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EXPECTATIONS IN THE CROSS SECTION: STOCK PRICE REACTIONS TO THE INFORMATION AND BIAS IN ANALYST-EXPECTED RETURNS

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BY
JOHNATHAN A. LOUDIS

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ABSTRACT

This paper provides evidence that the market does not efficiently incorporate expected returns implied by analyst price targets into prices. I use a novel decomposition to extract information and bias components from these analyst-expected returns and develop an asset pricing framework that helps interpret price reactions to each component. A one-standard-deviation increase in the information (bias) component is associated with a five (one) percentage point increase in announcement-month returns. The positive reaction to bias implies the market does not fully debias analyst-expected returns before incorporating them into prices. Prices overreact to bias and reverse their initial reaction within three to six months. Prices underreact to information and returns drift an additional one percentage point beyond their initial reaction in the following 12 months. Announcement-window returns forecast future returns, which provides model-free evidence of underreaction, and that underreaction dominates overreaction. Trading against underreaction generates average monthly returns of 1.12% with a Sharpe ratio of 1.08, and the returns survive controlling for exposure to many standard factors.

CHAPTER 1

EXPECTATIONS IN THE CROSS SECTION: STOCK PRICE REACTIONS TO THE INFORMATION AND BIAS IN ANALYST-EXPECTED RETURNS

1.1 Introduction

Identifying what information the market perceives as relevant and how it incorporates this information into prices is a first-order concern in finance. Sell-side analysts act as important information intermediaries and are one source of such information. Their forecasts have been shown to be biased in many ways, but have also been shown to contain useful information. More specifically, analyst price targets and the corresponding analyst-expected returns are biased on average (Bradshaw et al. (2013), Bonini et al. (2010), Brav and Lehavy (2003)) and in the cross section (Engelberg et al. (2018)). Despite being biased, price targets appear to contain useful information. Price changes are positively correlated with changes to price targets (Asquith et al. (2005), Brav and Lehavy (2003)), and analyst-expected returns can be used to forecast realized returns (Da et al. (2016), Gleason et al. (2013), Da and Schaumburg (2011)). Extant studies have not investigated whether prices respond differently to the biased and informative components in analyst-expected returns, nor have they investigated the extent to which the market is aware of the bias.

In this paper, I specify a novel decomposition that disentangles the information and bias components in analyst-expected returns and study price reactions to each component. The price reactions allow me to infer how the market updates its own expectations in response to the biased analyst-expected return signals. The decomposition divides analyst-expected returns into three parts: (1) the expected return conditional on the market's information set, (2) a bias component, and (3) a residual that I call the information component. I define the bias component to be a forecast of the analyst-expected return error conditional on the market's information set. The information component is then the difference between raw analyst-expected returns and the first two components. In theory, the information component contains noise that arises from bias that is orthogonal to the market's information set, which I account for in my framework.

I develop an expectations updating framework to help describe how the market incorporates the information and bias components into its own expectations. This framework takes seriously the idea that analyst-expected returns are signals the market observes and incorporates into expectations about returns. This signal processing interpretation distinguishes my paper from others in the literature that either explicitly or implicitly assume market expectations are facsimiles of analyst expectations.[1] Under a Bayesian learning paradigm, after observing the analyst-expected return signal, the market's posterior expected return is a convex combination of its prior expected return and the debiased analyst-expected return using optimal weights. I consider two ways in which the market might deviate from this ideal when updating expectations. First, it may apply non-optimal weights to debiased analyst-expected returns. Second, it may fail to properly correct for the forecastable bias in analyst-expected returns.

Next, I develop an asset pricing framework that relates each of these two mistakes to expected returns. The framework allows me to express expected returns as linear combinations of the information and bias components, where coefficients on these components are related to the two mistakes I describe above. The framework leads to six sets of empirical tests that I use to identify evidence of under- and overreaction to each component. To the extent the market is aware of and can extract the bias component, prices should only react to the information component during price target announcement months ("announcement months"). To the extent that the market efficiently incorporates analyst-expected returns into prices during announcement months, no further price reaction to the information or bias components should occur in subsequent months.

1. For examples, see Bouchaud et al. (2018), Bordalo et al. (2017), Bali et al. (2017), or Brav et al. (2005).

Price reactions are positively correlated with both components during announcement months. A one-standard-deviation increase in the information (bias) component is associated with a 5 (1) percentage point increase in announcement month returns. The positive correlation with bias indicates the market does not fully debias analyst-expected returns before incorporating them into prices; however, the relatively weak reaction to bias indicates the market does at least partially debias analyst-expected returns. Prices drift in the direction of their initial reaction to information and reverse their initial reaction to bias in subsequent months. A one-standard-deviation increase in the information component is associated with an increase in expected cumulative returns (including announcement-month returns) of about 6 percentage points over the next 12 months. This represents a 20% price drift beyond the initial announcement-month reaction. Cumulative returns (including announcement-month returns) reverse their initial reaction to bias, and their relationship with bias becomes statistically insignificant after three to six months. The information component is positively correlated with cumulative returns (excluding announcement-month returns) up to three months after the announcement month, which provides statistically significant evidence of underreaction. The bias component is negatively correlated with cumulative returns (excluding announcement-month returns) in the months after announcements, although this relationship is not statistically significant in my full sample; however, I do find statistically significant evidence of overreaction to bias in the smallest and largest quintiles of stocks.

Announcement-window returns cumulated over the five days surrounding price target announcements forecast returns in subsequent months. This result alleviates the concern that the underreaction I document is the result of model misspecification associated with estimating the bias component. It also implies that underreaction dominates overreaction in subsequent months.

The underreaction and overreaction I document are economically significant. A trading strategy that goes long stocks in the highest-information decile and short stocks in the lowest-information decile earns statistically significant average monthly returns of 1.12% with an annualized Sharpe ratio of 1.08. These returns survive adjusting for exposure to many standard factors, which suggests the information in analyst-expected returns is not simply the result of analysts using known factor models to generate their price targets. Within the smallest (largest) quintiles of stocks, a trading strategy that goes long stocks in the highest bias quintile and short stocks in the lowest bias quintile earns statistically significant average monthly returns of -0.88% (-0.82%) with an annualized Sharpe ratio of 0.62 (0.51). These results are consistent with results from my main tests, and provide additional evidence that the market underreacts to information and overreacts to bias.

Finally, I test whether the market is more efficient at incorporating analyst-expected returns into the prices of certain subsets of stocks relative to others. I find evidence that underreaction to information is stronger among small stocks, low-residual-analyst-coverage stocks, and low-turnover stocks relative to that among large stocks, stocks with high residual analyst coverage, and high-turnover stocks. Intuitively, the market incorporates the information component into the prices of low-attention stocks less efficiently than for high-attention stocks. This pattern in delayed price response is consistent with studies related to investor attention to news in other settings. It is also consistent with the notion that my information measure captures price-relevant news associated with price target announcements.

To establish my main results, I begin with a characterization of analyst-expected returns. They are positively biased. Median analyst-expected returns are 1.38% per month in my sample, whereas median realized returns are only 0.91% per month. They are also biased in the cross section relative to what standard firm-level forecasting characteristics would predict. For instance, the analyst-implied value premium is negative. Analysts expect value stocks to have low returns relative to growth stocks, which is the opposite of what we would expect based on historical data. I consider three sets of characteristics from the models in Lewellen (2015) as conditioning information in my analysis. The three models include either 3, 7, or 15 characteristics (Models 1, 2, and 3, respectively). Analyst-expected returns imply characteristic risk premia ("analyst-implied risk premia") that have both the wrong magnitude and sign when compared to risk premia estimated using realized returns for a majority of these characteristics. In my broadest specification, 11 of the 15 analyst-implied risk premia have the opposite sign as compared to those estimated using realized returns. I formally reject the null hypothesis that analyst-implied risk premia are jointly equivalent to those implied by realized returns in all three of the characteristics models I investigate. This is the sense in which analyst-expected returns are biased in the cross section.

Despite being biased, analyst-expected returns have statistically significant forecasting power in the cross section. In a univariate monthly cross-sectional regression of realized returns on analyst-expected returns, analyst-expected returns have a coefficient of 0.14% with a t-statistic of 2.42. For every 1% increase in analyst-expected returns, next month's expected returns increases by 0.14%. Analyst-expected returns have an average cross-sectional standard deviation of 1.48% (see Table 1.1), which implies a one-cross-sectional-standard-deviation increase in analyst-expected returns increases next month's expected returns by 0.20%. When adding 15 characteristic controls from Model 3 (Lewellen (2015)), the analyst-expected-return forecasting coefficient increases slightly to 0.15% with a t-statistic of 4.45. Adding these controls strengthens analyst-expected return forecasting power, providing evidence that analyst-expected returns contain information that is marginal to known return predictors.

Under my framework, the return predictability I document is the result of pricing errors related to expectational errors and inefficient information incorporation rather than rational risk premia. To my knowledge, this study is the first to decompose analyst-expected returns into information and bias components, and to document the contemporaneous underreaction to information and overreaction to bias.[2] My results help reconcile past findings that analyst-

2. Dechow and You (2017) study three components of analyst-expected return bias (1. Fundamentals bias related to errors in earnings forecasts, 2. Firm characteristics-related bias, and 3. Bias from analysts' incentives issues), setting up a return-decomposition framework similar to mine. The authors find analyst-

expected returns are biased, yet they can be used to forecast returns. The forecasting power originates from initial underreaction to the information component, and the fact that underreaction to information dominates overreaction to bias in subsequent months. Additionally, my evidence that the market partially corrects for bias implies that assuming market expectations mirror analyst expectations is misguided, at least in the case of analyst price targets.

The remainder of this paper is organized as follows. In Section 1.2, I briefly review related literature and my contributions. I present my analytical framework in Section 1.3, describe my data in Section 1.4, and present my main empirical results in Section 1.5. I present robustness checks and a discussion of my results in Section 1.6, and Section 1.7 concludes.

1.2 Literature Review

There exists a large literature related to analyst forecasts that I do not attempt to fully summarize here.[3] I instead focus on studies related to analyst price targets, which have received much less attention in the literature compared to analyst earnings forecasts and recommendations. For instance, recent papers related to analyst price targets including Bali et al. (2017), Bradshaw et al. (2013), and Bonini et al. (2010) explicitly mention a paucity of studies on analyst price targets relative to those on earnings forecasts and recommendations.

The price target literature most related to my paper falls into two categories. The first uses price targets to compute analyst-expected returns and compares these with known anomalies. My finding that analyst-expected returns are positively biased is in line with

expected return bias is dominated by the first two components, and the latter contributes relatively little to overall bias. Although their focus is on understanding the relative contributions of these components to overall bias, they also find a "purified" analyst-expected-return measure (i.e., one without their estimated bias) positively forecasts future returns. They interpret this finding as evidence that the market does not fully incorporate information in analyst-expected returns into prices immediately, although they do not present a framework for evaluating this interpretation. Additionally, their estimation of analyst-expected return bias is likely subject to an econometric issue that my approach avoids. I discuss these issues further in Online Appendix OA.12.

3. See Kothari et al. (2016) for a survey of the analyst forecasting literature with a particular focus on asset pricing. See Bradshaw (2011) and Ramnath et al. (2008) for more general surveys of this literature.

previous studies (Bradshaw et al. (2013), Bonini et al. (2010), and Brav and Lehavy (2003)). Evidence on the relationship between analyst-expected returns and cross-sectional anomalies is mixed. Brav et al. (2005) and Bali et al. (2017) find that analyst-implied risk premia generally have signs in line with expected signs for the anomaly characteristics they consider;[4] however, Engelberg et al. (2018) find that analyst-expected returns are negatively correlated with an aggregated anomaly exposure variable in the cross-section. The Engelberg et al. (2018) result is puzzling because (rational) expectations of returns should be positively correlated with the anomaly-exposure variable. Analysts appear to be correctly predicting the signs of some risk premia, but on the whole get the relationship incorrect for a broad set of anomalies. Note, though, that this aggregate anomaly exposure variable does not account for the relative magnitudes of different risk premia, nor does it account for correlation between risk premia. In my study, I consider a broader set of characteristics than in either Brav et al. (2005) or Bali et al. (2017). I also estimate analyst-implied risk premia for each characteristic jointly as opposed to the premium associated with an aggregated anomaly-exposure variable as in Engelberg et al. (2018). I find evidence consistent with that in Engelberg et al. (2018) in the sense that my analyst-implied risk premia have the opposite sign as most of the realized return-implied risk premia I study; however, the cross-sectional standard deviation in analyst-expected returns is 1.48%, whereas that of analyst-expected returns projected onto Model 2 characteristics is only 0.45%. This finding implies that a significant amount of variation in analyst-expected returns is unrelated to the standard characteristics-based anomalies, which leaves room for analyst-expected returns to be negatively related to many anomalies as documented by Engelberg et al. (2018) but also contain useful pricing information that forecasts returns.

4. These characteristics-based anomalies (and risk premium signs) include β (positive), size (negative), value (positive), idiosyncratic volatility (positive), and idiosyncratic skewness (positive). Brav et al. (2005) find, however, that analyst-expected returns imply a negative momentum premium. Their finding that analyst-expected returns imply a positive value premium was based on using Value Line analyst price targets as opposed to sell-side analyst price targets. This is contrary to my finding that the implied value premium is negative; however, when they use sell-side analyst price targets they also find a negative implied value premium.

The second strand of this literature documents the ability of analyst-expected returns to forecast realized returns. Da and Schaumburg (2011) show that industry-adjusted analyst-expected returns forecast realized returns in the cross-section. They argue that this forecasting power is the result of analysts' tendency to specialize in specific industries, and their ability to accurately assess within-industry relative valuation. Da et al. (2016) decompose price targets into components related to short-term earnings forecasts and price-to-earnings forecasts. They find that analyst-expected returns (also adjusted for industry) forecast returns in the cross-section, and that the forecasting power is related to both components in the decomposition. Gleason et al. (2013) try to infer which of two valuation methods (residual income model or PEG-ratio-based) were used to generate the price targets they study. They find that analyst-expected returns forecast abnormal returns independent of the inferred valuation model. They also find that analyst-expected returns based on price targets generated using a residual income model are better able to predict future returns. My results help explain the apparently contradictory findings that analyst-expected returns forecast realized returns even though they are negatively related to anomaly returns in the cross section. As noted above, there is a large amount of variation in analyst-expected returns that cannot be explained by characteristics, and this is exactly what I measure with the information component. It is this component that imbues analyst-expected returns with forecasting power.

Two other strands of literature related to analyst price targets are worth noting. The first studies the price impact of information in analyst reports upon release. This research typically uses event study methodologies to analyze price reactions to the hard information in analyst reports (e.g., earnings forecasts, recommendations, and price targets). These studies document that updates to analyst forecasts are positively correlated with cumulative abnormal returns around report releases (Asquith et al. (2005), Brav and Lehavy (2003)).[5]

5. Evidence also suggests such price reactions improve pricing efficiency. For instance, Chen et al. (2018) provide evidence from a natural experiment that analyst coverage leads to improved pricing efficiency. Crane and Crotty (2018) provide evidence that analyst are skilled at both interpreting news and generating new

The second evaluates price target accuracy, and includes studies by Bradshaw et al. (2013), Bonini et al. (2010), and Asquith et al. (2005). These studies generally conclude that price targets are inaccurate because realized prices fail to achieve analyst targets more than 50% of the time. There is wide consensus, though, that published analyst expectations are positively biased due to incentives issues (Ljungqvist et al. (2007), Jackson (2005), Hong and Kubik (2003), and Michaely and Womack (1999)). Analysts have incentive to issue overly optimistic estimates to support investment banking business, increase brokerage revenue, and to please management at covered firms. Regardless, my main research question is not whether price targets are biased or why they are biased, but rather whether the market is able to extract forecastable bias and efficiently incorporate the information in analyst-expected returns into prices. Price targets and the corresponding analyst-expected returns are known to be biased, so it seems reasonable that the market would attempt to correct for such bias when incorporating them into prices.

Another strand of literature studies how the market incorporates the information in analyst reports into its own expectations and, ultimately, into prices. For instance, La Porta (1996) finds evidence that the market shares excessive analyst optimism and pessimism related to long-term earnings growth prospects. Bordalo et al. (2017) revisit the apparent information-processing error documented by La Porta (1996) and explain it using a particular form of sub-optimal learning from past earnings growth that they label "diagnostic expectations." Bordalo et al. (2017) find evidence for this mechanism both in analysts' long-term earnings growth forecasts and in realized returns. Da and Warachka (2011) find evidence that analysts fail to update their long-term earnings growth expectations conditional on updates to their short-term earnings growth expectations, and that the market shares this expectational error. So (2013) sets up a simple Bayesian learning framework under which he finds evidence that the market overweights analyst earnings forecasts when updating expectations about future earnings. Grinblatt et al. (2018) also

price-relevant information.

concludes the market overweights analyst earnings forecasts and that this mistake affects the short leg of many standard anomalies. They find that anomaly shorts with high (low) forecasted bias tend to be overpriced (underpriced). I add to this literature by setting up a framework that links expected returns associated with price target announcements to specific information-processing mistakes made by the market. Unlike So (2013), who considers any deviation of analyst earnings forecasts from expected earnings conditional on observable information as bias, I allow for the possibility that similar deviations in analyst-expected returns also contain useful information. My analyst-expected return decomposition and finding of contemporaneous underreaction to information and overreaction to bias is new to the literature, and provides new evidence linking expectational errors to mispricing and corrections.

1.3 Analytical Framework

In this section, I develop the analytical framework I use to derive my main empirical tests. First, I decompose analyst-expected returns into components related to expected returns conditional on the market's information set, analyst bias, and noisy information. Next, I set up an expectations updating framework that describes how the market incorporates analyst-expected returns into its own expectations. The framework allows for two potential mistakes the market might make in the process. Finally, I set up an asset pricing framework that relates each of these mistakes to expected returns and derive testable implications.

1.3.1 Analyst-Expected Return Decomposition and Expectations Updating

Let $\mathcal{F}_t^M$ and $\mathcal{F}_t^A$ represent the information sets available at the end of month t to the market and analysts, respectively. As a convention, I refer to the last date in month t as "date t" throughout my analysis. I assume $\mathcal{F}_t^M \setminus \mathcal{F}_t^A \neq \emptyset$ (i.e. the analyst's information set, excluding information in the market's information set, is non-empty), and that $\mathcal{F}_t^M \setminus \mathcal{F}_t^A$

contains useful pricing information. Sources of such information could be analysts' superior industry knowledge, better information-processing capabilities, and so on. As a convention, I also assume price targets issued in month t are not in $\mathcal{F}_t^M$. Before observing the analyst price target, the market forms expectations over the price of stock j at the end of month $t+1$ conditional on $\mathcal{F}_t^M$, which I denote as $\mathbb{E}\left[P_{t+1}^j|\mathcal{F}_t^M\right]$. Analysts generate and publish a price target during month t for the price of stock j at the end of month $t+1$ using their information set $\mathcal{F}_t^A$.[6] I denote this price target as $\tilde{\mathbb{E}}\left[P_{t+1}^j|\mathcal{F}_t^A\right]$. When emphasizing the conditioning information is unimportant, I use the $\tilde{P}_{t,t+1}^j$ to denote the price target for brevity. I include a tilde above the expectation operator to represent the idea that analyst price targets are potentially biased measures of expected prices conditional on $\mathcal{F}_t^A$. This bias could be caused by analyst incentives issues or inefficient information processing.[7] Consider a decomposition of the analyst price target as follows:

$$\begin{aligned}\tilde{\mathbb{E}}\left[P_{t+1}^j|\mathcal{F}_t^A\right] \equiv\ & \mathbb{E}\left[P_{t+1}^j|\mathcal{F}_t^M\right] \\ & + \left(\mathbb{E}\left[P_{t+1}^j|\mathcal{F}_t^A \cup \mathcal{F}_t^M\right] - \mathbb{E}\left[P_{t+1}^j|\mathcal{F}_t^M\right]\right) \\ & + \left(\tilde{\mathbb{E}}\left[P_{t+1}^j|\mathcal{F}_t^A\right] - \mathbb{E}\left[P_{t+1}^j|\mathcal{F}_t^A \cup \mathcal{F}_t^M\right]\right). \end{aligned} \tag{1.1}$$

I define the two components of interest:

$$I_{t,t+1}^j \equiv \mathbb{E}\left[P_{t+1}^j|\mathcal{F}_t^A \cup \mathcal{F}_t^M\right] - \mathbb{E}\left[P_{t+1}^j|\mathcal{F}_t^M\right] \tag{1.2}$$

$$B_{t,t+1}^j \equiv \tilde{\mathbb{E}}\left[P_{t+1}^j|\mathcal{F}_t^A\right] - \mathbb{E}\left[P_{t+1}^j|\mathcal{F}_t^A \cup \mathcal{F}_t^M\right]. \tag{1.3}$$

6. Technically, analysts publish 12-month price targets. I describe how I transform these into implied 1-month price targets for my empirical analysis below.

7. My goal is not to explain the sources of such bias, but rather to study the market's reaction to it. Others have explored sources of analyst bias. For instance, Malmendier and Shanthikumar (2007) and Michaely and Womack (1999) find that analysts affiliated with a stock's underwriter tend to issue overly-optimistic recommendations. Ljungqvist et al. (2007) finds that analysts issue less biased recommendations and earnings forecasts for stocks with high institutional visibility as measured by institutional ownership.

$I^j_{t,t+1}$ is the price-relevant information in $\mathcal{F}^A_t \cup \mathcal{F}^M_t$ that is incremental to the information about future prices in $\mathcal{F}^M_t$. $B^j_{t,t+1}$ is the price target bias conditional on $\mathcal{F}^A_t \cup \mathcal{F}^M_t$, and contains no useful pricing information. Sources of such bias could be related to analyst incentives issues as noted earlier and noise in their price targets. Given these definitions, I can write the price target decomposition more compactly as

$$\tilde{P}^j_{t,t+1} = \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right] + B^j_{t,t+1} + I^j_{t,t+1}. \tag{1.4}$$

This notation shows that the analyst price target can be decomposed into three components: (1) the expected price conditional on $\mathcal{F}^M_t$, (2) the bias component, and (3) the information component.

$B^j_{t,t+1}$ can be further decomposed as follows:

$$\begin{aligned} B^j_{t,t+1} &= \mathbb{E}\left[\tilde{\mathbb{E}}\left[P^j_{t+1}|\mathcal{F}^A_t\right] - \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^A_t \cup \mathcal{F}^M_t\right]|\mathcal{F}^M_t\right] + B^{j,\perp}_{t,t+1} \\ &= \mathbb{E}\left[\tilde{P}^j_{t,t+1}|\mathcal{F}^M_t\right] - \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right] + B^{j,\perp}_{t,t+1}. \end{aligned} \tag{1.5}$$

Where $B^{j,\perp}_{t,t+1}$ represents the component of price target bias that is orthogonal to $\mathcal{F}^M_t$, $\mathbb{E}\left[\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^A_t \cup \mathcal{F}^M_t\right]|\mathcal{F}^M_t\right] \equiv \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]$ by the law of iterated expectations, and I have replaced $\tilde{\mathbb{E}}\left[P^j_{t+1}|\mathcal{F}^A_t\right]$ with $\tilde{P}^j_{t,t+1}$ to make it clear that this term represents a projection of the price target onto $\mathcal{F}^M_t$. $B^{j,\perp}_{t,t+1}$ is orthogonal to $\mathcal{F}^M_t$ so that $\mathbb{E}\left[B^{j,\perp}_{t,t+1}|\mathcal{F}^M_t\right] = 0$, but it adds noise to the conditionally debiased analyst price target: $\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right] = \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right] + I^j_{t,t+1} + B^{j,\perp}_{t,t+1}$. Given this noisy signal of expected future price, I describe how the market updates expectations about future prices given a prior informed by $\mathcal{F}^M_t$ and after observing the analyst price target, $\tilde{P}^j_{t,t+1}$, in Assumption 1.

Assumption 1 (Expectations updating): *After an analyst price target, $\tilde{P}^j_{t,t+1}$, is announced during month t, expectations of future stock prices in month $t+n$ are optimally* *updated according to*

$$\mathbb{E}\left[P^j_{t+n}|\mathcal{F}^M_t,\,\tilde{P}^j_{t,t+1}\right] \;=\; (1-\theta)\,\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right] + \theta\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\right], \quad (1.6)$$

but the market may incorrectly update expectations according to

$$\begin{aligned}\hat{\mathbb{E}}\left[P^j_{t+n}|\mathcal{F}^M_t,\,\tilde{P}^j_{t,t+1}\right] \;=&\; (1-\delta_n)\,\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right] + \delta_n\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\right] \\ &+\gamma_n\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right], \quad (1.7)\end{aligned}$$

where P^j_{t+n} is the price of stock j at the end of month $t+n$ and $n \geq 1$.

Updating according to equation (1.6) can be motivated by a Bayesian expectations framework where θ is the optimal Bayesian weight determined by the precisions of $\mathbb{E}\left[P^j_{t+n}|\mathcal{F}^M_t\right]$ and $B^{j,\perp}_{t,t+1}$. It also embodies the idea that $\tilde{P}^j_{t,t+1}$ may contain information about all future prices (i.e., not only about P^j_{t+1}). Updating according to equation (1.7) represents two mistakes market participants might make when incorporating analyst price targets into their expectations about future prices. First, market participants may use non-optimal weights $\delta_n \neq \theta$. Second, the market may fail to properly debias analyst price targets before updating expectations, which is represented by the last term in equation (1.7), $\gamma_n\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]$. I use $\hat{\mathbb{E}}$ to designate the distorted measure when market participants make such information-processing mistakes, and to distinguish if from the analyst bias-induced distorted measure, $\tilde{\mathbb{E}}$. It is implicit in this assumption that θ, δ_n, and γ_n are not functions of time t or firm j. I consider the case in which these parameters are functions of a firm's information environment at the end of my analysis. Additionally, I separate my sample into an early and late period in robustness checks, and find that the results from each subset are not qualitatively different from those in my main full-sample results.

Updating according to equation (1.7) encompasses updating according to equation (1.6) as a special case when $\delta_n = \theta$ and $\gamma_n = 0$. It also encompasses special cases where the market updates using non-optimal weights but debiases price targets correctly ($\delta_n \neq \theta$ and $\gamma_n = 0$), where the market updates using optimal weights but fails to debias price targets correctly ($\delta_n = \theta$ and $\gamma_n \neq 0$), and where the market both updates using non-optimal weights and fails to debias price targets correctly ($\delta_n \neq \theta$ and $\gamma_n \neq 0$). If $\gamma_n = \delta_n$, the market does not correct for any of the bias in analyst price targets, taking them at face value when updating expectations.

Equations (1.6) and (1.7) require a projection of price target bias onto $\mathcal{F}_t^M$ in order to extract the information component from analyst-expected returns. The accuracy of this projection ultimately depends on how well the information available to the econometrician matches the market's information set, and the model used for the projection. These issues can be avoided if there exists a price target that contains bias but no information. Assume a noisy price target signal, $\overline{P}^j_{t,t+1}$, exists such that

$$\overline{P}^j_{t,t+1} = \mathbb{E}\left[P^j_{t+1}|\mathcal{F}_t^M\right] + B^j_{t,t+1} + \overline{\varepsilon}^j_{t,t+1}, \tag{1.8}$$

where $\overline{\varepsilon}^j_{t,t+1}$ is random noise in $\overline{P}^j_{t,t+1}$ unrelated to $\mathbb{E}\left[P^j_{t+1}|\mathcal{F}_t^M\right]$ or $B^j_{t,t+1}$. Given such a signal, we can now compute an alternative noisy information measure according to

$$\overline{I}^j_{t,t+1} \equiv \tilde{P}^j_{t,t+1} - \overline{P}^j_{t,t+1}, \tag{1.9}$$

where I use $\overline{I}^j_{t,t+1}$ to distinguish this measure of the information component from that defined in equation (1.4), $I^j_{t,t+1}$. Given an analyst price target that contains bias but is devoid of private information, this construction allows me to extract the information component from $\tilde{P}^j_{t,t+1}$ without having to estimate $\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}_t^M\right]$ or $\left[P^j_{t+1}|\mathcal{F}_t^M\right]$. It also avoids issues related to discrepancies between the market's and econometrician's information sets as well as specification errors in models used to project bias onto those information sets. Results based on this construction of the information component will be useful as a robustness checks for some of my empirical tests, and I describe its empirical implementation in the Empirical Results section.

I can also express the price target decomposition in terms of analyst-expected returns where I normalize each component in equation (1.4) by the price at the month preceding the announcement month, P^j_{t-1}. This price is also the price at the beginning of announcement month t. I use this price as opposed to the end-of-announcement-month price so that I measure analyst-expected returns relative to prices that are not yet influenced by the market's reaction to announced price targets. The analogous analyst-expected return decomposition is then

$$\tilde{R}^j_{t,t+1} \equiv \mathbb{E}\left[R^j_{t+1}|\mathcal{F}^M_t\right] + b^j_{t,t+1} + i^j_{t,t+1}, \tag{1.10}$$

where R^j_{t+1} are realized returns in month $t+1$. I define $b^j_{t,t+1}$ to be the normalized conditional bias, which can be written as

$$b^j_{t,t+1} \equiv \mathbb{E}\left[\tilde{R}^j_{t,t+1}|\mathcal{F}^M_t\right] - \mathbb{E}\left[R^j_{t+1}|\mathcal{F}^M_t\right]. \tag{1.11}$$

Note that $b^j_{t,t+1}$ only contains the portion of $B^j_{t,t+1}$ from equation (1.5) that is conditional on the market's information set. The normalized information component, $i^j_{t,t+1}$, can then be computed as a residual from equation (1.10) and includes the orthogonal (normalized) bias component:

$$\begin{aligned} i^j_{t,t+1} &\equiv \tilde{R}^j_{t,t+1} - \mathbb{E}\left[R^j_{t+1}|\mathcal{F}^M_t\right] - b^j_{t,t+1} \\ &= \tilde{R}^j_{t,t+1} - \mathbb{E}\left[\tilde{R}^j_{t,t+1}|\mathcal{F}^M_t\right]. \end{aligned} \tag{1.12}$$

As in the case of the price target decomposition, this orthogonal bias component cannot be estimated by the econometrician or the market. This is, in theory, what makes my measure of information noisy. The price-normalized version of the alternative information measure, $\overline{I}^{j}_{t,t+1}$, is given by

$$\bar{i}^{j}_{t,t+1} \equiv \tilde{R}^{j}_{t,t+1} - \overline{R}^{j}_{t,t+1}, \tag{1.13}$$

where $\overline{R}^{j}_{t,t+1}$ is the analyst-expected return computed using $\overline{P}^{j}_{t,t+1}$ from equation (1.8). Note that, given the definitions in equations (1.10), (1.11), and (1.12), the updating equations (1.6) and (1.7) for conditional expected prices have analogs that can be expressed as updating equations for conditional expected returns.

1.3.2 Asset Pricing Framework and Empirical Tests

Next, I set up an asset pricing framework to link expected returns to the two updating mistakes described in equation (1.7). The framework yields six sets of empirical tests that I use to document evidence of under- and overreaction to the information and bias components in analyst-expected returns. I consider an economy where an asset's price today is simply the expected price at the end of the period.[8]

Assumption 2 (Pricing equation): *The price at the end of the current month, P^{j}_{t}, is set according to expectations about the price at the end of the next month, P^{j}_{t+1}, according to*

$$P^{j}_{t} = \hat{\mathbb{E}}\left[P^{j}_{t+1} | \mathcal{F}_t\right], \tag{1.14}$$

where $\mathcal{F}_t$ is the relevant information set at date t, and $\hat{\mathbb{E}}$ represents a potentially distorted measure as in equation (1.7).

8. This pricing condition is similar to that used by Bordalo et al. (2017) to explore implications of a particular kind of belief distortion ("diagnostic expectations") on asset prices. So (2013) uses a similar pricing condition with next-period earnings as the payoff rather than next-period price in order to investigate market participant expectations mistakes related to analyst earnings forecasts.

Assumptions 1 and 2 ignore the discounting so that I can focus on pricing effects from expectational errors and for simplicity. I incorporate effects related to discounting and expected returns from sources other than analyst price target effects into the framework as an extension in my robustness checks (see Online Appendix OA.1), but this modification does not change the conclusions from my main results.

I make one additional simplifying assumption to aid in the analysis.

Assumption 3 (Announcement month information): *The expected value of* P^j_{t+1} *conditional on the market's information set at time* t *is the same as that conditional on the market's information set at time* $t-1$ *(i.e.,* $\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right] = \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_{t-1}\right]$*).*

I use this assumption to prove Proposition 1 (below).[9] These assumptions lead to the following proposition.

Proposition 1 (Cumulative expected returns including announcement month): *Given Assumptions 1-3, when expectations are updated according to equation (1.7) and the market correctly incorporates information in analyst price targets over the following* N *months according to equation (1.6), the expected cumulative return on stock* j *from announcement month* t *to month* $t+n$ *(including month* t*) with* $0 \leq n \leq N$ *is*

$$\mathbb{E}\left[R^j_{t,t+n}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right] = \delta_n i^j_{t,t+1} + \gamma_n b^j_{t,t+1}, \tag{1.15}$$

9. Technical details on my use of Assumption 3 are provided in Appendix 2.4.1., which I use to eliminate a term related to $\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right] - \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_{t-1}\right]$ in equation (1.15) from Proposition 1. An alternative to this assumption under which my empirical tests based on Proposition 1 (Empirical Tests 1-4 below) would remain valid is the following: *Both* $i^j_{t,t+1}$ *and* $b_{t,t+1}$ *are orthogonal to the quantity* $\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right] - \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_{t-1}\right]$. This ensures that the coefficients I estimate are consistent estimates of δ_n and γ_n, even when the term related to $\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right] - \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_{t-1}\right]$ is omitted from the related regression. Another alternative but stronger assumption is the following: *The market receives no new information other than the price target during the announcement month.*

where $R^j_{t,t+n}$ are returns from the beginning of month t to the end of month $t+n$, $b^j_{t,t+1}$ is the bias component from equation (1.11), $i^j_{t,t+1}$ is the information component from equation (1.12), and δ_n and γ_n represent updating weights applied to expectations over prices in month n as in equation (1.7). Furthermore, if the market correctly incorporates the information in analyst price targets by month N, then $\delta_N = \theta$ and $\gamma_N = 0$.
Proof: See Appendix 2.4.1.

This proposition's implications are intuitive when $n = 0$. In this case, price changes during the announcement month are reactions to either or both of the information and bias components. If the information and bias components are not correctly incorporated into prices by the end of the announcement month, this proposition implies that future prices (i.e., when $n > 0$) will drift in a manner that corrects any initial mistakes.

Next, I derive a proposition that relates expected cumulative returns in the months following the announcement month to the two updating mistakes described in equation (1.7). This proposition only relies on Assumptions 1 and 2.

Proposition 2 (Cumulative expected returns excluding announcement month): *Given Assumptions 1-2, when expectations are updated during announcement month t according to equation (1.7) and the market correctly incorporates information in analyst price targets over the following N months according to equation (1.6), the expected difference between cumulative returns from the announcement month t to month $t+n$ (including month t) and the announcement month returns on stock j with $1 \leq n \leq N$ is*

$$\mathbb{E}\left[R^j_{t,t+n} - R^j_{t,t} | \mathcal{F}^M_t, \tilde{P}^j_{t,t+1}\right] = (\delta_n - \delta_0)\, i^j_{t,t+1} + (\gamma_n - \gamma_0)\, b^j_{t,t+1}, \tag{1.16}$$

where $R^j_{t,t+n}$ are returns from the beginning of month t to the end of month $t+n$ ($R^j_{t,t}$ are announcement-month returns), $b^j_{t,t+1}$ is the bias component from equation (1.11), $i^j_{t,t+1}$ is

the information component from equation (1.12), and δ_n *and* γ_n *represent updating weights applied to expectations over prices in month* n *as in equation (1.7). Furthermore, if the market correctly incorporates the information in analyst price targets by month* N*, then* $\delta_N - \delta_0 = \theta - \delta_0$ *and* $\gamma_N - \gamma_0 = -\gamma_0$*.*
Proof: See Appendix 2.4.2.

If the market initially underreacts (overreacts) to the information in the price target then $\theta > \delta_0$ ($\theta < \delta_0$), resulting in a positive (negative) correlation between $R^j_{t,t+n} - R^j_{t,t}$ and $i^j_{t,t+1}$ as the market fully incorporates the information into prices. Similarly, if the market does not correctly debias analyst-expected returns (i.e., if $\gamma_0 \neq 0$), then a reversal will occur following the initial reaction. For the remainder of the paper, I use the terms "debiased signal" as in equation (1.3.1) and "information component" interchangeably due to the expected return expressions in Propositions 1 and 2; however, any associated price reactions are, strictly speaking, reactions to the debiased signal.

Propositions 1 and 2 serve as an organizing framework for my empirical work that analyzes how the market incorporates analyst-expected returns into prices, and lead to the following six empirical tests.

Empirical Test 1 (Reaction to bias): *The market correctly debiases analyst-expected returns when forming expectations over future prices if* $\gamma_0 = 0$ *in equation (1.15).*

Empirical Test 2 (Bias reaction reversal): *The market corrects potential mispricing related to the initial reaction to* $b^j_{t,t+1}$ *by month* N *if* $\gamma_N = 0$ *in equation (1.15).*

Empirical Test 3 (Reaction to information): *The market does not initially react to* $i^j_{t,t+1}$ *when forming expectations over future prices if* $\delta_0 = 0$ *in equation (1.15).*

Empirical Test 4 (Information reaction reversal): *If $i^j_{t,t+1}$ contains no useful pricing information and the market corrects mispricing related to the initial reaction to $i^j_{t,t+1}$ by month N, then $\delta_N = 0$ in equation (1.15). If $i^j_{t,t+1}$ does contain useful pricing information and the market corrects mispricing related to the initial reaction to $i^j_{t,t+1}$ by month N, then $\delta_N = \theta$ in equation (1.15).*

Empirical Test 5 (Bias over/underreaction): *If the market applies the optimal weight to the bias in analyst-expected returns in its initial reaction to $b^j_{t,t+1}$, then $\gamma_n - \gamma_0 = 0$ for $n \geq 1$ in equation (1.16). If $\gamma_n - \gamma_0 > 0$, the market underreacted to bias and it is positively correlated with future returns. If $\gamma_n - \gamma_0 < 0$, the market overreacted to bias and it is negatively correlated with future returns.*

Empirical Test 6 (Information over/underreaction): *If the market applies the optimal weight to the information in analyst-expected returns in its initial reaction to $i^j_{t,t+1}$, then $\delta_n - \delta_0 = 0$ for $n \geq 1$ in equation (1.16). If $\delta_n - \delta_0 > 0$, the market underreacted to information and it is positively correlated with future returns. If $\delta_n - \delta_0 < 0$, the market overreacted to information and it is negatively correlated with future returns.*

Empirical Test 1 provides the null hypothesis that stock returns do not respond to the bias component in analyst-expected returns during the announcement month above and beyond that attributed to a correct debiasing of analyst-expected returns. A rejection of the null that $\gamma_0 = 0$ implies the market reacts to the bias component in analyst-expected returns during the announcement month. Empirical Test 2 provides the null hypothesis that the market eventually corrects its mistaken reaction to the bias component in analyst-expected returns. A rejection of the null that $\gamma_n = 0$ in any month $t + n$ after the announcement month t implies the price impact from the market's reaction to $b^j_{t,t+1}$ is still statistically significant n months after the announcement month.

Empirical Test 3 provides the null hypothesis that stock prices do not respond to the information component during the announcement month. A rejection of the null that $\delta_0 = 0$ implies the market reacts to the informative signal during the announcement month. Empirical Test 4 provides the null hypothesis that the initial reaction to the information component is not permanent. A rejection of the null that $\delta_n = 0$ in any month $t+n$ after the announcement month t implies the price impact from the market's reaction to $i^j_{t,t+1}$ is still statistically significant n months after the announcement month.

Empirical Test 5 provides the null hypothesis that the market optimally weights the bias component when updating expectations over future prices. A rejection of the null that $\gamma_n - \gamma_0 = 0$ implies the market uses non-optimal weights to update expectations over future prices, and the bias component predicts future returns. If the market underweights (overweights) this bias, the bias component is positively (negatively) correlated with future returns.

Empirical Test 6 provides the null hypothesis that the market optimally weights the information component when updating expectations over future prices. A rejection of the null that $\delta_n - \delta_0 = 0$ implies the market uses non-optimal weights to update expectations, and the information component predicts future returns. If the market underweights (overweights) this information, the information component is positively (negatively) correlated with future returns. Note that underweighting (overweighting) is synonymous with underreaction (overreaction).

I run two sets of these empirical tests to obtain my main results. The first set of tests uses $i^j_{t,t+1}$ as in equation (1.12) as a proxy for the information component, and the second set uses $\bar{i}^j_{t,t+1}$ as in equation (1.13). Implementing both sets of tests allows me to confirm that my results related to the information component are not a consequence of the models I use to estimate $b^j_{t,t+1}$ and $i^j_{t,t+1}$.

1.4 Data

My analysis requires analyst price targets, a set of conditioning information that is observable to the market, and realized returns. I obtain analyst price targets at the stock-month-analyst level from the IBES Unadjusted Detail file, which I use to construct my main price target measure, $\tilde{P}^j_{t,t+1}$. I also use the IBES Unadjusted Summary file to obtain IBES summary median price targets, which I use as proxies for $\overline{P}^j_{t,t+1}$ in equation (1.8) and ultimately to compute a proxy for $\bar{i}^j_{t,t+1}$ according in equation (1.13). For the set of conditioning information, I rely on firm-level characteristics investigated by Lewellen (2015), who employed three empirical models with 3, 7, and 15 characteristics. I construct these characteristics using firm-level accounting data from Compustat, and firm-level price and returns data from the Center for Research in Security Prices (CRSP). I describe the data and various filtering choices in more detail below.

1.4.1 Price Targets and Analyst-Expected Returns

Sell-side analyst reports represent a rich set of information that the market observes and incorporates into expectations about future cash flows and expected returns, and ultimately into prices. The most salient features of analyst reports are stock-specific buy/sell/hold recommendations, earnings forecasts, long-term earnings growth forecasts, and price targets. Price targets represent the price an analyst expects a stock to achieve within a given time horizon, with 12 months being the most common horizon.[10]

The IBES Unadjusted Detail database contains stock-date-analyst-level price target records beginning in March, 1999 and ending in December, 2017. I denote 12-month price targets issued in month t for stock j issued by analyst k as $\tilde{P}^{j,k}_{t,t+12}$. I use the median operator to aggregate price targets across analysts for a given stock-month, and compute

10. The official IBES definition is: "[The] Price target is the projected price level forecasted by the analyst within a specific time horizon. Note that while detail-level data can be collected for various time horizons, Thomson Reuters summary-level mean data is only calculated for targets with 12-month time horizons."

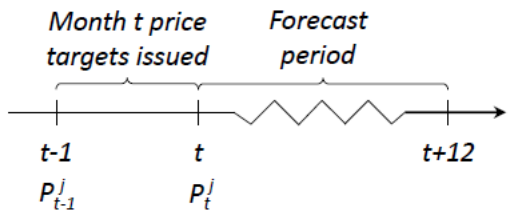
the associated implied 12-month return as

$$\tilde{R}^j_{t,t+12} = \frac{Median\left[\left\{\tilde{P}^{j,k}_{t,t+12}\right\}\right] - P^j_{t-1}}{P^j_{t-1}} + DY^j_t \tag{1.17}$$

When an analyst issues more than one price target in a given month for a given firm, I retain only the most recent target when computing the median price target across analysts. To capture the idea that this measure represents an analyst-expected return, I normalize by the price at the end of the previous month, P^j_{t-1}, because the price target can be issued anytime during month t. In this way, my analyst-expected-return measure is normalized by a price that does not include the market's reaction to the information in the analyst price target, which would be the case if I were to normalize by P^j_t. DY^j_t represents the analyst-expected dividend yield at the end of month t. This forecast is not explicitly provided by analysts, so I estimate it by assuming analysts expect dividend payments to be the same over the next year as in the past year (including month t). I include the dividend yield since the standard cross-sectional models that I use in my empirical tests have typically been applied to estimate expected returns cum dividends. I also include the dividend yield to be consistent with trading strategies I implement later, which follow the standard practice of using cum dividend returns. In robustness checks, I show that my main results are almost unchanged when I exclude the dividend yield from my measure of analyst-expected returns and use ex dividend realized returns in my main tests.

The timing is illustrated in Figure 1.1. Price targets are issued during month t (i.e., between dates $t-1$ and t, where I use "date t" to denote the actual date at the end of month t) for a 12-month horizon. I assume that these price targets become active at the end of month t irrespective of the particular date on which they are issued during month t so that all price targets issued in month t apply to the same time period. The analyst-expected return is the median of the most recent price targets issued by any analyst during month t for stock j normalized by the stock's price at the end of the previous month. In this sense,

Figure 1.1: Price Target and Analyst-Expected Return Timing



Notes: Price targets used to compute $\tilde{R}^j_{t,t+12}$ are issued during month t (i.e., between dates $t-1$ and t) and have a 12-month forecast horizon, which includes returns from t to $t+12$. P^j_{t-1} is the price of stock j at the end of month $t-1$ (i.e., before any of the month t price targets are issued). P^j_t is the price of stock j at the end of month t after all month t price targets have been issued.

it is the consensus expected return among analysts. I treat all analysts as homogeneous in my main results for simplicity and because past studies have failed to find economically meaningful differences in price target accuracy between analysts (Bradshaw et al. (2013), Bonini et al. (2010)). In Online Appendix OA.8 I investigate modifications to the price target aggregation to address concerns that analyst heterogeneity may drive my results; however, my main results are qualitatively unchanged by these modifications.

All of my analyses are at the monthly frequency so that they are comparable to standard characteristics-based expected returns models (e.g. from Lewellen (2015)), so I transform the 12-month analyst-expected return as follows:

$$\tilde{R}^j_{t,t+1} = \left[\tilde{R}^j_{t,t+12} + 1\right]^{1/12} - 1, \tag{1.18}$$

where I use $\tilde{R}^j_{t,t+1}$ to represent the implied one-month analyst-expected return. I denote the corresponding implied one-month price target as $\tilde{P}^j_{t,t+1}$, which corresponds to the price target I use when developing my framework in the previous section.

I winsorize analyst-expected returns at the 1% and 99% levels to mitigate the effects of outliers. My final analyst-expected return data set contains 331,420 stock-month records, and covers 7,190 unique firms. Analyst-expected returns have sizable coverage across CRSP records that meet my standard filters (described below), with an overall capitalization-weighted coverage of about 84%. The firm coverage is lower at about 46%, which is indicative of the fact that analysts tend to cover larger firms. The median monthly analyst-expected return across all stock-months is 1.38%, whereas the median realized return is only 0.91%. The median bias across all firm-months, computed by taking the median of the difference between firm-month analyst-expected returns and subsequent realized returns, is 0.39 percentage points. Analyst-expected return summary statistics by year can be found in Appendix 2.1, Table A-1.

1.4.2 Firm Characteristics and Realized Returns

I use CRSP and Compustat to construct firm characteristics and realized returns. I require stocks to be common shares (share codes 10 or 11) on the AMEX, NYSE, or NASDAQ (exchange codes 1, 2, or 3), and exclude stocks with prices less than $5 to avoid issues related to bid-ask bounce.

I consider 15 firm characteristics throughout this study based on those used in Lewellen (2015) including: $LogSize_t$, $LogB/M_t$, $Return_{t-11,t-1}$, $LogIssues_{t-35,t}$, $Accruals_t$, ROA_t, $LogAG_t$, $DY_{t-11,t}$, $LogReturn_{t-35,t-12}$, $LogIssues_{t-11,t}$, $Beta_t$, $StdDev_{t-11,t}$, $Turnover_{t-11,t}$, $Debt/Price_t$, and $Sales/Price_t$. A detailed description of each characteristic can be found in Appendix 2.2. When constructing the characteristics for each stock-month, I assume accounting data are available to the market four months after each firm's fiscal year end. I winsorize each characteristic at the 1% and 99% levels and remove any records that do not contain values for size, book-to-market, or momentum because these variables are used in all analyses. Summary statistics for each of these characteristics can be found in Appendix 2.2, Table A-2. I include two sets of summary statistics in this table. The first summarizes characteristics across all records in my 1999-2017 sample that meet my CRSP filters, and the second summarizes characteristics only for records with corresponding analyst-expected returns. Consistent with past research on analyst forecasts, firms with associated analyst-expected returns tend to be larger growth firms (i.e., large market capitalization, low book-to-market stocks). They also tend to be firms that have experienced relatively high recent growth as measured by $LogAG_t$ and have high turnover, $Turnover_{t-11,t}$. These observations are consistent with the tendency for analysts to cover stocks that generate relatively large trading revenue (Kothari et al. (2016), Jegadeesh et al. (2004)).

1.5 Empirical Results

I begin my empirical analysis by constructing proxies for the three analyst-expected return components described by the decomposition in equation (1.10). I construct each proxy for month t using only data up to and including that from month-t (i.e., given access to characteristics data and price targets, investors would have been able to construct month-t proxies at the end of month t). With these measures, I am able to run Empirical Tests 1-6 from Section 1.3.

Throughout the empirical analysis, I use three characteristics models with either 3, 7, or 15 characteristics as conditioning information. The characteristics and models follow those used in Lewellen (2015). Model 1 includes $LogSize_t$, $LogB/M_t$, and $Return_{t-11,t-1}$. Model 2 adds $LogIssues_{t-35,t}$, $Accruals_t$, ROA_t, and $LogAG_t$. Model 3 adds $DY_{t-11,t}$, $LogReturn_{t-35,t-12}$, $LogIssues_{t-11,t}$, $Beta_t$, $StdDev_{t-11,t}$, $Turnover_{t-11,t}$, $Debt/Price_t$, and $Sales/Price_t$. Each of these characteristics is described in more detail in Appendix 2.2.

