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First Impression Bias: Evidence from Analyst Forecasts*

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Abstract

We present evidence of first impression bias among finance professionals in the field. Equity analysts' forecasts, target prices, and recommendations suffer from first impression bias. If a firm performs particularly well (poorly) in the year before an analyst follows it, that analyst tends to issue optimistic (pessimistic) evaluations. Consistent with negativity bias, we find that negative first impressions have a stronger effect than positive ones. The market adjusts for analyst first impression bias with a lag. Finally, our findings contribute to the literature on experience effects. We show that a set of professionals in the field, equity analysts, apply U-shaped weights to their sequence of past experiences, with greater weight on first experiences and recent experiences than on intermediate ones.

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1. Introduction

Psychological research shows that information received first tends to overshadow information received later, and first impressions have a lasting effect on perceptions and future

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behavior (Anderson, 1981; Hogarth and Einhorn, 1992).[1] This first impression bias causes a decision-maker, assessing the outcomes of some process, to place undue weight on early experiences that contribute to an initial impression (Anderson, 1965, 1973, 1981; Anderson and Jacobson, 1965; Jones and Goethals, 1971; Berry, 1990; Hogarth and Einhorn, 1992). If the first impression is particularly positive, then assessments about the future tend to be unduly positive; the reverse is the case if the first impression is negative.

Despite a vast literature in social psychology about first impression bias (Uleman and Kressel, 2013), there is limited evidence as to whether this bias exists outside laboratory settings. We investigate whether first impression bias exists in a field setting with finance professionals. Specifically, we examine whether an analyst's first impressions (i.e., particularly positive or negative experiences) of a firm induce bias in analysts' forecasting behavior.[2] Analysts are professionals who have pecuniary incentives to make accurate forecasts (Hong, Kubik, and Solomon, 2000; Hong and Kubik, 2003; Wu and Zang, 2009). However, forecasting future outcomes is an inherently subjective endeavor, so analysts are potentially subject to first impression bias. We therefore hypothesize that if a firm performs particularly well in the year before an analyst follows that firm, the analyst will be optimistic in subsequent forecasts about the firm. Similarly, if the firm performs particularly poorly, the analyst will be pessimistic.

For several reasons, analysts' forecasting behavior provides an attractive setting for studying the effects of first impression bias in the field. First, both first impressions in the form of past firm performance and analysts' forecasting errors can be directly measured.

Second, analysts make forecasts about multiple firms, with different first impressions of different firms. This permits within-analyst testing of how the forecasting behavior of an analyst varies with first impressions. This helps address the fact that some analysts may be more optimistic or pessimistic, in general, relative to other analysts. We include analyst–year–quarter fixed effects in our main specifications to address this possibility.

Third, firms are often followed by several analysts. This allows us to measure forecast bias for an analyst relative to the consensus forecast. By using a relative measure of forecast bias, we can better distinguish first impression effects from how analysts are assessing the performance of the firm in a given time period. We also include firm fixed effects in our specifications to mitigate the effect of differing firm characteristics.

In comparison to investors, there is reason to expect that analysts are relatively less subject to extrapolative bias.[3] Investors may be prone to extrapolation biases due to the

1 In a seminal paper, Asch (1946) finds that if a person is described as "intelligent, industrious, impulsive, critical, stubborn, [and] envious," people form a more positive impression of that person than when the descriptors are used in reverse.

2 Systematic biases in sell-side equity analysts' forecasting behavior seem to derive in part from agency problems (see Bradshaw (2011) for a survey of the literature) and in part from psychological biases such as anchoring (Cen, Hilary, and Wei, 2013), overconfidence (Hilary and Menzly, 2006), and decision fatigue (Hirshleifer et al., 2019).

3 Analysts are incentivized to produce accurate forecasts and recommendations, because forecast accuracy is important for an analyst's career and it allows them to achieve and maintain all-star status (Stickel, 1992; Hilary and Hsu, 2013; Groysberg, Healy, and Maber, 2011). Analysts also have years of industry-specific experience in valuing equities, and they have assistants who aid them through detailed investigations of firms. We do not, however, mean to argue that analysts are more highly motivated and more sophisticated than investors, who directly benefit from their investments.

salience of experiencing a direct gain or loss when prices change. Analysts do not experience such direct gains and losses. Furthermore, it is easier to test for first impression bias for analysts than for investors. An especially attractive feature of the analyst setting is that there is a proxy for when a salient first impression occurs—that is, when coverage of the firm begins.

Our proxy for the first impression formed by an analyst about a firm is the abnormal stock return in the year before an equity analyst's first forecast of that firm. During this time, the analyst develops an understanding of the firm's operations, management's relationship with the board, and the position of the firm within its respective industry. We categorize a firm's performance as positive if it is at or above the 90th percentile in market returns within that industry for the year before the initiation of coverage, and we categorize a firm's performance as negative if it is below the 10th percentile.[4]

If performance is positive during an analyst's first impression period, we hypothesize that this leads to optimism in subsequent forecasts, and the opposite occurs if past performance is negative. Using a sample of 1,643,089 firm–announcement–analyst observations spanning 1984–2017, we show that equity analysts' first impressions of a firm have lasting effects on their future forecasting behavior for that same firm. In particular, analysts who experience abnormally positive first impressions suffer from a first impression bias that leads to future forecasts that are more optimistic than the consensus. Analysts who experience abnormally negative first impressions are, in contrast, more pessimistic than the consensus. The effect of having a positive or negative first impression leads to a bias that is roughly 9.6% of the average forecast error.[5]

Earnings forecasts can be evaluated according to a clearly identified and well-publicized event: an earnings announcement. In contrast, there is usually some ambiguity about the horizon of analysts' target prices or trading recommendations. Furthermore, the benchmark for assessing recommendation "errors" is ambiguous (e.g., absolute stock performance, performance relative to the industry, performance relative to the market). Nevertheless, we find that first impressions have similar effects even on these tasks that have less well-defined objectives. Positive first impressions lead to optimism, and negative first impressions lead to pessimism relative to the consensus for price targets. We also find that a positive first impression is associated with a 15.2% higher probability of the analyst recommending Buy, while a negative impression is associated with a 31.02% lower likelihood of an analyst recommending Buy. The opposite pattern holds for Sell recommendations, which are associated with negative first impressions.

We find that first impression bias persists over a substantial time horizon after the analyst starts to follow a stock. For EPS (earnings per share) forecasts, the bias exists for 36 months. Point estimates offer a suggestive indication that negative first impression effects last longer than the effects of positive first impressions. While the positive

4 Our main findings are robust to measuring performance using absolute as opposed to relative performance, using a continuous measure, and using alternative cutoffs for positive and negative.

5 Because the impressions we study are formed before an analyst makes her first forecast, our findings are not explained by the idea that analysts keep their forecasts sticky in order to maintain their reputations, as in Prendergast and Stole (1996). Furthermore, since our measure of analyst forecast bias is relative to the consensus, our findings are not driven by general differences across firms in assessed prospects or recent performance.

impression effect on EPS forecasts lasts for 24 months, the negative impression effect on EPS forecasts lasts at least for 72 months.

In a wide range of contexts, the influence of negative information and experiences is stronger than the influence of comparable positive information and experiences. This phenomenon, referred to as negativity bias, influences how people form impressions (Anderson, 1973).[6] For example, Richey et al. (1975) find in lab experiments that a single piece of negative information outweighs five comparable pieces of positive information when assessing an unknown individual. In addition to our suggestive evidence that negative impressions last longer, we find that a negative first impression has roughly double the economic effect on EPS forecasts and price targets of a positive first impression of equal or greater magnitude, and the effects on recommendations are at least three times as powerful for negative impressions.

There are different possible sources of first impression bias. One possible source is confirmation bias, the phenomenon in which people seek and overweight information that is consistent with their current beliefs (Jenkins and Ward, 1965; Crocker, 1982; Balzer, 1986; Rabin and Schrag, 1999; Pouget, Sauvagnat, and Villeneuve, 2017) and interpret contradictory information as supportive (Lord, Ross, and Lepper, 1979; Isenberg, 1986; Plous, 1991; Martell and Willis, 1993). Alternatively, if analysts have a limited attention capacity to allocate among tasks, they may choose to do most of their research on a stock before making their first forecast. Bayesian updating with limited attention paid to subsequent signals would lead future forecasts to more heavy weight insights gained early on, consistent with our results.

We next investigate whether investors understand and discount for analysts' first impression bias. We do this by testing the sensitivity of the cumulative abnormal returns to recommendation revisions by analysts who suffer from first impression bias.[7] If analysts exhibit confirmation bias, then an analyst with a positive first impression should be more likely to interpret news as positive, leading to more positive recommendation revisions (e.g., Sell to Hold, Hold to Buy). Efficient markets should understand that such positive revisions are weaker positive signals. In contrast, negative revisions from analysts with a positive first impression should be stronger negative signals. Alternatively, if analysts do not exhibit confirmation bias, this prediction does not apply.

We find that the market reacts less positively to positive recommendations and more negatively to negative recommendations made by analysts who have a positive impression of a firm. We find the opposite pattern for recommendations made by analysts who have a negative impression. This evidence is consistent with the market making some adjustment for analysts' biased interpretation of news.

To investigate whether the market adjusts fully for first impression bias, we also examine subsequent drift following recommendations. We find that the market continues to react negatively to the recommendations of positive impression analysts and react positively to the recommendations of negative impression analysts over the next 60 trading days. This suggests that the market does not fully adjust for the first impression bias initially. As a result, there is, on average, a gradual correction over time.

6 See, for example, Kanouse and Hanson (1971); Peeters and Czapinski (1990); Baumeister, et al. (2001); and the surveys of Taylor (1991) and Rozin and Royzman (2001).

7 Past research indicates that recommendation revisions are associated with strong price reactions (Womack, 1996).

Past research implies that analysts use pessimistically biased (and hence, beatable) earnings forecasts to curry favor with firm management in order to obtain better access to management's private information (Ke and Yu, 2006). This raises the possibility that negative first impression effects are driven by incentives to issue beatable forecasts. If it were the case that after strong performance more than after weak performance, analysts were less inclined to initiate coverage and then issue beatable forecasts (for agency reasons rather than psychological ones), this could explain a portion of our findings. However, since managers also prefer analysts to issue optimistic recommendations (Malmendier and Shanthikumar, 2014), this alternative explanation cannot explain why negative first impression analysts are issuing pessimistic recommendations. Nonetheless, we perform tests to address directly whether incentives to issue beatable forecasts can explain this portion of our results. Our findings suggest that issuing beatable forecasts explains, at best, little of our negative first impression results.

Under first impression bias, analysts place greater weights on their earliest experiences of the firms they follow. The finance literature, however, has often found that people put heavier weights on, and extrapolate more from, recent events than earlier events.[8] For example, Malmendier and Nagel (2016) show that individuals' expectations about future inflation are more strongly influenced by the recent experiences that they accumulate during their lifetimes, while Kuchler and Zafar (2019) show the same is true for estimates of aggregate economic outcomes. Our evidence of first impression bias provides a notable contrast with previous findings on the importance of recency.

