Does Limited Attention Matter in Security Analysis?
Evidence from Analysts' Reliance on Categories

Hae Mi Choi* and Swasti Gupta-Mukherjee†

ABSTRACT

Motivated by psychological evidence that individuals with limited attention rely on category-based inferences to simplify complex cognitive tasks, this paper examines whether security analysts are affected by limited attention in issuing earnings forecasts. Given the pervasiveness of assets being categorized into coarse groups (e.g. industries) in financial markets, we explore the implications of analysts' reliance on category-level information relative to firm-specific information in issuing forecasts. We find substantial dispersion in analysts' relative reliance on category-level information. As predicted if analysts' reliance on category-level information reflects limited attention, forecast errors increase with the analysts' propensity for relying on category-level information relative to firm-specific information. The reliance on category-level information increases with the analysts' tendency for rounding, and decreases with the analysts' private information, experience, All-star status, boldness, coverage, and brokerage size. The stock price reaction to forecast revisions is less (more) for analysts who have a high (low) relative reliance on category-level information, suggesting that revisions by analysts displaying more limited attention have less impact on stock prices. The likelihood of job separation increases with the analysts' relative reliance on category-level information. Our results suggest that security analysts, who play an important role in the price formation process, are susceptible to limited attention which affects their forecasting ability and career outcomes.

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1. Introduction

The volume of information in financial markets is huge. However, widely established evidence in the psychology literature suggests that the cognitive resources available to market participants to process this information is limited. While traditional economic models ignore these limits on the attention resources of agents, there is a recent and growing literature in financial economics that explores the implications of limited attention in financial markets. The existing evidence primarily relates to limited investor attention in explaining asset pricing anomalies (e.g. Hirshleifer, Lim, and Teoh (2009); DellaVigna and Pollet (2007, 2009); Cohen and Frazzini (2008); Da and Warachka (2011)). Fewer studies have focused specifically on sophisticated market participants, such as market makers (see Corwin and Coughenour (2005)), and money managers (e.g. Fang, Peress, and Zheng (2014); Chen, Cohen, and Lou (2014); Gupta-Mukherjee and Pareek (2015); Gupta-Mukherjee (2015)). The purpose of this study is to explore whether limited attention affects another category of market participants who have a crucial role to play in the price discovery process, namely, security analysts. By providing evidence on whether limited attention affects security analysts, this study seeks to shed new light on the information contained in analysts' earnings forecasts.

The first research question addressed in this study is whether the limited attention of security analysts is associated with their ability and forecast accuracy. We do this by relating a new metric of limited attention we propose in this study to other analyst attributes that have been linked to their ability by previous studies. The second research question is whether analysts who display more limited attention have, on average, a lower impact on stock prices. If the market rationally identifies analysts with limited attention who issue less informative forecasts, the stock price responses should be weaker for analysts who display limited attention. The third research question is whether exhibiting limited attention has real consequences for the analysts' reputation and career. To the extent that analysts' limited attention is associated with inferior ability, we expect that analysts who tend to exhibit limited attention should be more likely to experience job turnover.[1] Accordingly, we examine the relationship between our measure of analysts' limited attention and the likelihood of job turnover.

To characterize analysts' limited attention, we draw on the premise that market participants with limited attention will tend to rely more on "macro" information pertaining to a firm's broad category (category-level information), and less on "micro" firm-level information. Mullainathan (2002) argues that using categories results in an information processing bias when investors with limited attention use coarse categorizations and overly rely on an asset's category to infer about the asset.[2] In Peng and Xiong's (2006) model of investors with limited attention, investors process category-level information to the exclusion of asset-level information, more so when the investor is more cognitively constrained. In financial markets, such category-based oversimplifications during information processing could be widespread since the categorization of a large universe of assets and firms into coarse groups is prevalent in the process of organizing and disseminating information. In the stock market, these groups or categories are usually based on perceived shared attributes of the stocks, such as industry (e.g. Oil and Gas) or style (e.g. Growth). An example of category-level information is past returns of an industry (e.g. Oil and Gas), whereas the past returns of a stock (e.g. Exxon Mobil) is an example of firm-specific information.

Despite the theoretical studies mentioned above, there is still a considerable gap in our understanding of how limited attention in general, and category-based information processing in particular, may affect price discovery and market efficiency. At the crux of the issue is to what extent market participants use category-level information, and whether the use of categories has a non-trivial impact on the accuracy of their information processing. To the extent that analysts differ in their reliance on category-level information in issuing firm-level forecasts, the degree to which they do so could contain information

[1] See, for example, Mikhail, Walther, and Willis (1999) and Hong and Kubik (2003) who document that analysts' poor relative performance leads to job turnover.

[2] In a related paper, Mullainathan, Schwartzstein, and Shleifer (2008) study thinking based on coarse categorizations to explain persuasion in advertising and product branding.

about their limited attention, their forecast accuracy and, consequently, their contribution to the price discovery process for the stocks they follow.[3]

To begin the empirical analyses, we propose a parsimonious measure of an analyst's propensity for relying on category-level information relative to firm-specific information, called *Category Reliance* (*CAT_REL*). To construct *CAT_REL*, we first identify a stock categorization that is likely to play a role during security analysis. For the main tests, we consider a stock's official industry captured by its 2-digit SIC code as a salient and widely used, but often coarse, categorization. Next, an analyst's reliance on (i.e. use of) category-level information is computed in each year as the R^2 ($R^{2,category}$) of the cross-sectional regression of the forecast revisions on a set of variables representing past returns of the stock's 2-digit SIC industry category. So, the $R^{2,category}$ measure will be high when the analyst's forecast revisions are highly sensitive to the industries' price momentum, in the direction of the momentum or contrarian to the price momentum. Similarly, the analyst's reliance on firm-specific information is computed as the R2 ($R^{2,stock}$) of the cross-sectional regression of the forecast revisions on a set of variables representing past returns of the stock. The baseline specification of *CAT_REL* is computed for each analyst-year as the $R^{2,category}$, divided by one plus the $R^{2,stock}$. The interpretation is that an analyst's propensity to rely on category-level information relative to firm-level information is higher when her forecast revisions for stocks rely to a large extent on the information set proxying for the stocks' category-level information relative to the information set proxying for firm-specific information (i.e. $R^{2,category}$ is high relative to $R^{2,stock}$). A caveat in using this framework is that *CAT_REL* is based on analysts' reliance on public information, specifically the *type* of public information, and cannot account for category-level or asset-level private information. Also, since we use past returns to proxy for category-level and firm-level information in explaining analyst forecast revisions, *CAT_REL* is related to analysts' tendency to chase

[3] Note that out study pertains to firm analysts who issue firm-level forecasts and mainly analyze a firm's fundamentals, and assess higher level information about the firm's industry category to the extent it is relevant to the firm. We do not focus on industry analysts or "strategists" whose primary function is to form macroeconomic and/or industry outlooks (see Kadan et al. (2012) and Bradshaw (2012)), where the implications of relying on category-level information is expected to be different.

price momentum. However, we posit that *CAT_REL* captures whether an analyst is relying on category-level (e.g. industry-level) or firm-level price momentum, which we view as consistent with our central basis for the measure as a proxy for the propensity to rely on category-level information, due to limited attention or other reasons. As described later, we also consider alternative measures in robustness checks. In sum, our primary hypothesis in this paper is that a higher relative reliance on categories (*CAT_REL*) represents limited attention and lower ability of analysts, and should predict higher forecast errors and worse career outcomes.

We also note that the analysts' reliance on category-level information relative to firm-level information need not arise from limited attention, and could be rational. Hence, alternative hypotheses related to a higher relative reliance on categories are also plausible. The relation between the type of information used by analysts during security analysis and forecast errors depends not only on the analysts' ability to process the information accurately, but also on the precision of the information. So, it is plausible that analysts who rely on category-level information, such as industry-level information, do so rationally because the precision of category-level information they receive is high. Consistent with this possibility, Boni and Womack (2006) note that analysts are often viewed as industry specialists and are associated with industry and sector expertise. Thus, a higher relative reliance on category-level information may not be detrimental, and could also be beneficial, to forecast accuracy when analysts process information to issue forecasts.

The empirical evidence reported in our paper supports the hypothesis that analysts' relative reliance on categories is significantly and positively related to forecast errors. The economic significance is also large. A one standard deviation increase in *CAT_REL* leads to an increase of 3.0% to 5.3% in absolute forecast error relative to the mean forecast error (scaled by stock price), depending on the model specification. This finding is consistent with the interpretation that a higher relative reliance on category-level information captures limited attention of the analyst, and can be viewed as the antithesis of analyst ability. Moreover, we decompose our *CAT_REL* measure to show that forecast errors have a significantly positive relation with the proxy for analysts' reliance on category-level information ($R^{2,category}$), and a significantly negative relation with the proxy for analysts' reliance on firm-level information ($R^{2,stock}$). Thus, forecast errors are explained by the variation in the analysts' reliance on both category-level as well as firm-level information. These results hold in multivariate settings controlling for a variety of standard analyst and stock attributes that could affect forecast errors. Among other results, analysts' reliance on category-level information increases with the analysts' tendency for rounding their forecasts to nickel intervals. Consistent with an inverse relation between limited attention and measures of analyst ability, we also find that analysts' relative reliance on categories is negatively related to their private information, experience, boldness, past forecast accuracy, and all-star analyst status.

Having established that analysts' relative reliance on categories is associated with lower forecast accuracy, we next explore whether the stock market accounts for this in the stock price reactions to analyst forecast revisions. If the market discounts the information content in the forecasts issued by the analysts who exhibit more limited attention, we should observe a lower stock price response to forecast revisions by analysts who tend to rely more on category-level information relative to firm-level information. Our results support this notion, since we show that the cumulative abnormal returns (*CAR*s) around analyst forecast revisions significantly decreases with the analysts' *CAT_REL*.

Finally, we examine whether analysts' limited attention has a real effect on their reputation and career. If the analysts' tendency to rely on categories is associated with limits on their ability, and the market is aware of this cognitive limitation, we expect that such a tendency should have a negative impact on analysts' reputation and increase the likelihood of job turnover. Indeed, we find that analysts' tendency to rely on categories is associated with a higher likelihood of job turnover.

Our paper contributes to at least two strands of the literature. First, we contribute to the literature studying the biases and inaccuracies of analysts' forecasts (e.g. De Bondt and Thaler (1990), Francis, Hanna and Philbrick (1997), O'Brien, McNichols, and Hsiou-Wei (2005)).[4] In this literature, both

[4] There is significant evidence of systematic optimistic biases in analysts' earnings forecasts (Stickel (1990), Abarbanell (1991), Dreman and Berry (1995), Chopra (1998), Lim (2001), Hong and Kubik (2003), and Chen and Jiang (2007)).

behavioral and rational incentive-based explanations have been proposed to explain why analysts tend to issue biased (typically optimistic) forecasts.[5] For example, some studies posit that analysts' overconfidence about their ability leads them to systematically overweight or underweight information, leading to forecast biases, while others suggest that analysts' forecast bias is driven by trading commissions, informational advantage, or other career concerns.[6] To our knowledge, this is the first study to focus on potential biases in information processing arising from limited attention of security analysts in the framework of how they process category-level and firm-level information. Notably, our framework of an information processing bias linked to analysts' reliance on category-level information appears to be less directly tied to alternative incentive-based explanations than many studies on biases in analyst forecasts. For instance, while it is clear that analysts could issue optimistic forecasts with more forecast error due to economic incentives to increase trading commissions for their brokerage houses, it is not clear what economic incentive they may have to rely more on category-level information and less on firm-level information if this behavior is associated with less accurate forecasts.

Second, we significantly extend the growing literature on the role of limited attention in financial markets. Existing studies have focused on limited attention of investors (e.g. Hirshleifer, Lim, and Teoh (2009); DellaVigna and Pollet (2007, 2009); Cohen and Frazzini (2008); Da and Warachka (2011)), market makers (see Corwin and Coughenour (2005)), and money managers (e.g. Fang, Peress, and Zheng (2014); Chen, Cohen, and Lou (2014); Gupta-Mukherjee and Pareek (2015); Gupta-Mukherjee (2015)). This study departs from the existing literature on limited attention by examining a different group of market participants who could also be affected by limited attention, namely, security analysts. Notably,

[5] See Griffin and Tversky (1992), McNichols and O'Brien (1997), Jackson (2005), and Cowen et al. (2006) among others. Lim (2001) finds an average optimistic bias of 0.94% of stock price. Malmendier and Shanthikumar (2006) find that analysts tend to bias stock recommendations upward, particularly if they are affiliated with the underwriter.

