_{10} DISP_i + \beta_{11} MOM_i + \beta_{12} Mark\_Ret_i \\ & + \beta_{13} Coverage_i + \beta_{14} IND_i + \beta_{15} Year_i + \varepsilon_i \end{aligned}$$

Exhibit 7 ***Control Variables***



Description: This Exhibit details the primary variables we control for in our study (we also control for market return), with the addition of exclusions to analyst-related variables. Analyst-specific is distinguished from analyst-related on the basis of the former applying to individual analysts that we cannot control for, while analyst-related refers to control variables that we are able to consider through use of median forecasts. We group other control variables into “External Factors”.

Exhibit 8 ***Summary of Accuracy Measures and Model***

Sub-Hypothesis	**Accuracy Measure**	**Model Type**	**Model Specification**
The size of exclusions is positively associated with absolute target price forecast error.	*aTPE*	OLS	*(Eq. 1)* $aTPE_i = \beta_0 + \beta_1 aEXCL_i + \beta_2 aEFE_i + \beta_3 Neg\_GPS_i + \beta_4 Imp\_Ret_i + \beta_5 LMV_i + \beta_6 MB_i + \beta_7 LVOL_i + \beta_8 COV_i + \beta_9 Beta_i + \beta_{10} DISP_i + \beta_{11} MOM_i + \beta_{12} Mark\_Ret_i + \beta_{13} Coverage_i + \beta_{14} IND_i + \beta_{15} Year_i + \varepsilon_i$
The size of exclusions is negatively associated with the target price being met at any time during the forecast period.	*TP_Met_Any*	Logistic	*(Eq. 2)* $TP\_Met\_Any_i = \beta_0 + \beta_1 aEXCL_i + \beta_2 aEFE_i + \beta_3 Neg\_GPS_i + \beta_4 Imp\_Ret_i + \beta_5 LMV_i + \beta_6 MB_i + \beta_7 LVOL_i + \beta_8 COV_i + \beta_9 Beta_i + \beta_{10} DISP_i + \beta_{11} MOM_i + \beta_{12} Mark\_Ret_i + \beta_{13} Coverage_i + \beta_{14} IND_i + \beta_{15} Year_i + \varepsilon_i$
The size of exclusions is negatively associated with the target price being met at forecast period end date.	*TP_Met_End*	Logistic	*(Eq. 3)* $TP\_Met\_End_i = \beta_0 + \beta_1 aEXCL_i + \beta_2 aEFE_i + \beta_3 Neg\_GPS_i + \beta_4 Imp\_Ret_i + \beta_5 LMV_i + \beta_6 MB_i + \beta_7 LVOL_i + \beta_8 COV_i + \beta_9 Beta_i + \beta_{10} DISP_i + \beta_{11} MOM_i + \beta_{12} Mark\_Ret_i + \beta_{13} Coverage_i + \beta_{14} IND_i + \beta_{15} Year_i + \varepsilon_i$

Description: We partition our main hypothesis from section 3.1 into three "sub-hypotheses" to accommodate the differing definitions of target price forecast accuracy.

Exhibit 9 ***List of Variables for Main Regressions***

Variable	Expected Sign (*aTPE* / *TP_Met_Any* / *TP_Met_End)*	Definition
Dependent Variables:		
aTPE		Absolute target price forecast error, measured as the absolute difference between forecast price and actual price, divided by price at forecast date;
TP_Met_Any		Indicator variable taking the value of 1 if target price is met or exceeded at some point during the forecast period, and 0 otherwise;
TP_Met_End		Indicator variable taking the value of 1 if target price is met or exceeded at forecast period end date, and 0 otherwise.
Control Variables:		
aEXCL	+ / – / –	Exclusions for the period specified as the absolute difference between I/B/E/S actual earnings per share and GAAP earnings per share, scaled by stock price at closing date;
aEFE	+ / – / –	absolute earnings forecast error in the corresponding period scaled by stock price at closing date;
Neg_GPS	+ / – / –	an indicator variable that takes the value of 1 for firms with losses for the previous quarter;
Imp_Ret	+ / – / –	implicit return of the target price forecast specified as the target price divided by price at forecast date price minus 1;
LMV	– / + / +	log of market value of equity;
MB	– / + / +	market-to-book ratio to gauge the likelihood of the stock being over or undervalued;
LVOL	– / + / +	the trading volume of the firm that gauges its market liquidity;

COV	+ / + / ?	coefficient of variance specified as the standard deviation of share price in the previous quarter, divided by the mean of the share price for the previous quarter. Used to estimate the prior quarter's volatility;
Beta	+ / + / ?	firm's market beta to estimate the volatility of the share price for the entire year;
DISP	+ / – / –	the dispersion of analysts' forecasts, or "disagreement", specified as the standard deviation;
MOM	? / + / +	momentum of the share price in previous quarter;
Mark_Ret	? / ? / ?	the growth of the overall market in previous quarter;
Coverage	– / + / +	analyst coverage of the firm;
IND	*Dummy*	dummy variable to allow observations across different industries and absorb industry-specific effects;
Year	*Dummy*	dummy variable to allow observations across different years and absorb year-specific effects.

Description: This table presents the dependent and control variables for the main models. Please also see an extended list of variables and their definitions used throughout the study in the appendix.

3.2.2 Data

To conduct this study, quarterly data have been gathered from the Institutional Brokers' Estimate System (I/B/E/S), Compustat and the Center for Research in Security Prices (CRSP). I/B/E/S is an analyst tracking service that aggregates all data pertinent to analysts' forecasts of earnings and target prices. It has been used to obtain analysts' median (consensus) street earnings forecasts as well as actual earnings[12]. I/B/E/S is also used to obtain target prices set by analysts, which are compared directly to the 12-month ahead actual price in our analysis. Prior research documents that consensus forecasts, rather than individual analysts, are better measures for market expectations of earnings (Asthana, Balsam, & Mishra, 2011). I/B/E/S information is complemented with company-specific information obtained from the Compustat quarterly files that include items such as GAAP earnings-per-share, special items, and a number of other accounting-related items. The difference between I/B/E/S actual earnings-per-share and

[12] Please see Exhibit 1 for an explanation of analysts' forecast earnings and I/B/E/S actual earnings.

Compustat earnings-per-share approximately constitutes sell-side analysts' total exclusions[13]. Finally, CRSP is used to obtain daily stock prices for the chosen firms as well as market returns[14].

We use quarterly reports of listed firms found on the Standard & Poor's (S&P) 500 in the United States for the years between January 2004 and December 2013. This frequency of reporting, time frame, and country of domicile have been chosen for several reasons. Firstly, the majority of studies concerning both street earnings and target prices have been conducted in the United States, and as this study represents one of the first attempts to link the two, it seems most appropriate to study the country where the most attention has been placed. Moreover, the US has historically had the highest amount of target prices issued (Bilinski, Lyssimachou, & Walker, 2013) which allows for more data and robust analysis. Additionally, the S&P 500 represents the 500 largest US companies, which will ensure a larger analyst following and more forecasts. Secondly, we focus on a ten-year period. Prior studies have focused on shorter time periods. This time period facilitates an analysis over a complete economic cycle, which, depending on growth or decline, has been shown to affect accuracy. Thirdly, a larger time span will allow an analysis of analysts' error, optimism, and expertise over time

We impose several limitations on our data. First, we require fiscal year to end in conjunction with calendar year to mitigate timing overlaps that can confuse the annual data. We also require December as the fiscal month end to further mitigate potential timing issues. Finally, we adjust the data for large outliers by winsorizing to the first and 99th percentiles to remove large outliers[15]. The final sample consists of 10,114 firm-quarter observations for 647 firms across 62 industries[16].

[13] I/B/E/S does not receive information regarding exactly what items analysts exclude from their earnings forecasts. Instead, I/B/E/S is able to deduce what items were excluded based on their size. I/B/E/S then makes exclusions based on the majority rule (also discussed earlier) to the consensus earnings. See section 2.1.2 and Exhibit 1 for a summary of street and I/B/E/S actual earnings, as well as the majority rule.

[14] I/B/E/S, Compustat and CRSP were merged on the basis of ticker symbols and forecast period end dates for each quarter. CUSIPs are company identifiers used in each database and are commonly used as the identifier for merging databases. However, this is problematic as I/B/E/S and Compustat have different systems for CUSIPs. To remedy this issue, we spent significant time looking at every company's ticker symbol and manually matching them in cases where there was inconsistency. In the dataset, target price forecasts are matched directly with their 12-month ahead actual price. I/B/E/S reports target price forecasts in the middle of each month meaning our 12-month period is actually approximately 11 months and two weeks (e.g. target price consensus reported by I/B/E/S on the January 14 2010 is compared with the actual price on December 31 2010).

[15] Winsorizing is the practice of smoothing the top and bottom %. Winsorizing is consistently done in finance and accounting literature and was included in several of the street earnings literature (e.g. Doyle, Lundholm, & Soliman, 2003). This helps smooth both extreme outliers in the data that are not representative of more general populations, but also potential database entry errors.

[16] See Figure 5 in the appendix for a complete list of all companies used in this study. See Figure 2 in the appendix for a summary list of statistics for industry-specific information and descriptive statistics.

4 Descriptive Results

This section details the descriptive statistics of the target price forecast accuracy (error) measures, benchmarking the results with prior findings. We also provide descriptive statistics for some notable control variables to give insight into the dataset. Additionally, references to annual observations will be made to facilitate an understanding of how certain factors have changed over time and with the macroeconomic environment.

Exhibit 10 ***Summary Statistics***

Variable	*Mean*	*Standard deviation*	*Min*	*Max*
aTPE	43%	0.67	0%	516%
TP_Met_Any	61%	0.49	0	1
TP_Met_End	35%	0.48	0	1
aEXCL (per share)	0.29	0.68	0	4.89
aEFE	25%	1.09	0	251%
Imp_Ret	18%	0.74	-77%	541%
Neg_TP_Forecast	22%	0.42	0	1
EXCL_Dummy	86%	0.35	0	1
Signed_EXCL (per share)	0.02	0.58	-2.40	3.18

Description: This table presents descriptive statistics select variables for all firms across the observation period. (***Neg_TP_Forecast***) is added to allow observation of when target price forecasts are below stock price at forecast date; (***EXCL_Dummy***) is added to show when street earnings differ from GAAP earnings (i.e. exclusions were made), and finally (***Signed_EXCL***) is added to present the value of exclusions including their sign (+/–) as an alternative to (***aEXCL***).

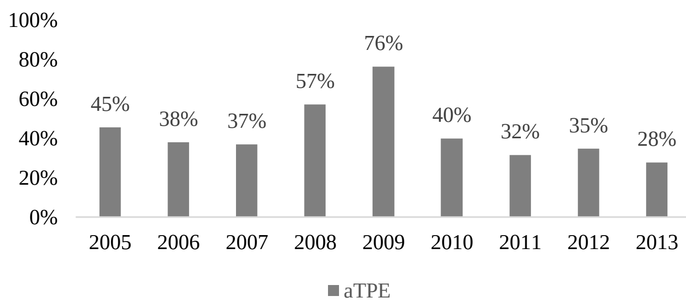
4.1 Descriptive Statistics for Dependent Variables

This section will present descriptive results for our target price forecast data, including our error (***aTPE***) and accuracy measures (***TP_Met_Any***) and (***TP_Met_End***). In general, our findings are consistent with prior research with regards to all three measures. Over the observation period, we document an average (***aTPE***) of 43%. This is in line Bradshaw, Huang, & Tan (2014) who find 45%. In their study of target price error across a number of countries, Bilinksi et al. (2013) find an average forecast error of 47.7%. However, for the US they find an error of 50.6%.

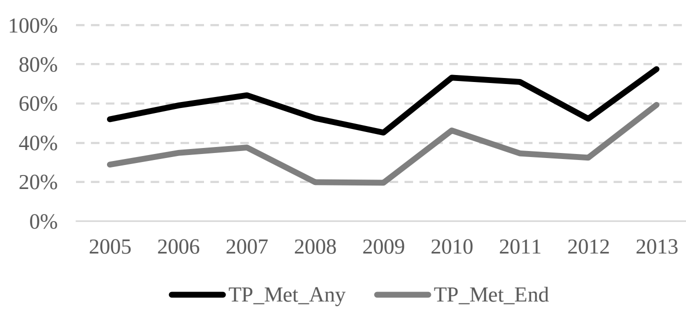
We find that during the observation period, 61.3% of target prices are met at some point (***TP_Met_Any***). Our findings fall within the range of accuracy found in prior research. Asquith, Mikhail & Au (2005) find that forecasts are met in 54% of cases. This is supported by Bilinski, Lyssimachou & Walker (2013) who find that target prices are met 52.9% of the time in their sample of US firms. Bradshaw, Huang, & Tan, (2014) document that prices are met about 64% of the time. The amount of target prices we find that are met or exceeded at forecast period end date is significantly lower. We document that target prices are met at the end of the forecast period (***TP_Met_End)*** an average of only 35% of the time. This finding fits in the range of prior research by Bonini et al (2010) and Bradshaw, Huang, & Tan (2013) of 20% and 38% respectively. See Exhibit 11 below for statistics regarding all accuracy measures.

