

2 Analysts' general forecast effort as determinant of earnings forecast accuracy

In this chapter, I introduce a new variable to measure the forecast effort an analyst devotes when making earnings forecasts. The main idea of my measure is considering not only the forecast effort that can be derived from an analyst's behavior for one specific firm, but also an analyst's general behavior with respect to other firms. Thus, I label my new effort measure "general forecast effort" and provide empirical evidence that it can explain differences in analysts' forecast accuracy. The following ideas and analyses largely base on my research study "How to measure Analyst Forecast Effort" which will be published as journal article in the *European Accounting Review*.⁶ I have presented this study at the 34th European Accounting Association Annual Congress in Rome (2011), at the American Accounting Association Annual Meeting in Denver (2011) and at the Accounting Seminar for doctoral students at the University of Cologne.

This chapter is organized as follows. I give an introduction in Section 2.1. In Section 2.2, I present a literature review and develop my hypotheses. I describe the research design and data sample in Section 2.3 and present the results in Section 2.4. In Section 2.5, I validate the explanatory power of my general forecast effort measure via a falsification test. Section 2.6 serves as conclusion.

2.1 Introduction

Analysts' earnings forecasts differ significantly regarding forecast accuracy. Accordingly, a large stream of earnings forecasting literature (e.g. Clement, 1999; Brown, 2001; Keung, 2010) identifies systematic differences in analyst characteristics (e.g. forecasting experience or available resources) that explain differences in forecast accuracy. It appears obvious that analysts who devote more time and effort can provide more accurate forecasts. Thus, a measure of "forecast effort" could help investors as well as researchers to identify accurate

⁶ See Gell et al. (2014). A very early version of this paper is included in the doctoral thesis of one of my coauthors; see Gell (2011).

forecasts.⁷ Thereby, investors could raise their expected returns and accounting researchers could improve their earnings prediction models.

In this context, the question arises how analysts' forecast effort can be measured. Commonly, the measure suggested by Jacob et al. (1999) is applied and the effort that an analyst devotes to the forecasts of a specific Firm X is measured from the number of forecasts the analyst issues for that specific firm, i.e. analysts revising forecasts for Firm X more frequently are assumed to devote more effort to that firm. I argue that this measure only takes available information on analyst behavior with respect to Firm X into consideration and believe that a firm-specific measure cannot fully capture forecast effort. I suggest that an effort measure should also consider analyst behavior regarding other firms; i.e. it should measure the analyst's *general* willingness to revise forecasts. Thus, I introduce such a measure and examine the effort an analyst *generally* devotes to forecasting earnings. I assume that analysts differ systematically in forecast effort and that an analyst who *generally* devotes more forecast effort than other analysts is likely to also devote more effort when forecasting a specific Firm X, although this effort might not be captured by a firm-specific measure.

I argue that a firm-specific measure cannot capture an analyst's entire effort because there might be reasons apart from low effort why the analyst does not revise her forecasts for a specific firm as frequently as other analysts. Imagine that Analyst A devotes more effort to the information research process than Analyst B. Due to her intensive research, A's information is superior, but A might consider her most recent forecast for Firm X as correct and thus not revise it. Therefore, an absent revision may merely be the result of a good outstanding forecast. However, a low number of forecast revisions is commonly interpreted as inferior information resulting from less forecast effort. On the other hand, Analyst B might revise her forecasts more frequently, because new public information (that is already included in A's forecast) is now available to her. I argue that an analyst who devotes high effort will revise her forecasts if necessary, but in some cases she might regard a revision as unnecessary. In those cases, a measure that is concentrated only on one Firm X might be too

⁷ I label the time and effort an analyst devotes when making forecasts as "forecast effort". For convenience, I use the term "high forecast effort" to describe that an analyst devotes a considerable amount of time and effort to her forecasts.

restrictive and could result in misleading inferences on the effort. I develop a measure that is based on the analyst's *general* behavior for all firms she covers. My measure reduces the noise that might distort the result when concentrating on only one firm.

I argue that my general effort measure can explain incremental differences in forecast accuracy that cannot be explained by the commonly applied firm-specific effort measure. I base my measure on the average number of forecasts an analyst issues for the firms she covers, and investigate the relationship between this measure of analyst's forecast effort and the accuracy of her earnings forecasts by enhancing Clement's (1999) regression approach. Several studies (e.g. Brown, 2001; Call et al., 2009) have enriched Clement's approach and identified additional forecast accuracy determinants. I control for those influencing factors and for the firm-specific effort measure, and find that my general effort measure has higher explanatory power regarding differences in forecast accuracy than the firm-specific measure (7.46% vs. 3.10%).

In order to validate my new effort measure I perform several additional analyses. I find that a higher [lower] level of forecast effort leads to better [worse] career perspectives, as I provide empirical evidence that analysts who expend higher [lower] forecast effort are more likely to move to a brokerage house of higher [lower] prestige in the next period. I also examine which factors influence the forecast effort an analyst devotes and find that analysts who face a portfolio of many new and unfamiliar firms expend more forecast effort to compensate for their lack of experience with the respective firms. Additionally, I find that forecast effort is determined by analyst's motivation resulting from the satisfaction from her previous career development: analysts who moved to a brokerage house of higher [lower] prestige within the last two years expend a higher [lower] level of forecast effort.

With my findings in this chapter, I make several contributions. Firstly, I introduce a new way to measure analysts' forecast effort and provide evidence that general forecast effort significantly affects earnings forecast accuracy. Empirical results verify that my new measure can better explain forecast accuracy differences than the commonly applied firm-specific effort measure. Thus, I help improving the measurement of forecast effort. For future research on earnings forecast accuracy, it is important to control for general forecast effort.

Secondly, a better understanding of forecast accuracy determinants helps investors and accounting researchers to choose more accurate earnings forecasts. Especially to investors, my general effort measure offers valuable advantages as it helps identifying analysts whose forecasts are generally more accurate. In contrast, a firm-specific effort measure only identifies accurate analysts for specific firms. Therefore, my general measure gives easier instructions to investors on which analysts' forecasts they should base their investment decisions.

Thirdly, I emphasize that it is important to consider analysts' general forecast characteristics in addition to firm-specific characteristics when examining forecast accuracy. A wide range of studies provides evidence that the accuracy of analysts' forecasts differs systematically, but most studies concentrate on differences in analysts' firm-specific characteristics. In contrast, I examine analysts' *general* behavior and find that it has substantial explanatory power. I even provide evidence that my new general effort measure is not only incremental to the commonly applied firm-specific effort measure, but also has higher explanatory power regarding differences in earnings forecast accuracy (7.46% vs. 3.10%).

2.2 Related studies and hypotheses development

2.2.1 Analysts' forecast effort

Prior studies consistently argue that analysts' effort exerts an impact on forecasts, but apply different measurement approaches. Grant and Rogers (1996) measure forecast effort based on the number of items included in an analyst's research report that are not in the company's financial statements. They argue that analysts have to devote high effort to forecast these items. Barth et al. (2001) introduce a measure for which they take all analysts who cover a specific firm in a specific year into consideration and calculate the average number of covered firms. They interpret a small number of covered firms as signal that the analysts would be able to spend relatively high effort on each firm. This measure is calculated equally for all analysts who cover the firm. By contrast, I attempt measuring each analyst's forecast effort individually and investigate the impact of individual analyst characteristics on forecast accuracy. Thus, I use the effort measure introduced by Jacob et al. (1999) as a

starting point. Jacob et al. (1999) count the number of earnings forecasts an analyst issues for a specific firm in a specific year and define this measure as forecast frequency, assuming that analysts who exhibit a higher forecast frequency devote more forecast effort to the specific firm. I argue that it is too restrictive to take only one firm into consideration as an analyst's behavior for other firms might also allow drawing inferences to her characteristics that cannot be seen from the behavior for one specific firm. Thus, I measure the forecast effort an analyst generally devotes. I argue that an analyst's general forecast effort enables drawing inferences as to the effort she devotes when forecasting a specific firm. I introduce my measure in Section 2.3.1.

2.2.2 Analysts' earnings forecast accuracy

With my measure I enhance the literature on earnings forecast accuracy. Analysts' forecasts differ significantly regarding accuracy and a large stream of literature identifies explanations resulting from systematic differences in (1) forecast-specific characteristics, (2) analysts' firm-specific characteristics or (3) analysts' general characteristics. Analyses of forecast-specific characteristics consider each earnings forecast separately and identify forecast characteristics that determine accuracy. Examinations of analysts' firm-specific characteristics investigate an analyst's characteristics regarding a specific Firm X and measure the impact on the analyst's earnings forecast accuracy for that Firm X. The widest perspective is applied when examining the impact of analysts' general characteristics on forecast accuracy. In the following I present a short overview of the three groups of forecast accuracy determinants.

(1) Forecast-specific characteristics

O'Brien (1988) examines differences in the accuracy of earnings forecasts and reveals that earnings forecasts are more accurate when issued closer to the earnings announcement. This finding is consistent with the early forecasting literature in arguing that analysts incorporate new information into their forecasts (e.g. Crichfield et al., 1978). A more recent stream of studies (e.g. Call et al., 2009; Keung, 2010) argues that analysts who issue supplementary forecasts (e.g. cash flow forecasts, sales forecasts) analyze a firm in more detail, resulting in

superior information. Consistent with the expectation that this information will also affect earnings forecast accuracy, these studies find a positive relationship between the existence of supplementary forecasts and the respective earnings forecast accuracy. The variables identified in these studies are strongly related to the new determinant I introduce in Chapter 3.⁸

(2) Analysts' firm-specific characteristics

Brown (2001) finds that an analyst's prior ability (measured via prior forecast accuracy) to forecast a specific firm's earnings is a good indicator for the accuracy of her earnings forecasts for that firm. Mikhail et al. (1997) argue that an analyst who follows the same firm for several years gains firm-specific knowledge, and provide evidence that forecast accuracy increases with forecast experience, i.e. the longer an analyst follows a specific firm. Moreover, Jacob et al. (1999) find that the accuracy of an analyst's forecasts for a specific firm increases with the effort she devotes to the forecasts of that firm.

(3) Analysts' general characteristics

This kind of measure considers an analyst's general behavior for all firms she covers in a given year. Clement (1999) finds that analysts' general forecasting experience positively impacts forecast accuracy. He also shows that analysts who face a more complex forecast portfolio (measured via the number of covered firms and industries) are less accurate and that analysts employed by larger brokerage houses issue more accurate forecasts which might be attributed to the availability of better research resources. In addition, Brown and Mohammad (2010) measure analyst's prior forecast ability at a general level, i.e. over all covered firms. Stickel (1992) finds that analysts with superior reputation forecast earnings more accurately. Analysts with superior reputation are defined as analysts who were named to *Institutional Investor's* All-America Research Team.⁹

⁸ In Chapter 3, I introduce a variable that is based on the number of different kinds of supplementary forecasts (such as cash flow or sales forecasts) an analyst issues. I provide evidence that it impacts the accuracy of the respective earnings forecast. However, I do not consider this variable for the examination of general forecast effort as this variable can only be calculated for periods starting in fiscal year 2003 (see Section 3.3) and I aim to use a large data sample for the investigation of general forecast effort.

⁹ The *Institutional Investor* sends questionnaires to portfolio managers, directors of research and other analysts who are asked to name the top analysts for each industry. On the basis of this data, the *Institutional Investor* publishes the top analysts (First Team, Second Team, Third Team, Runners-up) for each industry in the

2.2.3 Hypothesis development: Impact of forecast effort on accuracy

My study can be assigned to the stream of literature on analysts' general characteristics. I argue that analysts differ systematically regarding forecast effort and that a firm-specific measure cannot fully capture this effort. A firm-specific measure only considers available information on analyst behavior with respect to one firm, but an analyst might devote high forecast effort and not update her forecast for a specific firm for several reasons apart from low effort.

Imagine Analyst A who expends high effort and thus has superior information. Maybe she even has an affiliated relationship with the management. However, information that is new to other analysts and leads them to revise their forecasts might already be included in A's outstanding forecast. I argue that A would revise her forecast if necessary, but might regard her most recent forecast as correct. Analyst B, on the other hand, might expend lower effort than others but revise her forecast for a specific Firm X more frequently. The high frequency would be interpreted as high effort when only considering this firm, but there might be other reasons: Maybe Analyst B faces different incentive structures regarding Firm X and is requested to regularly publish new reports. It might also be the case that publicly available information (already included in forecasts by analysts who expend higher effort) is new to B and causes a revision. Nevertheless, B's revision is still based on inferior information and will be inferior compared to other analysts' forecasts.

Instead of only concentrating on one firm, I take account of an analyst's general forecasting behavior and measure her general willingness to revise forecasts. I use a general forecast effort measure and infer the effort devoted to Firm X. I expect this measure to be incremental to the firm-specific measure in explaining forecast accuracy differences and hypothesize:

H1: Analyst forecast effort measured at a general level is incremental to firm-specific forecast effort in explaining differences in analyst earnings forecast accuracy.

October issue of the magazine. See Hong et al. (2000), Clarke et al. (2007) or Leone and Wu (2007) for further discussions on the selection process.

2.2.4 Hypothesis development: Impact of forecast effort on career perspectives

Analysts' career perspectives are also widely discussed in the literature (e.g. Mikhail et al., 1999; Hong et al., 2000; Hong and Kubik, 2003; Ertimur et al., 2011). Mikhail et al. (1999) find that analysts who issue less accurate forecasts are more likely to change to another brokerage house in the next period. However, they do not distinguish between analysts being fired and moving voluntarily to another brokerage house that might be of higher prestige. Similar to Hong and Kubik (2003) and Ertimur et al. (2011), I aim to differentiate between analysts' movement to brokerage houses of higher or lower prestige. I argue that the forecast effort an analyst expends is recognized and rewarded by the brokerage houses, and therefore expect that analysts who expend a higher level of forecast effort have better career perspectives. I hypothesize:

H2: Analysts who expend more forecast effort have better career perspectives.

2.2.5 Hypotheses development: Factors that influence forecast effort

I argue that the forecast effort an analyst expends is partly determined by the difficulty of her forecast portfolio, i.e. analysts who face a portfolio of many new and unfamiliar firms have to expend more forecast effort to compensate for their lack of experience with the respective firms. I hypothesize:

H3: Analysts who face a portfolio of unfamiliar firms devote more effort to their forecasts.

Another factor that I expect to affect an analyst's forecast effort is her motivation resulting from the job satisfaction from her previous career development. If an analyst experiences changes in her environment, this should be reflected in the forecast effort she devotes. Analysts who have been rewarded in the past, e.g. by changing to a brokerage house of higher prestige, might be more satisfied in their job and be more motivated to devote a higher level of effort. Analysts who had to move to a brokerage house of lower prestige might feel unsatisfied and might lack motivation to expend the respective effort. I hypothesize:

H4: Analysts who moved to a brokerage house of higher [lower] reputation devote more [less] forecast effort.

2.3 Research design and data sample

2.3.1 Measurement of analysts' general forecast effort

Commonly, an analyst's forecast effort for a specific firm is proxied by her forecasting attitude regarding this firm. The literature applies the approach suggested by Jacob et al. (1999) and counts the number of earnings forecasts which analyst i issues for firm j in year t . This measure is defined as forecast frequency of analyst i for firm j in year t . I argue that this approach is too restrictive and believe that additional information on the analyst's characteristics can be derived from her behavior for other firms. Thus, I introduce an effort measure that considers analyst i 's general behavior in year t (i.e. her behavior for all other firms she covers in year t) and use it to proxy for her general forecast effort. For this purpose, I calculate the *average number* of forecasts analyst i issues for all covered firms except for firm j in a particular year t .

For the calculation, I first identify firm-specific forecast frequencies separately for each firm the analyst covers in year t and define $FREQ_{ijt}$ as the number of earnings forecasts analyst i issues for firm j in year t . This definition is consistent with Jacob et al. (1999) and is used as indicator for firm-specific forecast effort. Next, I calculate general forecast frequency ($GFREQ_{ijt}$) as the mean number of forecasts analyst i issues in year t for all covered firms $k = 1, \dots, J$, except firm j :

$$GFREQ_{ijt} = \frac{1}{J-1} \sum_{k=1, k \neq j}^J FREQ_{ikt}. \quad (1)$$

I use $GFREQ_{ijt}$ as measure of the general forecast effort analyst i devotes in year t to firm j that was not captured by a firm-specific measure. Note that I exclude firm j for the calculation of $GFREQ_{ijt}$ as I want to determine the additional effect that is not included in a firm-specific measure. Another reason to omit firm j for the calculation is that I control for

the firm-specific effort measure ($FREQ_{ijt}$) in my investigation and attempt to avoid capturing the same effect twice. Thus, $GFREQ_{ijt}$ is calculated differently for each firm j .

2.3.2 Examination of forecast accuracy

I base the forecast accuracy measure on absolute forecast errors calculated as the absolute difference between analyst i 's most recent forecast and the actual earnings value for firm j in year t .¹⁰

$$ACC_{ijt} = |\text{earnings forecast}_{ijt} - \text{actual earnings}_{jt}|. \quad (2)$$

I deflate the earnings forecasts as well as the actual earnings by the firm's security price two days before the forecast was announced; thus ACC_{ijt} is the price-deflated accuracy of analyst i 's forecast for firm j in year t . This procedure is consistent with Clement and Tse (2005) and allows the comparison of different companies. I apply a range-adjustment (Clement and Tse, 2003, 2005), and measure analyst i 's accuracy relative to all other analysts following firm j in year t . I use

$$RACC_{ijt} = \frac{ACC_{maxjt} - ACC_{ijt}}{ACC_{maxjt} - ACC_{minjt}}, \quad (3)$$

where ACC_{maxjt} [ACC_{minjt}] is the maximum [minimum] absolute forecast error of all analysts following firm j in year t . I thereby measure an analyst's *relative* forecast accuracy and eliminate firm and year specific influences. The value for $RACC_{ijt}$ increases with forecast accuracy and ranges from 0 (for the least accurate forecaster) to 1 (for the most accurate forecaster).

The following example illustrates the problem of unadjusted accuracy measures. Imagine Analyst A who issues a forecast for Firm X, and Analyst B who issues a forecast for Firm Y. If the forecasts by A and B have the same absolute forecast error, it cannot be concluded that A and B performed equally well. Analyst A might have performed relatively well compared to other analysts following Firm X, while B might have performed worse than other analysts

¹⁰ I use analyst i 's most recent forecast, but exclude those forecasts from the data sample that were issued within the last 30 days before the earnings announcement. See Section 2.3.5.

New Determinants of Analysts' Earnings Forecast
Accuracy

Klettke, T.

2014, XXI, 101 p. 1 illus., Softcover

ISBN: 978-3-658-05633-9