[6] Prior studies have found that analysts tend to issue more optimistic forecasts when career concerns are greater (Hong and Kubik (2003), and Hong, Kubik, and Solomon (2000)), or to maintain favorable relationships with management (Francis and Philbrick (1993)), or to obtain private information from management (Das, Levine, and Sivaramakrishnan (1998)).

security analysis is a compelling setting to find that limited attention matters since analysts are influential in price discovery and are viewed as sophisticated information intermediaries, presumably making them ex ante less prone to biases and cognitive constraints. Our findings broadly align with the premise of Griffin and Tversky (1992) who postulate that sophisticated agents or experts are more likely to exhibit biases like overconfidence than non-experts when faced with ambiguous and uncertain information.

The paper proceeds as follows. Section 2 introduces the key empirical metrics in this study: an analyst's *Category Reliance* (*CAT_REL*). Section 3 outlines the data. Section 4 reports empirical results. Section 5 concludes.

2. Background and Hypotheses Development

2.1. Limited Attention and Reliance on Categories

A voluminous literature in psychology suggests that individuals mentally access knowledge of similar situations when making judgements, and the categorization of information affects how information is accessed and processed (e.g. Chi, Feltovich, and Glaser (1981); Spivey (1987)). Thus, individuals have limited information processing capacity (i.e. limited attention) and rely on cognitive shortcuts involving broad categories, wherein they use the perceived attributes of the category to draw (often crude) inferences about the individual subjects in the category. For instance, a common manifestation of this is in conscious or subconscious racial profiling, where it is common to fall back on stereotypes which are prevalent in popular culture, such as "Blacks are good basketball players" and "Asians are good at math".

Despite being well-established in psychology, the notion of an over-reliance on categories as a channel by which limited attention affects inference is still underexplored in studying behavior in financial markets. Some theoretical studies have addressed the implications of category-based information processing in financial markets. Peng and Xiong (2006) model investors with limited attention who process category-level information to the exclusion of asset-specific information, a tendency that increases with the investors' cognitive constraints. Mullainathan's (2002) model posits that using coarse categories results in an information processing bias when investors with limited attention overly rely on an asset's category to infer about the asset. Empirical evidence is limited, with some exceptions such as Barberis and Shleifer (2003) addressing the asset pricing implications of investors categorizing assets into "styles".

2.2. Hypotheses: Limited Attention and Security Analysts

Although security analysts are commonly viewed as sophisticated information intermediaries in financial markets, some evidence alludes to the fact that they may not be immune to relying on simplifications when they process information. For example, Hopkins (1996) finds that accounting balance sheet classifications affect how analysts process information to access firm value. However, to our knowledge, no study to date has examined the limited attention of financial analysts in the context of their reliance on categories, and the implications of this for the quality and quantity of information production in security analysis.

In this study, we examine the extent to which an analyst displays limited attention, as captured by her propensity to rely on category-level information as opposed to firm-level information. Given that analysts tend to specialize by industry categories, covering multiple firms in the same industry (see Boni and Womack, 2006), analysts with limited attention may tend to simplify some of the information processing by relying on the "coarse" industry level information rather than the "finer" individual firm level information.[7]

[7] Hutton, Lee and Shu (2014) argue that firm insiders have an informational advantage over outside analysts for firm-level information. Thus, analysts could focus on being "industry specialists" and specialize in more macro information. However, this explanation cannot explain analysts' incentive to focus on industries at the cost of inaccurate firm earnings forecasts.

Our first set of hypotheses is about the effect of analysts' limited attention on their forecasting performance in terms of both quality and quantity of information produced. We call our measure of metric of an analyst's limited attention, measured by her propensity to rely more on the firms' categories (industries) relative to firm-specific information, as her "category reliance". When analysts oversimplify their information process to predict individual firms' earnings, by exhibiting a higher degree of category reliance, we would expect less accurate firms' earnings forecasts. This leads to our first hypothesis, stated as follows

Hypothesis 1 (*H1*): *Analysts' forecast accuracy declines with their category reliance*.

Moreover, it is plausible that analysts produce not only less accurate information when they are subject to limited attention, but also a smaller amount of information. Jacob, Lys, and Neale (1999) show that forecast frequency proxies for analyst effort in incorporating the latest information into forecasts. Following Jacob, Lys, and Neale (1999), we assume that an analyst who frequently revises her forecasts produces more information than an analyst who issues less frequent forecasts. To the extent that analysts' category reliance captures limited attention, our second hypothesis associated with less frequent forecast revisions can be stated as follows

Hypothesis 2 (*H2*): *Analysts' forecast frequency declines with their category reliance*.

Assuming that analysts' limited attention is associated with negative forecasting performance; we next develop testable hypotheses related to the reputational consequences of analysts' category reliance. Fama (1980) argues about the importance of reputation formation in the labor market in disciplining opportunistic behavior of managers. Hong Kubik, Soloman (2000) focus specifically on security analysts and find that reputational concerns influence analysts' behavior in herding with other analysts. They find that inexperienced analysts who have yet to build reputation are more likely to be terminated for inaccurate earnings forecasts. Prior evidence show that reputation matters for analysts when they issue earnings forecasts or stock recommendations.

We first examine the reputational effects of analysts' limited attention among investors in financial markets. Analysts' reputation among investors will decrease when limited attention is negatively associated with the analysts' forecasting ability. The credibility of the analyst's forecasts will decline and the market will discount the information produced by the analyst with a prior history of less accurate forecasts. We study the informativeness of the analysts' forecasts by examining the stock price impact of analyst forecast revisions, by testing our third hypothesis

Hypothesis 3 (*H3*): *The stock price impact of forecast revisions made by an analyst decreases with the analyst's category reliance*.

Finally, analysts' reputation is directly related to their career concerns. Mikhail, Walther, and Willis (1999) and Hong, Kubik, and Soloman (2000) document that poor relative performance leads to job turnover. Similarly, if the market identifies analysts with limited attention who rely more on category-wide information relative to firm-specific information, it should lead to diminished reputational effects and job turnover. Therefore, our fourth and final hypothesis can be stated as

Hypothesis 4 (*H4*): *Analysts who exhibit more category reliance experience a higher likelihood of job turnover*.

3. Measuring Analysts' Reliance on Categorization

Market participants could use many alternative categories for assets when they receive and process information. For the purposes of this study, we select a natural asset categorization that is likely to be a widespread feature in security analysis and information dissemination in the stock market. The 2-digit SIC industry code satisfies this criterion since the SIC code is a widely-used categorization of assets during information production and dissemination in financial markets, and security analysts typically specialize by industry.

Motivated by Peng and Xiong (2006) and other theoretical studies, our empirical premise in developing a metric of category-driven information processing is that it should increase with an analyst's tendency to rely more on category-level information and less on firm-specific information during security analysis. To implement this empirical framework, we first calculate the forecast revision issued by analyst *i* for firm *j* at time *t* in year *k* using the following formula:

$$Rev_{i,j,t,k} = \frac{F_{i,j,t,k} - F_{i,j,t-1,k}}{\left|F_{i,j,t-1,k}\right|} \tag{1}$$

where $F_{i,j,t,k}$ is the earnings forecast made by analyst *i* for firm *j* at time *t* in year *k*, and $F_{i,j,t-1,k}$ is the most recent forecast made by analyst *i*, firm *j* for the same forecast period prior to $F_{i,j,t,k}$. A forecast revision captures an event signaling new incorporation of information by the analyst.

Next, for each forecast revision, we match the prior returns of the stock and the stock's industry (defined based on 2-digit SIC codes), measured in the four months prior to the month in which the forecast revision was made.[8] The analyst's reliance on category-level information ($R^{2,category}$) is measured for each analyst *i* in each year *k* as the R^2 from the regression of forecast revisions by analyst *i* for firm *j* at time *t* in year *k* on lagged returns of the industry as follows

$$Rev_{i,j,t,k} = \beta_0 + \beta_1 \sum_{m=1}^{4} industryret_{j,t-m,k} + \varepsilon_{i,k} \tag{2}$$

Where $Rev_{i,j,t,k}$ is as defined in Equation (1); $industryret_{j,t-m,k}$ for firm *j* in month $t-m$ in year *k* is calculated as the average monthly stock returns across all firms in the same 2-digit SIC code as firm *j* in the month, where *m*=1, 2, 3, or 4 denotes one, two, three, or four month lags prior to time *t*.[9]

[8] Results are robust to including one or up to 12 months lagged returns. Our findings are also robust to alternative definitions of stock categories discussed in a later section, such as firm size, style, and Fama-French 48, NAICS, and GICS industry classifications.

[9] We only include analysts with at least 30 forecast revisions for given year. Forecast revisions, industry and firm returns are winsorized at the 1% value to minimize the effect of outliers or data errors.

Similarly, the analyst's reliance on firm-specific information ($R^{2,stock}$) is measured for each analyst *i* in each year *k* as the R^2 from the regression of forecast revisions by analyst *i* for firm *j* at time *t* in year *k* on lagged industry-adjusted stock returns of the stock as follows

$$Rev_{i,j,t,k} = \beta_0 + \beta_1 \sum_{m=1}^{4} stockret_{j,t-m,k} + \varepsilon_{i,k} \tag{3}$$

Here $stockret_{j,t-m,k}$ is firm *j*'s abnormal industry-adjusted stock return (firm return – industry return) in month $t-m$ in year *k*, where *m*=1, 2, 3, or 4 denotes one, two, three, or four month lags prior to time *t*.

We posit that the higher is the $R^{2,category}$ in Equation (2) relative to $R^{2,stock}$ in Equation (3), the more the analyst relies on category-level information relative to firm-specific information in making forecast revisions. Finally, we implement this intuition by constructing an analyst *i*'s *Category Reliance* (*CAT_REL*) in year *k* as

$$CAT\_REL_{i,k} = \frac{R^{2,category}}{1 + R^{2,stock}} \tag{4}$$

Here $R^{2,category}$ and $R^{2,stock}$ denote the R^2 from Equations (2) and (3), respectively.[10] Since our *CAT_REL* measure uses analysts' sensitivity to past price changes, it could contain similar information as the production of private information (*PPI*) measure in Hwang, Li, and Tong (2012). However, in the data used in this study, the correlation coefficient of *CAT_REL* with *PPI* is low (=-0.085), suggesting that *CAT_REL* and *PPI* contain different types of information. The relation between *CAT_REL* and other analyst attributes like *PPI* are formally examined in later sections.

3.1. Category Reliance: Caveats

[10] To ensure that the estimates are meaningful, we only use the measures obtained from 30 or more observations. The results are robust to alternative minimum cutoffs like 20 or 60 observations.

It is important to note some caveats and potential alternative interpretations of *CAT_REL* in Equation (4). Firstly, as noted earlier, high values of *CAT_REL* do not automatically imply limited attention or biases in information processing per se, and could also be high for analysts who rationally process more industry-level information. Based on *CAT_REL*, these analysts would appear similar to the analysts with limited attention, thus creating noise in the measure. Additionally, while this study argues that analysts associated with low *CAT_REL* exhibit less category-driven information processing, low *CAT_REL* values could also be a result of analysts using categories not captured in the empirical apparatus. Here, analysts who are actually relying on categories are likely misclassified as having low *CAT_REL*. However, the noise created by these potential measurement errors in the *CAT_REL* metric should typically work against finding empirically significant and robust results related to the category-based information processing of analysts.

4. Data and Variables

The analyst data are from Thomson Financial's I/B/E/S database for U.S. firms. We use annual earnings forecasts that are one-year-ahead forecasts and actual earnings are taken from I/B/E/S from 1996-2011. We use the unadjusted file to mitigate the rounding problem in I/B/E/S (see, for instance, Diether, Malloy, and Scherbina (2002)). Using I/B/E/S' split-adjustment factors, we adjust the unadjusted forecast so that it is on the same per-share basis as the unadjusted actual earnings. We obtain data on stock returns from the Center for Research in Security Prices (CRSP). Firm-level variables are obtained from Compustat Annual Updates, and institutional holdings data is from the Thomson Reuters Spectrum database. Spectrum collects quarterly data on stock holdings from the 13F reports that institutions are required to file if their holdings exceed $100 million. The holdings are aggregated over all institutions to arrive at the institutional holdings number.