Exhibit 11 ***Descriptive Evidence for Target Price Forecast Accuracy and Error***

Panel A. *Average absolute target price forecast error*



Panel B. *Average target prices met or exceed at any point and at period end*

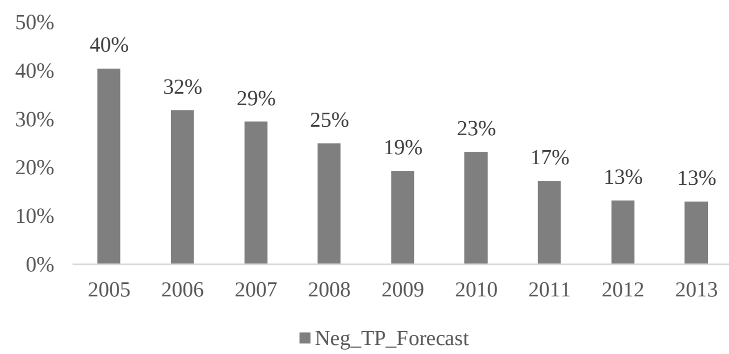


Description: These diagrams document the target price forecast error and accuracy for each year across the observation period. 2004 is not included as we did not have target price data for it, since forecasts were made 12 months before in 2003.

Taken together, and barring financial crisis years, the results show that analysts have forecasted target prices that are more often met and with a lower degree of error over the forecast period. This suggests that, in the context of our definitions of forecast accuracy, analysts have overall become better forecasters.

Prior research criticizes analysts' consistent optimism in target prices, we document that target prices were lower than share price (i.e. "pessimistic") on forecast date in about 22% of cases. We also note a declining trend in this observation over the period, with a surprisingly low amount of pessimism during crisis years (see Exhibit 12). It would appear that analysts underappreciated the impacts of the crisis and instead more often forecasted share price growth rather than decline. These findings support prior research with increasing optimistic (i.e. positive) forecasts.

Exhibit 12 ***Target Prices Below Price at Forecast Date***



Description: As can be seen, there is almost a consistently decreasing amount of target prices that are lower than the price at the forecast date.

4.2 Descriptive Statistics for Select Control Variables

Sell-side Analysts' Exclusions

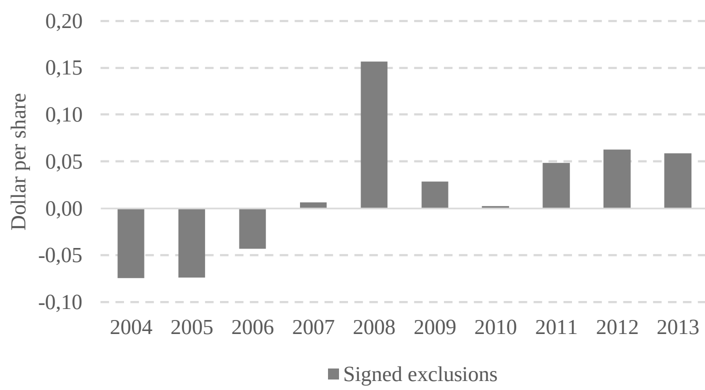
Over the observation period, there are average quarterly exclusions of about 2.2 cents per share (see Exhibit 13, Panel A), including the peak of 2008 when on average 15 cents per share were excluded[17]. This is slightly lower when compared with prior findings by Doyle, Lundholm & Soliman (2003), Bhattacharya et al. (2004), and Kolev, Marquadt & McVay (2008) who find, respectively, quarterly exclusions of about 3, 3.9 and 4 cents per share. Contrary to Bradshaw & Sloan (2002) who see an

[17] Refers to mean exclusions across each year according to their nominal values and considering the signs (+/–) of all exclusions.

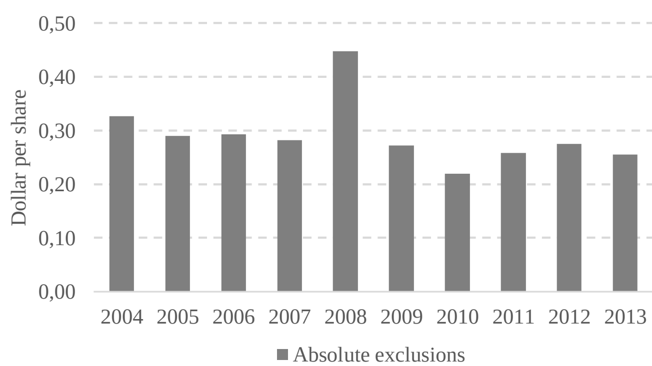
increasing amount of exclusions between 1986 and 1997, we find a decreasing trend in absolute exclusions per share (see Exhibit 13, panel B). Absolute exclusions decrease from around 30 cents per share being excluded at the beginning of the period, to around 25 cents per share being excluded at the end of the period with a peak in exclusions in 2008 at the height of the financial crisis at around 45 cents per share. Looking at Panel A in Exhibit 13, there is an increasing trend towards overall expense-related exclusions.

Exhibit 13 ***Sizes of Exclusions***

Panel A. *Mean size of signed exclusions across observation period*



Panel B. *Mean size of absolute of exclusions across observation period*

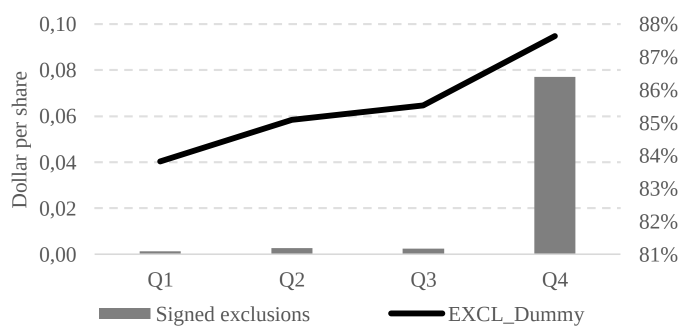


Description: Panel A shows mean exclusions across each year according to their nominal values and considering the signs (+/–) of all exclusions (i.e. signed exclusions). This captures the average size of exclusions considering both positive and negative exclusions. As we are concerned with the overall size of exclusions, we also consider the absolute value to see how large they were for each year in Panel B, regardless of sign (+/–).

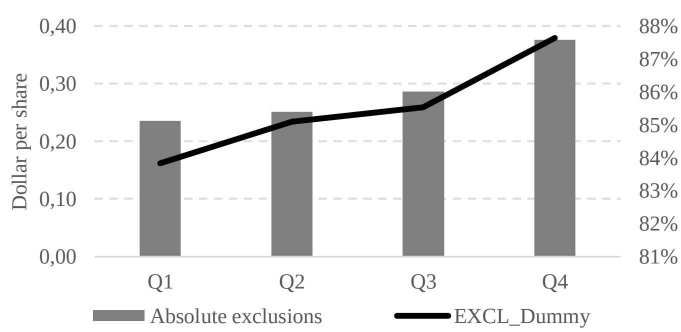
Bradshaw & Sloan (2002) find that firms make the highest number of exclusions in the fourth quarter of a fiscal year. This is consistent with the idea that firms attempt to show high earnings figures preceding the annual report. Our results are similar where we find that street earnings are most frequently different than GAAP earnings in quarter four and the highest average amount of exclusions is also in quarter four. Signed exclusions in quarter one through quarter three are very low, indicating that income items exclusion and exclusion of expenses are on average very similar in size. Quarter four signed exclusions is relatively high which shows that analysts' are more prone to exclude expenses at the end of the year when the annual reports are approaching. Looking at absolute exclusions, we also see the highest amount excluded in quarter four, at an average of 38 cents per share over the ten year period. An additional finding of interest is the number of observations that lack exclusions entirely. Doyle, Lundholm & Soliman (2003) find in a sample of 143,462 firm quarter observations, 65% of street earnings equal GAAP earnings. Our findings differ greatly with street equal to GAAP earnings in only 14% of the sample. Exhibit 14 presents both quarterly exclusions and how often street differs from GAAP earnings.

Exhibit 14 ***Quarterly Exclusions***

Panel A. *Average signed exclusions per share ($) and how often EPS_Actual differs from EPS_GAAP*



Panel B. *Average absolute exclusions per share ($) and how often EPS_Actual differs from EPS_GAAP*



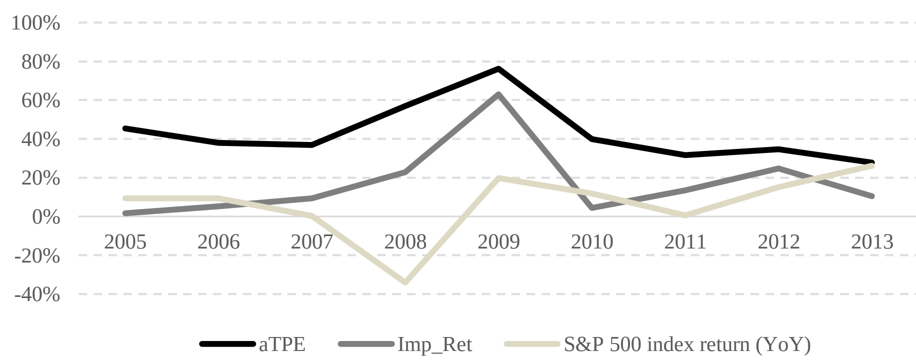
Description: Panel A shows that the highest average exclusions in dollar amounts were in quarter four, and disregarding sign in Panel B, the larqgest exclusions overall (in absolute terms) were made in quarter four as well. We also see that the number of observations where (***EPS_Actual)*** is different than (***EPS_GAAP***), i.e. exclusions were made, was in quarter four almost 88% of the time.

Implicit Return

Prior studies have documented average implicit returns in target prices as high as 37% (Asquith et al., 2005; Brav & Lehavy, 2003) and as low as 20% (Bilinski et al., 2013; Bradshaw, Huang, & Tan, 2013) compared with a market return of around 8% during similar time periods. We find an average implicit return over the observation period of 18%, compared with the period's average market return of about 6% per year[18]. The implicit return number is magnified by significant optimism in 2009[19] due to the fact that forecasts made 12 months ahead were significantly higher than the resulting stock prices after the downturn. Bilinksi et al. (2013) argue that declining implicit returns might partially be a result from SEC regulation in 2002 that prevented analysts' compensation from being tied to investment banking transactions and from offering favorable recommendations to firms so as to elicit future investment banking business. This could be seen in our results and explain why we document lower implicit return than prior research.

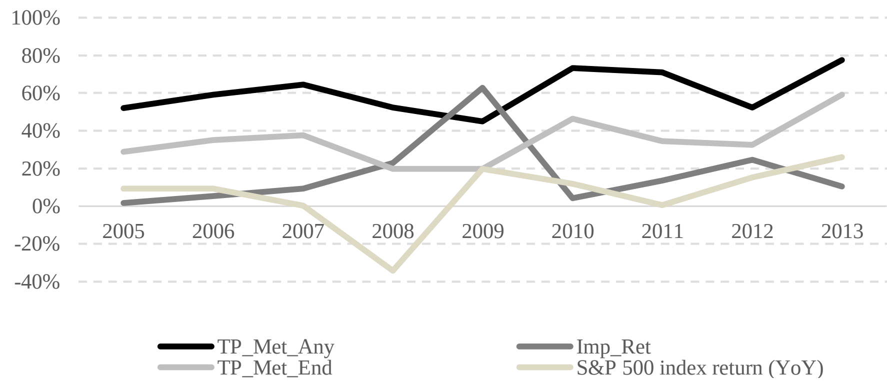
Exhibit 15 ***Implicit Return and Target Price Accuracy Measures***

Panel A: *Implicit return and absolute target price forecast error*



[18] This refers to a 6.0% return on a 12-month rolling basis.
[19] We find an average implied return of 63% for 2009. Removing 2009, we find an average implied return of 11.9%, which is significantly lower than prior studies. This suggests that analysts are becoming less optimistic.