To explore and delineate these differences more directly, we next investigate the comparative weights analysts place on first impressions versus more recent impressions. We find evidence consistent with a U-shape relationship between impressions and time. Analysts appear to place more weight on recent experiences and their earliest experiences and less weight on intermediate experiences. Our results do not show statistically significant differences between the weights placed on recent experiences and early experiences, which indicates that early experiences may have effects on behavior that are similar to recent experiences (Malmendier and Nagel, 2011).

Our article makes several contributions. Past studies find that investor participation in the stock market is influenced by individual experiences with macroeconomic shocks (Malmendier and Nagel, 2011) and negative initial investment performance (Arikan et al., 2018), which sometimes leads investors to cease trading altogether (Seru, Shumway, and Stoffman, 2009). Moreover, investors are reluctant to repurchase stocks that were previously sold for a loss (Strahilevitz, Odean, and Barber, 2011). We contribute to this literature by testing how first impressions affect the perceptions of capital market professionals.

First impressions have been shown to affect the behavior of auditors and tax professionals in a laboratory setting. Audit managers exhibit first impression bias when asked to subjectively evaluate subordinates' work product (Tan and Jamal, 2001). Anderson and Maletta (1999) find that auditors are susceptible to first impression bias when performing audit tasks in which low levels of inherent risk are present. SAS No. 58 auditors' reports

8 An extensive literature on extrapolation bias suggests that more recent outcomes have a larger effect than less recent ones on the expectations of market participants (Lakonishok, Shleifer and Vishny, 1994; Dechow and Sloan, 1997; Teoh, Welch, and Wong, 1998; Benartzi, 2001; Choi et al., 2009; Alti and Tetlock, 2014; Hirshleifer, Li, and Yu, 2015; Dittmar and Duchin, 2016; Barberis et al., 2015, 2018).

have been shown to positively affect assessments of subjects not included in the reports, such as the likelihood of fraud (Hatherly, Innes, and Brown, 1991; Brown, Collins, and Thornton, 1993).[9] Tax professionals have also been shown to seek out information supportive of their clients' preferred positions (Cloyd and Spilker, 1999; Kadous, Magro, and Spilker, 2008).[10] Our article differs from this research by providing what is, to our knowledge, the first archival evidence of first impression bias among professionals using field data.

First impression bias has been demonstrated in several other decision-making contexts. First impressions disproportionately affect personnel interviews (Cable and Gilovich, 1998), evaluations of fairness (Lind, Kray, and Thompson, 2001), evaluations of credibility (Nahari and Ben-Shakhar, 2013), and judicial decisions (Kerstholt and Jackson, 1998). Marketing research has identified first impression bias in choice of brands (Carlson, Meloy, and Russo, 2006), choice of wines (Mantonakis et al., 2009), choice of salespersons to buy from (Carney and Banaji, 2012), and even interpretations of online reviews (Kapoor and Piramuthu, 2009).[11] We show here that first impression bias, a staple in the psychological literature, influences finance professionals in the field.

2. Data and Descriptive Statistics

2.1 Data and Variables

Data on analysts' quarterly EPS forecasts, price targets, and stock recommendations were obtained from the Institutional Brokers' Estimate System (I/B/E/S) database. Similar to prior literature (Brown and Caylor, 2005; Kumar, 2010), we focus on one-quarter ahead earnings forecasts. Since the goal of this article is to examine the effect of first impressions on individual analysts' forecasts, we eliminate analyst codes that are associated with teams of analysts.[12]

The EPS forecast sample covers all quarterly earnings forecasts from 1984 to mid-2017. We limit our analysis to the first forecast each analyst issues within 90 days before the actual earnings announcement for each firm in the fiscal quarter in question. Our main dependent variable of interest for this sample is *Bias_EPS*. Following prior research (Clement, 1999; Jacob, Lys, and Neale, 1999; Hong and Kubik, 2003 and Cowen, Groysberg, and Healy, 2006), our *Bias_EPS* variable is the relative optimism against consensus forecast derived from all analysts' forecasting earnings of the same firm in the same fiscal quarter. The consensus forecast is calculated as the average value of the first forecasts of all analysts following the firm and the fiscal quarter in consideration. Thus, we define

9 Audit managers tend to subjectively evaluate subordinates' work product based on prior impressions (Tan and Jamal, 2001). Further, auditors are more likely to ignore inconsistent accounts if they use heuristics to assess risks (O'Donnell and Schultz, 2005), leading them to process information in ways they otherwise would not have (Desai and Nagar, 2016). Early-stage evaluations affect later-stage detailed assessments (Slovic et al., 2002).

10 See Ricchiute (2010) for a contrasting study that allows for levels of complexity that subjects are likely to face in real-world judgments.

11 Lim, Benbasat, and Ward (2000) show evidence that multimedia presentations of products reduce the influence of first impression bias in a laboratory setting.

12 We map analyst codes to analyst names and drop those with nonproper names. In particular, teams were removed from the sample by excluding analysts who had a slash (/), an ampersand (&), the word *and*, or the word *group* in their names.

$$Bias_EPS_{ijt} = \frac{\text{Value}_{ijt} - \text{Consensus}_{jt}}{\text{Standard Deviation}(\text{Value}_{ijt})},$$

where $\text{Value}_{\text{ijt}}$ is the value of the first earnings forecast analyst i issues for firm j in fiscal quarter t. The denominator, Standard Deviation($\text{Value}_{\text{ijt}}$), is the standard deviation of all forecasts made by all analysts $i \in I$, where I is the set of all first forecasts from all analysts forecasting earnings of firm j in fiscal quarter t. This helps standardize our measure of optimism across all earnings forecasts.

The price target sample covers all forecasts made between 1999 and 2016. Similar to EPS forecasts, we also use a relative optimism measure of price target forecasts. Because forecasts of target price do not correspond to any specific fiscal year, but rather simply what the price would be 1 year from the issue date, we consider a time window of a calendar quarter to compute consensus forecasts. Thus, we define

$$Bias_PT_{ijt} = \frac{\text{Value}_{ijt} - \text{Consensus}_{jt}}{\text{Standard Deviation}(\text{Value}_{ijt})},$$

where $\text{Value}_{\text{ijt}}$ is the forecasted price analyst i makes for firm j during calendar quarter t. $\text{Consensus}_{\text{jt}}$ is the average value of all price forecasts made during the same calendar quarter tfor firm j. The denominator is the standard deviation of all forecasts made in quarter q in order to standardize the optimism measure across forecasts of different firms.

The final sample contains analyst stock recommendations spanning the period from 1994 to 2016. For this sample, our dependent variables of interest are Buy_{ijt} and $Sell_{ijt}$. The variable Buy_{ijt} is a binary variable that equals 1 if the analyst i issues a Buy or Strong Buy recommendation about firm j in calendar quarter t, and 0 otherwise. The variable $Sell_{ijt}$ is a binary variable that equals 1 if the analyst i issues a Sell or Strong Sell recommendation about firm j in calendar quarter t, and 0 otherwise.

We capture the first impression of an analyst for a firm using the stock return performance of the firm over a period leading up to the month the analyst issues their first-ever forecast for the firm. In particular, our main measure of first impression takes the stock return of the firm starting 12 months before the month the first forecast is issued. We then define the analyst's first impression as positive if this stock return is in the top 10th percentile of all firms in the same industry during the same 13-month period. Similarly, we define the first impression as negative if the firm's stock return is in the bottom 10th percentile of all firms in its industry during the same time horizon.[13]

Data on stock returns were collected from the CRSP Monthly Returns database over the period of 1983–2017, 1 year before the I/B/E/S data, so as to compute stock returns that require data before January 1984. Based on monthly returns, we compute the corresponding 13-month returns during the time window of consideration, then we compare these against the returns of other firms in the same 2-digit industry SIC code and in the same 13-month period. We define our impression variables as follows:

> $FirstImpression_{ij}$. A categorical variable equal to 1 if, at the time of the first forecast analyst i issues for firm j, the [−12 month, 0 month] stock return of firm j is in the top 10th percentile of j's industry, −1 if at the time of the first forecast analyst i issues for firm j, the [−12 month, 0 month] stock return of firm j is in the bottom 10th percentile of j's industry, and 0 otherwise.

13 In Section 3.6, we show that our results are consistent across alternative measures of first impressions.

To investigate if there are asymmetric first impression effects, we replace the $FirstImpression_{ij}$ variable with the following two variables:

$PositiveImpression_{ij}$. An indicator variable, equal to 1 if, at the time of the first forecast analyst i issues for firm j, the [−12 month, 0 month] stock return of firm j is in the top 10th percentile of j's industry, and 0 otherwise.

$NegativeImpresion_{ij}$. An indicator variable equal to 1 if, at the time of the first forecast analyst i issues for firm j, the [−12 month, 0 month] stock return of firm j is in the bottom 10th percentile of j's industry, and 0 otherwise.

In other words, an analyst i has a positive first impression on firm j if $FirstImpression_{ij} = PositiveImpression_{ij} = 1$, a negative first impression if $FirstImpression_{ij} = -1$ and $NegativeImpression_{ij} = 1$, and a neutral first impression if all three variables are 0. The above three variables have no t subscripts because there can be only one first impression per analyst–firm pair and the impression remains with the analyst until she no longer follows the firm.

We define these variables based on firm performance relative to other firms in the same industry because analysts are typically specialized in certain industries and mostly follow firms in those industries (Clement, 1999; Jacob, Lys, and Neale, 1999). Therefore, we assume that they are likely to form their impressions based on industry-specific information. However, we verify in Subsection 3.6 that our results are robust to alternative measures of first impressions, such as continuous measures, measures based on absolute firm performance, and measures based on different performance cutoffs. We also control for various analyst characteristics that may affect her forecast bias, such as experience, job complexity, and specialization (Mikhail, Walther and Willis, 1997; Clement, 1999; Jacob, Lys, and Neale, 1999). The definitions of these variables are presented in Appendix A.

2.2 Descriptive Statistics

Table I presents the descriptive statistics of regression variables in each of the three samples. Panel A shows the mean, standard deviation, median, 25th percentile, and 75th percentile of the EPS forecast sample. The mean of *PositiveImpression* is about 11.8%, which is consistent with the fact that this measure of first impression is based on the top 10th percentile of stock returns. The mean of *NegativeImpression*, on the other hand, is lower at 3.1%. This suggests that analysts are less likely to follow a firm that is performing poorly. Thus, although there are 10% of firms that are classified as poor performing in our definition, there is not the same percentage of analysts who have negative first impressions, because not all these firms receive new coverage at that time. In contrast, the data suggest that analysts may prefer, or are incentivized to follow, firms that do well, because the mean of *PositiveImpression* is larger than 10%.[14]

By construction, the *Bias_EPS* variable has a mean close to zero. The analysts in the sample, on average, follow sixteen firms during a fiscal quarter, and they have roughly 9 years of experience forecasting earnings and 3 years of firm-specific experience. This long "tenure" feature of the data allows us to later explore whether the first impression effects decline as the analysts gain more experience in forecasting a firm's earnings.

14 We also find that positive first impressions are accompanied by returns in the 12 months before first forecast that are much greater than the negative returns accompanying negative first impressions.