Table 1 reports summary statistics on *CAT_REL* and other key variables used throughout the study. The mean (median) *CAT_REL* in the sample is 0.070 (0.025). The standard deviation is 0.060, suggesting that there is significant dispersion in *CAT_REL* across analysts in the sample. We describe data and variables in further detail as they appear in our later analyses.

5. Empirical Results

5.1. Determinants of Analysts' Reliance on Categories

In this section, we examine how the degree to which the analyst relies on category-level information relative to firm-specific information may be related to other analyst characteristics used in existing studies.

First, we explore the correlation between *CAT_REL* and other analyst characteristics in Table 2. All analyst-level variables are constructed from I/B/E/S data. The following analyst characteristics are considered: *Experience*, *Boldness*, *Rounding*, Production of Private Information (*PPI*), *All-star* analyst status, *Coverage*, brokerage size, the number of industries covered (*Industry Number*), and analyst past relative performance (*Avg_Rank*). *Experience* is the natural logarithm of the number of years since the analyst started issuing forecasts.[11] *Boldness* is the percentage of bold earnings forecasts issued by the analyst in a year, where a forecast is defined as bold if the forecast is above both the analyst's prior forecast and the immediate consensus forecast before the forecast revision, or if the forecast is below both the analyst's prior forecast and the consensus forecast immediately before the forecast revision. *Rounding* is the percentage of rounded earnings forecasts issued by the analyst in a year, where a forecast is a rounded forecast if it occurs at nickel intervals. An analyst is identified as an "All-star" analyst by the Institutional Investors magazine for a given year. *Coverage* is the number of firms covered by the analyst in the year. *Brokerage Size* is the log of the number of analysts that work in the brokerage firm. *Industry Number* is the number of different industries that an analyst covers in a given year.

[11] We measure analyst experience from the start year reported in IBES, and not the start year of our main sample period in order to limit the left-censoring count of analyst experience.

An analyst's production of private information (*PPI*) measure in a year follows from Hwang, Li and Tong (2013), where *PPI* is calculated as one minus the correlation between the analyst's forecast revisions in the year and prior stock price changes. The lower (higher) the correlation, the less (more) an analyst uses information in prior stock prices to revise forecasts and greater (less) amount of private information production.[12]

We compute analyst performance using the analyst's average forecast accuracy ranking (*Avg_Rank*). Following Hong and Kubik (2003), we measure analysts' relative forecast accuracy ranking for each firm they cover and assign a score between 0 and 100. First, analysts are sorted by their absolute forecast error and the analyst with the lowest absolute forecast error receives the first rank for that stock, and the second best analyst receives the second rank and onward until the worst analyst receives the highest rank. Similar to Hong and Kubik (2003), we adjust the rank by the number of analysts covering the firm as follows to obtain the rank for analyst *i* covering firm *j* in year *k*

$$score_{ik} = 100 - \frac{rank_{ik}}{number\ of\ anlayst_{jk}} \times 100$$

where $number\ of\ anlayst_{jk}$ is the number of analysts who cover the firm *j* in year *k*. According to this formula, an analyst with the rank of one receives a score of 100; the analyst who is the least accurate receives a score of 0. Next, we computed *Avg_Rank* as the average of all the scores of each analyst *i* for each year *k* in order to measure the average relative forecast accuracy of analyst *i* in year *k*. Since the implications of category reliance of an analyst could depend on the nature of industry covered by the analyst, we also compute a measure of industry competition to characterize industries. For each stock covered by an analyst in a year, we measure the degree of industry competition for the stock's industry using the Herfindahl Index (*H-index*) of sales for the stock's 2-digit SIC code, computed as the sum of squared weights of sales across all the firms in the industry in the year. For each analyst-year, we then

[12] In order to be consistent with Hwang, Li and Tong (2013), we also exclude analysts with less than 40 forecast revisions in a given year. We also require an analyst to have more than three years of experience.

calculate *Avg. H-index* as the average *H-index* across all firms the analyst issues forecast for in the year. All analyst attributes are measured at the analyst-year level in order to maintain consistency between the *CAT_REL* measure and other analyst characteristics. The *Category Reliance* (*CAT_REL*) is as defined in Equation (4).

In Table 2, we find that analysts' category reliance (*CAT_REL*) has a negative correlation with the degree of private information of the analyst (*PPI*), analyst experience (*Experience*), All-star status (*All Star*), , forecast boldness, the number of firms the analysts issues forecasts for (*Coverage*), brokerage size, past performance (*Avg. Rank*), the number of industries covered (*Industry Number*), and finally, industry competition (*Avg. H-Index*). Meanwhile, *CAT_REL* is positively correlated with the analysts' tendency to round forecasts.

In Table 3, we further explore the relationship between *CAT_REL* and the key explanatory variables in a multivariate setting. In addition to the analyst characteristics used in prior studies and reported in Table 2, we also consider the possibility that an analyst's *CAT_REL* could be related to the degree of competition in the industries covered by the analyst. For example, the number of firms in an industry could be mechanically related to the *CAT_REL* construct. Also, in a highly concentrated industry with few firms, industry-level information may correspond more closely to firm-specific information than in diffuse industries with many firms, likely leading to different implications for *CAT_REL* as a measure of limited attention.

Table 3 reports the results from regressions which estimate the determinants of analysts' category reliance using variations of the following regression specification:

$$CAT\_REL_{ik} = b_0 + b_1 Experience_{i,k-1} + b_2 Boldness_{i,k-1} + b_3 Rounding_{i,k-1} + b_4 All\ Star_{i,k-1} + b_5 PPI_{i,k-1} + b_6 Coverage_{i,k-1} + b_7 Brokerage\ Size_{i,k-1} + b_8(Avg\_Rank_{i,k-1}) + b_9 Industry\ Number_{i,k-1} + b_{10}(Avg.H - Index_{i.k-1}) + \psi_k + \varepsilon_{ijk} \tag{5}$$

where i, j, and k index analyst, firm, and year respectively. The explanatory variables are lagged by one year to reduce potential endogeneity between *CAT_REL* and other analyst forecast-based variables. The term ψ_k denotes the vector of year fixed effects. The *t*-statistics for the statistical significance tests are based on standard errors clustered by analyst.

All the analyst attributes included in the regressions have statistically significant relations with the analysts' category reliance, and the regression coefficients are consistent with the correlation-based results in Table 2. We find that an analyst's tendency to rely on categories decreases with analyst characteristics that are often viewed as proxying for superior ability, namely, the number of firms an analyst covers, the number of years of experience, an "All-star" analyst status, brokerage size, and the amount of private information production. In similar vein, analysts issuing more bold forecasts tend to rely less on category-level information versus firm-specific information, whereas analysts issuing more rounded forecasts tend to rely more on category-level information. Also, analysts covering stocks in more concentrated industries rely less on category-level information.

In sum, to the extent that we expect limited attention to have a negative association with proxies of analyst ability, the results are consistent with analysts' relative reliance on category-level information capturing limited attention and decreasing with ability.

5.2. Analyst Forecast Accuracy and Reliance on Categories

Next, we examine the relationship between analysts' reliance on categories and their earnings forecast accuracy. If analysts' reliance on categories reflects limited attention, we hypothesize that *CAT_REL* should have a negative association with forecast accuracy. Analysts' earnings forecasts, firms' actual earnings and earnings announcement dates are taken from the I/B/E/S annual update U.S. Detailed History datasets. The sample contains 64,741 individual analysts' earnings forecasts, in which we retain only the forecast closest to July (but not after July) in a particular year (see Hong and Kubik (2003)). Using this data, we construct analyst forecast error to represent the inverse of forecast accuracy.

Analyst forecast error (AFE_{ijk}) is computed as the absolute value of the adjusted forecast error of analyst *i*, forecasting earnings for firm *j* in July of year *k*. It is measured as the absolute difference between actual earnings and the analyst's forecast, normalized by the previous fiscal year-end price, multiplied by 100. The forecast accuracy variable is winsorized at the 1^{st} percentile and the 99^{th} percentile to reduce the impact of extreme outliers in earnings surprises, since these values might be the result of data errors.

As control variables, we include several individual analyst characteristics described in the previous section. Also, since Lim (2001) finds that forecast accuracy varies predictably as a function of firm size, analyst coverage, and firm-specific cash flow uncertainty, we construct firm characteristics as control variables from various dataset sources. Firm *j*'s size in year k ($Size_{jk}$) is calculated as the natural logarithm of the market value of equity, where the market value of equity is obtained from Compustat annual data (including the Research file). The market-to-book ratio ($Market/Book_{jk}$) for firm j in year k is calculated as the market value of the firm's equity at the end of the fiscal year plus the difference between the book value of the firm's assets and the book value of the firm's equity at the end of the year, divided by the book value of the firm's assets at the end of the year (see Fich and Shivdasani (2006)). We note that firm size and market-to-book ratios also serve as controls for the firm's risk characteristics (Fama and French (1992, 1993)). A firm j's cash flow volatility in year k ($Cashflow\ Volatility_{jk}$) is calculated as the standard deviation of the firm's cash flows over the past five years.[13] We only include firms with more than three years of consecutive cash flow data available to calculate the standard deviation. Since the presence of institutional investors also affects the incentives of analysts and the information environment of the firm (see Ljungqvist et al. (2006)), we also control for the percentage of institutional investors ($Institutional\ Holdings_{jk}$) for firm *j* in the last quarter of year *k*.

Table 4 reports the results from regressions examining the relationship between analysts' category reliance and their earnings forecast accuracy using variations of the specification in Equation (6) below:

$$\begin{aligned} AFE_{ijk} = {} & b_0 + b_1(CAT_{REL_{i,k-1}}) + b_1 Experience_{i,k-1} + b_2 Boldness_{i,k-1} \\ & + b_3 Rounding_{i,k-1} + b_4 All\ Star_{i,k-1} + b_5 PPI_{i,k-1} \\ & + b_6 Coverage_{i,k-1} + b_7 Brokerage\ Size_{i,k-1} + b_8(Avg\_Rank_{i,k-2}) \\ & + b_9 Industry\ Number_{i,k-1} + b_{10} Size_{j,k-1} + b_{11}(Market/Book_{j,k-1}) \\ & + b_{12}\left(Cashflow\ Volatility_{j,k-1}\right) + b_{13}(Institutional\ Holdings_{j,k-1}) \\ & + b_{14}(H - Index_{i,k-1}) + \psi_k + \varepsilon_{ijk} \end{aligned} \tag{6}$$

The term ψ_k denotes the vector of year fixed effects. Standard errors are clustered by analyst-year.

Table 4 reports the results of various specifications explaining forecast error. We find that analysts' reliance on category-level information is associated with larger forecast errors. The coefficient of *CAT_REL* is positive and statistically significant at the 5% level for all specifications. The economic significance is also large. For example, in specification (1), a one standard deviation increase in *CAT_REL* leads to an increase 5.3% in absolute forecast error relative to the mean forecast error (scaled

[13] Cash flow volatility is measured as the standard deviation of cash flow from operations in the past five years (Zhang 2006). Cash flow from operations is earnings before extraordinary items minus total accruals, scaled by average total assets, where total accruals are equals to changes in current asset minus changes in cash, changes in liabilities, and depreciation expense plus changes in short term debt.

by stock price). The qualitative results for *CAT_REL* remain unchanged on including additional analyst-level and firm-level control variables in columns (2)-(7). For example, in specifications (7), we include past industry returns and past abnormal stock returns that we used to calculate *CAT_REL* in order to control for any price momentum effects that the *CAT_REL* measure might reflect. Our results are robust to including these price momentum variables. Also, to examine the possibility that our measure of *CAT_REL* could be capturing analysts' past forecast ability, we include analysts' average accuracy ranking two years prior to the forecast issue year in specifications (4)-(7).[14] The positive relationship between *CAT_REL* and *AFE* remains significantly positive when we include past forecast performance of the analyst as well as experience, All-star dummy, and brokerage size, all of which have been used to proxy for analyst ability. Similar results are obtained in specification (3) when we include a dummy variable signifying an analyst being a bottom 10% performer in prior years.