1.5.1 Constructing Information and Bias Proxies

I construct the proxy for $b^j_{t,t+1}$ as the difference between analyst-expected returns projected onto characteristics and realized returns projected onto characteristics using historical data available at the end of month t. Given the estimate for $b^j_{t,t+1}$, I construct the proxy for $i^j_{t,t+1}$ as the residual from equation (1.10). These proxies are consistent with the definitions of bias and information described by equations (1.11) and (1.12), respectively, assuming that the set of characteristics captures the market's information set (more specifically, $\mathbb{E}\left[R^j_{t+1}|X^j_t\right] =$

$\mathbb{E}\left[R^j_{t+1}|\mathcal{F}^M_t\right]$ and $\mathbb{E}\left[\tilde{R}^j_{t,t+1}|X^j_t\right] = \mathbb{E}\left[\tilde{R}^j_{t,t+1}|\mathcal{F}^M_t\right]$).

I begin by estimating expected returns conditional on characteristics as in Lewellen (2015). Namely, I run 10-year rolling Fama and MacBeth (1973) regressions of realized monthly returns on characteristics using data beginning in 1989 so that I have access to the expected return measure when analyst price targets become available in 1999 as follows:

$$R^j_t = \mathbf{a_t} + \mathbf{c'_t} X^j_{t-1} + \mathbf{u^j_t}, \tag{1.19}$$

where I estimate a new set of coefficients $\mathbf{\hat{a}_t}$ and $\mathbf{\hat{c}_t}$ each month. I am careful to only use characteristics up to month $t-1$ and returns up to month t to estimate the rolling coefficients for month t. I then use these coefficients with month t characteristics, X^j_t, including the estimated intercept to compute the expected return measure for month $t+1$. In this way, I avoid look-ahead bias in my expected return estimates.

Next, I project analyst-expected returns onto characteristics using 10-year rolling Fama and MacBeth (1973) regressions as follows:

$$\tilde{R}^j_{t,t+1} = a_t + c'_t X^j_t + u^j_t, \tag{1.20}$$

where I again estimate a new set of coefficients $\hat{a}_t$ and $\hat{c}_t$ each month. I distinguish the estimated coefficients in this regression from those in equation (1.19) using a non-bold font. Due to the relatively short time series of price target data, I estimate this projection initially using just the first month's data. I progressively add more data for later estimates until the estimation includes 10 years of data, after which I begin the rolling estimation. The precision of characteristic coefficients in the analyst-expected return regressions is higher than those in the realized return regressions because analyst-expected returns are much less volatile than realized returns.

Table A-3 in Appendix 2.3 provides full-sample results for the regressions implied by equations (1.19) and (1.20) for each of the three characteristics models. 11 of the 15 analyst-implied risk premia consistently have the opposite sign as those implied by realized returns across all three models. I test the null hypothesis that the two sets of risk premia are jointly equivalent using two separate statistical tests in Online Appendix OA.2, and strongly reject the null across all three models and both tests. These results imply that analyst-expected returns are biased in the cross section relative to forecasts based on standard characteristics.

Given rolling estimates of equations (1.19) and (1.20), I estimate analyst-expected return bias as follows. First, let $\overline{\hat{\mathbf{a}}_{\mathbf{t}}}$ and $\overline{\hat{a}_t}$ represent rolling averages of the estimated time dummy coefficients, $\hat{\mathbf{a}}_{\mathbf{t}}$ and $\hat{a}_t$, up to date t. My proxy for $b^j_{t,t+1}$ is then

$$\hat{b}^j_{t,t+1} \quad = \quad \left(\overline{\hat{a}_t} - \overline{\hat{\mathbf{a}}_{\mathbf{t}}}\right) + \left(\hat{c}'_t - \hat{\mathbf{c}}'_{\mathbf{t}}\right) X^j_t, \tag{1.21}$$

where I use the hat here to indicate this value is estimated, although I drop it henceforth for simplicity. Given this estimate for $b^j_{t,t+1}$ and the conditional expected return from equation (1.19), I compute my information proxy as the residual from equation (1.10), which is consistent with the definition of $i^j_{t,t+1}$ in equation (1.12). Note that this information proxy is equivalent to the raw analyst-expected return minus the projection of analyst-expected returns onto characteristics according to equation (1.20) (i.e., $i^j_{t,t+1} = \tilde{R}^j_{t,t+1} - \mathbb{E}\left[\tilde{R}^j_{t,t+1}|X^j_t\right]$). This interpretation makes it clear that the information component is the component in analyst-expected returns that is orthogonal to the market's information set.

Next, I construct a proxy for $\bar{i}^j_{t,t+1}$ according to equation (1.13). I use 12-month median price targets from the IBES Unadjusted Summary file, $\overline{P}^j_{t,t+12}$, as a proxy for the price target described in equation (1.8). These price targets are an aggregation of all price targets IBES considers "active" during the announcement month, but may contain price targets that were issued up to 12 months ago. The IBES Unadjusted Summary price targets likely contain bias but relatively little new information. I use these price targets to compute a stale analyst-expected return, $\overline{R}^j_{t,t+12}$. I compute a proxy for $\bar{i}^j_{t,t+1}$ by subtracting $\overline{R}^j_{t,t+12}$ from $\tilde{R}^j_{t,t+12}$, where $\tilde{R}^j_{t,t+12}$ is as in equation (1.17) and $\overline{R}^j_{t,t+12}$ is calculated in the same way but uses the IBES Unadjusted Summary price target instead of my summary price target measure. This construction is consistent with the definition in equation (1.13); however, I do not use monthly versions of $\overline{R}^j_{t,t+12}$ and $\tilde{R}^j_{t,t+12}$ for this alternative information measure because I do not need to compare them with expected returns from a monthly characteristics model as I must to construct $i^j_{t,t+1}$.

Summary statistics for all empirical proxies related to the analyst-expected return decomposition are provided in Table 1.1. The table also reports regressions in which each measure is used to forecast one-month returns estimated using the Fama and MacBeth (1973) procedure. Panel A summarizes results for variables that are independent of the characteristics models (i.e., $\tilde{R}^j_{t,t+1}$ and $\bar{i}^j_{t,t+1}$). Panels B-D summarize variables computed according to Models 1-3, respectively.

The forecasting coefficient on analyst-expected returns is 0.14 and statistically significant (see Panel A), which implies that my measure of analyst-expected returns has forecasting power over returns in the cross section. Forecasting coefficients based on expected returns conditional on characteristics, $\mathbb{E}\left[R^j_{t+1}|X^j_t\right]$, in Panels B-D are similar to but slightly lower than results found in Lewellen (2015) over the 1974-2013 period. These estimated expected returns have forecasting coefficients that are lower than 1, which is most likely the result of noise in the expected return estimates associated with attenuation bias.

The projection of analyst-expected returns onto characteristics, $\mathbb{E}\left[\tilde{R}^j_{t,t+1}|X^j_t\right]$, is not a statistically significant forecaster of returns at the one-month horizon. According to Model 1, the coefficient is positive (but statistically insignificant), and according to Models 2 and 3, the coefficient is negative (but still statistically insignificant). Despite evidence in Table A-3 that many of the analyst-implied risk premia have signs opposite to those we would expect, analyst-expected returns projected onto characteristics are not negatively correlated with returns in a statistically significant way in my sample.

The information component in analyst-expected returns, $i^j_{t,t+1}$, has statistically significant forecasting power across all three characteristics models. It has a larger forecasting coefficient than the raw analyst-expected returns, which is consistent with the idea that analyst-expected returns contain relatively more noise than the information measure due to forecastable bias. According to Model 2 (Panel C), a 1% increase in $i^j_{t,t+1}$ leads to a 0.18 percentage point increase in expected monthly returns. Similarly, the model-free estimate of the information in analyst-expected returns, $\bar{i}^j_{t,t+1}$ (Panel A), has statistically significant forecasting power over returns. A 1% increase in $\bar{i}^j_{t,t+1}$ leads to a 0.013 percentage point increase in expected monthly returns. Note that $\bar{i}^j_{t,t+1}$ is based on 12-month price target changes. To make this forecasting coefficient (approximately) comparable to those associated with $i^j_{t,t+1}$, I multiply the coefficient by 12, yielding a value of 0.15. This value is quite similar to forecasting coefficients on $i^j_{t,t+1}$ across Models 1-3. Alternatively, a one-standard-deviation increase in $i^j_{t,t+1}$ ($\bar{i}^j_{t,t+1}$) leads to a 0.25% (0.30%) increase in expected monthly returns based on the reported cross-sectional standard deviations of these variables.

The bias component in analyst-expected returns yields statistically insignificant negative forecasting coefficients across all three models. To validate this measure as an ex-ante measure of analyst-expected return bias, I provide evidence that it forecasts realized bias in Online Appendix OA.13, where I also compare my analyst-expected return decomposition to the earnings forecast decomposition used in So (2013).

1.5.2 Debiased Analyst-Expected Returns Subsume the Forecasting Power of Raw Analyst-Expected Returns

In this section, I test whether debiased analyst-expected returns subsume raw analyst-expected return forecasting power. We would expect this to be the case if my bias measure really captures at least some component of analyst-expected return bias. To begin, I provide evidence that raw analyst-expected returns forecast next month's returns, but do not forecast returns beyond that. Adding characteristics controls improves the forecasting power. When all 15 characteristics are included, analyst-expected returns forecast cumulative returns up

Table 1.1: Analyst-Expected Return Decomposition Summary

	Avg	p10	Med	p90	Std	Slope	t-stat	R^2	N
Panel A: Model-independent variables									
	Summary statistics					**Forecasting**			
	Avg	**p10**	**Med**	**p90**	**Std**	**Slope**	**t-stat**	R^2	N
$\tilde{R}^j_{t,t+1}$	1.58	0.06	1.46	3.26	1.48	0.14	[2.42]	0.01	1,466
$\bar{i}^j_{t,t+1}$	-1.52	-23.98	0.50	19.17	23.68	0.01	[3.52]	0.01	1,208
Panel B: Model 1-related variables									
	Summary statistics					**Forecasting**			
	Avg	**p10**	**Med**	**p90**	**Std**	**Slope**	**t-stat**	R^2	N
$\mathbb{E}\left[R^j_{t+1}\vert X^j_t\right]$	0.96	0.45	0.94	1.48	0.45	0.42	[1.37]	0.01	3,174
$\mathbb{E}\left[\tilde{R}^j_{t,t+1}\vert X^j_t\right]$	1.86	1.33	1.87	2.37	0.40	0.13	[0.61]	0.01	1,466
$i^j_{t,t+1}$	-0.28	-1.85	-0.32	1.32	1.44	0.13	[2.63]	0.01	1,466
$b^j_{t,t+1}$	0.96	0.08	0.97	1.85	0.72	-0.08	[-0.53]	0.01	1,466
Panel C: Model 2-related variables									
	Summary statistics					**Forecasting**			
	Avg	**p10**	**Med**	**p90**	**Std**	**Slope**	**t-stat**	R^2	N
$\mathbb{E}\left[R^j_{t+1}\vert X^j_t\right]$	1.02	0.52	1.03	1.51	0.47	0.50	[2.50]	0.01	2,840
$\mathbb{E}\left[\tilde{R}^j_{t,t+1}\vert X^j_t\right]$	1.79	1.29	1.75	2.30	0.45	-0.10	[-0.54]	0.01	1,323
$i^j_{t,t+1}$	-0.27	-1.78	-0.28	1.24	1.36	0.18	[4.09]	0.01	1,323
$b^j_{t,t+1}$	0.85	0.04	0.75	1.74	0.79	-0.18	[-1.60]	0.02	1,323
Panel D: Model 3-related variables									
	Summary statistics					**Forecasting**			
	Avg	**p10**	**Med**	**p90**	**Std**	**Slope**	**t-stat**	R^2	N
$\mathbb{E}\left[R^j_{t+1}\vert X^j_t\right]$	1.01	0.38	1.04	1.61	0.56	0.51	[2.75]	0.01	2,824
$\mathbb{E}\left[\tilde{R}^j_{t,t+1}\vert X^j_t\right]$	1.79	1.23	1.68	2.49	0.54	-0.08	[-0.35]	0.03	1,317
$i^j_{t,t+1}$	-0.27	-1.78	-0.24	1.17	1.34	0.18	[4.50]	0.01	1,317
$b^j_{t,t+1}$	0.88	-0.02	0.71	2.00	0.92	-0.20	[-1.62]	0.02	1,317

Notes: Panel A summarizes variables that are independent of the characteristics model. Panels B, C, and D summarize variables computed using conditioning information from Models 1, 2, and 3, respectively. All summary statistics are reported in percent. $\tilde{R}^j_{t,t+1}$ are analyst-expected returns computed according to equation (1.18). $\mathbb{E}\left[R^j_{t+1}|X^j_t\right]$ are expected returns conditional on characteristics estimated using rolling Fama and MacBeth (1973) regressions with 10 years of monthly historical data. $\mathbb{E}\left[\tilde{R}^j_{t,t+1}|X^j_t\right]$ are analyst-expected returns projected onto characteristics using rolling Fama and MacBeth (1973) regressions with up to 10 years of rolling monthly historical data. $i^j_{t,t+1}$ is the information component in analyst-expected returns estimated as the residual from equation (1.10) given estimates of $\mathbb{E}\left[R^j_{t+1}|X^j_t\right]$ and $b^j_{t,t+1}$. $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). These values are based on annual analyst-expected returns (i.e., not transformed to monthly values), and, hence, are larger in magnitude than values associated with $i^j_{t,t+1}$, which are associated with a monthly frequency. $b^j_{t,t+1}$ is the bias component estimated according to equation (1.21). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records do not contain any marginal information. Summary statistics in the leftmost columns are based on the time series averages of cross-sectional values computed each month. I also report results from regressing the next month returns, R^j_{t+1}, on each variable using Fama and MacBeth (1973) regressions in the rightmost columns. Regressions are run at the 1-month frequency. All data is from 1999-2017 and corresponds to records for which analyst-expected returns are available along with the required characteristics for each model, although $\mathbb{E}\left[R^j_{t+1}|X^j_t\right]$ is estimated using all CRSP records. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags. t-statistics are reported in brackets.

to six months into the future. For brevity, I present these results in Appendix 2.3, Table A-4.

In order to test whether debiased analyst-expected returns subsume the forecasting power of raw analyst-expected returns, I run a horse race by including both variables in a series of cross-sectional regressions. Table 1.2 shows the related cross-sectional regression results, and includes combinations of analyst-expected returns and analyst-expected returns minus either bias or information as regressors. I include the latter variable as a placebo test because we would expect analyst-expected returns minus information, which are comprised of the conditional expected return component and the bias component, to have lower forecasting power than raw analyst-expected returns, which also contain the information component. Panels A, B, and C use information and bias components computed using either Model 1, 2, or 3 controls, respectively. Column I shows results from regressing next month's returns on raw analyst-expected returns (this result is repeated from Table 1.1 for comparison). Column II provides results from regressing next month's return on debiased analyst-expected returns, $\tilde{R}^j_{t,t+1} - b^j_{t,t+1}$ (note that by equation (1.10) we have $\tilde{R}^j_{t,t+1} - b^j_{t,t+1} \equiv E\left[R^j_{t+1}|X^j_t\right] + i^j_{t,t+1}$). Results in this column are consistent with the interpretation of $b^j_{t,t+1}$ as the bias component in analyst-expected returns. Removing this component from analyst-expected returns results in forecasting coefficients that are larger and more statistically significant that those obtained from the raw analyst-expected returns. Column III provides results from regressing next month's return on analyst-expected returns less the information component $(\tilde{R}^j_{t,t+1} - i^j_{t,t+1})$. Results in this column are consistent with the interpretation of $i^j_{t,t+1}$ as information. Removing this component from analyst-expected returns results in statistically insignificant forecasting coefficients across all three models.

To test whether debiased analyst-expected return forecasting power subsumes that of raw analyst-expected returns, I regress next month's return on both variables. Results from these regressions are presented in Column IV. Model 1-based regressions (Panel A) yield statistically insignificant coefficients on both $\tilde{R}^j_{t,t+1}$ and $\tilde{R}^j_{t,t+1} - b^j_{t,t+1}$; however, these estimates are likely subject to collinearity issues because the associated variance inflation factor is large (about 7). The coefficients on $\tilde{R}^j_{t,t+1} - b^j_{t,t+1}$ calculated using Models 2 and 3 (Panels B and C, respectively) are both positive and statistically significant at the 5% level, whereas corresponding coefficients on $\tilde{R}^j_{t,t+1}$ are statistically insignificant. Additionally, the variance inflation factors from these regressions (about 4 and 3, respectively) indicate that collinearity issues are less of a concern. These results provide evidence that the debiased analyst-expected returns subsume the forecasting power of raw analyst-expected returns in the cross-section.

Finally, Column V reports results from bivariate regressions of next month's return on $\tilde{R}^j_{t,t+1}$ and $\tilde{R}^j_{t,t+1} - i^j_{t,t+1}$. The resulting coefficients on $\tilde{R}^j_{t,t+1}$ are positive and statistically significant at the 5% level (or better) across all three models, and those on $\tilde{R}^j_{t,t+1} - i^j_{t,t+1}$ are statistically insignificant across all three models. Consistent with the interpretation of $i^j_{t,t+1}$ as an informative component in $\tilde{R}^j_{t,t+1}$, $\tilde{R}^j_{t,t+1} - i^j_{t,t+1}$ does not forecast returns in a univariate sense (Column III) nor does it subsume the forecasting power of $\tilde{R}^j_{t,t+1}$.

1.5.3 Main Empirical Tests

I run Empirical Tests 1-4 and 5-6 from Section 1.3 using the following regressions, respectively:

$$R^j_{t,t+n} = a_t + \delta_n i^j_{t,t+1} + \gamma_n b^j_{t,t+1} + \varepsilon^j_{t,t+n}, \tag{1.22}$$

$$R^j_{t,t+n} - R_{t,t} = a_t + (\delta_n - \delta_0)\, i^j_{t,t+1} + (\gamma_n - \gamma_0)\, b^j_{t,t+1} + \varepsilon^j_{t,t+n}, \tag{1.23}$$

where a_t are time dummies in each regression, $i^j_{t,t+1}$ is the information component in analyst-expected returns calculated according to either equation (1.12) or equation (1.13), $b^j_{t,t+1}$ is the bias component in analyst-expected returns estimated according to equation (1.21), and $R^j_{t,t+n}$ are realized returns on stock j from month t to month $t+n$ (i.e including

Table 1.2: Debiased Analyst-Expected Return Forecasting Regressions

Panel A: Model 1-related variables					
Model	**I**	**II**	**III**	**IV**	**V**
$\tilde{R}^j_{t,t+1}$	0.14			0.03	0.13
	[2.42]			[0.18]	[2.47]
$\tilde{R}^j_{t,t+1} - b^j_{t,t+1}$		0.16		0.12	
		[2.89]		[0.86]	
$\tilde{R}^j_{t,t+1} - i^j_{t,t+1}$			0.13		0.04
			[0.61]		[0.21]
VIF				7.52	1.06
R^2	0.01	0.01	0.01	0.02	0.02
N	1,466	1,466	1,466	1,466	1,466
Panel B: Model 2-related variables					
Model	**I**	**II**	**III**	**IV**	**V**
$\tilde{R}^j_{t,t+1}$	0.14			-0.07	0.17
	[2.42]			[-0.60]	[3.65]
$\tilde{R}^j_{t,t+1} - b^j_{t,t+1}$		0.21		0.26	
		[4.23]		[2.29]	
$\tilde{R}^j_{t,t+1} - i^j_{t,t+1}$			-0.10		-0.23
			[-0.54]		[-1.33]
VIF				4.13	1.09
R^2	0.01	0.01	0.01	0.02	0.02
N	1,466	1,323	1,323	1,323	1,323
Panel C: Model 3-related variables					
Model	**I**	**II**	**III**	**IV**	**V**
$\tilde{R}^j_{t,t+1}$	0.14			-0.08	0.17
	[2.42]			[-0.65]	[4.32]
$\tilde{R}^j_{t,t+1} - b^j_{t,t+1}$		0.22		0.28	
		[4.18]		[2.28]	
$\tilde{R}^j_{t,t+1} - i^j_{t,t+1}$			-0.08		-0.20
			[-0.35]		[-0.94]
VIF				3.08	1.13
R^2	0.01	0.01	0.03	0.03	0.03
N	1,466	1,317	1,317	1,317	1,317

Notes: Panels A, B, and C summarize cross-sectional (Fama and MacBeth (1973)) forecasting regressions using information and bias components computed using Models 1, 2, and 3, respectively. Results are run at the 1-month frequency using R^j_{t+1} (i.e. next month's return) as the dependent variable. $\tilde{R}^j_{t,t+1}$ are analyst-expected returns computed according to equation (1.18). $b^j_{t,t+1}$ is the bias component estimated according to equation (1.21). $i^j_{t,t+1}$ is the information component in analyst-expected returns estimated as the residual from equation (1.10) given estimates of $\mathbb{E}\left[R^j_{t+1}|X^j_t\right]$ and $b^j_{t,t+1}$. $\mathbb{E}\left[R^j_{t+1}|X^j_t\right]$ are expected returns conditional on characteristics estimated using rolling Fama and MacBeth (1973) regressions with 10 years of monthly historical data. All data is from 1999-2017 and corresponds to records for which analyst-expected returns are available along with the required characteristics for each model, although $\mathbb{E}\left[R^j_{t+1}|X^j_t\right]$ is estimated using all CRSP records. VIF are variance inflation factors computed as the time series averages of variance inflation factors computed for each monthly cross section. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags. t-statistics are reported in brackets.

announcement-month returns) with $n \geq 0$. I cross-sectionally z-transform all regressors so that each coefficient can be interpreted as the change in expected returns associated with a one-standard-deviation increase in the corresponding regressor.

Implications from Propositions 1 and 2 are expressed as time series phenomena at the firm level; however, they also hold in the cross section. Running cross-sectional tests as in equations (1.22) and (1.23) allows me to remove noise introduced by any aggregate phenomena that would be present in a time series version of the tests, thereby increasing the power of my tests. I run Empirical Tests 1-6 using estimates of $i^j_{t,t+1}$ and $b^j_{t,t+1}$ based on Model 2 (seven characteristics); however, results are similar when using characteristics from either Models 1 or 3 and are provided in Appendix 2.5.

Tables 1.3 and 1.4 show regression results based on Empirical Tests 1-4 and 5-6, respectively. The separation is based on the fact that Empirical Tests 1-4 require cumulative returns including announcement-month return as the dependent variable, whereas Empirical Tests 5-6 require these returns less announcement-month returns as the dependent variable. Panels A and B in each of these tables use either $i^j_{t,t+1}$ or $\bar{i}^j_{t,t+1}$ as the information variable, respectively. I also provide plots of the regression coefficients from Empirical Tests 1-4 in Figure 1.2 for illustration.

Empirical Test 1 tests the null that prices do not react to the bias component during the announcement month ($\gamma_0 = 0$). Results for this test are provided in Table 1.3, where the dependent variable is the announcement-month return, $R^j_{t,t}$. Panels A and B show results using $i^j_{t,t+1}$ and $\bar{i}^j_{t,t+1}$, respectively. Results in this table represent three different tests of the null hypothesis (one from the regression that includes $b^j_{t,t+1}$ as the only dependent variable, one that includes both $b^j_{t,t+1}$ and $i^j_{t,t+1}$, and one that includes both $b^j_{t,t+1}$ and $\bar{i}^j_{t,t+1}$). I strongly reject the null in all three cases. Announcement-month returns are positively correlated with the bias component. For every one-cross-sectional-standard-deviation increase in the bias measure, announcement-month returns increase by 0.89% according to the estimation that includes $i^j_{t,t+1}$ and $b^j_{t,t+1}$. Coefficient magnitudes are similar in the univariate and bivariate regressions, which is expected because $i^j_{t,t+1}$ and $b^j_{t,t+1}$ are constructed to be orthogonal.[11]

Empirical Test 2 tests the null that there is no permanent reaction to the bias component ($\gamma_n = 0$). γ_n is the forecasting coefficient on the bias component in analyst-expected returns in equation (1.22) for cumulative returns up to n months after the announcement month including announcement-month returns, $R^j_{t,t+n}$. Panels A and B in Table 1.3 show results using $i^j_{t,t+1}$ and $\bar{i}^j_{t,t+1}$, respectively. Results in the table test the null for $n \in \{1, 2, 3, 6, 12\}$. In regressions including $b^j_{t,t+1}$ only, I reject the null for $n = 1$, but fail to reject the null at standard significance levels for $n \geq 2$. In regressions including both $i^j_{t,t+1}$ and $b^j_{t,t+1}$, I reject the null for both $n = 1, 2$, but fail to reject the null for $n \geq 3$. In regressions including both $\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$, I reject the null for $n = 1, 2, 3$, but fail to reject the null for $n \geq 6$. In all three cases, γ_n decreases monotonically as n increases (except when $n = 12$ in regressions that include both the bias and information components). The first two empirical tests provide evidence that announcement-month returns are positively correlated with the bias component, but reverse this initial reaction over a period of three to six months.

Empirical Test 3 tests the null that prices do not react to the information component during the announcement month ($\delta_0 = 0$). Results for this test are provided in Table 1.3, where the dependent variable is the announcement-month return, $R^j_{t,t}$. Panels A and B show results using $i^j_{t,t+1}$ and $\bar{i}^j_{t,t+1}$, respectively. Results in this table represent four different tests of the null hypothesis (one from the regression that includes $i^j_{t,t+1}$ as the only dependent variable, one that includes $\bar{i}^j_{t,t+1}$ as the only dependent variable, one that includes both $i^j_{t,t+1}$ and $b^j_{t,t+1}$, and one that includes both $\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$). I strongly reject the null in all four cases. As with the reaction to bias, the positive δ_0 coefficients indicate that announcement-month returns are positively correlated with the information component. For every one-cross-sectional-standard-deviation increase in the information component, announcement-month

11. $i^j_{t,t+1}$ and $b^j_{t,t+1}$ are only approximately orthogonal in the empirical implementation due to the rolling cross-sectional regression estimation of $b^j_{t,t+1}$ in equation (1.21). They would be exactly orthogonal if I were to estimate information and bias using individual cross sections of data as opposed to rolling estimates.

returns increase by 5.06% according to the estimation that includes $i^j_{t,t+1}$ and $b^j_{t,t+1}$.

Empirical Test 4 tests the null that there is no permanent reaction to the information component ($\delta_n = 0$). Results for this test are provided in Table 1.3, where the dependent variables are cumulative returns including announcement-month returns, $R^j_{t,t+n}$. Panels A and B show results using $i^j_{t,t+1}$ and $\bar{i}^j_{t,t+1}$, respectively. Results in the table test the null for $n \in \{1, 2, 3, 6, 12\}$. I strongly reject the null across all regressions and all horizons. Additionally, regression coefficients on the information component are monotonically increasing in n across all regressions. For every one-cross-sectional-standard-deviation increase in the information measure, cumulative returns 12 months after the announcement month (including announcement-month returns) increase by 5.94% according to the estimation that uses both $i^j_{t,t+1}$ and $b^j_{t,t+1}$. Results from Empirical Tests 3 and 4 provide evidence that price changes are positively correlated with the information component and that these changes are permanent (up to at least 12 months).

Results from Empirical Tests 5 and 6 based on the regressions specified in equation (1.23) are provided in Table 1.4. Panels A and B show results using $i^j_{t,t+1}$ and $\bar{i}^j_{t,t+1}$, respectively. Empirical Test 5 tests for overreaction to the bias component during announcement months. Specifically, I test the null that $\gamma_n - \gamma_0 = 0$ based on Proposition 2. Estimated coefficients are negative across all horizons, but they are not statistically significant at standard levels (except for $n = 2$ in the estimation that uses $\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$, which is statistically significant at the 10% level). This result implies overreaction to bias is weak in the full sample of stocks; however, I provide evidence that overreaction to bias is statistically significant within the smallest and largest quintiles of stocks based on portfolio sorting exercises below (Section 1.5.5).

Finally, Empirical Test 6 tests for underreaction to the information component during announcement months. Specifically, I test the null that $\delta_n - \delta_0 = 0$ based on Proposition 2. In regressions that include only $i^j_{t,t+1}$, I reject the null at the 1% level for $n = 1$, the 5% level for $n = 2$, and the 10% level for $n = 3$ and $n = 6$, but fail to reject the null for $n = 12$. In regressions that include both $i^j_{t,t+1}$ and $b^j_{t,t+1}$, I reject the null at the 1% level for $n = 1$, the 5% level for $n = 2$, and the 10% level for $n = 3$, but fail to reject the null for $n \geq 6$. In regressions including $\bar{i}^j_{t,t+1}$ only and both $\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$I reject the null at standard significance levels for $n = 1, 2, 3, 6$, but fail to reject the null when $n = 12$. In all cases, coefficients on the information component are monotonically increasing in n (except for $\bar{i}^j_{t,t+1}$-only regressions when $n = 12$). These results provide evidence that the market underreacts to the information component during announcement months. For every one-cross-sectional-standard-deviation increase in the information measure (multiplied by the price ratio), the expected value of cumulative returns over the announcement month and following month (less announcement-month returns) increase by 0.31% according to the estimation that includes $i^j_{t,t+1}$ and $b^j_{t,t+1}$.

1.5.4 Announcement-Window Returns Forecast Future Returns

One may be concerned that the return predictability I observe in the previous section is related to the empirical models I use to estimate conditional expected returns and bias. In this section, I provide evidence that the information in analyst-expected returns forecasts future returns in a model-free manner. Specifically, I show that returns around price target announcements forecast returns in future months. I assemble announcement-window returns that cumulate returns from two days prior until two days after each price target announcement.[12] When two or more price targets are released in a given month, I cumulate returns over each announcement, add these together, and then divide by the total number of price targets issued in the month and use this as a proxy for announcement-window returns. If a price target is issued within two business days of the end of the month, I exclude it from my announcement-window returns because it would lead to mechanical correlation between

12. Results are similar when I use cumulative returns from one day before to one day after announcements; however, I use the two-day convention because it matches that used in related previous studies (Asquith et al. (2005) and Brav and Lehavy (2003)).

Table 1.3: Results Based on Empirical Tests 1-4 (Cumulative Return Tests, Model 2)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$i^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$i^j_{t,t+1}$	5.07	5.41	5.51	5.63	5.91	6.06							5.06	5.38	5.47	5.58	5.81	5.94
	[23.20]	[20.29]	[16.04]	[13.03]	[10.61]	[8.50]							[24.45]	[20.95]	[16.44]	[13.23]	[10.68]	[8.57]
$b^j_{t,t+1}$							0.78	0.64	0.45	0.38	0.10	0.14	0.89	0.77	0.60	0.54	0.28	0.34
							[4.96]	[2.73]	[1.37]	[0.91]	[0.16]	[0.18]	[6.14]	[3.54]	[1.94]	[1.35]	[0.44]	[0.47]
R^2	0.17	0.11	0.08	0.06	0.04	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.18	0.12	0.09	0.07	0.05	0.03
N	1,324	1,323	1,322	1,322	1,322	1,321	1,324	1,323	1,322	1,322	1,322	1,321	1,324	1,323	1,322	1,322	1,322	1,321

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$\bar{i}^j_{t,t+1}$	3.30	3.66	3.97	4.21	4.69	4.69							3.62	3.91	4.15	4.35	4.69	4.70
	[19.61]	[14.74]	[12.37]	[11.38]	[9.28]	[9.85]							[22.46]	[16.73]	[14.59]	[12.99]	[10.95]	[12.54]
$b^j_{t,t+1}$							0.78	0.64	0.45	0.38	0.10	0.14	1.21	1.07	0.86	0.82	0.48	0.48
							[4.96]	[2.73]	[1.37]	[0.91]	[0.16]	[0.18]	[8.35]	[4.82]	[2.71]	[1.97]	[0.67]	[0.66]
R^2	0.09	0.06	0.05	0.04	0.03	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.12	0.08	0.07	0.06	0.04	0.03
N	1,209	1,208	1,208	1,207	1,207	1,205	1,324	1,323	1,322	1,322	1,322	1,321	1,105	1,104	1,104	1,103	1,103	1,102

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) to implement Empirical Tests 1-4. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{t,t+n}$ are cumulative returns for stock j from month t to month $t+n$ ($n \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table 1.4: Results Based on Empirical Tests 5-6 (Post-Announcement-Month Return Tests, Model 2)

Panel A: Tests using $i^j_{t,t+1}$

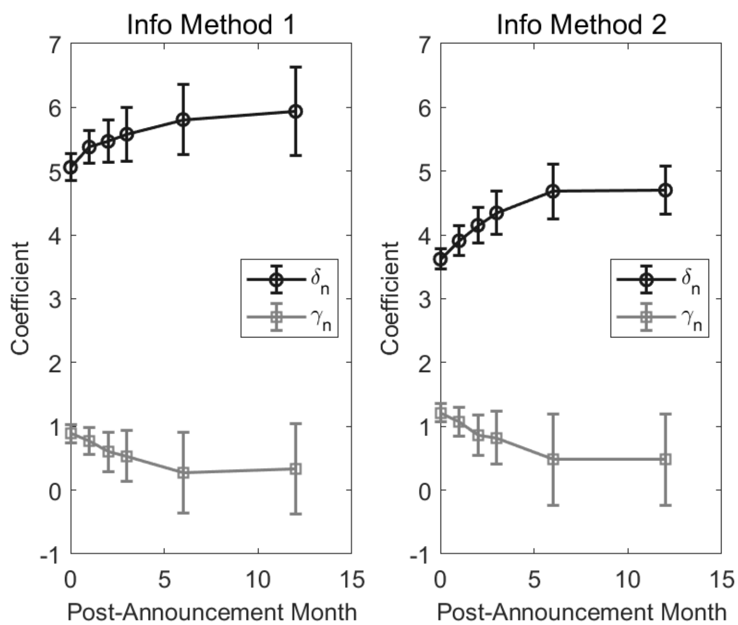
	$i^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$i^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$i^j_{t,t+1}$	0.34	0.44	0.55	0.83	0.97						0.31	0.40	0.50	0.74	0.85
	[3.56]	[2.38]	[1.88]	[1.82]	[1.50]						[3.35]	[2.21]	[1.76]	[1.63]	[1.36]
$b^j_{t,t+1}$						-0.13	-0.33	-0.40	-0.68	-0.64	-0.12	-0.29	-0.37	-0.64	-0.60
						[-1.29]	[-1.72]	[-1.45]	[-1.27]	[-0.96]	[-1.15]	[-1.58]	[-1.33]	[-1.21]	[-0.94]
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02
N	1,323	1,322	1,322	1,322	1,321	1,323	1,322	1,322	1,322	1,321	1,323	1,322	1,322	1,322	1,321

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$\bar{i}^j_{t,t+1}$	0.36	0.65	0.90	1.37	1.36						0.28	0.52	0.71	1.05	1.05
	[3.03]	[3.27]	[3.58]	[3.40]	[2.92]						[2.81]	[3.24]	[3.35]	[3.34]	[3.25]
$b^j_{t,t+1}$						-0.13	-0.33	-0.40	-0.68	-0.64	-0.14	-0.35	-0.40	-0.73	-0.74
						[-1.29]	[-1.72]	[-1.45]	[-1.27]	[-0.96]	[-1.32]	[-1.80]	[-1.35]	[-1.20]	[-1.17]
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.03	0.03	0.02	0.02	0.02
N	1,208	1,208	1,207	1,207	1,205	1,323	1,322	1,322	1,322	1,321	1,104	1,104	1,103	1,103	1,102

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.23) to implement Empirical Tests 5 and 6. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

Figure 1.2: Forecasting Coefficients for Realized Cumulative Returns on Information and Bias



Notes: This figure plots regression coefficients when realized cumulative returns (including those from the price target announcement month) are regressed on cross-sectionally z-transformed measures of the information and bias components according to equation (1.22) using the Fama and MacBeth (1973) procedure. Plotted values are based on regression estimates reported in Table 1.3. Error bars are based on standard errors computed from results in that table. The left panel uses my main method for computing the information component based on equation (1.12) (i.e., $i^j_{t,t+1}$), and the right panel uses an alternative method based on equation (1.13) (i.e., $\bar{i}^j_{t,t+1}$). The bias component is computed according to equation (1.21) for results in both panels using Model 2 (seven characteristics) as conditioning information. Data is from 1999-2017.

announcement-window returns and realized returns in the following month.

Returns around announcement days are presumably primarily a reaction to analyst announcements and largely unexpected. Based on the results in the previous section, we expect announcement-window returns to primarily reflect the information component in analyst-expected returns because the reaction to this component is much stronger than the the bias component during announcement months. Previous results also indicate that the underreaction to information is stronger than the overreaction to bias, so we expect announcement-window returns to be positively correlated with returns in future months.

I test this hypothesis in Table 1.5. Panel A reports results from regressions of cumulative realized returns (including announcement-month returns) on announcement-window returns. I include results without controls (left panel) as well as with seven firm characteristics from Model 2 as control variables (right panel). In both cases, announcement-window returns are positively correlated with announcement-month returns with coefficients that are greater than 1. This result implies that there is additional price reaction to announcements outside the announcement window but within the announcement month. The reaction to price target announcements appears to be permanent. Announcement window returns forecast cumulative future returns out to at least 12 months. Additionally, the forecasting coefficients are monotonically increasing in the forecasting horizon. Prices continue drifting in the direction of the initial announcement price reaction for up to 12 months after the announcement month. These results are similar to the patterns observed for regression coefficients on both $i^j_{t,t+1}$ and $\bar{i}^j_{t,t+1}$ in Table 1.3.[13]

Panel B reports regressions of cumulative realized returns (excluding announcement-month returns) on announcement-window returns. I include results without controls (left

13. The announcement-window returns are a function of the market's interpretation of both components in the analyst-expected return, so a more proper comparison might be with the forecasting power of some combination of $i^j_{t,t+1}$ and $b^j_{t,t+1}$. In unreported results, I find that the forecasting variables $i^j_{t,t+1} + b^j_{t,t+1}$ and $\left(\frac{5}{6}\right) i^j_{t,t+1} - \left(\frac{1}{6}\right) b^j_{t,t+1}$ (meant to mimic announcement month coefficients in Table 1.3) as independent forecasting variables produce forecasting coefficient patterns similar to those using announcement-window returns.

panel) as well as with seven firm characteristics from Model 2 as control variables (right panel). I also include regressions of announcement-month returns on announcement-window returns in the first columns of each sub-panel for comparison. In both cases (with and without controls), announcement-window returns forecast future cumulative returns in a statistically significant manner up to 12 months after the announcement month. Additionally, coefficients are nearly monotonically increasing with horizon (except for in month 12). These results indicate the market continues to impound announcement-window information into prices for at least six months after the announcement month, and are similar to patterns observed for regression coefficients on both $i^j_{t,t+1}$ and $\bar{i}^j_{t,t+1}$ in Table 1.4. The cross-sectional standard deviation of announcement-window returns is approximately 7.6%, indicating a one-standard-deviation increase in announcement-window returns forecasts an approximate 0.22% increase in expected returns in the following month according to the forecasting results without controls in Panel B. This magnitude is similar to the impact of the information component on next month's expected returns in Table 1.4.

1.5.5 Trading Strategies

The main goals of this section are to document the economic significance of, and provide alternative tests for underreaction to information and overreaction to bias. I investigate five related trading strategies that sort stocks into decile portfolios based on five different investment signals ($i^j_{t,t+1}$, $\bar{i}^j_{t,t+1}$, $b^j_{t,t+1}$, $\tilde{R}^j_{t,t+1}$, and s^j_t) with monthly rebalancing. The first four signals are as defined previously. The fifth (s^j_t) is meant to exploit the contemporaneous underreaction to information and overreaction to bias and uses a combination of the information and bias components, which I describe below. Average returns to these strategies help document the economic significance of the under- and overreaction. Trading strategy returns based on the information and bias components provide alternative tests for the statistical significance of the under- and overreaction, respectively.

Table 1.5: Realized Returns Regressed on Announcement-Window Returns

Panel A: Cumulative returns including announcement month

	No controls						**Model 2 controls**					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	R^j_{t}	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$R^j_{t,announce}$	1.14	1.18	1.21	1.24	1.30	1.32	1.08	1.12	1.13	1.16	1.21	1.25
	[74.74]	[56.82]	[40.66]	[34.37]	[26.50]	[26.62]	[82.91]	[67.44]	[50.79]	[41.94]	[32.48]	[24.98]
R^2	0.43	0.25	0.18	0.14	0.09	0.05	0.47	0.31	0.23	0.20	0.14	0.11
N	1,376	1,376	1,375	1,374	1,375	1,373	1,243	1,242	1,241	1,240	1,241	1,240

Panel B: Cumulative returns excluding announcement month

	No controls						**Model 2 controls**					
Dep. var.:	$R^j_{t,t}$	$R^j_{t+1,t+1}$	$R^j_{t+1,t+2}$	$R^j_{t+1,t+3}$	$R^j_{t+1,t+6}$	$R^j_{t+1,t+12}$	R^j_{t}	$R^j_{t+1,t+1}$	$R^j_{t+1,t+2}$	$R^j_{t+1,t+3}$	$R^j_{t+1,t+6}$	$R^j_{t+1,t+12}$
$R^j_{t,announce}$	1.14	0.03	0.04	0.06	0.10	0.08	1.08	0.02	0.02	0.04	0.07	0.06
	[74.74]	[3.00]	[2.61]	[2.90]	[3.63]	[2.57]	[82.91]	[3.06]	[2.25]	[2.72]	[3.48]	[1.94]
R^2	0.43	0.01	0.01	0.01	0.00	0.00	0.47	0.07	0.07	0.07	0.07	0.07
N	1,376	1,376	1,375	1,374	1,375	1,373	1,243	1,242	1,241	1,240	1,241	1,240

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) where I use announcement-window returns as a forecasting variable. Panel A uses cumulative returns including announcement-month returns as the dependent variable. Panel B uses cumulative returns excluding announcement-month returns as the dependent variable. I construct announcement-window returns in each month by summing together returns over the five days surrounding each price target announcement in each month, then sum across all price target announcements within a month, then divide by the total number of price targets issued in the month. I call this variable $R^j_{t,announce}$. $R^j_{t,t}$ are announcement-month returns. $R^j_{t,t+n}$ are cumulative returns from month t to $t+n$ (including returns from month t). $R^j_{t+1,t+n}$ are cumulative returns from month $t+1$ to month $t+n$ (including returns from month $t+1$). Regressions are run at the 1-month frequency. Data is from 1999-2017. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$, $R^j_{t,t+1}$, and $R^j_{t+1,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ and $R^j_{t+1,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ and $R^j_{t+1,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ and $R^j_{t+1,t+6}$ regressions, and 24 lags for$R^j_{t,t+12}$ and $R^j_{t+1,t+12}$ regressions. t-statistics are reported in brackets.

I present both average and risk-adjusted returns based on standard factor models.[14] In this way, I document whether the return patterns I observe can be explained by exposure to standard factors that have been previously used to explain expected returns in the cross-section. I consider six different factor models including (1) "FF3" (the Fama and French (1993) 3-factor model), (2) "FF3C" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor), (3) "FF3CL" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor and the Pastor and Stambaugh (2003) traded liquidity factor), (4) "FF5" (the Fama and French (2015) 5-factor model), (5) "FF5C" (the Fama and French (2015) 5-factor model augmented with the Carhart (1997) UMD factor, which was used as a baseline for comparison in Kelly et al. (2018)), and (6) "HXZ" (the Hou et al. (2015) 4-factor model).[15] Results from all strategies can be found in Table 1.6. Panel A shows results for equal-weighted portfolios, and Panel B shows results for value-weighted portfolios. I only report results related to the high- and low-decile portfolios, and corresponding long-short portfolios for brevity, but provide results for all portfolios in Online Appendix OA.3.

The first strategy sorts on $i^j_{t,t+1}$ computed using Model 2 characteristics. Average equal-weighted strategy long-short portfolio returns are economically and statistically significant at 1.12% per month, and have an annualized Sharpe ratio of 1.08. Average annual returns based on this strategy are about 14%. Long-short returns survive risk adjusting using all six models I investigate, with statistically significant alphas ranging from 1.00% to 1.22% per month. Value-weighting yields positive average returns that are economically significant at 0.48%, but are not statistically significant; however, risk-adjusted returns become statistically significant at standard levels across all models and range from 0.56% to 0.81%.

14. Expected returns based on covariances with factors in such models do not necessarily represent risk premia, as pointed out by Kozak et al. (2018). Rather, they may be associated with irrational mispricing. I simply use the term "risk-adjusted returns" here to follow the convention that has developed in the literature.

15. I would like to thank Lu Zhang for kindly providing me with updated factor data.

The second strategy sorts on on $\bar{i}^j_{t,t+1}$. Average equal-weighted long-short portfolio returns are economically and statistically significant at 1.24% per month, and have an annualized Sharpe ratio of 0.71. Average annual returns based on this strategy are about 13%. These long-short returns survive risk adjustment using all six models with alphas ranging from 0.84% to 1.26% per month. Average value-weighted long-short strategy returns are positive and significant at the 10% level; however, risk-adjusted returns become statistically insignificant for most models. These results imply the returns associated with the underreaction to $\bar{i}^j_{t,t+1}$ are strongest among relatively small stocks within the universe of stocks that have associated analyst price targets.

$i^j_{t,t+1}$ and $\bar{i}^j_{t,t+1}$ portfolio sorting results can be thought of as nonparametric counterparts to Empirical Test 6 when $n = 1$ (see Table 1.4). The fact that both equal-weighted long-short information-based strategies yield statistically significant positive returns is consistent with results in Table 1.4 and the interpretation that the market underreacts to the information component in analyst-expected returns. These trading strategy results also imply the return predictability associated with underreaction to information cannot be explained by exposure to these standard risk factors.

The third strategy sorts on $b^j_{t,t+1}$ computed using Model 2 characteristics. Average equal-weighted long-short portfolio returns are economically significant at -0.59% per month, but not statistically significant. This result is consistent with the weak statistical evidence for overreaction based on Empirical Test 5 documented in Table 1.4. In unreported results, a similar equal-weighted long-short trading strategy based on an alternative bias estimator documented in Online Appendix OA.4 yields average returns of -0.60% per month that are statistically significant at the 5% level. Average value-weighted long-short returns are economically significant at -1.04% and statistically significant at the 5% level without adjusting for exposure to risk factors. They are also significant at at least the 10% level after risk adjusting using four of the six factor models I investigate. This result implies that overreaction to bias is relatively stronger among large stocks. Consistent with this result, I will also show that overreaction to bias is statistically significant within the largest and smallest quintiles of stocks in an additional portfolio sorting exercise below.

Next, I consider a strategy that combines the information and bias components to exploit the contemporaneous under- and overreaction that I document in the previous section. I begin by estimating the regression specified in equation (1.22) for next-month returns ($k = 1$ and $n = 1$) in a rolling fashion to estimate coefficients $\hat{\delta}_t$ and $\hat{\gamma}_t$ at each month t without look-ahead bias. To estimate these parameters, I require at least 36 months of data. I progressively add more data for later estimates until the estimation includes 10 years of data, after which I begin a rolling estimation. I also cross-sectionally z-transform the dependent variables as I did for my main results in Table 1.4.

With estimates of $\hat{\delta}_t$and $\hat{\gamma}_t$ using data only up to and including that in month t, I construct a sorting variable as follows:

$$s_t^j = \hat{\delta}_t i_{t,t+1}^j + \hat{\gamma}_t b_{t,t+1}^j. \tag{1.24}$$

I use this variable to sort stocks into decile portfolios, and report average returns and risk-adjusted returns for the corresponding trading strategies in Table 1.6. Average equal-weighted long-short portfolio returns (Panel A) are economically and statistically significant at 0.81% per month, and have an annualized Sharpe ratio of 0.78. The average returns are lower than values based on the information-component-only strategy, which may be due to noise related to the rolling nature of the estimation behind this strategy. Value-weighted long-short average returns (Panel B) are similar to their equal-weighted counterparts, implying this effect is not concentrated among either small or large stocks.

Results for the equal-weighted raw analyst-expected return strategy are also reported in Table 1.6. Average long-short returns from this strategy are 0.92% per month and have a Sharpe ratio of 0.70, which is 35% lower than that from the $i_{t,t+1}^j$ strategy. Long-short returns survive risk adjustment based on all six factor models, implying that analysts are not simply using exposures to known factors to produce their price targets. Value-weighted long-short average returns are positive and statistically significant at the 10% level, and risk-adjusted average returns are typically positive and statistically significant. The analyst-expected return strategy performs relatively well among large stocks compared to the information component strategies. The fact that neither the $i^j_{t,t+1}$nor the $\bar{i}^j_{t,t+1}$ strategy perform as well on a value-weighted basis implies that the characteristics model I use may not capture some component of expected returns for larger stocks relative to smaller stocks that is consistently captured by analyst-expected returns. I investigate the relationship between the information and raw analyst-expected return strategies in more detail below.

Next, I conduct a more in-depth investigation of strategies based on the bias component to help understand whether statistically significant evidence of overreaction to $b^j_{t,t+1}$ exists within certain subsets of stocks. In particular, I perform a 5-by-5 conditional sort, first on size then on $b^j_{t,t+1}$. Average returns and associated t-statistics can be found below in Table 1.7 for both equal-weighted (Panel A) and value-weighted (Panel B) strategies. All average long-short strategy returns in $b^j_{t,t+1}$ (conditional on size) are negative when returns are either equal-weighted or value-weighted. Average long-short returns are statistically significant at standard levels for both equal-weighted and value-weighted strategies among the smallest- and largest-size-decile stocks. Despite the weak evidence for overreaction to bias across all stocks, these results provide statistically significant evidence of overreaction among small and, more interestingly, large stocks. These results are also economically significant and lead to average monthly returns of about 0.7% to 0.9% per month (when going long the low-$b^j_{t,t+1}$ portfolios and short the high-$b^j_{t,t+1}$ portfolios).

As documented above, returns to the long-short raw analyst-expected return strategy are nearly as high as to the information-based strategies and higher than the combined information and bias strategy. I now investigate whether returns to the raw analyst-expected return strategy can explain returns to the information and bias strategies by regressing information and bias-based long-short strategy returns on returns from the raw analyst-expected return long-short strategy. Results can be found below in Table 1.8.