Panel B: *Implicit return and target price accuracy measures*



Description: Panel A shows how closely target price forecast error follows implied return. Panel B shows the relationship between implied return and the target prices being met. Compared against market return, we also see high implicit return in 2009, due to the fact that the target prices set during 2008 were pre crisis.

Average implicit return was substantially larger than market returns across the entire forecast period. As previously discussed, the average implied return is heavily affected by the financial crisis, though in non-crisis years, there remains marked optimism (i.e. high implied return) around 12% that pervade every period.

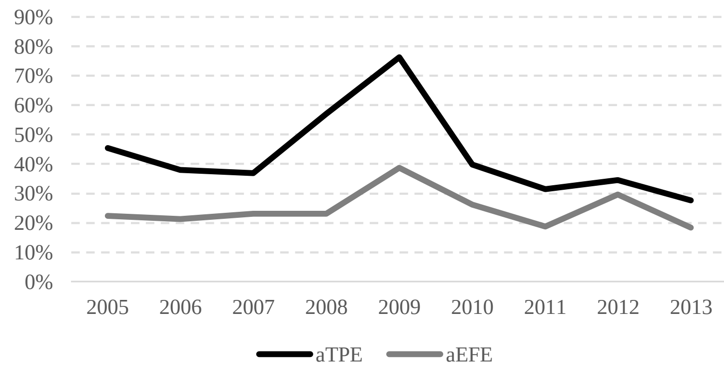
Earnings Forecast Error

We see that consensus earnings forecasts overshot actual earnings on average by 7.5%[20]. Absolute earnings forecast error, however, was markedly higher at an average of 24.9%. Unsurprisingly, forecast error was highest in 2009 but steadily improved in the ensuing years. When compared with absolute target price forecast error, there is also a noticeable trend between earnings and target price forecast error. The trend is similar when comparing earnings forecast error to if target prices are met, in that higher quality earnings forecasts (i.e more accurate earnings forecast) are accompanied with more target prices being met. Higher error in earnings forecasts is similarly met with lower likelihood of the target price being met.

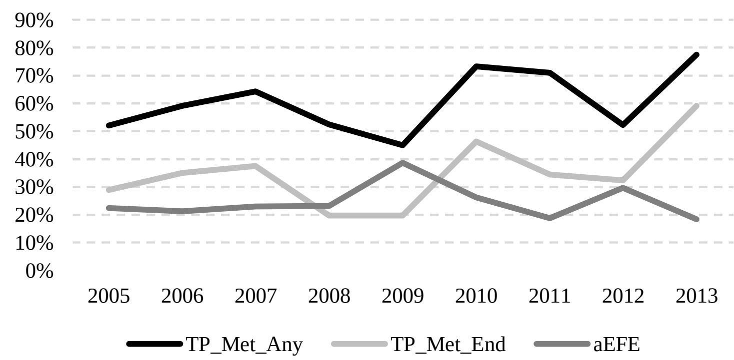
[20] This means that the mean of all EPS forecasts were 7.5% higher than the mean of EPS actuals.

Exhibit 16 ***Earnings Forecast Error and Target Price Forecast Error***

Panel A. *Comparing earnings forecast error with target price forecast error*



Panel B. *Comparing earnings forecast error and how often the target price is met*



Description: This exhibit presents earnings forecast errors in relation to both target price forecast error (Panel A) and likelihood that the target price is met (Panel B).

5 Analysis

5.1 Regression Results

Our results are largely consistent with prior literature in terms of the significance, and explanatory value of the control variables for target price accuracy (error)[21]. We find an adjusted robust R-squared of 0.70[22] for (***aTPE***), suggesting the model fits the data well. We also find that the dependent variables (***TP_Met_Any***) and **(*TP_Met_End*)** can be explained by our model to some extent. This threefold approach allows us to identify the drivers of target price forecast accuracy (error). The following analysis details the significant variables and compares them with prior studies.

Exhibit 17 ***Summary Statistics***

Variable	*Observations*	*Mean*	*Standard deviation*	*Min*	*Max*
aTPE	10114	43%	0.67	0.00	516%
TP_Met_Any	10114	61%	0.49	0	1
TP_Met_End	10114	35%	0.48	0	1
aEXCL	10114	0.01	0.04	0.00	0.33
aEFE	10114	0.01	0.03	0.00	0.26
Coverage	10114	12.48	6.14	1.00	42.00
COV	10114	0.06	0.05	0.01	0.31
LVOL	10114	14.76	1.04	12.60	17.66
Mark_Ret	10114	0.02	0.07	-0.24	0.13
MOM	10114	0.03	0.18	-0.52	0.62
LMV	10114	9.24	1.14	6.46	12.15
Beta	10114	1.18	0.56	0.18	3.10
MB	10114	3.02	3.41	-5.85	21.23
DISP	10114	5.34	4.57	0.61	28.90
Imp_Ret	10114	18%	0.74	-0.77	5.41
Neg_GPS	10114	11%	0.32	0	1

Description: This table presents descriptive statistics for all variables used in the regressions. Some variables are scaled, generally by stock price. Please see Figure 1 for definitions of the variables and how they are specified.

[21] We do not remove variables from our estimated since we are interested in comparing our results with prior literature.

[22] Our regression is adjusted for robustness and we use heteroskedastic robust standard errors. Although we control for heteroskedasticity, we still analyze the potential for heteroskedasticity in section 5.3.

Exhibit 18 ***Regression Results for Equations (Eq. 1), (Eq. 2), and (Eq. 3)***

	Error measure	Accuracy measures	
	aTPE	***TP_Met_Any***	***TP_Met_End***
aEXCL	1.713***	-3.474***	-7.902***
	(9.51)	(-4.57)	(-5.32)
aEFE	2.234***	-1.483	-4.217*
	(9.14)	(-1.33)	(-2.55)
Coverage	-0.002	-0.036***	-0.037***
	(-1.77)	(-6.05)	(-6.16)
COV	1.486***	-2.401***	-1.968**
	(10.20)	(-3.83)	(-2.60)
LVOL	-0.073***	0.221***	-0.080
	(-8.60)	(5.36)	(-1.95)
Mark_Ret	0.175*	-0.276	-0.453
	(2.57)	(-0.65)	(-1.04)
MOM	0.059	0.227	2.033***
	(1.81)	(1.59)	(13.16)
LMV	0.027***	-0.137***	0.159***
	(3.74)	(-3.61)	(4.08)
Beta	0.084***	0.176**	0.221***
	(6.95)	(2.86)	(3.42)
MB	0.010***	0.026**	0.025**
	(6.49)	(3.01)	(2.97)
DISP	-0.005***	0.047***	0.011
	(-3.40)	(6.41)	(1.46)
Imp_Ret	0.639***	-0.874***	-0.350***
	(38.23)	(-15.54)	(-6.35)
Neg_GPS	0.011	0.424***	0.360***
	(0.64)	(4.91)	(4.44)
Industry	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*
Constant	0.973***	-0.900	0.178
	(10.09)	(-1.72)	(0.34)
R-sqr	0.701		
d.f	10035		
BIC	8575.6	12449.5	12408.1

Note: * p<0.05, ** p<0.01, *** p<0.001 (two-tailed). We do not remove insignificant variables in order to maintain comparability with prior literature. P-values are in parentheses.

5.1.1 Do Exclusions Affect Analysts' Target Price Forecast Accuracy?

Consistent with our hypothesis, we find the size of exclusions (***aEXCL***) to be a significant factor affecting target price forecast accuracy. We document a positive and statistically significant relationship between (***aEXCL***) and (***aTPE***), suggesting that larger exclusions are associated with higher forecast error. The results can also be considered economically significant[23]. We also find that (***aEXCL***) is significant and negatively related to both (***TP_Met_Any***) and (***TP_Met_End***). (See Exhibit 18 for regression results).

Our findings are consistent with our hypothesis and our differing definitions of target price forecast accuracy. That is, we see that the overall size of exclusions are positively associated with target price forecast error and negatively related with the likelihood that the target price is met or exceeded either during the twelve-month period or at period end. This is in line with the notion that exclusions motivate target price forecasts that are optimistic. These results suggest that exclusions contribute to target prices that are set too highly and are less likely to be reached, while also contributing to greater forecast error at period end.

In this analysis we observe exclusions only in absolute terms to view how overall size affects accuracy. We have so far not considered the different types of exclusions. Therefore, to further enrich the analysis and provide some insight into our findings, we will analyze the correlations of positive and negative exclusions under additional analysis in section 5.2.1. Furthermore, we will analyze the correlation of special item and incremental-item exclusions (introduced in section 2.1.2) in section 5.2.2 to see if these further motivate the effects of exclusions on target price forecast accuracy.

5.1.2 Comparing Results with Prior Research

Implicit Return

Consistent with prior research and with our initial assumption, ***(Imp_Ret)*** is significant and remains one of the most explanatory variable for target price error. It is positively correlated with ***(aTPE)***, suggesting that the more highly optimistic analysts are of the stock's return, the higher magnitude of error at the forecast period end date. A higher implied return is also significantly correlated with a lower probability that the target price is met any time during the period as well as at end date.

Market and Stock Price Returns

Bradshaw et al. (2012) argues that past growth in the economy is associated with more optimistic forecasts, and thus higher error. Our results are consistent with this notion and we find that higher market return (***Mark_Ret***) is associated with higher target price forecast error (***aTPE)***. Bonini et al. (2010)

[23] We find that a one standard deviation increase in (***aEXCL***) increases the probability of (***aTPE***) by 7.3%.

document that historically growing economies (positive returns) are positively associated with target price forecasts being met but we find no significant association between market returns with either (***TP_Met_Any***) or (***TP_Met_End***).

We find that momentum (***MOM***) is one of the most explanatory variables for the target price being met at the forecast period end date (***TP_Met_End)***. The results are not significant for (***TP_Met_Any***) or absolute target price forecast error (***aTPE***), suggesting inconclusive evidence that stock-specific momentum facilitates a more accurate target price setting.

Volatility

Our two measures of volatility, (***COV***) and (***Beta***) are both significant and positively associated with target price forecast error. This is evidence that the level of volatility of the stock's historical returns over the previous quarter and year, respectively, causes larger differences between the forecast price and the price at period end date. This is consistent with the findings of Bradshaw et al. (2012) as well as Bilinski, Lyssimachou & Walker (2013). Our findings regarding accuracy, however, are somewhat mixed. In line with options pricing theory, we find that (***BETA***) is positively associated with target prices being met at some point and at forecast period end. (***COV***), on the other hand, it is negatively associated with (***TP_Met_Any***) and (***TP_Met_End***). Although this contradicts findings by Bilinski, Lyssimachou & Walker (2013), our data and time period is heavily weighted by target prices issued during and after the financial crisis, which had a strong negative effect on accuracy of target prices adhering to 2009 share prices. Low target price accuracy during crisis years coupled with high volatility in share prices could explain this negative association with (***COV***) and if target prices are met. Moreover, analysts could have underestimated the macroeconomic climate and forecasted too optimistically for stocks with high (***COV***).

Size and (Market) Liquidity

In line with the reasoning of Bonini et al. (2010), we find trading volume (***LVOL***) to be negatively related to forecast error and positively associated with if target prices are met at any time during the period. Intuitively it makes sense that trading volume should be positively associated with forecast accuracy since analysts market data is more frequent and accessible, which aids in a better understanding of how events affect the demand of the stock. To our surprise, we find that firm size (***LMV***) is positively related with higher target price forecast error (***aTPE***). This could be due to the fact that large companies could have more complex operations, making forecasting more difficult. With regards to (***TP_Met_Any***) and (***TP_Met_End***), our results are somewhat mixed. Larger firms are associated with lower probability that the target prices are met at any time during the period but higher probability that the target prices are met at end date.

Market-to-Book

Bonini et al. (2010) argue that accuracy should be reduced for firms with high (***MB***) ratios due to analysts' consistently optimistic forecasts. Bradshaw et al. (2014) contradict this argument and contend that analysts do have expertise, generally understand when (***MB***) ratios are high, and compensate by forecasting with a lower degree of optimism. Our results show that high market-to-book increases the likelihood of target prices being met at any time during the period, as well as being met at period end date. Our findings also suggests that (***MB***) is positively correlated with target price forecast error (***aTPE***). The reason for this might be that analysts make conservative forecasts for firms with high market-to-book ratios, in line with Bradshaw et al. (2014), therefore the likelihood of target prices being met increases but the absolute forecast error also increases.