To extent that analysts with limited attention might have a stronger incentive to herd, we control for analysts' tendency to herd by including the boldness measure. We also control for the degree of analysts' effort by including the likelihood of rounding forecasts, where prior literature has shown that analyst tend to round forecasts when they exert less effort (Dechow and You, 2012).

In Panel B, we decompose the *CAT_REL* measure into the two R-squared values ($R^{2,\text{category}}$ and $R^{2,\text{stock}}$) which were used to construct the measure, obtained from the cross-sectional regressions of forecast revisions on lagged industry returns (*Catrsqr*) and on stock abnormal returns (*Resrsqr*). We do this to explore whether the relation between forecast error and *CAT_REL* arises from variation in both the reliance on category-level information, and the reliance on firm-specific information measures, or one of the two. Based on our preferred interpretation of the *CAT_REL* measure, our prediction is that analysts' forecast accuracy decreases with the degree of reliance on categories ($R^{2,category}$), and increases with the degree of reliance on firm-specific information ($R^{2,stock}$). The findings are consistent with our prediction:

[14] We include analysts' average ranking at year *k-2* instead of *k-1*, since the past performance measure will be correlated with *CAT_REL* at year *k−1*.

the coefficient of *Catrsqr* is significantly positive and the coefficient of *Resrsqr* is significantly negative in regressions explaining forecast error. In sum, we find that analysts who appear more susceptible to limited attention tend to have lower forecast accuracy when issuing firms' earnings forecasts.

Next, we consider the analysts' average rankings instead of the absolute forecast error as an alternative measure of analyst forecast accuracy. As mentioned before, the average ranking measure is the average of the analysts' relative ranking (ranging from 0 to 100) across all firms that the analyst issues forecast for a given year (*Avg_Rank*). A high average ranking translates to high average forecast accuracy. This alternative measure provides information about the overall forecast accuracy of the analyst instead of his firm-specific forecast accuracy. We examine the effect of *CAT_REL* on *Avg_Rank,* since one possible explanation of analysts' reliance on industry-level information could be if it minimizes overall forecast error across all firms covered by the analyst.

The results explaining analysts' average accuracy rankings are reported in Table 5. The main results in Table 5 are consistent with those in Table 4, where *CAT_REL* has a negative and statistically significant relation with average accuracy rankings across all specifications. From the coefficient reported in specification (5), we find that a 1% increase in *CAT_REL* is associated with a 11% decrease in average forecast ranking, indicating an economically significant relation. Overall, our findings in Table 4 and Table 5 suggest that analysts' relative reliance on category-level information has a negative impact on earnings forecast accuracy.

5.3. Analyst Forecast Frequency and Reliance on Categories

In this section, we examine the effect of analysts' reliance on categories on the quantity of information produced by the analyst, whereas the previous section focused on forecast quality. It is possible that while the relative reliance on category-level information leads to lower quality information production (i.e. less forecast accuracy), it may lead to a higher quantity of information production by serving to speed up information processing. Forecast frequency of the analyst is a measure of the amount of information production (e.g. Jacob, Lys, and Neale (1999); Fang, Huang, and Karpoff (2015)). Jacob, Lys, and Neale (1999) find that forecast frequency proxies for analyst effort or the incorporation of the latest information into forecasts. Following prior studies, we use forecast frequency to measure the amount of information produced by the analyst. We construct the two following measures of forecast frequency: the natural logarithm of the total number of forecasts by analyst-year, and the natural logarithm of the average number of forecasts per firm by analyst-year.

Table 6 reports the results of regressions explaining the quantity of analysts' information production. Table 6 shows that, on average, an analyst's forecast frequency decreases with the level of reliance on categories. In specifications (1)-(3), the dependent variable is the natural logarithm of the total number of forecasts by analyst-year, and in specifications (4)-(6), the dependent variable is the natural logarithm of the average number of forecasts per firm by analyst-year. In all specifications, the coefficient of *CAT_REL* is significantly negative, which implies that there is less information production by analysts' who tend to rely on category-level relative to firm-specific information. So, to the extent that an analyst's reliance on category-level relative to firm-specific information indicates limited attention, analysts with more limited attention produce less information.

We also find other analyst characteristics to be related to the quantity of analysts' information production. For example, in general, forecast frequency decreases with the frequency of rounded forecasts (*Rounding*), and increases with the frequency of bold forecasts (*Boldness*). Also, the average degree of industry competition of stocks covered by an analyst (*Avg. H-index*) is positively associated with forecast frequency, which implies that analysts who cover firms in more concentrated industries tend to produce more frequent forecasts. We also find that all-star analysts and analysts who work in larger brokerage firms tend to issue more frequent forecasts.

Finally, we do not find evidence that analysts' category reliance is associated with more timely forecasts. When we measure forecast timeliness as the number of days between the previous earnings announcement and analysts' first forecast, we do not find any significant relationship between *CAT_REL* and timeliness (untabulated results).

In sum, the results so far show that analysts' tendency to rely more on category-level information and less on firm-specific information has a negative impact on both the quality and quantity of information produced by the analyst. We do not find evidence to support the alternative possibility that relying more on category-level information, while detrimental to quality of forecasts, may be a rational "mental short-cut" if the analyst seeks to increase the quantity of information production.

5.4. Implications of Analysts' Reliance on Categories

In this section, our broad goal is to investigate whether the market interprets the analysts' reliance on categories as a negative signal of analyst ability. To explore this, we first examine whether the impact of analysts on stock prices varies with their reliance on categories. Next, we examine whether analysts' reliance on categories predicts their career outcomes.

5.4.1.Stock Price Impact and Analysts' Reliance on Categories

Here, we investigate the relation between analysts' reliance on categories and their stock price impact. We compare the stock price response to an analyst's forecast revisions as a function of the analyst's category reliance (*CAT_REL*). We first identify each analyst forecast revision date and then measure the stock price response around the analyst forecast revision announcement window of [−1, +1] days. The stock price response, CAR_{ijk}, is the three-day cumulative abnormal return around analyst *i*'s forecast revision for firm *j* in year *k*. Analyst forecast revision, Rev_{ijk}, is the difference between analyst *i*'s forecast for firm *j* in year *k* and the analyst's prior forecast for the same firm-year, scaled by the absolute value of the latter. The most recent forecast revisions prior to the actual annual earnings announcement date are included in the analysis.

In Table 7, we run regressions explaining the stock price impact of forecast revisions. The main explanatory variable of interest is the effect of the interaction term between the (lagged) *CAT_REL* and the magnitude of the forecast revision. We use variations of the regression specification in Equation (7) below:

$$CAR_{ijk} = b_0 + b_1 CAT\_REL_{i,k-1} + b_2(CAT\_REL_{i,k-1} * Rev_{ijk}) + b_3 Rev_{ijk} + \boldsymbol{b}_4(Controls_{i,k-1}) + \boldsymbol{b}_5(Controls_{j,k-1}) + \psi_k + \varepsilon_{ijk} \tag{7}$$

Here $Controls_{i,k-1}$ is a vector of analyst characteristics measured in year k−1 serving as control variables; $Controls_{j,k-1}$ is a vector of stock-level control variables measured in year k−1.

From the results in Table 7, we find that the stock price responses to forecast revisions are lower for revisions made by analysts who tend to rely more on category-level information versus firm-specific information. The coefficient of the interaction term $CAT\_REL_{i,k-1} * Rev_{ijk}$ is significantly negative for all specifications. On average, the cumulative abnormal returns (*CAR*) around forecast revisions increases with the magnitude of the forecast revision, but this relation is weaker for revisions by analysts who tend to rely more on category-level information relative to firm-specific information. The results suggest that investors are able to distinguish analysts who have a stronger tendency to rely on category-level information relative to firm-specific information as issuing less informative forecasts, by responding less to forecast revisions made by these analysts. Broadly, the evidence supports the notion that the market identifies analysts with limited attention who tend to issue less informative forecasts.

5.4.2. Analysts' Reliance on Categories and Turnover

If analysts' limited attention is associated with lower forecast accuracy and other stock market participants interpret this as a signal of inferior forecasting ability, then the metrics of limited attention should have a negative relation with the analysts' reputation and, hence, their job turnover. We test this hypothesis by examining whether *CAT_REL* is associated with a higher likelihood of future job turnover, controlling for past forecast performance and other analyst attributes that have been shown to affect job turnover in the existing literature.

In order to identify analyst turnover, we look at whether the analyst issues earnings forecasts for any firm in the next year (see Hong Kubik, Soloman (2000)). We assume that the analyst has left his job position in year *k* if the analyst issued forecasts in the previous year *k*−1, but does not issue any forecasts in year *k*. We note that our identification strategy is limited since our turnover measure includes both voluntary and forced turnover, while forced turnover due to poor performance is more relevant to our hypothesis. However, this limitation in the identification strategy adds noise to our estimation of the relationship between job turnover and category reliance, which should typically bias against finding a significant relationship. [15]

The results using the Logit Probability model reported in Table 8 show that analysts' *CAT_REL* in year *k*−1 is significantly and positively associated with the likelihood of job turnover in year *k* in all specifications. We include year fixed effects to control for any times-specific factors, such as business cycle conditions, which could affect the labor market for analysts. The relation between *CAT_REL* and job turnover is also economically meaningful. In specification (3), a one standard deviation increase in *CAT_REL* leads to a 4% increase in the probability of job turnover (relative to the mean value).

To explore whether *CAT_REL* has a significant effect on job turnover in year *k* beyond the analysts' past forecasting performance, we also control for analysts' past performance in specifications (2)-(4) by including a two-year prior analyst forecast accuracy ranking as a measure of analysts' past performance . In specifications (5)-(7), we include an indicator variable which equals one if the analyst is ranked within the lowest 10% of accuracy for a forecast, based on the average ranking across all forecasts issued by the analyst in the year *k*−1. The positive relationship between *CAT_REL* and job turnover remains highly significant even after controlling for past forecasting performance. Using the logit probability model in

[15] Hong, Kubik, and Solomon (2000) supports the idea that sell-side analysts are not likely to switch industries for a better job, by noting that sell-side analysts, unlike buy-side analyst, are not likely to leave a job in the I/B/E/S sample to a better job. Moreover, the negative correlation between analyst performance and turnover in previous studies (Mikhail et al (1999), Groysberg et al (2011)) also mitigates our concerns on voluntary turnover. That is, analyst turnover is observed for analysts with low performance, rather than analysts with high performance, and Mikhail et al (1999) states that it is the worst performing analysts who leave their analyst database.

specification (4) where we include the interaction of the *Avg. Rank* and *CAT_REL*, we find that the likelihood of job separation for an analyst with low past ranking is higher if the analyst also has a higher tendency to rely on category-level versus firm-specific information. In specification (4), a one standard deviation increase in *CAT_REL* leads to a 8% increase in the probability of job turnover (relative to the mean value) when conditioning on past performance. In other words, the evidence is consistent with analysts being more likely to experience job separation following poor performance when it is coupled with a tendency to exhibit limited attention (as reflected in *CAT_REL*).

In conclusion, we find that analysts' reliance on categories has a significant effect on their career outcomes.

6. Robustness Tests: Alternative Measures

So far in the empirical analyses, we have used 2-digit SIC industry codes to define a stock's category, since it is a stable and natural category widely used in capital markets. In this section, we conduct robustness checks using alternative (and finer) definitions of stock categories, such as those that account for market capitalization of a stock or style (value versus growth) in addition to the industry identification.

For one set of robustness checks, stocks within an industry are sorted into quintile groups based on firm size or market-to-book ratio in the prior year. In these tests, stocks in the same size or market-to-book ratio quintile in the same industry are considered to be in the same category. The R^2 ($R^{2,category}$) of the cross-sectional regression of the forecast revisions on a set of variables representing past returns of the stock's 2-digit SIC industry and size (style) category is used to compute *CAT_REL*, with $R^{2,stock}$ being calculated using abnormal stock returns adjusted for the corresponding category. Additionally, we use three alternative industry classifications based on the Fama-French 48 industries, the four-digit North American Industry Classification System (NAICS) codes, and the Global Industry Classification Standard (GICS) groups as alternatives to the 2-digit SIC codes in computing *CAT_REL*. We repeat our main analyses including five alternative measures of *CAT_REL*, measured using the category classifications described above.