Table I. Summary statistics

This table presents the summary statistics for the regression variables of interest. Panel A reports variables in the EPS forecast sample. Panel B reports variables in the price target sample. Panel C reports variables in the recommendation sample. Appendix A contains the definitions of all variables.

Panel A: EPS forecast sample

Variable	Mean	SD	P25	Median	P75
FirstImpression	0.088	0.376	0.000	0.000	0.000
PositiveImpression	0.118	0.323	0.000	0.000	0.000
NegativeImpression	0.031	0.172	0.000	0.000	0.000
Bias_EPS	0.002	0.965	−0.694	0.000	0.692
Value	0.408	0.677	0.100	0.290	0.580
ForecastError	0.113	0.307	0.010	0.040	0.100
Forecast_Age	68.980	25.817	55.000	82.000	90.000
Firm_Exp	3.308	3.482	1.000	2.000	5.000
Specialization	0.569	0.495	0.000	1.000	1.000
Num_Firm	16.365	7.501	11.000	16.000	20.000
Num_Industry	4.379	2.571	2.000	4.000	6.000
Year_Exp	9.145	6.806	4.000	8.000	13.000

Panel B: Price target forecast sample

Variable	Mean	SD	P25	Median	P75
FirstImpression	0.090	0.389	0.000	0.000	0.000
PositiveImpression	0.125	0.331	0.000	0.000	0.000
NegativeImpression	0.035	0.183	0.000	0.000	0.000
Bias_PT	0.007	0.942	−0.707	0.000	0.707
Value	46.552	56.673	18.000	32.000	54.000
Firm_Exp	3.022	3.265	1.000	2.000	4.000
Specialization	0.578	0.494	0.000	1.000	1.000
Num_Firm	15.698	8.066	10.000	15.000	20.000
Num_Industry	3.952	2.448	2.000	3.000	5.000
Year_Exp	6.992	4.670	3.000	6.000	11.000

Panel C: Recommendation sample

Variable	Mean	SD	P25	Median	P75
FirstImpression	0.078	0.393	0.000	0.000	0.000
PositiveImpression	0.120	0.325	0.000	0.000	0.000
NegativeImpression	0.041	0.199	0.000	0.000	0.000
Buy	0.531	0.499	0.000	1.000	1.000
Sell	0.072	0.259	0.000	0.000	0.000
Firm_Exp	1.955	2.785	0.000	1.000	3.000
Specialization	0.454	0.498	0.000	0.000	1.000
Num_Firm	16.219	10.423	8.000	14.000	22.000
Num_Industry	3.485	2.273	2.000	3.000	5.000
Year_Exp	5.122	4.614	2.000	4.000	8.000

Qualitatively similar descriptive statistics can be found for price targets and recommendations, as shown in Panels B and C of Table I, respectively. In the price target sample, *PositiveImpression* has a mean value of 12.5%, while *NegativeImpression* has a mean value of 3.5%. The average price target is roughly $46.55, with a standard deviation slightly higher than the mean at $56.67. Panel C also shows that the mean of Buy is 0.531, implying that analysts issue Buy or Strong Buy recommendations roughly 53.1% of the time. On the other hand, the mean of Sell is 0.072, suggesting that Sell and Strong Sell recommendations are issued only 7.2% of the time. This descriptive evidence indicates that analysts issue Buy or Strong Buy recommendations significantly more frequently than they do Sell or Strong Sell recommendations.

Table II shows the Pearson correlation table of all the variables for the three samples separately. Consistent with our prediction, the correlation between *FirstImpression*, *PositiveImpression*, and the dependent variables of interest (i.e., *Bias_EPS* for EPS forecasts, *Bias_PT* for price targets, and *Buy* for recommendations) is positive, while the correlation between *NegativeImpression* and these variables are negative. This offers initial evidence showing that analysts with a positive first impression are more likely to bias their forecasts upwards, while analysts with a negative first impression are more likely to bias their forecasts downwards. Panel C also shows that positive impression analysts are less likely to recommend a Sell (correlation is −an0156), while negative impression analysts are more likely to recommend a Sell (correlation is 0.0415).

3. Identification and Regression Results

3.1 First Impression Effects

To assess whether an analyst's first impression is associated with biases in forecasts relative to other analysts following the same firm during that time, we estimate the following regression:

$$Y_{ijt} = \beta_0 + \beta_1\, FirstImpression_{ij} + Controls_{ijt} + Fixed\ \ Effects + \varepsilon_{ijt}, \tag{1}$$

where Y_{ijt} is either $Bias\_EPS_{ijt}$ or $Bias\_PT_{ijt}$, and $FirstImpression_{ij}$ is defined as in the previous section, reflecting whether analyst i has a positive or negative first impression of firm j. We control for various other determinants of analysts' relative bias, such as the age of the forecast, the number of firms and industries the analyst follows, the analyst's years of experience, her years of firm-specific experience, and industry specialization.[15] Finally, to facilitate identification of the first impression effects, we also include in the regressions firm and analyst–year–quarter fixed effects. The former is used to capture time-invariant heterogeneity at the firm level, and the latter absorbs unobservable time-varying analyst characteristics that might be correlated with both an analyst's first impression of a firm and her forecasts.

The coefficient of interest is β_1, which captures the effect of the first impression on analysts' forecasting bias relative to those who have a neutral first impression of the firm. Based on the discussion in the previous section, we expect β_1 to be positive. To allow for

15 All variables are defined in Appendix A.

Table II. Correlation tables

This table presents the correlations among the regression variables. Panel A reports the correlation coefficients for variables in the EPS forecast sample. Panel B reports the correlation coefficients for variables in the price target sample. Panel C reports the correlation coefficients for variables in the recommendation sample. Appendix A contains the definitions of all variables.

Panel A: EPS forecast sample

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	*FirstImpression*	1.0000									
(2)	*Positive Impression*	0.8860	1.0000								
(3)	*Negative Impression*	−0.5150	−0.0612	1.0000							
(4)	*Bias_EPS*	0.0064	0.0039	−0.0068	1.0000						
(5)	*Forecast_Age*	0.0033	0.0032	−0.0010	0.0527	1.0000					
(6)	*Firm_Exp*	−0.0017	−0.0169	−0.0274	0.0076	0.1340	1.0000				
(7)	*Specialization*	−0.0137	−0.0282	−0.0214	0.0001	0.0297	0.0768	1.0000			
(8)	*Num_Firm*	−0.0051	−0.0087	−0.0046	0.0013	0.0591	0.1710	0.1440	1.0000		
(9)	*Num_Industry*	0.0201	0.0173	−0.0119	0.0019	0.0421	0.1030	−0.3030	0.4010	1.0000	
(10)	*Year_Exp*	0.0018	−0.0063	−0.0154	−0.0019	0.1130	0.4910	0.0352	0.2560	0.1600	1.0000

Panel B: Price target forecast sample

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	*FirstImpression*	1.0000								
(2)	*PositiveImpression*	0.8810	1.0000							
(3)	*NegativeImpression*	−0.5320	−0.0692	1.0000						
(4)	*Bias_PT*	0.0155	0.0123	−0.0106	1.0000					
(5)	*Firm_Exp*	−0.0001	−0.0109	−0.0190	0.0239	1.0000				
(6)	*Specialization*	−0.0154	−0.0280	−0.0168	−0.0087	0.0853	1.0000			
(7)	*Num_Firm*	−0.0080	−0.0108	−0.0021	−0.0340	0.1830	0.2110	1.0000		
(8)	*Num_Industry*	0.0180	0.0157	−0.0102	−0.0041	0.1110	−0.2510	0.4490	1.0000	
(9)	*Year_Exp*	−0.0122	−0.0216	−0.0129	0.0112	0.5510	0.0481	0.3410	0.2510	1.0000

Panel C. Recommendation sample

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	*FirstImpression*	1.0000									
(2)	*Positive Impression*	0.8570	1.0000								
(3)	*Negative Impression*	−0.5690	−0.0674	1.0000							
(4)	*Buy*	0.0553	0.0372	−0.0474	1.0000						
(5)	*Sell*	−0.0353	−0.0156	0.0415	−0.2970	1.0000					
(6)	*Firm_Exp*	0.0112	−0.0062	−0.0316	−0.0881	0.0497	1.0000				
(7)	*Specialization*	−0.0007	−0.0186	−0.0262	−0.0344	0.0140	0.0527	1.0000			
(8)	*Num_Firm*	0.0032	−0.0035	−0.0121	−0.0256	0.0315	0.0715	0.3140	1.0000		
(9)	*Num_Industry*	0.0091	0.0067	−0.0072	0.0342	−0.0215	0.0060	−0.2150	0.4110	1.0000	
(10)	*Year_Exp*	0.0192	0.0085	−0.0230	−0.0708	0.0275	0.5630	0.0333	0.0538	0.0348	1.0000

possible correlation between the forecasts made by the same analyst, standard errors are clustered at the analyst level.[16]

To examine whether the first impression effect also influences analyst recommendation behavior, we employ the following logistic model and linear probability model:

$$\text{Prob}(X_{ijt}) = \text{f}(\ \beta_0 + \beta_1\, FirstImpression_{ij} + Controls_{ijt} + Fixed\ \ Effects + \varepsilon_{ijt}), \tag{2}$$

and

$$X_{ijt} = \beta_0 + \beta_1\, FirstImpression_{ij} + Controls_{ijt} + Fixed\ \ Effects + \varepsilon_{ijt} \tag{3}$$

Model (2) is a logistic regression model in which X_{ijt} can either be Buy_{ijt} or $Sell_{ijt}$, as defined in the previous section. In addition to the baseline set of control variables, we control for the number of Hold, Buy, and Sell recommendations from other analysts following the same firm during the same quarter period: Num_Holds_{jt}, Num_Buys_{jt}, Num_Sells_{jt}. Furthermore, we use the conditional form of logistic regression by controlling for either firm fixed effects or analyst–year–quarter fixed effects. However, we also use a linear probability model as shown in Equation (3) due to the computational limitation in which conditional logistic regressions do not permit more than one group of fixed effects at the same time.

When the dependent variable is Buy_{ijt}, the coefficient on $FirstImpression_{ij}$ is expected to be positive since we predict that positive first impression analysts are more likely to issue a Buy recommendation than neutral analysts, while negative first impression analysts are less likely to do so. With a symmetric argument, when the dependent variable is $Sell_{ijt}$, we predict that the coefficient on *FirstImpression* is negative. In other words, the more positive the first impression, the less likely the analyst would be to issue a Sell recommendation.

The results are presented in Table III. Column (1) reports the regression result for our earnings forecast test. The coefficient on $FirstImpression_{ij}$ is positive and statistically significant at the 1% level, consistent with our prediction. In terms of the economic magnitude, the coefficient estimate is about 0.012, which suggests that, compared to consensus earnings forecasts, having a positive (negative) first impression is associated with an optimistic (pessimistic) bias that is 9.6% of the mean forecast error.[17] Likewise, we observe similar results for price target forecasts. The coefficient on $FirstImpression_{ij}$ in Column (2) is also positive and statistically significant. This implies that the first impression effect is associated with an optimistic bias in price target forecasts.