Table 1.6: Long-short trading strategies

Panel A: Equal-weighted strategies

			Raw returns		FF3		FF3C		FF3CL		FF5		FF5C		HXZ	
Sorting Var.		**Avg. Sort Var.**	R^p_{t+1}	$t-stat$	α^{FF3}	$t-stat$	α^{FF3C}	$t-stat$	α^{FF3CL}	$t-stat$	α^{FF5}	$t-stat$	α^{FF5C}	$t-stat$	α^{HXZ}	$t-stat$
$i^j_{t,t+1}$	**Lo**	-2.68	0.56	[1.37]	-0.49	[-3.60]	-0.40	[-3.27]	-0.39	[-3.21]	-0.49	[-3.42]	-0.45	[-3.56]	-0.41	[-2.72]
	Hi	2.24	1.68	[3.40]	0.52	[3.32]	0.63	[4.46]	0.61	[4.32]	0.73	[4.55]	0.77	[5.33]	0.81	[5.39]
	Hi-Lo	4.92	1.12	[4.66]	1.01	[5.04]	1.03	[5.10]	1.00	[4.97]	1.22	[5.92]	1.22	[5.92]	1.22	[5.81]
$\bar{i}^j_{t,t+1}$	**Lo**	-46.57	0.43	[0.74]	-0.69	[-2.46]	-0.42	[-1.97]	-0.43	[-1.99]	-0.39	[-1.38]	-0.30	[-1.34]	-0.22	[-0.83]
	Hi	33.59	1.67	[3.65]	0.57	[3.50]	0.52	[3.23]	0.50	[3.08]	0.67	[4.09]	0.65	[4.07]	0.62	[3.77]
	Hi-Lo	80.15	1.24	[3.09]	1.26	[3.37]	0.94	[3.07]	0.93	[3.00]	1.07	[2.79]	0.95	[3.03]	0.84	[2.30]
$b^j_{t,t+1}$	**Lo**	-0.30	1.24	[3.08]	0.35	[1.68]	0.13	[0.91]	0.13	[0.89]	0.30	[1.40]	0.22	[1.45]	0.10	[0.49]
	Hi	2.48	0.66	[1.24]	-0.44	[-1.83]	-0.22	[-1.15]	-0.23	[-1.23]	-0.08	[-0.31]	0.01	[0.03]	0.02	[0.11]
	Hi-Lo	2.78	-0.59	[-1.43]	-0.79	[-1.99]	-0.35	[-1.34]	-0.36	[-1.38]	-0.38	[-0.92]	-0.21	[-0.78]	-0.07	[-0.20]
s^j_t	**Lo**	-0.68	0.48	[1.01]	-0.61	[-3.72]	-0.51	[-3.65]	-0.50	[-3.61]	-0.33	[-2.20]	-0.31	[-2.35]	-0.31	[-2.14]
	Hi	0.60	1.29	[2.94]	0.28	[1.84]	0.25	[1.65]	0.24	[1.58]	0.21	[1.33]	0.20	[1.30]	0.30	[1.88]
	Hi-Lo	1.29	0.81	[3.11]	0.89	[3.39]	0.76	[3.19]	0.74	[3.16]	0.54	[2.14]	0.51	[2.18]	0.61	[2.40]
$\tilde{R}^j_{t,t+1}$	**Lo**	-0.80	0.53	[1.35]	-0.48	[-4.31]	-0.42	[-4.03]	-0.42	[-3.94]	-0.52	[-4.42]	-0.49	[-4.54]	-0.46	[-3.49]
	Hi	4.55	1.44	[2.60]	0.21	[1.13]	0.35	[2.23]	0.34	[2.15]	0.61	[3.49]	0.66	[4.39]	0.66	[4.14]
	Hi-Lo	5.35	0.91	[3.03]	0.69	[3.26]	0.78	[3.78]	0.76	[3.68]	1.13	[5.60]	1.16	[5.87]	1.12	[5.34]

Panel B: Value-weighted strategies

			Raw returns		FF3		FF3C		FF3CL		FF5		FF5C		HXZ	
Sorting Var.		**Avg. Sort Var.**	R^p_{t+1}	$t-stat$	α^{FF3}	$t-stat$	α^{FF3C}	$t-stat$	α^{FF3CL}	$t-stat$	α^{FF5}	$t-stat$	α^{FF5C}	$t-stat$	α^{HXZ}	$t-stat$
$i^j_{t,t+1}$	**Lo**	-2.64	0.37	[0.98]	-0.49	[-2.74]	-0.43	[-2.45]	-0.41	[-2.32]	-0.40	[-2.14]	-0.38	[-2.06]	-0.40	[-2.15]
	Hi	1.85	0.85	[1.88]	0.07	[0.33]	0.20	[0.94]	0.19	[0.89]	0.33	[1.42]	0.37	[1.70]	0.41	[1.90]
	Hi-Lo	4.48	0.48	[1.50]	0.56	[1.91]	0.63	[2.14]	0.59	[2.02]	0.73	[2.36]	0.75	[2.44]	0.81	[2.68]
$\bar{i}^j_{t,t+1}$	**Lo**	-38.39	0.18	[0.34]	-0.63	[-2.19]	-0.37	[-1.63]	-0.37	[-1.63]	-0.34	[-1.14]	-0.24	[-1.02]	-0.19	[-0.71]
	Hi	28.93	1.02	[2.32]	0.19	[0.81]	0.11	[0.47]	0.10	[0.42]	0.37	[1.54]	0.33	[1.44]	0.26	[1.07]
	Hi-Lo	67.31	0.84	[1.89]	0.82	[1.93]	0.48	[1.34]	0.47	[1.31]	0.70	[1.60]	0.57	[1.56]	0.46	[1.08]
$b^j_{t,t+1}$	**Lo**	-0.23	1.00	[2.94]	0.37	[1.75]	0.16	[1.03]	0.16	[1.00]	0.39	[1.73]	0.30	[1.88]	0.18	[0.85]
	Hi	2.30	-0.04	[-0.08]	-0.81	[-2.89]	-0.60	[-2.48]	-0.59	[-2.42]	-0.31	[-1.11]	-0.23	[-0.97]	-0.36	[-1.39]
	Hi-Lo	2.54	-1.04	[-2.27]	-1.18	[-2.77]	-0.76	[-2.41]	-0.74	[-2.36]	-0.69	[-1.59]	-0.53	[-1.65]	-0.54	[-1.34]
s^j_t	**Lo**	-0.65	0.32	[0.69]	-0.70	[-3.50]	-0.60	[-3.32]	-0.60	[-3.29]	-0.38	[-2.00]	-0.36	[-2.03]	-0.35	[-1.97]
	Hi	0.52	0.90	[2.54]	0.12	[0.71]	0.07	[0.42]	0.06	[0.37]	0.06	[0.33]	0.04	[0.27]	0.05	[0.31]
	Hi-Lo	1.17	0.58	[1.88]	0.82	[2.78]	0.67	[2.52]	0.66	[2.48]	0.44	[1.53]	0.40	[1.53]	0.41	[1.48]
$\tilde{R}^j_{t,t+1}$	**Lo**	-0.69	0.45	[1.28]	-0.34	[-2.15]	-0.33	[-2.07]	-0.30	[-1.87]	-0.32	[-1.91]	-0.31	[-1.88]	-0.34	[-2.00]
	Hi	4.09	1.22	[2.25]	0.27	[0.93]	0.41	[1.54]	0.41	[1.51]	0.82	[2.94]	0.87	[3.28]	0.81	[3.08]
	Hi-Lo	4.78	0.77	[1.93]	0.60	[1.81]	0.74	[2.30]	0.70	[2.17]	1.14	[3.40]	1.18	[3.63]	1.15	[3.49]

Notes: Average monthly returns on portfolios that are sorted on either $i^j_{t,t+1}$, $\bar{i}^j_{t,t+1}$, $b^j_{t,t+1}$, s^j_t, or $\tilde{R}^j_{t,t+1}$ and rebalanced each month. Panel A equally-weights returns and Panel B value-weights returns. $i^j_{t,t+1}$ is estimated as a residual from equation (1.10) when $b^j_{t,t+1}$ is estimated using equation (1.21) and Model 2 (7 characteristics) using 10-year rolling Fama and MacBeth (1973) regressions ($\mathbb{E}\left[R^j_{t+1}|X^j_t\right]$ is estimated using equation (1.19) and Model 2 characteristics). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records do not contain any marginal information. s^j_t is estimated as described in equation (1.24). The first column reports average sorting variable values in each portfolio. Returns are also risk-adjusted using the following empirical factor models: 1. "FF3" (the Fama and French (1993) 3-factor model), 2. "FF3C" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor), 3. "FF3CL" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor and the Pastor and Stambaugh (2003) traded liquidity factor), 4. "FF5" (the Fama and French (2015) 5-factor model), 5. "FF5C" (the Fama and French (2015) 5-factor model augmented with the Carhart (1997) UMD factor, which was used as a baseline for comparison in Kelly et al. (2018)), and 6. "HXZ" (the Hou et al. (2015) 4-factor model). Portfolios are rebalanced at the 1-month frequency. Data is from 1999-2017. t-statistics are reported in brackets.

Table 1.7: Portfolios Double-Sorted on Size then $b^j_{t,t+1}$

Panel A: Equal-weighted strategies

Average returns	**Lo-$b^j_{t,t+1}$**	**2**	**3**	**4**	**Hi-$b^j_{t,t+1}$**	**Hi - Lo**
Small	1.73	1.53	1.36	1.23	0.85	-0.88
2	1.31	1.26	1.17	1.07	0.86	-0.46
3	1.06	1.08	1.09	0.94	0.61	-0.46
4	0.91	0.99	1.04	1.05	0.43	-0.48
Large	0.84	0.62	0.73	0.56	0.02	-0.82
t-statistics	**Lo-$b^j_{t,t+1}$**	**2**	**3**	**4**	**Hi-$b^j_{t,t+1}$**	**Hi - Lo**
Small	4.03	3.83	3.30	2.62	1.61	-2.68
2	3.03	3.31	2.94	2.43	1.51	-1.18
3	2.74	3.11	3.03	2.26	1.23	-1.24
4	2.43	3.30	3.18	2.97	0.94	-1.33
Large	2.50	2.29	2.59	1.79	0.05	-2.19

Panel B: Value-weighted strategies

Average returns	**Lo-$b^j_{t,t+1}$**	**2**	**3**	**4**	**Hi-$b^j_{t,t+1}$**	**Hi - Lo**
Small	1.78	1.56	1.44	1.46	1.08	-0.70
2	1.45	1.38	1.29	1.19	0.92	-0.53
3	1.23	1.18	1.25	1.05	0.70	-0.53
4	1.02	1.11	1.19	1.21	0.54	-0.47
Large	0.87	0.65	0.68	0.50	0.13	-0.73
t-statistics	**Lo-$b^j_{t,t+1}$**	**2**	**3**	**4**	**Hi-$b^j_{t,t+1}$**	**Hi - Lo**
Small	4.01	3.85	3.38	2.96	1.99	-2.04
2	3.37	3.66	3.24	2.71	1.64	-1.35
3	3.19	3.44	3.51	2.53	1.41	-1.41
4	2.72	3.68	3.65	3.40	1.19	-1.32
Large	2.66	2.39	2.46	1.59	0.34	-2.03

Notes: Average monthly returns to conditionally double-sorted portfolios first sorted into size quintile groups, then into $b^j_{t,t+1}$ quintile portfolios within each size group. Portfolios are rebalanced monthly. Panel A equally-weights returns and Panel B value-weights returns. $b^j_{t,t+1}$ is estimated using Model 2 (7 characteristics). There are an average of 53 stocks in each size-$b^j_{t,t+1}$-sorted portfolio. Data is from 1999-2017.

All equal-weighted information and bias-based strategies generate statistically significant average returns after controlling for exposure to the raw analyst-expected return long-short strategy. The alphas, ranging from 0.50% to 1.26%, also remain economically significant. Regressing value-weighted long-short returns to the $i^j_{t,t+1}$ strategy on returns to the value-weighted analyst-expected return long-short strategy yields a small and statistically insignificant alpha, but average returns to the original long-short value-weighted $i^j_{t,t+1}$ strategy were also statistically insignificant. The value-weighted $\bar{i}^j_{t,t+1}$ and s^j_t long-short strategy alphas are economically significant at 0.82% and 0.50%, respectively; however, only the $\bar{i}^j_{t,t+1}$ strategy average returns are statistically significant (at the 10% level). These results imply that the observed expected returns generated by information and bias strategies cannot be fully explained by exposure to returns to the raw analyst-expected return long-short strategy.

1.5.6 Information Environment-Dependent Weighting

Results in the previous sections indicate the market underweights the information component in analyst-expected returns when updating expectations about future prices on average across all stocks. In this section, I investigate whether updating mistakes vary across stocks in plausibly different information environments. My definition of "information environment" is deliberately vague here. It could be taken as a term that encompasses the amount of investor attention, information diffusion speed, the amount of news stories about a particular stock, and so on. I will be more concrete about how I identify stocks in different information environments presently.

Previous studies have documented a link between anomalies and information environment. For instance, Ben-Rephael et al. (2017) find that stocks with lower institutional attention demonstrate stronger post-earnings announcement drift (PEAD) and stronger reactions to changes in analyst recommendations. Hou et al. (2009) find PEAD to be stronger among low-turnover stocks. Using size and residual analyst coverage

Table 1.8: Information and bias strategy returns regressed on analyst-expected return strategy returns

$$R^{i/b\,strat.}_{t+1} = \alpha_t + \beta R^{\tilde{R}\,strat.}_{t+1} + \varepsilon_{t+1}$$

Panel A: Equal-weighted strategies			
Dep. strategy return:	R^{i}_{t+1}	$R^{\bar{i}}_{t+1}$	R^{s}_{t+1}
α	0.50	1.26	0.68
	[3.86]	[3.08]	[2.50]
β	0.68	-0.02	0.13
	[24.05]	[-0.25]	[1.48]
R^2	0.72	0.00	0.01
N	225	225	189
Panel B: Value-weighted strategies			
Dep. strategy return:	R^{i}_{t+1}	$R^{\bar{i}}_{t+1}$	R^{s}_{t+1}
α	0.04	0.82	0.50
	[0.17]	[1.82]	[1.60]
β	0.57	0.03	0.08
	[15.17]	[0.38]	[1.23]
R^2	0.51	0.00	0.01
N	225	225	189

Notes: Results from regressing information and bias-sorted long-short strategy returns from Table 1.6 on analyst-expected return-sorted long-short strategy returns from the same table. R^{i}_{t+1} is the long-short strategy return from the trading strategy based on $i^{j}_{t,t+1}$. $R^{\bar{i}}_{t+1}$ is the long-short strategy return from the trading strategy based on $\bar{i}^{j}_{t,t+1}$. R^{s}_{t+1} is the long-short strategy return from the trading strategy based on s^{j}_{t} from equation (1.24). $R^{\tilde{R}\,strat.}_{t+1}$ are returns to the raw analyst-expected return long-short strategy. Data is form 1999-2017. t-statistics are reported in brackets.

as proxies for the amount of information available about a given stock, Hong, Lim and Stein (2000) find that momentum profitability declines with firm size and analyst coverage. In all of these instances, the market appears to underweight information among low-information-environment stocks relatively more than among high-information-environment stocks.

My framework provides additional motivation for investigating under- and overreaction among stocks in different information environments. For stocks in high information environments, the optimal updating weight is likely smaller than for stocks in low information environments (i.e., $\theta_t^{j,High} < \theta_t^{j,Low}$) because more available information presumably leads to more precise priors on expected future price. If optimal updating weights are functions of information environment, differences in updating efficiency might arise across these groups as well. To test for such differential updating efficiency, I separate stocks along characteristics that are likely proxies for the information environment and investigate whether updating weights vary as a function of these proxies.

I define low information environment stocks as satisfying any of the following criteria: (1) having low market capitalization ($LogSize_t$), (2) having low residual analyst coverage, (3) having high volatility ($StdDev_{t-11,t}$), or (4) having low turnover ($Turn_{t-11,t}$).[16] I define analyst coverage to be the total number of price target records each month according to the IBES Unadjusted Summary file rather than my own monthly coverage measure. This proxy is a better measure of total analyst coverage because it is unlikely every analyst covering a stock will issue a new price target in a given month. Analyst coverage is a strongly increasing function of size. To control for the relationship between size and under- or overweighting when assessing the relationship with coverage, I estimate residual analyst coverage using a

16. Using such characteristics as information environment proxies has precedent. For instance, Loh and Stulz (2018) investigate the importance of analyst forecasts during bad times for firms in low versus high information environments defining low information environment stocks as those with: (1) no company guidance, (2) low institutional ownership, (3) high idiosyncratic risk, (4) small size, or (5) low analyst coverage. Hong, Lim and Stein (2000) provide evidence that information about low-residual-analyst-coverage stocks diffuses more slowly than that for high-residual-coverage stocks. Turnover has also been used as a proxy for investor attention (Hou et al. (2009)).

method to control for size similar to that in Hong, Lim and Stein (2000) and Nagel (2005). Namely, I estimate the relationship between log-coverage and size by running 10-year rolling Fama and MacBeth (1973) regressions of log-coverage on $LogSize_t$ and $LogSize_t^2$. I use residuals from this regression as a proxy for size-controlled analyst coverage. Results do not change significantly when I estimate residual analyst coverage separately each month (i.e., not in a rolling fashion).

I begin by separating stocks into different quintile subsets based on the information environment proxies described above. I then run Empirical Tests 1, 3, 5, and 6 on stocks within each subset by running regressions implied by equations (1.22) and (1.23). I only use announcement-month returns, $R_{t,t}$, as required by Empirical Tests 1 and 3 and next-month returns, $R_{t+1,t+1}$, as required by Empirical Tests 5 and 6 for brevity. This setup relaxes the part of Assumption 1 that implies δ_n, γ_n, and θ are constant in the cross section. In this case, I estimate the regression models separately within each subset of stocks, which yields new sets of coefficients $\delta_{n,m}$ and $\gamma_{n,m}$ (or $\delta_{n,m} - \delta_{0,m}$ and $\gamma_{n,m} - \gamma_{0,m}$), where m indexes the different subsets. Overall, I find patterns consistent with the notion that the market incorporates information into the prices of low-attention stocks more slowly than for high-attention stocks. This result gives more confidence that my information component captures price-relevant news, since it forecasts returns in cross-sections sorted by proxies for investor attention similar to news in other settings.

Results can be found in Table 1.9. I estimate $i^j_{t,t+1}$ and $b^j_{t,t+1}$ for these regressions using Model 3, which includes volatility and turnover as characteristics. Using Model 3 reduces the chance that risk premia associated with these characteristics are the cause of any return predictability indicated by the regressions. I also plot the coefficients on $i^j_{t,t+1}$ in Figure 1.3 to help with visualization of price reactions to the information component. I first discuss commonalities in patterns across all information environment proxies, and then discuss each proxy individually.

Prices react positively to both the information and bias components. The estimated

$\delta_{0,m}$ and $\gamma_{0,m}$ coefficients for announcement-month returns, $R_{t,t}$, are always positive and statistically significant across all subsets for each information environment proxy (Panels A-D). The estimated $\delta_{1,m} - \delta_{0,m}$ coefficients are always positive and typically statistically significant. This result provides evidence that the market underweights the information component during the announcement month across all subsets for each information environment proxy. The estimated $\gamma_{1,m} - \gamma_{0,m}$ coefficients are typically negative, although they are not statistically significant at standard levels. This result provides weak evidence for overreaction to bias. Overall, these patterns are in line with my findings in the previous sections.

Announcement-month return coefficients on the information component, $\delta_{0,m}$, are all positive and decreasing in size (Panel A). The small size coefficient ($\delta_{0,1}$) of 5.13 implies a one-standard-deviation increase in the information component increases announcement-month returns by 5.13%. The large size coefficient ($\delta_{0,5}$) of 3.85 implies a one-standard-deviation increase in the information component increases announcement-month returns by a 3.85%. The fact that announcement-month coefficients, $\delta_{0,m}$, are decreasing in size indicates that the market perceives the information component in analyst-expected returns to contain relatively more-precise pricing information about small stocks than about large stocks. $\delta_{1,m} - \delta_{0,m}$ is decreasing in size, which indicates the market underweights the information component relatively more for small stocks than for large stocks. This observation is consistent with the idea that small stocks receive relatively low attention, resulting in slower information incorporation into prices.

Announcement-month return coefficients on the information component, $\delta_{0,m}$, are all positive and approximately constant across the residual analyst coverage subsets (Panel B). A one-standard-deviation increase in the information component corresponds to an (approximately) 5% increase in announcement-month returns, which is consistent with my full-sample results in Table 1.3. The $\delta_{1,m} - \delta_{0,m}$ coefficients are decreasing in residual analyst coverage, which implies the market underweights the information component more for low-coverage stocks than for high-coverage stocks. As with the size subset results, this finding is consistent with slower information incorporation into prices of stocks that have low investor attention.

Post-announcement-month information component coefficients, $\delta_{1,m} - \delta_{0,m}$, associated with the volatility subsets (Panel C) are mostly flat but positive, indicating the market underweights the information component in analyst-expected returns similarly across all these subsets. The announcement month coefficients, $\delta_{0,m}$, for the volatility subsets are more interesting. The market weights the information component for the high-volatility subset more than that for the low-volatility subset. The fact that the post-announcement-month coefficients are relatively flat indicates the initial weights the market applies to the information across volatility subsets is directionally correct as a function of volatility. This result implies the market perceives the information component in analyst-expected returns for high-volatility stocks to be more precise and informative than that for low-volatility stocks.

Announcement-month coefficients, $\delta_{0,m}$, are increasing in stock turnover, yet post-announcement-month coefficients, $\delta_{1,m} - \delta_{0,m}$, are decreasing in turnover (Panel D). This finding provides evidence that analyst-expected returns contain more precise valuation information about high-turnover stocks than about low-turnover stocks, but also that the market underweights the information component for low-turnover stocks relatively more than for high-turnover stocks. These results are consistent with existing research that indicated analysts tend to provide more accurate forecasts for stocks that are highly visible to institutional investors, or those that generate brokerage profits.[17]

17. Gompers and Metrick (2001) show that institutional investors have a preference for investing in high-volatility and high-turnover stocks. Ljungqvist et al. (2007) finds that analyst recommendations and earnings forecasts are more accurate when institutional ownership is high, and Frankel et al. (2006) find that analyst reports are more informative for stocks with high potential brokerage profits such as those with high turnover, high volatility, and high institutional ownership.

Table 1.9: Empirical Tests 1, 3, and 5-6 Using Information Environment-Related Subsets

Panel A: Size subsets

	$R^{j,m}_{t,t} = a_{t,m} + \delta_{0,m} i^{j,m}_{t,t+1} + \gamma_{0,m} b^{j,m}_{t,t+1} + \varepsilon^{j,m}_{t,t}$					$R^{j,m}_{t,t+1} - R^{j,m}_{t,t} = a_{t,m} + \left(\delta_{1,m} - \delta_{0,m}\right) i^{j,m}_{t,t+1} + \left(\gamma_{1,m} - \gamma_{0,m}\right) b^{j,m}_{t,t+1} + \varepsilon^{j,m}_{t,t+1}$				
Size subset:	**Small**	**2**	**3**	**4**	**Large**	**Small**	**2**	**3**	**4**	**Large**
$i^{j}_{t,t+1}$	5.13	5.39	4.90	4.46	3.85	0.49	0.33	0.16	0.08	0.08
	[30.08]	[23.42]	[26.59]	[18.83]	[17.15]	[4.70]	[3.10]	[1.78]	[0.78]	[1.12]
$b^{j}_{t,t+1}$	1.17	1.41	1.30	1.01	0.70	-0.18	-0.18	-0.16	-0.19	-0.39
	[5.59]	[5.94]	[7.22]	[5.30]	[3.35]	[-1.20]	[-1.43]	[-1.05]	[-1.07]	[-1.79]
R^2	0.21	0.21	0.20	0.18	0.16	0.04	0.04	0.04	0.05	0.05
N	263	263	263	263	263	263	263	263	263	263

Panel B: Coverage subsets (controlling for size)

	$R^{j,m}_{t,t} = a_{t,m} + \delta_{0,m} i^{j,m}_{t,t+1} + \gamma_{0,m} b^{j,m}_{t,t+1} + \varepsilon^{j,m}_{t,t}$					$R^{j,m}_{t,t+1} - R^{j,m}_{t,t} = a_{t,m} + \left(\delta_{1,m} - \delta_{0,m}\right) i^{j,m}_{t,t+1} + \left(\gamma_{1,m} - \gamma_{0,m}\right) b^{j,m}_{t,t+1} + \varepsilon^{j,m}_{t,t+1}$				
Coverage subset:	**Lo**	**2**	**3**	**4**	**Hi**	**Lo**	**2**	**3**	**4**	**Hi**
$i^{j}_{t,t+1}$	4.72	4.84	4.89	4.87	5.04	0.45	0.33	0.29	0.24	0.08
	[20.22]	[24.12]	[25.76]	[29.27]	[21.77]	[4.17]	[3.43]	[3.15]	[2.67]	[0.86]
$b^{j}_{t,t+1}$	1.93	1.70	1.36	1.24	0.89	0.01	-0.04	0.04	-0.22	-0.27
	[10.92]	[6.62]	[5.52]	[7.27]	[4.57]	[0.07]	[-0.30]	[0.29]	[-1.50]	[-1.51]
R^2	0.20	0.20	0.20	0.20	0.20	0.04	0.04	0.04	0.04	0.05
N	264	263	263	263	263	264	263	263	263	263

Panel C: Volatility subsets

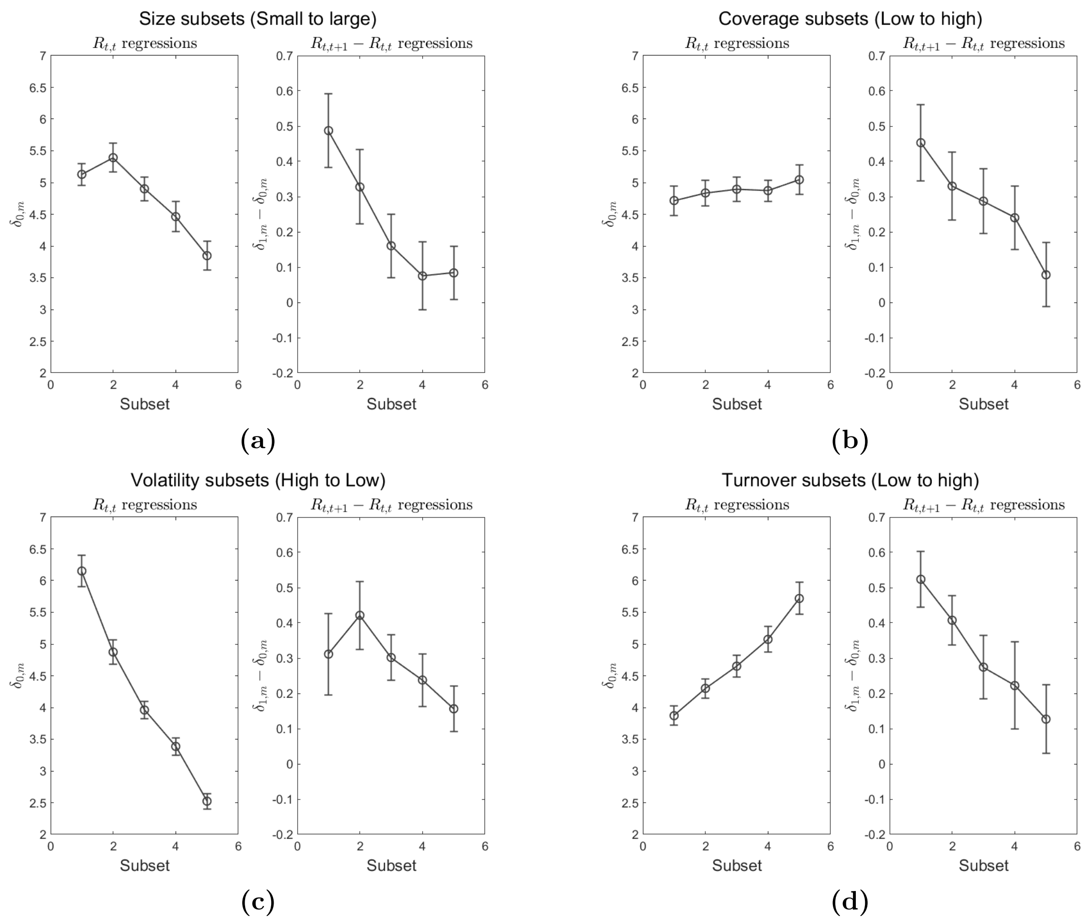
	$R^{j,m}_{t,t} = a_{t,m} + \delta_{0,m} i^{j,m}_{t,t+1} + \gamma_{0,m} b^{j,m}_{t,t+1} + \varepsilon^{j,m}_{t,t}$					$R^{j,m}_{t,t+1} - R^{j,m}_{t,t} = a_{t,m} + \left(\delta_{1,m} - \delta_{0,m}\right) i^{j,m}_{t,t+1} + \left(\gamma_{1,m} - \gamma_{0,m}\right) b^{j,m}_{t,t+1} + \varepsilon^{j,m}_{t,t+1}$				
Volatility subset:	**Hi**	**4**	**3**	**2**	**Lo**	**Hi**	**4**	**3**	**2**	**Lo**
$i^{j}_{t,t+1}$	6.15	4.87	3.96	3.39	2.52	0.31	0.42	0.30	0.24	0.16
	[25.17]	[25.15]	[29.01]	[24.58]	[20.66]	[2.70]	[4.38]	[4.66]	[3.18]	[2.40]
$b^{j}_{t,t+1}$	1.74	0.57	0.59	0.53	0.41	-0.16	-0.20	-0.17	-0.09	-0.19
	[8.29]	[3.76]	[4.25]	[4.54]	[3.36]	[-1.40]	[-1.35]	[-1.27]	[-0.67]	[-1.32]
R^2	0.22	0.18	0.15	0.13	0.10	0.03	0.02	0.02	0.02	0.02
N	263	263	263	263	263	263	263	263	263	263

Panel D: Turnover subsets

	$R^{j,m}_{t,t} = a_{t,m} + \delta_{0,m} i^{j,m}_{t,t+1} + \gamma_{0,m} b^{j,m}_{t,t+1} + \varepsilon^{j,m}_{t,t}$					$R^{j,m}_{t,t+1} - R^{j,m}_{t,t} = a_{t,m} + \left(\delta_{1,m} - \delta_{0,m}\right) i^{j,m}_{t,t+1} + \left(\gamma_{1,m} - \gamma_{0,m}\right) b^{j,m}_{t,t+1} + \varepsilon^{j,m}_{t,t+1}$				
Turnover subset:	**Lo**	**2**	**3**	**4**	**Hi**	**Lo**	**2**	**3**	**4**	**Hi**
$i^{j}_{t,t+1}$	3.87	4.30	4.65	5.07	5.72	0.52	0.41	0.27	0.22	0.13
	[25.67]	[28.53]	[27.58]	[25.18]	[22.66]	[6.56]	[5.88]	[3.05]	[1.80]	[1.30]
$b^{j}_{t,t+1}$	1.50	1.26	1.38	1.04	1.37	-0.06	0.16	0.14	-0.08	-0.24
	[8.24]	[5.97]	[6.61]	[6.23]	[7.47]	[-0.38]	[1.18]	[0.99]	[-0.62]	[-1.81]
R^2	0.17	0.18	0.18	0.20	0.21	0.04	0.03	0.03	0.03	0.04
N	263	263	263	263	263	263	263	263	263	263

Notes: Fama and MacBeth (1973) regressions using the specifications in equations (1.22) and (1.23) (left panels and right panels, respectively) for different subsets of stocks. Panels A-D sort stocks into quintile subsets based on on size, residual coverage, volatility, and turnover, respectively, which are indexed by $m \in \{1, 2, 3, 4, 5\}$. Subsets are sorted so that the leftmost subsets are associated with firms in low information environments and rightmost subsets are associated with firms in high information environments, although this interpretation is more ambiguous for turnover. $b^{j}_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using 15 control characteristics from Model 3 and 10-year rolling Fama and MacBeth (1973) regressions. Analyst-expected return information $i^{j}_{t,t+1}$ is computed according to equation (1.12). $R^{j}_{t,t}$ is the return on stock j in month t (i.e., the announcement month). $R^{j}_{t,t+1}$ is the cumulative return on stock j over the announcement month t and month $t+1$. Regressions are run at the 1-month frequency. I control log-coverage for size using a similar approach as used by Nagel (2005). Namely, I estimate the relationship between $Log\left(NUMPTG^{j}_{t,t+1} + 1\right)$ and size by running 10-year rolling Fama and MacBeth (1973) regressions of the variable on $LogSize_t$ and $LogSize^2_t$, and take the residual from this regression each period as the information environment proxy controlling for size. $NUMPTG^{j}_{t,t+1}$ are the number of price targets in a given month t issued for stock j according to the IBES Unadjusted Summary file. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags. t-statistics are reported in brackets.

Figure 1.3: Plots of $\delta_{0,m}$ and $\delta_{1,m} - \delta_{0,m}$ Coefficients from Empirical Tests 1, 3 and 5 Using Information Environment-Related Subsets



(a) (b) (c) (d)

Notes: This figure plots coefficients on $i^j_{t,t+1}$ based on regression results in Table 1.9 from estimating equations (1.22) for $n = 0$ (left panels) and (1.23) for $n = 1$ (right panels) within each subset of data. Figures (a-d) plots results for size, coverage (residual), volatility, and turnover subsets, respectively. These plots are based on regression results presented and described more fully in Table 1.9, and error bars are based on standard errors computed for that table. Data is from 1999-2017.

1.6 Robustness and Discussion

1.6.1 Robustness Checks

I implement seven sets of robustness checks on the results from my six main empirical tests. First, if discount factors and other sources of expected returns are correlated with my measures of bias and information in the cross-section, they could be the cause of my observed return predictability. To address this concern, I extend my framework to allow for discounting and expected returns associated with sources other than price target announcement effects over my multi-period tests. I provide the associated modified versions of Propositions 1 and 2 in Online Appendix OA.1. Empirical tests based on this extension yield the similar conclusions as my main results in Tables 1.3 and 1.4.

Second, my estimate of the bias component is less efficient than a forecast that projects realized bias onto observable characteristics directly rather than computing bias from estimates of realized and analyst-expected return projections onto characteristics as in equation (1.21). The former method requires estimating half as many parameters as the latter.[18] To address this concern, I forecast bias directly and re-run my main empirical tests in Online Appendix OA.4. Results are robust to this alternative bias estimate.

Third, price targets only became popular in the late 1990s, and the market may have needed time to learn about the biases inherent in these forecasts. To address this concern, I re-run my main empirical tests using different time subsamples (1999-2007 and 2008-2017) in Online Appendix OA.5. Results in each subsample are similar to my main results; however, overreaction to bias is weaker in the later subsample. This result suggests the market may learn about the bias in analyst-expected returns and improve related expectations updating

18. I use the method described by equation (1.21) for my main estimate of bias because it allows me to use data before 1999 when estimating $E\left[R^j_{t+1}|X_t\right]$. In the case of the alternative bias estimate, I project $\tilde{R}^j_{t,t+1} - R^j_{t+1}$ onto X_t, which limits me to using data during and after 1999. In fact, due to the large amount of noise in R^j_{t+1}, I use data from 1999-2001 to estimate the first projection of $\tilde{R}^j_{t,t+1} - R^j_{t+1}$ onto X_t, effectively eliminating three of my 19 years of data.

mistakes as time goes on. The underreaction to information is similar in the later period to that in my main results, though, which implies that the market has not improved upon updating mistakes related to underreaction to information.

Fourth, my analyst-expected return measure assumes that analysts expect dividends to be the same over the next year as realized dividends over the past year. To address the concern that this may not be an accurate assumption, I re-run my entire analysis excluding this dividend yield from my analyst-expected return measure and using ex-dividend realized returns. Results are essentially unchanged from my main results, and are provided in Online Appendix OA.6.

Fifth, one might be concerned that the projection of analyst-expected returns onto characteristics may not capture all sources of bias in analyst-expected returns. Specifically, firm-specific bias may exist that is unrelated to any of the firm characteristics. To address this concern, I add firm fixed effects to the projection in Online Appendix OA.7 and re-run my main empirical tests. This modification does not alter the conclusions of my main empirical tests.

Sixth, I have implicitly assumed that analysts are homogeneous in my analysis. To address the concern that heterogeneity effects may drive my results, I consider using other methods for computing firm-month price targets (i.e., other than using the median, as in equation (1.17)) in Online Appendix OA.8 including using (1) the average of stock-month price targets across all analysts, (2) price targets from firm-months where only one price target is issued, or the same target is issued by multiple analysts, (3) only the first price target issued for each stock-month, (4) only the last price target issued for each stock-month, (5) averages of individual analysts' expected returns (not price targets) computed using individual price targets normalized by the stock price two days before the target is issued, and (6) two different subsets of individual analyst price targets designated as either bold (high-innovation) or herding (low-innovation) based on definitions similar to those for earnings forecasts in Clement and Tse (2005) and Gleason and Lee (2003). My main results do not change qualitatively in any of these specifications. In the case of the bold- and herding-based subsets, using bold price targets yields results similar to my main results; however, information and bias components extracted using herding price targets are not associated with statistically significant evidence of under- or overreaction. This finding implies that my main results are not driven by my original price target aggregation choice, and that analyst heterogeneity is likely not the cause of my results.

Gleason and Lee (2003) find that updates to analyst earnings forecasts forecast returns in the cross section. Womack (1996) find that entrance and exit to and from the highest and lowest recommendation categories can also be used to forecast returns in the cross section. Changes to price targets are correlated with changes to earnings forecasts and recommendations (Asquith et al. (2005)), so it is possible that the underreaction and overreaction that I document are subsumed by these previously-documented effects. In my final set of robustness checks (Online Appendix OA.11), I find including controls for these effects weakens the statistical significance of my main information underreaction results; however, the magnitudes of the estimated coefficients are similar to my main results and are typically significant at (at least) the 10% level. Additionally, coefficients related to bias overreaction typically become more statistically significant and increase in magnitude. These results indicate that the under- and overreaction I document are related to previously-documented return forecastability originating from earnings forecasts and recommendations changes, but are not subsumed by these effects.

I also run a portfolio sorting exercise using price target announcement-window returns as a sorting variable rather than the information component in analyst-expected returns in Online Appendix OA.9. Announcement-window returns provide model-free measures of the market's reaction to price target announcements, and provide a model-free method for demonstrating delayed price reaction to analyst price target announcements. Long-short equal-weighted portfolios sorted on announcement-window returns earn statistically significant positive returns, although they are slightly lower than those obtained from sorting on the information component in analyst-expected returns. Lower average returns for this strategy are expected because announcement-window returns are also contaminated with the initial incorrect reaction to bias. Average returns from this strategy also survive risk adjustment using standard factor models. Returns on the long-short value-weighted portfolio are positive but not statistically significant, which is consistent with my value-weighted $i^{j}_{t,t+1}$-strategy results. This provides further evidence that underreaction is concentrated among relatively small stocks (i.e., relative to the size of other covered stocks), although liquidity is not likely to be a concern because analysts tend to cover relatively large and liquid stocks.

1.6.2 Discussion

I have provided evidence that prices underreact to an information component in analyst-expected returns and overreact to a bias component. My methodology cannot fully distinguish between two competing mechanisms that might explain these results. They could be driven by information-processing mistakes as described in my framework. This interpretation relies on the implicit assumption that all market participants have access to analyst price targets during announcement months. Alternatively, if some market participants receive price target information in months after the announcement month, my results could be driven by slow information diffusion or private information effects as in Hong and Stein (1999) or Grossman and Stiglitz (1980), respectively. However, slow information diffusion and private information effects are unlikely to be the main drivers of my results for the following reason. If price drift related to the information component in analyst-expected returns were driven by slow information diffusion or delayed learning of private information, we would expect a positive price drift related to the bias component as well. This postulate assumes that market participants who potentially receive price targets in months after the announcement month make the same information-processing errors as those who receive the targets during the announcement month. The fact that the reaction to bias reverses in months after price target announcements implies the effects I document are not solely the result of additional market participants first gaining access to price targets and incorporating that information into their expectations in the months after announcement months. If this mechanism is present, it is dominated by reversals related to the initial reaction to bias.

My finding that prices demonstrate delayed reactions to the information component in analyst-expected returns is similar to the post-earnings announcement drift (PEAD) phenomenon. In the case of PEAD, positive (negative) earnings announcement news is associated with positive (negative) expected returns over the next three quarters (Bernard and Thomas (1989)). As noted above, a trading strategy based on the market's delayed reaction to the information component in analyst-expected returns yields average monthly returns of 1.12%-1.24% (annual average returns of about 13%-14%). To put this magnitude in context, the PEAD phenomenon has been shown to generate annualized average returns of 17%-18% (Bernard and Thomas (1989)).[19] Chordia et al. (2009) provide evidence that a significant fraction of the paper trading profits related to PEAD are concentrated among highly illiquid stocks. Illiquidity effects are less likely to drive my results because stocks with analyst coverage tend to be relatively large and liquid (for instance, the average Amihud (2002) illiquidity measure for all stocks that meet the CRSP filters during my sample period is 0.57, whereas that for stocks with associated analyst-expected return records is only 0.07); however, a full investigation of this issue is beyond the scope of the current study. I provide evidence that my information strategy survives controlling for the PEAD effect in Online Appendix OA.10.2. First, I show that PEAD-strategy returns are relatively weak among stocks with analyst-expected return records. Second, average returns to my information strategy survive controlling for the PEAD effect when conditionally double-sorting portfolios first on standardized unexpected earnings and then on my information component. This finding is corroborated by cross-sectional regressions of next-month returns on both $i^j_{t,t+1}$

19. Depending on the particular strategy employed, other estimates of average annualized PEAD strategy returns range from 10% (Chordia and Shivakumar (2006)) to 25% (Foster et al. (1984)).

and standardized unexpected earnings. To further mitigate the concern that price targets simply contain information from earnings announcements, I run my main tests using analyst-expected returns computed excluding price targets issued near earnings announcements in Online Appendix OA.10.1 and find that results are similar to my main results.

My subsample results are consistent with theories and other results that link underreaction to investor inattention. Hong and Stein (1999) provide a theory to explain price underreaction to news such as that related to PEAD. A key assumption they make is that news diffuses slowly, and therefore prices demonstrate delayed reactions to news. Hou et al. (2009) finds evidence that the PEAD phenomenon weakens with investor attention, for which turnover is taken to be a proxy. More recently, Ben-Rephael et al. (2017) use a direct measure of institutional attention to show that lower attention is associated with a stronger PEAD effect as well as more delayed reactions to updated analyst recommendations. Size, coverage, and turnover proxies are plausibly all related to investor attention, and I find that underweighting is relatively higher among all the low-attention subsets than the high-attention subsets within these proxies. The fact that the updating patterns I observe across these subsets is similar to observations in previous studies also provides more confidence that my information component is a valid measure of price-relevant information in analyst-expected returns.

The bias component overreaction I document is novel. Overreaction usually arises in models that attempt to explain underreaction, but only with delay after underreaction occurs (see, for instance, Hong and Stein (1999), Barberis et al. (1998), and Daniel et al. (1998)). In my case, I document overreaction to the bias component that is contemporaneous with underreaction to the information component. Investors do not fully debias analyst-expected returns when forming expectations over future prices; however, we can infer that the market partially corrects for bias because the reaction to it is not as strong as to the information component. Few asset pricing studies directly identify information and bias components in news and study price reactions to each component. One exception is a study by Cavallo et al. (2016), who find evidence that households are able to debias inflation signals before incorporating these signals into expectations about future inflation. These results imply the market's ability to debias price-relevant signals is likely dependent on the specific signals being used and assets being studied.

1.7 Conclusions

In this paper, I use a novel decomposition to extract information and bias components from analyst-expected returns and find evidence that the market underreacts to information and overreacts to bias. These results are robust to a number of modifications to my empirical design, and I also present two examples of model-free evidence of underreaction. I set up a framework to explain how such mispricing can exist in the economy as the result of two information processing mistakes. The framework allows me to infer how the market updates its own expectations in the presence of biased analyst-expected return signals using asset prices, and contributes to the growing literature that links explicitly stated expectations of returns to expected returns (see, for example, Greenwood and Shleifer (2014)). The framework also implies the market does not fully debias analyst-expected returns before incorporating them into their own expectations; however, the relatively weak initial reaction to bias relative to information implies that the market does partially debias analyst-expected returns. This implies that the practice of using analyst forecasts as proxies for market expectations is misguided, at least in the case of analyst-expected returns.

Previous studies on analyst price targets have focused on either price reactions to these targets (Asquith et al. (2005), Brav and Lehavy (2003)), or how the corresponding analyst-expected returns are related to cross-sectional anomalies (Engelberg et al. (2018), Bali et al. (2017), Brav et al. (2005)). They have not considered whether the market reacts differently to information and bias components in analyst-expected returns. My paper fills this gap by providing a decomposition that identifies these components, and by showing that prices react differently to each.

My results raise a number of interesting avenues for future research. First, investigating whether the market makes similar errors in other settings is important for understanding how the market incorporates biased signals into prices and whether the effects I document are a more general phenomenon. Second, my finding that the market underweights the information component in analyst-expected returns is surprising given results in So (2013), who finds evidence that the market overweights analyst earnings forecasts. As I discuss in Online Appendix OA.13, one potential resolution might be to incorporate the idea that earnings forecasts contain both information and bias rather than bias alone, as in So (2013). Additionally, developing a unified framework that allows for information and bias components in both price targets and earnings forecasts may provide new insights into the relationship between asset prices, expectations of returns, and expectations of cash flows. Finally, some evidence already shows that sell-side analysts improve pricing efficiency (Chen et al. (2018)). My subsample results indicate these effects vary in the cross section. Analyst price targets provide relatively more precise information about high-volatility, low-turnover stocks. My results also show that information incorporation is relatively less efficient for low-information-environment stocks. These considerations are important when evaluating how sell-side analyst industry regulations such as MiFID II might influence pricing efficiency, particularly for low-information-environment stocks.

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CHAPTER 2

APPENDIX

2.1 Analyst-Expected Return Summary Statistics

Table A-1: Analyst-Expected Return Summary Statistics

Year	No. firms	No. analysts	Cap. coverage	Firm coverage	$\tilde{R}^j_{t,t+1}$	R^j_{t+1}	Bias
1999	2,928	1.92	73.32	26.46	2.25	-0.22	2.57
2000	3,108	2.08	80.70	30.43	2.46	0.65	1.76
2001	2,886	2.36	78.81	35.58	1.92	0.61	1.20
2002	2,756	2.58	81.99	38.79	1.59	-0.82	2.35
2003	2,831	2.53	83.32	42.30	1.45	3.07	-1.72
2004	2,984	2.59	81.07	42.10	1.27	1.15	0.04
2005	3,026	2.60	79.77	43.76	1.22	1.12	-0.08
2006	3,078	2.64	83.02	44.29	1.22	0.77	0.33
2007	3,033	2.75	81.14	45.34	1.23	-0.38	1.61
2008	2,760	3.14	86.31	50.91	1.28	-2.87	4.13
2009	2,457	3.34	88.43	54.84	1.59	2.56	-1.04
2010	2,553	3.42	86.18	55.07	1.60	2.31	-0.80
2011	2,564	3.70	88.05	55.99	1.35	-0.04	1.42
2012	2,483	3.65	86.78	54.33	1.37	1.57	-0.23
2013	2,513	3.88	88.65	56.15	1.23	2.00	-0.81
2014	2,617	3.76	86.19	54.11	1.14	0.96	0.14
2015	2,665	3.85	87.13	55.70	1.23	-0.50	1.78
2016	2,572	3.87	88.85	58.24	1.20	2.00	-0.79
2017	2,517	3.87	88.95	57.18	1.06	1.28	-0.25
All years	7,190	3.12	84.24	46.19	1.38	0.91	0.39

Notes: Data are constructed using the IBES Unadjusted Detail database, which covers 1999-2017. "No. firms" are the total number of unique PERMNOs with at least one price target reported in the corresponding year. "No. analysts" are the average number of analysts associated with each firm-month price target within each year. "Cap. Coverage" is the fraction (in percent) of the total market capitalization (relative to the filtered CRSP data) with corresponding analyst-expected return records (average of monthly values within each year). "Firm Coverage" is the number of firms with at least one price target in a given month as a fraction (in percent) of total firms with records in the month based on the filtered CRSP data, averaged across all months in each year. The $\tilde{R}^j_{t,t+1}$ column reports the median of all analyst-expected returns in percent (transformed to monthly frequency) in each year. The R^j_{t+1} column reports the median of all realized monthly returns for firm-months following analyst price target announcements for a given year, in percent. "Bias" is the median realized analyst-expected return bias calculated as $\tilde{R}^j_{t,t+1} - R^j_{t+1}$ across all firm-months in a given year, in percent.

2.2 Firm Characteristics Details and Summary Statistics

This section provides details on the firm characteristics I use as conditioning information. I use three models that include different sets of characteristics as in Lewellen (2015). Model 1 uses characteristics 1-3, Model 2 uses characteristics 1-7, and Model 3 uses characteristics 1-15. I construct this data using both the CRSP and Compustat databases.

1. $LogSize_t$- Log of the market capitalization (in millions, computed by multiplying stock price, PRC, with shares outstanding, SHROUT) in the current month.

2. $LogB/M_t$ - Log of previous fiscal year book value divided by current month's market value. Book value is constructed according to Davis et al. (2000). "BE is the book value of stockholders' equity (SEQ), plus balance sheet deferred taxes and investment tax credit (TXDITC) (if available), minus the book value of preferred stock. Depending on availability, redemption (PSTKRV), liquidation (PSTKL), or par value (PSTK) (in that order) were used to estimate the book value of preferred stock. Stockholders' equity is the value reported by Moody's or Compustat, if it is available. If not, stockholders' equity was measured by the book value of common equity (CEQ) plus the par value of preferred stock (PSTK), or the book value of assets (AT) minus total liabilities (LT) (in that order)."

3. $Return_{t-11,t-1}$ - Simple total return over the past 12 months excluding the most recent month. I require return data for all 11 months.