Table 9 reports the results of the effect of analysts' reliance on categories on forecast accuracy, stock price impact, and job turnover using the five alternative category definitions which are as follows: industry-firm size, industry-style, Fama-French 48 industries, and industry by 4-digit NAICS and GICS codes. Panel A reports the relationship between the five alternative *CAT_REL* measures and analyst forecast accuracy. The results remain materially unchanged from the baseline specification of Category Reliance used earlier in Table 4. In Panel B, we examine how the alternative specifications of *CAT_REL* are related to the stock price impact of analysts' forecast revisions. We also find results unchanged from the previous findings in Table 7, indicating that investors respond less to forecast revisions made by analysts who tend to exhibit more category reliance in their forecasts. Finally, in Panel C, we repeat the analyst job turnover analyses using these alternative *CAT_REL* measures. The results remain similar to those in Table 8, where we find that higher *CAT_REL* leads to an increased likelihood of job turnover. In sum, all our main results are robust to alternative categories that analysts might rely on when they issue earnings forecasts.

Lastly, we reexamine the relationship between analysts' category reliance and their forecast accuracy using a relative measure of category reliance. So far we have used the absolute level of analysts' category reliance measure and have shown that stronger category reliance is associated with larger forecast errors. Here, we examine whether analysts' category reliance relative to other analysts covering the same firm similarly leads to lower forecast accuracy. We construct a relative category reliance measure (*AbCAT_REL*), which is the difference between an analyst's *CAT_REL* and the average *CAT_REL* value of all analysts covering the same firm in a given year. The regression specification is similar to that in Table 4. From Table 10, we find that the coefficient of *AbCAT_REL* is positive throughout all specifications. When we look at the effect of relative CAT_REL on forecast accuracy, we find that the economic significance increases.

7. Conclusion

This paper shows that the limited attention of security analysts, as reflected in their propensity to rely on "macro" category-level as opposed to "micro" firm-level information, has a significant relation with their forecast accuracy. Consistent with prior literature in psychology and economics, our main finding is that analysts who ex ante exhibit a higher tendency to rely on category-level versus firm-specific information have more limited attention, and less ability to issue accurate forecasts which move stock prices. In empirical tests where we consider the analysts' reliance on category-level and firm-level information separately, forecast accuracy decreases with the analysts' reliance on category-level information, and increases with the analysts' reliance on firm-level information. These results hold in multivariate settings controlling for a variety of factors that could affect forecast errors. Among other results, we find that analysts' relative reliance on categories decreases with proxies of analyst ability, namely, number of firms covered, experience, private information, boldness, All-star status, brokerage size, and past forecast accuracy. Also, analysts' relative reliance on categories increases with their tendency for rounding. As further evidence supporting our main finding, we find that the stock price reaction to forecast revisions is lower, and likelihood of job separation is higher, for analysts who display more limited attention based on our metric of reliance on category-level versus firm-level information.

Our results have important implications for evaluating the information contained in analysts' earnings forecasts− an issue that has interested academics and investors for a long time. First, our study draws attention to security analysts being seemingly susceptible to similar biases that affect other less sophisticated market participants. Given the crucial role analysts play in price formation and market efficiency, it is valuable if investors can ex ante calibrate their susceptibility to limited attention and behavioral biases, which subsequently affect the information content of their forecasts. Second, we provide fresh insights in the debate on analysts' forecast biases by exploring a type of information processing bias that is more difficult to explain using the rational economic incentives of analysts, such as optimism and overconfidence which have been the focus of previous studies. A fundamental question raised by the evidence we uncover and other studies on analysts' behavioral biases that remains largely unexplored is whether incentives and labor market forces can meaningfully mitigate the effects of behavioral biases and limited attention on security analysts.

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TABLE 1
Summary Statistics of Key Variables

Table 1 reports the descriptive statistics for the main variables. The sample period is from 1996 to 2011. Category Reliance (*CAT_REL*) is measured for analyst *i* in year *k* as the R-squared of the cross-sectional regression of forecast revisions (*rev*) on lagged industry returns, scaled by one plus the R-squared of the cross-sectional regression of forecast revisions (*rev*) on lagged abnormal stock returns. *Experience* is the natural logarithm of the number of years analyst *i* issues a forecast for a firm, averaged across the firms the analyst covers in year *k*. *All-star* is an indicator variable which equals one if the analyst is included in the All-star analyst list by the Institutional Investors magazine in year *k*. *Boldness* is the percentage of bold earnings forecasts issued by analyst *i* in year *k*, where a forecast is defined as bold if the forecast is above both the analyst's prior forecast and the immediate consensus forecast before the forecast revision, or if the forecast is below both the analyst's prior forecast and the consensus forecast immediately before the forecast revision. *Rounding* is the percentage of rounded earnings forecasts issued by the analyst *i* in year *k*, where a forecast is a rounded forecast if it occurs at nickel intervals. *PPI* is the measure of analyst *i*'s private information in year *k* as one minus the correlation between the analyst's forecast revisions in year *k* and prior stock price changes. *Coverage* is the number of firms covered by the analyst *i* in year *k*. *Brokerage Size* is measured by the log of the number of analysts in a given brokerage firm in year *k*. *Industry Number* is the number of different industries covered by the analyst in year *k*. *Size* is the natural logarithm of the market value of equity for firm *j* in year *k*. *Market/Book* is the market-to-book ratio of firm *j* in year *k* calculated as the market value of the firm's equity at the end of year *k* plus the difference between the book value of the firm's assets and the book value of the firm's equity in year *k*, divided by the book value of firm *j*'s assets in year *k*. *Cashflow volatility* is the standard deviation of cash flow from operations in the past 5 years (with a minimum of 3 years) of firm *j* in year *k*, where cash flow from operating activity is earnings before extraordinary items minus total accruals, scaled by average total assets. *Institutional Holdings* is the percentage of institutional investor holdings in firm *j* at year *k*. *H-Index* of firm *j*'s industry is the Herfindahl index of sales for firm *j*'s 2-digit SIC code, computed as the sum of squared weights of sales across all the firms in the industry in year *k*.

	Mean	Stddev	Median
Analyst Characteristics			
CAT_REL	0.070	0.060	0.025
AFE	2.086	4.415	0.689
Experience	1.910	0.778	1.946
All Star	0.136	0.343	0.000
Boldness	0.150	0.150	0.178
Rounding	0.024	0.026	0.018
PPI	0.828	0.159	0.826
Coverage	3.000	0.836	2.996
Brokerage Size	3.678	1.029	3.829
Industry Number	3.077	1.809	3.000
Firm Characteristics			
Size	7.667	1.788	7.581
Market/Book	2.177	1.787	1.538
Cashflow Volatility	0.135	0.133	0.091
Institutional Holdings	0.666	0.248	0.697
H-Index	0.058	0.037	0.046

TABLE 2
Correlation Matrix of Key Variables

Table 2 reports the correlation coefficients between the main variables. Category Reliance (*CAT_REL*) is measured for analyst *i* in year *k* as the R-squared of the cross-sectional regression of forecast revisions (*rev*) on lagged industry returns, scaled by one plus the R-squared of the cross-sectional regression of forecast revisions (*rev*) on lagged abnormal stock returns. *Experience* is the natural logarithm of the number of years analyst *i* issues a forecast for a firm, averaged across the firms the analyst covers in year *k-1*. *All-star* is an indicator variable which equals one if the analyst is included in the All-star analyst list by the Institutional Investors magazine in year *k-1*. *Boldness* is the percentage of bold earnings forecasts issued by analyst *i* in year *k-1*, where a forecast is defined as bold if the forecast is above both the analyst's prior forecast and the immediate consensus forecast before the forecast revision, or if the forecast is below both the analyst's prior forecast and the consensus forecast immediately before the forecast revision. *Rounding* is the percentage of rounded earnings forecasts issued by the analyst *i* in year *k-1*, where a forecast is a rounded forecast if it occurs at nickel intervals. *PPI* is the measure of analyst *i*'s private information in year *k* as one minus the correlation between the analyst's forecast revisions in year -1*k* and prior stock price changes. *Coverage* is the number of firms covered by the analyst *i* in year *k-1*. *Avg_Rank* is the average forecast accuracy ranking of the analyst *i* in year *k-1*, where the analyst's relative accuracy ranking is computed following Hong and Kubik (2003). *Brokerage Size* is measured by the log of the number of analysts in a given brokerage firm in year *k-1*. *Industry Number* is the number of different industries covered by the analyst in year *k-1*. *Avg. H-index* is the Herfindahl index of sales for a firm's 2-digit SIC code, computed as the sum of squared weights of sales across all the firms in the industry in year *k*−1, averaged across the firms the analyst *i* covers in year *k*−1. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

	CAT_REL	*Experience*	*All Star*	*Boldness*	*Rounding*	*PPI*	*Coverage*	*Avg_Rank*	*Brokerage Size*	*Industry Number*
Experience	-0.067***									
All Star	-0.017**	0.022***								
Boldness	-0.06***	-0.018**	0.023***							
Rounding	0.031***	0.088***	0.092***	-0.059***						
PPI	-0.052***	-0.024***	-0.018**	0.013*	-0.024***					
Coverage	-0.182***	0.232***	0.066***	-0.122***	0.079***	0.046***				
Avg_Rank	-0.017**	-0.002	0.022***	0.016**	0.023***	0.012	-0.031***			
Brokerage Size	-0.020***	0.014**	0.354***	0.034***	0.029***	-0.001	0.017**	0.046***		
Industry Number	-0.094***	0.122***	0.018**	-0.076***	0..071***	-0.050***	0.357***	-0.015**	-0.088***	
Avg. H-index	-0.038***	0.054***	0.011	0.077***	0.023***	-0.118***	-0.033***	-0.008	0.023***	0.249***

TABLE 3
Determinants of Category Reliance

Table 3 reports the coefficients from regressions explaining analysts' Category Reliance (*CAT_REL*). The dependent variable is *CAT_REL* measured for each analyst *i* in year *k*, which is the R-squared of the cross-sectional regression of forecast revisions (*rev*) on lagged industry returns, scaled by one plus the R-squared of the cross-sectional regression of forecast revisions (*rev*) on lagged abnormal stock returns. *Experience* is the natural logarithm of the number of years analyst *i* issues a forecast for a firm, averaged across the firms the analyst covers in year *k*−1. *All-star* is an indicator variable which equals one if the analyst is included in the All-star analyst list by the Institutional Investors magazine in year *k-1*. *Boldness* is the percentage of bold earnings forecasts issued by the analyst *i* in year *k*−1, where a forecast is defined as bold if the forecast is above both the analyst's prior forecast and the immediate consensus forecast before the forecast revision, or if the forecast is below both the analyst's prior forecast and the consensus forecast immediately before the forecast revision. *Rounding* is the percentage of rounded earnings forecasts issued by the analyst *i* in year *k*−1, where a forecast is a rounded forecast if it occurs at nickel intervals. *PPI* is the measure of analyst *i*'s private information in year *k*−1, calculated as one minus the correlation between the analyst's forecast revisions and prior stock price changes in year *k*−1. *Coverage* is the number of firms covered by the analyst *i* in year *k*−1. *Brokerage Size* is measured by the log of the number of analysts in a given brokerage firm in year *k*. *Industry Number* is the number of different industries covered by the analyst in year *k*. *Avg_Rank* is the average forecast accuracy ranking of the analyst *i* in year *k*−1, where the analyst's relative accuracy ranking is computed following Hong and Kubik (2003). *Avg. H-index* is the Herfindahl index of sales for a firm's 2-digit SIC code, computed as the sum of squared weights of sales across all the firms in the industry in year *k*−1, averaged across the firms the analyst *i* covers in year *k*−1. All specifications include year fixed effects. Standard errors are clustered by analyst and reported in parentheses. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Experience	-0.006***										-0.001
	(0.001)										(0.001)
All Star		-0.007***									-0.002
		(0.002)									(0.002)
Boldness			-0.026***								-0.031***
			(0.004)								(0.005)
Rounding				0.059**							0.118***
				(0.023)							(0.023)
PPI					-0.020***						-0.018***
					(0.003)						(0.003)
Coverage						-0.038***					-0.040***
						(0.002)					(0.002)
Brokerage Size							-0.002***				-0.002**
							(0.001)				(0.001)
Avg_Rank								-0.003			-0.005**
								(0.002)			(0.002)
Industry Number									-0.004***		-0.001**
									(0.000)		(0.000)
Avg. H-index										-0.053***	-0.048***
										(0.017)	(0.018)
Constant	0.105***	0.096***	0.100***	0.094***	0.108***	0.203***	0.103***	0.109***	0.107***	0.099***	0.255***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.005)	(0.002)	(0.008)	(0.001)	(0.001)	(0.012)
N	19171	18553	19509	19613	17310	19613	18553	19217	19272	19290	16219
R-sq	0.019	0.017	0.017	0.015	0.018	0.050	0.017	0.015	0.022	0.015	0.060
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 4
Category Reliance and Analyst Forecast Accuracy