Earnings

We find that losses in previous periods (***Neg_GPS***) have low significance and don't appear to influence target price forecast error. On the other hand, we find that (***Neg_GPS***) is significant and positively related to the target price being met both during the forecast period and at the end. This contradicts findings by Bonini et al. (2010), though it is in line with the idea that previous losses might motivate analysts to forecast less optimistically and therefore set a target price that is more likely to be met.

Earnings forecast errors (***aEFE***) were also found to be significant for target price forecast accuracy. The results showed a significant and positive relation to (***aTPE***). However, no significance was found for (***TP_Met_Any***). Finally, we find that (***aEFE***) is significant and negatively related to (***TP_Met_End*).** The findings are in line with the idea that higher quality inputs (i.e. more accurate earnings forecasts) lead to target prices that are more likely to be met (by period end) and are closer to the actual price at period's end.

Coverage

Asquith et al. (2014) and Bradshaw et al. (2014) reason that a higher number of analysts should facilitate more accurate target prices, since competition ought to make analysts compete on quality of their forecasts. **(*Coverage*)** is not found to be an explanatory variable for target price forecast error, but is negatively associated with both **(*TP_Met_Any*)** and **(*TP_Met_End*)**. This could be explained by the so-called “herding behavior”, meaning that analysts tend to follow preceding target prices and recommendations. The first target price that is released becomes the bench-mark for the ensuing target prices.

Asthana, Balsam & Mishra (2011) also argue that analyst “disagreement” (***DISP***) over target prices, proxied as higher differences between analyst-specific target prices (standard deviation), increases forecast error. We, however, find that (***DISP***) reduces target price forecast error. We also find a positive relationship between (***DISP***) and if the target prices are met at any time during the period. Evidently, more disagreement between the analysts leads to more accurate target prices and less absolute error. This supports the argument that when analysts’ do not demonstrate herding behavior, the consensus forecasts becomes more accurate.

General Findings

The different models employed in this study offer fundamentally different analyses of target price forecast accuracy. Our findings suggest that drivers of higher accuracy are not necessarily mitigators of error (and vice versa). This underlines the importance of a multifaceted approach to defining forecast accuracy in target price studies. As a more general conclusion, we find over the observation period that analysts forecast with lower forecast error while at the same time forecasting target prices that are more consistently met. These findings are in line with Bilinksi et al. (2013). This suggests that, per both definitions, analysts are becoming more accurate, both in terms of how often price targets are met, but also with regards to how close forecasts are to actual prices at period end. Also consistent with Bilinksi et al. (2013), we find a large deterioration of forecast accuracy during crisis years and a larger degree of forecast error.

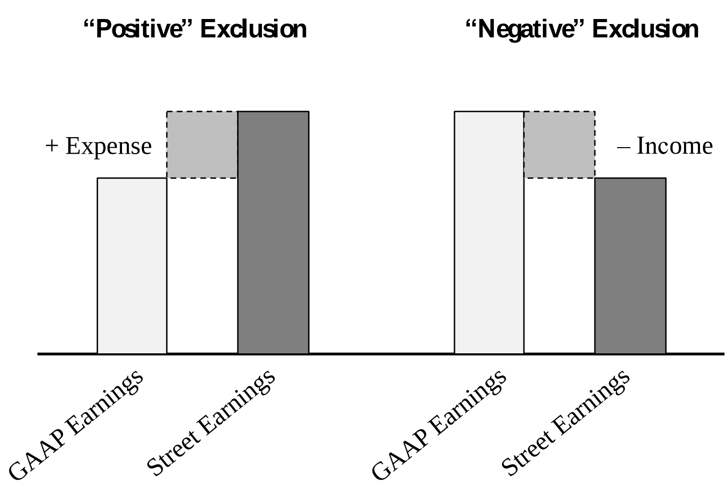
5.2 Additional Analysis

In section 5.1, we found the size of exclusions to be significant determinants of target price forecast error and negatively associated with the target price being met. However, what we did not capture was the effects of different types of exclusions. That is, we viewed only absolute exclusion and did not distinguish between positive or negative exclusions. Thus, to enhance our findings, we make this distinction in the following section.

5.2.1 Distinguishing Between Income and Expense Exclusions

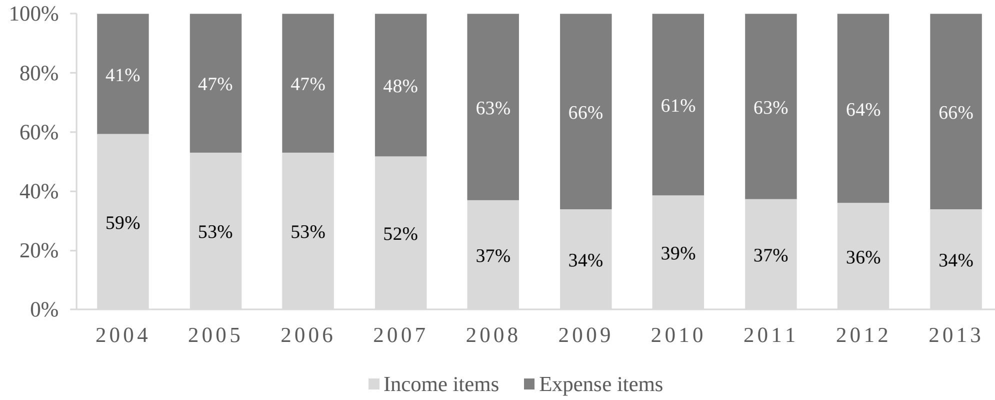
We are interested in the effects of signed exclusions, or positive and negative. Positive exclusions refer to scenarios when (***EPS_Actual***) is larger than (***EPS_GAAP***), implying that expenses were excluded, creating an upward-adjusting or positive effect. We find an increasing trend of expense items being excluded and that GAAP earnings are lower than street earnings in about 57% of cases (see Exhibit 20). This is line with Gu & Chen (2004) and is evidence that exclusions are predominantly expense items. Negative exclusions refer to when (***EPS_Actual***) is smaller than (***EPS_GAAP***), suggesting that income-related items were excluded (see Exhibit 19). We distinguish between positive and negative exclusions using the dummy variable (***EXCL_Pos***). Given our findings that (***aEXCL***) was positively related to (***aTPE***) and negatively related to (***TP_Met_Any***) and (***TP_Met_End***), it would appear that (***aEXCL***) was similar to Scenario 2 in Exhibit 5, where exclusions have somewhat of an upward-adjusting effect. Therefore, we expect to see (***EXCL_Pos***) positively correlated with (***aTPE***), and negatively associated with both (***TP_Met_Any***) and (***TP_Met_End***) to reflect expense-related exclusions creating the upward-adjusting effect on earnings.

Exhibit 19 ***Difference Between Positive (Expense) and Negative (Income) Exclusions***



Description: As can be seen, "positive" exclusions include expense-related exclusions that are added back and increase street earnings from GAAP whereas "negative" exclusions include income-related exclusions that are subtracted from GAAP and decrease street earnings.

Exhibit 20 ***Income and Expense Exclusions***



Description: Income item exclusions refer to when (EPS_Actual) is less than (EPS_GAAP), implying income items were removed to lower overall earnings. Expense exclusions refer to when (EPS_Actual) is greater than (EPS_GAAP), indicating that expense items were removed, increasing overall earnings.

To observe the differences between positive and negative exclusions, we modify the model to include a dummy variable that indicates when exclusions are positive. Therefore, the adjusted model *(Eq. 4)* is specified as follows:

$$
\begin{aligned}
Accuracy\ Measure &= \beta_0 + \beta_1 aEXCL_i + \beta_2 EXCL\_Pos_i + \beta_3 Neg\_GPS_i + \beta_4 Imp\_Ret_i + \beta_5 LMV_i + \beta_6 MB_i \\
&+ \beta_7 LVOL_i + \beta_8 COV_i + \beta_9 Beta_i + \beta_{10} DISP_i + \beta_{11} MOM_i + \beta_{12} Mark\_Ret_i \\
&+ \beta_{13} Coverage_i + \beta_{14} IND_i + \beta_{15} Year_i + \beta_{16} aEFE_i + \varepsilon_i
\end{aligned}
$$

Exhibit 21 ***Results Distinguishing between Positive and Negative Exclusions***

	Error measure	Accuracy measures	
	aTPE	***TP_Met_Any***	***TP_Met_End***
aEXCL	1.707***	-3.621***	-7.971***
	(9.52)	(-4.74)	(-5.33)
EXCL_Pos	-0.109***	0.427***	0.271***
	(-13.50)	(8.54)	(5.43)
aEFE	2.096***	-1.282	-4.195*
	(8.67)	(-1.14)	(-2.51)
Coverage	-0.002	-0.036***	-0.037***
	(-1.84)	(-6.00)	(-6.10)
COV	1.490***	-2.429***	-1.922*
	(10.27)	(-3.86)	(-2.54)
LVOL	-0.063***	0.189***	-0.102*
	(-7.62)	(4.55)	(-2.45)
Mark_Ret	0.175**	-0.276	-0.454
	(2.59)	(-0.65)	(-1.04)
MOM	0.054	0.252	2.051***
	(1.67)	(1.76)	(13.26)
LMV	0.019**	-0.109**	0.178***
	(2.64)	(-2.85)	(4.54)
Beta	0.081***	0.187**	0.228***
	(6.81)	(3.03)	(3.52)
MB	0.010***	0.028**	0.026**
	(6.26)	(3.21)	(3.07)
DISP	-0.005***	0.048***	0.011
	(-3.42)	(6.50)	(1.51)
Imp_Ret	0.647***	-0.948***	-0.393***
	(38.42)	(-16.04)	(-6.89)
Neg_GPS	0.011	0.425***	0.361***
	(0.63)	(4.89)	(4.44)
Industry	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*
Constant	0.947***	-0.928	0.159
	(10.00)	(-1.77)	(0.30)
R-sqr	0.707		
d.f	10034		
BIC	8389.1	12385.3	12387.6

Note: * p<0.05, ** p<0.01, *** p<0.001 (two-tailed). We do not remove insignificant variables to maintain comparability with prior literature.

Contrary to our expectations, we find (***EXCL_Pos)*** to be negatively associated with (***aTPE***) and positively related to (***TP_Met_Any***) and (***TP_Met_End***). Negative exclusions were thus positively correlated with (***aTPE***) and negatively related to (***TP_Met_Any***) and (***TP_Met_End***). Generally, this suggests that expense-related exclusions help to improve target price forecast accuracy, while income-related exclusions are the drivers of more error and lower likelihood of the target price being met. We expected (***EXCL_Pos***) to create the upward-adjusting effect seen in Scenario 2 in Exhibit 5. This was not the case. To better understand our results, we analyze exclusions making an additional distinction.

5.2.2 Distinguishing Between Special- and Incremental-Item Exclusions

This section will provide an additional analysis of our data, considering recent developments specifically in street earnings literature. As discussed in section 2.1.2, recent research regarding exclusions has made separations into special and incremental-item exclusions (see Exhibit 2). We believe that providing a similar distinction in our data could provide interesting results and could help us to better understand why excluding expense items increases accuracy. As incremental items are comprised of subjective exclusions, while special items are objective exclusions comprised of firm-defined nonrecurring items, we expect to find differences in the explanatory value of the different exclusions.

We create a special-item exclusions variable (***EXCL_Spec***), defined as special items per share, based on data obtained from Compustat. We also create incremental-item exclusions (***EXCL_Incr***) defined as the difference between total (signed) exclusions and (***EXCL_Spec***)[24]. To maintain consistency with our dependent variables, we view these on absolute bases. Our expectations are limited The adjusted equation (*Eq. 5*) is therefore as follows:

$$\begin{aligned} Accuracy\ Measure \\ = \ & \beta_0 + \beta_1 EXCL\_Spec_i + \beta_2 EXCL\_Incr_i + \beta_3 aEFE_i + \beta_4 Neg\_GPS_i + \beta_5 Imp\_Ret_i \\ & + \beta_6 LMV_i + \beta_7 MB_i + \beta_8 LVOL_i + \beta_9 COV_i + \beta_{10} Beta_i + \beta_{11} DISP_i + \beta_{12} MOM_i \\ & + \beta_{13} Mark\_Ret_i + \beta_{14} Coverage_i + \beta_{15} IND_i + \beta_{16} Year_i + \varepsilon_i \end{aligned}$$

[24] Defining (***EXCL_Incr***) as the difference between Compustat-defined special items and total exclusions (***EXCL***) assumes that analysts' *always* exclude Compustat-defined special items. While this is the precedent set by prior research, it is nonetheless an assumption that likely does not hold in all cases. Without specific information regarding these exclusions, we are unaware of a better method for making this distinction. It is hence a minor limitation for this additional analysis.

Exhibit 22 ***Results Distinguishing Between Special- and Incremental-Item Exclusions***

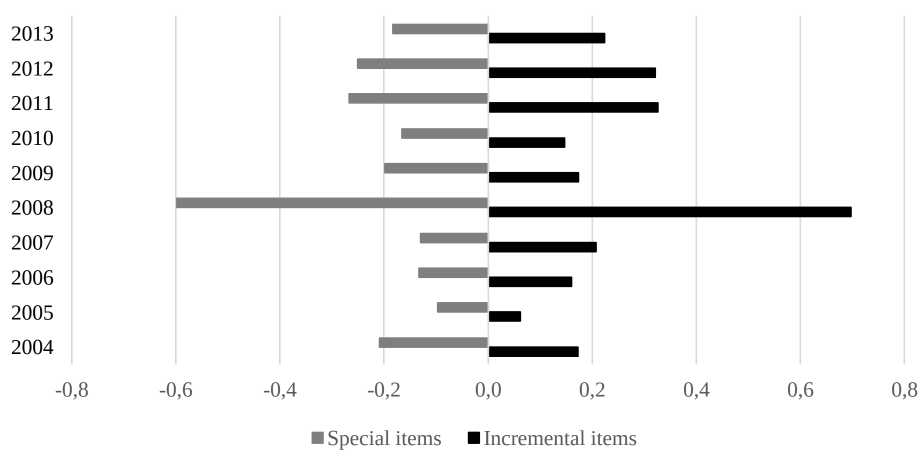
	Error measure	Accuracy measures	
	aTPE	***TP_Met_Any***	***TP_Met_End***
EXCL_Spec	-2.301***	1.515	6.910**
	(-7.24)	(1.02)	(3.04)
EXCL_Incr	1.558***	-2.041*	-6.655***
	(8.54)	(-2.45)	(-4.41)
aEFE	2.205***	-2.276*	-4.551**
	(8.64)	(-1.97)	(-2.67)
Coverage	-0.002	-0.038***	-0.038***
	(-1.34)	(-6.28)	(-6.28)
COV	1.510***	-2.181***	-1.806*
	(10.27)	(-3.43)	(-2.36)
LVOL	-0.065***	0.209***	-0.095*
	(-7.40)	(4.97)	(-2.27)
Mark_Ret	0.151*	-0.282	-0.471
	(2.18)	(-0.65)	(-1.07)
MOM	0.053	0.232	2.013***
	(1.62)	(1.61)	(12.91)
LMV	0.019**	-0.130***	0.172***
	(2.59)	(-3.36)	(4.36)
Beta	0.082***	0.201**	0.244***
	(6.67)	(3.22)	(3.73)
MB	0.010***	0.030***	0.027**
	(6.32)	(3.47)	(3.21)
DISP	-0.005**	0.048***	0.011
	(-3.25)	(6.46)	(1.55)
Imp_Ret	0.637***	-0.883***	-0.353***
	(36.31)	(-15.56)	(-6.36)
Neg_GPS	0.021	0.407***	0.347***
	(1.20)	(4.67)	(4.24)
Industry	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*
Constant	0.908***	-1.114*	0.042
	(8.47)	(-2.05)	(0.08)
R-square	0.704		
d.f	9812		
BIC	8414.3	12159.8	12163.7

Note: * p<0.05, ** p<0.01, *** p<0.001 (two-tailed). We do not remove insignificant variables in order to maintain comparability with prior literature and main regression results.

We find (***EXCL_Spec***) to be significant and negatively correlated with (***aTPE***) and positively correlated with (***TP_Met_End***)[25] while, we find (***EXCL_Incr***) to be positively associated with (***aTPE***) and negatively associated with ***(TP_Met_Any***) and (***TP_Met_End***).

In section 5.2.1, we found that (***EXCL_Pos***) (expense-related exclusions) were associated with higher overall accuracy. We were unable to offer a definitive explanation as to why this might be. However, as seen in Exhibit 23, special-item exclusions are consistently negative, i.e. expense-related, and positively related with overall accuracy. Thus, there is an overlap between (***EXCL_Pos***) and (***EXCL_Spec***). Given that these types of exclusions contribute to higher accuracy, it seems that accuracy is increased when analysts only exclude objective special items. Taken together, these findings suggest that analysts are more accurate when excluding objective special items (***EXCL_Spec***) and are less accurate when they make additional exclusions (***EXCL_Incr***). Therefore, it appears that analysts don't add value with additional exclusions.

Exhibit 23 ***Incremental- and Special-Item Exclusions***



Description: Incremental items are calculated as the difference between total exclusions and special-item exclusions. This is why they are consistently positive.

[25] (***EXCL_Spec***) was positively correlated with (***TP_Met_Any***) though did not prove to be significant.

5.3 Robustness Tests

This section will conduct several robustness tests the assumptions of the research method and the validity of our dataset. We need to determine whether our models and data are robust enough for our interpretations to be reliable. First of all, we use winsorized data at the 1% level throughout the paper, which limits the effects that extreme outliers might have on our results. Other issues might be omitted endogenous effects that are firm-specific. We therefore conduct a regression for (***aTPE***) controlling for firm-fixed effects, which removes the effects of firm-specific factors that might influence the data. We then conduct additional tests to examine the potential for heteroskedasticity and potential multicollinearity in the dataset.

5.3.1 Controlling for Fixed Effects

We want to account for unobserved heterogeneity in correlations with the dependent variables as well as with the independent variables. Our dataset is structured as panel data with regards to firm-specific and time-specific effects. Essentially, there may be firm- and time-specific reasons why the size of exclusions affects the size of forecast error. This unobserved heterogeneity is controlled for by absorbing fixed effects in the regression.

Exhibit 24 ***Results When Absorbing Fixed Effects***

	Error measure	Accuracy measures	
	aTPE	***TP_Met_Any***	***TP_Met_End***
aEXCL	0.934***	-1.933*	-4.506***
	(9.60)	(-2.33)	(-3.47)
aEFE	1.969***	1.069	-0.417
	(13.06)	(0.77)	(-0.22)
Coverage	-0.014***	0.013	0.005
	(-14.27)	(1.54)	(0.62)
COV	0.985***	-1.184	-1.384
	(11.34)	(-1.64)	(-1.70)
LVOL	-0.027**	0.748***	0.007
	(-3.24)	(10.39)	(0.10)
Mark_Ret	-0.091*	1.359***	1.392***
	(-2.09)	(3.92)	(3.92)
MOM	0.049*	-0.061	1.785***
	(2.56)	(-0.38)	(11.01)
LMV	-0.043***	1.349***	1.446***
	(-4.04)	(14.52)	(15.87)
Beta	0.053***	0.540***	0.407***
	(5.26)	(6.55)	(5.04)
MB	0.007***	0.046**	0.043***
	(4.54)	(3.14)	(3.34)
DISP	0.003**	-0.020*	-0.049***
	(2.89)	(-1.97)	(-4.77)
Imp_Ret	0.564***	-1.942***	-0.994***
	(79.36)	(-21.43)	(-11.64)
Neg_GPS	0.008	0.622***	0.469***
	(0.71)	(6.25)	(5.24)
Fixed Effects	*Yes*	*Yes*	*Yes*
Constant	1.091***		
	(6.48)		
R-sqr	0.538		
d.f	9721		
BIC	4249.4	8887.4	9519.1

Note: * p<0.05, ** p<0.01, *** p<0.001 (two-tailed). We do not remove insignificant variables to maintain comparability with prior literature and main regression.

When controlling for firm-fixed effects in the regression, we see that some variables become significant and others have a smaller correlation with forecast error than before. Previously, we could not find any correlation between coverage and forecast error (***aTPE***) but when controlling for fixed effects, coverage becomes significant. Controlling for fixed effects had a similar effect on momentum, which became moderately significant. A negative change in significance is seen in dispersion (***DISP***) showing that some of the explanatory value was due to endogenous effects. We also see no significant change in (***aEXCL***) suggesting that it remains a positively correlated determinant of target price forecast error and negatively correlated determinant of accuracy. In general, we can see that our data is not tainted with heterogeneity between variables and no explanatory variable has to be rejected when controlling for firm-fixed effects. Our R-squared went from 0.70 to 0.538, which means some of the explanatory value in the model is due to endogenous effects though our model does still hold significant explanatory value.

5.3.2 Assessing Multicollinearity

We test our dataset for multicollinearity to see if there is correlation between predictor variables that could provide artificial correlations for our regressions or otherwise cloud our results. To do this, we provide Pearson and Spearman correlation matrices that identify the correlation between individual variables. Pearson's correlation is a measure of the association between two continuous variables. It shows the pairwise distance between the data points in a univariate relationship between two variables. Absolute values above 0.7 indicate correlation between regressors that is too high and can bias the data and result in unreliable model results. We see no Pearson correlation coefficient above 0.6, which indicates that we do not appear to have a problem with multicollinearity in our model.

Spearman rank correlation also measures the association between two variables but is suited for ordinal variables as well. It is also useful when assessing non-linear univariate relationship between two variables. We see no correlation coefficient that indicates too high correlation between variables. In summary, it appears our data is free from multicollinearity issues. Please see Exhibit 24 for correlation matrices.

Exhibit 25 *Pearson Correlation Matrix*

	Coverage	*COV*	*LVOL*	*Mark_Ret*	*MOM*	*LMV*	*Beta*	*MB*	*DISP*	*Imp_Ret*	*EXCL*	*aEFE*	*Neg_GPS*
Coverage	1.00												
COV	-0.08	1.00											
LVOL	0.44	0.23	1.00										
Mark_Ret	0.06	-0.17	-0.06	1.00									
MOM	0.00	-0.23	-0.07	0.36	1.00								
LMV	0.48	-0.33	0.44	0.03	0.07	1.00							
Beta	-0.04	0.48	0.14	0.00	0.03	-0.34	1.00						
MB	0.01	-0.07	-0.09	0.00	0.08	0.13	-0.14	1.00					
DISP	0.17	0.13	0.06	-0.00	-0.00	0.15	0.13	0.05	1.00				
Imp_Ret	0.00	0.17	0.22	0.00	0.03	-0.12	0.14	-0.12	0.31	1.00			
aEXCL	-0.04	0.25	0.15	-0.08	-0.12	-0.15	0.18	-0.11	0.16	0.38	1.00		
aEFE	-0.06	0.43	0.22	-0.05	-0.14	-0.25	0.33	-0.16	0.18	0.40	0.49	1.00	
Neg_GPS	-0.05	0.15	0.09	0.03	0.04	-0.22	0.23	-0.06	-0.00	0.20	0.17	0.23	1.00

Description: coefficients of over 0.7, or multiple coefficients over 0.5, are indicative of potential multicollinearity in the data that could be causing artificial significance in the dataset. It does not appear that we have any issues with multicollinearity.

Exhibit 26 *Spearman Correlation Matrix*

	Coverage	*COV*	*LVOL*	*Mark_Ret*	*MOM*	*LMV*	*Beta*	*MB*	*DISP*	*Imp_Ret*	*EXCL*	*aEFE*	*Neg_GPS*
Coverage	1.00												
COV	-0.09	1.00											
LVOL	0.42	0.25	1.00										
Mark_Ret	0.03	-0.10	-0.01	1.00									
MOM	0.01	-0.08	-0.08	0.39	1.00								
LMV	0.52	-0.33	0.42	0.00	0.06	1.00							
Beta	-0.00	0.53	0.16	0.02	0.03	-0.30	1.00						
MB	-0.02	-0.19	-0.20	-0.01	0.12	0.18	-0.21	1.00					
DISP	0.22	0.12	0.02	0.01	0.00	0.20	0.15	0.01	1.00				
Imp_Ret	0.07	0.14	0.26	0.01	0.02	-0.06	0.11	-0.23	0.22	1.00			
aEXCL	-0.04	0.15	0.09	-0.01	-0.03	-0.13	0.14	-0.19	-0.05	0.02	1.00		
aEFE	-0.02	0.38	0.29	0.01	-0.09	-0.24	0.37	-0.40	0.15	0.29	0.14	1.00	
Neg_GPS	-0.02	0.13	0.11	0.05	0.04	-0.18	0.21	-0.15	-0.03	0.10	0.13	0.20	1.00

5.3.3 Assessing Heteroskedasticity

When running OLS regressions, it is assumed that the error term has a constant variance. If this is not true, heteroskedasticity is apparent and our results might not be reliable. Our estimated coefficients would still be useful but our F-tests, t-tests and significance level would not be reliable. We run White's test for heteroskedasticity which is based on the residuals of the fitted model and makes no assumption about the form of heteroskedasticity, meaning it can detect non-linear heteroskedasticity as well, compared to the Breusch-Pagan test which only detects linear forms of heteroskedasticity. Based on the results of the test, we can reject the null hypothesis of homoskedasticity, as the p-value is 0.000. The p-value is defined as the minimum value of significance for which the null hypothesis is rejected, and since we are testing at a 5% significance level the test suggests that heteroskedasticity is present in our model. This could pose a problem for the interpretation of our rsults but the issue is alleviated by using heteroskedastic-consistent standard errors (HCSE) in our regression models.

Exhibit 27 ***White's Test for Heteroskedasticity***

White's	Test for Ho: homoskedasticity		
	Against Ha: unrestricted heteroskedasticity		
Source	Chi^2	Degrees of freedom	P-value
Heteroskedasticity	2434.16	103	0.0000
Skewness	55.91	13	0.0000
Kurtosis	8.83	1	0.0030
Total	**2498.90**	**117**	**0.0000**

6 Conclusions

We study how the size of exclusions affect sell-side analysts' target price forecast accuracy for firms listed on the S&P 500 between 2004 and 2013. We find that analyst accuracy has increased over the period and overall optimism has decreased. Furthermore, the size of exclusions (on an absolute basis) has decreased slightly. While prior research argues that exclusions (potentially) help to produce earnings that are more persistent, we present evidence that the size exclusions are statistically and economically significant factors that decrease overall target price forecast accuracy. We find that exclusions are positively related with forecast error and negatively related with the target price being met. Given that target prices have been shown to be more value relevant than earnings, these findings are disconcerting and bring into question the value relevance of exclusions. Connecting exclusions to target prices has so far largely been overlooked in extant research. A potential reason for this is that target price setting is largely an unmonitored activity, and analysts' jobs are not dependent on target price forecast accuracy (e.g. Bonini et al., 2010). Nonetheless, we present evidence that the concern regarding exclusions is warranted.

As the first attempt to link exclusions and target prices, we cannot offer a definitive explanation as to why this relationship exist. We postulate that the positive association between exclusions and forecast error (and negative association between exclusions and the target price being met) might be partially explained by relative valuation such as price-to-earnings ratios, which literature finds are consistently-used methods for determining target prices. If this is the case, marginal exclusions could cause significant differences in the target price, depending on the exclusion decision.

In addition to our main findings, we attempt to further investigate the effects of exclusions by distinguishing between both income- and expense-related exclusions as well as incremental- and special-item exclusions. We find that expense-related and special-item exclusions contribute to overall forecast accuracy. Given that these items consist primarily of objective (special) items, this presents evidence that analysts are more accurate when not making additional (incremental) exclusions. Given their vital role in the capital markets as intermediaries of financial information, this questions their expertise and suggests that analysts' additional exclusions don't add any value to the target price forecasting process.

Contributions

Our study is fruitful to the target price literature, but also for its contribution to the ongoing debate regarding the value relevance of non-GAAP earnings exclusions. We employ a model that controls for several analyst-related factors and a number of firm-specific control variables based on the prevailing research within the target price forecast accuracy studies. We provide some resolution to the conflicting opinions of how certain firm-specific factors affect forecast accuracy, such as market-to-book ratios and share price momentum. Furthermore, we observe a period that has so far not been studied in forecast accuracy research, providing insight into how macroeconomic factors affect analysts' exclusions and target prices. Our most significant research contribution however is the identification of analysts' exclusions as inhibiting overall forecasting ability. We also provide evidence that different types of exclusions affect forecast accuracy differently.

Finally, our study highlights the importance of a broader question that has received limited attention in prior studies: what exactly is target price accuracy? While prior research has employed similar models to our study, few have commented on target price forecast accuracy in such a way as to consider the differing definitions. Considering a multifaceted approach allows for a more comprehensive assessment of forecast accuracy and an understanding of the drivers for error and accuracy. Our findings reinforce the idea that these measures must be used in conjunction with one another to be able to more easily understand target price accuracy.

7 Limitations

This study is subject to several limitations. These include factors such as omitted variables, timing differences, and database-related issues. While we do not believe that the reliability of our results are heavily affected by these factors, we acknowledge the possibility.

Omitted Variable Limitations

First, the derivation of our model was based on a small number of prior studies that aimed to examine different determinants of target price forecast accuracy. Analysts' individual abilities and ties to brokerage houses have been shown to affect accuracy for a variety of reasons. Clement (1999) found a negative relationship between earnings forecast accuracy and number of firms followed. Mikhail et al. (1997) argue that accuracy is also correlated with the analysts' own experience with the firm. These associations have been confirmed in target price studies. In their study observing the characteristics of individual analysts, Bradshaw, Brown, & Huang (2013) found a negative relationship with accuracy and numbers of firms followed as well as number of industries covered. This is consistent with the notion that the more an analyst's attention is spread across a number of firms or industries, the less they can specialize and focus. Bradshaw, Brown, & Huang (2013) also found a positive relationship between analyst-specific experience and past accuracy. Furthermore, the size of the brokerage house the analyst is employed by was similarly correlated with higher accuracy, in line with the idea that accuracy improves with higher availability of resources. Although these analyst-specific factors cannot be controlled for, we have attempted to control for other analyst-*related* control factors like earnings forecast error, disagreement, and total firm coverage. Moreover, a consensus-based measure however alleviates other influential factors such as analysts' own incentives, compensation and motivation to generate investment banking business that have been also shown to affect accuracy (Bradshaw, Brown, & Huang, (2013); Baik et al., 2009; Brown et al., 2015). Furthermore, given the finding by Bradshaw (2002) that analysts tend to issue target prices in conjunction with favorable recommendations, using consensus numbers ensures available target price data for every quarter, where it might otherwise be disregarded by analysts following an unfavorable recommendation.

A more recent study by Bilinksi et al. (2013) identified an additional set of factors that affect target price accuracy. In their study observing a number of different countries, they find that institutional and regulatory factors such as enforcement of accounting standards, quality of accounting disclosures and concentration of ownership were notable determinants of forecast accuracy across countries. In general, they find that higher disclosure quality is positively associated with target price accuracy whereas enforcement has a negative association. This, they argue, is attributed to the fact that more strict adherence to accounting standards increases the amount of transitory items included in net income, thereby reducing predictability of future earnings. As this study focuses exclusively on companies in the United States, these factors are not controlled for.

Regression Model Limitations

Our study was conducted under the assumption that sell-side analysts make exclusion decisions and target price forecasts that are period dependent and are not heavily influenced by prior period (i.e. autocorrelated). Had we assumed forecasts were interrelated we would have employed a panel data analysis, would have considered autocorrelation, and subsequently given slightly different regression results. We do not believe these would be significantly different from our results. Furthermore, we have attempted to take care of this potential issue in the fixed effects regression in section 5.3.1, which showed that our results still hold.

Timing Limitations

Stock price returns have been shown to affect target price forecast accuracy. Studies find sometimes-significant stock price movements in the days preceding the announcement of target price forecasts as the market anticipates the forecasts. Since we use median figures, we are unable to identify a specific date that these forecasts are made and are therefore unable to perfectly control for these movements. We believe, however, that these considerations would not meaningfully impact our results.

Target prices are not forecasted at only one point in time, but are generally revised. Prior target price studies have occasionally considered this in their studies, though, as we were interested in the accuracy from initial forecast date, we have considered simply the initial forecast and compared it with the actual price twelve months later. Were we to consider revisions, our accuracy and error results would likely be affected and biased towards higher overall accuracy.

Our chosen time period that encompasses the financial crisis has, in some cases, strong impacts on the dataset. This was intentional, as we were curious to see the effects of the financial crisis on target price forecast accuracy. However, these impacts might have yielded results that are not representative of more general findings regarding exclusions and target price accuracy. We do not believe this is the case, but we acknowledge the impact of the financial crisis.

Database-related Limitations

The databases we have used – I/B/E/S, Compustat, and CRSP – are not without their own set of limitations. These databases are vulnerable to input error where numbers can be incorrectly entered and therefore influence the dataset. We winsorize our data in part to remove the likelihood that these errors affect our results. I/B/E/S receives analysts' information, but does not receive information regarding exactly what exclusions were made. Thus, when determining consensus (median) forecasts, I/B/E/S must themselves back out the implied exclusions made by analysts. They then apply the "majority rule" to the consensus forecast, where they consider the majority of exclusions (backed out) and apply this to the actual earnings. Therefore, our study does not perfectly reflect the exact exclusions made by analysts, but rather the implied exclusions by I/B/E/S.

Generalizability

We believe our results are generalizable and applicable to other contexts, including different time spans, geographies, and capital markets. However, as previously explored, institutional and regulatory factors have been shown to affect how accounting information is presented by firms and how analysts' make forecasts. These factors, while not hindering a similar research design, might affect the comparability of the results. Moreover, differing capital markets might have varying numbers of analysts that make target price forecasts, limiting the overall reliability of the findings.

8 Future Research Potential

As our study constitutes (to our knowledge) the first attempt to link exclusions to target prices, we believe our findings open several avenues for future research for both target price studies and exclusions. Prior studies have identified analyst- and brokerage house-specific factors as determinants of target price forecast accuracy. Future research might therefore use analyst-specific data rather than consensus (median) data to identify if the association between exclusions and forecast error holds. This would facilitate cross-sectional analysis of other control variables as mentioned above, and more closely analyze how exclusions affect target price forecast error on the individual analyst level.

Future studies might also attempt to further explore the distinction between positive and negative exclusions, and between special-item and incremental-item exclusions. Our findings suggest that it is expense and special-item exclusions that lend to increased forecast accuracy. Christensen et al. (2011) problematize the fact that analysts follow managements' exclusions, arguing that analysts simply become agents for echoing managements' pro forma earnings. They find that analysts have a tendency to follow managements' incremental (subjective) exclusions through pro forma earnings guidance. Since we document that accuracy is decreased when incremental exclusions are made, future research could control for management's influence and provide an interesting perspective on Christensen et al.'s (2011) study with regards to how management's guidance affects target price formulation.

Our study suggests that exclusions are associated with higher forecast error. Because investors, to some extent, pay attention to target prices, there are value implications for the capital markets. Therefore, future research might try to deduce what type of earnings yields the most consistently accurate target prices (i.e. street, GAAP or otherwise). In line with the suggestion above, research might attempt to find whether target prices are more accurate when certain exclusions are themselves "excluded" from earnings derivation. This would provide further insight into whether street earnings represent the best alternative to other measures, despite the negative implications of exclusions for overall target price forecast accuracy.

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Appendix

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Figure 1 ***Summary of Variables Used Throughout the Study***

Variable	Expected Sign (*aTPE* / *TP_Met_Any* / *TP_Met_End)*	Definition
Dependent Variables:		
aTPE		Absolute target price forecast error, measured as the difference between forecast price and actual price;
TP_Met_Any		indicator variable taking the value of 1 if target price is met or exceeded at some point during the forecast period, and 0 otherwose;
TP_Met_End		indicator variable taking the value of 1 if target price is met or exceeded at forecast period end date.
Control Variables:		
aEXCL	+ / – / –	exclusions for the period specified as the absolute difference between analysts' actual earnings per share and GAAP earnings per share, scaled by stock price;
aEFE	+ / – / –	Absolute earnings forecast error in the corresponding period scaled by stock price;
Neg_GPS	+ / – / –	an indicator variable that takes the value of 1 for firms with losses for the previous quarter;
Imp_Ret	+ / – / –	implicit return of the target price forecast if the target price is met at the end of the forecast;
LMV	– / + / +	log of market value of equity;
MB	? / ? / ?	market-to-book ratio to gauge the likelihood of the stock being over or undervalued;
LVOL	– / + / +	the trading volume of the firm that gauges its market liquidity;

COV	+ / + / ?	coefficient of variance specified as the standard deviation of share price in the previous quarter, divided by the mean of the share price for the previous quarter. Used to estimate the prior quarter's volatility;
Beta	+ / + / ?	firm's market beta to estimate the volatility of the share price for the entire year;
DISP	+ / – / –	the dispersion of analysts' forecasts, or "disagreement", specified as the standard deviation;
MOM	? / + / +	momentum of the share price in previous quarter;
Mark_Ret	? / + / +	the growth of the overall market in previous quarter;
Coverage	– / + / +	analyst coverage of the firm;
IND	*Dummy*	dummy variable to allow observations across different industries;
Year	*Dummy*	dummy variable to allow observations across different years;

Other Variables:

EPS_Street	Analysts' quarterly *forecast* earnings obtained by I/B/E/S;
EPS_Actual	reported earnings adjusted for majority rule exclusions by I/B/E/S;
EPS_GAAP	quarterly GAAP earnings obtained by Compustat;
EXCL_Pos	positive exclusions if EPS_Street > EPS_GAAP; indicative of expense-related exclusions;
EXCL_Neg	negative exclusions if EPS_Street < EPS_GAAP; indicative of income-related exclusions
EXCL_Spec	Special-item exclusions per share;
EXCL_Incr	Incremental-item exclusions per share, specified as the difference between total exclusions and special-item exclusions.
Neg_TP_Forecast	indicator variables for whether target price is below stock price at forecast date;
EXCL_Dummy	indicator variable for when street EPS_Actual ≠ EPS_GAAP, i.e. exclusions were made;
Signed_EXCL	exclusions including their sign (+/–).

Figure 2 ***Accuracy Measures Across Industries***

Industry	*aEXCL/share ($)*	*aTPE*	*TP_Met_Any*	*TP_Met_End*
Aerospace & Defense	0.13	22.4%	73.1%	47.4%
Air Freight & Logistics	0.12	21.9%	50.0%	26.0%
Airlines	0.83	70.0%	38.6%	22.8%
Auto Components	0.55	69.6%	47.6%	26.6%
Automobiles	1.74	55.4%	74.4%	50.0%
Banks	0.49	76.4%	64.8%	34.5%
Beverages	0.24	25.4%	61.9%	35.3%
Biotechnology	0.31	41.6%	50.2%	31.7%
Building Products	0.25	37.0%	58.8%	23.5%
Capital Markets	0.34	40.8%	68.4%	41.0%
Chemicals	0.21	27.4%	66.7%	42.6%
Commercial Services & Supplies	0.20	29.8%	49.1%	26.9%
Communications Equipment	0.15	36.9%	64.8%	42.3%
Construction & Engineering	0.20	39.5%	53.6%	35.7%
Construction Materials	0.11	25.0%	87.9%	39.4%
Consumer Finance	0.20	34.1%	63.3%	29.1%
Containers & Packaging	0.31	34.3%	52.7%	33.5%
Distributors	0.01	17.5%	67.6%	50.0%
Diversified Financial Services	0.67	46.2%	59.9%	32.2%
Diversified Telecommunication Ser	0.20	26.6%	61.3%	36.5%
Electric Utilities	0.19	33.8%	68.2%	39.4%
Electrical Equipment	0.26	41.2%	45.4%	26.9%
Electronic Equipment, Instruments	0.16	55.0%	39.4%	16.1%
Energy Equipment & Services	0.22	44.4%	54.9%	26.2%
Food & Staples Retailing	0.12	21.6%	67.6%	42.6%
Food Products	0.26	48.8%	53.5%	32.3%
Gas Utilities	0.13	27.1%	71.8%	32.1%
Health Care Equipment & Supplies	0.23	24.9%	60.6%	31.7%
Health Care Providers & Services	0.28	57.5%	52.4%	31.8%
Health Care Technology	0.27	60.8%	25.0%	7.5%
Hotels, Restaurants & Leisure	0.21	35.7%	74.5%	44.1%
Household Durables	0.27	36.9%	62.2%	33.9%
Household Products	0.26	31.9%	33.8%	26.5%
IT Services	0.41	62.8%	51.3%	32.0%
Independent Power and Renewable E	0.63	118.7%	48.5%	27.6%
Industrial Conglomerates	0.11	25.0%	55.6%	36.8%
Insurance	1.44	45.5%	59.8%	34.5%
Internet & Catalog Retail	0.35	69.3%	68.5%	46.9%
Internet Software & Services	0.54	58.0%	51.6%	31.5%

Leisure Products	0.19	32.9%	72.5%	48.0%
Life Sciences Tools & Services	0.19	21.5%	69.1%	46.0%
Machinery	0.40	44.6%	59.8%	37.1%
Media	0.30	60.4%	60.7%	41.4%
Metals & Mining	0.63	57.7%	51.2%	26.8%
Multi-Utilities	0.16	18.0%	74.4%	42.8%
Oil, Gas & Consumable Fuels	0.53	41.3%	58.3%	30.6%
Paper & Forest Products	0.36	43.9%	77.3%	37.9%
Personal Products	0.07	32.5%	58.8%	29.4%
Pharmaceuticals	0.29	21.6%	62.5%	39.4%
Professional Services	0.10	19.3%	77.9%	37.5%
Real Estate Investment Trusts (RE	0.17	29.8%	82.6%	45.7%
Real Estate Management & Developm	0.30	52.1%	64.5%	32.3%
Road & Rail	0.38	47.4%	57.5%	36.8%
Semiconductors & Semiconductor Eq	0.16	38.1%	61.4%	27.2%
Software	0.16	24.9%	70.2%	35.1%
Specialty Retail	0.37	49.7%	67.2%	39.7%
Technology Hardware, Storage & Pe	0.28	46.3%	61.6%	34.3%
Textiles, Apparel & Luxury Goods	0.59	58.4%	46.8%	26.6%
Thrifts & Mortgage Finance	0.12	62.6%	48.5%	23.5%
Tobacco	0.32	31.2%	60.0%	40.0%
Trading Companies & Distributors	0.13	28.0%	58.8%	42.6%
Wireless Telecommunication Servic	0.30	98.6%	48.1%	22.2%

Description: This table presents descriptive statistics for absolute size of exclusions, and our accuracy (and error) measures. We use absolute size of exclusions (as opposed to mean) to capture the total size of all exclusions, regardless of sign (+/–).

Figure 3 ***Summary Results of Relationship Between Exclusions and Accuracy Measures***

	aTPE	***TP_Met_Any***	***TP_Met_End***
aEXCL	+	–	–
EXCL_Spec	–	*NS*	+
EXCL_Incr	+	–	–
EXCL_Pos	–	+	+
EXCL_Neg	+	–	–

Description: this table presents our results for our regressions and the signs indicating a positive (+) or negative (–) relationship. Non-significance is denoted by (*NS*).

Figure 4 S&P 500 Company List

1ST DATA	BRUNSWICK CP	DOW CHEMICAL	HERCULES INC	MEDIMMUNE INC	PRICELINE.COM	THE BANK OF NEW
3M CO	BURLINGTON NRTHN	DOW JONES & CO	HERSHEY	MEDTRONIC INC	PRINCIPAL FINANC	THERMO ELECTRON
5TH 3RD BCP OH	C R BARD INC	DR PEPPER SNAPPL	HERSHEY FOODS	MELLON FIN. CORP	PROGRESSIVE OHIO	THERMO FISHER SC
7-ELEVEN INC	C.H. ROBINSON WW	DTE ENERGY	HESS CORP	MERCK & CO	PROLOGIS	THOS & BETTS
A T & T CP	C.I.T. GROUP INC	DUKE ENERGY CORP	HILTON HOTELS	MERCURY INTERACT	PROVIDIAN FINL	TIFFANY AND COMP
ABBOTT LABS	CA INC	DUN&BRADSTRT	HJ HEINZ	MERRILL LYNCH	PRUDENTIAL FIN	TIME WARNER CABL
ABBVIE	CABLEVISION SYS	DYNEGY INC	HLTHSOUTH CP	METLIFE INC	PUB SVC ENTERS	TITANIUM METALS
ABERCROM & FITCH	CABOT OIL & GAS	E I DUPONT	HOME DEPOT INC	METROPCS COMM	PUBLIC STORAGE	TJX COS INC
ACE LTD	CAESARS ENTERT	E*TRADE FINANCIA	HONEYWELL INTL	MGIC INVT CORP W	PULTE HOMES INC	TORCHMARK CP
ACTAVIS INC	CALPINE CORP	EASTMAN CHEMICAL	HOSPIRA	MICHAEL KORS	PVH CORP	TOTAL SYSTEM SVC
ADC TELECOM	CAMERON INTL	EASTMAN KODAK	HOST HOTELS & RE	MICROCHIP TECH	QEP RESOURCES IN	TRANE INC
ADV MICRO DEVICE	CAPITAL ONE FINL	EATON CORP	HUDSON CITY BANC	MILLIPORE CP	QLOGIC CORP	TRANSOCEAN INC
AES CORP	CAREMARK RX INC	EATON CP	HUMANA INC	MOHAWK INDS INC	QUANTA SERVICES	TRAVELERS COS IN
AETNA INC	CARMAX INC.	EBAY INC	HUNTINGT BCSH OH	MOLSON COORS	QUEST DIAGNOSTIC	TRIBUNE CO
AFFILIATED COMP	CATERPILLAR INC	ECOLAB INC	IAC/INTERACTIVE	MONDELEZ INT	QUESTAR CP	TRIPADVISOR INC
AFLAC INC	CB RICH ELLIS GR	EDISON INTL	ILL TOOL WORKS	MONSTER BEVERAGE	QWEST COMMUNIC	TUPPERWARE
AGL RESOURCES	CBRE GROUP INC	EDS	IMS HEALTH INC	MONSTER WORLDWIDE	RALPH LAUREN COR	UNION PACIFIC CP
AIRGAS INC	CBS CORP	EDWARDS LIFESC	INGERSOLL-RAND	MOODY'S CORP.	RANGE RESOURCES	UNION PLANTER TN
AK STEEL HOLDING	CELGENE CP	EL PASO CO	INTEGRYS ENERGY	MORGAN STANLEY	RAYTHEON CO	UNISYS CP
AKAMAI TECH	CENTERPOINT ENER	ELECTRONIC ARTS	INTEL CP	MOSAIC CO	REALOGY HOLDINGS	UNITEDHEALTH GRP
ALBERTO-CULVER	CENTEX CP	ELECTRONIC DATA	INTERACTIVE CORP	MOTOROLA SOLUTIO	RED HAT INC	UNIVISION COMMS
ALBERTSONS INC	CENTURYLINK INC	ELI LILLY	INTERCONTINENTAL	MURPHY OIL CP	REEBOK INTL LTD	UNOCAL CP
ALCOA INC.	CEPHALON INC	EMBARQ CORP	INTERPUBLIC GRP	MYLAN LABS INC	REGENERON PHARMA	UNUM GROUP
ALEXION PHARM	CERNER CP	EMC CP MASS	INTL BUS MACH	NABORS INDS LTD	REGIONS FINL COR	UNUMPROVIDENT
ALLEGHENY ENERGY	CF INDUSTRIES	ENERGYSOLUTIONS	INTL FLAV & FRAG	NASDAQ OMX GROUP	REPUBLIC SERVICE	URBAN OUTFITTERS
ALLEGIANT BANC	CHARLES SCHWAB	ENGELHARD CP	INTL PAPER CO	NATIONAL OILWELL	REYNOLDS AMERICA	US BANCORP
ALLERGAN INC	CHARTER 1 FIN OH	ENSCO INTL	INTUITIVE SURGIC	NATL CITY CP OH	ROBERT HALF INTL	US STEEL CORP
ALLIANCE DATA	CHESAPEAKE ENERG	ENSCO PLC	INVESCO LTD	NATL SEMICON	ROHM & HAAS	UST INC
ALLIED WASTE IND	CHEVRON TEXACO	ENTERGY CP	INVESCO PLC	NAVISITE INC	ROPER INDS INC	UTD PARCEL SVC
ALLSTATE CP	CHICAGO MERCANTI	EOG RESOURCES	IRON MOUNTAIN	NCR CORPORATION	ROSS STORES INC	UTD TECH
ALLTEL CP	CHIPOTLE MEXICAN	EQUIFAX INC	ITT INDUS INC	NETAPP INC	ROWAN COS	VALERO ENERGY CP

S&P 500 cont.