4. $LogIssues_{t-35,t}$ - Log of total shares, SHROUT, in current month minus log of total shares 36 months ago (adjusted for splits using CFASHR).

5. $Accruals_t$ - I use the same definition as in Freyberger et al. (2017) (which is also that used by Lewellen (2015) and is based on Sloan (1996)). Change in non-cash working capital minus depreciation (DP) scaled by lagged total assets (AT). Non-cash working capital is the difference between non-cash current assets and current liabilities (LCT),

debt in current liabilities (DLC) and income taxes payable (TXP). Non-cash current assets are current assets (ACT) minus cash and short-term investments (CHE). So, accruals are given by $[\Delta ACT - \Delta CHE - (\Delta LCT + \Delta DLC + \Delta TXP)] / AT$ where Δ represents changes over the two most recent fiscal years. I set missing sub-component values to zero when constructing accruals.

6. ROA_t - Income before extraordinary items (IB) from most recent fiscal year divided by total assets (AT) from the previous fiscal year.

7. $LogAG_t$ - Log of total assets (AT) from most recent fiscal year minus log of total assets from previous fiscal year. This is the log version of the investment characteristic in Fama and French (2015).

8. $DY_{t-11,t}$- Dividend yield over the past year (split-adjusted dividends per share over the past year divided by adjusted share price from current month).

9. $LogReturn_{t-35,t-12}$ - Log total return over the past 36 months excluding the past 12 months (long-term reversal).

10. $LogIssues_{t-11,t}$ - Log of total shares, SHROUT, in current month minus log of total shares 12 months ago (adjusted for splits, using CFASHR).

11. $Beta_t$ - I compute this as in Frazzini and Pedersen (2014) instead of as in Lewellen (2015).

12. $StdDev_{t-11,t}$ - Annualized volatility of stock returns over previous year computed by summing daily log returns; I require at least 120 non-missing return observations and annualize all values to be on a 252 day basis. Note that Lewellen (2015) uses a monthly version of this, so his estimated values are lower by a factor of approximately $1/\sqrt{12}$.

13. $Turn_{t-11,t}$ - Average monthly turnover over past year defined as the total monthly volume (VOL) divided by the total shares outstanding (SHROUT) each month.

14. $Debt/Price_t$ - Long-term debt (DLTT) plus short-term debt (DLC) from most recent fiscal year divided by current month's price.

15. $Sales/Price_t$ - Net sales (SALE) from most recent fiscal year divided by current month's price

Table A-2: Characteristics Summary

	All stocks			**Covered stocks**		
	Avg	**Std**	**N**	**Avg**	**Std**	**N**
R^j_{t+1}	1.00	11.84	3,152	1.07	11.37	1,456
$LogSize_t$	6.51	1.76	3,167	7.47	1.52	1,463
$LogB/M_t$	-0.76	0.86	3,167	-0.95	0.83	1,463
$Return_{t-11,t-1}$	0.17	0.45	3,167	0.18	0.45	1,463
$LogIssues_{t-35,t}$	0.09	0.25	2,840	0.11	0.25	1,322
$Accruals_t$	-0.03	0.07	3,033	-0.03	0.07	1,408
ROA_t	0.03	0.14	3,033	0.04	0.14	1,408
$LogAG_t$	0.11	0.23	3,034	0.13	0.24	1,408
$DY_{t-11,t}$	0.01	0.02	3,167	0.01	0.02	1,463
$LogReturn_{t-35,t-12}$	0.15	0.52	2,835	0.19	0.51	1,321
$LogIssues_{t-11,t}$	0.03	0.11	3,167	0.04	0.12	1,463
$Beta_t$	0.96	0.50	2,846	1.10	0.47	1,324
$StdDev_{t-11,t}$	0.45	0.20	3,167	0.44	0.18	1,463
$Turnover_{t-11,t}$	0.16	0.14	3,167	0.21	0.15	1,463
$Debt/Price_t$	0.60	1.27	3,154	0.50	1.07	1,457
$Sales/Price_t$	1.30	2.22	3,166	1.06	1.62	1,463

Notes: Reported values are time series averages of monthly cross-sectional averages, standard deviations, and total records. R^j_{t+1} represent monthly realized returns on stock j. All other variables are described in more detail in Appendix 2.2. I remove all records missing $LogSize_t$, $LogB/M_t$, or $Return_{t-11,t-1}$ since these characteristics are used in all models I consider. The left set of columns reports summary statistics for all records that meet the CRSP filtering criteria, whereas the right set of columns includes only records with corresponding analyst-expected returns. Data is from 1999-2017.

2.3 Analyst-Expected Returns, Risk Premia, and Forecasting Power

2.3.1 Analyst-Implied and Realized Return-Implied Risk Premia

Results from running cross-sectional regressions of either realized returns or analyst-expected returns on characteristics from each of the three characteristics models are provided in Table A-3. I estimate all models using z-score-transformed characteristics to aid in comparing model coefficients across characteristics. I compute the z-score-transformed values for each characteristic by subtracting its cross-sectional mean and dividing by its cross-sectional standard deviation each period. Therefore, estimated risk premia can be interpreted as the marginal impact of a one-cross-sectional-standard-deviation increase in a characteristic on a stock's expected monthly return. Although the population of firms with analyst-expected returns is slightly different from my filtered CRSP population based on characteristics (see Table A-2), I include all CRSP records that meet my filters during the 1999-2017 period (as opposed to just those with corresponding analyst-expected return records) to improve the precision of the realized return-implied risk premia. This inclusion accounts for the larger reported sample size for the realized return regressions relative to the analyst-expected return regressions. My main conclusions do not change if I restrict the realized return sample to those with corresponding analyst-expected return records.

Across all three models, realized return and analyst-expected return characteristic risk premia have different estimated signs for the following 11 characteristics: $LogB/M_t$, $Return_{t-12,t-1}$, $LogIssues_{t-35,t}$, ROA_t, $LogAG_t$, $LogReturn_{t-35,t-12}$, $LogIssues_{t-11,t}$, $Beta_t$, $StdDev_{t-11,t}$, $Debt/Price_t$, and $Sales/Price_t$. Analysts expect a negative value premium ($LogB/M_t$). This observation is consistent with the theory in Lakonishok et al. (1994) that proposes part of the value premium is caused by overly optimistic expectations for glamour stocks, and overly pessimistic expectations for value stocks. It is also consistent with empirical evidence in Jegadeesh et al. (2004), who find that analysts promote glamour stocks (high-momentum, high-growth, high-volume, and relatively expensive stocks). Consistent with the intuition that analysts recommend glamour stocks to generate trading and investment banking business, analysts assign a positive risk premium to $LogIssues_{t-35,t}$ and $LogIssues_{t-11,t}$, whereas the realized return-based risk premium is negative. Analysts promote stocks that have had recent issuances despite the fact that this characteristic leads to predictably negative returns. Interestingly, analysts appear to predict both returns associated with short-term momentum and long-term reversals with the wrong sign. This finding is consistent with the theory proposed by Barberis et al. (1998), who argue short-term underreaction and long-term overreaction associated with momentum and reversals can be explained by the well-known heuristics related to conservatism and representativeness, respectively. Analyst-expected returns also imply a negative risk premium on market β, which is both inconsistent with conventional theories of risk (e.g., the CAPM) as well as findings in other studies of analyst-expected returns (Brav et al. (2005), Bali et al. (2017)).[A-1] It is interesting that realized returns imply a negative risk premium on $StdDev_{t-11,t}$ consistent with the finding in Ang et al. (2006); however, analysts assign this characteristic a positive risk premium. In this respect, analyst-expected returns are consistent with the theoretical sign associated with this risk premium in Merton (1987) and other empirical evidence in the literature (Bali et al. (2017)).

Realized returns and analyst-expected returns imply risk premia of the same sign for the following four characteristics: $LogSize_t$, $Accruals_t$, $DY_{t-11,t}$, and $Turnover_{t-11,t}$. The fact that analysts correctly anticipate the sign of the size premium has been documented in other studies (Brav et al. (2005), Bali et al. (2017)). The fact that analyst-expected returns properly forecast the sign of the $Accruals_t$ risk premium is interesting because previous

A-1. One potential cause for the discrepancy between my results related to β and those in these references is that they both aggregate individual analyst price targets over significantly longer historical windows than my 1-month window. Bali et al. (2017) use a 12-month past window to aggregate individual analyst price targets in the IBES Unadjusted Detail database, and Brav et al. (2005) use First Call consensus estimates, which likely have the same staleness issue as in the IBES Unadjusted Summary file because price targets included in consensus estimates may contain targets issued up to 12 months in the past.

studies have found evidence that analysts do not properly account for the low persistence of accruals on future earnings. The the market appears to share these misperceptions and firms with high accruals tend to have low returns (Bradshaw et al. (2001), Teoh and Wong (2002)).

Many analyst-implied risk premia have the opposite sign as those implied by realized returns. To formally compare the two sets of risk premia, I set up two tests in Online Appendix OA.2. Each tests the null that the two sets of coefficients are jointly equivalent, and I strongly reject this null for all three models in both tests. The fact that the two sets of risk premia differ is the sense in which analyst-expected returns are biased in the cross section.

Table A-3: Realized Return and Analyst-Expected Return Risk Premia

Panel A: Model 1 (3 characteristics)						
Dependent var.:	R^j_{t+1}			$\tilde{R}^j_{t,t+1}$		
	Coeff	**t-stat**	R^2	**Coeff**	**t-stat**	R^2
$LogSize_t$	-0.03	[-0.43]	0.03	-0.36	[-15.88]	0.07
$LogB/M_t$	0.21	[1.60]		-0.22	[-16.54]	
$Return_{t-11,t-1}$	0.24	[2.05]		-0.15	[-5.89]	
N	3,174			1,466		

Panel B: Model 2 (7 characteristics)						
Dependent var.:	R^j_{t+1}			$\tilde{R}^j_{t,t+1}$		
	Coeff	**t-stat**	R^2	**Coeff**	**t-stat**	R^2
$LogSize_t$	-0.09	[-1.34]	0.04	-0.25	[-11.73]	0.10
$LogB/M_t$	0.10	[0.93]		-0.19	[-17.16]	
$Return_{t-11,t-1}$	0.18	[1.59]		-0.15	[-7.24]	
$LogIssues_{t-35,t}$	-0.13	[-3.29]		0.12	[19.76]	
$Accruals_t$	-0.01	[-0.23]		-0.04	[-4.83]	
ROA_t	0.14	[2.05]		-0.19	[-16.43]	
$LogAG_t$	-0.12	[-2.78]		0.04	[5.84]	
N	2,840			1,324		

Panel C: Model 3 (15 characteristics)						
Dependent var.:	R^j_{t+1}			$\tilde{R}^j_{t,t+1}$		
	Coeff	**t-stat**	R^2	**Coeff**	**t-stat**	R^2
$LogSize_t$	-0.20	[-2.47]	0.08	-0.06	[-3.09]	0.15
$LogB/M_t$	0.01	[0.20]		-0.11	[-12.77]	
$Return_{t-11,t-1}$	0.19	[2.15]		-0.16	[-8.67]	
$LogIssues_{t-35,t}$	-0.06	[-1.88]		0.06	[10.26]	
$Accruals_t$	-0.01	[-0.35]		-0.02	[-3.19]	
ROA_t	0.10	[1.85]		-0.15	[-15.42]	
$LogAG_t$	-0.08	[-2.32]		0.02	[3.60]	
$DY_{t-11,t}$	-0.02	[-0.69]		-0.00	[-0.33]	
$LogReturn_{t-35,t-12}$	-0.04	[-0.69]		0.03	[2.40]	
$LogIssues_{t-11,t}$	-0.06	[-1.66]		0.04	[8.27]	
$Beta_t$	0.16	[1.17]		-0.09	[-4.10]	
$StdDev_{t-11,t}$	-0.24	[-2.98]		0.45	[19.59]	
$Turnover_{t-11,t}$	-0.10	[-1.46]		-0.09	[-10.27]	
$Debt/Price_t$	-0.12	[-2.66]		0.00	[0.30]	
$Sales/Price_t$	0.10	[2.01]		-0.02	[-2.12]	
N	2,824			1,317		

Notes: Fama and MacBeth (1973) regressions of realized monthly returns (left columns) or analyst-expected returns (right columns) on characteristics. Panels A, B, and C use models with 3, 7, and 15 characteristics, respectively. Regressions are run at the 1-month frequency. All characteristics are cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected (percent) return next month. All data is from 1999-2017. Although the population of firms with analyst-expected returns is slightly different than my filtered CRSP population based on characteristics (see Table A-2), I use all CRSP records to improve the precision of the realized return-implied risk premia. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags. t-statistics are reported in brackets.

2.3.2 *Analyst-Expected Returns Forecast Realized Returns*

Despite the fact that analyst-expected returns generally imply risk premia of the wrong sign compared to those implied by realized returns, analyst-expected returns forecast returns in the cross section. To demonstrate the forecasting power, I regress realized returns on analyst-expected returns both with and without characteristic controls from Models 1-3 in Table A-4. Panel A shows results when realized returns are regressed on analyst-expected returns without any characteristic controls. Panels B-D control for characteristics from Models 1-3, respectively. Adding the characteristics as controls in the regression allows us to interpret the resulting analyst-expected return coefficient as the marginal contribution analyst-expected returns have on next month's expected return after controlling for these characteristics (and the related bias).

When I include no controls (Panel A), analyst-expected returns positive and statistically significant coefficients at the one-month horizon, but coefficients become statistically insignificant at longer horizons. The forecasting coefficient is 0.14 at the one-month horizon, which implies a 1% increase in analyst-expected returns in month t corresponds to an increase in expected returns of 0.14% in month $t+1$. Alternatively, this regression coefficient implies a one-standard-deviation increase in analyst-expected returns corresponds to a 0.21% increase in expected returns in the next month based on the average analyst-expected return cross-sectional standard deviation of 1.48% (Table 1.1). These values are large considering the unconditional median monthly return in my sample is 0.91% (see Table A-1).

The forecasting power is not subsumed by including controls (Panels B-D). Analyst-expected returns consistently have economically and statistically significant forecasting power across all three models at the one-month horizon, with coefficients ranging from 0.10 to 0.15. For every 1% increase in analyst-expected returns, there is a 0.10%-0.15% increase in expected returns over the next month. The magnitude and statistical significance of coefficients on analyst-expected returns increases as more conditioning information is added, providing some evidence that the analyst-expected return forecasting power is less likely to be the result of omitted variable bias related to standard firm characteristics. When including characteristic controls, the analyst-expected return forecasting power extends into months beyond the first. For example, under Model 3, the analyst-expected return forecasting coefficient is statistically significant at the 10% level for cumulative returns up to six months after the announcement month.

These results provide evidence that analyst-expected returns contain information about future returns that is orthogonal to information in standard firm characteristics. This finding is expected given the results in Panel A and the fact that analyst-expected returns are biased relative to what the characteristics predict.

Table A-4: Analyst-Expected Return Forecasting Regressions

Panel A: No controls					
Dep. var.:	$R^j_{t+1,t+1}$	$R^j_{t+1,t+2}$	$R^j_{t+1,t+3}$	$R^j_{t+1,t+6}$	$R^j_{t+1,t+12}$
$\tilde{R}_{t,t+1}$	0.14	0.16	0.16	0.11	-0.21
	[2.42]	[1.47]	[0.91]	[0.39]	[-0.54]
R^2	0.01	0.01	0.01	0.01	0.01
N	1,466	1,465	1,464	1,465	1,464

Panel B: Model 1 controls					
Dep. var.:	$R^j_{t+1,t+1}$	$R^j_{t+1,t+2}$	$R^j_{t+1,t+3}$	$R^j_{t+1,t+6}$	$R^j_{t+1,t+12}$
$\tilde{R}_{t,t+1}$	0.10	0.11	0.09	0.01	-0.33
	[2.12]	[1.16]	[0.58]	[0.06]	[-0.89]
R^2	0.05	0.05	0.05	0.05	0.05
N	1,466	1,465	1,464	1,465	1,464

Panel C: Model 2 controls					
Dep. var.:	$R^j_{t+1,t+1}$	$R^j_{t+1,t+2}$	$R^j_{t+1,t+3}$	$R^j_{t+1,t+6}$	$R^j_{t+1,t+12}$
$\tilde{R}_{t,t+1}$	0.15	0.17	0.18	0.22	0.12
	[3.81]	[2.27]	[1.48]	[1.10]	[0.40]
R^2	0.07	0.07	0.07	0.07	0.07
N	1,323	1,322	1,322	1,322	1,321

Panel D: Model 3 controls					
Dep. var.:	$R^j_{t+1,t+1}$	$R^j_{t+1,t+2}$	$R^j_{t+1,t+3}$	$R^j_{t+1,t+6}$	$R^j_{t+1,t+12}$
$\tilde{R}_{t,t+1}$	0.15	0.19	0.20	0.25	0.13
	[4.45]	[3.07]	[2.27]	[1.76]	[0.55]
R^2	0.12	0.12	0.12	0.12	0.12
N	1,317	1,316	1,315	1,316	1,314

Notes: Fama and MacBeth (1973) regressions of realized future returns on analyst-expected returns, $\tilde{R}^j_{t,t+1}$. Panels A uses no controls. Panels B, C, and D use models with 3, 7, and 15 characteristics as controls, respectively.$R^j_{t+1,t+n}$ are cumulative returns for stock j from month $t+1$ to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$). Data is from 1999-2017. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t+1,t+1}$ regressions, 6 lags for $R^j_{t+1,t+2}$ regressions, 8 lags for $R^j_{t+1,t+3}$ regressions, 12 lags for $R^j_{t+1,t+6}$ regressions, and 24 lags for $R^j_{t+1,t+12}$ regressions. t-statistics are reported in brackets.

2.4 Proofs of Propositions 1 and 2

2.4.1 Proof of Proposition 1

I begin with deriving Proposition 1 under the case where $n = 0$ (i.e., for announcement month expected returns) and then turn to the case where $n \geq 1$. Under Assumption 1, the market updates expectations about future prices according to equation (1.7):

$$\hat{\mathbb{E}}\left[P_{t+1}^{j}|\mathcal{F}_{t}^{M},\, \tilde{P}_{t,t+1}^{j}\right] = (1-\delta_0)\,\mathbb{E}\left[P_{t+1}^{j}|\mathcal{F}_{t}^{M}\right]+\delta_0\left[\tilde{P}_{t,t+1}^{j} - \mathbb{E}\left[B_{t,t+1}^{j}|\mathcal{F}_{t}^{M}\right]\right]+\gamma_0\mathbb{E}\left[B_{t,t+1}^{j}|\mathcal{F}_{t}^{M}\right].$$

By Assumption 2, the market will set price P_t^j such that

$$P_t^j = \hat{\mathbb{E}}\left[P_{t+1}^{j}|\mathcal{F}_{t}^{M},\, \tilde{P}_{t,t+1}^{j}\right].$$

Under Assumptions 1 and 2, the price will just adjust to the value given above during the announcement month without including any risk premium adjustment or incorporation of other information. The announcement-month return is then

$$R_{t,t}^{j} = \frac{\hat{\mathbb{E}}\left[P_{t+1}^{j}|\mathcal{F}_{t}^{M},\, \tilde{P}_{t,t+1}^{j}\right] - P_{t-1}^{j}}{P_{t-1}^{j}}.$$

I can also express P_{t-1}^j as

$$\begin{aligned}
P_{t-1}^{j} &= \mathbb{E}\left[P_{t}^{j}|\mathcal{F}_{t-1}^{M}\right] \\
&= \mathbb{E}\left[\mathbb{E}\left[P_{t+1}^{j}|\mathcal{F}_{t}^{M}\right]|\mathcal{F}_{t-1}^{M}\right] \\
&= \mathbb{E}\left[P_{t+1}^{j}|\mathcal{F}_{t-1}^{M}\right] \\
&= \mathbb{E}\left[P_{t+1}^{j}|\mathcal{F}_{t}^{M}\right],
\end{aligned}$$

where the first line follows from Assumption 2 (pricing equation), the second line follows again from Assumption 2, the third line follows from the law of iterated expectations, and the fourth line follows from Assumption 3 ($\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right] = \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_{t-1}\right]$). Combining these expressions yields

$$\begin{aligned}
R^j_{t,t} &= \frac{\hat{\mathbb{E}}\left[P^j_{t+1}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right] - P^j_{t-1}}{P^j_{t-1}} \\
&= \frac{\hat{\mathbb{E}}\left[P^j_{t+1}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right] - \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]}{P^j_{t-1}} \\
&= \frac{(1-\delta_0)\,\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right] + \delta_0\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\right]}{P^j_{t-1}} \\
&\quad + \frac{\gamma_0\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right] - \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]}{P^j_{t-1}} \\
&= \frac{\delta_0\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right] - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\right] + \gamma_0\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]}{P^j_{t-1}} \\
&\equiv \frac{\delta_0\left(I^j_{t,t+1} + B^{j,\perp}_{t,t+1}\right) + \gamma_0\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]}{P^j_{t-1}} \\
&\equiv \delta_0 i^j_{t,t+1} + \gamma_0 b^j_{t,t+1}, \qquad \text{(A-1)}
\end{aligned}$$

where the second to last line follows from the analyst price target decomposition in equation (1.4). The last line follows from the definitions of $i^j_{t,t+1}$ and $b^j_{t,t+1}$ in equations (1.12) and (1.11), respectively.

Next, for the case where $n \geq 1$, the realized return from $t-1$ to $t+n$ is

$$R^j_{t,t+n} = \frac{P^j_{t+n} - P^j_{t-1}}{P^j_{t-1}}.$$

Taking the expectation with respect to information at the end of month t yields the expected cumulative return

$$\mathbb{E}\left[R^j_{t,t+n}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right] \;=\; \frac{\hat{\mathbb{E}}\left[P^j_{t+n}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right] - P^j_{t-1}}{P^j_{t-1}}.$$

Applying Assumption 1 yields

$$\begin{aligned}\mathbb{E}\left[R^j_{t,t+n}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right] \;&=\; \frac{(1-\delta_n)\,\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right] + \delta_n\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\right]}{P^j_{t-1}}\\ &\quad+\frac{\gamma_n\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right] - P^j_{t-1}}{P^j_{t-1}}.\end{aligned}$$

As in the first part of this proof, we have $P^j_{t-1} = \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]$, so

$$\begin{aligned}\mathbb{E}\left[R^j_{t,t+n}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right] \;&=\; \frac{(1-\delta_n)\,\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right] + \delta_n\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\right]}{P^j_{t-1}}\\ &\quad+\frac{\gamma_n\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right] - \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]}{P^j_{t-1}}\\ &=\; \frac{\delta_n\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right] - \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]\right] + \gamma_n\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]}{P^j_{t-1}}\\ &\equiv\; \frac{\delta_n\left(I^j_{t,t+1} + B^{j,\perp}_{t,t+1}\right) + \gamma_n\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]}{P^j_{t-1}}\\ &\equiv\; \delta_n i^j_{t,t+1} + \gamma_n b^j_{t,t+1}, \qquad\text{(A-2)}\end{aligned}$$

where the second to last line follows from the analyst price target decomposition in equation (1.4). The last line follows from the definitions of $i^j_{t,t+1}$ and $b^j_{t,t+1}$ in equations (1.12) and (1.11), respectively.

2.4.2 Proof of Proposition 2

Given results from Proposition 1 above, the proof for Proposition 2 is trivial; however, I will not simply begin with the result from Proposition 1 so that I can show why Assumption 3 is not necessary for Proposition 2. Given Assumptions 1 and 2, we can express the expected difference between $R^j_{t,t+n}$ and $R^j_{t,t}$ as

$$\begin{aligned}
\mathbb{E}\left[R^j_{t,t+n} - R^j_{t,t}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right] &= \frac{\hat{\mathbb{E}}\left[P^j_{t+n}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right] - P^j_{t-1}}{P^j_{t-1}} - \frac{\hat{\mathbb{E}}\left[P^j_{t+1}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right] - P^j_{t-1}}{P^j_{t-1}} \\
&= \frac{\hat{\mathbb{E}}\left[P^j_{t+n}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right] - \hat{\mathbb{E}}\left[P^j_{t+1}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right]}{P^j_{t-1}} \\
&= \frac{(1-\delta_n)\,\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right] + \delta_n\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\right] + \gamma_n\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]}{P^j_{t-1}} \\
&\quad - \frac{(1-\delta_0)\,\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right] + \delta_0\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\right] + \gamma_0\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]}{P^j_{t-1}} \\
&= \frac{(\delta_n-\delta_0)\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right] - \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]\right]}{P^j_{t-1}} \\
&\quad + \frac{(\gamma_n-\gamma_0)\,\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]}{P^j_t} \\
&\equiv (\delta_n-\delta_0)\,\frac{\left(I^j_{t,t+1} + B^{j,\perp}_{t,t+1}\right)}{P^j_{t-1}} + (\gamma_n-\gamma_0)\,\frac{\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]}{P^j_{t-1}} \\
&\equiv (\delta_n-\delta_0)\, i^j_{t,t+1} + (\gamma_n-\gamma_0)\, b^j_{t,t+1}, \qquad \text{(A-3)}
\end{aligned}$$

where the second to last line follows from the analyst price target decomposition in equation (1.4). The last line follows from the definitions of $i^j_{t,t+1}$ and $b^j_{t,t+1}$ in equations (1.12) and (1.11), respectively. Note that Assumption 3 is not needed for Proposition 2 because the terms related to P^j_{t-1} in the numerator cancel in this case (in line 2 of the expressions above).

2.5 Empirical Tests: Models 1 and 3

In this section, I run my main empirical tests using Models 1 and 3 (3 and 15 characteristics, respectively) to estimate analyst-expected return bias according to equation (1.21). I compute expected returns conditional on characteristics according to these models as well, then compute the implied information component according to equation (1.10). Results can be found in Tables A-5, A-6, A-7, and A-8. Results are qualitatively similar to those in my main results based on Model 2 (7 characteristics).

Table A-5: Results Based on Empirical Tests 1-4 (Cumulative Return Tests, Model 1)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$i^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$i^j_{t,t+1}$	5.23	5.51	5.60	5.64	5.69	5.38							5.25	5.51	5.60	5.64	5.66	5.37
	[22.41]	[18.50]	[13.85]	[11.18]	[8.79]	[6.73]							[23.71]	[19.15]	[14.28]	[11.39]	[8.84]	[6.65]
$b^j_{t,t+1}$							1.04	0.96	0.86	0.87	0.89	1.41	1.19	1.14	1.06	1.08	1.12	1.64
							[6.06]	[3.64]	[2.30]	[1.86]	[1.21]	[1.47]	[7.12]	[4.53]	[2.94]	[2.37]	[1.54]	[1.75]
R^2	0.16	0.10	0.07	0.06	0.03	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.18	0.12	0.09	0.07	0.05	0.03
N	1,466	1,466	1,465	1,464	1,465	1,464	1,466	1,466	1,465	1,464	1,465	1,464	1,466	1,466	1,465	1,464	1,465	1,464

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$\bar{i}^j_{t,t+1}$	3.30	3.66	3.97	4.21	4.69	4.69							3.46	3.80	4.09	4.36	4.88	5.11
	[19.61]	[14.74]	[12.37]	[11.38]	[9.28]	[9.85]							[20.92]	[15.81]	[13.32]	[12.13]	[9.76]	[9.95]
$b^j_{t,t+1}$							1.04	0.96	0.86	0.87	0.89	1.41	1.44	1.39	1.28	1.33	1.34	1.87
							[6.06]	[3.64]	[2.30]	[1.86]	[1.21]	[1.47]	[9.00]	[5.61]	[3.61]	[2.91]	[1.72]	[1.96]
R^2	0.09	0.06	0.05	0.04	0.03	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.12	0.08	0.06	0.06	0.04	0.04
N	1,209	1,208	1,208	1,207	1,207	1,205	1,466	1,466	1,465	1,464	1,465	1,464	1,214	1,213	1,213	1,212	1,212	1,210

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) to implement Empirical Tests 1-4. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using 3 control characteristics from Model 1 estimated using 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{t,t+n}$ are cumulative returns for stock j from month t to month $t+n$ ($n \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table A-6: Results Based on Empirical Tests 5-6 (Post-Announcement-Month Return Tests, Model 1)

Panel A: Tests using $i^j_{t,t+1}$															
	$i^j_{t,t+1}$ **only**					$b^j_{t,t+1}$ **only**					$i^j_{t,t+1}$ **and** $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$i^j_{t,t+1}$	0.27	0.36	0.39	0.44	0.11						0.26	0.35	0.37	0.40	0.07
	[2.29]	[1.49]	[1.05]	[0.77]	[0.14]						[2.24]	[1.46]	[1.03]	[0.70]	[0.09]
$b^j_{t,t+1}$						-0.07	-0.18	-0.17	-0.15	0.37	-0.05	-0.13	-0.11	-0.08	0.43
						[-0.64]	[-0.83]	[-0.55]	[-0.25]	[0.44]	[-0.45]	[-0.63]	[-0.37]	[-0.14]	[0.54]
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02
N	1,466	1,465	1,464	1,465	1,464	1,466	1,465	1,464	1,465	1,464	1,466	1,465	1,464	1,465	1,464

Panel B: Tests using $\bar{i}^j_{t,t+1}$															
	$\bar{i}^j_{t,t+1}$ **only**					$b^j_{t,t+1}$ **only**					$\bar{i}^j_{t,t+1}$ **and** $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$\bar{i}^j_{t,t+1}$	0.36	0.65	0.90	1.37	1.36						0.34	0.61	0.89	1.41	1.61
	[3.03]	[3.27]	[3.58]	[3.40]	[2.92]						[3.12]	[3.38]	[3.77]	[3.67]	[3.63]
$b^j_{t,t+1}$						-0.07	-0.18	-0.17	-0.15	0.37	-0.06	-0.17	-0.12	-0.11	0.41
						[-0.64]	[-0.83]	[-0.55]	[-0.25]	[0.44]	[-0.58]	[-0.82]	[-0.39]	[-0.17]	[0.50]
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02
N	1,208	1,208	1,207	1,207	1,205	1,466	1,465	1,464	1,465	1,464	1,213	1,213	1,212	1,212	1,210

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.23) to implement Empirical Tests 5 and 6. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using 3 control characteristics from Model 1 estimated using 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

Table A-7: Results Based on Empirical Tests 1-4 (Cumulative Return Tests, Model 3)

Panel A: Tests using $i^j_{t,t+1}$																		
	$i^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$i^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$i^j_{t,t+1}$	4.94	5.27	5.39	5.51	5.80	5.97							4.93	5.24	5.35	5.46	5.69	5.82
	[24.23]	[22.49]	[18.84]	[15.95]	[14.47]	[10.76]							[26.09]	[23.93]	[19.80]	[16.54]	[14.81]	[11.22]
$b^j_{t,t+1}$							0.93	0.79	0.57	0.49	0.25	0.37	1.14	1.02	0.82	0.75	0.52	0.68
							[5.07]	[2.71]	[1.37]	[0.92]	[0.29]	[0.38]	[6.41]	[3.61]	[2.03]	[1.44]	[0.64]	[0.72]
R^2	0.16	0.10	0.07	0.06	0.04	0.02	0.03	0.03	0.03	0.02	0.02	0.02	0.19	0.13	0.10	0.08	0.06	0.04
N	1,317	1,317	1,316	1,315	1,316	1,314	1,317	1,317	1,316	1,315	1,316	1,314	1,317	1,317	1,316	1,315	1,316	1,314
Panel B: Tests using $\bar{i}^j_{t,t+1}$																		
	$\bar{i}^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$\bar{i}^j_{t,t+1}$	3.30	3.66	3.97	4.21	4.69	4.69							3.64	3.91	4.15	4.33	4.65	4.66
	[19.61]	[14.74]	[12.37]	[11.38]	[9.28]	[9.85]							[22.08]	[16.61]	[14.17]	[12.42]	[10.34]	[12.42]
$b^j_{t,t+1}$							0.93	0.79	0.57	0.49	0.25	0.37	1.37	1.22	1.00	0.93	0.59	0.64
							[5.07]	[2.71]	[1.37]	[0.92]	[0.29]	[0.38]	[7.93]	[4.37]	[2.48]	[1.77]	[0.69]	[0.73]
R^2	0.09	0.06	0.05	0.04	0.03	0.02	0.03	0.03	0.03	0.02	0.02	0.02	0.13	0.09	0.07	0.06	0.05	0.04
N	1,209	1,208	1,208	1,207	1,207	1,205	1,317	1,317	1,316	1,315	1,316	1,314	1,100	1,099	1,099	1,098	1,098	1,096

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) to implement Empirical Tests 1-4. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using 15 control characteristics from Model 3 estimated using 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{t,t+n}$ are cumulative returns for stock j from month t to month $t+n$ ($n \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table A-8: Results Based on Empirical Tests 5-6 (Post-Announcement-Month Return Tests, Model 3)

Panel A: Tests using $i^j_{t,t+1}$															
	$i^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$i^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$i^j_{t,t+1}$	0.33	0.44	0.55	0.85	1.00						0.30	0.41	0.51	0.75	0.85
	[4.32]	[3.23]	[2.61]	[2.85]	[2.18]						[4.24]	[3.08]	[2.47]	[2.46]	[1.87]
$b^j_{t,t+1}$						-0.13	-0.35	-0.44	-0.68	-0.55	-0.11	-0.31	-0.40	-0.63	-0.49
						[-0.99]	[-1.41]	[-1.21]	[-1.02]	[-0.66]	[-0.84]	[-1.27]	[-1.10]	[-0.95]	[-0.60]
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.02
N	1,317	1,316	1,315	1,316	1,314	1,317	1,316	1,315	1,316	1,314	1,317	1,316	1,315	1,316	1,314

Panel B: Tests using $\bar{i}^j_{t,t+1}$															
	$\bar{i}^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$\bar{i}^j_{t,t+1}$	0.36	0.65	0.90	1.37	1.36						0.27	0.50	0.68	1.00	0.99
	[3.03]	[3.27]	[3.58]	[3.40]	[2.92]						[2.75]	[3.08]	[3.07]	[3.07]	[3.19]
$b^j_{t,t+1}$						-0.13	-0.35	-0.44	-0.68	-0.55	-0.14	-0.36	-0.44	-0.76	-0.71
						[-0.99]	[-1.41]	[-1.21]	[-1.02]	[-0.66]	[-1.05]	[-1.45]	[-1.18]	[-1.07]	[-0.95]
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.03
N	1,208	1,208	1,207	1,207	1,205	1,317	1,316	1,315	1,316	1,314	1,099	1,099	1,098	1,098	1,096

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.23) to implement Empirical Tests 5 and 6. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using 15 control characteristics from Model 3 estimated using 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

CHAPTER 3

ONLINE APPENDIX

OA.1 Propositions 1 and 2 with Discounting and Expected Returns Unrelated to Price Target Announcements

OA.1.1 Updated Assumptions and Propositions 1a and 2a

In this subsection I relax Assumptions 1 and 2 to allow for a risk premium in months subsequent to the announcement month. I still maintain the assumption that there is no risk premium in the announcement month, because announcement-month returns are dominated by announcement-window returns and adding a risk premium would unnecessarily complicate the analysis. The modified Assumptions 1 and 2 are as follows.

Assumption 1a: *After observing an analyst price target, $\tilde{P}^j_{t,t+1}$, in month t the market optimally updates expected future stock prices according to*

$$\mathbb{E}\left[P^j_{t+n}|\mathcal{F}^M_t,\,\tilde{P}^j_{t,t+1}\right] = \left[(1-\theta)\,\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]+\theta\left[\tilde{P}^j_{t,t+1}-\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\right]\right]\left(1+\overline{R}^j_t\right)^{n-1}, \quad \text{(OA-1)}$$

but may incorrectly update according to

$$\begin{aligned}\hat{\mathbb{E}}\left[P^j_{t+n}|\mathcal{F}^M_t,\,\tilde{P}^j_{t,t+1}\right] = {} & \left[(1-\delta_n)\,\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]+\delta_n\left[\tilde{P}^j_{t,t+1}-\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\right]\right. \\ & \left. +\gamma_n\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\right]\left(1+\overline{R}^j_t\right)^{n-1}, \quad \text{(OA-2)}\end{aligned}$$

where P^j_{t+n} is the price of stock j in month $t+n$ with $n \geq 1$ and $\overline{R}^j_t$ is a discount rate that the market agrees upon for stock j at the end of month t.

Assumption 2a: *The price P^j_t is set according to expectations about next period's price, P^j_{t+1}, according to*

$$P_t^j = \frac{\hat{\mathbb{E}}\left[P_{t+1}^j|\mathcal{F}_t\right]}{1+\overline{R}_t^j}, \tag{OA-3}$$

where $\hat{\mathbb{E}}$ represents a potentially distorted measure as in equation (OA-2), and $\overline{R}_t^j$ is a discount rate that the market agrees upon for stock j at the end of month t.

Some comments about these assumptions are in order. These assumptions rely on the market agreeing on an appropriate discount rate for stock j, and that it remains the same as its value at the end of date t for all future relevant dates $t+n$. To the extent that discount rates for a given stock are slow-moving, and my horizons are not too large, this is a reasonable assumption. Finally, consider expectations about P_{t+1}^j at the end of date t according to equation (OA-1):

$$\mathbb{E}\left[P_{t+1}^j|\mathcal{F}_t^M,\, \tilde{P}_{t,t+1}^j\right] = (1-\theta)\,\mathbb{E}\left[P_{t+1}^j|\mathcal{F}_t^M\right] + \theta\left[\tilde{P}_{t,t+1}^j - \mathbb{E}\left[B_{t,t+1}^j|\mathcal{F}_t^M\right]\right].$$

Then, according to equation (OA-1) the price P_t^j is set according to

$$P_t^j = \frac{(1-\theta)\,\mathbb{E}\left[P_{t+1}^j|\mathcal{F}_t^M\right] + \theta\left[\tilde{P}_{t,t+1}^j - \mathbb{E}\left[B_{t,t+1}^j|\mathcal{F}_t^M\right]\right]}{1+\overline{R}_t^j}.$$

That is, the price at the end of the announcement month t is just the expected price at the end of month $t+1$ with the appropriate discount rate applied. Finally, given information in $\mathcal{F}_t^M$ and the analyst price target issued at date t, expectations of prices at dates after $t+1$ are just the expectations of the date $t+1$ price inflated by the appropriate discount rate. These new assumptions lead to the following versions of Propositions 1 and 2.

Proposition 1a (Cumulative expected returns including announcement month): *Given Assumptions 1a, 2a, and 3, when expectations are updated according to equation (OA-2) and correctly incorporate information in analyst price targets over the following n months according to equation (OA-1), the expected cumulative return on stock j from* *announcement month t to $t+n$ (including month t) with $n \geq 0$ is*

$$\mathbb{E}\left[R^j_{t,t+n}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right] = \left[\left(1+\overline{R}^j_t\right)^n - 1\right]\frac{P^j_t}{P^j_{t-1}} + \delta_n\left[\left(1+\overline{R}^j_t\right)^{n-1} i^j_{t,t+1}\right] + \gamma_n\left[\left(1+\overline{R}^j_t\right)^{n-1} b^j_{t,t+1}\right], \tag{OA-4}$$

where $R^j_{t,t+n}$ represents returns from the beginning of month t to the end of month $t+n$, and $\delta_n$and γ_n represent updating weights applied to expectations over prices in month n. Furthermore, if the market correctly incorporates the information in analyst price targets by month N, then $\delta_N = \theta$ and $\gamma_N = 0$.

Proof: See below.

Proposition 2a (Cumulative expected returns excluding announcement month): *Given Assumptions 1a and 2a, the expected difference between returns on stock j from month t to $t+n$ (including month t) and month t with $n \geq 1$ is*

$$\begin{aligned}\mathbb{E}\left[R^j_{t,t+n} - R^j_{t,t}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right] &= \left[\left(1+\overline{R}^j_t\right)^n - 1\right]\frac{P^j_t}{P^j_{t-1}} \\ &+ \left[\frac{\left(1+\overline{R}^j_t\right)^n \delta_n - \delta_0}{1+\overline{R}^j_t}\right] i^j_{t,t+1} \\ &+ \left[\frac{\left(1+\overline{R}^j_t\right)^n \gamma_n - \gamma_0}{1+\overline{R}^j_t}\right] b^j_{t,t+1},\end{aligned} \tag{OA-5}$$

where $R^j_{t,t+n}$ represents returns from the beginning of month t to the end of month $t+n$, and $\delta_n$and γ_n represent updating weights applied to expectations over prices in month n. Furthermore, if the market correctly incorporates the information in analyst price targets by month N, then $\delta_N - \delta_0 = \theta - \delta_0$ and $\gamma_N - \gamma_0 = 0$.

Proof: See below.

OA.1.2 Empirical Tests Based on Propositions 1a and 2a

In this section, I implement Empirical Tests 1a-6a (i.e., the analogous tests based on Propositions 1a and 2a above). To do this, I consider regressions of the following form:

$$R^j_{t,t} = a_t + \delta_0 \frac{i^j_{t,t+1}}{1+\overline{R}^j_t} + \gamma_0 \frac{b^j_{t,t+1}}{1+\overline{R}^j_t} + \varepsilon^j_{t,t} \tag{OA-6}$$

$$\begin{aligned} R^j_{t,t+n} &= a_t + b\left[\left(1+\overline{R}^j_t\right)^n - 1\right]\frac{P^j_t}{P^j_{t-1}} + \delta_n\left[\left(1+\overline{R}^j_t\right)^{n-1} i^j_{t,t+1}\right] \\ &\quad + \gamma_n\left[\left(1+\overline{R}^j_t\right)^{n-1} b^j_{t,t+1}\right] + \varepsilon^j_{t,t+n} \end{aligned} \tag{OA-7}$$

$$\begin{aligned} R^j_{t,t+n} - R^j_{t,t} &= a_t + b\left[\left(1+\overline{R}^j_t\right)^n - 1\right]\frac{P^j_t}{P^j_{t-1}} \\ &\quad + (\delta_n - \delta_0)\left[\left(1+\overline{R}^j_t\right)^{n-1} i^j_{t,t+1}\right] \\ &\quad + (\gamma_n - \gamma_0)\left[\left(1+\overline{R}^j_t\right)^{n-1} b^j_{t,t+1}\right] + \varepsilon^j_{t,t+n}, \end{aligned} \tag{OA-8}$$

where all variables are as defined previously. A few comments are in order about these specifications. First, I use expected returns from Kelly et al. (2018) as proxies for $\overline{R}^j_t$ because they are more accurate measures of stock-level expected returns than my own expected return measures conditional on characteristics.[OA-1] Second, I make the following assumption in equation (OA-8):

$$\frac{1}{1+\overline{R}^j_t} \approx \frac{\left(1+\overline{R}^j_t\right)^n}{1+\overline{R}^j_t}.$$

These two variable are extremely collinear for low values of n, so estimating the regression directly implied by Proposition 2a results in standard issues associated with highly collinear

OA-1. I would like to thank Seth Pruitt for providing me with this data.

regressors.[OA-2]

Results can be found below in Tables OA-1 and OA-2, and are generally in line with those from my main tests reported in Tables 1.3 and 1.4. Table OA-1 presents results from Empirical Tests 1a-4a. First, I reject the null hypotheses in Empirical Tests 1a and 3a that there is no reaction to the bias and information components in analyst-expected returns in the announcement month. The announcement month coefficients on the bias and information terms in Table OA-1 are positive and statistically significant in both Panels A and B (i.e., using both information component measures). I fail to reject the null from Empirical Test 2a that the coefficients on the bias component are different than zero beginning at the six month horizon in both panels. I reject the null from Empirical Test 4a that the coefficients on the information component are zero for all horizons investigated. Finally, results from Empirical Tests 5a and 6a are provided in Table OA-2. When using $i^j_{t,t+1}$ as the information component measure, I reject the null that $\delta_n - \delta_0 = 0$ for $n = 1$ (i.e., the coefficient on $\left(1 + \overline{R}^j_t\right)^{n-1} \bar{i}^j_{t,t+1}$ when $n = 1$ is statistically significant and positive), but fail to reject it for $n \geq 2$. When using $\bar{i}^j_{t,t+1}$ as the information component measure, I reject this null at all horizons investigated and again find that estimated coefficients are positive. I cannot reject the null that $\gamma_n - \gamma_0 = 0$ at any horizon. These results again lead to the same conclusion as in my main results: the market underweights the information component in analyst-expected returns when updating expectations about future prices; however, there is not statistically significant evidence that the market overweights the bias component in these unconditional tests (i.e., not splitting the data into size subsets, for instance).

There is one salient difference between the patterns I observe here and those in my main results. Namely, the coefficient on $\left(1 + \overline{R}^j_t\right)^{n-1} i^j_{t,t+1}$ in Panel A of Table OA-1 decreases at the 6- and 12-month horizons. This could be the result of attenuation bias introduced by errors in the estimate of $\overline{R}^j_t$ interacting with the $i^j_{t,t+1}$ estimate and compounding at

OA-2. Cross-sectional regressions of one on the other using either my expected return estimates or those from Kelly et al. (2018) yield average R-squared values >99% when $n = 0$, and >80% or >60%, respectively, when $n = 6$.

longer horizons, however, a further investigation of this issue is beyond the scope of my analysis. The analogous coefficients on $\left(1+\overline{R}_t^j\right)^{n-1}\bar{i}_{t,t+1}^j$ in Panel B are approximately non-decreasing across all horizons, which is further support for the permanent nature of the impact of the information component on prices. These findings are also likely related to assumptions behind regression equations (OA-6)-(OA-8) becoming less accurate at longer horizons.

Table OA-1: Results Based on Empirical Tests 1a-4a (Cumulative Return Tests, Model 2)

Panel A: Tests using $i^j_{t,t+1}$						
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$\left[\left(1+\overline{R}^j_t\right)^n - 1\right]\frac{P^j_t}{P^j_{t-1}}$		1.83	1.20	1.01	0.79	0.63
		[16.81]	[16.92]	[15.68]	[14.09]	[11.46]
$\left(1+\overline{R}^j_t\right)^{n-1} i^j_{t,t+1}$	5.30	5.30	5.27	5.23	4.92	4.01
	[22.97]	[18.85]	[14.94]	[12.20]	[9.72]	[8.47]
$\left(1+\overline{R}^j_t\right)^{n-1} b^j_{t,t+1}$	1.19	1.18	0.97	0.90	0.65	0.78
	[7.21]	[4.43]	[2.56]	[1.79]	[0.80]	[1.08]
R^2	0.19	0.16	0.14	0.13	0.12	0.13
N	1,059	1,059	1,059	1,059	1,059	1,059

Panel B: Tests using $\bar{i}^j_{t,t+1}$						
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$\left[\left(1+\overline{R}^j_t\right)^n - 1\right]\frac{P^j_t}{P^j_{t-1}}$		2.20	1.39	1.13	0.85	0.66
		[18.87]	[18.77]	[17.26]	[15.48]	[12.47]
$\left(1+\overline{R}^j_t\right)^{n-1} \bar{i}^j_{t,t+1}$	3.98	4.40	4.67	4.88	5.19	4.93
	[19.45]	[15.02]	[12.84]	[11.11]	[8.41]	[7.75]
$\left(1+\overline{R}^j_t\right)^{n-1} b^j_{t,t+1}$	1.30	1.29	1.06	1.02	0.81	0.97
	[8.12]	[4.74]	[2.68]	[1.89]	[0.89]	[1.29]
R^2	0.12	0.13	0.12	0.12	0.12	0.14
N	879	879	879	879	879	879

Notes: Fama and MacBeth (1973) regressions using the specification in equations (OA-6) and (OA-7) to implement Empirical Tests 1a-4a. $\overline{R}^j_t$ is stock-month level expected return data from Kelly et al. (2018) and is available until 2014. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. P^j_{t-1} is the end-of-month stock price in the month before the announcement month, and P^j_t is the end-of-month stock price in the announcement month. $R^j_{t,t+n}$ are cumulative returns for stock j from month $t+1$ to month $t+n$ ($n \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 1999-2014 to to expected return data availability from Kelly et al. (2018). $i^j_{t,t+1}$, $\bar{i}^j_{t,t+1}$, and $b^j_{t,t+1}$ are cross-sectionally z-transformed as in my main results so as to be comparable with my main results in Table 1.3. Results are similar if I apply the z-transformation to $\left(1+\overline{R}^j_t\right)^{n-1} i^j_{t,t+1}$, $\left(1+\overline{R}^j_t\right)^{n-1} \bar{i}^j_{t,t+1}$, and $\left(1+\overline{R}^j_t\right)^{n-1} b^j_{t,t+1}$. Realized returns are in percent. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table OA-2: Results Based on Empirical Tests 5a-6a (Post-Announcement-Month Return Tests, Model 2)

Panel A: Tests using $i^j_{t,t+1}$					
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$\left[\left(1+\overline{R}^j_t\right)^n - 1\right] \frac{P^j_t}{P^j_{t-1}}$	0.67	0.63	0.64	0.61	0.55
	[11.93]	[14.43]	[13.98]	[12.65]	[10.76]
$\left(1+\overline{R}^j_t\right)^{n-1} i^j_{t,t+1}$	0.27	0.28	0.28	0.15	-0.35
	[2.60]	[1.37]	[0.91]	[0.31]	[-0.63]
$\left(1+\overline{R}^j_t\right)^{n-1} b^j_{t,t+1}$	-0.06	-0.25	-0.31	-0.51	-0.28
	[-0.42]	[-1.05]	[-0.87]	[-0.74]	[-0.42]
R^2	0.04	0.04	0.05	0.07	0.10
N	1,059	1,059	1,059	1,059	1,059

Panel B: Tests using $\bar{i}^j_{t,t+1}$					
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$\left[\left(1+\overline{R}^j_t\right)^n - 1\right] \frac{P^j_t}{P^j_{t-1}}$	0.68	0.63	0.63	0.61	0.55
	[11.18]	[13.92]	[13.93]	[13.17]	[11.36]
$\left(1+\overline{R}^j_t\right)^{n-1} \bar{i}^j_{t,t+1}$	0.36	0.68	0.93	1.39	1.49
	[3.05]	[3.51]	[3.49]	[3.11]	[3.25]
$\left(1+\overline{R}^j_t\right)^{n-1} b^j_{t,t+1}$	-0.08	-0.30	-0.33	-0.49	-0.21
	[-0.57]	[-1.16]	[-0.79]	[-0.61]	[-0.31]
R^2	0.04	0.05	0.05	0.07	0.10
N	879	879	879	879	879

Notes: Fama and MacBeth (1973) regressions using the specification in equation (OA-8) to implement Empirical Tests 5a and 6a. $\overline{R}^j_t$ is stock-month level expected return data from Kelly et al. (2018) and is available until 2014. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. P^j_{t-1} is the end-of-month stock price in the month before the announcement month, and P^j_t is the end-of-month stock price in the announcement month. $R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 1999-2014 to to expected return data availability from Kelly et al. (2018). $i^j_{t,t+1}$, $\bar{i}^j_{t,t+1}$, and $b^j_{t,t+1}$ are cross-sectionally z-transformed and realized returns are in percent, as in my main results so as to be comparable with my main results in Table 1.4. Results are similar if I apply the z-transformation to $\left(1+\overline{R}^j_t\right)^{n-1} i^j_{t,t+1}$, $\left(1+\overline{R}^j_t\right)^{n-1} \bar{i}^j_{t,t+1}$, and $\left(1+\overline{R}^j_t\right)^{n-1} b^j_{t,t+1}$. Realized returns are in percent. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

OA.1.3 Proofs of Propositions 1a and 2a

Proof of Proposition 1a

I begin by deriving Proposition 1a under the case where $n = 0$ (i.e., for announcement month expected returns) and then turn to the case where $n \geq 1$. Under Assumption 1a, the market updates expectations about future prices according to equation (1.7):

$$\hat{\mathbb{E}}\left[P^j_{t+1}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right] = (1-\delta_0)\,\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]+\delta_0\left[\tilde{P}^j_{t,t+1}-\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\right]+\gamma_0\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right].$$

By Assumption 2a, the market will set price P^j_t such that

$$P^j_t = \frac{\hat{\mathbb{E}}\left[P^j_{t+1}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right]}{1+\overline{R}^j_t}.$$

The announcement-month return is then

$$R^j_{t,t} = \frac{\frac{\hat{\mathbb{E}}\left[P^j_{t+1}|\mathcal{F}^M_t,\tilde{P}^j_{t,t+1}\right]}{1+\overline{R}^j_t} - P^j_{t-1}}{P^j_{t-1}}.$$

I can also express P^j_{t-1} as

$$\begin{aligned} P^j_{t-1} &= \mathbb{E}\left[P^j_t|\mathcal{F}^M_{t-1}\right] \\ &= \mathbb{E}\left[\frac{\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]}{1+\overline{R}^j_t}|\mathcal{F}^M_{t-1}\right] \\ &= \frac{\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_{t-1}\right]}{1+\overline{R}^j_t} \\ &= \frac{\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]}{1+\overline{R}^j_t}, \end{aligned}$$

where the first line follows from Assumption 2a (no risk premium in the announcement month), the second line follows from Assumption 2a (discount using $\overline{R}_t^j$ in months after the announcement month), the third line follows from the law of iterated expectations, and the last line follows from Assumption 3 ($\mathbb{E}\left[P_{t+1}^j|\mathcal{F}_t^M\right] = \mathbb{E}\left[P_{t+1}^j|\mathcal{F}_{t-1}^M\right]$). Combining these expressions yields

$$
\begin{aligned}
R_{t,t}^j &= \frac{\frac{\hat{\mathbb{E}}\left[P_{t+1}^j|\mathcal{F}_t^M,\tilde{P}_{t,t+1}^j\right]}{1+\overline{R}_t^j} - P_{t-1}^j}{P_{t-1}^j} \\
&= \frac{\frac{\hat{\mathbb{E}}\left[P_{t+1}^j|\mathcal{F}_t^M,\tilde{P}_{t,t+1}^j\right]}{1+\overline{R}_t^j} - \frac{\mathbb{E}\left[P_{t+1}^j|\mathcal{F}_t^M\right]}{1+\overline{R}_t^j}}{P_{t-1}^j} \\
&= \frac{(1-\delta_0)\,\mathbb{E}\left[P_{t+1}^j|\mathcal{F}_t^M\right] + \delta_0\left[\tilde{P}_{t,t+1}^j - \mathbb{E}\left[B_{t,t+1}^j|\mathcal{F}_t^M\right]\right]}{P_{t-1}^j\left(1+\overline{R}_t^j\right)} \\
&\quad + \frac{\gamma_0\mathbb{E}\left[B_{t,t+1}^j|\mathcal{F}_t^M\right] - \mathbb{E}\left[P_{t+1}^j|\mathcal{F}_t^M\right]}{P_{t-1}^j\left(1+\overline{R}_t^j\right)} \\
&= \frac{\delta_0\left[\tilde{P}_{t,t+1}^j - \mathbb{E}\left[P_{t+1}^j|\mathcal{F}_t^M\right] - \mathbb{E}\left[B_{t,t+1}^j|\mathcal{F}_t^M\right]\right] + \gamma_0\mathbb{E}\left[B_{t,t+1}^j|\mathcal{F}_t^M\right]}{P_{t-1}^j\left(1+\overline{R}_t^j\right)} \\
&\equiv \frac{\delta_0\left(I_{t,t+1}^j + B_{t,t+1}^{j,\perp}\right) + \gamma_0\mathbb{E}\left[B_{t,t+1}^j|\mathcal{F}_t^M\right]}{P_{t-1}^j\left(1+\overline{R}_t^j\right)} \\
&\equiv \frac{\delta_0}{1+\overline{R}_t^j}i_{t,t+1}^j + \frac{\gamma_0}{1+\overline{R}_t^j}b_{t,t+1}^j, \qquad \text{(OA-9)}
\end{aligned}
$$

where the second to last line follows from the analyst price target decomposition in equation (1.4). The last line follows from the definitions of $i_{t,t+1}^j$ and $b_{t,t+1}^j$ in equations (1.12) and (1.11), respectively. The only difference between this and that from Proposition 1 is that the information and bias components are normalized by the discount rate. Note that if we set $\overline{R}_t^j = 0$, the original Proposition 1 obtains.

Next, for the case where $n \geq 1$, the realized return from t to $t+n$ (including that in month t) is

$$R_{t,t+n} \equiv \frac{P^j_{t+n} - P^j_{t-1}}{P^j_{t-1}}.$$

Taking the expectation with respect to information at the end of month t yields the expected cumulative return as of date t:

$$\mathbb{E}\left[R^j_{t,t+n}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right] = \frac{\hat{\mathbb{E}}\left[P^j_{t+n}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right] - P^j_{t-1}}{P^j_{t-1}}.$$

Applying Assumption 1a yields

$$\mathbb{E}\left[R^j_{t,t+n}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right] = \frac{(1-\delta_n)\,\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]\left(1+\overline{R}^j_t\right)^{n-1} + \delta_n\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\right]\left(1+\overline{R}^j_t\right)^{n-1}}{P^j_{t-1}} + \frac{\gamma_n \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\left(1+\overline{R}^j_t\right)^{n-1} - P^j_{t-1}}{P^j_{t-1}}.$$

As above, we have $P^j_{t-1} = \frac{\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]}{1+\overline{R}^j_t}$, so

$$
\begin{aligned}
\mathbb{E}\left[R^j_{t,t+n}|\mathcal{F}^M_t,\, \tilde{P}^j_{t,t+1}\right] &= \frac{(1-\delta_n)\,\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]\left(1+\overline{R}^j_t\right)^n + \delta_n\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\right]\left(1+\overline{R}^j_t\right)^n}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} \\
&\quad + \frac{\gamma_n\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\left(1+\overline{R}^j_t\right)^n - \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} \\
&= \frac{\delta_n\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right] - \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]\right]\left(1+\overline{R}^j_t\right)^n}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} \\
&\quad + \frac{\gamma_n\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\left(1+\overline{R}^j_t\right)^n}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} + \frac{\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]\left(1+\overline{R}^j_t\right)^n - \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} \\
&= \frac{\delta_n\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right] - \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]\right]\left(1+\overline{R}^j_t\right)^n}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} \\
&\quad + \frac{\gamma_n\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\left(1+\overline{R}^j_t\right)^n}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} + \frac{\left(\left(1+\overline{R}^j_t\right)^n - 1\right)\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} \\
&= \left[\left(1+\overline{R}^j_t\right)^n - 1\right]\frac{\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]}{P^j_t\left(1+\overline{R}^j_t\right)}\frac{P^j_t}{P^j_{t-1}} \\
&\quad + \frac{\delta_n I^j_{t,t+1}\left(1+\overline{R}^j_t\right)^n + \gamma_n\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\left(1+\overline{R}^j_t\right)^n}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} \\
&\equiv \left[\left(1+\overline{R}^j_t\right)^n - 1\right]\frac{P^j_t}{P^j_{t-1}} \\
&\quad + \delta_n\left(1+\overline{R}^j_t\right)^{n-1} i^j_{t,t+1} + \gamma_n\left(1+\overline{R}^j_t\right)^{n-1} b^j_{t,t+1}, \qquad \text{(OA-10)}
\end{aligned}
$$

where the second to last line follows from the analyst price target decomposition in equation (1.4). The last line follows from this original definitions of $b^j_{t,t+1}$ and $i^j_{t,t+1}$ in equations (1.11) and (1.12). Note that if we set $\overline{R}^j_t = 0$, the original Proposition 1 obtains.

Proof of Proposition 2a

Given results from Proposition 1a above, the proof for Proposition 2a is trivial; however, I will not simply begin with the result from Proposition 1a so that I can show why Assumption 3 is not necessary for Proposition 2a. Given Assumptions 1a and 2a, we can express the expected difference between $R^j_{t,t+n}$ and $R^j_{t,t}$ as

$$\begin{aligned}
\mathbb{E}\left[R^j_{t,t+n} - R^j_{t,t}|\mathcal{F}^M_t, \tilde{P}^j_{t,t+1}\right] &= \frac{\hat{\mathbb{E}}\left[P^j_{t+n}|\mathcal{F}^M_t, \tilde{P}^j_{t,t+1}\right] - P^j_{t-1}}{P^j_{t-1}} - \frac{\frac{\hat{\mathbb{E}}\left[P^j_{t+1}|\mathcal{F}^M_t, \tilde{P}^j_{t,t+1}\right]}{1+\overline{R}^j_t} - P^j_{t-1}}{P^j_{t-1}} \\
&= \frac{(1-\delta_n)\,\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]\left(1+\overline{R}^j_t\right)^n + \delta_n\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\right]\left(1+\overline{R}^j_t\right)^n}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} \\
&\quad + \frac{\gamma_n \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\left(1+\overline{R}^j_t\right)^n}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} \\
&\quad - \frac{(1-\delta_0)\,\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right] + \delta_0\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\right] + \gamma_0 \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} \\
&= \frac{\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]\left(1+\overline{R}^j_t\right)^n}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} \\
&\quad + \frac{\delta_n\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right] - \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]\right]\left(1+\overline{R}^j_t\right)^n}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} \\
&\quad + \frac{\gamma_n \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]\left(1+\overline{R}^j_t\right)^n}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} \\
&\quad - \frac{\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right] + \delta_0\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right] - \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]\right] + \gamma_0 \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} \\
&= \frac{\left(\left(1+\overline{R}^j_t\right)^n - 1\right)\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} \\
&\quad + \frac{\left(\delta_n\left(1+\overline{R}^j_t\right)^n - \delta_0\right)\left[\tilde{P}^j_{t,t+1} - \mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right] - \mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]\right]}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} \\
&\quad + \frac{\left(\gamma_n\left(1+\overline{R}^j_t\right)^n - \gamma_0\right)\mathbb{E}\left[B^j_{t,t+1}|\mathcal{F}^M_t\right]}{P^j_{t-1}\left(1+\overline{R}^j_t\right)} \\
&= \frac{\left(\left(1+\overline{R}^j_t\right)^n - 1\right)\mathbb{E}\left[P^j_{t+1}|\mathcal{F}^M_t\right]}{P^j_t\left(1+\overline{R}^j_t\right)}\frac{P^j_t}{P^j_{t-1}} \\
&\quad + \frac{\left(\delta_n\left(1+\overline{R}^j_t\right)^n - \delta_0\right)}{1+\overline{R}^j_t} i^j_{t,t+1} + \frac{\left(\gamma_n\left(1+\overline{R}^j_t\right)^n - \gamma_0\right)}{1+\overline{R}^j_t} b^j_{t,t+1} \\
&= \left[\left(1+\overline{R}^j_t\right)^n - 1\right]\frac{P^j_t}{P^j_{t-1}} \\
&\quad + \frac{\left(\delta_n\left(1+\overline{R}^j_t\right)^n - \delta_0\right)}{1+\overline{R}^j_t} i^j_{t,t+1} + \frac{\left(\gamma_n\left(1+\overline{R}^j_t\right)^n - \gamma_0\right)}{1+\overline{R}^j_t} b^j_{t,t+1}. \qquad \text{(OA-11)}
\end{aligned}$$

The last line follows from the definitions of $i^j_{t,t+1}$ and $b^j_{t,t+1}$ in equations (1.12) and (1.11), respectively. Note that if we set $\overline{R}^j_t = 0$, the original Proposition 2 obtains.

OA.2 Testing the Joint Equivalence of Risk Premia

In this section, I develop two tests to test the joint equivalence of estimated characteristic risk premia based on realized returns and those based on analyst-expected returns in two ways. In order to run these tests, I must jointly estimate the coefficients (i.e., results in my main paper based on Fama and MacBeth (1973) regressions cannot be used for this purpose). In a first test, I set up a seemingly unrelated regression (SUR) system for the estimate and test whether characteristic coefficients are jointly equivalent. In a second test, I forecast analyst-expected return bias directly and test whether all coefficients are jointly zero. Both tests yield the same result: I reject that realized return-implied risk premia and analyst-implied risk premia are jointly equivalent across all three characteristics models.

Let $\tilde{R}^j_{t,t+1}$ represent analyst-expected returns and consider a projection onto characteristics X^j_t according to

$$\tilde{R}^j_{t,t+1} = a_t + c' X^j_t + u^j_t, \tag{OA-12}$$

where a^t is a time fixed effect and u^j_t is a residual that captures analyst expectations that are unrelated to the predictor variables such as private information. I assume $\mathbb{E}\left[u^j_t\right] = 0$. I also assume this error is independent of the explanatory variables (i.e., $\mathbb{E}\left[X^j_t u^j_t\right] = 0$). With these assumptions, I can consistently estimate parameters a_t and c in using ordinary least squares (OLS).

Next, consider a projection of realized returns onto the same characteristics according to

$$R^j_{t,t+1} = \mathbf{a_t} + \mathbf{c}' X^j_t + \mathbf{u}^j_{t,t+1}. \tag{OA-13}$$

The equation is analogous to equation (OA-12) with parameters and errors in bold to distinguish the two. I again rely on the standard OLS assumptions that $\mathbb{E}_t\left[\mathbf{u}^j_{t,t+1}\right] = 0$ and $\mathbb{E}_t\left[X^j_t \mathbf{u}^j_{t,t+1}\right] = 0$, which allows me to interpret OLS estimates of $\mathbf{a_t}$ and $\hat{\mathbf{c}}$ as consistent estimates of $\mathbf{a_t}$ and $\mathbf{c}$. I can then test the rational expectations null that $c = \mathbf{c}$ using the test statistic presented in the following proposition.

Proposition OA-1: *Let equations (OA-12) and (OA-13) define a seemingly unrelated regression system. Assume that the process* $\left\{\tilde{R}^j_{t,t+1}, R^j_{t,t+1}, X^j_t\right\}$ *is stationary and ergodic, and all moments are such that asymptotic distributions exist. Also assume* $\mathbb{E}\left[u^j_t\right] = 0\ \forall j$, $\mathbb{E}\left[X^j_t u^j_t\right] = 0\ \forall j$, $\mathbb{E}_t\left[\mathbf{u}^j_{t,t+1}\right] = 0\ \forall j$ and $\mathbb{E}_t\left[X^j_t \mathbf{u}^j_{t,t+1}\right] = 0\ \forall j$. *Then under the null hypothesis of rational expectations,* $N\left(R\hat{\beta}_N\right)'\left(R'\hat{\Omega}_N R\right)\left(R\hat{\beta}_N\right) \xrightarrow{d} \chi^2_K$ *as* $N \to \infty$ *where* N *is the number of firms in each cross-section,* $\hat{\beta}_N$ *is the estimate of a stacked set of analyst-expected return (c) and realized return coefficients* ($\mathbf{c}$), $\hat{\Omega}_N$ *is a consistent estimator of* $var\left(\beta_N\right)$, *and* R *is a* $K \times (2(T+K))$ *is a set of linear restrictions on* c *and* $\mathbf{c}$ *in* β *to test the null hypothesis that all differences between matching predictive variable coefficients are jointly zero.*

Proof: See below.

Proposition OA-1 provides a test statistic to test whether coefficients on predictive variables in equations (OA-12) and (OA-13) are jointly equivalent under the null that analysts have rational expectations (conditional on characteristics) over returns. Results from these regressions and the rational expectations test are reported for each of the three characteristics models in Panels A-C of Table OA-3, respectively. Although the population of firms with analyst-expected returns is slightly different than my filtered CRSP population based on characteristics (see Table A-2), I use all CRSP records to improve the precision of the realized return-implied risk premia. The rightmost columns in each panel report the χ^2 statistic and p-value associated with the null hypothesis that $c = \mathbf{c}$. The null is strongly rejected in all three models, indicating that coefficients in each model implied by realized returns and those implied by analyst-expected returns are not jointly equivalent. Results are similar when I limit the realized return sample to records with corresponding analyst-expected returns.

Table OA-3: Realized and Analyst-Expected Returns Regressed on Characteristics

Panel A: Model 1 (3 characteristics)								
Dep. var.:	R^j_{t+1}			$\tilde{R}^j_{t,t+1}$				
	Coeff	**t-stat**	R^2	**Coeff**	**t-stat**	R^2	χ^2	$p-\chi^2$
$LogSize_t$	-0.04	[-0.52]	0.13	-0.35	[-31.45]	0.14	41.97	0.00
$LogB/M_t$	0.23	[1.67]		-0.22	[-27.90]			
$Return_{t-12,t-1}$	0.31	[2.19]		-0.14	[-9.79]			
N	714,153			331,418				
Panel B: Model 2 (7 characteristics)								
Dep. var.:	R^j_{t+1}			$\tilde{R}^j_{t,t+1}$				
	Coeff	**t-stat**	R^2	**Coeff**	**t-stat**	R^2	χ^2	$p-\chi^2$
$LogSize_t$	-0.11	[-1.38]	0.13	-0.24	[-24.89]	0.16	60.60	0.00
$LogB/M_t$	0.12	[1.00]		-0.18	[-27.07]			
$Return_{t-11,t-1}$	0.24	[1.78]		-0.13	[-11.44]			
$LogIssues_{t-35,t}$	-0.16	[-3.24]		0.12	[28.68]			
$Accruals_t$	-0.03	[-0.96]		-0.04	[-8.58]			
ROA_t	0.18	[2.03]		-0.19	[-26.56]			
$LogAG_t$	-0.14	[-2.45]		0.05	[8.11]			
N	638,977			299,128				
Panel C: Model 3 (15 characteristics)								
Dep. var.:	R^j_{t+1}			$\tilde{R}^j_{t,t+1}$				
	Coeff	**t-stat**	R^2	**Coeff**	**t-stat**	R^2	χ^2	$p-\chi^2$
$LogSize_t$	-0.18	[-1.93]	0.13	-0.06	[-6.10]	0.18	172.29	0.00
$LogB/M_t$	0.04	[0.47]		-0.11	[-21.14]			
$Return_{t-11,t-1}$	0.24	[1.85]		-0.14	[-14.52]			
$LogIssues_{t-35,t}$	-0.06	[-1.69]		0.06	[13.74]			
$Accruals_t$	-0.02	[-0.74]		-0.02	[-5.30]			
ROA_t	0.17	[2.49]		-0.15	[-23.27]			
$LogAG_t$	-0.10	[-2.06]		0.02	[4.96]			
$DY_{t-11,t}$	-0.03	[-0.86]		-0.02	[-3.08]			
$LogReturn_{t-35,t-12}$	-0.12	[-1.27]		0.03	[4.77]			
$LogIssues_{t-11,t}$	-0.11	[-2.27]		0.03	[7.20]			
$Beta_t$	0.10	[0.66]		-0.07	[-6.19]			
$StdDev_{t-11,t}$	-0.18	[-1.50]		0.41	[30.15]			
$Turnover_{t-11,t}$	-0.07	[-0.77]		-0.07	[-11.56]			
$Debt/Price_t$	-0.11	[-2.64]		-0.02	[-2.86]			
$Sales/Price_t$	0.11	[2.30]		-0.01	[-2.10]			
N	635,357			297,672				

Notes: Regressions are run as a seemingly unrelated system at the monthly frequency according to equations (OA-12) and (OA-13). Panels A, B, and C use models with 3, 7, and 15 characteristics, respectively. All characteristics are cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected (percent) return next month. All data is from 1999-2017. Realized return panel regressions use all records that meet the CRSP filters and have corresponding characteristic values (i.e., these may not have corresponding analyst-expected return records). The last two columns contain the chi-squared statistic and associated p-value for the null hypothesis that realized return and analyst-expected return coefficients are jointly equivalent ($c = \mathbf{c}$). Standard errors are clustered on time (separately for each explanatory variable in the seemingly unrelated regressions). t-statistics are reported in brackets.

Proof of Proposition OA-1 I begin by noting that equations (OA-12) and (OA-13) define a system of seemingly unrelated regressions (SURs), since it is likely that the error terms in each equation are correlated. I therefore estimate this as a SUR system. To be concrete about matrix dimensions, assume that there are T periods, N firms, and K predictors. Let $\tilde{R}_{t,t+1}$ represent the stacked vector of all analyst-expected returns at time t so that it is a $N \times 1$ vector. Next, define $\tilde{R}$ as a stacked vector comprised of $\tilde{R}_{t,t+1}$ so that it is a $(NT) \times 1$ vector. Similarly, define X as the vector of predictors stacked by firms then time. Additionally, assume that X is also augmented by the time dummies so that its dimensions are $(NT) \times (T + K)$. I also augment c with the time dummy coefficients and call this variable C, similarly define $\mathbf{c}$ and $\mathbf{C}$. Let the errors, u_t^j, be stacked into u, and $\mathbf{u}_{t+1}^j$ be stacked in $\mathbf{u}$. Then, the stacked version of equation (OA-12) can be written as

$$\tilde{R} = XC + u, \tag{OA-14}$$

and the stacked version of equation (OA-13) can be written as

$$R = X\mathbf{C} + \mathbf{u}. \tag{OA-15}$$

Defining $\mathbf{X} \equiv I_2 \otimes X$, the OLS estimator for the SUR system is

$$\hat{\beta}_N \equiv \begin{bmatrix} \hat{C} \\ \hat{\mathbf{C}} \end{bmatrix} = \left[\mathbf{X}'\mathbf{X}\right]^{-1} \left[\mathbf{X}' \begin{bmatrix} \tilde{R} \\ R \end{bmatrix}\right], \tag{OA-16}$$

where I_2 is a 2×2 identity matrix. The asymptotic variance of the estimated parameters is (for fixed N and as $T \to \infty$)

$$\sqrt{N}\left(\hat{\beta}_N - \beta\right) \to \mathcal{N}\left(0,\ E\left[\mathbf{X}'\mathbf{X}\right]^{-1} S_w E\left[\mathbf{X}'\mathbf{X}\right]^{-1}\right), \tag{OA-17}$$

where S_w is the covariance matrix of the error terms. I compute this by clustering on time and firm, which corrects for both correlation between errors within a particular period (similar to the well-known procedure developed in Fama and MacBeth (1973)) as well as potential correlation over time.

Note that since all predictors are the same in both equations, that there is no efficiency gain from estimating using SUR and GLS.[OA-3] I therefore estimate this using a system ordinary least squares estimator.[OA-4] Under this specification, I can use standard software packages that incorporate clustering algorithms to estimate the error covariance matrix for inference.

Next, I derive the test statistic. Note that β represents the stacked vector of C and $\mathbf{C}$. I would like to test jointly whether the differences between all c and $\mathbf{c}$[OA-5] coefficients are zero. Let $\mathbf{0}_T$ and $\mathbf{1}_K$ represent vectors of zeros and ones where the number of elements are equal to T and K. The following result follows from standard arguments. Under the null hypothesis of rational expectations

$$N\left(R\hat{\beta}_N\right)'\left(R\hat{\Omega}_N R'\right)^{-1}\left(R\hat{\beta}_N\right)\xrightarrow{d}\chi^2_K,$$

where R is a $K\times(2(T+K))$ matrix comprised of zeros, ones, and negative ones that selects corresponding predictive variable coefficients from B and $\mathbf{B}$ for the test. for instance, in the case where $T=2$ and $K=2$ (i.e., 2 periods of data and 2 predictive variables), we have

$$R=\begin{bmatrix}1&0&0&0&-1&0&0&0\\0&1&0&0&0&-1&0&0\end{bmatrix},$$

where I have assumed the dummy variables are added in rows of $\mathbf{X}$ after the characteristics. $\hat{\Omega}_N$ is a consistent estimate of the covariance matrix in equation (OA-17).

In my second test, I run an analyst bias forecasting regression according to

OA-3. See Wooldridge (2010) Theorem 7.6.

OA-4. Wooldridge (2010) Section 7.3.2.

OA-5. Recall that c and $\mathbf{c}$ correspond to the elements of C and $\mathbf{C}$, respectively, that load on the predictive variables X.

$$\tilde{R}^j_{t,t+1} - R^j_{t+1} = a_{t+1} + c' X^j_t + u^j_{t+1}. \tag{OA-18}$$

I estimate this using a pooled regression, then simply use a χ^2 test to test the null that $c = 0$ (i.e., that all characteristic coefficients are jointly zero). Results for this estimation and test can be found below in Table OA-4. The null is strongly rejected in all three models, indicating that coefficients in each model implied by realized returns and those implied by analyst-expected returns are not jointly equivalent. Both tests imply that analyst-implied characteristic premia are not equivalent to those implied by realized returns, which supports similar findings in Engelberg et al. (2018) that a similar measure of analyst-expected returns is negatively correlated with an aggregated anomaly characteristic exposure variable.

Table OA-4: Analyst-Expected Return Bias Regressed on Characteristics

Panel A: Model 1 (3 characteristics)					
	Coeff	**t-stat**	R^2	χ^2	$p-\chi^2$
$LogSize_t$	-0.12	[-1.24]	0.17	18.71	0.00
$LogB/M_t$	-0.33	[-2.77]			
$Return_{t-12,t-1}$	-0.43	[-2.87]			
N	329,869				

Panel B: Model 2 (7 characteristics)					
	Coeff	**t-stat**	R^2	χ^2	$p-\chi^2$
$LogSize_t$	0.08	[0.92]	0.18	66.55	0.00
$LogB/M_t$	-0.22	[-2.12]			
$Return_{t-11,t-1}$	-0.34	[-2.44]			
$LogIssues_{t-35,t}$	0.30	[6.45]			
$Accruals_t$	-0.06	[-1.17]			
ROA_t	-0.32	[-4.41]			
$LogAG_t$	0.18	[2.92]			
N	297,710				

Panel C: Model 3 (15 characteristics)					
	Coeff	**t-stat**	R^2	χ^2	$p-\chi^2$
$LogSize_t$	0.16	[1.62]	0.18	115.58	0.00
$LogB/M_t$	-0.16	[-2.03]			
$Return_{t-11,t-1}$	-0.32	[-2.34]			
$LogIssues_{t-35,t}$	0.16	[3.61]			
$Accruals_t$	-0.06	[-1.19]			
ROA_t	-0.27	[-4.15]			
$LogAG_t$	0.13	[2.67]			
$DY_{t-11,t}$	0.03	[0.74]			
$LogReturn_{t-35,t-12}$	0.10	[1.11]			
$LogIssues_{t-11,t}$	0.16	[3.21]			
$Beta_t$	0.10	[0.62]			
$StdDev_{t-11,t}$	0.24	[1.72]			
$Turnover_{t-11,t}$	0.02	[0.32]			
$Debt/Price_t$	0.13	[2.04]			
$Sales/Price_t$	-0.09	[-1.05]			
N	296,257				

Notes: Regressions are run using a pooled estimator at the monthly frequency according to equation (OA-18). Panels A, B, and C use models with 3, 7, and 15 characteristics, respectively. All characteristics are cross-sectionally z-transformed and analyst-expected return error ($\tilde{R}^j_{t,t+1} - R^j_{t+1}$) is multiplied by 100, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected expected analyst-expected return error next month in percent. All data is from 1999-2017. The last two columns contain the chi-squared statistic and associated p-value for the null hypothesis that coefficients are jointly equal to zero ($c = 0$). Standard errors are clustered on time. t-statistics are reported in brackets.

OA.3 Trading Strategies: Detailed

Table OA-5: Portfolios Sorted on $i^j_{t,t+1}$ (Model 2)

Panel A: Equal-weighted portfolios

		Raw returns		FF3		FF3C		FF3CL		FF5		FF5C		HXZ	
	$\overline{i^p_{t,t+1}}$	$\overline{R^p_{t+1}}$	$t-stat$	α^{FF3}	$t-stat$	α^{FF3C}	$t-stat$	α^{FF3CL}	$t-stat$	α^{FF5}	$t-stat$	α^{FF5C}	$t-stat$	α^{HXZ}	$t-stat$
Lo	-2.68	0.56	[1.37]	-0.49	[-3.60]	-0.40	[-3.27]	-0.39	[-3.21]	-0.49	[-3.42]	-0.45	[-3.56]	-0.41	[-2.72]
2	-1.46	0.94	[2.60]	0.01	[0.09]	0.08	[0.73]	0.08	[0.70]	-0.10	[-0.77]	-0.07	[-0.60]	-0.03	[-0.18]
3	-1.01	0.97	[2.90]	0.10	[0.92]	0.13	[1.16]	0.13	[1.18]	-0.04	[-0.34]	-0.03	[-0.23]	0.01	[0.11]
4	-0.69	1.01	[3.17]	0.19	[1.85]	0.20	[1.89]	0.17	[1.66]	0.07	[0.63]	0.07	[0.67]	0.09	[0.78]
5	-0.41	1.18	[3.67]	0.35	[3.57]	0.37	[3.75]	0.35	[3.57]	0.21	[2.13]	0.22	[2.26]	0.28	[2.54]
6	-0.15	1.12	[3.47]	0.30	[3.20]	0.30	[3.20]	0.27	[2.93]	0.19	[2.01]	0.20	[2.04]	0.22	[2.17]
7	0.12	1.22	[3.64]	0.39	[3.92]	0.41	[4.12]	0.38	[3.86]	0.30	[2.93]	0.31	[3.05]	0.35	[3.16]
8	0.44	1.22	[3.41]	0.34	[3.27]	0.36	[3.50]	0.31	[3.18]	0.25	[2.31]	0.26	[2.45]	0.33	[2.93]
9	0.90	1.26	[3.12]	0.30	[2.67]	0.37	[3.46]	0.33	[3.17]	0.26	[2.14]	0.28	[2.57]	0.40	[3.30]
Hi	2.24	1.68	[3.40]	0.52	[3.32]	0.63	[4.46]	0.61	[4.32]	0.73	[4.55]	0.77	[5.33]	0.81	[5.39]
Hi-Lo	4.92	1.12	[4.66]	1.01	[5.04]	1.03	[5.10]	1.00	[4.97]	1.22	[5.92]	1.22	[5.92]	1.22	[5.81]

Panel B: Value-weighted portfolios

		Raw returns		FF3		FF3C		FF3CL		FF5		FF5C		HXZ	
	$\overline{i^p_{t,t+1}}$	$\overline{R^p_{t+1}}$	$t-stat$	α^{FF3}	$t-stat$	α^{FF3C}	$t-stat$	α^{FF3CL}	$t-stat$	α^{FF5}	$t-stat$	α^{FF5C}	$t-stat$	α^{HXZ}	$t-stat$
Lo	-2.64	0.37	[0.98]	-0.49	[-2.74]	-0.43	[-2.45]	-0.41	[-2.32]	-0.40	[-2.14]	-0.38	[-2.06]	-0.40	[-2.15]
2	-1.44	0.68	[2.00]	-0.03	[-0.20]	-0.01	[-0.06]	0.01	[0.06]	-0.08	[-0.50]	-0.07	[-0.44]	-0.09	[-0.59]
3	-1.00	0.57	[1.83]	-0.10	[-0.61]	-0.10	[-0.61]	-0.08	[-0.46]	-0.16	[-0.93]	-0.16	[-0.93]	-0.20	[-1.17]
4	-0.68	0.69	[2.31]	0.11	[0.83]	0.09	[0.64]	0.09	[0.63]	0.02	[0.16]	0.01	[0.10]	0.02	[0.17]
5	-0.41	0.75	[2.55]	0.17	[1.33]	0.18	[1.45]	0.17	[1.35]	0.14	[1.04]	0.15	[1.09]	0.14	[1.09]
6	-0.15	0.56	[1.91]	0.02	[0.18]	0.01	[0.06]	-0.01	[-0.11]	-0.06	[-0.53]	-0.07	[-0.57]	-0.03	[-0.27]
7	0.13	0.45	[1.55]	-0.12	[-1.13]	-0.13	[-1.22]	-0.12	[-1.15]	-0.22	[-2.00]	-0.22	[-2.01]	-0.20	[-1.88]
8	0.44	0.71	[2.16]	0.12	[0.88]	0.12	[0.87]	0.11	[0.82]	0.20	[1.42]	0.20	[1.40]	0.11	[0.77]
9	0.88	0.66	[1.87]	0.07	[0.43]	0.08	[0.54]	0.06	[0.40]	0.10	[0.62]	0.11	[0.66]	0.14	[0.91]
Hi	1.85	0.85	[1.88]	0.07	[0.33]	0.20	[0.94]	0.19	[0.89]	0.33	[1.42]	0.37	[1.70]	0.41	[1.90]
Hi-Lo	4.48	0.48	[1.50]	0.56	[1.91]	0.63	[2.14]	0.59	[2.02]	0.73	[2.36]	0.75	[2.44]	0.81	[2.68]

Notes: Average monthly returns on $i^j_{t,t+1}$-sorted portfolios that are rebalanced each month (Panel A equally-weights returns and Panel B value-weights returns). $i^j_{t,t+1}$ is estimated as a residual from equation (1.10) when $b^j_{t,t+1}$ is estimated using equation (1.21) and Model 2 (7 characteristics) using 10-year rolling Fama and MacBeth (1973) regressions ($\mathbb{E}\left[R^j_{t+1}|X^j_t\right]$ is estimated using equation (1.19) and Model 2 characteristics). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records do not contain any marginal information. Overlines represent sample averages. Returns are also risk-adjusted using the following empirical factor models: 1. "FF3" (the Fama and French (1993) 3-factor model), 2. "FF3C" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor), 3. "FF3CL" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor and the Pastor and Stambaugh (2003) traded liquidity factor), 4. "FF5" (the Fama and French (2015) 5-factor model), 5. "FF5C" (the Fama and French (2015) 5-factor model augmented with the Carhart (1997) UMD factor, which was used as a baseline for comparison in Kelly et al. (2018)), and 6. "HXZ" (the Hou et al. (2015) 4-factor model). Portfolios are rebalanced and regressions are run at the 1-month frequency. Data is from 1999-2017. t-statistics are reported in brackets.

Table OA-6: Portfolios Sorted on $\bar{i}^{j}_{t,t+1}$ (Model 2)

Panel A: Equal-weighted portfolios

		Raw returns		FF3		FF3C		FF3CL		FF5		FF5C		HXZ	
	$\overline{\bar{i}^{p}}_{t,t+1}$	$\overline{R^{p}_{t+1}}$	$t-stat$	α^{FF3}	$t-stat$	α^{FF3C}	$t-stat$	α^{FF3CL}	$t-stat$	α^{FF5}	$t-stat$	α^{FF5C}	$t-stat$	α^{HXZ}	$t-stat$
Lo	-46.57	0.43	[0.74]	-0.69	[-2.46]	-0.42	[-1.97]	-0.43	[-1.99]	-0.39	[-1.38]	-0.30	[-1.34]	-0.22	[-0.83]
2	-17.78	0.65	[1.41]	-0.29	[-1.29]	-0.11	[-0.57]	-0.11	[-0.61]	-0.25	[-1.10]	-0.18	[-0.96]	-0.04	[-0.19]
3	-9.98	0.84	[2.09]	-0.07	[-0.48]	0.04	[0.27]	0.01	[0.08]	-0.11	[-0.72]	-0.07	[-0.52]	-0.00	[-0.02]
4	-5.10	0.76	[2.10]	-0.07	[-0.51]	-0.02	[-0.16]	-0.04	[-0.26]	-0.14	[-1.02]	-0.12	[-0.91]	-0.08	[-0.49]
5	-1.25	1.07	[3.17]	0.23	[2.21]	0.26	[2.53]	0.23	[2.23]	0.15	[1.36]	0.16	[1.52]	0.19	[1.56]
6	2.16	1.11	[3.54]	0.32	[3.27]	0.31	[3.20]	0.29	[3.00]	0.14	[1.49]	0.14	[1.50]	0.19	[1.86]
7	5.42	1.09	[3.49]	0.28	[2.74]	0.26	[2.50]	0.23	[2.29]	0.16	[1.50]	0.15	[1.43]	0.19	[1.69]
8	9.22	1.15	[3.58]	0.30	[3.13]	0.26	[2.81]	0.25	[2.71]	0.19	[1.88]	0.17	[1.80]	0.18	[1.86]
9	14.86	1.24	[3.50]	0.32	[2.69]	0.27	[2.36]	0.26	[2.24]	0.32	[2.59]	0.31	[2.53]	0.29	[2.41]
Hi	33.59	1.67	[3.65]	0.57	[3.50]	0.52	[3.23]	0.50	[3.08]	0.67	[4.09]	0.65	[4.07]	0.62	[3.77]
Hi-Lo	80.15	1.24	[3.09]	1.26	[3.37]	0.94	[3.07]	0.93	[3.00]	1.07	[2.79]	0.95	[3.03]	0.84	[2.30]

Panel B: Value-weighted portfolios

		Raw returns		FF3		FF3C		FF3CL		FF5		FF5C		HXZ	
	$\overline{\bar{i}^{p}_{t,t+1}}$	$\overline{R^{p}_{t+1}}$	$t-stat$	α^{FF3}	$t-stat$	α^{FF3C}	$t-stat$	α^{FF3CL}	$t-stat$	α^{FF5}	$t-stat$	α^{FF5C}	$t-stat$	α^{HXZ}	$t-stat$
Lo	-38.39	0.18	[0.34]	-0.63	[-2.19]	-0.37	[-1.63]	-0.37	[-1.63]	-0.34	[-1.14]	-0.24	[-1.02]	-0.19	[-0.71]
2	-17.26	0.48	[1.13]	-0.22	[-1.04]	-0.07	[-0.36]	-0.06	[-0.31]	-0.04	[-0.18]	0.02	[0.09]	-0.04	[-0.20]
3	-9.80	0.54	[1.47]	-0.11	[-0.61]	-0.01	[-0.08]	-0.01	[-0.05]	-0.00	[-0.02]	0.03	[0.18]	0.06	[0.36]
4	-5.04	0.66	[2.03]	0.09	[0.52]	0.10	[0.58]	0.12	[0.72]	0.01	[0.05]	0.01	[0.08]	0.04	[0.25]
5	-1.22	0.79	[2.52]	0.21	[1.48]	0.23	[1.58]	0.20	[1.39]	0.19	[1.28]	0.20	[1.32]	0.17	[1.17]
6	2.11	0.65	[2.29]	0.11	[0.83]	0.08	[0.65]	0.06	[0.45]	-0.00	[-0.01]	-0.01	[-0.07]	0.02	[0.11]
7	5.36	0.60	[2.21]	0.05	[0.46]	0.00	[0.01]	0.00	[0.02]	-0.08	[-0.68]	-0.10	[-0.86]	-0.06	[-0.54]
8	9.12	0.59	[2.03]	0.00	[0.00]	-0.06	[-0.47]	-0.07	[-0.52]	-0.07	[-0.45]	-0.09	[-0.63]	-0.13	[-0.88]
9	14.60	0.78	[2.33]	0.08	[0.48]	-0.01	[-0.04]	-0.01	[-0.03]	0.13	[0.68]	0.09	[0.52]	0.05	[0.27]
Hi	28.93	1.02	[2.32]	0.19	[0.81]	0.11	[0.47]	0.10	[0.42]	0.37	[1.54]	0.33	[1.44]	0.26	[1.07]
Hi-Lo	67.31	0.84	[1.89]	0.82	[1.93]	0.48	[1.34]	0.47	[1.31]	0.70	[1.60]	0.57	[1.56]	0.46	[1.08]

Notes: Average monthly returns on $\bar{i}^{j}_{t,t+1}$-sorted portfolios that are rebalanced each month (Panel A equally-weights returns and Panel B value-weights returns). $\bar{i}^{j}_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). I remove records where $\bar{i}^{j}_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records do not contain any marginal information. Overlines represent sample averages. Returns are also risk-adjusted using the following empirical factor models: 1. "FF3" (the Fama and French (1993) 3-factor model), 2. "FF3C" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor), 3. "FF3CL" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor and the Pastor and Stambaugh (2003) traded liquidity factor), 4. "FF5" (the Fama and French (2015) 5-factor model), 5. "FF5C" (the Fama and French (2015) 5-factor model augmented with the Carhart (1997) UMD factor, which was used as a baseline for comparison in Kelly et al. (2018)), and 6. "HXZ" (the Hou et al. (2015) 4-factor model). Portfolios are rebalanced and regressions are run at the 1-month frequency. Data is from 1999-2017. t-statistics are reported in brackets.

Table OA-7: Portfolios Sorted on $b^j_{t,t+1}$ (Model 2)

Panel A: Equal-weighted portfolios

		Raw returns		**FF3**		**FF3C**		**FF3CL**		**FF5**		**FF5C**		**HXZ**	
	$\overline{b^p_{t,t+1}}$	$\overline{R^p_{t+1}}$	$t-stat$	α^{FF3}	$t-stat$	α^{FF3C}	$t-stat$	α^{FF3CL}	$t-stat$	α^{FF5}	$t-stat$	α^{FF5C}	$t-stat$	α^{HXZ}	$t-stat$
Lo	-0.30	1.24	[3.08]	0.35	[1.68]	0.13	[0.91]	0.13	[0.89]	0.30	[1.40]	0.22	[1.45]	0.10	[0.49]
2	0.18	1.01	[3.36]	0.24	[2.41]	0.16	[1.92]	0.12	[1.52]	0.03	[0.35]	0.01	[0.08]	0.08	[0.79]
3	0.38	1.12	[3.65]	0.33	[3.69]	0.29	[3.39]	0.27	[3.14]	0.13	[1.57]	0.12	[1.48]	0.18	[1.89]
4	0.54	1.25	[3.92]	0.42	[4.11]	0.44	[4.30]	0.42	[4.15]	0.21	[2.16]	0.22	[2.33]	0.32	[2.64]
5	0.68	1.29	[3.81]	0.42	[3.97]	0.46	[4.41]	0.43	[4.15]	0.19	[1.92]	0.21	[2.25]	0.34	[2.75]
6	0.83	1.15	[3.29]	0.27	[2.29]	0.33	[3.03]	0.32	[2.91]	0.09	[0.76]	0.12	[1.13]	0.21	[1.52]
7	0.99	1.23	[3.19]	0.24	[1.99]	0.34	[3.28]	0.33	[3.15]	0.17	[1.30]	0.21	[1.96]	0.28	[1.93]
8	1.20	1.18	[2.99]	0.21	[1.45]	0.34	[3.08]	0.32	[2.87]	0.18	[1.22]	0.24	[2.09]	0.31	[1.96]
9	1.51	1.04	[2.29]	-0.01	[-0.08]	0.16	[1.19]	0.13	[0.97]	0.16	[0.81]	0.22	[1.54]	0.22	[1.20]
Hi	2.48	0.66	[1.24]	-0.44	[-1.83]	-0.22	[-1.15]	-0.23	[-1.23]	-0.08	[-0.31]	0.01	[0.03]	0.02	[0.11]
Hi-Lo	2.78	-0.59	[-1.43]	-0.79	[-1.99]	-0.35	[-1.34]	-0.36	[-1.38]	-0.38	[-0.92]	-0.21	[-0.78]	-0.07	[-0.20]

Panel B: Value-weighted portfolios

		Raw returns		**FF3**		**FF3C**		**FF3CL**		**FF5**		**FF5C**		**HXZ**	
	$\overline{b^p_{t,t+1}}$	$\overline{R^p_{t+1}}$	$t-stat$	α^{FF3}	$t-stat$	α^{FF3C}	$t-stat$	α^{FF3CL}	$t-stat$	α^{FF5}	$t-stat$	α^{FF5C}	$t-stat$	α^{HXZ}	$t-stat$
Lo	-0.23	1.00	[2.94]	0.37	[1.75]	0.16	[1.03]	0.16	[1.00]	0.39	[1.73]	0.30	[1.88]	0.18	[0.85]
2	0.18	0.65	[2.42]	0.07	[0.63]	-0.01	[-0.09]	-0.03	[-0.32]	-0.05	[-0.41]	-0.08	[-0.74]	-0.09	[-0.83]
3	0.38	0.63	[2.24]	0.08	[0.73]	0.05	[0.50]	0.05	[0.49]	-0.06	[-0.57]	-0.07	[-0.64]	-0.05	[-0.48]
4	0.53	0.85	[3.13]	0.25	[2.27]	0.30	[2.83]	0.31	[2.89]	0.10	[0.91]	0.12	[1.20]	0.22	[1.92]
5	0.68	0.59	[1.82]	-0.02	[-0.14]	0.03	[0.16]	0.02	[0.12]	-0.21	[-1.29]	-0.19	[-1.19]	-0.06	[-0.36]
6	0.82	0.14	[0.38]	-0.52	[-3.23]	-0.44	[-2.89]	-0.43	[-2.80]	-0.47	[-2.78]	-0.44	[-2.75]	-0.44	[-2.72]
7	0.98	0.69	[1.90]	-0.01	[-0.04]	0.12	[0.81]	0.11	[0.72]	0.04	[0.25]	0.09	[0.60]	0.10	[0.59]
8	1.19	0.61	[1.49]	0.02	[0.07]	0.20	[1.07]	0.17	[0.90]	0.16	[0.69]	0.23	[1.19]	0.28	[1.28]
9	1.50	0.49	[1.08]	-0.28	[-1.22]	-0.09	[-0.48]	-0.13	[-0.69]	-0.09	[-0.39]	-0.02	[-0.11]	-0.00	[-0.01]
Hi	2.30	-0.04	[-0.08]	-0.81	[-2.89]	-0.60	[-2.48]	-0.59	[-2.42]	-0.31	[-1.11]	-0.23	[-0.97]	-0.36	[-1.39]
Hi-Lo	2.54	-1.04	[-2.27]	-1.18	[-2.77]	-0.76	[-2.41]	-0.74	[-2.36]	-0.69	[-1.59]	-0.53	[-1.65]	-0.54	[-1.34]

Notes: Average monthly returns on $b^j_{t,t+1}$-sorted portfolios that are rebalanced each month (Panel A equally-weights returns and Panel B value-weights returns). $b^j_{t,t+1}$ is estimated using equation (1.21) and Model 2 (7 characteristics) using 10-year rolling Fama and MacBeth (1973) regressions ($\mathbb{E}\left[R^j_{t+1}|X^j_t\right]$ is estimated using equation (1.19) and Model 2 characteristics). Overlines represent sample averages. Returns are also risk-adjusted using the following empirical factor models: 1. "FF3" (the Fama and French (1993) 3-factor model), 2. "FF3C" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor), 3. "FF3CL" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor and the Pastor and Stambaugh (2003) traded liquidity factor), 4. "FF5" (the Fama and French (2015) 5-factor model), 5. "FF5C" (the Fama and French (2015) 5-factor model augmented with the Carhart (1997) UMD factor, which was used as a baseline for comparison in Kelly et al. (2018)), and 6. "HXZ" (the Hou et al. (2015) 4-factor model). Portfolios are rebalanced and regressions are run at the 1-month frequency. Data is from 1999-2017. t-statistics are reported in brackets.

Table OA-8: Portfolios Sorted on s_t^j in equation (1.24) (Model 2)

Panel A: Equal-weighted portfolios

		Raw returns		FF3		FF3C		FF3CL		FF5		FF5C		HXZ	
	$\overline{s_t^p}$	$\overline{R_{t+1}^p}$	$t-stat$	α^{FF3}	$t-stat$	α^{FF3C}	$t-stat$	α^{FF3CL}	$t-stat$	α^{FF5}	$t-stat$	α^{FF5C}	$t-stat$	α^{HXZ}	$t-stat$
Lo	-0.68	0.48	[1.01]	-0.61	[-3.72]	-0.51	[-3.65]	-0.50	[-3.61]	-0.33	[-2.20]	-0.31	[-2.35]	-0.31	[-2.14]
2	-0.32	0.90	[2.14]	-0.09	[-0.83]	-0.02	[-0.25]	-0.02	[-0.22]	0.03	[0.24]	0.04	[0.46]	0.08	[0.73]
3	-0.19	0.96	[2.43]	0.01	[0.15]	0.07	[0.76]	0.07	[0.79]	0.07	[0.75]	0.09	[0.98]	0.13	[1.32]
4	-0.10	0.90	[2.39]	-0.01	[-0.18]	0.01	[0.11]	0.01	[0.08]	-0.02	[-0.22]	-0.01	[-0.14]	0.03	[0.39]
5	-0.02	1.05	[2.92]	0.18	[2.44]	0.21	[2.97]	0.20	[2.93]	0.17	[2.29]	0.18	[2.53]	0.25	[3.21]
6	0.06	0.97	[2.78]	0.11	[1.67]	0.11	[1.77]	0.11	[1.71]	0.12	[1.77]	0.12	[1.81]	0.13	[1.95]
7	0.13	1.11	[3.18]	0.25	[3.76]	0.25	[3.69]	0.24	[3.65]	0.23	[3.29]	0.23	[3.28]	0.25	[3.45]
8	0.21	1.09	[3.12]	0.23	[2.95]	0.22	[2.80]	0.21	[2.76]	0.17	[2.10]	0.16	[2.08]	0.22	[2.66]
9	0.32	1.12	[2.98]	0.21	[2.14]	0.19	[1.97]	0.19	[1.91]	0.11	[1.13]	0.11	[1.11]	0.19	[1.84]
Hi	0.60	1.29	[2.94]	0.28	[1.84]	0.25	[1.65]	0.24	[1.58]	0.21	[1.33]	0.20	[1.30]	0.30	[1.88]
Hi-Lo	1.29	0.81	[3.11]	0.89	[3.39]	0.76	[3.19]	0.74	[3.16]	0.54	[2.14]	0.51	[2.18]	0.61	[2.40]

Panel B: Value-weighted portfolios

		Raw returns		FF3		FF3C		FF3CL		FF5		FF5C		HXZ	
	$\overline{s_t^p}$	$\overline{R_{t+1}^p}$	$t-stat$	α^{FF3}	$t-stat$	α^{FF3C}	$t-stat$	α^{FF3CL}	$t-stat$	α^{FF5}	$t-stat$	α^{FF5C}	$t-stat$	α^{HXZ}	$t-stat$
Lo	-0.65	0.32	[0.69]	-0.70	[-3.50]	-0.60	[-3.32]	-0.60	[-3.29]	-0.38	[-2.00]	-0.36	[-2.03]	-0.35	[-1.97]
2	-0.32	0.65	[1.72]	-0.22	[-1.44]	-0.16	[-1.12]	-0.15	[-1.06]	-0.09	[-0.59]	-0.08	[-0.52]	-0.08	[-0.56]
3	-0.19	1.03	[3.03]	0.25	[1.78]	0.29	[2.15]	0.29	[2.17]	0.32	[2.24]	0.33	[2.39]	0.32	[2.25]
4	-0.09	0.57	[1.59]	-0.25	[-2.18]	-0.24	[-2.04]	-0.23	[-2.01]	-0.28	[-2.33]	-0.28	[-2.31]	-0.27	[-2.24]
5	-0.02	0.61	[1.82]	-0.16	[-1.22]	-0.11	[-0.91]	-0.11	[-0.86]	-0.10	[-0.76]	-0.09	[-0.70]	-0.09	[-0.67]
6	0.06	0.72	[2.39]	0.02	[0.17]	0.05	[0.63]	0.06	[0.68]	0.04	[0.43]	0.05	[0.57]	0.08	[0.84]
7	0.13	0.60	[2.05]	-0.09	[-0.96]	-0.09	[-0.90]	-0.08	[-0.84]	-0.12	[-1.15]	-0.11	[-1.13]	-0.10	[-1.04]
8	0.21	0.70	[2.28]	-0.01	[-0.12]	-0.04	[-0.35]	-0.04	[-0.41]	0.02	[0.19]	0.01	[0.12]	-0.08	[-0.69]
9	0.32	0.79	[2.60]	0.08	[0.77]	0.05	[0.46]	0.05	[0.49]	0.01	[0.11]	0.00	[0.04]	-0.01	[-0.10]
Hi	0.52	0.90	[2.54]	0.12	[0.71]	0.07	[0.42]	0.06	[0.37]	0.06	[0.33]	0.04	[0.27]	0.05	[0.31]
Hi-Lo	1.17	0.58	[1.88]	0.82	[2.78]	0.67	[2.52]	0.66	[2.48]	0.44	[1.53]	0.40	[1.53]	0.41	[1.48]

Notes: Average monthly returns on combined information and bias components using s_t^j from equation (1.24) that are rebalanced each month (Panel A equally-weights returns and Panel B value-weights returns). $i_{t,t+1}^j$ is estimated as a residual from equation (1.10) when $b_{t,t+1}^j$ is estimated using equation (1.21) and Model 2 (7 characteristics) using 10-year rolling Fama and MacBeth (1973) regressions ($\mathbb{E}\left[R_{t+1}^j|X_t^j\right]$ is estimated using equation (1.19) and Model 2 characteristics). Overlines represent sample averages. Returns are also risk-adjusted using the following empirical factor models: 1. "FF3" (the Fama and French (1993) 3-factor model), 2. "FF3C" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor), 3. "FF3CL" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor and the Pastor and Stambaugh (2003) traded liquidity factor), 4. "FF5" (the Fama and French (2015) 5-factor model), 5. "FF5C" (the Fama and French (2015) 5-factor model augmented with the Carhart (1997) UMD factor, which was used as a baseline for comparison in Kelly et al. (2018)), and 6. "HXZ" (the Hou et al. (2015) 4-factor model). Portfolios are rebalanced and regressions are run at the 1-month frequency. Data is from 1999-2017. t-statistics are reported in brackets.

Table OA-9: Portfolios Sorted on $\tilde{R}^j_{t,t+1}$

Panel A: Equal-weighted portfolios

		Raw returns		**FF3**		**FF3C**		**FF3CL**		**FF5**		**FF5C**		**HXZ**	
	$\overline{\tilde{R}^p_{t,t+1}}$	$\overline{R^p_{t+1}}$	$t-stat$	α^{FF3}	$t-stat$	α^{FF3C}	$t-stat$	α^{FF3CL}	$t-stat$	α^{FF5}	$t-stat$	α^{FF5C}	$t-stat$	α^{HXZ}	$t-stat$
Lo	-0.80	0.53	[1.35]	-0.48	[-4.31]	-0.42	[-4.03]	-0.42	[-3.94]	-0.52	[-4.42]	-0.49	[-4.54]	-0.46	[-3.49]
2	0.35	0.89	[2.62]	0.02	[0.20]	0.06	[0.57]	0.06	[0.51]	-0.10	[-0.89]	-0.08	[-0.76]	-0.03	[-0.21]
3	0.76	0.94	[2.99]	0.13	[1.41]	0.14	[1.44]	0.13	[1.38]	0.01	[0.12]	0.01	[0.16]	0.03	[0.29]
4	1.06	1.08	[3.40]	0.27	[2.80]	0.28	[2.97]	0.26	[2.78]	0.13	[1.38]	0.14	[1.49]	0.19	[1.70]
5	1.33	1.14	[3.54]	0.31	[3.42]	0.31	[3.38]	0.29	[3.15]	0.19	[2.04]	0.19	[2.06]	0.24	[2.39]
6	1.59	1.08	[3.21]	0.24	[2.53]	0.26	[2.70]	0.23	[2.46]	0.18	[1.79]	0.18	[1.88]	0.22	[2.05]
7	1.89	1.17	[3.25]	0.30	[3.10]	0.32	[3.39]	0.29	[3.14]	0.26	[2.59]	0.27	[2.73]	0.30	[2.93]
8	2.26	1.12	[2.75]	0.15	[1.20]	0.22	[1.78]	0.17	[1.46]	0.22	[1.66]	0.24	[1.93]	0.26	[1.92]
9	2.83	1.27	[2.79]	0.24	[1.88]	0.33	[2.84]	0.27	[2.49]	0.37	[2.83]	0.41	[3.38]	0.47	[3.56]
Hi	4.55	1.44	[2.60]	0.21	[1.13]	0.35	[2.23]	0.34	[2.15]	0.61	[3.49]	0.66	[4.39]	0.66	[4.14]
Hi-Lo	5.35	0.91	[3.03]	0.69	[3.26]	0.78	[3.78]	0.76	[3.68]	1.13	[5.60]	1.16	[5.87]	1.12	[5.34]

Panel B: Value-weighted portfolios

		Raw returns		**FF3**		**FF3C**		**FF3CL**		**FF5**		**FF5C**		**HXZ**	
	$\overline{\tilde{R}^p_{t,t+1}}$	$\overline{R^p_{t+1}}$	$t-stat$	α^{FF3}	$t-stat$	α^{FF3C}	$t-stat$	α^{FF3CL}	$t-stat$	α^{FF5}	$t-stat$	α^{FF5C}	$t-stat$	α^{HXZ}	$t-stat$
Lo	-0.69	0.45	[1.28]	-0.34	[-2.15]	-0.33	[-2.07]	-0.30	[-1.87]	-0.32	[-1.91]	-0.31	[-1.88]	-0.34	[-2.00]
2	0.37	0.68	[2.33]	0.06	[0.42]	0.03	[0.22]	0.04	[0.31]	-0.02	[-0.15]	-0.03	[-0.22]	-0.07	[-0.48]
3	0.77	0.76	[2.67]	0.17	[1.45]	0.17	[1.41]	0.15	[1.24]	0.10	[0.83]	0.10	[0.82]	0.09	[0.73]
4	1.07	0.61	[2.07]	0.07	[0.67]	0.06	[0.55]	0.06	[0.58]	0.01	[0.07]	0.00	[0.04]	0.02	[0.21]
5	1.33	0.50	[1.81]	-0.07	[-0.75]	-0.10	[-1.09]	-0.10	[-1.11]	-0.13	[-1.29]	-0.14	[-1.43]	-0.14	[-1.43]
6	1.59	0.73	[2.42]	0.15	[1.19]	0.13	[1.03]	0.12	[0.97]	0.13	[0.98]	0.12	[0.93]	0.11	[0.83]
7	1.88	0.35	[0.99]	-0.22	[-1.51]	-0.20	[-1.38]	-0.20	[-1.35]	-0.14	[-0.92]	-0.14	[-0.89]	-0.20	[-1.35]
8	2.25	0.53	[1.45]	-0.09	[-0.57]	-0.07	[-0.41]	-0.06	[-0.39]	0.01	[0.07]	0.02	[0.11]	0.04	[0.22]
9	2.80	0.76	[1.74]	0.05	[0.26]	0.14	[0.73]	0.10	[0.52]	0.25	[1.22]	0.28	[1.41]	0.34	[1.73]
Hi	4.09	1.22	[2.25]	0.27	[0.93]	0.41	[1.54]	0.41	[1.51]	0.82	[2.94]	0.87	[3.28]	0.81	[3.08]
Hi-Lo	4.78	0.77	[1.93]	0.60	[1.81]	0.74	[2.30]	0.70	[2.17]	1.14	[3.40]	1.18	[3.63]	1.15	[3.49]

Notes: Average monthly returns on $\tilde{R}^j_{t,t+1}$-sorted portfolios that are rebalanced each month (Panel A equally-weights returns and Panel B value-weights returns). Overlines represent sample averages. Returns are also risk-adjusted using the following empirical factor models: 1. "FF3" (the Fama and French (1993) 3-factor model), 2. "FF3C" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor), 3. "FF3CL" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor and the Pastor and Stambaugh (2003) traded liquidity factor), 4. "FF5" (the Fama and French (2015) 5-factor model), 5. "FF5C" (the Fama and French (2015) 5-factor model augmented with the Carhart (1997) UMD factor, which was used as a baseline for comparison in Kelly et al. (2018)), and 6. "HXZ" (the Hou et al. (2015) 4-factor model). Portfolios are rebalanced and regressions are run at the 1-month frequency. Data is from 1999-2017. t-statistics are reported in brackets.

OA.4 Empirical Tests Using Alternative Analyst Bias Estimate

In this section, I forecast of analyst-expected return bias directly then use this to estimate the information and bias components in analyst-implied returns. Namely, instead of estimating equations (1.19) and (1.20) and computing bias using equation (1.21), I instead estimate the following regression:

$$\tilde{R}^j_{t-1,t} - R^j_t = a_t + c'_t X^j_{t-1} + u^j_t, \tag{OA-19}$$

where $\tilde{R}^j_{t,t+1} - R^j_{t+1}$ is the realized analyst-expected return bias. I estimate this regression each period using the Fama and MacBeth (1973) technique in a rolling fashion using up to 10 years of data, and require at least 36 months of data. I require 36 months of data as opposed to only 1 month as in the estimation in equation (1.20) since this estimation contains more noise due to the inclusion of realized returns. I then forecast bias each period using:$b^j_{t,t+1}$Where $\overline{a}_t$ is the average time fixed effect across all regression periods up to and including date t, and $\hat{c}_t$ is the estimated set of characteristic coefficients.

This estimation has an efficiency advantage over that based on equations (1.19), (1.20), and (1.20) since it only needs to estimate one set of c_t coefficients each period. It has the disadvantage that it requires more periods for estimation due to noise in realized returns. For instance, with my main estimation I can use realized return data for 10 years before the analyst price target data begins in March, 1999 to estimate equation (1.19), then use the single period of analyst-expected return data from March, 1999 to estimate equation (1.20) so that I can estimate analyst-expected return bias beginning in April, 1999. Since I require 36 months of data to estimate equation (OA-19), my first bias forecast using this technique is in April, 2002.

Results from all empirical tests when using this bias component estimate are shown below in Tables OA-10 and OA-11. Note that expected returns conditional on characteristics is estimated as before, but now the information component is computed as a residual according to equation (1.12) with the new bias component estimate.

Table OA-10: Results Based on Empirical Tests 1-4 (Cumulative Return Tests, Model 2, Alternative Bias Estimation)

	$i^j_{t,t+1}$ **only**						$b^j_{t,t+1}$ **only**						$i^j_{t,t+1}$ **and** $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$i^j_{t,t+1}$	4.87	5.22	5.35	5.48	5.75	6.09							4.98	5.30	5.40	5.51	5.76	6.11
	[25.13]	[20.98]	[16.57]	[13.53]	[10.45]	[7.53]							[25.14]	[20.84]	[16.40]	[13.26]	[10.24]	[7.84]
$b^j_{t,t+1}$							0.35	0.17	0.01	-0.04	-0.13	-0.28	0.55	0.41	0.25	0.20	0.12	0.05
							[2.93]	[0.91]	[0.04]	[-0.11]	[-0.29]	[-0.48]	[3.73]	[2.06]	[0.92]	[0.61]	[0.27]	[0.08]
R^2	0.18	0.12	0.09	0.07	0.04	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.19	0.13	0.10	0.08	0.05	0.03
N	1,371	1,371	1,371	1,370	1,371	1,371	1,371	1,371	1,371	1,370	1,371	1,371	1,371	1,371	1,371	1,370	1,371	1,371

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) to implement Empirical Tests 1-4. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions with at least 36 months of data for each estimate. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $R^j_{t,t+n}$ are cumulative returns for stock j from month $t+1$ to month $t+n$ ($n \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table OA-11: Results Based on Empirical Tests 5-6 (Post-Announcement-Month Return Tests, Model 2, Alternative Bias Estimation)

	$i^j_{t,t+1}$ **only**					$b^j_{t,t+1}$ **only**					$i^j_{t,t+1}$ **and** $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$i^j_{t,t+1}$	0.35	0.48	0.60	0.88	1.21						0.32	0.42	0.51	0.78	1.12
	[4.05]	[3.00]	[2.41]	[2.20]	[1.95]						[3.68]	[2.53]	[2.01]	[1.92]	[1.93]
$b^j_{t,t+1}$						-0.17	-0.34	-0.39	-0.48	-0.64	-0.14	-0.32	-0.38	-0.47	-0.59
						[-1.92]	[-2.08]	[-1.79]	[-1.47]	[-1.34]	[-1.63]	[-1.90]	[-1.65]	[-1.42]	[-1.28]
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02
N	1,371	1,371	1,370	1,371	1,371	1,371	1,371	1,370	1,371	1,371	1,371	1,371	1,370	1,371	1,371

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.23) to implement Empirical Tests 5 and 6. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions with at least 36 months of data for each estimate. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

OA.5 Empirical Tests: Time Subsets

In this section, I run the main empirical tests on two different subsets of data: 1. Data from 1999-2007, and 2. Data from 2008-2017. Results provided in Tables OA-12, OA-13, OA-14, and OA-15.

Table OA-12: Results Based on Empirical Tests 1-4 (Cumulative Return Tests, Model 2, 1999-2007)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$i^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$i^j_{t,t+1}$	5.37	5.80	5.92	6.05	6.36	6.34							5.39	5.78	5.87	6.01	6.25	6.20
	[15.12]	[13.79]	[10.82]	[8.61]	[7.25]	[7.29]							[16.12]	[14.15]	[10.95]	[8.58]	[7.11]	[6.86]
$b^j_{t,t+1}$							0.40	0.17	-0.20	-0.42	-1.07	-0.79	0.80	0.61	0.28	0.07	-0.54	-0.29
							[1.90]	[0.50]	[-0.45]	[-0.72]	[-1.05]	[-0.75]	[3.80]	[1.82]	[0.59]	[0.11]	[-0.51]	[-0.27]
R^2	0.16	0.11	0.08	0.06	0.04	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.18	0.13	0.09	0.08	0.05	0.04
N	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$\bar{i}^j_{t,t+1}$	3.52	4.10	4.66	5.06	5.98	5.53							3.80	4.18	4.61	4.94	5.60	5.30
	[10.78]	[8.52]	[8.02]	[7.87]	[7.70]	[8.25]							[12.75	[9.41]	[8.62]	[7.87]	[7.61]	[8.60]
$b^j_{t,t+1}$							0.40	0.17	-0.20	-0.42	-1.07	-0.79	1.01	0.75	0.36	0.21	-0.55	-0.28
							[1.90]	[0.50]	[-0.45]	[-0.72]	[-1.05]	[-0.75]	[5.58]	[2.42]	[0.82]	[0.34]	[-0.46]	[-0.26]
R^2	0.10	0.07	0.06	0.05	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.12	0.09	0.07	0.06	0.05	0.04
N	1,121	1,120	1,121	1,121	1,121	1,121	1,266	1,266	1,266	1,266	1,266	1,266	1,028	1,027	1,028	1,028	1,028	1,028

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) to implement Empirical Tests 1-4. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{t,t+n}$ are cumulative returns for stock j from month $t+1$ to month $t+n$ ($n \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 1999-2007. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table OA-13: Results Based on Empirical Tests 5-6 (Post-Announcement-Month Return Tests, Model 2, 1999-2007)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$i^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$i^j_{t,t+1}$	0.43	0.54	0.68	0.99	0.97						0.39	0.48	0.62	0.86	0.81
	[2.59]	[1.63]	[1.28]	[1.22]	[0.97]						[2.35]	[1.46]	[1.16]	[1.06]	[0.82]
$b^j_{t,t+1}$						-0.23	-0.60	-0.81	-1.47	-1.19	-0.19	-0.53	-0.74	-1.34	-1.09
						[-1.33]	[-2.03]	[-1.87]	[-1.62]	[-1.11]	[-1.09]	[-1.77]	[-1.63]	[-1.46]	[-1.03]
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.03
N	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$\bar{i}^j_{t,t+1}$	0.59	1.15	1.55	2.46	2.02						0.37	0.80	1.14	1.80	1.49
	[2.62]	[3.33]	[3.73]	[4.24]	[3.02]						[1.93]	[2.73]	[2.96]	[3.71]	[3.38]
$b^j_{t,t+1}$						-0.23	-0.60	-0.81	-1.47	-1.19	-0.26	-0.66	-0.81	-1.57	-1.29
						[-1.33]	[-2.03]	[-1.87]	[-1.62]	[-1.11]	[-1.52]	[-2.09]	[-1.60]	[-1.40]	[-1.23]
R^2	0.02	0.02	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.03
N	1,120	1,121	1,121	1,121	1,121	1,266	1,266	1,266	1,266	1,266	1,027	1,028	1,028	1,028	1,028

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.23) to implement Empirical Tests 5 and 6. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information.$R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 1999-2007. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

Table OA-14: Results Based on Empirical Tests 1-4 (Cumulative Return Tests, Model 2, 2008-2017)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$i^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$i^j_{t,t+1}$	4.80	5.07	5.15	5.26	5.49	5.79							4.77	5.02	5.10	5.19	5.40	5.68
	[18.81]	[15.68]	[12.49]	[10.43]	[8.03]	[5.05]							[19.85]	[16.47]	[13.12]	[11.01]	[8.44]	[5.31]
$b^j_{t,t+1}$							1.12	1.07	1.04	1.11	1.20	1.05	0.96	0.91	0.89	0.96	1.03	0.95
							[5.33]	[3.50]	[2.43]	[2.10]	[1.68]	[1.13]	[4.86]	[3.26]	[2.26]	[1.98]	[1.58]	[1.06]
R^2	0.17	0.11	0.08	0.06	0.04	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.19	0.12	0.09	0.07	0.05	0.03
N	1,374	1,374	1,374	1,372	1,375	1,375	1,374	1,374	1,374	1,372	1,375	1,375	1,374	1,374	1,374	1,372	1,375	1,375

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$\bar{i}^j_{t,t+1}$	3.10	3.28	3.34	3.43	3.48	3.87							3.46	3.67	3.75	3.81	3.84	4.12
	[25.67]	[20.88]	[15.15]	[14.48]	[9.60]	[6.66]							[23.71]	[19.70]	[18.51]	[20.46]	[14.12]	[9.27]
$b^j_{t,t+1}$							1.12	1.07	1.04	1.11	1.20	1.05	1.38	1.35	1.31	1.37	1.43	1.21
							[5.33]	[3.50]	[2.43]	[2.10]	[1.68]	[1.13]	[6.43]	[4.46]	[3.06]	[2.60]	[2.07]	[1.41]
R^2	0.09	0.06	0.04	0.03	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.12	0.08	0.06	0.05	0.04	0.03
N	1,287	1,286	1,287	1,285	1,287	1,287	1,374	1,374	1,374	1,372	1,375	1,375	1,173	1,172	1,173	1,171	1,173	1,174

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) to implement Empirical Tests 1-4. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{t,t+n}$ are cumulative returns for stock j from month $t+1$ to month $t+n$ ($n \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 2008-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table OA-15: Results Based on Empirical Tests 5-6 (Post-Announcement-Month Return Tests, Model 2, 2008-2017)

Panel A: Tests using $i^j_{t,t+1}$															
	$i^j_{t,t+1}$ **only**					$b^j_{t,t+1}$ **only**					$i^j_{t,t+1}$ **and** $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$i^j_{t,t+1}$	0.26	0.35	0.43	0.69	0.96						0.24	0.33	0.40	0.62	0.89
	[2.54]	[1.89]	[1.56]	[1.47]	[1.15]						[2.52]	[1.86]	[1.54]	[1.41]	[1.15]
$b^j_{t,t+1}$						-0.04	-0.08	-0.03	0.06	-0.10	-0.05	-0.09	-0.04	0.02	-0.12
						[-0.39]	[-0.37]	[-0.09]	[0.12]	[-0.14]	[-0.45]	[-0.40]	[-0.12]	[0.04]	[-0.17]
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02
N	1,374	1,374	1,372	1,375	1,375	1,374	1,374	1,372	1,375	1,375	1,374	1,374	1,372	1,375	1,375

Panel B: Tests using $\bar{i}^j_{t,t+1}$															
	$\bar{i}^j_{t,t+1}$ **only**					$b^j_{t,t+1}$ **only**					$\bar{i}^j_{t,t+1}$ **and** $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$\bar{i}^j_{t,t+1}$	0.15	0.21	0.31	0.36	0.71						0.20	0.26	0.33	0.36	0.61
	[1.93]	[1.40]	[1.80]	[1.11]	[1.24]						[2.60]	[2.29]	[2.41]	[1.28]	[1.22]
$b^j_{t,t+1}$						-0.04	-0.08	-0.03	0.06	-0.10	-0.02	-0.08	-0.03	0.04	-0.19
						[-0.39]	[-0.37]	[-0.09]	[0.12]	[-0.14]	[-0.21]	[-0.36]	[-0.11]	[0.09]	[-0.31]
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02
N	1,286	1,287	1,285	1,287	1,287	1,374	1,374	1,372	1,375	1,375	1,172	1,173	1,171	1,173	1,174

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.23) to implement Empirical Tests 5 and 6. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 2008-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

OA.6 Empirical Tests: Excluding the Dividend Yield

One potential concern with my main analysis is that including dividend yields in equation (1.17) is not representative of analyst expectations. To address this concern, I run my main empirical tests in this section where I exclude the dividend yield from my analyst-expected return measure and from realized returns used in the tests. The analyst-expected return measure I use in this section is calculated as

$$\tilde{R}^j_{t,t+12} = \frac{\tilde{P}^j_{t,t+12} - P^j_{t-1}}{P^j_{t-1}}, \tag{OA-20}$$

I then apply the same monthly transformation to this measure as in equation (1.18) for my tests. The information and bias components are then computed as described in the main paper using these modified analyst-expected returns and ex dividend realized returns. Results can be found in Tables OA-16 and OA-17. This modification does not qualitatively change the main conclusions from my original tests.

Table OA-16: Results Based on Empirical Tests 1-4 without Dividend Yield in Realized Returns (Cumulative Return Tests)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$i^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$i^j_{t,t+1}$	5.09	5.45	5.57	5.71	6.05	6.31							5.08	5.42	5.53	5.66	5.95	6.19
	[23.07]	[20.14]	[15.88]	[12.94]	[10.57]	[8.63]							[24.33]	[20.79]	[16.28]	[13.14]	[10.64]	[8.67]
$b^j_{t,t+1}$							0.81	0.71	0.54	0.50	0.31	0.53	0.93	0.85	0.71	0.67	0.50	0.75
							[5.11]	[2.95]	[1.62]	[1.18]	[0.46]	[0.70]	[6.40]	[3.84]	[2.25]	[1.66]	[0.78]	[1.05]
R^2	0.17	0.11	0.08	0.06	0.04	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.19	0.12	0.09	0.08	0.05	0.04
N	1,324	1,323	1,322	1,322	1,322	1,321	1,324	1,323	1,322	1,322	1,322	1,321	1,324	1,323	1,322	1,322	1,322	1,321

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$\bar{i}^j_{t,t+1}$	3.29	3.66	3.96	4.20	4.67	4.66							3.62	3.91	4.16	4.35	4.70	4.73
	[19.43]	[14.62]	[12.28]	[11.30]	[9.22]	[9.90]							[22.25]	[16.63]	[14.53]	[12.96]	[10.91]	[12.51]
$b^j_{t,t+1}$							0.81	0.71	0.54	0.50	0.31	0.53	1.24	1.14	0.95	0.94	0.69	0.87
							[5.11]	[2.95]	[1.62]	[1.18]	[0.46]	[0.70]	[8.52]	[5.05]	[2.97]	[2.23]	[0.96]	[1.21]
R^2	0.09	0.06	0.05	0.04	0.03	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.12	0.08	0.07	0.06	0.04	0.03
N	1,209	1,208	1,208	1,207	1,207	1,205	1,324	1,323	1,322	1,322	1,322	1,321	1,105	1,104	1,104	1,103	1,103	1,102

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) to implement Empirical Tests 1-4 excluding dividends from realized returns. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{t,t+n}$ are cumulative returns for stock j from month $t+1$ to month $t+n$ ($k \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table OA-17: Results Based on Empirical Tests 5-6 without Dividend Yield in Realized Returns (Post-Announcement-Month Return Tests)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$i^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$i^j_{t,t+1}$	0.36	0.48	0.61	0.95	1.19						0.33	0.44	0.57	0.86	1.08
	[3.70]	[2.51]	[2.04]	[2.02]	[1.80]						[3.48]	[2.35]	[1.92]	[1.84]	[1.68]
$b^j_{t,t+1}$						-0.10	-0.27	-0.32	-0.51	-0.28	-0.09	-0.24	-0.28	-0.46	-0.23
						[-1.00]	[-1.41]	[-1.13]	[-0.94]	[-0.43]	[-0.85]	[-1.25]	[-1.01]	[-0.87]	[-0.37]
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02
N	1,323	1,322	1,322	1,322	1,321	1,323	1,322	1,322	1,322	1,321	1,323	1,322	1,322	1,322	1,321

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$\bar{i}^j_{t,t+1}$	0.36	0.65	0.90	1.36	1.33						0.29	0.53	0.72	1.07	1.08
	[3.03]	[3.26]	[3.56]	[3.38]	[2.93]						[2.85]	[3.29]	[3.40]	[3.39]	[3.38]
$b^j_{t,t+1}$						-0.10	-0.27	-0.32	-0.51	-0.28	-0.10	-0.29	-0.31	-0.56	-0.38
						[-1.00]	[-1.41]	[-1.13]	[-0.94]	[-0.43]	[-1.01]	[-1.47]	[-1.04]	[-0.90]	[-0.60]
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.03	0.03	0.02	0.02	0.02
N	1,208	1,208	1,207	1,207	1,205	1,323	1,322	1,322	1,322	1,321	1,104	1,104	1,103	1,103	1,102

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.23) to implement Empirical Tests 5 and 6 excluding dividends from realized returns. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using 3 control characteristics from Model 1 estimated using 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

OA.7 Empirical Tests: Firm Fixed Effects

In this section, I estimate analyst-expected return bias using a projection of analyst-expected returns onto both characteristics and stock fixed effects. This helps alleviate the concern that analysts might be perpetually optimistic or pessimistic about certain firms independent of the observable characteristics for which I control. Namely, instead of projecting analyst-expected returns onto characteristics as in equation (1.20), I instead estimate the following regression:

$$\tilde{R}^j_{t-1,t} = a_t + a_j + c_t' X^j_{t-1} + u^j_t. \tag{OA-21}$$

Due to the stock fixed effects, I estimate this regression each period using pooled OLS. I still am careful to avoid look-ahead bias and estimate this in a rolling fashion using up to 10 years of data. I also estimate equation (1.19), and compute a proxy for bias as in equation (1.21). As in the Fama and MacBeth (1973) procedure, I include averaged historical time fixed effects in the return forecasts and analyst-expected return projections that I use to estimate bias. Using this measure of bias, I calculate the corresponding proxy for information component as the residual to equation (1.10). Results from all empirical tests when using this bias component estimate are shown below in Tables OA-18 and OA-19. This modification does not qualitatively change the main conclusions from my original tests.

Table OA-18: Results Based on Empirical Tests 1-4 (Cumulative Return Tests, Model 2, Firm Fixed Effects)

	$i^j_{t,t+1}$ **only**						$b^j_{t,t+1}$ **only**						$i^j_{t,t+1}$ **and** $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$i^j_{t,t+1}$	4.75	5.12	5.25	5.37	5.62	6.13							4.90	5.23	5.34	5.44	5.62	5.97
	[25.06]	[23.87]	[21.40]	[18.89]	[18.71]	[14.76]							[29.07]	[27.25]	[24.09]	[21.05]	[20.92]	[16.00]
$b^j_{t,t+1}$							1.58	1.45	1.26	1.17	0.82	0.41	1.98	1.88	1.71	1.63	1.29	0.90
							[9.29]	[5.54]	[3.36]	[2.43]	[1.13]	[0.43]	[12.73]	[7.52]	[4.70]	[3.48]	[1.84]	[0.98]
R^2	0.15	0.10	0.07	0.06	0.04	0.02	0.03	0.02	0.02	0.02	0.02	0.01	0.19	0.13	0.09	0.08	0.05	0.04
N	1,337	1,337	1,336	1,335	1,336	1,335	1,337	1,337	1,336	1,335	1,336	1,335	1,337	1,337	1,336	1,335	1,336	1,335

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) to implement Empirical Tests 1-4. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equations (OA-21), (1.19), and (1.21) using seven control characteristics from Model 2 estimated using pooled OLS. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $R^j_{t,t+n}$ are cumulative returns for stock j from month $t+1$ to month $t+n$ ($n \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table OA-19: Results Based on Empirical Tests 5-6 (Post-Announcement-Month Return Tests, Model 2, Firm Fixed Effects)

	$i^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$i^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$i^j_{t,t+1}$	0.36	0.49	0.61	0.85	1.33						0.33	0.44	0.53	0.70	1.03
	[6.39]	[5.64]	[4.48]	[4.56]	[4.60]						[6.20]	[5.06]	[3.89]	[3.46]	[3.25]
$b^j_{t,t+1}$						-0.13	-0.32	-0.42	-0.76	-1.17	-0.09	-0.27	-0.36	-0.69	-1.09
						[-1.07]	[-1.37]	[-1.22]	[-1.26]	[-1.40]	[-0.80]	[-1.16]	[-1.04]	[-1.13]	[-1.32]
R^2	0.00	0.01	0.01	0.00	0.00	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
N	1,337	1,336	1,335	1,336	1,335	1,337	1,336	1,335	1,336	1,335	1,337	1,336	1,335	1,336	1,335

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.23) to implement Empirical Tests 5 and 6. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equations (OA-21), (1.19), and (1.21) using seven control characteristics from Model 2 estimated using pooled OLS. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

OA.8 Robustness Checks Related to Price Target Aggregation, Analyst Heterogeneity, and Announcement Timing

There is a large literature related to analyst heterogeneity. For instance, analysts with more timely earnings forecasts and those who issue more bold earnings forecasts tend to be more accurate (Hong, Kubik and Solomon (2000), Cooper et al. (2001), and Clement and Tse (2005)). Additionally, different analysts may have different incentives to issue biased estimates based on their specific career concerns. I have abstracted out this detail from my main price target measure (the median of all individual analyst price targets issued for a given firm in a given month), however, this heterogeneity could impact the accuracy of my aggregated price targets. Additionally, analysts can learn from price changes or other analyst price targets within the announcement month and incorporate this information into their target. In this section, I explore other specifications of my monthly firm-level price target measures to mitigate some of these concerns. Namely, I consider six different choices for computing my firm-month level analyst-expected-return measure using 1. The average of firm-month price targets across multiple analysts, 2. Price targets from firm-months where only one price target is issued, or the same target is issued by multiple analysts, 3. Only the first price target issued for each firm-month, 4. Only the last price target issued for each firm-month, 5. Averages of individual analysts' expected returns (not price targets) computed using individual price targets normalized by the stock price two days before the target is issued, and 6. Two different subsets of price targets designated as either bold (high-innovation) or herding (low-innovation) based on definitions similar to those for earnings forecasts in Clement and Tse (2005) (Gleason and Lee (2003)). I find that my main results do not change qualitatively, so that my main results are not driven by my original price target aggregation choice. I report results from these robustness checks in the subsections below.

OA.8.1 Analyst Price Targets Using Mean Aggregator

In this section, I consider aggregating firm-month price targets across analysts according to

$$\tilde{R}^{j}_{t,t+12} \equiv \frac{Mean\left[\left\{\tilde{P}^{j,k}_{t,t+12}\right\}\right] - P^{j}_{t-1}}{P^{j}_{t-1}} + DY^{j}_{t}. \tag{OA-22}$$

This is similar to my main specification in equation (1.17), but aggregates using the mean operator rather than the median operator. I again transform this measure of analyst-expected annual returns to the monthly frequency using equation (1.18). Results from my main empirical tests using this alternative analyst-expected return specification can be found in Tables OA-20 and OA-21. These are analogous to my main results in Tables 1.3 and 1.4. The point estimates and t-statistics are similar here to those in my main results, and the results from my six empirical tests are qualitatively the same. Using this modified price target aggregator does not qualitatively change my main results.

Table OA-20: Results Based on Empirical Tests 1-4 (Cumulative Return Tests, Model 2, Mean Price Target)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$i^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$i^j_{t,t+1}$	5.05	5.39	5.48	5.60	5.88	6.05							5.04	5.36	5.43	5.55	5.77	5.92
	[23.05]	[20.06]	[15.88]	[12.89]	[10.33]	[8.20]							[24.34]	[20.73]	[16.30]	[13.09]	[10.40]	[8.27]
$b^j_{t,t+1}$							0.76	0.62	0.43	0.36	0.08	0.12	0.86	0.74	0.57	0.51	0.25	0.31
							[4.84]	[2.63]	[1.30]	[0.86]	[0.13]	[0.16]	[5.94]	[3.39]	[1.84]	[1.26]	[0.39]	[0.43]
R^2	0.17	0.11	0.08	0.06	0.04	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.18	0.12	0.09	0.07	0.05	0.03
N	1,324	1,323	1,322	1,322	1,322	1,321	1,324	1,323	1,322	1,322	1,322	1,321	1,324	1,323	1,322	1,322	1,322	1,321

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$\bar{i}^j_{t,t+1}$	3.03	3.38	3.68	3.93	4.38	4.42							3.41	3.68	3.92	4.11	4.40	4.42
	[16.84]	[12.92]	[10.87]	[10.08]	[8.13]	[7.75]							[19.95]	[15.15]	[13.09]	[11.73]	[9.94]	[9.29]
$b^j_{t,t+1}$							0.76	0.62	0.43	0.36	0.08	0.12	1.23	1.09	0.88	0.82	0.45	0.48
							[4.84]	[2.63]	[1.30]	[0.86]	[0.13]	[0.16]	[8.64]	[4.97]	[2.78]	[1.96]	[0.64]	[0.67]
R^2	0.08	0.06	0.05	0.04	0.03	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.11	0.08	0.06	0.05	0.04	0.03
N	1,346	1,345	1,345	1,343	1,343	1,340	1,324	1,323	1,322	1,322	1,322	1,321	1,229	1,228	1,228	1,227	1,227	1,224

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) to implement Empirical Tests 1-4 using the mean aggregator described in equation (OA-22) to construct firm-month analyst price targets and analyst-expected returns. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{t,t+n}$ are cumulative returns for stock j from month t to month $t+n$ ($n \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table OA-21: Results Based on Empirical Tests 5-6 (Post-Announcement-Month Return Tests, Model 2, Mean Price Target)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$i^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$i^j_{t,t+1}$	0.34	0.43	0.54	0.82	0.98						0.31	0.39	0.50	0.72	0.85
	[3.55]	[2.31]	[1.84]	[1.75]	[1.46]						[3.34]	[2.14]	[1.72]	[1.56]	[1.33]
$b^j_{t,t+1}$						-0.13	-0.33	-0.41	-0.68	-0.64	-0.12	-0.30	-0.38	-0.64	-0.60
						[-1.30]	[-1.73]	[-1.46]	[-1.27]	[-0.96]	[-1.18]	[-1.59]	[-1.35]	[-1.22]	[-0.94]
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02
N	1,323	1,322	1,322	1,322	1,321	1,323	1,322	1,322	1,322	1,321	1,323	1,322	1,322	1,322	1,321

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$\bar{i}^j_{t,t+1}$	0.34	0.64	0.89	1.33	1.35						0.27	0.50	0.70	0.98	0.98
	[2.84]	[3.04]	[3.31]	[2.99]	[2.44]						[2.72]	[3.01]	[3.10]	[2.87]	[2.29]
$b^j_{t,t+1}$						-0.13	-0.33	-0.41	-0.68	-0.64	-0.14	-0.36	-0.42	-0.78	-0.75
						[-1.30]	[-1.73]	[-1.46]	[-1.27]	[-0.96]	[-1.40]	[-1.85]	[-1.44]	[-1.30]	[-1.19]
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.03	0.03	0.02	0.02	0.02
N	1,345	1,345	1,343	1,343	1,340	1,323	1,322	1,322	1,322	1,321	1,228	1,228	1,227	1,227	1,224

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.23) to implement Empirical Tests 5 and 6 using the mean aggregator described in equation (OA-22) to construct firm-month analyst price targets and analyst-expected returns. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

OA.8.2 Restricting Analysis to Months with Single Price Targets

In this subsection, I reproduce my main results using price targets from months in which only one target is issued, or months where all issued targets are equivalent. In this way, I mitigate concerns that analysts who issue targets later in the month incorporate different additional information in their targets (including previously issued targets) than the first analyst to issue a target. Results can be found below in Tables OA-22 and OA-23, which are analogous to my main results in Tables 1.3 and 1.4. The point estimates and t-statistics are similar here to those in my main results, and the results from my six empirical tests are qualitatively the same. This modification does not qualitatively change my main results.

Table OA-22: Results Based on Empirical Tests 1-4 (Cumulative Return Tests, Model 2, Single Price Target)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$i^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$i^j_{t,t+1}$	4.19	4.54	4.63	4.79	5.06	5.04							4.17	4.49	4.57	4.73	4.95	4.95
	[16.75]	[16.53]	[13.70]	[11.12]	[8.80]	[7.15]							[17.33]	[16.74]	[13.77]	[11.10]	[8.72]	[7.23]
$b^j_{t,t+1}$							1.08	0.94	0.76	0.65	0.34	0.35	1.14	1.02	0.87	0.77	0.46	0.52
							[6.18]	[3.72]	[2.21]	[1.54]	[0.55]	[0.48]	[7.35]	[4.48]	[2.71]	[1.95]	[0.78]	[0.74]
R^2	0.12	0.07	0.05	0.04	0.03	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.14	0.09	0.07	0.06	0.04	0.03
N	545	544	545	545	546	548	545	544	545	545	546	548	545	544	545	545	546	548

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$\bar{i}^j_{t,t+1}$	2.40	2.83	3.12	3.39	3.83	3.86							2.70	3.08	3.28	3.52	3.71	3.55
	[13.39]	[12.00]	[11.09]	[10.44]	[9.18]	[8.74]							[15.11]	[13.39]	[12.41]	[11.11]	[9.99]	[10.77]
$b^j_{t,t+1}$							1.08	0.94	0.76	0.65	0.34	0.35	1.31	1.15	0.95	0.87	0.46	0.55
							[6.18]	[3.72]	[2.21]	[1.54]	[0.55]	[0.48]	[7.51]	[4.59]	[2.81]	[2.10]	[0.71]	[0.78]
R^2	0.06	0.04	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.09	0.07	0.05	0.05	0.04	0.03
N	474	473	474	474	475	476	545	544	545	545	546	548	426	425	426	426	426	427

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) to implement Empirical Tests 1-4 using price targets from months in which only one target is issued, or months where all issued targets are equivalent. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{t,t+n}$ are cumulative returns for stock j from month t to month $t+n$ ($n \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table OA-23: Results Based on Empirical Tests 5-6 (Post-Announcement-Month Return Tests, Model 2, Single Price Target)

Panel A: Tests using $i^j_{t,t+1}$															
	$i^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$i^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$i^j_{t,t+1}$	0.35	0.44	0.59	0.85	0.84						0.31	0.39	0.54	0.75	0.76
	[3.77]	[2.65]	[2.19]	[1.99]	[1.48]						[3.32]	[2.35]	[2.01]	[1.77]	[1.38]
$b^j_{t,t+1}$						-0.14	-0.31	-0.43	-0.75	-0.72	-0.12	-0.27	-0.38	-0.70	-0.66
						[-1.24]	[-1.54]	[-1.55]	[-1.54]	[-1.13]	[-1.06]	[-1.36]	[-1.35]	[-1.45]	[-1.06]
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.02	0.02	0.02	0.03	0.02	0.02
N	544	545	545	546	548	544	545	545	546	548	544	545	545	546	548

Panel B: Tests using $\bar{i}^j_{t,t+1}$															
	$\bar{i}^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$\bar{i}^j_{t,t+1}$	0.44	0.72	0.99	1.44	1.45						0.38	0.57	0.82	1.01	0.83
	[3.73]	[4.35]	[4.98]	[4.62]	[3.59]						[3.44]	[3.95]	[4.24]	[3.78]	[2.78]
$b^j_{t,t+1}$						-0.14	-0.31	-0.43	-0.75	-0.72	-0.16	-0.36	-0.45	-0.86	-0.77
						[-1.24]	[-1.54]	[-1.55]	[-1.54]	[-1.13]	[-1.43]	[-1.80]	[-1.57]	[-1.61]	[-1.23]
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.02	0.03	0.03	0.03	0.02	0.03
N	473	474	474	475	476	544	545	545	546	548	425	426	426	426	427

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.23) to implement Empirical Tests 5 and 6 using price targets from months in which only one target is issued, or months where all issued targets are equivalent. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

OA.8.3 Using Only the First Price Target Issued Each Month

In this subsection, I reproduce my main results using only the first price target issued each month to compute my analyst-expected-return measure. In this way, I mitigate concerns that analysts who issue targets later in the month incorporate different additional information in their targets (including previously issued targets) than the first analyst to issue a target. Results can be found below in Tables OA-24 and OA-25, which are similar to my main results in Tables 1.3 and 1.4. This modification does not qualitatively change my main results.

Table OA-24: Results Based on Empirical Tests 1-4 (Cumulative Return Tests, Model 2, First Price Target)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$i^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$i^j_{t,t+1}$	3.44	3.69	3.73	3.84	4.03	4.11							3.42	3.65	3.68	3.78	3.93	3.98
	[18.77]	[16.87]	[13.48]	[10.76]	[8.59]	[6.57]							[19.45]	[17.10]	[13.55]	[10.70]	[8.47]	[6.53]
$b^j_{t,t+1}$							0.70	0.56	0.36	0.29	0.04	0.12	0.78	0.65	0.47	0.41	0.16	0.27
							[4.40]	[2.32]	[1.08]	[0.68]	[0.05]	[0.16]	[5.12]	[2.81]	[1.44]	[0.98]	[0.25]	[0.36]
R^2	0.08	0.05	0.04	0.03	0.02	0.01	0.02	0.02	0.02	0.01	0.01	0.01	0.10	0.07	0.05	0.04	0.03	0.02
N	1,323	1,323	1,322	1,321	1,322	1,320	1,323	1,323	1,322	1,321	1,322	1,320	1,323	1,323	1,322	1,321	1,322	1,320

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$\bar{i}^j_{t,t+1}$	1.63	1.89	2.08	2.31	2.70	2.70							1.78	1.97	2.13	2.30	2.54	2.52
	[10.24]	[8.34]	[7.23]	[6.66]	[5.50]	[5.13]							[12.20]	[9.85]	[8.84]	[7.91]	[6.67]	[6.83]
$b^j_{t,t+1}$							0.70	0.56	0.36	0.29	0.04	0.12	0.86	0.68	0.47	0.39	0.05	0.12
							[4.40]	[2.32]	[1.08]	[0.68]	[0.05]	[0.16]	[5.91]	[2.96]	[1.39]	[0.90]	[0.07]	[0.16]
R^2	0.03	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.01	0.05	0.04	0.04	0.03	0.03	0.02
N	1,211	1,211	1,210	1,209	1,209	1,206	1,323	1,323	1,322	1,321	1,322	1,320	1,102	1,102	1,101	1,100	1,100	1,098

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) to implement Empirical Tests 1-4 using only the first price target issued each month to compute analyst-expected returns. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{t,t+n}$ are cumulative returns for stock j from month t to month $t+n$ ($n \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table OA-25: Results Based on Empirical Tests 5-6 (Post-Announcement-Month Return Tests, Model 2, First Price Target)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$i^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$i^j_{t,t+1}$	0.25	0.29	0.39	0.59	0.65						0.23	0.26	0.36	0.50	0.54
	[3.19]	[1.94]	[1.61]	[1.52]	[1.16]						[2.98]	[1.78]	[1.48]	[1.30]	[1.00]
$b^j_{t,t+1}$						-0.14	-0.33	-0.41	-0.66	-0.58	-0.13	-0.31	-0.39	-0.63	-0.54
						[-1.32]	[-1.73]	[-1.46]	[-1.22]	[-0.84]	[-1.23]	[-1.62]	[-1.35]	[-1.17]	[-0.81]
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02
N	1,323	1,322	1,321	1,322	1,320	1,323	1,322	1,321	1,322	1,320	1,323	1,322	1,321	1,322	1,320

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$\bar{i}^j_{t,t+1}$	0.26	0.45	0.68	1.06	1.03						0.20	0.34	0.52	0.75	0.70
	[2.51]	[2.69]	[3.14]	[2.90]	[2.31]						[2.32]	[2.78]	[3.12]	[3.04]	[2.64]
$b^j_{t,t+1}$						-0.14	-0.33	-0.41	-0.66	-0.58	-0.18	-0.40	-0.48	-0.81	-0.75
						[-1.32]	[-1.73]	[-1.46]	[-1.22]	[-0.84]	[-1.70]	[-1.95]	[-1.54]	[-1.28]	[-1.14]
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02
N	1,211	1,210	1,209	1,209	1,206	1,323	1,322	1,321	1,322	1,320	1,102	1,101	1,100	1,100	1,098

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.23) to implement Empirical Tests 5 and 6 using only the first price target issued each month to compute analyst-expected returns. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information.$R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

OA.8.4 Using Only the Last Price Target Issued Each Month

In this subsection, I reproduce my main results using only the last price target issued each month to compute my analyst-expected-return measure. I do this as an alternative to the choice to use the first price target issued each month in the previous subsection. Results can be found below in Tables OA-26 and OA-27, which are similar to my main results in Tables 1.3 and 1.4. This modification does not qualitatively change my main results.

Table OA-26: Results Based on Empirical Tests 1-4 (Cumulative Return Tests, Model 2, Last Price Target)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$i^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$i^j_{t,t+1}$	4.82	5.15	5.25	5.39	5.65	5.85							4.79	5.11	5.20	5.33	5.55	5.72
	[22.38]	[19.41]	[15.65]	[12.99]	[10.70]	[9.02]							[23.56]	[20.04]	[16.05]	[13.18]	[10.78]	[9.07]
$b^j_{t,t+1}$							0.80	0.67	0.48	0.41	0.13	0.17	0.89	0.78	0.61	0.55	0.28	0.34
							[5.06]	[2.81]	[1.44]	[0.97]	[0.20]	[0.22]	[6.23]	[3.57]	[1.96]	[1.37]	[0.45]	[0.47]
R^2	0.15	0.09	0.07	0.05	0.03	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.17	0.11	0.08	0.07	0.05	0.03
N	1,324	1,323	1,323	1,322	1,322	1,321	1,324	1,323	1,323	1,322	1,322	1,321	1,324	1,323	1,323	1,322	1,322	1,321

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$\bar{i}^j_{t,t+1}$	3.29	3.65	3.93	4.18	4.65	4.69							3.49	3.79	4.02	4.24	4.57	4.65
	[20.09]	[14.54]	[12.10]	[11.02]	[8.90]	[9.84]							[22.09]	[15.79]	[13.59]	[11.98]	[10.16]	[11.27]
$b^j_{t,t+1}$							0.80	0.67	0.48	0.41	0.13	0.17	1.16	1.02	0.81	0.77	0.43	0.49
							[5.06]	[2.81]	[1.44]	[0.97]	[0.20]	[0.22]	[7.83]	[4.51]	[2.51]	[1.81]	[0.60]	[0.66]
R^2	0.08	0.06	0.04	0.04	0.03	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.11	0.08	0.06	0.05	0.04	0.03
N	1,244	1,243	1,242	1,241	1,241	1,238	1,324	1,323	1,323	1,322	1,322	1,321	1,136	1,136	1,135	1,134	1,134	1,132

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) to implement Empirical Tests 1-4 using only the last price target issued each month to compute analyst-expected returns. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{t,t+n}$ are cumulative returns for stock j from month t to month $t+n$ ($n \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table OA-27: Results Based on Empirical Tests 5-6 (Post-Announcement-Month Return Tests, Model 2, Last Price Target)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$i^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$i^j_{t,t+1}$	0.33	0.44	0.56	0.83	1.01						0.31	0.40	0.53	0.75	0.90
	[3.70]	[2.50]	[2.07]	[1.97]	[1.75]						[3.55]	[2.38]	[1.99]	[1.79]	[1.60]
$b^j_{t,t+1}$						-0.13	-0.32	-0.39	-0.67	-0.63	-0.11	-0.29	-0.36	-0.63	-0.59
						[-1.24]	[-1.68]	[-1.42]	[-1.25]	[-0.95]	[-1.10]	[-1.55]	[-1.31]	[-1.19]	[-0.92]
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02
N	1,323	1,323	1,322	1,322	1,321	1,323	1,323	1,322	1,322	1,321	1,323	1,323	1,322	1,322	1,321

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$\bar{i}^j_{t,t+1}$	0.36	0.63	0.89	1.35	1.37						0.29	0.52	0.74	1.07	1.12
	[3.15]	[3.26]	[3.56]	[3.35]	[3.21]						[2.92]	[3.24]	[3.37]	[3.33]	[3.54]
$b^j_{t,t+1}$						-0.13	-0.32	-0.39	-0.67	-0.63	-0.13	-0.34	-0.40	-0.73	-0.67
						[-1.24]	[-1.68]	[-1.42]	[-1.25]	[-0.95]	[-1.27]	[-1.75]	[-1.35]	[-1.19]	[-1.04]
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.03	0.02	0.02	0.02	0.02
N	1,243	1,242	1,241	1,241	1,238	1,323	1,323	1,322	1,322	1,321	1,136	1,135	1,134	1,134	1,132

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.23) to implement Empirical Tests 5 and 6 using only the last price target issued each month to compute analyst-expected returns. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

OA.8.5 Averaging Individual Analyst-Expected Returns Computed Using Two-Day Prior Price

In this subsection, I reproduce my main results using an analyst-expected-return measure that is aggregated directly from individual analyst-expected returns as follows. First, for each analyst-firm-month I compute the analyst-expected return using the stock price two days before the target is issued. In this way, this analyst-expected return is analyst-specific and recognizes that when issuing price targets an analyst observes market data (in particular, prices) until just before the price target is issued. I then compute my firm-month-level analyst-expected return summary measure by averaging all individual analyst-expected returns for a given firm-month. Results can be found below in Tables OA-28 and OA-29, which are similar to my main results in Tables 1.3 and 1.4.[OA-6] This modification does not qualitatively change my main results.

OA-6. I do not provide results using $\bar{i}^{j}_{t,t+1}$ since my measure of the the stale price target ($\overline{P}^{j}_{t,t+12}$) from IBES is normalized to compute $\overline{R}^{j}_{t,t+12}$ in equation (1.13) is normalized by the beginning-of-month price rather than the prices two days before each analyst issues her price target. This would make the implied bias between the different measures, $\tilde{R}^{j}_{t,t+1}$ and $\overline{R}^{j}_{t,t+1}$, have different price bases, which is a problem for my setup. This analysis should work if I normalize the stale price target by the same price as each individual analyst price target, but I leave this for future work.

Table OA-28: Results Based on Empirical Tests 1-4 (Cumulative Return Tests, Model 2, Individual Analyst-Expected Returns)

	$i^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$i^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$i^j_{t,t+1}$	1.65	1.89	1.96	2.00	2.10	1.95							1.68	1.90	1.95	1.98	2.04	1.89
	[12.59]	[10.72]	[8.02]	[6.70]	[4.77]	[2.60]							[12.73]	[10.53]	[7.87]	[6.51]	[4.63]	[2.63]
$b^j_{t,t+1}$							0.57	0.44	0.25	0.18	-0.05	0.04	0.62	0.49	0.32	0.25	0.03	0.15
							[3.55]	[1.83]	[0.76]	[0.44]	[-0.08]	[0.06]	[3.80]	[2.06]	[0.95]	[0.60]	[0.04]	[0.21]
R^2	0.03	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.01	0.05	0.04	0.04	0.03	0.02	0.02
N	1,324	1,323	1,322	1,321	1,322	1,321	1,324	1,323	1,322	1,321	1,322	1,321	1,324	1,323	1,322	1,321	1,322	1,321

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) to implement Empirical Tests 1-4 using firm-month-level analyst-expected returns computed as the average across analysts of each analyst-firm-month-level analyst-expected return, which is computed using the stock price from two days before the target is issued. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $R^j_{t,t+n}$ are cumulative returns for stock j from month t to month $t+n$ ($n \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table OA-29: Results Based on Empirical Tests 5-6 (Post-Announcement-Month Return Tests, Model 2, Individual Analyst-Expected Returns)

	$i^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$i^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$i^j_{t,t+1}$	0.25	0.32	0.36	0.48	0.35						0.22	0.28	0.31	0.39	0.26
	[3.48]	[2.35]	[1.86]	[1.42]	[0.58]						[3.16]	[2.10]	[1.59]	[1.18]	[0.45]
$b^j_{t,t+1}$						-0.13	-0.32	-0.40	-0.63	-0.53	-0.12	-0.31	-0.38	-0.61	-0.49
						[-1.26]	[-1.69]	[-1.44]	[-1.19]	[-0.75]	[-1.19]	[-1.60]	[-1.37]	[-1.15]	[-0.72]
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02
N	1,323	1,322	1,321	1,322	1,321	1,323	1,322	1,321	1,322	1,321	1,323	1,322	1,321	1,322	1,321

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.23) to implement Empirical Tests 5 and 6 using firm-month-level analyst-expected returns computed as the average across analysts of each analyst-firm-month-level analyst-expected return, which is computed using the stock price from two days before the target is issued. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

OA.8.6 Bold and Herding Price Target Subsets

A large literature documents that some analysts' forecasts are more accurate than others. In this section, I attempt to isolate price targets that contain more information about firm prospects than others. In order to do this, I adopt the methodology used in Clement and Tse (2005) and Gleason and Lee (2003) to identify bold (high-innovation) and herding (low-innovation) earnings forecasts. The idea is that earnings forecasts that deviate more from the consensus and an analyst's last forecast (bold forecasts) are likely to contain more information than forecasts that are close to consensus and an analyst's last forecast (herding forecasts). I define bold price targets as those that are both above (below) the analyst's last target and above (below) the current consensus price target. The current consensus price target is computed as the median of the most recent price targets issued by all analysts for a given firm over the past three months up until the current price target is issued. Results from my main tests using analyst-expected returns computed using only bold price targets are given in Tables OA-30 and OA-31. Results from my main test using analyst-expected returns computed using only herding price targets are given in Tables OA-32 and OA-33.

I begin by discussing results from the cumulative return regressions that include announcement-month returns in Tables OA-30 and OA-32. The bold target-based results are qualitatively the same as my main results, however, the herding target-based results are quite different. For instance, in Panel A of Table OA-32, the month-zero coefficients on $i^j_{t,t+1}$ are much lower than in my main results or those that use bold price targets. For instance, the coefficient on $i^j_{t,t+1}$ from the bivariate regression Panel A of Table OA-32 (i.e., that from the herding-based results) is only 2.10 compared to 6.08 in Panel A of Table OA-30 (bold-based results) or 5.06 in Panel A of Table 1.3 (main results). The month-zero coefficients on $\bar{i}^j_{t,t++1}$ are negative but statistically insignificant, again providing evidence that the herding targets contain little or no new information. Interestingly, the cumulative return coefficients (including the announcement month) on $i^j_{t,t+1}$ and $\bar{i}_{t,t+1}$ are increasing for the bold target-based results (as in my main results), but those on $i^j_{t,t+1}$ are decreasing for the herding-based results. The $b^j_{t,t+1}$coefficients in the bold target-based results are similar to those in my main results. There is an initial positive price reaction (month-zero coefficient of 0.73 in Panel A of Table OA-30), which decreases and becomes statistically insignificant by month two (month six in the case of regressions with $\bar{i}^j_{t,t+1}$). The $b^j_{t,t+1}$ coefficients behave similarly in the case of the herding target-based results, indicating that the market does not partially debias the herding targets before (incorrectly) incorporating them into prices.[OA-7]

Next, I discuss results from the cumulative return regressions that exclude announcement-month returns in Tables OA-31 and OA-33. The bold target-based results are again qualitatively similar to my main results, however, the herding target-based results are quite different. In this case, none of the regression coefficients are statistically significant and indicate there is no statistically significant underreaction to information component or overreaction to the bias component in these analyst-expected returns.

Overall, these results imply that the market takes the bold price targets more seriously than the herding targets. It reacts to the information and bias components in the bold targets similarly to that in my main results, however, there is little evidence of strong reactions to these components in the herding price target subset. These results are consistent with the findings in Clement and Tse (2005) that bold earnings forecasts are more accurate and that market prices react more to these forecasts than to herding forecasts. These results imply that much of my main results may be driven by bold forecasts rather than herding forecasts. It also implies that my price target aggregation choice used for my main results (i.e., using the median of targets issued each month) yields similar results to what we would obtain if we ignored analyst price targets that plausibly contain less price-relevant information (i.e., herding forecasts).

OA-7. Note that all regressors in these regressions have been z-transformed, however, the cross-sectional standard deviations of information component across the main, bold, and herding specifications are similar (ranging from 1.24-1.43) as are those of the bias component (ranging from 0.62-0.82). I could therefore transform these coefficients to those that would arise when using the non-z-transformed data and the interpretations would be similar.

Table OA-30: Results Based on Empirical Tests 1-4 (Cumulative Return Tests, Model 2, Only Bold Targets)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$i^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$i^j_{t,t+1}$	6.13	6.48	6.61	6.75	7.14	7.56							6.08	6.41	6.54	6.69	7.06	7.48
	[25.21]	[23.03]	[18.36]	[15.54]	[12.38]	[10.15]							[26.30]	[23.66]	[18.70]	[15.71]	[12.55]	[10.19]
$b^j_{t,t+1}$							0.69	0.58	0.35	0.24	-0.10	-0.28	0.73	0.62	0.41	0.29	-0.02	-0.17
							[3.87]	[2.35]	[1.02]	[0.52]	[-0.14]	[-0.37]	[4.44]	[2.70]	[1.26]	[0.66]	[-0.03]	[-0.23]
R^2	0.24	0.16	0.12	0.09	0.06	0.04	0.03	0.02	0.02	0.02	0.02	0.02	0.26	0.17	0.13	0.11	0.08	0.05
N	596	595	595	594	593	590	596	595	595	594	593	590	596	595	595	594	593	590

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$\bar{i}^j_{t,t+1}$	4.62	4.99	5.35	5.75	6.26	6.60							4.90	5.24	5.52	5.87	6.32	6.63
	[18.84]	[13.55]	[11.02]	[9.40]	[7.29]	[6.95]							[18.21]	[14.39]	[11.66]	[9.94]	[7.45]	[7.18]
$b^j_{t,t+1}$							0.69	0.58	0.35	0.24	-0.10	-0.28	1.26	1.18	1.01	0.94	0.57	0.35
							[3.87]	[2.35]	[1.02]	[0.52]	[-0.14]	[-0.37]	[9.11]	[5.77]	[3.50]	[2.38]	[0.88]	[0.52]
R^2	0.16	0.11	0.09	0.07	0.05	0.04	0.03	0.02	0.02	0.02	0.02	0.02	0.19	0.13	0.10	0.09	0.07	0.05
N	608	607	607	605	605	601	596	595	595	594	593	590	564	563	562	561	561	557

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) to implement Empirical Tests 1-4 where analyst-expected returns are computed using only bold price targets. Bold price targets are defined as those that are both above (below) the analyst's last target and above (below) the current consensus price target. The current consensus price target is computed as the median of the most recent price targets issued by all analysts for a given firm over the past three months up until the current price target is issued. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{t,t+n}$ are cumulative returns for stock j from month t to month $t+n$ ($n \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table OA-31: Results Based on Empirical Tests 5-6 (Post-Announcement-Month Return Tests, Model 2, Only Bold Targets)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$i^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$i^j_{t,t+1}$	0.34	0.47	0.61	0.99	1.37						0.32	0.46	0.60	0.97	1.35
	[3.59]	[2.72]	[2.23]	[2.20]	[2.05]						[3.55]	[2.69]	[2.28]	[2.23]	[2.13]
$b^j_{t,t+1}$						-0.10	-0.34	-0.45	-0.78	-0.96	-0.10	-0.32	-0.44	-0.76	-0.92
						[-0.89]	[-1.70]	[-1.40]	[-1.33]	[-1.47]	[-0.89]	[-1.66]	[-1.41]	[-1.33]	[-1.45]
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.03
N	595	595	594	593	590	595	595	594	593	590	595	595	594	593	590

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$\bar{i}^j_{t,t+1}$	0.35	0.72	1.12	1.62	1.93						0.32	0.60	0.95	1.39	1.67
	[2.15]	[2.66]	[2.95]	[2.56]	[2.60]						[2.30]	[2.49]	[2.76]	[2.30]	[2.46]
$b^j_{t,t+1}$						-0.10	-0.34	-0.45	-0.78	-0.96	-0.07	-0.25	-0.33	-0.70	-0.93
						[-0.89]	[-1.70]	[-1.40]	[-1.33]	[-1.47]	[-0.64]	[-1.27]	[-1.09]	[-1.20]	[-1.45]
R^2	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.04	0.03	0.03	0.03	0.03
N	607	607	605	605	601	595	595	594	593	590	563	562	561	561	557

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.23) to implement Empirical Tests 5 and 6 where analyst-expected returns are computed using only bold price targets. Bold price targets are defined as those that are both above (below) the analyst's last target and above (below) the current consensus price target. The current consensus price target is computed as the median of the most recent price targets issued by all analysts for a given firm over the past three months up until the current price target is issued. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

Table OA-32: Results Based on Empirical Tests 1-4 (Cumulative Return Tests, Model 2, Only Herding Targets)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$i^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$i^j_{t,t+1}$	2.14	2.15	1.98	1.91	1.93	1.83							2.10	2.07	1.87	1.81	1.77	1.57
	[14.46]	[10.93]	[8.93]	[7.10]	[4.91]	[2.88]							[15.73]	[11.48]	[8.86]	[6.73]	[4.62]	[2.72]
$b^j_{t,t+1}$							0.39	0.22	-0.10	-0.18	-0.38	-0.42	0.42	0.25	-0.06	-0.14	-0.35	-0.38
							[2.19]	[0.75]	[-0.25]	[-0.34]	[-0.41]	[-0.43]	[2.37]	[0.86]	[-0.14]	[-0.25]	[-0.39]	[-0.40]
R^2	0.05	0.03	0.02	0.02	0.02	0.01	0.03	0.03	0.03	0.03	0.03	0.03	0.07	0.06	0.05	0.05	0.04	0.04
N	456	456	455	454	453	449	456	456	455	454	453	449	456	456	455	454	453	449

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$\bar{i}^j_{t,t+1}$	-0.14	-0.14	-0.10	0.01	-0.00	-0.06							-0.14	-0.20	-0.25	-0.20	-0.29	-0.34
	[-1.05]	[-0.68]	[-0.42]	[0.03]	[-0.01]	[-0.11]							[-1.16]	[-1.21]	[-1.28]	[-0.90]	[-0.97]	[-0.90]
$b^j_{t,t+1}$							0.39	0.22	-0.10	-0.18	-0.38	-0.42	0.40	0.18	-0.15	-0.25	-0.40	-0.58
							[2.19]	[0.75]	[-0.25]	[-0.34]	[-0.41]	[-0.43]	[2.16]	[0.62]	[-0.34]	[-0.44]	[-0.43]	[-0.57]
R^2	0.02	0.02	0.01	0.01	0.01	0.01	0.03	0.03	0.03	0.03	0.03	0.03	0.05	0.04	0.04	0.04	0.04	0.04
N	411	411	411	410	409	405	456	456	455	454	453	449	384	384	383	382	382	378

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) to implement Empirical Tests 1-4 where analyst-expected returns are computed using only herding targets. Herding targets are defined as those that are not bold. Bold price targets are defined as those that are both above (below) the analyst's last target and above (below) the current consensus price target. The current consensus price target is computed as the median of the most recent price targets issued by all analysts for a given firm over the past three months up until the current price target is issued. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{t,t+n}$ are cumulative returns for stock j from month t to month $t+n$ ($n \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table OA-33: Results Based on Empirical Tests 5-6 (Post-Announcement-Month Return Tests, Model 2, Only Herding Targets)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$i^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$i^j_{t,t+1}$	0.01	-0.17	-0.24	-0.22	-0.35						-0.03	-0.24	-0.30	-0.34	-0.56
	[0.06]	[-1.04]	[-1.00]	[-0.55]	[-0.55]						[-0.36]	[-1.49]	[-1.28]	[-0.90]	[-1.01]
$b^j_{t,t+1}$						-0.17	-0.50	-0.59	-0.79	-0.84	-0.18	-0.49	-0.57	-0.80	-0.85
						[-1.11]	[-1.89]	[-1.49]	[-1.01]	[-0.92]	[-1.20]	[-1.88]	[-1.47]	[-1.04]	[-0.96]
R^2	0.01	0.01	0.01	0.01	0.01	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.04	0.04
N	456	455	454	453	449	456	455	454	453	449	456	455	454	453	449

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$\bar{i}^j_{t,t+1}$	0.01	0.04	0.15	0.13	0.04						-0.06	-0.11	-0.06	-0.15	-0.23
	[0.05]	[0.27]	[0.84]	[0.41]	[0.09]						[-0.70]	[-0.99]	[-0.42]	[-0.74]	[-0.77]
$b^j_{t,t+1}$						-0.17	-0.50	-0.59	-0.79	-0.84	-0.21	-0.54	-0.65	-0.81	-1.00
						[-1.11]	[-1.89]	[-1.49]	[-1.01]	[-0.92]	[-1.35]	[-1.92]	[-1.59]	[-1.02]	[-1.07]
R^2	0.01	0.01	0.01	0.01	0.01	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.04	0.04
N	411	411	410	409	405	456	455	454	453	449	384	383	382	382	378

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.23) to implement Empirical Tests 5 and 6 where analyst-expected returns are computed using only herding targets. Herding targets are defined as those that are not bold. Bold price targets are defined as those that are both above (below) the analyst's last target and above (below) the current consensus price target. The current consensus price target is computed as the median of the most recent price targets issued by all analysts for a given firm over the past three months up until the current price target is issued. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

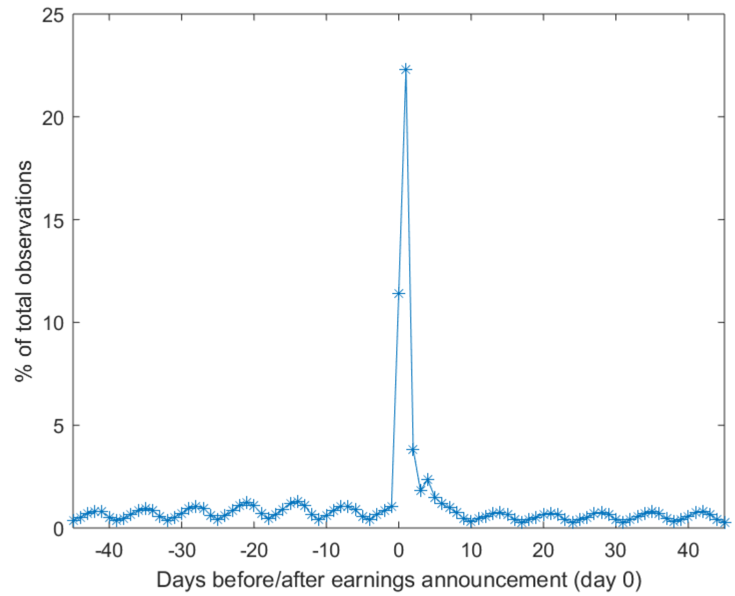
OA.9 Trading Strategies: Announcement-Window Returns

Table OA-34: Portfolios Sorted on Announcement-Window Returns

Panel A: Equal-weighted															
		Raw returns		**FF3**		**FF3C**		**FF3CL**		**FF5**		**FF5C**		**HXZ**	
	$\overline{R^j_{t,announce}}$	$\overline{R^p_{t+1}}$	$t-stat$	α^{FF3}	$t-stat$	α^{FF3C}	$t-stat$	α^{FF3CL}	$t-stat$	α^{FF5}	$t-stat$	α^{FF5C}	$t-stat$	α^{HXZ}	$t-stat$
Lo	-12.62	0.66	[1.25]	-0.51	[-2.52]	-0.36	[-2.04]	-0.36	[-2.01]	-0.23	[-1.12]	-0.18	[-0.98]	-0.20	[-1.03]
2	-5.30	0.90	[2.10]	-0.10	[-0.65]	-0.01	[-0.03]	-0.02	[-0.13]	-0.09	[-0.55]	-0.05	[-0.36]	0.02	[0.10]
3	-2.90	1.08	[2.88]	0.17	[1.36]	0.23	[1.98]	0.19	[1.63]	0.10	[0.75]	0.12	[1.02]	0.19	[1.36]
4	-1.37	1.04	[3.06]	0.20	[1.73]	0.25	[2.22]	0.22	[1.96]	0.11	[0.98]	0.13	[1.21]	0.20	[1.45]
5	-0.14	1.08	[3.39]	0.28	[2.93]	0.29	[3.06]	0.26	[2.79]	0.13	[1.37]	0.13	[1.47]	0.20	[1.86]
6	1.00	0.96	[3.02]	0.14	[1.62]	0.16	[1.88]	0.13	[1.59]	0.02	[0.22]	0.03	[0.36]	0.10	[1.05]
7	2.28	1.09	[3.41]	0.28	[3.13]	0.30	[3.33]	0.28	[3.11]	0.18	[1.98]	0.19	[2.10]	0.26	[2.50]
8	3.95	1.18	[3.50]	0.32	[3.46]	0.33	[3.51]	0.29	[3.21]	0.20	[2.14]	0.21	[2.20]	0.28	[2.72]
9	6.61	1.20	[3.25]	0.28	[2.72]	0.29	[2.85]	0.27	[2.66]	0.31	[2.85]	0.31	[2.91]	0.30	[2.93]
Hi	14.75	1.43	[2.98]	0.32	[2.14]	0.35	[2.32]	0.35	[2.33]	0.61	[4.32]	0.62	[4.36]	0.52	[3.55]
Hi-Lo	27.37	0.77	[2.89]	0.84	[3.35]	0.71	[3.01]	0.71	[2.99]	0.84	[3.28]	0.79	[3.30]	0.73	[2.78]
Panel B: Value-weighted															
		Raw returns		**FF3**		**FF3C**		**FF3CL**		**FF5**		**FF5C**		**HXZ**	
	$\overline{R^j_{t,announce}}$	$\overline{R^p_{t+1}}$	$t-stat$	α^{FF3}	$t-stat$	α^{FF3C}	$t-stat$	α^{FF3CL}	$t-stat$	α^{FF5}	$t-stat$	α^{FF5C}	$t-stat$	α^{HXZ}	$t-stat$
Lo	-10.92	0.36	[0.69]	-0.53	[-1.97]	-0.40	[-1.55]	-0.41	[-1.57]	-0.22	[-0.79]	-0.17	[-0.65]	-0.31	[-1.13]
2	-5.19	0.59	[1.46]	-0.21	[-1.14]	-0.14	[-0.78]	-0.11	[-0.65]	-0.05	[-0.25]	-0.02	[-0.12]	-0.04	[-0.22]
3	-2.87	0.73	[2.17]	0.09	[0.68]	0.10	[0.72]	0.10	[0.70]	0.11	[0.79]	0.12	[0.80]	0.05	[0.38]
4	-1.35	0.70	[2.33]	0.12	[0.95]	0.14	[1.10]	0.12	[0.91]	0.02	[0.17]	0.03	[0.24]	0.06	[0.47]
5	-0.12	0.48	[1.69]	-0.04	[-0.31]	-0.06	[-0.52]	-0.10	[-0.80]	-0.13	[-1.03]	-0.14	[-1.10]	-0.12	[-0.95]
6	1.00	0.57	[2.09]	0.01	[0.09]	0.00	[0.03]	-0.02	[-0.14]	-0.10	[-0.92]	-0.10	[-0.91]	-0.03	[-0.30]
7	2.26	0.69	[2.39]	0.11	[1.02]	0.09	[0.80]	0.08	[0.75]	0.02	[0.21]	0.02	[0.14]	0.04	[0.37]
8	3.90	0.67	[2.17]	0.08	[0.65]	0.09	[0.73]	0.06	[0.54]	0.05	[0.40]	0.06	[0.44]	0.09	[0.72]
9	6.45	0.79	[2.33]	0.14	[0.85]	0.12	[0.74]	0.13	[0.81]	0.15	[0.88]	0.14	[0.84]	0.10	[0.61]
Hi	13.26	0.91	[1.85]	0.03	[0.13]	0.05	[0.19]	0.06	[0.24]	0.54	[2.12]	0.54	[2.10]	0.33	[1.27]
Hi-Lo	24.18	0.54	[1.38]	0.57	[1.47]	0.45	[1.17]	0.47	[1.23]	0.76	[1.89]	0.71	[1.81]	0.64	[1.59]

Notes: Average returns on $R^j_{t,announce}$-sorted portfolios. Panel A uses equal weighting of portfolio constituents and Panel B uses value weighting. Overlines represent sample averages (i.e., $\overline{R^j_{t,announce}}$ are the within portfolio constituent average announcement-window returns, etc.). Returns are also risk-adjusted using the following empirical factor models: 1. "FF3" (the Fama and French (1993) 3-factor model), 2. "FF3C" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor), 3. "FF3CL" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor and the Pastor and Stambaugh (2003) traded liquidity factor), 4. "FF5" (the Fama and French (2015) 5-factor model), 5. "FF5C" (the Fama and French (2015) 5-factor model augmented with the Carhart (1997) UMD factor, which was used as a baseline for comparison in Kelly et al. (2018)), and 6. "HXZ" (the Hou et al. (2015) 4-factor model). Portfolios are rebalanced and regressions are run at the 1-month frequency. Data is from 1999-2017. t-statistics are reported in brackets.

Figure OA-1: Price Targets Issued Each Day Relative to Earnings Announcement Date



Notes: Number of price targets issued each day relative to earnings announcement dates. Values are reported as a percent of the total number of individual analyst price targets in the sample from 1999-2017.

OA.10 Analyst-Expected Returns and Earnings Announcements

One might be concerned that the information component captures information in earnings announcements, which might lead to the return predictability I observe with respect to the information component. In fact, 47% of the individual analyst price targets in my data set are announced either on earnings announcement days or in the next six days (see Figure OA-1). Even if this channel were to contribute to the information component in cases where price targets are released just after earnings announcements, it is unlikely to explain my findings related to bias. It is hard to rationalize how earnings announcements contain bias related to my bias component, or why the market might react to such a component. Regardless, I investigate the relationship between my results and earnings announcements in two ways. First, I eliminate all price targets released just after earnings announcements from my data set and re-run my main analysis. Second, I include controls for standardized unexpected earnings associated with earnings announcements.

OA.10.1 Eliminating Earnings-Report Price Targets from Analysis

According to Figure OA-1, analysts regularly issue price targets on non-earnings-announcement dates; however, there is a distinct increase in the number of price targets issued on earnings dates (day 0 in the figure) and during the subsequent week. In this section, I eliminate price targets issued either on earnings announcement dates or in the subsequent six days to investigate whether my results simply reflect the possibility that price targets contain earnings announcement news. This could lead to the return predictability I observe. Results can be found below in Tables OA-35 and OA-36, which are similar to my main results in Tables 1.3 and 1.4. This modification does not qualitatively change my main results.

Table OA-35: Results Based on Empirical Tests 1-4 (Cumulative Return Tests, Model 2, Excluding Price Targets Issued Near Earnings Announcements)

Panel A: Tests using $i^j_{t,t+1}$																		
	$i^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$i^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$i^j_{t,t+1}$	4.50	4.78	4.88	5.00	5.28	5.37							4.47	4.73	4.82	4.93	5.15	5.21
	20.24	18.27	14.27	11.27	9.05	7.37							21.48	18.94	14.63	11.45	9.10	7.38
$b^j_{t,t+1}$							0.77	0.60	0.41	0.33	0.05	-0.04	0.87	0.71	0.54	0.46	0.20	0.14
							4.38	2.32	1.14	0.71	0.07	-0.05	5.43	2.97	1.59	1.06	0.29	0.19
R^2	0.13	0.08	0.06	0.05	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.15	0.10	0.08	0.06	0.05	0.03
N	1,048	1,047	1,047	1,046	1,046	1,045	1,048	1,047	1,047	1,046	1,046	1,045	1,048	1,047	1,047	1,046	1,046	1,045

Panel B: Tests using $\bar{i}^j_{t,t+1}$																		
	$\bar{i}^j_{t,t+1}$ only						$b^j_{t,t+1}$ only						$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$\bar{i}^j_{t,t+1}$	2.84	3.13	3.39	3.62	4.05	4.08							3.06	3.27	3.50	3.70	4.02	4.06
	15.86	11.95	9.79	9.07	7.48	6.96							17.60	13.28	11.05	9.90	8.54	8.33
$b^j_{t,t+1}$							0.77	0.60	0.41	0.33	0.05	-0.04	1.11	0.92	0.71	0.65	0.29	0.18
							4.38	2.32	1.14	0.71	0.07	-0.05	6.69	3.74	2.01	1.41	0.38	0.23
R^2	0.07	0.05	0.04	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.10	0.07	0.06	0.05	0.04	0.03
N	981	979	979	978	978	976	1,048	1,047	1,047	1,046	1,046	1,045	899	897	897	896	896	894

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) to implement Empirical Tests 1-4. Price targets issued on earnings announcement dates and in the following six days are eliminated from the data before constructing analyst-expected returns used in this analysis. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $R^j_{t,t+n}$ are cumulative returns for stock j from month t to month $t+n$ ($n \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table OA-36: Results Based on Empirical Tests 5-6 (Post-Announcement-Month Return Tests, Model 2, Excluding Price Targets Issued Near Earnings Announcements)

Panel A: Tests using $i^j_{t,t+1}$

	$i^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$i^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$i^j_{t,t+1}$	0.28	0.38	0.49	0.78	0.84						0.25	0.35	0.45	0.68	0.72
	3.14	2.14	1.67	1.68	1.29						2.91	1.99	1.57	1.49	1.13
$b^j_{t,t+1}$						-0.17	-0.35	-0.44	-0.72	-0.81	-0.16	-0.33	-0.42	-0.69	-0.77
						-1.54	-1.76	-1.52	-1.28	-1.21	-1.46	-1.66	-1.43	-1.24	-1.20
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.02	0.03	0.02	0.03	0.02	0.02
N	1,047	1,047	1,046	1,046	1,045	1,047	1,047	1,046	1,046	1,045	1,047	1,047	1,046	1,046	1,045

Panel B: Tests using $\bar{i}^j_{t,t+1}$

	$\bar{i}^j_{t,t+1}$ only					$b^j_{t,t+1}$ only					$\bar{i}^j_{t,t+1}$ and $b^j_{t,t+1}$				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$\bar{i}^j_{t,t+1}$	0.29	0.54	0.77	1.20	1.20						0.21	0.44	0.63	0.96	0.97
	2.40	2.61	3.02	2.97	2.38						1.99	2.53	2.78	3.01	2.62
$b^j_{t,t+1}$						-0.17	-0.35	-0.44	-0.72	-0.81	-0.19	-0.40	-0.48	-0.82	-0.95
						-1.54	-1.76	-1.52	-1.28	-1.21	-1.79	-1.92	-1.52	-1.28	-1.44
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.02	0.03	0.03	0.03	0.02	0.03
N	979	979	978	978	976	1,047	1,047	1,046	1,046	1,045	897	897	896	896	894

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.23) to implement Empirical Tests 5 and 6. Price targets issued on earnings announcement dates and in the following six days are eliminated from the data before constructing analyst-expected returns used in this analysis. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

OA.10.2 Analyst-Expected Return Strategies and Post-Earnings Announcement Drift

In this sub-section, I investigate whether to the analyst-expected return trading strategies I document in Section 1.5.5 can be explained by the post-earnings announcement drift phenomenon. This is an important consideration, since analysts may issue price targets just before earnings announcements and the information they incorporate in these price targets may be correlated with standard measures of unexpected earnings.

I construct a measure of standardized unexpected earnings (SUE) according to the methodology in Chordia and Shivakumar (2006). Specifically, I estimate unexpected returns by subtracting realized quarterly earnings before extraordinary items from four quarters ago from the current quarter's earnings, then divide this difference by the standard deviation of the difference over the past eight quarters. I eliminate any records without at least 8 quarters of unexpected earnings. I use Compustat's "RDQ" variable to determine when each quarter's earnings are announced, and begin using each SUE record as a signal after the announcement month. I only use SUE signals for up to four months after the latest quarterly earnings announcement month to avoid stale data, which is also the methodology used by Chordia and Shivakumar (2006).

I construct a standard monthly trading strategy with rebalancing each month. This is slightly different that the six-month overlapping strategy used in Chordia and Shivakumar (2006) because I find that average strategy returns decrease when rolling months are added, and I want to compare the PEAD strategy to my monthly strategies.[OA-8] I begin by implementing the monthly PEAD strategy using data from 1963-2017 to verify that the strategy generates excess returns. Equal- and value-weighted strategy results can be found in Table OA-37. The long-short equal-weighted strategy in Panel A yields statistically significant average returns of 1.11% per month, which is comparable to values in related

OA-8. Note that the rolling strategy employed by Chordia and Shivakumar (2006) is similar to those in Jegadeesh and Titman (1993).

studies such as Chordia and Shivakumar (2006). The equal-weighted strategy returns also survive risk adjustment using all factor models considered. The value-weighted strategy yields lower average returns of 0.55% per month. This is statistically significant at standard levels, however, the significance is lower than in the equal-weighted strategy. Additionally, the statistically significance is eliminated when risk-adjusting using the FF5C and HXZ models. This result is consistent with findings in Chordia et al. (2009) that PEAD strategy returns are concentrated among low-liquidity stocks (and assuming that large stock are relatively liquid).

Next, I consider implementing the PEAD strategy over the period from 1999-2017, and only using SUE_t^j records for which I have corresponding analyst-expected return records. Average returns from implementing this strategy can be found in Table OA-38. The average number of stocks in each monthly cross-section is about 1,300, similar to those reported in Tables 1.3 and 1.4. The long-short equal-weighted strategy in Panel A yields average returns of 0.46% per month, which are only marginally statistically significant at the 10% level and lower than average returns over the full sample reported in Table OA-37. The average returns are statistically significant under risk adjustment from all factor models except the HXZ model. The value-weighted strategy yields statistically insignificant lower average returns of 0.43% per month. Average returns become statistically significant when risk-adjusting using the FF3, FF3C, and FF3CL models, however, remain statistically insignificant when risk-adjusting using the FF5, FF5C, and HXZ models. These results imply that the PEAD effect is relatively weak among the subsample of stocks for which analyst-expected returns exist. This is consistent with the finding that the PEAD strategy is weak among relatively liquid stocks (Chordia et al. (2009)), and the fact that analysts tend to cover larger, more liquid stocks.

Finally, I consider whether the information and bias-based strategies I document in Section 1.5.5 can be explained by the post-earnings announcement effect. I do this by conditionally double-sorting stocks into 5x5 portfolios first on SUE_t^j then, within each of the five SUE_t^j categories, on $i_{t,t+1}^j$. I report the average returns and t-statistics in Table OA-39. Panel A sorts on SUE_t^j then $i_{t,t+1}^j$. In this case, the long-short ($i_{t,t+1}^j$) average returns within each of the five SUE_t^j categories have positive and statistically significant average returns ranging from 0.56-0.86%. This implies that the information component strategy based on $i_{t,t+1}^j$ that I document survives controlling for the more well-known PEAD effect. Panel B presents risk-adjusted returns (i.e., α's) according to the Fama and French (1993) 3-factor model, which are consistent with the raw-return results in Panel A. These results indicate that the strategies I document based on the information component in analyst-expected returns are not subsumed by the PEAD effect although returns are slightly weakened when controlling for PEAD. I also provide regression-based evidence that the underreaction I document is distinct from post-earnings-announcement-drift effects in Table OA-40. Results are consistent with my portfolio sorting results that indicate the post-earnings announcement drift effect is weak among stocks with price targets (i.e. covered stocks). Controlling for SUE_t^j has little effect on the univariate $i_{t,t+1}^j$ and $b_{t,t+1}^j$ coefficients.

Table OA-37: Portfolios Sorted on SUE (1963-2017)

Panel A: Equal-weighted

		Raw returns		**FF3**		**FF3C**		**FF3CL**		**FF5**		**FF5C**		**HXZ**	
	$\overline{SUE_t^j}$	$\overline{R_{t+1}^p}$	$t-stat$	α^{FF3}	$t-stat$	α^{FF3C}	$t-stat$	α^{FF3CL}	$t-stat$	α^{FF5}	$t-stat$	α^{FF5C}	$t-stat$	α^{HXZ}	$t-stat$
Lo	-1.97	0.46	[1.58]	-0.62	[-7.17]	-0.42	[-6.36]	-0.40	[-6.18]	-0.53	[-5.98]	-0.39	[-5.69]	-0.35	[-3.93]
2	-0.98	0.65	[2.42]	-0.39	[-5.36]	-0.24	[-4.00]	-0.23	[-3.94]	-0.38	[-5.02]	-0.27	[-4.38]	-0.24	[-2.87]
3	-0.45	0.74	[2.85]	-0.28	[-4.41]	-0.16	[-2.96]	-0.16	[-2.95]	-0.27	[-4.05]	-0.18	[-3.20]	-0.17	[-2.28]
4	-0.13	0.95	[3.75]	-0.06	[-1.00]	0.02	[0.30]	0.01	[0.12]	-0.09	[-1.47]	-0.03	[-0.53]	-0.01	[-0.12]
5	0.10	1.10	[4.40]	0.09	[1.59]	0.14	[2.32]	0.12	[2.11]	0.02	[0.27]	0.05	[0.93]	0.05	[0.79]
6	0.33	1.29	[5.28]	0.30	[5.53]	0.32	[5.67]	0.31	[5.57]	0.21	[3.86]	0.23	[4.16]	0.24	[3.75]
7	0.64	1.34	[5.49]	0.37	[6.51]	0.37	[6.35]	0.37	[6.30]	0.28	[4.85]	0.28	[4.91]	0.26	[4.10]
8	1.07	1.39	[5.63]	0.41	[6.22]	0.38	[5.71]	0.38	[5.60]	0.32	[4.82]	0.30	[4.55]	0.27	[3.79]
9	1.66	1.50	[6.05]	0.52	[7.55]	0.51	[7.26]	0.51	[7.20]	0.44	[6.38]	0.43	[6.26]	0.39	[5.23]
Hi	2.93	1.57	[6.25]	0.60	[6.73]	0.56	[6.15]	0.56	[6.13]	0.45	[5.67]	0.42	[5.30]	0.35	[4.32]
Hi-Lo	4.90	1.11	[7.64]	1.22	[8.97]	0.98	[8.22]	0.96	[8.08]	0.98	[7.45]	0.81	[7.16]	0.70	[6.62]

Panel B: Value-weighted

		Raw returns		**FF3**		**FF3C**		**FF3CL**		**FF5**		**FF5C**		**HXZ**	
	$\overline{SUE_t^j}$	$\overline{R_{t+1}^p}$	$t-stat$	α^{FF3}	$t-stat$	α^{FF3C}	$t-stat$	α^{FF3CL}	$t-stat$	α^{FF5}	$t-stat$	α^{FF5C}	$t-stat$	α^{HXZ}	$t-stat$
Lo	-1.95	0.61	[2.16]	-0.42	[-3.45]	-0.21	[-1.91]	-0.19	[-1.72]	-0.27	[-2.13]	-0.11	[-1.04]	-0.09	[-0.79]
2	-0.98	0.73	[3.03]	-0.25	[-2.70]	-0.14	[-1.60]	-0.15	[-1.65]	-0.18	[-1.86]	-0.10	[-1.13]	-0.12	[-1.20]
3	-0.45	0.80	[3.27]	-0.18	[-1.85]	-0.09	[-0.90]	-0.08	[-0.86]	-0.15	[-1.53]	-0.08	[-0.85]	-0.07	[-0.63]
4	-0.13	0.93	[3.94]	-0.01	[-0.08]	0.00	[0.06]	0.00	[0.02]	-0.02	[-0.21]	-0.01	[-0.06]	-0.03	[-0.36]
5	0.10	0.89	[3.98]	-0.02	[-0.28]	-0.02	[-0.25]	-0.03	[-0.33]	-0.13	[-1.51]	-0.12	[-1.37]	-0.10	[-1.21]
6	0.33	1.13	[5.08]	0.23	[2.88]	0.23	[2.76]	0.22	[2.69]	0.11	[1.31]	0.11	[1.38]	0.12	[1.44]
7	0.64	1.03	[4.53]	0.14	[1.68]	0.08	[0.95]	0.09	[1.06]	-0.01	[-0.13]	-0.04	[-0.55]	-0.07	[-0.95]
8	1.07	0.97	[4.26]	0.09	[1.12]	0.02	[0.23]	0.01	[0.10]	0.05	[0.57]	-0.00	[-0.04]	-0.02	[-0.21]
9	1.67	1.04	[4.42]	0.15	[1.96]	0.09	[1.22]	0.09	[1.14]	0.13	[1.64]	0.09	[1.12]	0.09	[1.10]
Hi	3.12	1.16	[5.13]	0.35	[3.87]	0.26	[2.93]	0.26	[2.94]	0.20	[2.41]	0.14	[1.73]	0.11	[1.36]
Hi-Lo	5.08	0.55	[2.97]	0.77	[4.42]	0.47	[3.02]	0.45	[2.89]	0.47	[2.75]	0.25	[1.72]	0.20	[1.34]

Notes: Average returns on SUE_t^j-sorted portfolios. Panel A uses equally weights portfolio constituents and Panel B uses value weights constituents. Overlines represent sample averages (i.e., $\overline{SUE_t^j}$ are the within portfolio constituent average announcement-window returns, etc.). I use all records for which SUE_t^j exists and do not filter out records without corresponding analyst-expected return records. The average number of stocks in each monthly cross section is 2,776. Returns are also risk-adjusted using the following empirical factor models: 1. "FF3" (the Fama and French (1993) 3-factor model), 2. "FF3C" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor), 3. "FF3CL" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor and the Pastor and Stambaugh (2003) traded liquidity factor), 4. "FF5" (the Fama and French (2015) 5-factor model), 5. "FF5C" (the Fama and French (2015) 5-factor model augmented with the Carhart (1997) UMD factor, which was used as a baseline for comparison in Kelly et al. (2018)), and 6. "HXZ" (the Hou et al. (2015) 4-factor model). Portfolios are rebalanced and regressions are run at the 1-month frequency. Data is from 1963-2017. t-statistics are reported in brackets.

Table OA-38: Portfolios Sorted on SUE (1999-2017, only records with analyst-expected returns)

Panel A: Equal-weighted

		Raw returns		FF3		FF3C		FF3CL		FF5		FF5C		HXZ	
	$\overline{SUE_t^j}$	$\overline{R_{t+1}^p}$	$t-stat$	α^{FF3}	$t-stat$	α^{FF3C}	$t-stat$	α^{FF3CL}	$t-stat$	α^{FF5}	$t-stat$	α^{FF5C}	$t-stat$	α^{HXZ}	$t-stat$
Lo	-1.93	0.79	[1.80]	-0.27	[-1.72]	-0.11	[-0.97]	-0.07	[-0.62]	-0.12	[-0.74]	-0.06	[-0.51]	0.02	[0.16]
2	-0.96	1.02	[2.61]	0.02	[0.20]	0.13	[1.37]	0.12	[1.23]	0.01	[0.08]	0.05	[0.53]	0.17	[1.31]
3	-0.45	1.06	[2.70]	0.05	[0.44]	0.12	[1.29]	0.12	[1.24]	0.05	[0.42]	0.08	[0.78]	0.17	[1.39]
4	-0.13	1.07	[2.89]	0.11	[0.95]	0.17	[1.53]	0.14	[1.28]	-0.01	[-0.07]	0.02	[0.16]	0.12	[0.96]
5	0.10	1.32	[3.64]	0.38	[3.57]	0.41	[3.84]	0.39	[3.66]	0.26	[2.34]	0.27	[2.52]	0.33	[2.93]
6	0.35	1.17	[3.36]	0.28	[2.88]	0.31	[3.24]	0.27	[2.94]	0.17	[1.67]	0.18	[1.88]	0.25	[2.31]
7	0.67	1.17	[3.45]	0.31	[3.00]	0.33	[3.10]	0.30	[2.88]	0.21	[1.91]	0.21	[1.99]	0.22	[2.05]
8	1.10	1.18	[3.50]	0.36	[3.45]	0.34	[3.32]	0.30	[3.02]	0.25	[2.31]	0.24	[2.28]	0.23	[2.23]
9	1.69	1.23	[3.55]	0.40	[3.32]	0.40	[3.34]	0.35	[3.04]	0.34	[2.73]	0.34	[2.75]	0.32	[2.57]
Hi	2.89	1.25	[3.91]	0.48	[3.90]	0.44	[3.64]	0.40	[3.39]	0.31	[2.65]	0.29	[2.58]	0.28	[2.47]
Hi-Lo	4.83	0.46	[1.87]	0.75	[3.46]	0.55	[3.26]	0.47	[2.93]	0.43	[1.98]	0.36	[2.11]	0.25	[1.46]

Panel B: Value-weighted

		Raw returns		FF3		FF3C		FF3CL		FF5		FF5C		HXZ	
	$\overline{SUE_t^j}$	$\overline{R_{t+1}^p}$	$t-stat$	α^{FF3}	$t-stat$	α^{FF3C}	$t-stat$	α^{FF3CL}	$t-stat$	α^{FF5}	$t-stat$	α^{FF5C}	$t-stat$	α^{HXZ}	$t-stat$
Lo	-1.91	0.36	[0.92]	-0.33	[-1.77]	-0.20	[-1.23]	-0.15	[-0.91]	-0.13	[-0.68]	-0.08	[-0.49]	-0.05	[-0.29]
2	-0.96	0.51	[1.49]	-0.23	[-1.67]	-0.18	[-1.35]	-0.17	[-1.31]	-0.09	[-0.63]	-0.07	[-0.53]	-0.10	[-0.66]
3	-0.45	0.61	[1.80]	-0.13	[-0.96]	-0.07	[-0.52]	-0.06	[-0.42]	-0.10	[-0.67]	-0.07	[-0.52]	-0.04	[-0.30]
4	-0.14	0.80	[2.57]	0.14	[1.10]	0.13	[1.04]	0.11	[0.87]	0.07	[0.53]	0.07	[0.53]	0.09	[0.73]
5	0.10	0.51	[1.67]	-0.08	[-0.54]	-0.05	[-0.39]	-0.05	[-0.37]	-0.19	[-1.30]	-0.18	[-1.23]	-0.16	[-1.10]
6	0.36	0.81	[2.90]	0.24	[2.21]	0.25	[2.24]	0.21	[1.98]	0.13	[1.16]	0.14	[1.20]	0.19	[1.71]
7	0.68	0.84	[2.90]	0.29	[2.68]	0.25	[2.38]	0.26	[2.46]	0.18	[1.65]	0.17	[1.57]	0.17	[1.57]
8	1.10	0.54	[1.66]	-0.02	[-0.10]	-0.03	[-0.18]	-0.09	[-0.55]	-0.06	[-0.37]	-0.07	[-0.40]	-0.04	[-0.22]
9	1.70	0.59	[1.89]	0.04	[0.27]	-0.01	[-0.10]	-0.02	[-0.16]	0.03	[0.25]	0.01	[0.11]	0.01	[0.05]
Hi	3.00	0.79	[2.86]	0.33	[2.53]	0.26	[2.15]	0.26	[2.12]	0.14	[1.12]	0.12	[0.99]	0.13	[1.05]
Hi-Lo	4.91	0.43	[1.56]	0.66	[2.53]	0.47	[2.06]	0.41	[1.82]	0.27	[1.04]	0.20	[0.89]	0.18	[0.76]

Notes: Average returns on SUE_t^j-sorted portfolios. Panel A uses equally weights portfolio constituents and Panel B uses value weights constituents. Overlines represent sample averages (i.e., $\overline{SUE_t^j}$ are the within portfolio constituent average announcement-window returns, etc.). I use only records for which both SUE_t^j and a corresponding analyst-expected return record exist. The average number of stocks in each monthly cross section is 1,305. Returns are also risk-adjusted using the following empirical factor models: 1. "FF3" (the Fama and French (1993) 3-factor model), 2. "FF3C" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor), 3. "FF3CL" (the Fama and French (1993) 3-factor model augmented with the Carhart (1997) UMD factor and the Pastor and Stambaugh (2003) traded liquidity factor), 4. "FF5" (the Fama and French (2015) 5-factor model), 5. "FF5C" (the Fama and French (2015) 5-factor model augmented with the Carhart (1997) UMD factor, which was used as a baseline for comparison in Kelly et al. (2018)), and 6. "HXZ" (the Hou et al. (2015) 4-factor model). Portfolios are rebalanced and regressions are run at the 1-month frequency. Data is from 1999-2017, and only uses SUE_t^j signals for records with corresponding analyst-expected return records. t-statistics are reported in brackets.

OA.11 Controlling for Other Information in Analyst Reports

Gleason and Lee (2003) find that updates to analyst earnings forecasts predict returns in the cross section. Womack (1996) find that entrance and exit to and from the highest and lowest recommendation categories can also be used to forecast returns in the cross section. Asquith et al. (2005) find that updates to price targets are correlated with updates to earnings forecasts and recommendations by about 20%-30%, so it is possible that the underreaction and overreaction that I document are related to these previously-documented effects. In this section, I investigate this possibility by re-running my main empirical tests including controls related to earnings forecast and recommendation updates.

I begin by constructing stock-month level consensus earnings forecasts from individual analyst earnings forecasts using the IBES Unadjusted Detail database. I compute consensus earnings forecasts each month at the stock level as the median of all forecasts issued in a given month for a given stock. This is similar to my construction of my stock-month price target measure. I consider two different measures to represent updates to earnings forecasts. I compute the first measure as follows:

$$\Delta EPS1_t^j \equiv \frac{EPS_t^j - EPS_{t-1}^j}{P_{t-1}^j}, \tag{OA-23}$$

where EPS_t^j is the consensus EPS estimate across analysts for stock j in month t and P_{t-1}^j is the price of stock j at the end of month $t-1$ (this is consistent with my information and bias component normalization convention). This measure is similar to one used by Gleason and Lee (2003). I compute the second measure as follows:

$$\Delta EPS2_t^j \equiv \frac{EPS_t^j - \overline{EPS}_t^j}{P_{t-1}^j}, \tag{OA-24}$$

where $\overline{EPS}_t^j$ is the median consensus EPS forecast from the IBES Unadjusted Summary database for stock j during month t. This measure is motivated by my own alternate

Table OA-39: Portfolios Double-Sorted on SUE then Information Measures

Panel A: Sorted on SUE_t^j then $i_{t,t+1}^j$ (Model 2)						
Average returns	**Lo-$i_{t,t+1}^j$**	**2**	**3**	**4**	**Hi-$i_{t,t+1}^j$**	**Hi - Lo**
Lo-SUE_t^j	0.44	0.66	0.96	0.74	1.00	0.56
2	0.60	0.72	1.00	0.93	1.34	0.75
3	0.75	1.00	1.15	1.20	1.42	0.66
4	0.62	0.88	0.90	1.30	1.48	0.86
Hi-SUE_t^j	0.81	1.02	1.05	1.03	1.58	0.77
t-statistics	**Lo-$i_{t,t+1}^j$**	**2**	**3**	**4**	**Hi-$i_{t,t+1}^j$**	**Hi - Lo**
Lo-SUE_t^j	0.98	1.61	2.55	1.79	1.95	1.94
2	1.42	1.98	2.83	2.51	2.85	2.92
3	1.90	3.02	3.57	3.43	3.13	2.79
4	1.76	2.77	2.79	3.87	3.28	3.32
Hi-SUE_t^j	2.32	3.26	3.43	3.04	3.62	3.16

Panel B: Fama-French 3-factor α (Model 2)						
Average returns	**Lo-$i_{t,t+1}^j$**	**2**	**3**	**4**	**Hi-$i_{t,t+1}^j$**	**Hi - Lo**
Lo-SUE_t^j	-0.33	-0.10	0.24	0.03	0.20	0.53
2	-0.20	-0.02	0.30	0.19	0.45	0.65
3	-0.05	0.32	0.49	0.49	0.54	0.59
4	-0.06	0.25	0.24	0.62	0.61	0.67
Hi-SUE_t^j	0.10	0.37	0.44	0.38	0.81	0.72
t-statistics	**Lo-$i_{t,t+1}^j$**	**2**	**3**	**4**	**Hi-$i_{t,t+1}^j$**	**Hi - Lo**
Lo-SUE_t^j	-1.80	-0.68	1.74	0.19	1.09	1.95
2	-1.32	-0.13	2.09	1.48	2.77	2.80
3	-0.34	2.38	3.73	3.71	3.58	2.69
4	-0.44	1.82	2.04	4.73	3.43	2.98
Hi-SUE_t^j	0.60	2.64	3.12	2.74	4.30	3.41

Notes: Average returns to conditionally double-sorted equal-weighted portfolios first sorted into SUE_t^j quintiles, then into $i_{t,t+1}^j$ quintiles (Panel A) and the associated α's based on the Fama and French (1993) 3-factor model. $i_{t,t+1}^j$ is estimated using Model 2 (7 characteristics). There are an average of 52 stocks in each SUE_t^j-$i_{t,t+1}^j$-sorted portfolio. Data is from 1999-2017. t-statistics are reported in brackets.

Table OA-40: Realized returns regressed on SUE_t^j, $i_{t,t+1}^j$, and $b_{t,t+1}^j$

$R_{t+1}^j = \alpha_t + b \cdot SUE_t^j + c \cdot i_{t,t+1}^j + d \cdot b_{t,t+1}^j + \varepsilon_{t+1}^j$					
Model	**I**	**II**	**III**	**IV**	**V**
SUE_t^j	0.11			0.10	0.08
	[1.75]			[1.63]	[1.42]
$i_{t,t+1}^j$		0.26		0.26	0.23
		[3.71]		[3.75]	[3.37]
$b_{t,t+1}^j$			-0.15		-0.12
			[-1.53]		[-1.25]
R^2	0.01	0.01	0.02	0.01	0.03
N	1,306	1,323	1,323	1,306	1,306

Notes: Fama and MacBeth (1973) regression results from regressing next month's returns, R_{t+1}^j, on SUE_t^j, $i_{t,t+1}^j$, and $b_{t,t+1}^j$. SUE_t^j are standardized unexpected earnings constructed according to the methodology in Chordia and Shivakumar (2006). $b_{t,t+1}^j$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i_{t,t+1}^j$ is computed according to equation (1.12). I limit the sample to stock-months that contain records for each of these three variables. Each variable is cross-sectionally z-transformed and R_{t+1}^j is in percent, so each coefficient can be interpreted as the marginal effect a one standard deviation increase in the independent variables during month t has on expected returns (in percent) in the following month. Data is from 1999-2017. t-statistics are reported in brackets.

analyst-expected return information measure.

Next, I construct dummy variables to indicate whether a recommendation for stock j in month t either (1) entered the IBES strong buy category ($ENTERBUY_t^j$), (2) exited the IBES strong buy category ($EXITBUY_t^j$), (3) entered the IBES sell category ($ENTERSELL_t^j$), or (4) exited the IBES sell category ($EXITSELL_t^j$). The choice of these dummy variables is based on similar dummies used by Womack (1996). One slight difference is that their study was done at the individual analyst level, so that each of these dummies represented an indicator for relevant individual analyst-level recommendation changes. Since my unit of measure is at the stock-month level, I set each of these indicators to "1" for a given stock-month if any analyst covering the stock updated her recommendation according to one of these designations. For instance, if there are two analysts covering a stock and one moves from a buy to a strong buy rating, then I would set the $ENTERBUY_t^j$ dummy to "1" for that stock-month. If the second analyst moves her recommendation from a strong buy to a buy, I would also set $LEAVEBUY_t^j$ to "1" for the given stock-month. I allow an analyst's previous recommendation to be up to 11 months old for inclusion when constructing these dummies.

I re-run Empirical Tests 1-4 including different combinations of these controls below in Tables OA-41 and OA-42, which use $i_{t,t+1}^j$ or $\bar{i}_{t,t+1}^j$ as the information measure, respectively. Results are consistent with my main results in Table 1.3. The announcement month reactions to information and bias are not subsumed by reactions to changes in earnings forecasts or recommendations. Similarly, information coefficients remain positive and statistically significant for at least 12 months after the announcement months, whereas the bias coefficients consistently become statistically insignificant within three to six months after announcement months.

I re-run Empirical Tests 5-6 including different combinations of these controls below in Tables OA-43 and OA-44. Results are similar to my main results in Table 1.4. Coefficients on the information component in regressions with $R_{t+1,t+1}^j$ as the dependent variable (i.e.

returns in the first month after the announcement month) remain statistically significant at standard levels. Additionally, some of the coefficients on the bias component in are statistically significant at the 10% level. This implies that controlling for earnings forecast and recommendation updates provides stronger regression support for overreaction to bias than in my main results. Overall, controlling for these effects weakens my main results, but does not subsume them.

Table OA-41: Results Based on Empirical Tests 1-4 with $i^j_{t,t+1}$ (Cumulative Return Tests, Model 2, Earnings Forecast and Recommendation Controls)

	With $\Delta EPA1^j_t$ only						**With $\Delta EPA1^j_t$ and Recs**						**With $\Delta EPA2^j_t$ only**						**With $\Delta EPA2^j_t$ and Recs**					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$i^j_{t,t+1}$	4.71	4.89	4.97	5.02	5.09	5.09	4.60	4.76	4.87	4.91	4.94	4.92	5.05	5.34	5.43	5.50	5.66	5.72	4.98	5.26	5.35	5.42	5.54	5.57
	[23.58]	[20.58]	[14.48]	[11.93]	[9.90]	[7.82]	[21.62]	[18.66]	[13.68]	[11.44]	[9.99]	[7.71]	[24.09]	[20.71]	[15.92]	[12.91]	[10.90]	[8.61]	[22.43]	[19.40]	[15.26]	[12.71]	[11.26]	[8.78]
$b^j_{t,t+1}$	0.88	0.71	0.53	0.47	-0.02	0.06	0.88	0.71	0.57	0.51	0.03	0.18	0.92	0.82	0.66	0.63	0.31	0.40	0.93	0.84	0.66	0.62	0.32	0.45
	[5.58]	[3.08]	[1.62]	[1.13]	[-0.03]	[0.08]	[5.44]	[3.04]	[1.80]	[1.29]	[0.04]	[0.23]	[6.16]	[3.67]	[2.13]	[1.59]	[0.48]	[0.54]	[6.26]	[3.77]	[2.15]	[1.58]	[0.50]	[0.60]
$\Delta EPS1^j_t$	1.69	1.82	1.96	2.05	2.06	2.38	1.67	1.83	1.96	2.04	2.10	2.49												
	[18.84]	[16.08]	[13.07]	[11.34]	[6.06]	[5.56]	[19.37]	[17.07]	[13.75]	[12.00]	[6.64]	[6.03]												
$\Delta EPS2^j_t$													1.73	2.00	2.09	2.19	2.29	2.82	1.69	1.97	2.05	2.12	2.22	2.72
													[18.58]	[16.19]	[12.91]	[11.40]	[8.52]	[7.07]	[19.06]	[16.57]	[13.19]	[11.96]	[8.83]	[7.84]
$ENTERBUY^j_t$							0.98	0.94	0.98	1.02	1.09	0.81							1.08	0.96	0.98	1.00	0.98	0.79
							[7.64]	[4.98]	[4.66]	[4.70]	[2.27]	[1.29]							[8.87]	[5.33]	[4.65]	[4.50]	[1.94]	[1.16]
$EXITBUY^j_t$							-1.87	-1.95	-2.10	-2.05	-2.13	-2.90							-2.22	-2.40	-2.58	-2.61	-2.84	-3.72
							[-7.43]	[-6.84]	[-5.77]	[-4.55]	[-3.29]	[-3.59]							[-7.83]	[-7.31]	[-6.05]	[-5.12]	[-3.97]	[-3.81]
$ENTERSELL^j_t$							0.24	0.59	-0.03	-1.00	-1.22	-0.85							0.15	0.56	0.02	-0.58	-1.10	-0.89
							[0.53]	[1.09]	[-0.04]	[-1.49]	[-1.24]	[-0.58]							[0.31]	[0.94]	[0.02]	[-0.71]	[-1.00]	[-0.62]
$EXITSELL^j_t$							1.80	1.52	1.73	1.67	1.31	1.67							1.56	1.35	1.28	1.51	1.28	2.04
							[4.96]	[3.85]	[2.62]	[1.99]	[1.16]	[1.31]							[3.90]	[2.98]	[2.01]	[1.98]	[1.17]	[1.45]
R^2	0.21	0.13	0.10	0.08	0.06	0.04	0.22	0.14	0.11	0.09	0.07	0.05	0.21	0.14	0.11	0.09	0.06	0.04	0.22	0.15	0.12	0.10	0.07	0.05
N	900	900	900	900	900	899	908	908	907	907	908	907	1,188	1,189	1,188	1,187	1,187	1,186	1,196	1,197	1,196	1,195	1,196	1,194

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) to implement Empirical Tests 1-4. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\Delta EPS1^j_t$ is computed according to equation (OA-23). $\Delta EPS2^j_t$ is computed according to equation (OA-24). $ENTERBUY^j_t$, $EXITBUY^j_t$, $ENTERSELL^j_t$, and $EXITSELL^j_t$ are indicator variables that are set to "1" if any analyst makes the corresponding recommendation change during month t for stock j relative to their previous recommendation. $R^j_{t,t+n}$ are cumulative returns for stock j from month t to month $t+n$ ($n \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed (except for indicator variables) and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table OA-42: Results Based on Empirical Tests 1-4 with $\bar{i}^{j}_{t,t+1}$ (Cumulative Return Tests, Model 2, Earnings Forecast and Recommendation Controls)

	With $\Delta EPA1^j_t$ only						**With $\Delta EPA1^j_t$ and Recs**						**With $\Delta EPA2^j_t$ only**						**With $\Delta EPA2^j_t$ and Recs**					
Dep. var.:	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$	$R^j_{t,t}$	$R^j_{t,t+1}$	$R^j_{t,t+2}$	$R^j_{t,t+3}$	$R^j_{t,t+6}$	$R^j_{t,t+12}$
$\bar{i}^j_{t,t+1}$	3.37	3.59	3.83	3.96	4.28	4.24	3.28	3.48	3.71	3.81	4.12	4.04	3.45	3.68	3.94	4.13	4.48	4.43	3.33	3.58	3.84	4.01	4.33	4.24
	[20.15]	[15.29]	[12.37]	[11.08]	[9.41]	[9.75]	[19.71]	[14.94]	[12.12]	[11.16]	[10.26]	[10.43]	[21.11]	[15.33]	[13.01]	[11.71]	[9.83]	[10.19]	[20.11]	[14.94]	[12.79]	[11.91]	[10.83]	[12.09]
$b^j_{t,t+1}$	1.08	0.88	0.66	0.60	0.05	0.04	1.03	0.87	0.71	0.67	0.15	0.18	1.21	1.08	0.87	0.84	0.51	0.48	1.20	1.08	0.88	0.87	0.51	0.52
	[7.19]	[3.91]	[2.06]	[1.44]	[0.06]	[0.04]	[6.63]	[3.88]	[2.35]	[1.71]	[0.22]	[0.24]	[8.40]	[4.84]	[2.70]	[2.01]	[0.69]	[0.65]	[8.30]	[4.82]	[2.81]	[2.13]	[0.75]	[0.70]
$\Delta EPS1^j_t$	1.76	1.86	1.92	1.97	1.95	2.21	1.72	1.86	1.93	1.98	2.04	2.40												
	[18.22]	[16.12]	[14.39]	[13.00]	[6.78]	[6.13]	[19.71]	[17.62]	[15.68]	[13.82]	[7.73]	[6.97]												
$\Delta EPS2^j_t$													1.71	1.98	1.99	2.02	2.03	2.51	1.66	1.95	1.95	1.98	2.02	2.55
													[15.86]	[14.22]	[12.09]	[11.59]	[9.24]	[10.00]	[16.32]	[14.73]	[12.25]	[11.84]	[9.23]	[9.36]
$ENTERBUY^j_t$							1.70	1.64	1.66	1.65	1.80	1.17							1.96	1.90	1.93	1.88	1.88	1.41
							[10.07]	[7.39]	[6.64]	[6.38]	[3.46]	[1.83]							[12.06]	[8.57]	[7.95]	[7.56]	[3.49]	[2.08]
$EXITBUY^j_t$							-2.21	-2.21	-2.32	-2.37	-2.31	-2.92							-2.61	-2.73	-2.82	-2.83	-2.96	-3.60
							[-8.83]	[-7.87]	[-6.94]	[-5.66]	[-3.77]	[-3.77]							[-9.84]	[-8.96]	[-7.74]	[-6.34]	[-4.63]	[-4.18]
$ENTERSELL^j_t$							-1.15	-0.66	-1.26	-2.52	-3.00	-2.91							-1.33	-1.03	-1.55	-2.48	-3.29	-3.19
							[-2.51]	[-1.21]	[-1.91]	[-4.13]	[-3.40]	[-2.30]							[-2.79]	[-1.91]	[-2.46]	[-3.86]	[-3.33]	[-2.61]
$EXITSELL^j_t$							0.74	0.63	0.94	0.94	0.08	0.38							0.75	0.81	0.59	0.84	0.30	0.93
							[1.77]	[1.32]	[1.25]	[1.00]	[0.06]	[0.25]							[1.81]	[1.67]	[0.82]	[0.96]	[0.25]	[0.57]
R^2	0.15	0.10	0.08	0.07	0.05	0.04	0.16	0.11	0.09	0.08	0.06	0.05	0.14	0.10	0.08	0.07	0.05	0.04	0.16	0.11	0.09	0.08	0.06	0.05
N	773	773	773	773	773	772	780	780	780	779	780	778	998	999	998	997	997	996	1,004	1,005	1,005	1,003	1,003	1,002

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.22) to implement Empirical Tests 1-4. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $\Delta EPS1^j_t$ is computed according to equation (OA-23). $\Delta EPS2^j_t$ is computed according to equation (OA-24). $ENTERBUY^j_t$, $EXITBUY^j_t$, $ENTERSELL^j_t$, and $EXITSELL^j_t$ are indicator variables that are set to "1" if any analyst makes the corresponding recommendation change during month t for stock j relative to their previous recommendation. $R^j_{t,t+n}$ are cumulative returns for stock j from month t to month $t+n$ ($n \in \{0, 1, 2, 3, 6, 12\}$) including those in the announcement month. Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed (except for indicator variables) and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{t,t}$ regressions, 4 lags for $R^j_{t,t+1}$ regressions, 6 lags for $R^j_{t,t+2}$ regressions, 8 lags for $R^j_{t,t+3}$ regressions, 12 lags for $R^j_{t,t+6}$ regressions, and 24 lags for $R^j_{t,t+12}$ regressions. t-statistics are reported in brackets.

Table OA-43: Results Based on Empirical Tests 5-6 with $i^j_{t,t+1}$(Post-Announcement-Month Return Tests, Model 2, Earnings Forecast and Recommendation Controls)

	With $\Delta EPA1^j_t$ only					With $\Delta EPA1^j_t$ and Recs					With $\Delta EPA2^j_t$ only					With $\Delta EPA2^j_t$ and Recs				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$i^j_{t,t+1}$	0.18	0.26	0.29	0.37	0.34	0.16	0.27	0.30	0.34	0.29	0.29	0.38	0.44	0.61	0.65	0.27	0.36	0.42	0.55	0.56
	[1.99]	[1.32]	[1.03]	[0.86]	[0.58]	[1.92]	[1.45]	[1.09]	[0.89]	[0.54]	[3.14]	[2.03]	[1.54]	[1.42]	[1.09]	[3.03]	[1.96]	[1.49]	[1.36]	[0.98]
$b^j_{t,t+1}$	-0.17	-0.36	-0.43	-0.93	-0.87	-0.17	-0.33	-0.39	-0.88	-0.75	-0.10	-0.27	-0.32	-0.63	-0.57	-0.10	-0.29	-0.34	-0.64	-0.54
	[-1.57]	[-1.80]	[-1.47]	[-1.58]	[-1.25]	[-1.65]	[-1.75]	[-1.40]	[-1.59]	[-1.09]	[-0.97]	[-1.41]	[-1.14]	[-1.15]	[-0.86]	[-0.97]	[-1.54]	[-1.24]	[-1.20]	[-0.82]
$\Delta EPS1^j_t$	0.12	0.26	0.35	0.37	0.66	0.15	0.29	0.36	0.43	0.80										
	[1.96]	[2.68]	[2.58]	[1.15]	[1.59]	[2.55]	[3.06]	[2.85]	[1.42]	[1.98]										
$\Delta EPS2^j_t$											0.27	0.36	0.45	0.55	1.05	0.28	0.35	0.43	0.51	0.99
											[4.84]	[3.77]	[3.45]	[2.38]	[2.99]	[5.02]	[3.75]	[3.49]	[2.30]	[3.13]
$ENTERBUY^j_t$						-0.04	0.01	0.06	0.10	-0.21						-0.11	-0.09	-0.07	-0.11	-0.33
						[-0.32]	[0.06]	[0.37]	[0.23]	[-0.35]						[-0.99]	[-0.61]	[-0.42]	[-0.23]	[-0.49]
$EXITBUY^j_t$						-0.07	-0.23	-0.18	-0.26	-1.02						-0.16	-0.35	-0.38	-0.61	-1.47
						[-0.53]	[-1.28]	[-0.63]	[-0.49]	[-1.51]						[-1.26]	[-1.83]	[-1.36]	[-1.15]	[-1.90]
$ENTERSELL^j_t$						0.36	-0.23	-1.25	-1.49	-1.06						0.41	-0.08	-0.72	-1.26	-1.00
						[1.06]	[-0.56]	[-2.84]	[-2.05]	[-0.88]						[1.34]	[-0.20]	[-1.43]	[-1.55]	[-0.85]
$EXITSELL^j_t$						-0.29	-0.10	-0.14	-0.48	-0.11						-0.22	-0.30	-0.06	-0.25	0.53
						[-1.11]	[-0.20]	[-0.20]	[-0.54]	[-0.10]						[-0.83]	[-0.62]	[-0.09]	[-0.29]	[0.46]
R^2	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
N	900	900	900	900	899	908	907	907	908	907	1,189	1,188	1,187	1,187	1,186	1,197	1,196	1,195	1,196	1,194

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.23) to implement Empirical Tests 5 and 6. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. Given this value for bias, analyst-expected return information $i^j_{t,t+1}$ is computed according to equation (1.12). $\Delta EPS1^j_t$ is computed according to equation (OA-23). $\Delta EPS2^j_t$ is computed according to equation (OA-24). $ENTERBUY^j_t$, $EXITBUY^j_t$, $ENTERSELL^j_t$, and $EXITSELL^j_t$ are indicator variables that are set to "1" if any analyst makes the corresponding recommendation change during month t for stock j relative to their previous recommendation. $R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

Table OA-44: Results Based on Empirical Tests 5-6 with $\bar{i}^j_{t,t+1}$ (Post-Announcement-Month Return Tests, Model 2, Earnings Forecast and Recommendation Controls)

	With $\Delta EPA1^j_t$ only					With $\Delta EPA1^j_t$ and Recs					With $\Delta EPA2^j_t$ only					With $\Delta EPA2^j_t$ and Recs				
Dep. var.:	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$	$R^j_{1,1}$	$R^j_{1,2}$	$R^j_{1,3}$	$R^j_{1,6}$	$R^j_{1,12}$
$\bar{i}^j_{t,t+1}$	0.21	0.46	0.59	0.90	0.86	0.20	0.43	0.54	0.83	0.75	0.23	0.49	0.68	1.04	0.98	0.24	0.50	0.68	1.01	0.91
	[2.09]	[2.58]	[2.55]	[2.68]	[2.39]	[1.91]	[2.39]	[2.37]	[2.78]	[2.21]	[2.21]	[2.90]	[3.07]	[3.16]	[2.88]	[2.24]	[2.88]	[3.09]	[3.39]	[3.00]
$b^j_{t,t+1}$	-0.20	-0.43	-0.49	-1.05	-1.07	-0.15	-0.32	-0.38	-0.89	-0.87	-0.13	-0.35	-0.38	-0.71	-0.74	-0.13	-0.33	-0.35	-0.70	-0.69
	[-1.93]	[-2.17]	[-1.64]	[-1.61]	[-1.57]	[-1.55]	[-1.82]	[-1.39]	[-1.61]	[-1.38]	[-1.23]	[-1.76]	[-1.28]	[-1.14]	[-1.14]	[-1.21]	[-1.70]	[-1.20]	[-1.22]	[-1.08]
$\Delta EPS1^j_t$	0.09	0.15	0.19	0.16	0.41	0.13	0.20	0.24	0.30	0.64										
	[1.42]	[1.62]	[1.51]	[0.56]	[1.09]	[2.23]	[2.34]	[2.05]	[1.10]	[1.80]										
$\Delta EPS2^j_t$											0.26	0.27	0.30	0.31	0.76	0.28	0.28	0.31	0.35	0.85
											[4.42]	[2.73]	[2.29]	[1.43]	[2.89]	[4.69]	[2.81]	[2.50]	[1.69]	[3.11]
$ENTERBUY^j_t$						-0.05	-0.04	-0.04	0.09	-0.59						-0.06	-0.03	-0.08	-0.10	-0.59
						[-0.41]	[-0.23]	[-0.19]	[0.17]	[-0.98]						[-0.43]	[-0.19]	[-0.39]	[-0.19]	[-0.89]
$EXITBUY^j_t$						0.01	-0.10	-0.15	-0.10	-0.71						-0.10	-0.19	-0.20	-0.34	-0.97
						[0.09]	[-0.59]	[-0.53]	[-0.20]	[-1.12]						[-0.80]	[-1.05]	[-0.75]	[-0.67]	[-1.39]
$ENTERSELL^j_t$						0.50	-0.08	-1.36	-1.85	-1.69						0.29	-0.18	-1.13	-1.99	-1.81
						[1.42]	[-0.17]	[-3.04]	[-2.39]	[-1.60]						[0.94]	[-0.44]	[-2.61]	[-2.35]	[-1.88]
$EXITSELL^j_t$						-0.17	0.13	0.15	-0.65	-0.29						0.02	-0.19	0.08	-0.41	0.28
						[-0.56]	[0.24]	[0.21]	[-0.69]	[-0.22]						[0.06]	[-0.38]	[0.12]	[-0.45]	[0.19]
R^2	0.04	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.03	0.03
N	773	773	773	773	772	780	780	779	780	778	999	998	997	997	996	1,005	1,005	1,003	1,003	1,002

Notes: Fama and MacBeth (1973) regressions using the specification in equation (1.23) to implement Empirical Tests 5 and 6. $b^j_{t,t+1}$ is analyst-expected return bias and is estimated according to equation (1.21) using seven control characteristics from Model 2 and 10-year rolling Fama and MacBeth (1973) regressions. $\bar{i}^j_{t,t+1}$ is the information component in analyst-expected returns computed according to equation (1.13). For tests using $\bar{i}^j_{t,t+1}$, I remove records where $\bar{i}^j_{t,t+1} = 0$ since many of these are associated with months where the IBES Summary price targets only come from one report, which is the same as those used to construct my main measure of price targets so that these records contain both the same bias and information. $\Delta EPS1^j_t$ is computed according to equation (OA-23). $\Delta EPS2^j_t$ is computed according to equation (OA-24). $ENTERBUY^j_t$, $EXITBUY^j_t$, $ENTERSELL^j_t$, and $EXITSELL^j_t$ are indicator variables that are set to "1" if any analyst makes the corresponding recommendation change during month t for stock j relative to their previous recommendation. $R^j_{1,n}$ is shorthand for $R^j_{t,t+n} - R_{t,t}$, which are cumulative returns for stock j from month t to month $t+n$ ($n \in \{1, 2, 3, 6, 12\}$) minus those in the announcement month t as specified in equation (1.23). Regressions are run at the 1-month frequency. Data is from 1999-2017. All data is cross-sectionally z-transformed and realized returns are in percent, so regression coefficients can be interpreted as the marginal effect of a one-standard-deviation increase in the explanatory variable on the expected percent return next month. Standard errors are adjusted using the Newey and West (1987) methodology with 4 lags for $R^j_{1,1}$ regressions, 6 lags for $R^j_{1,2}$ regressions, 8 lags for $R^j_{1,3}$ regressions, 12 lags for $R^j_{1,6}$ regressions, and 24 lags for $R^j_{1,12}$ regressions. t-statistics are reported in brackets.

OA.12 Discussion of Analyst-Expected Return Error Estimation in Dechow and You (2017)

I now compare my estimation of analyst-expected return bias and information with that in Dechow and You (2017) to highlight the differences between my paper and theirs, and to highlight a potential issue that obscures the interpretation of their results related to return forecastability. The main goal of their paper is to identify which of three error types (misinterpreting return implications of firm risk characteristics, analyst incentives issues, and fundamentals forecasting errors) are the main drivers in analyst-expected return error. They use the term "error" to capture the same concept as my analyst-expected return "bias". They find that the primary error drivers are mistakes related to related to risk characteristics such as size, idiosyncratic volatility, and book-to-market ratio. This result indicates that my choice to model analyst-expected return bias conditional on observable firm characteristics captures a large fraction of the total analyst-expected return error. They also conclude that incentives issues only marginal explanatory power over analyst-expected return errors, and that fundamentals-related errors have "limited impact".

After estimating predictable analyst-expected return error, which is expected error conditional on observable information, the authors subtract this error from analyst-expected returns to compute a "purified" analyst-expected-return measure. They find that it forecasts future returns better than the raw analyst-expected-return measure. They also find that implementing a long-short strategy that goes long stocks with high purified returns and short stocks with low purified returns yields statistically significant positive returns. They use this to conclude that the market appears to underreact to information in analyst target price announcements, however, they fail to address the fact that their purified measure may still contain information related to analyst-expected return bias. This is caused by potential attenuation bias in their estimates, which I outline below.

The authors decompose analyst-expected returns as follows:[OA-9]

$$ImpliedReturn = \Big(ExpectedReturn_m + AnalystInformation_{t,t+12}\Big) - DivYield + Error_{AR} + Error_{AF} + Error_{AI}, \quad \text{(OA-25)}$$

where $ExpectedReturn_m$ is the firm's expected return,[OA-10] $AnalystInformation_{t,t+12}$ is the price relevant information in the analyst-expected return measured at time t with a horizon of time $t+12$, $Div - Yield$ is the dividend yield[OA-11], $Error_{AR}$ is analyst-expected return error related to risk,[OA-12] $Error_{AF}$ represents errors related to fundamental errors,[OA-13] and $Error_{AI}$ represents errors related to analyst incentives issues.[OA-14] This decomposition is similar to my analyst-expected return decomposition in equation (1.10). The only differences are that I include expected dividend yields in my definition of analyst-expected returns, and I do not decompose the analyst-expected return bias into separate components. To the extent that my conditioning variables correlate with the observable

OA-9. I begin using the notation in Dechow and You (2017), but soon transition to my own notation so that I can compare their results with my own more clearly.

OA-10. According to the authors, "The expected return is not a well-defined concept, but we assume it is the return required by the marginal investor holding a diversified portfolio." The "m" subscript represents the idea that this is a market expectation.

OA-11. Dechow and You (2017) subtract the past dividend yield form analyst-expected return, assuming that the expected future yield is the same as the past yield and that analysts account for this when estimating price targets. The assumption that the expected dividend yield is the same as the past dividend yield is common (see, for instance, Brav et al. (2005)). I do not account for the dividend yield in my main specification since it likely does not account for much cross-sectional variation in returns. Note that Brav et al. (2005) found that not including the dividend correction did not change their results materially.

OA-12. The authors define "risk" as exposure to standard cross-sectional characteristics such as size, idiosyncratic volatility, and β. In this way, their $Error_{AR}$ term captures analyst-expected errors that are similar to my definition of analyst-expected return bias.

OA-13. This represents the effect that earnings forecast errors have on analyst-expected returns.

OA-14. The authors use observable characteristics such as trading volume, external financing, and institutional holdings. This definition of error overlaps with my definition of bias to the extent my observable characteristics overlap with the three used by Dechow and You (2017). Although not exactly the same, my turnover variable is related to their volume variable, and my issuance variables are similar to their external financing variables. I do not control for institutional holdings.

variables used in Dechow and You (2017), my estimate of analyst-expected return bias should capture similar information as $Error_{AR} + Error_{AI}$. As noted above, Dechow and You (2017) find that $Error_{AF}$ have little ability to explain total analyst-expected return errors, so the fact that I omit characteristics in my models related to analyst earnings forecasts should not affect differences in results significantly.

The authors then use the following definitions to arrive at the relationship between analyst-expected returns and characteristics, which informs their main regression specifications:

$$\begin{aligned} FutureCumDividendReturn \equiv & \left(ExpectedReturn_m + AnalystInformation_{t,t+12}\right) \\ & + \left(UnexpectedReturn_{mA}\right), \end{aligned} \tag{OA-26}$$

where the $UnexpectedReturn_{mA}$ is now an unexpected return conditional on both market information as well as the information content in analyst-expected returns according to

$$UnexpectedReturn_{mA} \equiv UnexpectedReturn_m - AnalystInformation_{t,t+12}, \tag{OA-27}$$

so that the analyst-expected returns in equation (OA-25) can now be written as

$$\begin{aligned} ImpliedReturn = & \left[(FutureCumDividendReturn) - (DivYield)\right] \\ & + \left(Error_{AR} + Error_{AF} + Error_{AI}\right) - \left(UnexpectedReturn_{mA}\right). \end{aligned} \tag{OA-28}$$

Based on this, they define analyst-expected return error according to

$$
\begin{aligned}
ImpliedReturnForecastBias\ (FBIAS) &= ImpliedReturn - FutureExDividendReturn \\
&= (Error_{AR} + Error_{AF} + Error_{AI}) \\
&\quad - (UnexpectedReturn_{mA})\,. \qquad \text{(OA-29)}
\end{aligned}
$$

To estimate the analyst-expected return errors, the authors first project analyst-expected returns onto future returns and characteristics as follows:

$$
\begin{aligned}
IMPRET_t &= \beta_0 + \beta_1 DIVYIELD_t + \beta_2 RET_{t+1} + \beta_3 CO_t + \beta_4 DISPARITY_t + \beta_5 BETA_t \\
&\quad + \beta_6 IDVOL_t + \beta_7 SIZE_t + \beta_8 BM_t + \beta_9 LEVERAGE_t + \beta_{10} ILLIQ_t \\
&\quad + \beta_{11} VOLUME_t + \beta_{12} EXTFIN_t + \beta_{13} IHOLD_t + \varepsilon_t, \qquad \text{(OA-30)}
\end{aligned}
$$

where the regressors are the obvious standard firm characteristics (and CO_t is characteristic optimism as defined in So (2013)). Note that RET_{t+1} is a future return and is used as a measure of $ExpectedReturn_m$, the market expected return. Since it is a realized return, it is very a noisy measure. This implies that we would expect β_2 to have significant attenuation bias. Given estimates from this regression, the authors estimate the predictable component of analyst-expected return error (FBIAS) according to

$$
\begin{aligned}
PERROR_t &= \beta_{0,t-1} + \beta_{1,t-1} DIVYIELD_t + \beta_{3,t-1} CO_t + \beta_{4,t-1} DISPARITY_t + \beta_{5,t-1} BETA_t \\
&\quad + \beta_{6,t-1} IDVOL_t + \beta_{7,t-1} SIZE_t + \beta_{8,t-1} BM_t + \beta_{9,t-1} LEVERAGE_t + \beta_{10,t-1} ILLIQ_t \\
&\quad + \beta_{11,t-1} VOLUME_t + \beta_{12,t-1} EXTFIN_t + \beta_{13,t-1} IHOLD_t, \qquad \text{(OA-31)}
\end{aligned}
$$

where the $t-1$ subscripts indicate that the coefficients were estimated using characteristics data up to month $t-1$ and return data up to the end of date t so that look-ahead bias is not a concern. The authors then compute their "purified" analyst-expected-return measure according to

$$PURIFIED_t \equiv IMPRET_t - PERROR_t. \tag{OA-32}$$

I argue that the attenuation bias in β_2 is an issue for this calculation, since it contaminates the measure of $PERROR_t$ as follows. For simplicity of exposition and to relate the setup in Dechow and You (2017) to my own, I now begin using my own notation for the variables where appropriate but maintain that of Dechow and You (2017) where necessary for making comparisons. I assume that the set of conditioning characteristics for stock j is described by the vector X_t^j and that this vector contains a constant term. I assume that expected returns conditional on these characteristics can be expressed as

$$\mathbb{E}\left[R_{t+1}^j | X_t^j\right] = \mathbf{c}_t' X_t^j. \tag{OA-33}$$

Similarly, I assume that analyst-expected returns can be projected onto these characteristics as

$$\mathbb{E}\left[\tilde{R}_{t,t+1}^j | X_t^j\right] = c_t' X_t^j. \tag{OA-34}$$

Here I have replaced $IMPRET_t$ with my expression for the analyst-expected return, $\tilde{R}_{t,t+1}^j$. These last two expressions are the same as equations (1.19) and (1.20) in my main paper. Ideally, we would like to estimate the predictable component of analyst-expected returns as: $b_{t,t+1}^j$This definition comes from taking expectations over the definition of analyst-expected return error in equation (OA-29), along with the specifications of $\mathbb{E}\left[R_{t+1}^j | X_t^j\right]$ and $\mathbb{E}\left[\tilde{R}_{t,t+1}^j | X_t^j\right]$ above. This is the same as my definition of analyst-expected return bias, $b_{t,t+1}^j$, as in equation (1.21) so I replace $PERROR_t^j$ with $b_{t,t+1}^j$. The issue is that this is not necessarily what the estimate of $PERROR_t^j$ in Dechow and You (2017) given the attenuation bias issue I highlighted above. To estimate $PERROR_t^j$, Dechow and You (2017) first estimate the regression equation (OA-30):

$$\tilde{R}^j_{t,t+1} = \beta_2 \left(\mathbf{c}'_t X^j_t + i^j_{t,t+1} + \varepsilon^j_{t,mA} \right) + \overline{c}^j_t X^j_t + \varepsilon_t, \tag{OA-35}$$

where I have replace the realized return variable using the definition of future returns in equation (OA-26) and the conditional expectation in equation (OA-33). I have also replaced $AnalystInformation_{t,t+12}$ with my information component variable, $i^j_{t,t+1}$, for brevity since they capture the same information (i.e., information in analyst-expected returns orthogonal to market expected return conditional on X^j_t and orthogonal to forecastable analyst-expected return bias). Here $\overline{c}^j_t X^j_t$ is the forecastable component of analyst-expected return error and is defined by $\overline{c}^j_t \equiv c'_t - \mathbf{c}'_t$ in equation (OA-35). This is what we would like to estimate to compute $PERROR^j_t$. To the extent that $\overline{c}^j_t X^j_t$ captures analyst-expected return error, according to equation (OA-28) we expect the unbiased estimate of β_2 to be 1 such that equation (OA-34) becomes

$$\begin{aligned} E\left[\tilde{R}^j_{t,t+1} | X^j_t\right] &= \mathbf{c}'_t X^j_t + \overline{c}^j_t X^j_t \\ &= c'_t X^j_t, \end{aligned}$$

so, given an unbiased estimate of β_2, the regression in equation (OA-30) will yield analyst-expected returns conditional on characteristics as in equation (OA-34). Note that by definition $i^j_{t,t+1}$, $\varepsilon^j_{t,mA}$ and ε_t are orthogonal to X^j_t and go to zero when taking expectations conditional on X^j_t. Given an unbiased estimate of β_2, the estimate of predictable analyst-expected return error is given by $PERROR^i_t = \left(c'_t - \mathbf{c}'_t \right) X^j_t$ as desired and the proposed calculation of purified analyst-expected returns in equation (OA-32) yields

$$
\begin{aligned}
PURIFIED_t^j &= \tilde{R}_{t,t+1}^j - PERROR_t^j \\
&= b_t' X_t^j + i_{t,t+1}^j + \left(c_t' - \mathbf{c}_t'\right) X_t^j - \left(c_t' - \mathbf{c}_t'\right) X_t^j \\
&= c_t' X_t^j + i_{t,t+1}^j.
\end{aligned}
$$

It is clear this purified analyst-expected-return measure is meant to capture components of expected returns that are predictable conditional on characteristics as well as components indicated by the information in analyst-expected returns, which is really the component of analyst-expected returns that is orthogonal to observable information in X_t^j (i.e., the same as my definition of information, $i_{t,t+1}^j$).

What happens to the estimated $PERROR_t^j$ if we allow β_2 to have attenuation bias (i.e., $\beta_2 < 1$)? In the extreme case, assume full attenuation such that $\beta_2 = 0$. In this case, the estimate of $\bar{c}_t$ in equation (OA-35) becomes c_t such that the estimate of predicable analyst-expected return error is $PERROR_t^j = c_t^j X_t^j$. The estimated purified analyst-expected return calculation in with this extreme attenuation bias is then

$$
\begin{aligned}
PURIFIED_t^j &= \tilde{R}_{t,t+1}^j - PERROR_t^j \\
&= c_t' X_t^j + i_{t,t+1}^j + \left(c_t' - \mathbf{c}_t'\right) X_t^j - c_t^j X_t^j \\
&= \left(c_t' - \mathbf{c}_t'\right) X_t^j + i_{t,t+1}^j \\
&= b_{t,t+1}^j + i_{t,t+1}^j,
\end{aligned}
$$

so that the purified analyst-expected-return measure is now a combination of what I call the bias and information components in analyst-expected returns.

Table 3 in Dechow and You (2017) report their estimates of β_2 for a number of different specifications related to equation (OA-30). Estimates range between 0.054 and 0.074, suggesting that attenuation bias is an issue (these values are significantly lower than 1). The analysis I presented herein indicates that, with this attenuation bias, the interpretation of the purified analyst-expected-return measure in Dechow and You (2017) becomes blurred. Depending on the severity of the bias, it could represent expected returns conditional on characteristics ($c_t' X_t^j$) plus analyst-expected return information ($i_{t,t+1}^j$), or it could represent forecastable analyst-expected return bias ($b_{t,t+1}^j$) plus information ($i_{t,t+1}^j$). The attenuation bias also blurs the interpretation of $PERROR_t^j$, since it could represent the true forecastable bias component $b_{t,t+1}^j = \left(c_t' - \mathbf{c}_t'\right) X_t^j$, or simply analyst-expected returns projected onto characteristics, $c_t^j X_t^j$, in cases of extreme attenuation bias. My bias estimation method avoids these issues, since it does not rely on future realized returns as a proxy for expected returns when estimating the relationship between analyst-expected return errors and observable characteristics.

OA.13 Forecasting Realized Analyst-Expected Return Bias and a Comparison with So (2013)

So (2013) points out the fact that previous efforts to forecast analyst earnings forecast error by projecting forecast errors onto observable characteristics is subject to omitted variables bias since analyst private information or incentives might be correlated with observable characteristics. To alleviate this concern, So (2013) first estimates expected earnings for firm j conditional on observable information at time t, $\hat{E}_t^j$,[OA-15] using a standard earnings forecasting model. He then subtracts this from analyst earnings forecasts for period t, $AF_{j,t}$ (available in period $t-1$), to arrive at an *ex ante* analyst earnings forecast error measure, $\hat{FE}_t^j \equiv \hat{E}_t^j - AF_t^j$. The analyst-expected return error analog in my setup would be $A\hat{R}E_t^j \equiv \mathbb{E}\left[R_t^j | X_{t-1}^j\right] - \tilde{R}_{t-1,t}^j$, where I use $A\hat{R}E_t^j$ to designate the "analyst-expected return error" for stock j for returns realized in period t. So (2013) shows that $\hat{FE}_t^j$ forecasts realized error, $RE_t^j = E_t^j - AF_t^j$, and that a strategy that goes long stocks with positive errors and short stocks with negative errors earning positive average returns. So (2013) takes this as evidence that the market overweights information in analyst earnings forecasts when updating expectations about future earnings. When analysts forecast earnings below (above) those expected conditional on characteristics, these stocks become under priced (overpriced) leading to predictable future returns.

An issue with this analysis arises if there is some useful information, I_t^j, in analyst earnings forecasts about earnings at date t that is orthogonal to observable information at date $t-1$. Now the analyst forecast is comprised of the conditional expectation of earnings, bias B_t^j that may have some components correlated with observable characteristics and others orthogonal, and information orthogonal to observable characteristics: $AF_t^j = \hat{\mathbb{E}}_t^j + B_t^j + I_t^j$. Given this information and the earnings forecast conditional on characteristics, the expected earnings are $\overline{\hat{E}}_t^j = \hat{E}_t^j + I_t^j$ and the expected analyst forecast error is $\overline{\hat{FE}}_t^j = \hat{E}_t^j + I_t^j - AF_t^j$.

OA-15. This is the earnings forecast based on estimating a cross-sectional regression and using historical characteristics data, then using characteristics from period $t-1$ to arrive at the period t earnings forecast.

The error forecasting regression in Table 3 in So (2013) is:[OA-16]

$$E_t^j - AF_t^j = a_t + b\left(\hat{E}_t^j - AF_t^j\right) + \varepsilon_t^j.$$

Now, if we take expectations conditional on observable information but not I_t^j, $\hat{E}_t^j$ is a consistent estimate of $\mathbb{E}\left[E_t^j | X_{t-1}^j\right]$ and we expect $b = 1$. However, if we also condition on I_t^j, we have

$$\begin{aligned}
\mathbb{E}\left[E_t^j - AF_t^j | X_{t-1}^j, I_t^j\right] &= \left(\hat{E}_t^j + I_t^j\right) - \left(\hat{E}_t^j + \mathbb{E}\left[B_t^j | X_{t-1}^j, I_t^j\right] + I_t^j\right) \\
&= -\mathbb{E}\left[B_t^j | X_{t-1}^j, I_t^j\right],
\end{aligned}$$

but

$$\begin{aligned}
\hat{E}_t^j - AF_t^j &= \hat{E}_t^j - \left(\hat{E}_t^j + B_t^j + I_t^j\right) \\
&= -B_t^j - I_t^j.
\end{aligned}$$

Even with an estimate of $\hat{E}_t^j$, when the analyst earnings forecast contains information about future earnings that is orthogonal to characteristics, we expect the regression coefficient b to have attenuation bias due to noise added by I_t^j. Note that the coefficients estimated in So (2013) Table 3 are less than 1, but it is impossible to determine whether this is a symptom of noise in the $\hat{E}_t^j$ estimate, the fact that there is relevant earnings information in the analyst forecast, or both.

I would like to show that my measure of bias forecasts realized bias, but want to be careful to account for the fact that analyst-expected returns might contain relevant pricing information. In my case, I assume analyst-expected returns can be decomposed as follows:

OA-16. Note that So (2013) scales by total assets, which I omit here for simplicity.

$$\tilde{R}^j_{t,t+1} = \mathbb{E}\left[R_{t+1}|X^j_t\right] + b^j_{t,t+1} + i^j_{t,t+1}.$$

According to equation (1.3.2), returns in the month following the announcement month are

$$R^j_{t,t+1} - R^j_{t,t} = (\gamma_1 - \gamma_0)\, b^j_{t,t+1} + (\delta_1 - \delta_0)\, i^j_{t,t+1} + \varepsilon^j_{t+1},$$

where I multiply $b^j_{t,t+1}$ by $\gamma_1 - \gamma_0$ and $i^j_{t,t+1}$ by $\delta_1 - \delta_0$ due to information processing inefficiencies that may result in these components forecasting returns during month $t+1$, as described by Proposition 2 and shown in Table 1.4. We then have

$$\tilde{R}^j_{t,t+1} - R^j_{t+1} \approx (1 - (\gamma_1 - \gamma_0))\, b^j_{t,t+1} + (1 - (\delta_1 - \delta_0))\, i^j_{t,t+1} - \varepsilon^j_{t+1}. \quad \text{(OA-36)}$$

This makes it clear that $\tilde{R}^j_{t,t+1} - R^j_{t+1}$ (k.e. the difference between analyst-expected returns and the realized return in the month following price target announcements) contains information about the bias and information components in analyst-expected returns. Since I assume that the majority of the information component $i^j_{t,t+1}$ is incorporated into prices during the announcement month, we do not expect it to be reflected in realized returns R^j_{t+1} in the following month. I therefore consider a regression of the form

$$\tilde{R}^j_{t,t+1} - R^j_{t+1} = a_{t+1} + b \cdot b^j_{t,t+1} + c \cdot i^j_{t,t+1} + d \cdot \mathbb{E}\left[R^j_{t+1}|X^j_t\right] + e^j_{t+1}. \quad \text{(OA-37)}$$

We expect $b = 1 - (\gamma_1 - \gamma_0)$ and $c = 1 - (\delta_1 - \delta_0)$ jointly according to the decomposition in equation (OA-36). Unfortunately, there is also noise in my estimates of $b^j_{t,t+1}$ and $i^j_{t,t+1}$, just as there is noise in the estimates of $\hat{FE}^j_t$ in So (2013). Given this, I expect $b < 1 - (\gamma_1 - \gamma_0)$ and $c < 1 - (\delta_1 - \delta_0)$ in this regression. Results can be found below in Table OA-45. Results indicate that both $b^j_{t,t+1}$ and $\tilde{i}_{t,t+1}$ have marginal forecasting power over $\tilde{R}^j_{t,t+1} - R^j_{t+1}$, as we expect based on equation (OA-36). I also include conditional expected returns, $\mathbb{E}\left[R^j_{t+1}|X^j_t\right]$, as a control, which does not significantly affect these results.

Table OA-45: Realized Bias Forecasting Regressions

Model:	**I**	**II**	**III**	**IV**
$b^j_{t,t+1}$	0.67		0.67	0.62
	[5.80]		[5.90]	[2.58]
$i^j_{t,t+1}$		0.80	0.83	0.84
		[16.98]	[18.55]	[19.67]
$\mathbb{E}\left[R^j_{t+1}\|X^j_t\right]$				-0.12
				[-0.26]
R^2	0.02	0.02	0.03	0.05
N	1,323	1,323	1,323	1,323

Notes: Realized analyst-expected return bias ($\tilde{R}^j_{t,t+1} - R^j_{t+1}$) on analyst-expected return bias $b^j_{t,t+1}$ and information $i^j_{t,t+1}$ from the announcement month t according to regression in equation (OA-37) estimated using the Fama and MacBeth (1973) procedure. $i^j_{t,t+1}$ is the information component in analyst-expected returns estimated using equation (1.10). $b^j_{t,t+1}$ is the estimated bias computed according to equation (1.21). $\mathbb{E}\left[R^j_{t+1}|X^j_t\right]$ values are estimated using Model 2 (7 characteristics) and using rolling Fama and MacBeth (1973) regressions with 10 years of monthly historical data. Regressions are run at the 1-month frequency. All data is from 1999-2017 and corresponds to records for which analyst-expected returns are available along with the required characteristics for each model, although standard errors are adjusted using the Newey and West (1987) methodology with 4 lags. t-statistics are reported in brackets.