Table 4 reports the coefficients from regressions explaining analysts' forecast accuracy. The dependent variable is analyst forecast error (*AFE*) for analyst *i* for firm *j* in year *k*, which is the absolute forecast error (actual minus analysts' forecast earnings) scaled by the stock price in year *k*−1. In Panel A, Category Reliance (*CAT_REL*) is measured for analyst *i* in year *k*−1 as the R-squared of the cross-sectional regression of forecast revisions (*rev*) on lagged industry returns, scaled by one plus the R-squared of the cross-sectional regression of forecast revisions (*rev*) on lagged abnormal stock returns. In Panel B, we replace *CAT_REL* with the two R-squared values of the cross-sectional regressions of forecast revisions on lagged industry returns (*Catrsqr*) and firms' stock returns (*Resrsqr*), measured for analyst *i* in year *k*−1. *Experience* is the natural logarithm of the number of years analyst *i* issues a forecast for a firm, averaged across the firms the analyst covers in year *k*−1. *All-star* is an indicator variable which equals one if the analyst is included in the All-star analyst list by the Institutional Investors magazine in year *k*. *Boldness* is the percentage of bold earnings forecasts issued by the analyst *i* in year *k*−1, where a forecast is defined as bold if the forecast is above both the analyst's prior forecast and the immediate consensus forecast before the forecast revision, or if the forecast is below both the analyst's prior forecast and the consensus forecast immediately before the forecast revision. *Rounding* is the percentage of rounded earnings forecasts issued by the analyst *i* in year *k*−1, where a forecast is a rounded forecast if it occurs at nickel intervals. *PPI* is the measure of analyst *i*'s private information in year *k*−1, calculated as one minus the correlation between the analyst's forecast revisions and prior stock price changes in year *k*−1. *Coverage* is the number of firms covered by the analyst *i* in year *k*−1. *Brokerage Size* is measured by the log of the number of analysts in a given brokerage firm in year *k*. *Industry Number* is the number of different industries covered by the analyst in year *k*. *Avg_Rank* is the average forecast accuracy ranking of the analyst *i* in year *k*−2, where the analyst's relative accuracy ranking is computed following Hong and Kubik (2003). *Bottom 10% Flag* is an indicator variable which equals one if the analyst's average forecast accuracy ranking in year *k*−2 is in the lowest 10% of the sample. *Size* is the natural logarithm of the market value of equity of firm *j* in year *k*−1. *Market/Book* is the market-to-book ratio calculated as the market value of firm *j*'s equity at the end of year *k*−1 plus the difference between the book value of the firm's assets and the book value of the firm's equity in year *k*−1, divided by the book value of the firm's assets in year *k*−1. *Cashflow volatility* for firm *j* in year *k*−1 is the standard deviation of cash flow from operations in the past 5 years (with a minimum of 3 years), where cash flow from operating activity is earnings before extraordinary items minus total accruals, scaled by average total assets. *Institutional holdings* is the percentage of institutional investor holdings in firm *j* in year *k*−1. *H-index* is the Herfindahl index of sales for firm *j*'s 2-digit SIC code, computed as the sum of squared weights of sales across all the firms in the industry in year *k*−1. *Lag Industry Return*, *Lag2 Industry Return*, *Lag3 Industry Return*, and *Lag4 Industry Return* are the 1-, 2-, 3-, and 4-month lagged industry returns, respectively, for firm *j* measured prior to the month of the forecast. *Lag Stock Return*, *Lag2 Stock Return*, *Lag3 Stock Return*, and *Lag4 Stock Return* are the 1-, 2-, 3-, and 4-month lagged abnormal stock returns, respectively, for firm *j* measured prior to the month of the forecast. All specifications include year fixed effects. Standard errors are clustered by analyst-year and reported in parentheses. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CAT_REL	2.193***	1.770**	1.385**	1.385**	1.227**	1.377**	1.478**
	(0.686)	(0.770)	(0.574)	(0.585)	(0.581)	(0.573)	(0.575)
Experience		-0.137***	-0.130**	-0.143**	-0.132**	-0.041	-0.043
		(0.052)	(0.058)	(0.061)	(0.061)	(0.060)	(0.060)
Boldness		-0.656***	-0.630**	-0.634**	-0.598**	-0.194	-0.214
		(0.249)	(0.258)	(0.265)	(0.267)	(0.255)	(0.254)
Rounding		9.785***	10.383***	10.432***	10.746***	10.258***	10.145***
		(1.549)	(1.600)	(1.620)	(1.640)	(1.572)	(1.572)
All Star		0.119	0.147	0.158	0.185*	0.362***	0.358***
		(0.098)	(0.102)	(0.103)	(0.106)	(0.101)	(0.101)
PPI		0.407*	0.486**	0.546**	0.475**	0.476**	0.454**
		(0.210)	(0.214)	(0.219)	(0.218)	(0.210)	(0.211)
Coverage		-0.449***	-0.424***	-0.415***	-0.365***	-0.791***	-0.783***
		(0.138)	(0.140)	(0.138)	(0.138)	(0.157)	(0.157)
Brokerage Size		-0.101***	-0.120***	-0.122***	-0.121***	-0.031	-0.032
		(0.034)	(0.035)	(0.036)	(0.038)	(0.036)	(0.036)
Past Bottom 10% Flag			0.018				
			(0.067)				
Past Accuracy Ranking				-0.003	-0.003	-0.004	-0.004
				(0.003)	(0.003)	(0.003)	(0.003)
Industry Number					-0.022	0.001	0.001
					(0.021)	(0.021)	(0.021)
H-index					-1.908***	-3.269***	-3.297***
					(0.397)	(0.374)	(0.372)
Size						-0.618***	-0.615***
						(0.018)	(0.018)
Market/Book						-0.517***	-0.513***
						(0.020)	(0.020)
Cashflow Volatility						1.119***	1.152***
						(0.274)	(0.272)
Institutional Holdings						-1.710***	-1.693***
						(0.150)	(0.150)
Lag Industry Return							-0.172
							(0.423)
Lag2 Industry Return							0.357
							(0.340)
Lag3 Industry Return							-0.953***
							(0.363)
Lag4 Industry Return							-1.876***
							(0.406)
Lag Stock Return							-0.097
							(0.097)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lag2 Stock Return							0.033
							(0.106)
Lag3 Stock Return							-0.062
							(0.079)
Lag4 Stock Return							-0.012
							(0.113)
Constant	2.248***	3.836***	3.744***	3.852***	3.942***	11.646***	11.628***
	(0.055)	(0.479)	(0.480)	(0.455)	(0.456)	(0.539)	(0.539)
N	64741	62225	58645	56718	55509	55509	55509
R-sq	0.027	0.032	0.031	0.030	0.031	0.108	0.109
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Catrsqr	2.099***	1.678**	1.361**	1.361**	1.213**	1.385**	1.481***
	(0.626)	(0.695)	(0.540)	(0.550)	(0.547)	(0.538)	(0.540)
Resrsqr	-2.011***	-2.299***	-2.134***	-2.200***	-2.197***	-2.714***	-2.729***
	(0.497)	(0.504)	(0.497)	(0.513)	(0.518)	(0.491)	(0.493)
Experience		-0.137***	-0.131**	-0.143**	-0.132**	-0.041	-0.043
		(0.052)	(0.057)	(0.061)	(0.061)	(0.060)	(0.060)
Boldness		-0.681***	-0.651**	-0.657**	-0.620**	-0.220	-0.240
		(0.249)	(0.257)	(0.264)	(0.266)	(0.254)	(0.253)
Rounding		9.736***	10.334***	10.372***	10.685***	10.187***	10.067***
		(1.547)	(1.598)	(1.619)	(1.638)	(1.569)	(1.569)
All Star		0.118	0.146	0.159	0.186*	0.364***	0.360***
		(0.098)	(0.101)	(0.103)	(0.105)	(0.100)	(0.100)
PPI		0.403*	0.483**	0.539**	0.469**	0.468**	0.444**
		(0.210)	(0.213)	(0.218)	(0.217)	(0.209)	(0.210)
Coverage		-0.486***	-0.460***	-0.454***	-0.408***	-0.846***	-0.838***
		(0.136)	(0.139)	(0.137)	(0.137)	(0.155)	(0.155)
Brokerage Size		-0.098***	-0.117***	-0.119***	-0.118***	-0.027	-0.028
		(0.034)	(0.035)	(0.036)	(0.038)	(0.036)	(0.036)
Past Bottom 10% Flag			0.017				
			(0.067)				
Past Accuracy Ranking				-0.003	-0.003	-0.004	-0.004
				(0.003)	(0.003)	(0.003)	(0.003)
Industry Number					-0.020	0.003	0.003
					(0.021)	(0.021)	(0.021)
H-index					-1.911***	-3.283***	-3.309***
					(0.397)	(0.374)	(0.372)
Size						-0.621***	-0.618***
						(0.018)	(0.018)
Market/Book						-0.514***	-0.510***
						(0.020)	(0.020)
Cashflow Volatility						1.089***	1.125***
						(0.273)	(0.271)
Institutional Holdings						-1.719***	-1.702***
						(0.149)	(0.150)
Lag Industry Return							-0.226
							(0.423)
Lag2 Industry Return							0.345
							(0.340)
Lag3 Industry Return							-1.002***
							(0.364)
Lag4 Industry Return							-1.868***
							(0.406)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lag Stock Return							-0.093
							(0.098)
Lag2 Stock Return							0.028
							(0.106)
Lag3 Stock Return							-0.064
							(0.079)
Lag4 Stock Return							-0.013
							(0.113)
Constant	2.358***	4.080***	3.973***	4.099***	4.193***	11.986***	11.972***
	(0.057)	(0.469)	(0.476)	(0.455)	(0.455)	(0.538)	(0.537)
N	64741	62225	58645	56718	55509	55509	55509
R-sq	0.027	0.032	0.031	0.031	0.032	0.109	0.110
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 5
Category Reliance and Average Accuracy Ranking