For analyst recommendations, the regressions from Columns (3)–(8) also show statistically significant results that are consistent with our predictions. A positive first impression is associated with a higher likelihood of issuing Buy recommendations and a lower likelihood of issuing Sell recommendations. In contrast, a negative first impression is associated with a lower likelihood of issuing Buy recommendations and a higher likelihood of issuing Sell recommendations.

16 The main results are robust if we two-way clustered standard errors at the analyst and firm levels (see Table B1 of Appendix B).

17 We multiply the effect in Column (1) by the standard deviation of *Value* then divide by the mean of *Forecast_Error* in Table 1.

Table III. First impression effects

This table presents the regression estimates of the first impression effect on analyst bias in EPS forecasts, price target forecasts, and recommendations. Observations are at the analyst–firm–quarter level. The independent variable of interest is *FirstImpression*, a categorical variable that equals 1 if the analyst has a positive first impression of the firm, −1 if the analyst has a negative first impression of the firm, and 0 otherwise. In Column (1), the dependent variable, *Bias_EPS*, is a measure of the analyst's relative bias in EPS forecasts compared to all analysts who follow the same firm in the same fiscal quarter. In Column (2), the dependent variable, *Bias_PT*, is a measure of the analyst's relative bias compared to all analysts who produce price target forecasts for the same firm in the same quarter. Columns (3)–(6) present conditional logistic regressions in which the dependent variables are either *Buy* (an indicator variable equal to 1 if the analyst issues a Buy recommendation and 0 otherwise) or *Sell* (an indicator variable equal to 1 if the analyst issues a Sell recommendation and 0 otherwise). Columns (7)–(8) present OLS regressions in which the dependent variable is either *Buy* or *Sell*. Appendix A contains the definitions of all variables used in the regressions. Robust standard errors are clustered at the analyst level (except for Columns (3) and (5), where they are clustered at the firm level due to conditional logit's computational limitations) and presented in parentheses. ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

Variable	*Bias_EPS* OLS (1)	*Bias_PT* OLS (2)	*Buy* Logit (3)	*Buy* Logit (4)	*Sell* Logit (5)	*Sell* Logit (6)	*Buy* OLS (7)	*Sell* OLS (8)
FirstImpression	0.0158***	0.0274***	0.2090***	0.2072***	−0.2287***	−0.2065***	0.0385***	−0.0097***
	(0.0031)	(0.0047)	(0.0085)	(0.0095)	(0.0169)	(0.0199)	(0.0020)	(0.0012)
Forecast_Age	0.0027***							
	(0.0001)							
Firm_Exp	0.0002	0.0063***	−0.0350***	−0.0394***	0.0397***	0.0427***	−0.0067***	0.0021***
	(0.0005)	(0.0009)	(0.0016)	(0.0022)	(0.0028)	(0.0039)	(0.0005)	(0.0003)
Specialization	−0.0004	−0.0030	−0.0369***	−0.0367***	−0.0696***	0.0274	0.0028	−0.0010
	(0.0035)	(0.0060)	(0.0084)	(0.0105)	(0.0165)	(0.0213)	(0.0025)	(0.0014)
Num_Holds			−0.1600***	−0.1047***	0.0842***	0.0821***	−0.0200***	0.0048***
			(0.0024)	(0.0025)	(0.0044)	(0.0043)	(0.0005)	(0.0003)
Num_Buys			0.1321***	0.1255***	−0.1966***	−0.2201***	0.0143***	−0.0073***
			(0.0021)	(0.0025)	(0.0053)	(0.0059)	(0.0005)	(0.0002)
Num_Sells			−0.3305***	−0.2961***	0.2904***	0.2240***	−0.0466***	0.0178***

(continued)

Table III. Continued

Variable	*Bias_EPS* OLS (1)	*Bias_PT* OLS (2)	*Buy* Logit (3)	*Buy* Logit (4)	*Sell* Logit (5)	*Sell* Logit (6)	*Buy* OLS (7)	*Sell* OLS (8)
			(0.0073)	(0.0068)	(0.0094)	(0.0084)	(0.0012)	(0.0010)
Num_Firm			−0.0055***		0.0175***			
			(0.0004)		(0.0007)			
Num_Industry			0.0286***		−0.0413***			
			(0.0018)		(0.0040)			
Year_Exp			−0.0093***		−0.0008			
			(0.0009)		(0.0019)			
Firm FE	Yes	Yes	Yes	No	Yes	No	Yes	Yes
Analyst–Year–Quarter FE	Yes	Yes	No	Yes	No	Yes	Yes	Yes
Obs.	1,643,086	1,310,580	650,634	650,634	650,634	650,634	650,634	650,634
R^2/Pseudo R^2	0.22	0.26	0.04	0.03	0.04	0.05	0.39	0.36

3.2 Asymmetric First Impression Effects

To examine whether the effects of a positive impression and a negative impression differ in magnitude, we rerun models (1), (2), and (3) by replacing $FirstImpression_{ij}$ with $PositiveImpression_{ij}$ and $NegativeImpression_{ij}$:

$$Y_{ijt} = \beta_0 + \beta_1 PositiveImpression_{ij} + \beta_2 NegativeImpression_{ij} + Controls_{ijt} + Fixed\ Effects + \varepsilon_{ijt}, \tag{4}$$

$$\text{Prob}(X_{ijt}) = \text{f}(\beta_0 + \beta_1 PositiveImpression_{ij} + \beta_2 NegativeImpression_{ij} + Controls_{ijt} + Fixed\ Effects + \varepsilon_{ijt}), \tag{5}$$

and

$$X_{ijt} = \beta_0 + \beta_1 PositiveImpression_{ij} + \beta_2 NegativeImpression_{ij} + Controls_{ijt} + Fixed\ Effects + \varepsilon_{ijt} \tag{6}$$

The coefficients of interest are β_1 and β_2. The former is expected to be positive while the latter is expected to be negative. We also predict that the negative first impression effect is stronger than the positive one.

Table IV summarizes the findings. Consistent with Table III, the coefficient on $PositiveImpression_{ij}$ indicates that positive first impression analysts are more likely to issue optimistic EPS forecasts, optimistic price target forecasts, and Buy recommendations, but they are less likely to issue Sell recommendations relative to other analysts covering the same firm. The opposite is true for negative first impressions. The coefficient on $NegativeImpression_{ij}$ is larger than the coefficient on $PositiveImpression_{ij}$ in all cases. In the OLS regressions of Columns (1) and (2), the difference in magnitude of the effects is also statistically significant. For EPS forecasts, the difference in magnitude is $0.0288 - 0.0116 = 0.0172$, which is statistically significant at the 5% level ($p = 0.028$). For price target forecasts, the difference in magnitude, $0.0424 - 0.0223 = 0.0201$, is statistically significant at the 10% level ($p = 0.086$). We also have similar results for analyst recommendations in which the coefficient estimates in Columns (7) and (8) indicate that a negative first impression has a stronger effect on an analyst's forecast behaviors than a positive first impression.

3.3 First Impression Effects over Time

We would expect the first impression effect could weaken over time as the analyst continues following the same firm and accumulates more firm-specific experience. To assess whether and when the first impression effect disappears, we re-estimate the baseline regression models in Subsections 3.1 and 3.2, progressively keeping only forecasts made farther away from the initial forecast of each analyst–firm pair. In particular, we estimate the first impression effects in the following subsamples: all forecasts (baseline), subsamples excluding forecasts made in the first 3, 6, 12, 18, 24, 36, 48, 72, and 120 months, respectively. Table V presents the results.

Panel A shows the first impression effects for quarterly EPS forecasts. Consistent with the previous results, the coefficient for a positive impression is positive across all subsamples, while the coefficient for a negative impression is negative. However, the effects become statistically insignificant starting roughly after the 36th month of coverage. These

Table IV. Asymmetric first impression effects

This table presents the asymmetric first impression effect on analyst bias in EPS forecasts, price target forecasts, and recommendations. Observations are at the analyst–firm–quarter level. *PositiveImpression* is an indicator that equals 1 if the analyst has a positive first impression of the firm she follows. *NegativeImpression* is an indicator that equals 1 if the analyst has a negative first impression of the firm she follows. In Column (1), the dependent variable, *Bias_EPS*, is a measure of the analyst's relative bias in EPS forecasts compared to all analysts who follow the same firm in the same fiscal quarter. In Column (2), the dependent variable, *Bias_PT*, is a measure of the analyst's relative bias compared to all analysts who produce price target forecasts for the same firm in the same quarter. Columns (3)–(6) present conditional logistic regressions in which the dependent variables are either *Buy* (an indicator variable equal to 1 if the analyst issues a Buy recommendation and 0 otherwise) or *Sell* (an indicator variable equal to 1 if the analyst issues a Sell recommendation and 0 otherwise). Columns (7)–(8) present OLS regressions in which the dependent variable is either *Buy* or *Sell*. Appendix A contains the definitions of all variables used in the regressions. Robust standard errors are clustered at the analyst level (except for Columns (3) and (5), in which they are clustered at the firm level due to conditional logit's computational limitations) and presented in parentheses. ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

	Bias_EPS	*Bias_PT*	*Buy*	*Buy*	*Sell*	*Sell*	*Buy*	*Sell*
	OLS	OLS	Logit	Logit	Logit	Logit	OLS	OLS
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PositiveImpression	0.0116***	0.0223***	0.1415***	0.1255***	−0.1316***	−0.0298	0.0247***	−0.0026*
	(0.0036)	(0.0057)	(0.0103)	(0.0111)	(0.0220)	(0.0245)	(0.0024)	(0.0013)
NegativeImpression	−0.0288***	−0.0424***	−0.3714***	−0.4087***	0.3763***	0.4871***	−0.0724***	0.0269***
	(0.0067)	(0.0096)	(0.0174)	(0.0197)	(0.0269)	(0.0326)	(0.0041)	(0.0027)
Forecast_Age	0.0027***							
	(0.0001)							
Firm_Exp	0.0002	0.0063***	−0.0352***	−0.0395***	0.0400***	0.0431***	−0.0067***	0.0021***
	(0.0005)	(0.0009)	(0.0016)	(0.0022)	(0.0027)	(0.0040)	(0.0005)	(0.0003)
Specialization	−0.0005	−0.0032	−0.0381***	−0.0402***	−0.0680***	0.0336	0.0025	−0.0008
	(0.0035)	(0.0060)	(0.0084)	(0.0105)	(0.0165)	(0.0213)	(0.0025)	(0.0014)
Num_Holds			−0.1599***	−0.1048***	0.0842***	0.0829***	−0.0200***	0.0048***
			(0.0024)	(0.0025)	(0.0044)	(0.0043)	(0.0005)	(0.0003)
Num_Buys			0.1319***	0.1249***	−0.1964***	−0.2190***	0.0143***	−0.0073***

(continued)