ALPHA NATURAL RE	CHIRON CP	EQUITY OFFICE	JANUS CAPITAL	NETFLIX INC.	RR DONNELLEY	VENTAS INC
ALTERA CP	CHUBB CP	EQUITY RESID	JC PENNEY	NEW YORK TIMES	RYDER SYS	VERISIGN INC
ALTRIA GROUP INC	CIGNA CP	EXELON CORP	JEFFERSON-PILOT	NEWELL RUBBER	SABRE HOLDINGS C	VERITAS SOFTWARE
AMAZON.COM INC.	CINERGY CORP	EXPEDIA INC	JOHN HANCOCK	NEWFIELD EXPLORA	SAFECO CP	VERIZON COMM
AMER TOWER CP-A	CINN FINANCIAL	EXPEDITORS INTL	JOHNSON & JOHNSN	NEWMONT MNG HLD	SAFEWAY INC	VERTEX PHARMACEU
AMEREN CP	CINTAS CP	EXPRESS SCRIPTS	JONES APPAREL GR	NEWS CORP A SHS	SALESFORCE.COM I	VF CP
AMERICAN CAPITAL	CIRCUIT CITY	EXXON MOBIL CORP	JONES GROUP INC	NEXTEL COMMUN	SANDISK CORP	VIACOM INC
AMERIPRISE FINAN	CITIGROUP INC.	FACEBOOK INC	JP MORGAN CHASE	NEXTERA ENERGY I	SANTANDER BANC	VIRTUS INVESTMEN
AMERN ELEC PWR	CITRIX SYSTEMS	FANNIE MAE	JUNIPER NETWORKS	NICOR INC	SCANA CP	VISTEON
AMERN EXPRESS	CLEVELAND CLIFFS	FASTENAL CO	KANSAS CITY SO	NIELSEN HOLDING	SCHERING-PLO	VORNADO RLTY TR
AMERN GREETINGS	CLIFFS NATURAL R	FEDERATED INVEST	KELLOGG CO	NIKE INC	SCHLUMBERGER LTD	VULCAN MATLS CO
AMERN INTL GROUP	CME GROUP INC	FEDEX CORP	KERR-MCGEE	NISOURCE INC	SCI ATLANTA	WACHOVIA CORP
AMERN PWR CONVER	CMS ENERGY CORP	FIDELITY NATNL I	KEYCORP	NOBLE ENERGY INC	SCRIPPS NETWORKS	WAL-MART STRS
AMETEK INC	COCA COLA CO	FIRST HORIZON	KEYSPAN CP	NORDSTROM INC	SEALED AIR CP	WASH MUTUAL INC
AMGEN	COGNIZANT TECH	FIRST SOLAR	KIMBERLY CLARK	NORFOLK SOUTHERN	SEARS, ROEBUCK	WASTE MGMT. INC
AMPHENOL CORP	COLGATE PALMOLVE	FIRSTENERGY CORP	KIMCO REALTY COR	NORTH FK BCPN NY	SEMPRA ENERGY	WATERS CORP
AMSOUTH BCP AL	COMCAST	FISERV INC	KINDER MORGAN	NORTHN TR CP IL	SHERWIN-WMS	WEATHERFORD INTL
ANADARKO PETE CO	COMERICA INC MI	FISHER SCI INTL	KING PHARM	NORTHN TRUST	SIEBEL SYSTEMS	WELLPOINT HEALTH
ANDREW CP	COMMERCE BANCORP	FLEET BOSTON FIN	KNIGHT RIDDER IN	NORTHROP GRUMMAN	SIGMA ALDRICH	WELLS FARGO
ANHEUSER BUSCH	COMP SCIENCES	FLIR SYSTEMS	KOHLS CORP	NOVELL INC	SIGMA-ALDRICH	WENDYS INTL INC
ANTHEM INC	COMPUWARE CORP	FLOWSERVE CORP	KRAFT FOODS GROU	NOVELLUS SYSTEMS	SIMON PROPERTY	WESTERN UNION CO
AON CP	COMVERSE TECH	FLUOR CORP	KROGER	NRG ENERGY INC.	SMITH INTL INC	WEYERHAEUSER CO
APACHE CP	CONAGRA FOOD INC	FMC TECH	L-3 COMMUN HLDGS	NUCOR CP	SMUCKER, JM 'A'	WHIRLPOOL CP
APART INV & MGMT	CONCORD EFS	FORD MOTOR CO	LA PACIFIC CORP	NVIDIA CORP	SNAP-ON INC	WILLIAMS COS
APPLIED MICRO	CONOCOPHILLIPS	FOREST LABS	LABORATORY CORP	NYSE EURONEXT	SOLECTRON CORP	WINDSTREAM
ARCH-DAN-MIDLAND	CONS EDISON INC	FOSSIL INC	LEGG MASON INC	NYSE GROUP INC	SOUTHN CO	WINN-DIXIE STORE
ARCHSTONE SMITH	CONSOL ENERGY	FREDDIE MAC	LEGGETT & PLATT	O'REILLY AUTO	SOUTHTRUST CP AL	WISCONSIN ENERGY
ASSURANT INC	CONSOLIDATED EDI	FREESCALE SEMICO	LEHMAN BRO HLDG	OCCIDENTAL PETE	SOUTHWEST AIRLS	WM WRIGLEY JR
AT&T INC	CONSTELLAT BRAN	FRONTIER COMM	LEUCADIA NATL	OFFICE DEPOT	SOUTHWSTN ENERGY	WORTHINGTON INDS
AUTODESK INC	CONVERGYS GROUP	FRPT MCMO COPPER	LEXMARK INTL INC	OFFICEMAX	SPECTRA ENERGY	WPX ENERGY INC
AUTONATION INC.	COOPER CAMERON	GAMESTOP CORP	LIFE TECHNOLOGIE	OMNICOM GROUP	SPRINT CORP PCS	WW GRAINGER
AVALONBAY COMM	COOPER INDS LTD	GANNETT INC	LINCOLN NATL	ONEOK INC	SPRINT NEXTEL	WYETH

S&P 500 cont.

AVERY DENNISON	COOPER TIRE	GAP INC	LOCKHEED MARTIN	ORACLE CORP	ST JUDE MEDICAL	WYNDHAM WORLDWID
AVIS BUDGET GROU	CORNING INC.	GARMIN	LOEWS CP	OWENS ILLINOIS	ST PAUL COS INC	WYNN RESORTS
AVON PRODS INC	COVENTRY HLTH	GATEWAY INC	LORILLARD INC	P G & E CORP	STANLEY BLACK	XCEL ENERGY INC
BAKER HUGHES INC	CRANE CO	GEN DYNAMICS	LOWES CO	PACCAR INC	STANLEY WORKS	XEROX CP
BALL CP	CROWN CASTLE INT	GEN ELECTRIC US	LSI CORP	PACTIV CORP	STAPLES INC	XILINX
BANK OF AMERICA	CSX CP	GEN GROWTH PROP	LUCENT TECH	PATTERSON COMPAN	STARWOOD H&R	XL CAP LIMITED
BANK OF NEW YORK	CTRYWIDE FINCL	GEN MILLS INC	LYONDELLBASELL I	PAYCHEX	STATE STREET	XL GROUP PLC
BANK OF NY CO IN	CUMMINS INC	GEN MOTORS CP	M & T BANK CORP	PEABODY ENERGY	STERICYCLE INC.	XTO ENERGY INC
BANK ONE CP OH	CVS CAREMARK COR	GENERAL MOTORS	MACERICH COMPANY	PENTAIR INC	STRYKER CP	XYLEM INC
BARR INC	CVS CORP	GENON ENERGY	MACY'S INC	PEOP ENERGY CP	SUN MICROSYSTEMS	YAHOO! INC
BAUSCH LOMB	DANA HLDG CORP	GENUINE PARTS	MANITOWOC INC	PEOPLES BANK CT	SUNGARD DATA SYS	YUM! BRANDS INC
BAXTER INTL	DANAHER CP	GENWORTH FINANCI	MANOR CARE	PEOPLES UNITED F	SUNOCO INC	ZIMMER HOLDINGS
BB&T CP	DARDEN REST INC	GENZYME	MARATHON OIL CP	PEOPLESOFT INC	SUNTRUST BKS GA	ZIONS BANCORP
BEAM INC	DAVITA INC	GEORGIA-PACIFIC	MARATHON PETROLE	PEPCO HOLDINGS	SUPERVALU INC	ZOETIS INC
BEAR STEARNS	DDR CORP	GILEAD SCIENCES	MARRIOTT INTL	PEPSICO INC	SYMANTEC CORP	
BED BATH & BEYON	DEAN FOODS CO	GILLETTE CO	MARSH & MCLENNAN	PERKINELMER INC	SYMBOL TECH	
BELLSOUTH CP	DELL INC	GOLDEN W FINL CA	MARSHALL& ILSLEY	PETSMART INC	SYNOVUS FINL COR	
BEMIS INC	DELPHI AUTOMOTIV	GOLDMAN SACHS	MASCO CP	PFIZER INC	T ROWE GROUP	
BERKSHIRE HATHAW	DELTA AIR LINES	GOODRICH CORP	MASSEY ENERGY	PHELPS DODGE	TARGET CORP	
BEST BUY INC	DELUXE CORP	GOODYEAR TIRE	MASTERCARD	PHILIP MORRIS IN	TECO ENERGY INC	
BIG LOTS INC	DENBURY RESOURCE	GOOGLE	MATTEL INC	PHILLIPS 66	TEKTRONIX INC	
BIOGEN IDEC INCO	DENTSPLY INTL	GRT LAKES CHEM	MAY DEPT STORES	PINNACLE WST CAP	TELLABS	
BJ SVCS CO	DEVEL DIVER RLTY	GUIDANT CORP	MAYTAG CP	PIONEER NAT RES	TEMPLE INLAND IN	
BLACK & DECKER	DEVON ENERGY COR	H&R BLOCK	MBIA INC	PITNEY/BOWES	TENET HEALTHCARE	
BLACKROCK INC	DIAMOND OFFSHORE	HALLIBURTON	MBNA CORP	PLUM CREEK TIMBE	TERADATA	
BMC SOFTWARE	DILLARD INC	HARLEY-DAVIDSON	MCAFEE	PMC-SIERRA INC	TERADYNE INC	
BOEING CO	DIRECTV	HARTFORD FIN SVC	MCDERMOTT INTL	PNC FIN SER	TEREX CP	
BORGWARNER INC	DISCOVERY HOLDIN	HASBRO INC.	MCDONALDS CP	POWER-ONE INC.	TESORO	
BOSTON PROP	DOLLAR GENERAL	HCA HOLDINGS INC	MCKESSON CORP	PP&L CORP	TESORO PETE	
BOSTON SCIENTIFI	DOLLAR TREE INC	HCP INC	MEAD JOHNSON NUT	PPG INDS	TEXAS INSTRS	
BRISTOL-MYERS SQ	DOMINION RES INC	HEALTH CARE REIT	MEADWESTVACO CP	PRAXAIR	TEXAS INSTRUMENT	
BROADCOM CP CL A	DOVER CP	HEALTH MANAGEMET	MEDCO HEALTH SOL	PRECISION CSTPTS	TEXTRON	

Figure 5 ***Summary Statistics for non-Winsorized Data***

Variable	*Observations*	*Mean*	*Standard deviation*	*Min*	*Max*
aTPE	13933	0.52	1.65	0	44.94
TP_Met_Any	13783	0.61	0.49	0	1
TP_Met_End	13431	0.35	0.48	0	1
aEXCL	15457	0.38	2.62	0	61.24
EXCL_Spec	15102	0.03	0.50	0	40.64
EXCL_incr	15102	0.06	1.43	0	27.66
EFE	15671	0.27	2.11	-29.00	51.00
Coverage	15702	12.48	6.14	1.00	42.00
COV	15067	0.06	0.06	0	1.01
LVOL	15067	14.76	1.07	11.01	20.53
Mark_Ret	15585	0.02	0.07	-0.24	0.13
MOM	15422	0.04	0.50	-0.92	37.03
Beta	12611	1.19	0.57	-0.14	4.66
LMV	13088	9.24	1.17	2.79	13.13
MB	13026	3.05	6.18	-98.93	98.73
DISP	15602	5.66	8.02	0	289.00
Imp_Ret	14229	0.28	2.12	-0.96	94.54
Neg_GPS	13800	0.11	0.32	0	1
EXCL_Pos	15457	0.57	0.49	0	1
EXCL_Dummy	15457	0.86	0.35	0	1
Neg_TP_Forecast	13783	0.22	0.42	0	1

Description: This table presents the summary descriptive statistics for the raw, non-Winsorized data.