Table 5 reports the coefficients from regressions explaining analysts' relative forecast accuracy rankings. The dependent variable is *Avg_Rank* which is the natural logarithm of the average forecast accuracy ranking of analyst *i* in year *k*, where the relative accuracy ranking measure is computed following Hong and Kubik (2003). Category Reliance (*CAT_REL*) is measured in year *k*−1 for analyst *i* as the R-squared of the cross-sectional regression of forecast revisions (*rev*) on lagged industry returns, scaled by one plus the R-squared of the cross-sectional regression of forecast revisions (*rev*) on lagged abnormal stock returns. *Experience* is the natural logarithm of the number of years analyst *i* issues a forecast for a firm, averaged across the firms the analyst covers in year *k*−1. *All-star* is an indicator variable which equals one if the analyst is included in the All-star analyst list by the Institutional Investors magazine in year *k-1*. *Boldness* is the percentage of bold earnings forecasts issued by the analyst *i* in year *k*−1, where a forecast is defined as bold if the forecast is above both the analyst's prior forecast and the immediate consensus forecast before the forecast revision, or if the forecast is below both the analyst's prior forecast and the consensus forecast immediately before the forecast revision. *Rounding* is the percentage of rounded earnings forecasts issued by the analyst *i* in year *k*−1, where a forecast is a rounded forecast if it occurs at nickel intervals. *PPI* is the measure of analyst *i*'s private information in year *k*−1, calculated as one minus the correlation between the analyst's forecast revisions and prior stock price changes in year *k*−1. *Coverage* is the number of firms covered by the analyst *i* in year *k*−1. *Brokerage Size* is measured by the log of the number of analysts in a given brokerage firm in year *k*. *Industry Number* is the number of different industries covered by the analyst in year *k-1*. *Avg. H-index* is the Herfindahl index of the firm's industry, averaged across the firms the analyst covers in year *k*−1. All specifications include year fixed effects. Standard errors are clustered by analyst and reported in parentheses. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
CAT_REL	-0.064*	-0.058*	-0.090**	-0.111***	-0.112***
	(0.034)	(0.035)	(0.037)	(0.038)	(0.038)
Experience		-0.004	-0.004	-0.001	-0.001
		(0.004)	(0.004)	(0.004)	(0.004)
All Star		0.021**	0.021**	0.015	0.015
		(0.008)	(0.008)	(0.009)	(0.009)
Boldness			0.026	0.017	0.020
			(0.022)	(0.022)	(0.022)
Rounding			0.309***	0.318***	0.321***
			(0.082)	(0.082)	(0.082)
PPI			0.019	0.021	0.019
			(0.014)	(0.014)	(0.014)
Coverage				-0.027**	-0.028**
				(0.011)	(0.011)
Brokerage Size				0.000	0.000
				(0.000)	(0.000)
Industry Number					0.001
					(0.002)
Avg. H-index					-0.097
					(0.079)
Constant	3.909***	3.913***	3.892***	3.959***	3.966***
	(0.004)	(0.009)	(0.016)	(0.033)	(0.034)
N	18845	18236	16172	16172	16163
R-sq	0.001	0.002	0.004	0.005	0.005
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

TABLE 6
Category Reliance and Forecast Frequency

Table 6 reports the coefficients from regressions explaining analysts' forecast frequency. In specifications (1)-(3), the dependent variable is the natural logarithm of the total number of forecasts issued by analyst *i* in year *k*. In specifications (4)-(6), the dependent variable is the natural logarithm of the average number of forecasts issued by analyst *i* per firm covered in year *k*. Category Reliance (*CAT_REL*) is measured in year *k*−1 for analyst *i* as the R-squared of the cross-sectional regression of forecast revisions (*rev*) on lagged industry returns, scaled by one plus the R-squared of the cross-sectional regression of forecast revisions (*rev*) on lagged abnormal stock returns. *Experience* is the natural logarithm of the number of years analyst *i* issues a forecast for a firm, averaged across the firms the analyst covers in year *k*−1. *All-star* is an indicator variable which equals one if the analyst is included in the All-star analyst list by the Institutional Investors magazine in year *k-1*. *Boldness* is the percentage of bold earnings forecasts issued by the analyst *i* in year *k*−1, where a forecast is defined as bold if the forecast is above both the analyst's prior forecast and the immediate consensus forecast before the forecast revision, or if the forecast is below both the analyst's prior forecast and the consensus forecast immediately before the forecast revision. *Rounding* is the percentage of rounded earnings forecasts issued by the analyst *i* in year *k*−1, where a forecast is a rounded forecast if it occurs at nickel intervals. *PPI* is the measure of analyst *i*'s private information in year *k*−1, calculated as one minus the correlation between the analyst’s forecast revisions and prior stock price changes in year *k*−1. *Coverage* is the number of firms covered by the analyst *i* in year *k*−1. *Brokerage Size* is measured by the log of the number of analysts in a given brokerage firm in year *k*. *Industry Number* is the number of different industries covered by the analyst in year *k-1*. *Avg. H-index* is the Herfindahl index of the firm's industry, averaged across the firms the analyst covers in year *k*−1. All specifications include year fixed effects. Standard errors are clustered by analyst and reported in parentheses. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
CAT_REL	-2.286***	-1.216***	-1.160***	-0.409***	-0.712***	-0.678***
	(0.035)	(0.082)	(0.082)	(0.019)	(0.050)	(0.050)
Experience		-0.004	-0.011		-0.010	-0.013
		(0.014)	(0.014)		(0.010)	(0.010)
All Star		0.079***	0.083***		0.055***	0.058***
		(0.021)	(0.020)		(0.016)	(0.015)
Boldness		0.315***	0.235***		0.356***	0.300***
		(0.043)	(0.042)		(0.030)	(0.029)
Rounding		-0.723***	-0.682***		-0.588***	-0.546***
		(0.237)	(0.235)		(0.166)	(0.165)
PPI		-0.093***	-0.064**		-0.041**	-0.026
		(0.030)	(0.030)		(0.020)	(0.020)
Coverage		0.678***	0.730***		-0.140***	-0.100***
		(0.024)	(0.026)		(0.018)	(0.019)
Brokerage Size		0.032***	0.025***		0.022***	0.017***
		(0.008)	(0.008)		(0.006)	(0.006)
Industry Number			-0.025***			-0.020***
			(0.004)			(0.003)
Avg. H-index			1.453***			0.913***
			(0.182)			(0.127)
Constant	4.001***	2.156***	2.014***	1.353***	1.787***	1.694***
	(0.010)	(0.083)	(0.084)	(0.006)	(0.059)	(0.060)
N	36596	12678	12503	36596	12678	12503
R-sq	0.229	0.267	0.278	0.095	0.118	0.122
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 7
Category Reliance and Stock Price Impact

Table 7 reports the coefficients from regressions explaining stock price responses to analysts' forecast revisions. The dependent variable is the stock price response, *CAR*, which is the 3-day cumulative abnormal return [-1, 1] around analyst *i*'s forecast revision for firm *j* in year *k*. Analyst forecast revision, *Rev*, is the difference between analyst *i*'s forecast for firm *j* in year *k* and the analyst's prior forecast for the same firm-year, scaled by the absolute value of the latter. The most recent forecast revisions prior to the actual annual earnings announcement date are included. Category Reliance (*CAT_REL*) is measured in year *k*−1 for analyst *i* as the R-squared of the cross-sectional regression of forecast revisions (*rev*) on lagged industry returns, scaled by one plus the R-squared of the cross-sectional regression of forecast revisions (*rev*) on lagged abnormal stock returns. *Experience* is the natural logarithm of the number of years analyst *i* issues a forecast for a firm, averaged across the firms the analyst covers in year *k*−1. *All-star* is an indicator variable which equals one if the analyst is included in the All-star analyst list by the Institutional Investors magazine in year *k-1*. *Boldness* is the percentage of bold earnings forecasts issued by the analyst *i* in year *k*−1, where a forecast is defined as bold if the forecast is above both the analyst's prior forecast and the immediate consensus forecast before the forecast revision, or if the forecast is below both the analyst's prior forecast and the consensus forecast immediately before the forecast revision. *Rounding* is the percentage of rounded earnings forecasts issued by the analyst *i* in year *k*−1, where a forecast is a rounded forecast if it occurs at nickel intervals. *PPI* is the measure of analyst *i*'s private information in year *k*−1, calculated as one minus the correlation between the analyst's forecast revisions and prior stock price changes in year *k*−1. *Coverage* is the number of firms covered by the analyst *i* in year *k*−1. *Brokerage Size* is measured by the log of the number of analysts in a given brokerage firm in year *k-1*. *Industry Number* is the number of different industries covered by the analyst in year *k*. *Horizon* is the natural logarithm of the number of days from the analyst forecast issue date for firm *j* to the actual earnings announcement date for firm *j*. *Size* is the natural logarithm of the market value of equity of firm *j* in year *k*−1. *Market/Book* is the market-to-book ratio calculated as the market value of firm *j*'s equity at the end of year *k*−1 plus the difference between the book value of the firm's assets and the book value of the firm's equity in year *k*−1, divided by the book value of the firm's assets in year *k*−1. *Cashflow Volatility* for firm *j* in year *k*−1 is the standard deviation of cash flow from operations in the past 5 years (with a minimum of 3 years), where cash flow from operating activity is earnings before extraordinary items minus total accruals, scaled by average total assets. *Institutional Holdings* is the percentage of institutional investor holdings in firm *j* in year *k*−1. All specifications include year fixed effects. Standard errors are clustered by firm-analyst and reported in parentheses. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
CAT_REL	-0.356	-0.275	-0.338	-0.291	-0.203	-0.252
	(0.403)	(0.416)	(0.416)	(0.404)	(0.418)	(0.418)
*CAT_REL*Rev*	-4.631***	-4.128***	-4.160***	-4.982***	-4.508***	-4.541***
	(1.519)	(1.581)	(1.580)	(1.571)	(1.623)	(1.623)
Rev	2.288***	2.275***	2.284***	2.803***	2.920***	2.940***
	(0.135)	(0.139)	(0.139)	(0.540)	(0.551)	(0.551)
PPI				0.152	0.169	0.224
				(0.165)	(0.170)	(0.170)
*PPI*Rev*				-0.585	-0.738	-0.752
				(0.592)	(0.608)	(0.607)
Experience		0.064	0.065*		0.062	0.064
		(0.040)	(0.040)		(0.040)	(0.040)
All Star		-0.050	-0.056		-0.049	-0.055
		(0.076)	(0.076)		(0.076)	(0.076)
Boldness		-0.246	-0.208		-0.269	-0.237
		(0.215)	(0.216)		(0.217)	(0.218)
Rounding		-0.328	-1.321		-0.274	-1.262
		(0.982)	(0.981)		(0.981)	(0.981)
Horizon		0.928***	0.985***		0.921***	0.978***
		(0.202)	(0.202)		(0.203)	(0.203)
Brokerage Size		0.014	0.015		0.016	0.016
		(0.025)	(0.025)		(0.025)	(0.025)
Coverage		-0.071	-0.071		-0.067	-0.068
		(0.064)	(0.064)		(0.064)	(0.064)
Size			-0.023			-0.024
			(0.017)			(0.017)
Market/Book			-0.091***			-0.091***
			(0.035)			(0.035)
Cashflow Volatility			-1.565***			-1.584***
			(0.406)			(0.406)
Institutional Holdings			0.265**			0.274**
			(0.129)			(0.129)
Constant	-0.018	-4.969***	-4.983***	-0.150	-5.090***	-5.151***
	(0.039)	(1.103)	(1.136)	(0.145)	(1.106)	(1.137)
N	47491	46009	46009	47421	45946	45946
R-sq	0.026	0.027	0.028	0.026	0.027	0.028
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 8
Category Reliance and Analyst Turnover