Table IV. Continued

Variable	*Bias_EPS* OLS (1)	*Bias_PT* OLS (2)	*Buy* Logit (3)	*Buy* Logit (4)	*Sell* Logit (5)	*Sell* Logit (6)	*Buy* OLS (7)	*Sell* OLS (8)
			(0.0021)	(0.0025)	(0.0052)	(0.0059)	(0.0005)	(0.0002)
Num_Sells			−0.3295***	−0.2942***	0.2894***	0.2207***	−0.0464***	0.0177***
			(0.0072)	(0.0068)	(0.0093)	(0.0084)	(0.0012)	(0.0010)
Num_Firm			−0.0055***		0.0175***			
			(0.0004)		(0.0007)			
Num_Industry			0.0285***		−0.0412***			
			(0.0018)		(0.0040)			
Year_Exp			−0.0092***		−0.0010			
			(0.0009)		(0.0019)			
Firm FE	Yes	Yes	Yes	No	Yes	No	Yes	Yes
Analyst–Year–Quarter FE	Yes	Yes	No	Yes	No	Yes	Yes	Yes
Obs.	1,643,086	1,310,580	650,634	650,634	650,634	650,634	650,634	650,634
R^2/Pseudo R^2	0.22	0.26	0.04	0.03	0.04	0.05	0.39	0.36

Table V. First impression effects over time

This table presents the regression estimates of the first impression effect on analyst bias in EPS forecasts, price target forecasts, and recommendations over time. Observations are at the analyst–firm–quarter level. Panel A shows the results for EPS forecasts using the specification in Column (1) of Tables III and IV. Panel B shows the results for price target forecasts using the specification in Column (2) of Tables III and IV. Panels C and D show the results for recommendations using specifications from Columns (4) and (6), respectively, of Tables III and IV. These regressions use the same set of control variables and fixed effects as those in the baseline results (Table III). Each column differs depending on which forecasts are used in the estimation. [t,∞] means that forecasts made before month *t* are dropped, and $t=0$ refers to the month in which the analyst issues her first forecast for the firm. Appendix A contains the definitions of all variables used in the regressions. Robust standard errors are clustered at the analyst level and presented in parentheses. ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

Panel A: EPS forecasts

Variable	Dependent variable: *Bias_EPS*									
Only forecasts in	[0,∞]	[3,∞]	[6,∞]	[12,∞]	[18,∞]	[24,∞]	[36,∞]	[48,∞]	[72,∞]	[120,∞]
FirstImpression	0.0158***	0.0110***	0.0115***	0.0127***	0.0128***	0.0112**	0.0093*	0.0094	0.0136*	0.0246*
	(0.0031)	(0.0034)	(0.0036)	(0.0040)	(0.0044)	(0.0047)	(0.0054)	(0.0062)	(0.0080)	(0.0132)
PositiveImpression	0.0116***	0.0085**	0.0090**	0.0105**	0.0115**	0.0096*	0.0041	0.0021	0.0060	0.0330**
	(0.0036)	(0.0039)	(0.0042)	(0.0046)	(0.0050)	(0.0054)	(0.0063)	(0.0073)	(0.0095)	(0.0160)
NegativeImpression	−0.0288***	−0.0192**	−0.0200**	−0.0205**	−0.0173*	−0.0171*	−0.0273**	−0.0342***	−0.0389**	0.0035
	(0.0067)	(0.0076)	(0.0081)	(0.0089)	(0.0097)	(0.0103)	(0.0116)	(0.0131)	(0.0158)	(0.0282)
Obs.	1,643,086	1,405,753	1,304,045	1,123,821	977,131	851,575	657,344	513,353	317,896	120,959

Panel B: Price target forecasts

Variable	Dependent variable: *Bias_PT*									
Only forecasts in	[0,∞]	[3,∞]	[6,∞]	[12,∞]	[18,∞]	[24,∞]	[36,∞]	[48,∞]	[72,∞]	[120,∞]
FirstImpression	0.0274***	0.0168***	0.0146***	0.0131**	0.0120*	0.0089	0.0083	0.0063	0.0167	−0.0560*

(continued)

Table V. Continued

Panel B: Price target forecasts

Variable	Dependent variable: *Bias_PT*									
Only forecasts in	[0,∞]	[3,∞]	[6,∞]	[12,∞]	[18,∞]	[24,∞]	[36,∞]	[48,∞]	[72,∞]	[120,∞]
	(0.0047)	(0.0053)	(0.0056)	(0.0063)	(0.0071)	(0.0079)	(0.0095)	(0.0112)	(0.0157)	(0.0311)
PositiveImpression	0.0223***	0.0131**	0.0121*	0.0104	0.0097	0.0091	0.0084	0.0047	0.0159	−0.0694*
	(0.0057)	(0.0065)	(0.0069)	(0.0078)	(0.0087)	(0.0097)	(0.0117)	(0.0138)	(0.0194)	(0.0381)
NegativeImpression	−0.0424***	−0.0282**	−0.0224*	−0.0220*	−0.0191	−0.0090	−0.0084	−0.0117	−0.0193	0.0147
	(0.0096)	(0.0111)	(0.0119)	(0.0132)	(0.0145)	(0.0160)	(0.0187)	(0.0223)	(0.0311)	(0.0585)
Obs.	1,643,086	1,405,753	1,304,045	1,123,821	977,131	851,575	657,344	513,353	317,896	120,959

Panel C: Recommendations: *Buy*

Variable	Dependent variable: *Buy*									
Only recommendations in	[0,∞]	[3,∞]	[6,∞]	[12,∞]	[18,∞]	[24,∞]	[36,∞]	[48,∞]	[72,∞]	[120,∞]
FirstImpression	0.2072***	0.0866***	0.0653***	0.0481***	0.0367**	0.0219	0.0143	0.0235	0.0089	−0.0449
	(0.0095)	(0.0127)	(0.0135)	(0.0150)	(0.0166)	(0.0186)	(0.0225)	(0.0271)	(0.0386)	(0.0697)
PositiveImpression	0.1255***	0.0573***	0.0399**	0.0212	0.0189	0.0096	0.0009	0.0206	0.0072	−0.0417
	(0.0111)	(0.0148)	(0.0156)	(0.0176)	(0.0193)	(0.0219)	(0.0265)	(0.0319)	(0.0458)	(0.0846)

(continued)

Table V. Continued

Panel C: Recommendations: *Buy*										
Variable	Dependent variable: *Buy*									
Only recommendations in	[0,∞]	[3,∞]	[6,∞]	[12,∞]	[18,∞]	[24,∞]	[36,∞]	[48,∞]	[72,∞]	[120,∞]
NegativeImpression	−0.4087***	−0.1685***	−0.1377***	−0.1275***	−0.0911**	−0.0608	−0.0548	−0.0320	−0.0139	0.0546
	(0.0197)	(0.0270)	(0.0287)	(0.0320)	(0.0358)	(0.0395)	(0.0487)	(0.0585)	(0.0842)	(0.1521)
Obs.	650,634	400,006	363,067	298,448	247,271	206,418	148,431	108,682	59,993	18,063

Panel D: Recommendations: *Sell*										
Variable	Dependent variable: *Sell*									
Only Recommendations in	[0,∞]	[3,∞]	[6,∞]	[12,∞]	[18,∞]	[24,∞]	[36,∞]	[48,∞]	[72,∞]	[120,∞]
FirstImpression	−0.2065***	−0.1141***	−0.0893***	−0.0546*	−0.0495	−0.0365	−0.0208	0.0161	0.1296*	0.1374
	(0.0199)	(0.0244)	(0.0257)	(0.0286)	(0.0323)	(0.0357)	(0.0423)	(0.0514)	(0.0759)	(0.1286)
PositiveImpression	−0.0298	−0.0086	0.0078	0.0175	0.0022	0.0080	0.0180	0.0307	0.1294	0.0534
	(0.0245)	(0.0297)	(0.0310)	(0.0342)	(0.0384)	(0.0429)	(0.0499)	(0.0600)	(0.0871)	(0.1635)
NegativeImpression	0.4871***	0.3169***	0.2845***	0.2125***	0.1726***	0.1495**	0.1235	0.0239	−0.1302	−0.3377
	(0.0326)	(0.0430)	(0.0461)	(0.0530)	(0.0581)	(0.0642)	(0.0783)	(0.0956)	(0.1437)	(0.2421)
Obs.	650,634	400,006	363,067	298,448	247,271	206,418	148,431	108,682	59,993	18,063

results also suggest that the negative first impression effect lasts longer than the effect of a positive first impression (statistically insignificant starting after the 72nd month). Similarly, Panel B provides evidence that the first impression effects also fade over time for price target forecasts. In particular, the effects are no longer statically significant after the first 18 months.

Panels C and D present the results for analyst recommendations in which the variables Buy_{ijt} and $Sell_{ijt}$ are used, respectively. In both tables, we use conditional logistic regressions with analyst–year–quarter fixed effects. The evidence is similar to that of the EPS and price target cases: the effects of a first impression fade over time, the effects of a negative impression last longer, and these effects generally become statistically insignificant after the 24th month.

3.4 Comparing Experience Effects

Under first impression bias, analysts place greater weights on their earliest experiences of the firms they follow. The finance literature, however, has often found that people place heavier weights on, and extrapolate more from, recent events than earlier events. For example, Malmendier and Nagel (2016) show that individuals' expectations about future inflation are more strongly influenced by the more recent experiences they accumulate during their lifetimes. So, evidence of first impression bias provides a notable contrast with previous findings.

In this section, we compare the effect of early experiences with the effect of other past experiences to shed light on the relative importance of each impression on analyst forecast biases. To do so, we consider a simple approach of defining three variables that capture the ordering of experiences of an analysts' forecasting earnings of a firm: first impression, intermediate impression, and recent impression.[18]

Specifically, we estimate the following regression model:

$$\begin{aligned} Bias_EPS_{ijt} = \beta_0 &+ \beta_1 FirstImpression_{c_{ij}} + \beta_2 IntermediateImpression_{c_{ijt}} \\ &+ RecentImpression_{c_{ijt}} + \beta_3 Controls_{ijt} + Fixed\ \ Effects + \varepsilon_{ijt}. \end{aligned} \tag{7}$$

Provided that m is the month of the forecast in quarter t and 0 is the month of the first forecast analyst i issues for firm j, $FirstImpression\_c_{ij}$ of analyst i on firm j is the [−12 month, 0 month] stock return of firm j minus the [−12 month, 0 month] average stock return of j's industry. The variable $RecentImpression\_c_{ijt}$ is the [$m-12$ month, m month] stock return of firm j minus the [$m-12$ month, m month] average stock return of j's industry. Also, $IntermediateImpression\_c_{ijt}$ is the 13-month stock return of firm j in the center of the intermediate range [1 month, $m-13$ month] minus the 13-month average stock return of j's industry over the same period.[19]

18 Doing so imposes a semiparametric structure on the weights placed on experiences by analysts over time. Using three categories allows us to statistically compare early-to-intermediate, intermediate-to-recent, and early-to-recent experience weightings.

19 The intermediate range [1 month, $m-13$ month] can be longer than 13 months depending on the value of t. We impose the 13-month restriction to facilitate comparison across the other two impressions that are also defined over 13-month windows. We define the intermediate impression at the center of [1 month, $m-13$ month] because we believe it would most likely reflect the analyst's impression of a firm between her first and most recent impression. However, the results are similar if we choose alternative definitions, such as [1 month, 13 month].

We use continuous measures of experiences to capture differences in the return performance of different firms over extended time periods. Coarsened variables, such as binary indicators, would reduce the power to identify effects owing to potential collinearity in the measures of recent impressions across analysts. We also require that the length of the sample of forecasts, m, be greater than 26 months, so that periods can be of similar length without overlapping among the three impressions. Finally, since we have documented that the first impression effect fades over time, we conduct this analysis using subsamples consisting only of forecasts made in the first 5, 4, or 3 years. Placing an upper bound on the length of time since first impressions helps to ensure that analysts in the sample are still affected by the first impression bias. To further increase the power of our test, we model analyst forecast bias for EPS forecasts, since we have the largest number of observations for this type of forecast.

The coefficients of interest in Equation (7) are β_1, β_2, and β_3. Given the findings in our previous sections, we expect β_1 to be positive. Similarly, based on the prior literature, β_3 is also expected to be positive.[20] However, neither our results nor the literature lead to a strong prediction about the sign or magnitude of β_2.

The results are shown in Table VI. The coefficient on *RecentImpression_c* is positive and statistically significant, consistent with the findings in prior literature that analysts use recent information about firms to make their forecasts and there is a positive relationship between the two. The coefficient on *FirstImpression_c* is still positive and statistically significant across all specifications, suggesting that an analyst suffers from first impression bias even after controlling for other impressions. Interestingly, the coefficient on *IntermediateImpression_c*, even though generally positive, is not statistically different from zero. This is consistent with analysts placing greater emphasis on initial first impressions and on recent impressions.

To further assess the relative importance among the three impressions, we describe hypothesis tests at the end of Table VI. First, we test whether the first impression effect is stronger than the intermediate impression effect. The one-tailed p-values across the three specifications reject the null hypothesis that first impressions are weaker than, or just as strong as, intermediate impressions. Second, we test whether there is a difference in the effect of the recent impression and first impression on analysts' forecasts. We fail to reject the null hypothesis that they are of equal magnitude, as evidenced by the two-tailed p-values greater than 0.1 in all three specifications. Finally, the one-tailed p-values in the last row reject the null hypothesis in favor of the alternative that the recent impression has a larger impact than the intermediate impression. Taken together, these results suggest that analysts use U-shaped weights when forecasting earnings, placing a higher emphasis on the most recent information and the earliest information signals they receive about the firm, but not necessarily the signals in between.

20 It should be clear that, due to different coverage initiation dates, first impressions and intermediate impressions differ across analysts forecasting for the same firm at the same time. This allows for identification of both β_1 and β_2. Note that even though analysts forecasting the same firms are subject to similar recent impressions, there are still differences in recent impressions depending on the exact month in which each analyst issues her forecast. Thus, the fact that our dependent variable is standardized based on forecasts made from the same firm in the same fiscal quarter does not preclude the estimation of β_3.

Table VI. Comparing different impressions

This table presents the regression results on whether the impression effect follows a U-shaped function. Observations are at the analyst–firm–quarter level. The dependent variable, *Bias_EPS*, is a measure of the analyst's relative bias in EPS forecasts compared to all analysts who follow the same firm in the same fiscal quarter. Provided that *t* is the month of the current analyst forecast in question and 0 denotes the month of the first forecast the analyst issues for the firm, *FirstImpression_c* is the difference between the firm's 13-month return and the average industry 13-month return over the time window [−12, 0], *RecentImpression_c* is the difference between the firm's 13-month return and the average industry 13-month return over the time window [$t-12$, *t*], and *ItermediateImpression_c* is the difference between the firm's 13-month return and the average industry 13-month around the center point of [1, $t-13$]. The same set of controls, firm fixed effects, and analyst–year–quarter fixed effects are included. Column (1) shows the results using a subsample of forecasts made within the first 5 years. Column (2) shows the results using a subsample of forecasts made within the first 4 years. Column (3) shows the results using a subsample of forecasts made within the first 3 years. Appendix A contains the definitions of all variables used in the regressions. Robust standard errors are clustered at the analyst level and presented in parentheses. ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

	Dependent variable: *Bias_EPS*		
Variable	Forecasts within the first 5 years (1)	Forecasts within the first 4 years (2)	Forecasts within the first 3 years (3)
FirstImpression_c	0.0203***	0.0154**	0.0189*
	(0.0058)	(0.0068)	(0.0108)
IntermediateImpression_c	0.0065	0.0047	−0.0079
	(0.0048)	(0.0058)	(0.0092)
RecentImpression_c	0.0294***	0.0290***	0.0120
	(0.0071)	(0.0080)	(0.0118)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Analyst–Year–Quarter FE	Yes	Yes	Yes
p-value (H_0: *FirstImpression_c* ≤ *IntermediateImpression_c*)	0.0250**	0.1018*	0.0217**
p-value (H_0: *RecentImpression_c* = *FirstImpression_c*)	0.2969	0.1780	0.6491
p-value (H_0: *RecentImpression_c* ≤ *IntermediateImpression_c*)	0.0017***	0.0040***	0.0844*
Obs.	406,267	298,501	156,871
R^2	0.34	0.37	0.43

3.5 Market Reaction Test

In this section, we investigate whether the market accounts for the first impression effect among equity analysts. Since previous research (e.g. Womack, 1996) indicates that recommendation revisions have high information content and are associated with strong price reactions, we focus on the subsample of event dates that include recommendation revisions.

If analysts exhibit confirmation bias, then a positive first impression analyst should be more likely to interpret news as positive, leading to more positive recommendation revisions. Efficient markets should understand that such positive revisions are weaker positive signals. In contrast, negative revisions from positive first impression analysts should be stronger negative signals. Both of these cases make the reactions less favorable (either less positive or more negative) for positive first impression analysts. Similar reasoning implies that the opposite is the case for negative first impression analysts.

We therefore hypothesize that investors will react more negatively on the days that positive first impression analysts make recommendation revisions, compared to the days when other analysts make revisions. As a null hypothesis, if analysts do not exhibit confirmation bias, the prediction is that there is no effect of first impressions on revisions. To test between these predictions, we estimate the following models:

$$CAR[-1,1]_{ijt} = \beta_0 + \alpha_1 FirstImpression_{ij} + \beta_2 Rec_{Revisio}n_{ijt} + Controls_{ijt} + Fixed\ \ Effects + \varepsilon_{ijt}, \tag{8}$$

and

$$CAR[-1,1]_{ijt} = \beta_0 + \beta_1 PositiveImpression_{ij} + \beta_2 NegativeImpression + \beta_3 Rec_{Revisio}n_{ijt} + Controls_{ijt} + Fixed\ \ Effects + \varepsilon_{ijt} \tag{9}$$

where $CAR[-1,1]_{ijt}$ is the 3-day market-adjusted excess return for firm j centered on the recommendation revision issued by analyst i at time t. We also control for $Rec\_Revision_{ijt}$, a variable that equals 1 if there is an upward revision (i.e., from Sell or Hold to Buy), equals -1 if there is a downward revision (i.e., from Buy or Hold to Sell), and 0 otherwise.

Based on past research, we expect the coefficient on $Rec\_Revision_{ijt}$ to be positive, which means that the market reacts in the same direction with analyst revisions. The coefficients of interest are α_1 in Equation (8) and β_1 and β_2 in Equation (9). If investors understand the first impression bias, they can identify which analysts have a positive or negative first impression of the firms they follow, and then investors can adjust their reactions appropriately. Our predicted market reaction pattern would be present if α_1 is negative and if β_1 is negative while β_2 is positive.[21]

21 As we showed earlier, positive first impression analysts have a greater propensity to issue Buy forecasts and a lesser propensity to issue Sell forecasts. This means positive signals should be interpreted less positively by the market when coming from this analyst. Moreover, negative signals, because they are so rare, should be interpreted more negatively. In both cases (i.e., less positive and more negative reactions), there should be a negative effect on reactions to recommendations by positive first impression analysts. The converse should be true for negative first impression analysts. In other words, investors would discount everything coming from biased analysts, in the opposite direction of that bias, no matter what it is.

Panel A of Table VII presents the market reaction results. Consistent with our predictions, in the first two columns, the coefficient on $FirstImpression_{ij}$ is negative and statistically significant. In the last two columns, the coefficients on $PositiveImpression_{ij}$ and $NegativeImpression_{ij}$ are negative and positive, respectively, and statistically significant at the 1% level. These results are consistent with the market partially impounding the first impression effect.

To assess for possible reversals subsequent to the recommendation revision announcements, we repeat the estimation, replacing the dependent variable with $CAR[2,60]$, which represents the 59-day cumulative market-adjusted abnormal returns after the event date. The results in Panel B of Table VII indicate that the market continues to react negatively to positive impression analysts and react positively to negative impression analysts. The magnitudes of the coefficients in Columns (2) and (4) are slightly higher than their counterparts in Panel A, suggesting that the market cannot fully undo the first impression bias initially and, as a result, must gradually correct for it over time. Taken together, the results from Table VII highlight a capital market implication of the analyst impression bias.

3.6 Measurement Robustness

To ensure that these results are not driven by our definition of analyst first impressions, we examine four alternative measures of first impressions. The first one is $FirstImpression\_c_{ij}$, defined in Section 3.4. This is a continuous measure that captures analyst *i*'s first impression of firm *j* based on firm *i*'s performance relative to its industry's average.

Next, we consider different percentile cutoffs when comparing relative return performance. In particular, $PositiveImpression\_5_{ij}$ and $NegativeImpression\_5_{ij}$ are indicator variables equal to 1 if the 13-month period return of firm *j* is in the top and bottom 5th percentile of its industry, respectively, and 0 otherwise. The variables $PositiveImpression\_20_{ij}$ and $NegativeImpression\_20_{ij}$ are defined similarly, but with the 20th percentile cutoff.

Finally, we consider the case in which first impressions are formed based on absolute firm performance. Specifically, we define $PositiveImpression\_a_{ij}$ and $NegativeImpression\_a_{ij}$ as indicator variables equal to 1 if the 13-month period return of firm *j* is in the top and bottom 10th percentile of all firms. Using these alternative definitions, we rerun our main analysis of Table IV and report the results in Table VIII. The coefficient estimates across all specifications are consistent with the main findings, which suggests that our results are robust to alternative measures of analyst first impressions.

3.7 Alternative Explanations

Past research has provided evidence that analyst conflicts of interest detract from forecast accuracy (see the survey of Bradshaw (2011)), but there is no obvious reason such incentives might bias analysts toward their first impressions. As we study first impressions made before an analyst makes her forecast, our findings are not explained by analysts maintaining their reputations through sticky forecasts, as in Prendergast and Stole (1996). The fact that we measure forecast bias with respect to the consensus also indicates that our findings are not driven by general differences across firms in assessed prospects.

For example, an extensive literature studies the tendency of market participants to overextrapolate from recent past performance (e.g., Lakonishok, Shleifer and Vishny, 1994; Dechow and Sloan, 1997; Teoh, Welch, and Wong, 1998; Benartzi, 2001; Choi et al.,

Table VII. Market reaction tests

This table presents the OLS regression estimates of the market reaction to *PositiveImpression* and *PositiveImpression* analysts when they revise their stock recommendations. Panel A shows the results for the initial market reactions. Panel B shows the reversal results. Observations are at the analyst–firm–quarter level. The sample is restricted to observations in which there is a stock recommendation revision. The dependent variable in Panel A, *CAR*[−1, 1], represents the 3-day cumulative market-adjusted returns around the recommendation revision date. The dependent variable in Panel B, *CAR*[2, 60], represents the 59-day cumulative market-adjusted returns after the recommendation revision date. *Rec_Revision* is a variable that equals 1 if there is a positive revision (i.e., from Sell to Buy or from Hold to Buy), −1 if there is a negative revision (i.e., from Buy to Sell or from Hold to Sell), and 0 otherwise. The independent variable of interest in Columns (1) and (2) is *FirstImpression*. The independent variables of interest in Columns (3) and (4) are *PostiveImpression* and *NegativeImpression*. All specifications include the baseline set of control variables. Appendix A contains the precise definitions of all variables used in the regressions. Robust standard errors are clustered at the analyst level and presented in parentheses. ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

Panel A: Initial reactions

	Dependent variable: $CAR[-1,1]$			
Variable	(1)	(2)	(3)	(4)
FirstImpression	−0.0044***	−0.0022***		
	(0.0004)	(0.0005)		
PositiveImpression			−0.0045***	−0.0012*
			(0.0005)	(0.0006)
NegativeImpression			0.0042***	0.0050***
			(0.0008)	(0.0010)
Rec_Revision	0.0412***	0.0392***	0.0412***	0.0392***
	(0.0005)	(0.0006)	(0.0005)	(0.0006)
Controls	Yes	Yes	Yes	Yes

(continued)

Table VII. Continued

Panel A: Initial reactions

Variable	Dependent variable: $CAR[-1,1]$ (1)	(2)	(3)	(4)
Firm FE	No	Yes	No	Yes
Analyst–Year–Quarter FE	No	Yes	No	Yes
Obs.	410,124	410,124	410,124	410,124
R^2	0.05	0.43	0.05	0.43

Panel B: Reversals

Variable	Dependent variable: $CAR[2,60]$ (1)	(2)	(3)	(4)
FirstImpression	−0.0020*	−0.0064***		
	(0.0010)	(0.0012)		
PositiveImpression			−0.0015	−0.0043***
			(0.0012)	(0.0014)
NegativeImpression			0.0043**	0.0122***
			(0.0021)	(0.0024)
Rec_Revision	0.0120***	0.0055***	0.0120***	0.0055***
	(0.0007)	(0.0008)	(0.0007)	(0.0008)
Controls	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Analyst–Year–Quarter FE	No	Yes	No	Yes
Obs.	410,124	410,124	410,124	410,124
R^2	0.00	0.48	0.00	0.48

Table VIII. Measurement robustness

This table repeats the regression analysis in Table IV using alternative first impression measures. Observations are at the analyst–firm–quarter level. *FirstImpression_c* is a continuous measure of an analyst's first impression of a firm, measured as the difference between the firm's 13-month return and the average industry 13-month return over the time window [−12, 0]. *PositiveImpression_5* and *NegativeImpression_5* are measures of first impressions using relative firm performance in which the cutoffs are the top and bottom 5th percentile returns in the industry. *PositiveImpression_20* and *NegativeImpression_20* are measures of first impressions using relative firm performance in which the cutoffs are the top and bottom 20th percentile returns in the industry. *PositiveImpression_a* and *NegativeImpression_a* are measures of first impressions using absolute firm performance in which the cutoffs are the top and bottom 10th percentile returns of all firms in the sample. The baseline set of control variables and fixed effects is used in all specifications. Appendix A contains the precise definitions of all variables used in the regressions. Robust standard errors are clustered at the analyst level and presented in parentheses. ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

Variable	*Bias_EPS* OLS (1)	*Bias_PT* OLS (2)	*Buy* Logit (3)	*Buy* Logit (4)	*Sell* Logit (5)	*Sell* Logit (6)	*Buy* OLS (7)	*Sell* OLS (8)
FirstImpression_c	0.0059***	0.0132***	0.1094***	0.0978***	−0.1210***	−0.0699***	0.0158***	−0.0029***
	(0.0014)	(0.0022)	(0.0077)	(0.0068)	(0.0140)	(0.0160)	(0.0013)	(0.0006)
PositiveImpression_5	0.0151***	0.0256***	0.1731***	0.1403***	−0.1626***	−0.0141	0.0304***	−0.0032*
	(0.0048)	(0.0077)	(0.0133)	(0.0143)	(0.0296)	(0.0327)	(0.0032)	(0.0017)
NegativeImpression_5	−0.0383***	−0.0356**	−0.4511***	−0.4917***	0.4769***	0.6408***	−0.0912***	0.0403***
	(0.0104)	(0.0148)	(0.0280)	(0.0293)	(0.0392)	(0.0476)	(0.0061)	(0.0042)
PositiveImpression_20	0.0134***	0.0183***	0.0985***	0.0987***	−0.1038***	−0.0455**	0.0191***	−0.0032***
	(0.0027)	(0.0049)	(0.0081)	(0.0088)	(0.0173)	(0.0196)	(0.0019)	(0.0011)
NegativeImpression_20	−0.0200***	−0.0305***	−0.2900***	−0.3187***	0.2968***	0.3772***	−0.0541***	0.0181***
	(0.0041)	(0.0066)	(0.0115)	(0.0128)	(0.0193)	(0.0240)	(0.0027)	(0.0018)
PositiveImpression_a	0.0125***	0.0186***	0.1523***	0.1252***	−0.1216***	−0.0205	0.0250***	−0.0020
	(0.0035)	(0.0060)	(0.0099)	(0.0111)	(0.0214)	(0.0244)	(0.0024)	(0.0013)
NegativeImpression_a	−0.0292***	−0.0447***	−0.4021***	−0.4280***	0.3971***	0.5104***	−0.0753***	0.0286***
	(0.0069)	(0.0096)	(0.0162)	(0.0187)	(0.0265)	(0.0329)	(0.0039)	(0.0026)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	Yes	No	Yes	Yes
Analyst-Year-Quarter FE	Yes	Yes	No	Yes	No	Yes	Yes	Yes

2009; Alti and Tetlock, 2014; Barberis et al., 2015). This raises the possibility that an optimism-inducing effect of analyst first impressions (i.e., pre-coverage returns) might derive from a general extrapolation that applies just as strongly or more strongly to recent impressions. However, by measuring analyst bias relative to the consensus, our methodology mitigates this concern.

One potential alternative explanation for our findings in the case of negative first impressions could come from an analyst's strategic incentive to issue beatable EPS forecasts. In particular, underperforming firms may have a demand for analysts to issue low earnings forecasts in order for them to beat the analyst consensus. We believe this is unlikely to be the explanation for our findings, for two reasons. First, if an analyst is strategically biasing her forecast to adhere to management, we would expect her to speak in two tongues: issuing pessimistic (hence beatable) earnings forecasts on the one hand, but issuing Buy recommendations on the other (Malmendier and Shanthikumar, 2014). However, our previous results show that negative first impression analysts tend to issue Sell recommendations instead. Second, while this alternative explanation speaks to negative first impressions, it does not explain the positive first impression results.

Nevertheless, to empirically assess this alternative explanation, we perform three tests and report the results in Table B1 of Appendix B. First, the incentive to beat the consensus forecast is stronger when firms plan to have a seasoned equity offering (SEO) in the near future (Richardson, Teoh, and Wysocki, 2004). Thus, we examine whether the negative first impression effect is stronger for firms that will have an SEO within 1 year of the analyst forecast in question.

Second, we test directly whether negative impression analysts try to curry favor with management by exhibiting two-tongue behavior (i.e., a pessimistic earnings forecast accompanied by a Buy recommendation—see Malmendier and Shanthikumar 2014). Furthermore, we test whether first impression effects remain after controlling for two-tongue behavior.

Finally, analysts who act strategically by issuing beatable forecasts first issue optimistic forecasts and then walk down their estimates to offer a beatable benchmark later (Richardson, Teoh, and Wysocki, 2004). We examine whether negative impression analysts are more likely to walk down their forecasts. We also test whether the negative first impression bias remains after controlling for walk-down behavior.

The results are reported in Table B1. The results of the SEO tests are shown in the first four columns. The coefficients on the interaction term are not statistically significant, suggesting that the negative first impression effect is not stronger for firms having an SEO in the upcoming year. The next two columns present the results of our two-tongue tests. The coefficient estimate in Column (5) reveals that negative first impression analysts do not speak in two tongues more than other analysts. Further, as shown in Column (6), we find that our first impression effects remain similar after controlling for analyst two-tongue behaviors.

The last three columns show the results of the walk-down tests. Since prior literature finds evidence of analysts opportunistically walking down their annual earnings forecasts (Matsumoto, 2002; Bartov, Givoly, and Hayn, 2002; Richardson, Teoh, and Wysocki, 2004), we perform our tests with annual earnings forecasts. The negative coefficient on *NegativeImpression* in Column (7) suggests that these analysts are not likely to act opportunistically and walk down their forecasts. In Column (8), controlling for walk-down behavior, we also see that the negative impression effect remains significant. The effect is also very similar to the baseline effect shown in Column (9). Together, the results in this table indicate that analysts' incentive to issue beatable forecasts is unlikely to be a driving force behind our findings.

4. Conclusion

We present evidence that finance professionals in the field are subject to first impression bias. Equity analysts suffer from first impression bias in their forecasts of the earnings prospects of the firms that they cover. If a firm performs particularly well in the year before an analyst follows that firm, the analyst is optimistic in subsequent EPS forecasts. Similarly, if the firm performs particularly poorly, the analyst is pessimistic. These effects carry over to price targets and recommendations.

Consistent with the pervasive negativity bias found in the psychology literature, we find that negative first impressions are associated with effects that are larger and appear to last longer. Our results are unlikely to be explained by analysts issuing beatable forecasts. Our evidence suggests that the market partially adjusts for this behavioral bias in its reactions to analyst recommendations. Finally, our findings contribute to the literature on experience effects by showing that analysts apply U-shaped weights to their past experiences, with greater weight on first experiences and recent experiences than on intermediate ones.

Our findings suggest a possible practical implication for the management of finance professionals. For example, when assigning analysts to follow a particularly successful or unsuccessful firm, brokerages may benefit from designing procedures to compensate for the first impression biases of analysts in generating future forecasts, price targets, and recommendations.

Appendix A: Variable Descriptions and Computations

Table A1. Dependent variables

Abbreviation	Calculation	Description
Bias_EPS	$\frac{\text{Forecast}-\text{Consensus}}{\text{Standard Deviation of Forecasts}}$	Analyst's bias against consensus EPS forecast of the firm in the fiscal quarter in consideration.
Bias_PT	$\frac{\text{Price Target}-\text{Consensus PT of the same Quarter}}{\text{Standard Deviation of PT in the same Quarter}}$	Analyst's bias against consensus price target of the same calendar quarter in which she issues her price target.
Buy	Equals 1 if the analyst issues a Buy or Strong Buy, and 0 otherwise.	Indicator variable if the analyst issues a Buy or Strong Buy.
Sell	Equals 1 if the analyst issues a Sell or Strong Sell, and 0 otherwise.	Indicator variable if the analyst issues a Sell or Strong Sell.

(continued)

Table A1. Continued

Abbreviation	Calculation	Description
CAR[−1, 1]	Cumulative market-adjusted returns CAR[−1, 1]	Cumulative market-adjusted returns in 3 days around the analyst recommendation revision announcement.
CAR[2, 60]	Cumulative market-adjusted returns CAR[2, 60]	Cumulative market-adjusted returns in 59 days after the analyst recommendation revision announcement.

Table A2. Independent variables of interest

Abbreviation	Calculation	Description
$FirstImpression_{ij}$	Equals 1 if, when analyst *i* issues her first forecast for firm *j*, the [−12 month, 0 month] stock return of firm *j* is in the top 10th percentile of *j*'s industry. Equals −1 if, when analyst *i* issues her first forecast for firm *j*, the [−12 month, 0 month] stock return of firm *j* is in the bottom 10th percentile of *j*'s industry. And 0 otherwise.	Categorical variable indicating the analyst's first impression of the firm in consideration, based on the firm's relative performance.
$PositiveImpression_{ij}$	Equals 1 if, when analyst *i* issues her first forecast for firm *j*, the [−12 month, 0 month] stock return of firm *j* is in the top 10th percentile of *j*'s industry, and 0 otherwise.	Indicator variable if the analyst has a positive first impression of the firm in consideration, based on the firm's relative performance.
$NegativeImpression_{ij}$	Equals 1 if, when analyst *i* issues her first forecast for firm *j*, the [−12 month, 0 month] stock return of firm *j* is in the bottom 10th percentile of *j*'s industry, and 0 otherwise.	Indicator variable if the analyst has a negative first impression of the firm in consideration, based on the firm's relative performance.

Table A3. Other variables

Abbreviation	Calculation	Description
Forecast_Age	Earnings announcement date minus EPS forecast date.	The number of days between the analyst's first EPS forecast and earnings announcement.
Forecast_Error	| Forecast—Actual |	The absolute value of the difference between a firm's actual earnings of a fiscal quarter and an analyst's first earnings forecast for the firm in that quarter.
Num_Firm	The number of distinct firms the analyst follows in a particular year.	The number of distinct firms the analyst follows in a particular year.
Num_Industry	The number of distinct industries the analyst follows in a particular year.	The number of distinct industries the analyst follows in a particular year.
Year_Exp	Current year—First year the analyst appears in the sample.	The analyst's years of experience up to the year in consideration.
Firm_Exp	Current year—First year the analyst starts following the firm in consideration in the sample.	The analyst's firm-specific years of experience up to the year in consideration.
Specialization	Equals 1 if the analyst follows at least five firms in the same industry, and 0 otherwise.	Indicator for the analyst's industry specialization.
Num_Holds	The number of Hold recommendations made by all other analysts for the same firm in the same quarter.	The number of Hold recommendations made by all other analysts for the same firm in the same quarter.
Num_Buys	The number of Buy recommendations made by all other analysts for the same firm in the same quarter.	The number of Buy recommendations made by all other analysts for the same firm in the same quarter.
Num_Sells	The number of Sell recommendations made by all other analysts for the same firm in the same quarter.	The number of Sell recommendations made by all other analysts for the same firm in the same quarter.
Value	In the EPS sample, it is the raw analyst earnings forecast. In the Price Target sample, it is the raw stock price forecast.	In the EPS sample, it is the raw analyst earnings forecast. In the Price Target sample, it is the raw stock price forecast.
Rec_Revision	Equals 1 if the analyst revises to a Buy recommendation from either a Hold or a Sell recommendation, equals -1 if the analyst revises to a Sell recommendation from either a Hold or a Buy recommendation, and 0 otherwise.	Captures an analyst's recommendation revision.

(continued)

Table A3. Continued

Abbreviation	Calculation	Description
FirstImpression_c$_{ij}$	A continuous measure of analyst i's first impression of firm j, calculated as firm j's return [−12 month, 0 month] minus the average industry return [−12 month, 0 month]	Continuously captures an analyst's first impression of a firm based on the firm's relative performance over a 13-month period leading up to the month of the first forecast.
IntermediateImpression_c$_{ijt}$	A continuous measure of analyst i's intermediate impression on firm j, calculated as firm i's return [a month, b month] minus the average industry return [a month, b month], where $a = \text{int}\left(\frac{1+(t-13)}{2}\right) - 6$ and $b = \text{int}\left(\frac{1+(t-13)}{2}\right) + 6$, and t is the month of the forecast in question ($a \geq 1$ and $b \leq t - 13$).	Continuously captures an analyst's intermediate impression of a firm, based on the firm's relative performance over a 13-month period centered between the ending point of the first impression and the starting point of the recent impression.
RecentImpression_c$_{ijt}$	A continuous measure of analyst i's recent impression of firm j, calculated as firm i's return [t − 12 month, t month] minus average industry return [t − 12 month, t month], where t is the month of the forecast in question.	Continuously captures an analyst's recent impression of a firm, based on the firm's relative performance over a 13-month period ending with the month of the forecast in question.
PositiveImpression_5$_{ij}$	Equals 1 if, when analyst i issues her first forecast for firm j, the [−12 month, 0 month] stock return of firm j is in the top 5th percentile of j's industry, and 0 otherwise.	Indicator variable if the analyst has a positive first impression of the firm in consideration, based on the firm's relative performance.
NegativeImpression_5$_{ij}$	Equals 1 if, when analyst i issues her first forecast for firm j, the [−12 month, 0 month] stock return of firm j is in the bottom 5th percentile of j's industry, and 0 otherwise.	Indicator variable if the analyst has a negative first impression of the firm in consideration, based on the firm's relative performance.
PositiveImpression_20$_{ij}$	Equals 1 if, when analyst i issues her first forecast for firm j, the [−12 month, 0 month] stock return of firm j is in the top 20th percentile of j's industry, and 0 otherwise.	Indicator variable if the analyst has a positive first impression of the firm in consideration, based on the firm's relative performance.
NegativeImpression_20$_{ij}$	Equals 1 if, when analyst i issues her first forecast for firm j, the [−12 month, 0 month] stock return of firm j is in the bottom	Indicator variable if the analyst has a negative first impression of the firm in consideration, based on the firm's relative performance.

(continued)

Table A3. Continued

Abbreviation	Calculation	Description
	20th percentile of *j*'s industry, and 0 otherwise.	
PositiveImpression_a$_{ij}$	Equals 1 if, when analyst *i* issues her first forecast for firm *j*, the [−12 month, 0 month] stock return of firm *j* is in the top 10th percentile of all firms, and 0 otherwise.	Indicator variable if the analyst has a positive first impression of the firm in consideration, based on the firm's absolute performance.
NegativeImpression_a$_{ij}$	Equals 1 if, when analyst *i* issues her first forecast for firm *j*, the [−12 month, 0 month] stock return of firm *j* is in the bottom 10th percentile of all firms, and 0 otherwise.	Indicator variable if the analyst has a negative first impression of the firm in consideration, based on the firm's absolute performance.

Appendix B

Table B1. Alternative explanation: beatable forecasts

This table presents regression results to test the alternative explanation of negative impression analysts' intentionally issuing beatable forecasts. Observations are at the analyst–firm–quarter level. Columns (1)–(4) present cross-sectional test results based on SEOs that use quarterly earnings forecasts, price target forecasts, and recommendation data. Columns (5)–(6) report test results using the *TwoTongue* measure (Malmendier and Shanthikumar, 2014) using quarterly earnings forecast data. Columns (7)–(9) report the walk-down test results in the annual earnings forecast setting (Matsumoto, 2002; Bartov, Givoly, and Hayn, 2002; Richardson, Teoh, and Wysocki, 2004). The dependent variables are *Bias_EPS*, *Bias_PT*, *Buy*, *Sell*, *TwoTongue*, and *WalkDown*. The first four variables are defined as before. *TwoTongue* is an indicator variable that equals 1 if the analyst issues a pessimistic (hence beatable) earnings forecast and a Buy recommendation during the same fiscal quarter. *WalkDown* is an indicator variable that equals 1 if the analyst's first annual earnings forecast of a fiscal year is greater than the actual reported annual earnings and her last annual earnings forecast of the same fiscal quarter is lower than the actual reported annual earnings. *PositiveImpression* and *NegativeImpression* are defined as before. *SEO* is an indicator variable that equals 1 if there is an upcoming SEO within 1 year of the forecast or recommendation in question. The baseline set of control variables and fixed effects is used in all specifications. Appendix A contains the definitions of all variables used in the regressions. Robust standard errors are clustered at the analyst level and presented in parentheses. ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

	SEO tests				Two-tongue tests		Walk-down tests		
	Bias_EPS	*Bias_PT*	*Buy*	*Sell*	*TwoTongue*	*Bias_EPS*	*WalkDown*	*Bias_EPS*	*Bias_EPS*
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NegativeImpression	−0.0327***	−0.0491***	−0.0766***	0.0267***	0.0002	−0.0304***	−0.0015	−0.1899***	−0.1904***
	(0.0070)	(0.0103)	(0.0044)	(0.0028)	(0.0009)	(0.0067)	(0.0022)	(0.0089)	(0.0089)
SEO	0.0058	−0.0284***	0.0464***	−0.0073***					
	(0.0039)	(0.0046)	(0.0030)	(0.0015)					
NegativeImpression × *SEO*	0.0241	0.0265	0.0184	0.0049					
	(0.0201)	(0.0231)	(0.0137)	(0.0092)					
TwoTongue						−0.7717***			
						(0.0043)			

(continued)

Table B1. Continued

	SEO tests				Two-tongue tests		Walk-down tests		
Variable	*Bias_EPS* (1)	*Bias_PT* (2)	*Buy* (3)	*Sell* (4)	*TwoTongue* (5)	*Bias_EPS* (6)	*WalkDown* (7)	*Bias_EPS* (8)	*Bias_EPS* (9)
WalkDown								0.3614***	
								(0.0044)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst–Year–Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,619,474	957,347	588,095	588,095	1,637,221	1,637,221	643,234	643,234	643,234
R^2	0.22	0.30	0.42	0.38	0.20	0.23	0.18	0.22	0.21

Table B2. Main results: two-way clustered standard errors

This table repeats the OLS regressions in Table IV, but standard errors are two-way clustered at the analyst and firm levels. Standard errors are presented in parentheses. ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

Variable	*Bias_EPS* OLS (1)	*Bias_PT* OLS (2)	*Buy* OLS (3)	*Sell* OLS (4)
PositiveImpression	0.0116***	0.0223***	0.0247***	−0.0026*
	(0.0039)	(0.0059)	(0.0025)	(0.0013)
NegativeImpression	−0.0288***	−0.0424***	−0.0724***	0.0269***
	(0.0074)	(0.0099)	(0.0043)	(0.0027)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Analyst−Year−Quarter FE	Yes	Yes	Yes	Yes
Obs.	1,643,086	1,310,580	650,634	650,634
R^2/Pseudo R^2	0.22	0.26	0.39	0.36

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