Table 8 reports the coefficients from regressions predicting the likelihood of analysts' job separation using the logit model. The dependent variable is analyst turnover measured at the analyst-year level, which equals one for analyst *i* in year *k* if the analyst issued forecasts in year *k*−1 and stops issuing forecasts in year *k*, and zero otherwise. Category Reliance (*CAT_REL*) is measured in year *k*−1 for analyst *i* as the R-squared of the cross-sectional regression of forecast revisions (*rev*) on lagged industry returns, scaled by one plus the R-squared of the cross-sectional regression of forecast revisions (*rev*) on lagged abnormal stock returns. *Bottom 10% Flag* is an indicator variable which equals one if analyst *i*'s average forecast accuracy ranking in year *k*−1 is in the lowest 10% of the sample, and zero otherwise. *Avg_Rank* is the average forecast accuracy ranking of analyst *i* in year *k*−1, where the analyst's relative accuracy ranking is computed following Hong and Kubik (2003). *Experience* is the natural logarithm of the number of years analyst *i* issues a forecast for a firm, averaged across the firms the analyst covers in year *k*−1. *All-star* is an indicator variable which equals one if the analyst is included in the All-star analyst list by the Institutional Investors magazine in year *k-1*. *Boldness* is the percentage of bold earnings forecasts issued by the analyst *i* in year *k*−1, where a forecast is defined as bold if the forecast is above both the analyst's prior forecast and the immediate consensus forecast before the forecast revision, or if the forecast is below both the analyst's prior forecast and the consensus forecast immediately before the forecast revision. *Rounding* is the percentage of rounded earnings forecasts issued by the analyst *i* in year *k*−1, where a forecast is a rounded forecast if it occurs at nickel intervals. *PPI* is the measure of analyst *i*'s private information in year *k*−1, calculated as one minus the correlation between the analyst's forecast revisions and prior stock price changes in year *k*−1. *Coverage* is the number of firms covered by analyst *i* in year *k*−1. *Brokerage Size* is measured by the log of the number of analysts in a given brokerage firm in year *k-1*. *Industry Number* is the number of different industries covered by the analyst in year *k*. *Avg. H-index* is the Herfindahl index of the firm's industry, averaged across the firms the analyst *i* covers in year *k*−1. All specifications include year fixed effects. Robust standard errors clustered by year are reported in parentheses. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CAT_REL	0.520***	0.821***	2.477***	6.071***	0.856***	2.464***	1.604*
	(0.109)	(0.122)	(0.582)	(2.002)	(0.115)	(0.585)	(0.889)
Past Accuracy Ranking		-0.009***	-0.001	0.008			
		(0.001)	(0.003)	(0.005)			
*CAT_REL*Past Ranking*				-0.074*			
				(0.039)			
Bottom 10% indicator					0.525***	-0.059	-0.202
					(0.038)	(0.092)	(0.138)
*CAT_REL*Bottom Flag*							1.408
							(1.127)
Experience			1.623***	1.626***		1.617***	1.618***
			(0.081)	(0.081)		(0.081)	(0.081)
All Star			-0.497***	-0.490***		-0.497***	-0.494***
			(0.152)	(0.152)		(0.152)	(0.152)
Boldness			1.264***	1.232***		1.277***	1.271***
			(0.322)	(0.328)		(0.323)	(0.324)
Rounding			-0.832	-0.865		-0.783	-0.852
			(1.637)	(1.636)		(1.631)	(1.636)
PPI			-0.194	-0.184		-0.171	-0.167
			(0.236)	(0.237)		(0.237)	(0.237)
Coverage			-0.060	-0.066		-0.048	-0.051
			(0.136)	(0.136)		(0.138)	(0.138)
Brokerage Size			0.125***	0.124***		0.126***	0.127***
			(0.045)	(0.045)		(0.045)	(0.045)
Industry Number			0.050*	0.052*		0.049*	0.050*
			(0.028)	(0.028)		(0.028)	(0.028)
Avg. H-index			-1.660	-1.759		-1.297	-1.380
			(1.266)	(1.256)		(1.320)	(1.322)
Constant	0.671***	1.203***	-1.665***	-2.078***	0.353***	-1.733***	-1.638***
	(0.041)	(0.073)	(0.508)	(0.549)	(0.048)	(0.482)	(0.483)
N	43330	37959	15501	15501	43330	15513	15513
chi2	6364.54	5683.84	3515.14	3509.79	6322.45	3531.00	3523.87

TABLE 9
Robustness Checks with Alternative Specifications of Category Reliance

Table 9 reports the coefficients from regressions repeating the main analyses using five alternative measures of analysts' category reliance (*CAT_REL*). The first measure of *CAT_REL* is computed using stock categories defined based on industry-firm size groups, where stocks in the same industry and quintile of firm size (market capitalization) within the industry in the year form a category. The second measure of *CAT_REL* uses stock categories based on industry-style groups, where stocks in the same industry and quintile of market-to-book ratio within the industry in the year form a category. The third measure of *CAT_REL* uses stock categories based on the Fama-French 48 industry classifications. The fourth measure of *CAT_REL* uses stock categories based on the 4-digit NAICS industry codes. The fifth measure uses GICS industry groups. Panel A reports the coefficients from regressing *AFE*, which is the absolute forecast error (actual minus analysts' forecast earnings) scaled by the stock price, on each of the five alternative *CAT_REL* measures in the previous year. Panel B reports the coefficients from regressing stock price impact (measured using CARs) of analyst forecast revisions on the five alternative *CAT_REL* measures in the previous year. Panel C reports the coefficients from logit regressions predicting analysts' job turnover using the five alternative *CAT_REL* measures in the previous year. All specifications include year fixed effects (FE). Analyst-level and firm-level control variables used in previous Tables are included when appropriate. Analyst-level (suppressed) control variables include *All-star ranking*, *PPI*, *Experience*, *Boldness*, *Rounding*, *Coverage*, *Brokerage Size*, *Industry Number*, *Bottom 10% Flag*, and *Avg_Rank*. Firm-level (suppressed) control variables include the stocks' *Market/Book ratio*, *Cash flow volatility*, *Institutional holdings*, and *Avg. H-index*. Standard errors (reported in parentheses) are clustered by analyst-year in Panel A, by firm-analyst in Panel B, and year in Panel C. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Panel A: Regressions Explaining Forecast Error

Category Definition	Industry-Size	Industry-Style	FF48	NAICS4	GICS
CAT_REL	0.926*	2.027***	2.358***	3.244***	1.230***
	(0.494)	(0.519)	(0.473)	(0.585)	(0.568)
Analyst controls	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Panel B: Regressions Explaining Stock Price Impact

Category Definition	Industry-Size	Industry-Style	FF48	NAICS4	GICS
CAT_REL**Rev*	-5.862***	-5.042**	-1.781*	-5.104**	-1.852***
	(2.06)	(2.4)	(0.946)	(2.48)	(0.545)
CAT_REL	0.233	-0.107	-0.476	-0.177	-0.761*
	(0.572)	(0.613)	(0.557)	(0.706)	(0.421)
Analyst controls	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Panel C: Regressions Explaining Analyst Turnover

Category Definition	Industry-Size	Industry-Style	FF48	NAICS4	GICS
CAT_REL	2.239***	2.633***	3.415***	2.001***	2.543***
	(0.211)	(0.214)	(0.189)	(0.331)	(0.745)
CAT_REL**Bottom 10% Flag*	2.161***	2.275***	1.341***	1.501***	0.794
	(0.245)	(0.244)	(0.207)	(0.399)	(0.975)
Analyst controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

TABLE 10
Abnormal Category Reliance and Analyst Forecast Accuracy

Table 10 reports the coefficients from regressions explaining analysts' forecast accuracy using an alternative measure of category reliance. The dependent variable is analyst forecast error (*AFE*) for analyst *i* for firm *j* in year *k*, which is the absolute forecast error (actual minus analysts' forecast earnings) scaled by the stock price in year *k*−1. Abnormal Category Reliance (*AbCAT_REL*) is the deviation from mean category reliance (*CAT_REL*) of all analysts covering the same firm in year *k*-1. *Experience* is the natural logarithm of the number of years analyst *i* issues a forecast for a firm, averaged across the firms the analyst covers in year *k*−1. *All-star* is an indicator variable which equals one if the analyst is included in the All-star analyst list by the Institutional Investors magazine in year *k*. *Boldness* is the percentage of bold earnings forecasts issued by the analyst *i* in year *k*−1, where a forecast is defined as bold if the forecast is above both the analyst's prior forecast and the immediate consensus forecast before the forecast revision, or if the forecast is below both the analyst's prior forecast and the consensus forecast immediately before the forecast revision. *Rounding* is the percentage of rounded earnings forecasts issued by the analyst *i* in year *k*−1, where a forecast is a rounded forecast if it occurs at nickel intervals. *PPI* is the measure of analyst *i*'s private information in year *k*−1, calculated as one minus the correlation between the analyst's forecast revisions and prior stock price changes in year *k*−1. *Coverage* is the number of firms covered by the analyst *i* in year *k*−1. *Brokerage Size* is measured by the log of the number of analysts in a given brokerage firm in year *k*. *Industry Number* is the number of different industries covered by the analyst in year *k*. *Avg_Rank* is the average forecast accuracy ranking of the analyst *i* in year *k*−2, where the analyst's relative accuracy ranking is computed following Hong and Kubik (2003). *Bottom 10% Flag* is an indicator variable which equals one if the analyst's average forecast accuracy ranking in year *k*−2 is in the lowest 10% of the sample. *Size* is the natural logarithm of the market value of equity of firm *j* in year *k*−1. *Market/Book* is the market-to-book ratio calculated as the market value of firm *j*'s equity at the end of year *k*−1 plus the difference between the book value of the firm's assets and the book value of the firm's equity in year *k*−1, divided by the book value of the firm's assets in year *k*−1. *Cashflow volatility* for firm *j* in year *k*−1 is the standard deviation of cash flow from operations in the past 5 years (with a minimum of 3 years), where cash flow from operating activity is earnings before extraordinary items minus total accruals, scaled by average total assets. *Institutional holdings* is the percentage of institutional investor holdings in firm *j* in year *k*−1. *H-index* is the Herfindahl index of sales for firm *j*'s 2-digit SIC code, computed as the sum of squared weights of sales across all the firms in the industry in year *k*−1. *Lag Industry Return*, *Lag2 Industry Return*, *Lag3 Industry Return*, and *Lag4 Industry Return* are the 1-, 2-, 3-, and 4-month lagged industry returns, respectively, for firm *j* measured prior to the month of the forecast. *Lag Stock Return*, *Lag2 Stock Return*, *Lag3 Stock Return*, and *Lag4 Stock Return* are the 1-, 2-, 3-, and 4-month lagged abnormal stock returns, respectively, for firm *j* measured prior to the month of the forecast. All specifications include year fixed effects. Standard errors are clustered by analyst-year and reported in parentheses. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AbCAT_REL	3.313***	2.956***	2.767***	2.838***	2.836***	1.094**	1.074**
	(0.485)	(0.529)	(0.447)	(0.459)	(0.460)	(0.439)	(0.439)
Experience		-0.132**	-0.127**	-0.143**	-0.132**	-0.044	-0.046
		(0.052)	(0.058)	(0.061)	(0.061)	(0.060)	(0.060)
Boldness		-0.686***	-0.651**	-0.655**	-0.616**	-0.211	-0.231
		(0.249)	(0.257)	(0.264)	(0.266)	(0.255)	(0.254)
Rounding		9.731***	10.311***	10.344***	10.637***	10.326***	10.234***
		(1.544)	(1.598)	(1.619)	(1.637)	(1.574)	(1.575)
All Star		0.129	0.155	0.167	0.193*	0.360***	0.355***
		(0.098)	(0.101)	(0.103)	(0.105)	(0.100)	(0.100)
PPI		0.419**	0.504**	0.569***	0.505**	0.458**	0.433**
		(0.213)	(0.214)	(0.219)	(0.218)	(0.211)	(0.212)
Coverage		-0.426***	-0.392***	-0.380***	-0.333**	-0.797***	-0.792***
		(0.135)	(0.139)	(0.137)	(0.137)	(0.156)	(0.156)
Brokerage Size		-0.101***	-0.120***	-0.121***	-0.119***	-0.029	-0.030
		(0.034)	(0.035)	(0.036)	(0.038)	(0.036)	(0.036)
Past Bottom 10% Flag			0.018				
			(0.067)				
Past Accuracy Ranking				-0.003	-0.003	-0.004	-0.004
				(0.003)	(0.003)	(0.003)	(0.003)
Industry Number					-0.019	0.001	0.001
					(0.021)	(0.021)	(0.021)
H-index					-1.966***	-3.308***	-3.339***
					(0.399)	(0.375)	(0.373)
Size						-0.614***	-0.611***
						(0.018)	(0.018)
Market/Book						-0.515***	-0.511***
						(0.020)	(0.020)
Cashflow Volatility						1.146***	1.177***
						(0.274)	(0.271)
Institutional Holdings						-1.711***	-1.696***
						(0.150)	(0.150)
Lag Industry Return							-0.159
							(0.424)
Lag2 Industry Return							0.380
							(0.341)
Lag3 Industry Return							-0.918**
							(0.363)
Lag4 Industry Return							-1.794***
							(0.403)
Lag Stock Return							-0.097
							(0.097)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lag2 Stock Return							0.032
							(0.106)
Lag3 Stock Return							-0.067
							(0.080)
Lag4 Stock Return							-0.011
							(0.113)
Constant	2.578***	4.029***	3.868***	3.972***	4.042***	11.806***	11.807***
	(0.044)	(0.438)	(0.463)	(0.438)	(0.439)	(0.528)	(0.527)
N	64741	62225	58645	56718	55509	55509	55509
R-sq	0.028	0.033	0.032	0.031	0.032	0.108	0.109
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes