Do Investors Fully Unravel Persistent Pessimism in Analysts' Earnings Forecasts?

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April 2017

ABSTRACT: This study presents evidence suggesting that investors do not fully unravel predictable pessimism in sell-side analysts' earnings forecasts. We show that measures of prior consensus and individual analyst forecast pessimism are predictive of both the sign of firms' earnings surprises and the stock returns around earnings announcements. That is, we find that firms with a relatively high probability of forecast pessimism experience significantly higher announcement returns than those with a low probability. Importantly, we show these findings are driven by predictable pessimism in analysts' short-term forecasts as opposed to optimism in their longer-term forecasts. We further find that this mispricing is related to the difficulty investors have in identifying differences in expected forecast pessimism. Overall, we conclude that market prices do not fully reflect the conditional probability that a firm meets or beats earnings expectations as a result of analysts' pessimistically biased short-term forecasts.

JEL classification: G12, G14, G20

Keywords: Analyst forecast bias, forecast pessimism, earnings announcements, mispricing, earnings surprise, benchmark beating, analyst incentives

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I. INTRODUCTION

Forecasts of earnings by sell-side analysts are notorious for their systematic biases. On average, these forecasts are overly optimistic when measured more than a quarter ahead of a firm's earnings announcement, while they become pessimistic during the quarter before the earnings announcement (e.g., Matsumoto 2002; Richardson et al. 2004; Brown and Caylor 2005). Prior research suggests that factors such as incentives to generate trading commissions or win investment banking deals (e.g., Cowen et al. 2006; Lin and McNichols 1998), self-selection in coverage (e.g., McNichols and O'Brien 1997), and behavioral biases (e.g., Bradshaw et al. 2016) contribute to observed optimism in analysts' forecasts, while the prospect of access to management leads analysts to lower their forecasts and become pessimistic before earnings announcements to help firms beat expectations (e.g., Ke and Yu 2006; Hilary and Hsu 2013).[1]

Besides the timing and underlying sources of bias, key differences between the systematic optimism and pessimism in analysts' forecasts are the magnitude and visibility of bias. On average, the magnitude of the pessimistic bias in analysts' short-term forecasts is substantially smaller than that of the optimistic bias in longer-term forecasts (Abarbanell and Lehavy 2003; Richardson et al. 2004; Durtschi and Easton 2005). From an investor's perspective, this makes analysts' forecast pessimism less salient than forecast optimism. On the other hand, pessimism in short-term forecasts could be more salient as these forecasts determine the sign and magnitude of firms' quarterly earnings surprises, and data on firms' most recent earnings surprises are readily available to investors through a variety of public sources.

[1] In this study, we focus on the forecast bias that arises when analysts issue forecasts that deviate from their true, privately held, beliefs about a firm's earnings. Hence, optimism (pessimism) refers to forecasts issued above (below) the analysts' true beliefs. This differs from selection bias, where analysts do forecast their true beliefs but only for a subset of firms, such as those for which their beliefs are favorable (see McNichols and O'Brien 1997 for more explanation on the differences between forecast bias and selection bias).

This study examines whether predictable pessimism in short-term forecasts is fully reflected in market prices. Specifically, it tests whether measures that capture variation in the probability of forecast pessimism predict stock returns around firms' earnings announcements. If investors fully unravel predictable forecast pessimism, announcement returns should not be predictable based on such measures. Examining the market pricing of predictable forecast pessimism is novel as the literature has mainly focused on the market pricing of predictable analyst forecast errors, in general (e.g., Abarbanell and Bernard 1992; La Porta 1996; Frankel and Lee 1998; Ramnath 2002; So 2013), and of predictable optimism, more specifically (e.g., Dechow and Sloan 1997; Dechow et al. 2000; Diether et al. 2002; Bradshaw et al. 2006; Hribar and McInnis 2012). As explained above, the pessimistic bias in analysts' forecasts is unique in that the source, timing, and visibility of bias differ from that of optimistic bias in forecasts.

The systematic pessimism in analysts' short-term earnings forecasts has persisted since the 1990s (e.g., Brown and Caylor 2005) and is well publicized by the financial media (Zweig 2011; Gryta et al. 2016). Investors are thus likely aware of the relatively high *unconditional* probability that a firm's earnings beat analysts' expectations. Consistent with this notion, Keung et al. (2010) show that investors discount firms' earnings surprises when earnings exactly meet or just beat analysts' expectations. Nevertheless, we argue that it is unclear whether market prices fully reflect *conditional* probabilities of forecast pessimism *before* earnings announcements for two reasons.

First, not all firms and analysts exhibit similar degrees of forecast pessimism (e.g., Butler and Lang 1991; Hilary and Hsu 2013; Bissessur and Veenman 2016). For instance, Bissessur and Veenman (2016) show that forecasts are more likely pessimistic when a firm's earnings are more certain and analysts' private information is more precise (e.g., as a result of managers guiding some analysts' forecasts to beatable levels, see Cotter et al. 2006). The consequence of this variation is that the ex-ante identification of variation in forecast pessimism requires investors to understand more detailed data than just a firm's previous-quarter earnings surprise. To the extent investors are constrained in determining statistics that capture ex-ante variation in forecast pessimism, prices may not fully reflect the predictive value of these statistics (e.g., Bloomfield 2002; Hong et al. 2007; Cohen and Lou 2012).

Second, even if sophisticated investors can unravel predictable forecast bias, it is unclear whether pricing errors induced by less sophisticated investors would be arbitraged away. Trading on the pricing errors requires investors to take positions before earnings announcements and turn over their portfolios (at least) monthly. Earnings announcements elicit nontrivial increases in pre-announcement uncertainty (Cohen et al. 2007; Barber et al. 2013) and increases in systematic risk (Patton and Verardo 2012; Barth and So 2014; Savor and Wilson 2016), which elevate the costs of trading before earnings announcements (Krinsky and Lee 1996; So and Wang 2014; Levi and Zhang 2015). Moreover, Novy-Marx and Velikov (2016) show that strategies that require portfolio turnover of more than 50 percent per month fail to produce positive returns after accounting for transaction costs. Thus, announcement return predictability can exist even in the presence of sophisticated investors.

Using quarterly earnings announcements over the period 1986–2015, we first show that measures of the persistence in prior consensus and individual analysts' forecast pessimism strongly predict whether a firm will report a nonnegative earnings surprise. To assess whether market prices fully reflect this predictive value, we conduct standard asset pricing tests that predict returns in earnings announcement months based on ex-ante forecast pessimism measures, controlling for a large set of other characteristics. We find significant and strong positive associations between prior forecast pessimism and returns measured either as monthly or short-window announcement returns. These findings suggest that investors do not fully unravel predictable forecast pessimism.

To better understand the source of this mispricing, we compute measures of past consensus forecast pessimism for time series of different lengths. Consistent with investors using recent information on firms' earnings surprises, measures based on the sign of the most recent four quarterly earnings surprises have weak predictive power for announcement returns. Extending the time-series to 12 past quarters, however, substantially increases the return differences between firms with high and low probabilities of forecast pessimism. Similarly, we find that our measure of past individual analyst forecast pessimism, which is calculated based on each analyst's portfolio of firms covered, has stronger return predictive ability when its measurement becomes more complex. These findings suggest that forecast pessimism statistics are less likely fully priced when they are less readily available and their computation is more complex.

Our research relates to the literature on the pricing of predictable errors and bias in analyst forecasts. The key difference with this literature is that we examine bias in analysts' short-term (quarterly) earnings forecasts, whereas the literature mostly focuses on longer-term forecasts (i.e., more than one quarter ahead). To illustrate the importance of this difference, we re-compute our measures for analysts' forecasts measured earlier in event-time. We confirm that these earlier forecasts are systematically *optimistic* and show that our main findings are explained only by statistics based on short-term forecasts, not by those based on longer-term forecasts. This confirms that our findings capture unique pricing errors due to predictable forecast pessimism.

It is important to note that we aim to document whether the systematic pessimism in analysts' short-term forecasts leads to market frictions, not to identify an implementable trading strategy.[2] Consistent with the argument that sophisticated investors might not fully arbitrage away the pricing errors we find, supplemental analyses reveal that return predictability is stronger for smaller firms, which are costlier to trade and arbitrage (Fama and French 2008). Still, our findings are not solely driven by the smallest firms and reflect a market friction that affects a broad cross-section of analyst-covered firms.

Prior research on post-earnings announcement drift (PEAD) (e.g., Abarbanell and Bernard 1992; Livnat and Mendenhall 2006) shows that earnings surprises predict returns and that part of these returns materialize around earnings announcements. While this literature focuses on the extent to which investors under-react to information in extreme earnings surprises, we focus on persistence in the *sign* of analysts' forecast errors and its pricing. A key distinction is that we focus on the market's *over*weighting of the earnings expectations set gradually before the earnings announcement, instead of the *under*weighting of information revealed at the previous earnings announcement.[3] Moreover, we show empirically that PEAD is unlikely to be a viable explanation for our findings, as there is limited evidence of PEAD around earnings announcements for the sample that we investigate.

This paper makes the following contributions. First, we contribute to the literature on the valuation of predictable analyst forecast errors. This literature suggests market prices do not fully

[2] Lewellen (2010, 461) posits that "patterns like post-earnings-announcement drift and the accrual anomaly can help us to understand better how the market processes information even if the underlying predictability falls within the bounds of transaction costs. In short, anomalies are interesting even when they cannot be exploited by investors."

[3] Da et al. (2014) illustrate the subtle but important distinction between information that is gradually released (e.g., earnings forecasts) versus information released at discrete intervals (e.g., earnings announcements). Their "frog-in-the-pan" hypothesis suggests that investors are relatively less attentive to information signals that arrive frequently in small amounts. Tests of differences in return momentum support their hypothesis. This hypothesis could also explain why investors fail to fully unravel subtle differences in the valuation implications of qualitative attributes of individual analysts' forecast revisions (e.g., Gleason and Lee 2003).

unravel predictable analyst forecast errors and optimism (e.g., Dechow et al. 2000; Hribar and McInnis 2012; So 2013). For example, similar to So (2013) we show that investors fail to fully adjust analysts' earnings forecasts for predictable errors. We complement So (2013) by showing how predictable variation in the *sign* of analysts' *short-term* forecast errors leads to market pricing errors. In this regard, we also contribute to the literature on investor learning, which shows investors are Bayesian and use time series of prior forecast errors to learn about analyst ability (e.g., Chen et al. 2005) or to adjust forecasts for predictable errors (e.g., Hilary and Hsu 2013). This literature does not test whether investors' learning and de-biasing of analyst research is complete. We show it is not: the less salient the predictable component of forecast pessimism, the less complete investors' de-biasing of analyst research.

Second, we contribute to the literature on the market valuation of firms meeting or beating earnings expectations (MBE). This literature examines post-announcement valuation premiums of firms that meet or beat expectations (e.g., Bartov et al. 2002; Kasznik and McNichols 2002; Bhojraj et al. 2009; Abarbanell and Park 2017). In contrast, we examine *ex-ante* forecast characteristics and the extent to which these are reflected in prices before earnings announcements.[4] Our study suggests that the persistent pessimism in analysts' short-term forecasts leads to mispricing. Given analysts' continued reliance on private interaction with managers (Green et al. 2014; Soltes 2014; Brown et al. 2015)—which creates incentives for analysts to please managers and forecast pessimistically—these frictions are unlikely to soon disappear.

[4] Ma and Markov (2017) examine investors' valuations of the predictive ability of firms' history of MBE (among other factors). They show that investors do not attach valuation weights to firms' MBE history in predicting nonnegative earnings surprises, while the autocorrelation in MBE suggests they should. Using a Mishkin framework, however, the authors cannot reject the null of efficient pricing and conclude that investors correctly anticipate the implications of past MBE for future returns. A major difference is our focus on earnings announcement returns versus their focus on full-quarter returns. Our focus on announcement returns reduces noise and helps to more precisely capture the point at which investors' errors in expectation are revealed and corrected.

Lastly, our study contributes to the literature on earnings-related anomalies. In contrast to other anomalies, we show that the returns associated with analyst forecast pessimism remain strong in recent years despite increased arbitrage and stock liquidity (e.g., Richardson et al. 2010; Green et al. 2011; Chordia et al. 2014). This further suggests that our findings are distinct from other phenomena such as the accrual anomaly and PEAD, that also induce predictable announcement returns, but which have largely disappeared. Nevertheless, our findings are consistent with recent work showing that less salient aspects of firms' previous earnings announcements can still induce substantial mispricing (see, e.g., Chang et al. 2017 on the mispricing of seasonal earnings patterns).

II. BACKGROUND AND PREDICTIONS

Analyst Forecast Bias

Sell-side analysts' forecasts are a key source of information for investors in setting earnings expectations (e.g., Givoly and Lakonishok 1979; Lys and Sohn 1990; Stickel 1991), but prior research also suggests these forecasts are systematically biased. Forecast bias has been shown to result from analyst incentives to generate trading commissions, win investment banking deals, and obtain access to management.[5]

Early research focuses on the causes and consequences of optimistic bias and errors in analysts' longer-term (i.e., annual and more-than-one-quarter ahead) forecasts, while later studies find that analysts' short-term forecasts are systematically pessimistic. For example, Richardson et al. (2004) show that forecasts are too optimistic early in the year but switch to being pessimistic shortly before earnings announcements. Consistent with analysts catering to managers' preferences for optimistic long-term forecasts and positive earnings surprises, they show that this

[5] See, for example, Francis and Philbrick (1993), Dugar and Nathan (1995), Das et al. (1998), Lin and McNichols (1998), Hong and Kubik (2003), Ke and Yu (2006), and Feng and Mcvay (2010). Other studies have linked forecast biases to analysts' loss functions (e.g., Gu and Wu 2003) and behavioral biases (e.g., Bradshaw et al. 2016).

walk-down is strongest when managers have incentives to issue equity or sell shares on personal accounts after the earnings announcement. Other studies confirm that pleasing managers with pessimistic forecasts before earnings announcements helps analysts gain access to management (Ke and Yu 2006; Hilary and Hsu 2013).[6] Thus, a key difference between analysts' longer-term forecasts and their short-term forecasts is that the objectives to generate trading commissions and win investment banking deals typically incentivize analysts to be overly optimistic in their longer-term forecasts, while access to management incentivizes them to be pessimistic shortly before earnings announcements.

Investors' Pricing of Predictable Forecast Bias

The literature suggests that analysts' forecast errors and bias exhibit predictable patterns. Investors understanding this predictability should adjust their valuations of firms' earnings surprises (i.e., actual earnings adjusted for the consensus forecast). In this regard, Keung et al. (2010) find that investors anticipate the high unconditional probability that the average firm will meet or beat analysts' earnings expectations and, ex-post, discount zero and small positive earnings surprises. This suggests that investors unravel a predictable component of forecast errors. Similarly, the literature on investor learning shows that investors are Bayesian and use time-series of individual analysts' prior forecast errors to learn about analyst-specific forecasting ability. For example, prior research shows that investors respond more strongly to the forecast revisions of high-ability analysts (e.g., Park and Stice 2000; Chen et al. 2005; Brown and Mohammad 2010). Hilary and Hsu (2013) also conclude that investors are Bayesian and take into consideration the consistency of individual analysts' prior forecast errors.

[6] Despite recent regulations such as Reg FD, mounting evidence in the literature indicates that access to management is still a key source of information for analysts (Mayew 2008; Green et al. 2014; Soltes 2014; Brown et al. 2015).

The literature on investor learning does not show whether investor learning and de-biasing of analyst research is complete. In fact, several studies provide evidence suggesting investors do not *fully* unravel predictable errors and bias in forecasts. Abarbanell and Bernard (1992) show that analysts' forecast errors are correlated over time and that prices do not fully reflect this autocorrelation.[7] Frankel and Lee (1998) model predictable errors in analyst forecasts and show that these errors are associated with future returns. Diether et al. (2002) document a negative relation between analyst forecast dispersion and returns and conjecture that self-selection in coverage by optimistic analysts may explain this relation. So (2013) compares analysts' forecasts of earnings with forecasts based on firm fundamentals and, by showing that differences between these forecasts predict returns, concludes that investors do not fully unravel predictable forecast errors. Dechow and Sloan (1997) show that investors overweight the overly optimistic long-term earnings expectations of analysts (see also La Porta 1996), and Dechow et al. (2000) document that such overweighting explains the return underperformance of firms issuing equity.

These studies largely focus on analysts' longer-term forecasts, which are systematically optimistic.[8] The systematic pessimism in analysts' short-term forecasts issued in the quarter before earnings announcements is a more recent phenomenon and is likely more visible to investors. Because short-term forecasts affect the expectation-component of firms' earnings surprises, investors have more precise information on short-term forecast errors than longer-term forecast errors. For instance, Yahoo! Finance provides data on firms' most recent four consensus earnings

[7] See also Mendenhall (1991), Doyle et al. (2006), and Livnat and Mendenhall (2006).

[8] For example, So (2013) relies on consensus analyst forecasts of annual earnings released in the fifth month of the current fiscal year. Assuming that annual earnings are announced in the second month after the end of the fiscal year, this implies a forecast horizon of about nine months. So (2013 Table 1) reports that the average error in these forecasts is significantly negative, consistent with "analysts facing incentives to issue optimistic forecasts" (p. 623).

surprises. If investors correctly use these recent forecast errors to assess the extent of current forecast bias, stock prices should reflect this information.[9]

Still, mispricing can arise if a precise assessment of expected forecast bias requires investors to compute relatively complex statistics. Hirshleifer and Teoh (2003) suggest that investors may not fully appreciate detailed value relevant information (e.g., conditional probabilities of forecast bias) due to their limited information processing abilities and instead may rely more on simple statistics (e.g., unconditional probabilities of forecast bias). Bloomfield (2002) posits that, even if investors are rational, the costs of extracting firm-specific information impede prices from fully reflecting all information and that information that is more costly to process will be less completely reflected in prices. As an illustration of this point, Cohen and Lou (2012) find that differences in the complexity of processing a piece of industry information leads conglomerates' prices to reflect the information with a delay, compared to prices of comparable standalone firms. Balakrishnan et al. (2010) show that stock prices do not fully reflect conditional probabilities of losses, consistent with investors having difficulty in forecasting and valuing loss firms.

We conjecture that it is costlier for investors to determine the conditional probability of forecast pessimism for a specific firm-quarter than to determine the unconditional probability of forecast pessimism for the average firm. To assess the latter, information on the average fraction of firms in the cross-section that beat analyst expectations would suffice. To assess the former, more detailed data on prior consensus and individual analyst forecast errors would be needed. While the fraction of firms beating expectations is relatively stable across earnings seasons,

[9] Lawrence et al. (2017) show that page views for analyst estimates on Yahoo! Finance, a key source of financial information to retail investors, spike around earnings announcement dates. The Yahoo! Finance analyst-estimates page contains information on consensus forecasts for the upcoming quarters and years, as well as firms' most recent four quarterly earnings surprises. The evidence in Lawrence et al. (2017) suggests that even retail investors pay considerable attention to analyst estimates and recent earnings surprises.

forecast pessimism does vary substantially across firms and analysts. Some firms are more likely to beat expectations than others, for example because lower earnings forecast uncertainty facilitates analysts in inducing a small pessimistic bias in their forecasts (Bissessur and Veenman 2016) or because analysts' incentives to obtain access to management's information varies across firms (Ke and Yu 2006; Hilary and Hsu 2013). In addition, studies such as Butler and Lang (1991) show that individual analysts display persistent pessimism and optimism over time.

Overall, we conclude that the nature (i.e., pessimistic) and potential consequences (for earnings surprises and market reactions to earnings announcements) of bias in analysts' short-term forecasts are unique and investors' ability to unravel persistent pessimism in forecasts is unclear. Providing evidence on this issue can contribute to a better understanding of the potential costs and market frictions that result from the systematic pessimism in analyst earnings forecasts and, more generally, the MBE phenomenon. Even if sophisticated investors can identify pricing errors driven by less sophisticated investors, the elevated costs of arbitraging away these pricing errors before earnings announcements (e.g., So and Wang 2014; Levi and Zhang 2015) and the relatively high turnover associated with such strategies (e.g., Frazzini et al. 2015; Novy-Marx and Velikov 2016) can result in systematic mispricing of persistent forecast pessimism.[10]

III. RESEARCH DESIGN

Prior Forecast Pessimism Measures

Given prior evidence that forecast pessimism is persistent and predictable at both the firm- and analyst-level (e.g., Butler and Lang 1991; Hilary and Hsu 2013; Bissessur and Veenman 2016), we construct two measures of pessimism in analysts' prior earnings forecasts to capture

[10] See Lee and So (2015, Chapter 5) for a comprehensive review of the frictions that hinder trading signals from being reflected in market prices and arbitraged away by sophisticated investors.

variation in the probability of current forecast pessimism. First, we compute a firm-specific measure (*Pess_consensus*) that captures the fraction of the most recent 12 quarterly earnings surprises that were positive (i.e., the consensus was pessimistic) versus negative (i.e., the consensus was optimistic). Earnings surprises are determined as the difference between firms' quarterly earnings per share and the consensus forecast of earnings per share before the earnings announcement, which is the mean of individual analysts' most recent forecasts.

Second, we exploit analysts' coverage of multiple firms and construct a measure that is based on the prior pessimism of the individual analysts that contribute to the current consensus forecast (*Pess_individual*). Specifically, at each point in time, we compute the fraction of the nonzero forecast errors that turned out to be pessimistic in the most recent 12 months for a specific analyst, based on the forecast errors made by the analyst for *any* firm.[11] We average these analyst-specific scores across the analysts in the current consensus to obtain a firm-quarter measure. Figure 1 illustrates the measurement of this variable in event-time. Essentially, the measure captures variation in expected forecast pessimism that can be identifed by exploiting analysts' prior forecast errors across the multiple firms they cover. To the extent that the persistence of forecast pessimism varies across both firms *and* individual analysts, *Pess_individual* can be used to identify variation in the probability of forecast pessimism incremental to what is captured in *Pess_consensus*.

- INSERT FIGURE 1 ABOUT HERE -

Sample Selection

Table 1 presents the sample selection criteria. We initially obtain over 1.9 million monthly observations from the CRSP monthly stock file for the period 1986–2015, for firms listed on

[11] The use of individual analysts' prior forecast errors for the full portfolio of firms they cover is similar in spirit to Brown and Mohammad (2010). They argue and find that measurements based on portfolios of firms provide more precise estimates of the construct of interest, in their case the individual analyst's forecast ability.

NYSE, AMEX, or NASDAQ with ordinary common shares outstanding. Observations with stock prices below $5 at the end of the previous month are eliminated to ensure that our results are not driven by small and illiquid stocks (Jegadeesh and Titman 1993). Next, we merge the observations with I/B/E/S and require each firm to be covered by at least two individual analysts that forecast current-quarter earnings per share.[12]

- INSERT TABLE 1 ABOUT HERE -

We also require precise data on firms' earnings announcement dates. While both Compustat and I/B/E/S provide these data, the values of the announcement dates can differ. To ensure we pick the most accurate announcement date, we follow the procedure described in Dellavigna and Pollet (2009). Specifically, if the Compustat and I/B/E/S announcement dates differ for a specific fiscal quarter, we take the earlier date of the two. If the announcement dates are similar, we pick the previous trading day for announcements made before 1990. For announcements made in or after 1990, we pick the exact date on which Compustat and I/B/E/S agree.

We require data on each firm's most recent four quarterly earnings surprises for our measures of prior forecast pessimism and eliminate a small number of observations for which the four most recent quarterly earnings surprises all equal $0.00 per share, as our classification of prior forecast pessimism is based on nonzero earnings surprises.[13] Lastly, to ensure the public availability of information before the measurement of returns, accounting data are matched with returns at least four months after a firm's fiscal year.[14] After excluding observations for which data on control variables are not available, we obtain a final sample of 670,265 monthly observations, out of which

[12] All tests using analysts' forecasts of earnings per share are based on I/B/E/S data unadjusted for stock splits. Diether et al. (2002) and Payne and Thomas (2003) highlight the problems associated with the standard I/B/E/S files that are split-adjusted and rounded to the nearest cent. In our case, the use of split-adjusted data would incorrectly classify some earnings surprises as zero cents.

[13] In the calculation of consensus forecasts and earnings surprises, we eliminate forecasts older than 180 days at the time of the earnings announcement and announcements that occur more than 180 days after the fiscal quarter-end.

[14] As do Fama and French (1993), we delete firms with negative book values of equity.

225,283 are months with quarterly earnings announcements (33.6 percent). In tests using ex-post earnings surprises and announcement date abnormal returns, the announcement-month sample is slightly reduced to 224,048 and 224,145 observations, respectively.

Prior research suggests that the timing of earnings announcements conveys information and that early (late) announcements are associated with higher (lower) future returns (Chambers and Penman 1984). To ensure that any differences in return predictability are not driven by hindsight bias, we also follow prior research (e.g., Cohen et al. 2007; Barber et al. 2013) and additionally estimate expected earnings announcement months. Specifically, expected earnings announcement months are estimated based on the announcement date of the same quarter of the prior fiscal year. If the earnings announcement date of the same quarter of the prior fiscal year is unavailable, we extrapolate the earnings announcement date from the previous fiscal quarter (or two or three quarters back). For brevity, we do not tabulate the results based on expected earnings announcement months, as these are qualitatively highly similar to results based on actual earnings announcement months.[15]

Portfolio Tests, Return Measurement, and Earnings Surprises

Our initial tests are based on calendar-time portfolio analyses. For each of the 360 months in our sample, observations are assigned to quintile portfolios based on the values of our prior forecast pessimism measures in month *t-1*. For each month and quintile portfolio, we compute the portfolio's average (equal-weighted) return in month *t* and average the monthly portfolio returns across the 360 months. In all tests, we adjust the standard errors of the portfolio-average returns

[15] We identify 225,767 observations as expected earnings announcement months (33.7 percent). Untabulated statistics reveal that 88.56 percent of these months correctly predict the actual earnings announcement month.

for autocorrelation based on Newey and West (1987).[16] Returns are measured as the raw monthly return (including distributions) or the size-adjusted earnings announcement return measured over the [0,+2] trading day window around the earnings announcement date.[17] Based on the definition of earnings surprises described earlier, we construct a price-scaled earnings surprise variable (*Surprise*), as well as an indicator variable (*Nonneg*) that equals 1 if the earnings surprise (rounded to cents per share) is zero or positive, and 0 otherwise.[18]

Cross-Sectional Regressions

We formally test the return predictability of our forecast pessimism measures in a multiple cross-sectional regression framework using monthly Fama and MacBeth (1973) regressions. As Fama and French (2008) explain, multiple cross-sectional regression slopes provide a direct way of estimating the marginal relation between a factor and future returns that is incremental to other factors identified to have return predictive ability. We therefore control for a wide range of factors related to firms' earnings surprises, future (earnings announcement) returns, or both. Based on the 360 monthly regressions, we obtain average coefficient estimates and again adjust standard errors for autocorrelation based on Newey and West (1987).

We control for size and book-to-market (Fama and French 1992), short-term return reversal (Jegadeesh 1990), momentum (Jegadeesh and Titman 1993), idiosyncratic volatility (Ang et al.

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[16] Following Greene (2012), we set the number of lags equal to the smallest integer equal to or greater than $T^{1/4}$, where T is the maximum number of time periods. Given the maximum of T=360 in our setting, we set the number of lags equal to five ($360^{1/4}$=4.36). Choosing alternative numbers of lags has no material consequences for the inferences drawn.

[17] Throughout the paper, size-adjusted returns are calculated by subtracting from raw returns the value-weighted average returns to size-matched portfolios based on CRSP NYSE/AMEX/NASDAQ deciles (CRSP file "erdport1"). While our results are qualitatively similar when using alternative short windows around earnings announcement, we choose the window starting at day 0 because (1) our announcement date identification procedure reduces the possibility that earnings are actually announced on day -1 and (2) many earnings announcements occur after market close, rendering day +1 the first day on which a market reaction can be observed (Berkman and Truong 2009).

[18] In contrast to our measurement of the prior forecast pessimism measures, variable *Nonneg* includes earnings surprises of $0.00 per share to ensure we do not truncate our sample based on ex-post realizations of earnings surprises.

2006), institutional ownership (D'Avolio 2002; Nagel 2005), analyst coverage (Lee and So 2017), and asset growth (Cooper et al. 2008). We additionally control for several earnings-related measures that have been linked to returns, specifically, firms' operating profitability (Ball et al. 2015), the most recently announced seasonally differenced change in quarterly earnings, and the four most recent quarterly earnings surprises. The latter two controls help rule out the possibility that our results are merely capturing post-earnings announcement drift, which also materializes around subsequent earnings announcements (e.g., Livnat and Mendenhall 2006).

IV. RESULTS

Descriptive Statistics

Table 2 presents summary statistics (Panel A) and correlations (Panel B) for our test (*Pess_consensus* and *Pess_individual*) and control variables. The summary statistics and correlations are averages of the statistics calculated for each of the 360 months in our sample, in line with the subsequent portfolio and regression analyses that are similarly based on monthly estimations. Appendix A presents detailed variable definitions. All continuous variables, except the (announcement) returns presented later, are winsorized to the 1st and 99th percentiles of their distributions to control for outliers.

- INSERT TABLE 2 ABOUT HERE -

The summary statistics in Panel A confirm that the average analyst forecast used in our study is pessimistic, consistent with prior findings on analysts' short-term forecasts (e.g., Richardson et al. 2004; Ke and Yu 2006; Hilary and Hsu 2013). The means for *Pess_consensus* and *Pess_individual* of 0.575 and 0.587, respectively, suggest that 57.5 and 58.7 percent of the consensus and individual forecasts result in a positive earnings surprise (recall that zero forecast errors are ignored in the determination). The median firm size averages $839 million, which indicates that our sample is comprised of relatively large firms. This is not surprising given the focus on firms covered by at least two analysts.

All other variables have distributional characteristics that are largely in line with the related literature. For example, average book-to-market is substantially below one and the statistics for prior earnings change and consensus earnings surprise variables are almost identical to those in Livnat and Mendenhall (2006, Table 1-B). Some of the variables' distributions, such as those of *Analyst following* and *Asset growth*, are skewed, but our use of portfolio ranks in the main regression tests controls for the potential effects of such skewness.

The correlations in Panel B show that our prior forecast pessimism measures are positively correlated, but far from perfectly (Spearman correlation: 0.344), which suggests the potentially incremental information in each of the measures. Importantly, both measures are also positively correlated with *Operating profitability* and the variables that capture the four most recent earnings surprises ($Q_{-\tau}$ *earnings surprise*). Given that these variables have been identified as correlated with future stock returns (Ball et al. 2015; Livnat and Mendenhall 2006), it is essential we control for these variables in our cross-sectional regressions.

Portfolio Test Results

Panel A of Table 3 presents differences in earnings surprises and returns between portfolios of high and low prior consensus forecast pessimism (*Pess_consensus*). The first column shows that *Pess_consensus* has substantial variation, with low (Q1) firms displaying pessimism in only 27 percent of prior (nonzero) earnings surprises and high (Q5) firms displaying pessimism in 89 percent of prior surprises. Comparable to the evidence on autocorrelation in earnings surprise *levels* (Mendenhall 1991; Abarbanell and Bernard 1992; Ali et al. 1992; Milian 2015), the second column of Panel A shows that our measure that captures the *sign* of prior consensus earnings surprises is strongly predictive of the sign of the current earnings surprise. Specifically, firms in the lowest quintile report a nonnegative earnings surprise 51 percent of the time, while firms in the highest quintile report a nonnegative surprise 74 percent of the time. The 23 percentage point difference is statistically highly significant (*t*-statistic = 28.48). Thus, these figures confirm that forecast pessimism is persistent and that our measure identifies substantial variation in the probability of pessimism in the current consensus forecast.

- INSERT TABLE 3 ABOUT HERE -

To test whether market prices fully reflect these differences in probabilities, we tabulate differences in returns across the portfolios. Consistent with investors not fully unraveling differences in conditional probabilities, we find economically and statistically significant differences in returns across the *Pess_consensus* portfolios. For the full sample of observations, returns are 48 basis points higher for the Q5 portfolio compared with Q1. Consistent with these return differences reflecting mispricing that is corrected at subsequent earnings announcements, the return difference decreases for non-announcement (EA=0) months and is strongest in earnings announcement (EA=1) months: 81 basis points (*t*-statistic = 5.04). Of these monthly return differences, the largest part is concentrated in the three-day abnormal returns around the earnings announcement (50 basis points), again highly significant (*t*-statistic = 5.49).[19]

Panel B presents the same analyses for our measure of prior individual forecast pessimism (*Pess_individual*). Results confirm that *Pess_individual* captures variation in the probability of forecast pessimism and this variation is not fully reflected in prices. For instance, the announcement month return difference between the high (Q5) and low (Q1) portfolios of

[19] The positive average monthly and short-window returns observed around earnings announcements are consistent with the literature on the earnings announcement premium (Ball and Kothari 1991; Cohen et al. 2007; Frazzini and Lamont 2007; Barber et al. 2013; Savor and Wilson 2016).

Pess_individual equals 80 basis points (*t*-statistic = 4.37), and a large part of this difference is realized in the three-day earnings announcement window (41 basis points, *t*-statistic = 4.70). To assess whether *Pess_individual* captures incremental variation in expected forecast pessimism, and whether the results in Table 3 simply reflect previously documented findings (e.g., PEAD), we test the return predictive ability in multiple cross-sectional regressions in the following sections.

Panel C provides additional portfolio tests consistent with the asset pricing literature. For both measures, we calculate abnormal monthly portfolio returns by running calendar-time portfolio regressions of the Fama and French (1993) three-factor model augmented with the momentum factor (Carhart 1997), where firms are assigned to quintile portfolios at the end of the month before their earnings announcements. The intercept (alpha) from this estimation measures the average abnormal monthly portfolio return. In addition to providing an estimate of abnormal returns, these tests allow us to assess the exposure of the abnormal return spreads to traditional asset pricing factors. Lastly, we run these tests for both equal- (EW) and value-weighted (VW) portfolios to assess the sensitivity of the abnormal returns to firm size.

All estimates of abnormal returns in Panel C are statistically and economically significant, although the value-weighted portfolio analysis based on *Pess_consensus* is only marginally significant at $p<0.10$. These results suggest that the return spreads for *Pess_consensus* are determined mostly by the smaller firms in our sample, while firm size has limited influence on the return spreads for *Pess_individual*. These findings are consistent with recent consensus earnings surprises being more salient for larger firms, while the generally higher number of analysts covering larger firms could potentially increase the complexity of the *Pess_individual* measure (we test the latter in Table 6).[20]

Consistent with the abnormal returns being unique and not driven by traditional risk factors, the hedge (Q5–Q1) portfolio returns are orthogonal to the market factor and correlated with the SMB and HML factors in ways opposite to what would be expected if the abnormal returns capture risk premia (i.e., the coefficients are negative instead of positive). The value-weighted return spreads for *Pess_individual* are positively correlated with the momentum factor (UMD), but the abnormal returns captured by the intercept remain high at 81 basis points.

Overall, results in Table 3 confirm that our prior forecast pessimism measures capture substantial variation in the probability of current forecast pessimism. The results also suggest that market prices do not fully reflect differences in these probabilities across firms, as evidenced by the predictable differences in future (earnings announcement) returns.

Cross-Sectional Regression Tests: Predicting (Nonnegative) Earnings Surprises

Before turning to our multiple return regressions, we first examine the association between the forecast pessimism measures and the probability of subsequent nonnegative earnings surprises after controlling for the firm-characteristics introduced earlier. Table 4 presents the results. While our main predictions and analyses relate to the sign of the earnings surprise (pessimism versus optimism), we present analyses based on both signed earnings surprises (*Surprise*), scaled by stock price, and an indicator variable for non-negative surprises (*Nonneg*). To facilitate the interpretation of differences in coefficients across the variables, we replace variables with their monthly quintile

[20] Although the value-weighted results speak to the ability to practically implement a trading strategy, note that they should also be viewed with caution since they overweight the largest firms in our portfolio return calculation. Value-weighted portfolio results could understate the extent of market frictions for the typical firm.

ranks scaled between 0 and 1. As a result, coefficients capture differences in the outcome variable between firms in the high (Q5) and low (Q1) quintiles of a variable.

- INSERT TABLE 4 ABOUT HERE -

The first two columns of Table 4 present results from OLS regressions with *Surprise* as the dependent variable. Both prior pessimism measures are significantly and incrementally positively associated with subsequent earnings surprises. The association strengthens when we focus on a measure that combines the consensus and individual pessimism measures (*Pess_combined*). Note, however, that the use of a continuous measure of earnings surprises could potentially understate the strength of our findings given that pessimistic earnings surprises tend to be relatively smaller in magnitude (Abarbanell and Lehavy 2003; Durtschi and Easton 2005). We therefore draw our main inferences from the use of the *Nonneg* indicator variable as the dependent variable.

Results based on *Nonneg* confirm that both *Pess_consensus* and *Pess_individual* are strongly positively associated with non-negative earnings surprise incidence after other factors are controlled for and, as expected, results strengthen relative to those based on the continuous measure of earnings surprise. Again, each measure has significant incremental explanatory power. In other words, we find that our measure based on individual analysts' prior forecast errors—for their portfolios of covered firms—captures incremental variation in the probability of current forecast pessimism over the variation captured by prior consensus forecast pessimism.

The combined measure is most strongly associated with the probability of a nonnegative earnings surprise. To assess the economic significance of this result, we also compute the marginal effect of changing *Pess_combined* from Q1 to Q5 on the probability that *Nonneg* = 1, holding all other factors constant at their means. We calculate this marginal effect each month and average it across the 360 months in the sample. Results suggest an economically significant difference in the probability of a nonnegative surprise between firms in the high and low quintiles. Firms in Q5 are 16 percentage points more likely to report a nonnegative earnings surprise than firms in Q1.

Results on the control variables are generally consistent with expectations. We highlight some important insights. Consistent with the consensus forecast reflecting news with a delay, the probability of a nonnegative surprise varies with recent returns. For instance, the difference in probability of a nonnegative surprise between firms with high and low prior-month returns equals 11 percentage points. Because new information is not fully reflected in forecasts, the consensus is understated (overstated) and is more likely to induce a positive (negative) earnings surprise with positive (negative) recent news. Given the existence of return reversals and momentum (Jegadeesh 1990; Jegadeesh and Titman 1993), this link with subsequent earnings surprise signs highlights the importance of controlling for recent returns. Consistent with the autocorrelation in earnings surprises, *Nonneg* is positively associated with the previous-quarter earnings surprise and, to a lesser extent, the earnings surprise of two to four quarters ago. Similarly, the most recent earnings change is positively related to *Nonneg*. These findings and the significant coefficients on other firm characteristics confirm the importance of controlling for these factors.

Cross-Sectional Regression Tests: Predicting (Announcement) Returns

We test the return predictability of our prior forecast pessimism measures using the monthly cross-sectional regressions in Table 5. As in Table 4, we transform all variables into quintile ranks and scale the ranks between 0 and 1. Each coefficient therefore reflects the average incremental return difference between firms in the highest and lowest quintile of the variable.

- INSERT TABLE 5 ABOUT HERE -

Consistent with the portfolios analyses, both *Pess_consensus* and *Pess_individual* are significantly and incrementally positively associated with returns in earnings announcement months. Combining the measures (*Pess_combined*), the abnormal return difference between firms with high and low probabilities of forecast pessimism equals a statistically and economically significant 79 basis points per month (*t*-statistic = 4.90). Focusing on the short-window announcement returns, the abnormal return difference is equal to 74 basis points (*t*-statistic = 7.76). The finding that most of the return differences materialize around earnings announcements is consistent with a mispricing explanation.[21]

Results on the control variables are generally consistent with expectations. Some noteworthy findings are the significant negative and positive coefficient on previous month and previous year returns, respectively, consistent with return reversal (Jegadeesh 1990) and momentum (Jegadeesh and Titman 1993), and important given the link between recent returns and earnings surprises shown in Table 4. Idiosyncratic return volatility relates negatively to short-window announcement returns (Berkman et al. 2009).[22] Consistent with Lee and So (2017), analyst coverage is positively associated with returns.[23] Consistent with Ball et al. (2015), operating profitability is positively associated with returns, but, in support of their conclusion that this effect is unlikely driven by mispricing, it is not significantly related to returns around future earnings announcements.[24]

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[21] These findings are more consistent with mispricing than a risk-based explanation, because expected returns should be small over such short windows (e.g., Bernard and Thomas 1989; La Porta et al. 1997; Fama 1998; Lee 2001; Lewellen 2010).

[22] Interestingly, inconsistent with the findings of Ang et al. (2006), idiosyncratic return volatility is not significantly related to full-month returns. This is consistent with Berkman et al. (2009), who find a run-up in prices before earnings announcements and a sharp decline after announcements related to idiosyncratic return volatility. In untabulated analyses, we similarly find idiosyncratic return volatility to be significantly positively related to returns in the days leading up the earnings announcements. The pre- and post-announcement returns cancel out, which explains the lack of a significant association between idiosyncratic return volatility and announcement-month returns.

[23] Lee and So (2017) find that the "abnormal" component of measures of analyst coverage relates positively to returns. They define abnormal coverage as the level of coverage not explained by firm size, share turnover, and lagged returns. Because we control for these factors in our analyses (except for turnover), our multiple regression coefficient on analyst coverage can similarly be viewed as capturing the effect of abnormal coverage.

[24] Consistent with Milian (2015), we find a negative relation between lagged earnings surprises and earnings announcement returns. We revisit this issue later when examining the existence of PEAD in our sample.

In untabulated analyses, we also examine return predictability based on expected earnings announcement months and find results that are qualitatively similar. The abnormal return difference equals 69 basis points based on expected earnings announcement months (*t*-statistic = 4.59), which suggests that the timing of earnings announcements has limited influence on the results. Moreover, untabulated tests reveal a significant return difference of 32 basis points even when using the full set of monthly observations including non-announcement months (*t*-statistic = 3.81). When estimated only for non-announcement months, the coefficient on *Pess_combined* suggests an abnormal return difference of only 17 basis points (*p*-value: 0.073).

In Figure 2, we examine return predictability based on the forecast pessimism measures for the trading days around the earnings announcement. Specifically, we replace the dependent variable in Table 5 with the size-adjusted daily return for each trading day in the [-10,+10] window around the earnings announcement and present the coefficient on *Pess_combined* for each day in this window. Consistent with the return predictability reflecting mispricing, return differences are significant only for days in the short announcement window [-1,+2] and are largest one day after the announcement (41 basis points, *t*-statistic = 5.20).

- INSERT FIGURE 2 ABOUT HERE -

Figure 2 also addresses potential alternative explanations. Berkman et al. (2009) show how short-sale constraints lead to price run-ups before earnings announcements when uncertainty rises, and to declines in prices when earnings announcements resolve this uncertainty. So and Wang (2014) show that earnings announcements are associated with increased return reversals because market makers demand compensation for the risks of liquidity provision before anticipated information events. Barber et al. (2013) show that earnings announcement premia materialize in the days before earnings announcements. The findings in Figure 2 indicate no reversal in return differences and no concentration of abnormal return differences in the days before the earnings announcement, suggesting our main findings are unlikely a reflection of short-sale constraints, liquidity provision, or earnings announcement premia.

Figure 3 highlights the robustness of our findings over time. This analysis is important, given that recent studies document stark reductions in the power of return predictive signals as a result of increased arbitrage activities, public knowledge over these signals, and increases in stock liquidity (Richardson et al. 2010; Green et al. 2011; Chordia et al. 2014; McLean and Pontiff 2016). As in Berkman et al. (2009), we plot the averages of the abnormal announcement returns for the quarters in our sample, where abnormal returns are the monthly cross-sectional regression coefficients on *Pess_combined* in Table 5 with $BHAR_t[0,2]$ as dependent variable. Following Chordia et al. (2014), we also plot the five-year moving average of the monthly cross-sectional regression coefficients.

- INSERT FIGURE 3 ABOUT HERE -

Figure 3 shows that the return differences are robust across different periods and, in fact, appear strongest in the second part of the sample. Out of the 120 quarters in our sample, 95 (79 percent) have a positive average abnormal announcement return spread. By the end of our sample period, the (untabulated) five-year moving average of the coefficient on *Pess_combined* reflects an abnormal return difference of 99 basis points between firms with high and low probabilities of forecast pessimism. These findings suggest that unlike, for example, the accrual anomaly or PEAD, the return predictability of analyst forecast pessimism has not disappeared in recent years.

Complexity of Forecast Pessimism Statistics and Mispricing

This section explores the association between returns and measures of forecast pessimism that vary in their degree of availability and complexity from an investor's perspective. We first test whether statistics that identify differences in consensus forecast pessimism over a longer time series are less fully reflected in prices. Panel A of Table 6 presents results of estimating cross-sectional regressions in which we vary the number of quarters used to construct *Pess_consensus* from one to 12.[25] We find that measures of consensus forecast pessimism using the four most recent quarters have, at best, weakly significant predictive power for returns. This is not surprising, as consensus earnings surprise data for firms' most recent four quarters are readily available to investors (through sources such as Yahoo! Finance). More importantly, return differences become strong and significant (at $p<0.05$) for time-series of eight and 12 quarters of earnings surprises, that is, for data that are less readily available. Specifically, abnormal announcement return differences are 44 and 59 basis points for eight and 12 quarters of data, respectively. Untabulated results based on announcement month returns are qualitatively highly similar.[26]

- INSERT TABLE 6 ABOUT HERE -

In Panel B we vary the complexity of information that enters the calculation of the individual pessimism measure. If the complexity of calculating this measure for a firm-quarter drives the return predictability that we document, then our findings should be concentrated in those cases in which the statistic is based on the prior forecast errors of more analysts, and for more firms, compared with cases where the statistic is based on fewer analysts and firms. We therefore split the sample into subsamples of high versus low analyst coverage, as well as a split based on a high versus low number of analyst-firm combinations entering the calculation of *Pess_individual*.

[25] Because we use only nonzero earnings surprises for the measurement, the estimation using only one prior quarter of earnings surprise data is based on a slightly reduced sample.

[26] Consistent with *Pess_individual* capturing *incremental* information over the prior consensus pessimism measure, the coefficient on *Pess_individual* becomes gradually smaller (but remains highly significant) as we lengthen the time-series of consensus forecast pessimism. For instance, the difference in announcement returns between firms with high and low values of *Pess_individual* equals 62 (35) basis points when we use only one (12) prior quarters of data to construct the consensus forecast pessimism measure. These findings confirm that the longer time-series of prior consensus forecast pessimism data partly capture the same more complex information that is reflected in the individual analyst forecast pessimism measure.

Consistent with the findings being concentrated among observations where the measure is more complex, regression results confirm that announcement return differences are significant only for the high analyst coverage and the high analyst-firm partitions of the sample.

Overall, these findings are consistent with investors not fully unraveling persistent pessimism in analysts' earnings forecasts. As the statistics that capture differences in conditional probabilities of forecast pessimism become more complex for investors, the evidence of mispricing strengthens.

Short-Term Pessimism versus Long-Term Optimism

The nature of bias in analysts' short-term forecasts differs fundamentally from that in their longer-term forecasts. Diether et al. (2002) and Scherbina (2008) posit that the observed optimism in forecasts, due to analysts' self-selection in coverage (McNichols and O'Brien 1997), is not fully reflected in market prices and leads to predictable patterns in returns around future earnings announcements. Such self-selection bias, however, reduces as time passes and analysts start to reveal their pessimistic expectations before earnings are announced (Barron et al. 2013). Therefore, the bias in short-term forecasts we examine cannot be explained by analysts' self-selection in coverage (of firms about which they hold favorable expectations) because the forecasts are systematically pessimistic, not optimistic.

Other studies examine predictable forecast errors more generally and use longer-term forecasts issued relatively early in the year (e.g., Frankel and Lee 1998; Hribar and McInnis 2012; So 2013). Besides being optimistic, on average, these longer-term forecasts are not directly related to the expectation-component of firms' earnings surprises because analysts commonly revise their initial forecasts. That is, while optimistic bias in longer-term forecasts can boost prices and lead to negative returns when pricing errors are gradually corrected, the short-term forecasts more directly affect firms' earnings surprises and the returns realized around earnings announcements.[27]

Still, to address potential concerns that our findings merely reflect prior evidence on the pricing errors of predictable forecast optimism, or predictable forecast errors more generally, we repeat our analyses using forecasts measured at an earlier point in event-time. Specifically, we exploit the observation that while analysts' average short-term forecasts are pessimistic, their longer-term (i.e., more than one quarter ahead) forecasts tend to be optimistic. If our findings merely reflect prior evidence on the market mispricing of forecast optimism and errors, they should be driven by these longer-term forecasts.

- INSERT TABLE 7 ABOUT HERE -

Table 7 replicates our earlier tests using forecast pessimism measures based on short- and long-term forecasts. The long-term forecasts are defined as the forecasts issued before the previous quarter earnings announcement. Because not all analysts issue two-quarters-ahead forecasts and to allow for a fair comparison, we re-compute our short-term pessimism measures using only quarters for which each analyst issues both a short- and long-term forecast. Panel A presents descriptive statistics on the measures. Consistent with forecast pessimism, the means for the short-term measures are significantly greater than 0.5. The means for the longer-term measures are significantly lower than 0.5, which is consistent with forecast optimism.

When we rerun our main analyses using both short- and long-term measures in Panel B, we find strong evidence that the predictability of the earnings surprise sign and the announcement

[27] As an illustration of this point, So (2013) finds that the mispricing of analysts' annual earnings forecasts is corrected partly around the first quarterly earnings announcement after portfolio formation (before the annual earnings announcement) and that most of the mispricing is corrected in non-announcement periods. In contrast, we focus on the forecast errors that directly map into earnings surprises and on mispricing that is predominantly corrected at the announcement of the earnings that analysts forecasted.

returns is explained only by our measures based on short-term forecasts. For the measures based on longer-term forecasts, which are optimistic on average (Panel A), none of the coefficients are positive and significant in explaining earnings announcement returns. Untabulated results are qualitatively highly similar when we focus on monthly returns instead of the short-window returns. Overall, these findings confirm the unique nature of the short-term forecast bias we examine and suggest our findings do not simply capture previously documented relations between predictable forecast optimism, forecast errors, and future stock returns.

V. ADDITIONAL ANALYSES

Return Predictability, Firm Size, and Transaction Costs

Fama and French (2008) argue for assessing the robustness of a return predictive signal across different firm size classes. Because many signals derive their predictive ability only from the subset of smallest firms, they often do not reflect implementable trading strategies. This is because smaller firms have significantly higher trading costs and limits to arbitrage. Although our primary interest lies in documenting whether the systematic pessimism in analysts' short-term forecasts leads to market frictions—not in identifying an implementable trading strategy—carefully examining the robustness of our results across different firm size classes does help to better understand why mispricing is not arbitraged away by sophisticated investors.

- INSERT TABLE 8 ABOUT HERE -

Panel A of Table 8 presents abnormal returns (alphas) for quintile portfolios based on *Pess-_combined* for firms designated in Fama and French (2008) as "microcap" (firms with market capitalization below the 20th percentile of NYSE firms), "all-but-microcap," and "big" (market capitalization above the 50th percentile). Based on the pool of all firm size classes, the high-low hedge return alpha for *Pess_combined* equals 95 basis points per month. This figure jumps to 134 basis points for microcaps, consistent with these firms being costlier to trade and arbitrage. The hedge return alpha for the all-but-microcap sample is still 76 basis points and highly significant, suggesting our findings are not purely driven by the smallest firms and reflect a market friction that affects a broad cross-section of firms.

Focusing on big firms, hedge return alphas are smaller and less significant (53 basis points, *t*-statistic = 2.13). This reduction is consistent with the conjecture that the costs of trading on mispricing before earnings announcements, which are larger in smaller firms, prevent pricing errors from being corrected. Barber et al. (2013) show that the earnings announcement premium—which is linked to firms' systematic risk exposure (Patton and Verardo 2012; Savor and Wilson 2016)—is largest for smaller firms. Moreover, So and Wang (2014) report that smaller firms experience more extreme pre-announcement price movements, and Levi and Zhang (2015) find that smaller firms have greater increases in bid-ask spreads before earnings announcements.

Panels B and C replicate the analyses of Panel A for the two forecast pessimism measures separately. In line with the value-weighted portfolio results in Table 3, return spreads for *Pess_consensus* are strongest among smaller firms. This is consistent with consensus earnings surprises being more salient for larger firms, leading to less mispricing, and the lower costs of trading larger firms. Still, the monthly return spread equals a significant 51 basis points among the biggest firms. Interestingly, results for *Pess_individual* are less concentrated in smaller firms, with a significant abnormal return spread of 77 basis points among the biggest firms. The lack of a substantial reduction in return spreads for the largest firms can be reconciled with our finding in Table 6 that firms with higher analyst coverage (often larger firms) are associated with more mispricing.

To put these return spreads into perspective, we compare them to the trading cost estimates in Novy-Marx and Velikov (2016). Trading on the pricing errors we uncover requires investors to rebalance an investment portfolio at least once per month and take new positions in firms expected to announce earnings in each coming month. Novy-Marx and Velikov (2016) show that most anomalies do not generate significant return spreads net of transactions when turnover is more than 50 percent per month. For strategies with high turnover (>90 percent per month), they compute transaction costs in excess of 100 basis points per month for value-weighted portfolios. For instance, for the short-term reversal strategy (Jegadeesh 1990), which also relies on monthly portfolio turnover, they compute transaction costs of 165 basis points per month.[28] Although transaction costs have declined in the second half of our sample (e.g., Chordia et al. 2014), the combination of the results in Novy-Marx and Velikov (2016) and the relatively high costs of trading before earnings announcements suggests the return spreads we document might not exceed transaction costs, explaining why the mispricing is not arbitraged away.

Contrasting Evidence on Post-Earnings Announcement Drift

The cross-sectional regressions control for the four most recent quarterly earnings surprises. Although the lack of significant positive coefficients on these variables in Table 5 provides no strong evidence on PEAD, a remaining concern could be that our measures of prior forecast pessimism simply capture the underlying concept in PEAD better than the separate prior earnings surprise variables do. Therefore, we return to our portfolio analyses and test for PEAD in our sample.

- INSERT TABLE 9 ABOUT HERE -

Results in Table 9 show that there is some evidence of PEAD in our sample, but that our main results our unlikely explained by PEAD. Panel A shows an abnormal return (alpha) spread of 28

[28] Using proprietary trading data from a large investment firm, Frazzini et al. (2015, Table A5) similarly document negative net spreads for the reversal strategy.

basis points between months with high and low prior earnings surprises. This spread increases to 36 basis points in earnings announcement months. Tests based on announcement returns, however, suggest no significant differences, which is inconsistent with PEAD. Given that our main results are concentrated around the earnings announcement date (see Table 5 and Figure 2), these findings suggest our main results are unlikely a manifestation of PEAD.

The lack of significant PEAD announcement return differences is consistent with the literature that shows PEAD has disappeared in recent times (e.g., Chordia et al. 2014; Milian 2015). To further assess this result, we split our sample into two sub-periods of 15 years each, 1986-2000 and 2001-2015, respectively. Consistent with the earlier literature on PEAD that uses analyst-based earnings surprises (e.g., Livnat and Mendenhall 2006), Panel B suggests the first half of our sample displays evidence of PEAD with significant abnormal return spreads of 73 and 75 basis points for non-announcement and announcement months, respectively. Also, we find a significant difference in abnormal announcement returns of 28 basis points.

Panel C shows that for the second half of the sample period, monthly returns are not different across firms with high and low prior earnings surprises. Focusing on announcement returns, we find a significantly *negative* spread, opposite to results for the first half of the sample. Firms in the lower four quintiles have comparable announcement returns, while firms in the highest quintile significantly underperform. This finding is not consistent with PEAD, but in line with recent findings in Milian (2015), who shows that unsophisticated arbitrage leads to the reversal of the announcement return predictability.

Overall, we conclude from the analyses in Table 9 that our main findings are unlikely a reflection of previously documented evidence on PEAD.

Additional Controls

Prior studies show that accruals are negatively correlated with subsequent returns (e.g., Sloan 1996; Richardson et al. 2005). Similarly, Bradshaw et al. (2001) show that accruals predictably relate to analysts' forecast errors. We did not explicitly control for accruals in our main tests because the requirement of accrual data would restrict the sample to firms with these data available, resulting in nonrandom sample attrition of, mostly, financial firms. Because we have no conceptual reason for excluding these firms from our sample, we chose not to control for accrual measures in our main tests.[29] In untabulated analyses, we control for measures of operating accruals (Sloan 1996) and total accruals (Richardson et al. 2005)—based on both balance-sheet and cash-flow data—and find that our results are not affected.

Another potentially important control is firms' external financing. Bradshaw et al. (2006) show that stocks are overvalued and analysts' forecasts are overly optimistic for firms that raise equity and debt, which leads to predictable future returns. In untabulated analyses, we control for Bradshaw et al.'s (2006) measure of external financing and again find that our main inferences are not affected. We draw the same conclusion when using a measure of equity issues based on Fama and French (2008). Finally, because our measure of prior consensus forecast pessimism relies on firms' most recent 12 quarterly earnings surprises, we additionally examine the effect of controlling for the magnitude of these surprises beyond the four most recent quarters already included in the regressions. Again, inferences are unchanged.

[29] The financial firms in our final sample display no discernible differences in forecast pessimism compared with nonfinancial firms, and our main results are very similar when financial firms (SIC codes 6000–6999) are dropped from the sample. In addition, accrual measures are mechanically correlated with asset growth (e.g., Richardson et al. 2010), which we do explicitly control for given limited data requirements.

VI. SUMMARY AND CONCLUSIONS

On average, analysts' latest forecasts of earnings before quarterly earnings announcements are slightly pessimistic, and the majority of firms meet or beat earnings expectations each earnings season. We show that market prices do not fully reflect the conditional probability that a firm meets or beats analyst earnings expectations. Specifically, we show that measures of prior consensus and individual analyst forecast pessimism predict the sign of firms' subsequent earnings surprises, and evidence of predictable differences in subsequent earnings announcement returns suggests that investors do not fully unravel this predictability.

Our results are robust to a long list of controls and do not weaken in recent years with increased arbitrage and trading liquidity. In additional tests, we find that the mispricing of predictable forecast pessimism relates to the difficulty investors have in identifying differences in expected forecast pessimism, as mispricing is strongest based on longer time series of prior earnings surprises and based on more complex measures of individual analysts' prior forecast errors. Moreover, we show that our findings are driven by predictable pessimism in short-term forecasts, not by the well-known optimism in longer-term forecasts.

Our study contributes to the literature on the market pricing and investor learning of predictable error and bias in analysts' forecasts, the literature that examines valuation premia of firms that consistently meet or beat earnings expectations, and the literature on earnings-related anomalies in general. We conclude that the persistent pessimism in analysts' short-term earnings forecasts is not fully reflected in market prices. Given analysts' strong and continued reliance on their interaction with firm managers and their incentives to please managers with forecasts that firms can beat, we expect these frictions are unlikely to dissipate in the near future.

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APPENDIX A

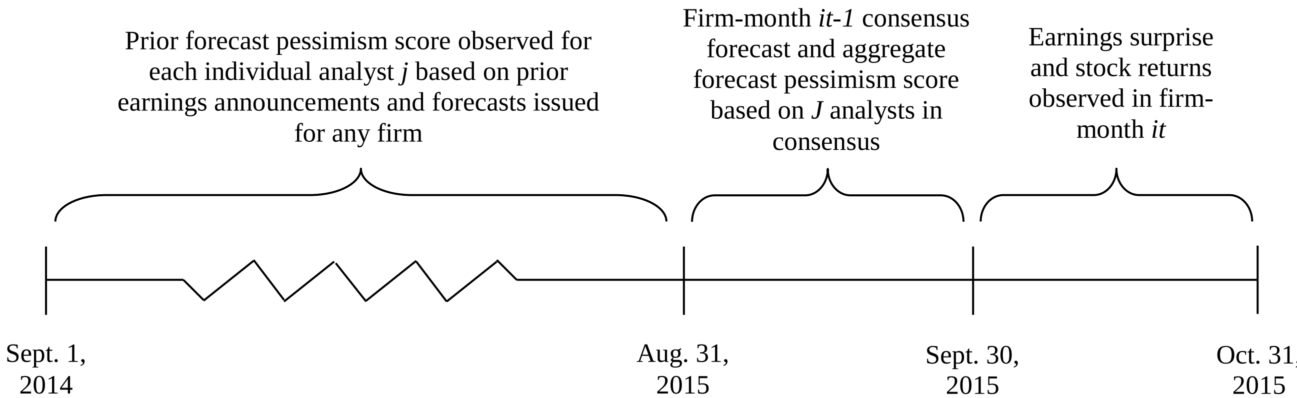
Variable Definitions

Test variables:	
$Pess\_consensus_{t-1}$	Fraction of the firm's most recent twelve quarterly earnings announcements before month *t-1* for which the consensus analyst forecast resulted in a positive earnings surprise (the consensus forecast was pessimistic) instead of a negative earnings surprise (the consensus forecast was optimistic), ignoring all earnings surprises of $0.00 per share, where earnings surprises are determined as the difference between actual quarterly earnings per share and the mean of individual analysts' latest forecasts of earnings per share before the quarterly earnings announcement, both determined using the I/B/E/S unadjusted detail files and rounded to cents per share; a minimum of four prior quarterly earnings surprises are required for the calculation including at least one earnings surprise not equal to $0.00 per share;
$Pess\_individual_{t-1}$	Firm-month aggregated measure of individual analysts' prior forecast pessimism, determined as the firm-month average of the prior forecast pessimism for each individual analyst with an outstanding quarterly earnings forecast in the current month, where prior forecast pessimism for an analyst is measured as the fraction of all forecasts made by the analyst (including forecasts observed for any firm) of earnings announced over the preceding year that resulted in a positive forecast error, ignoring all earnings surprises of $0.00 per share, and where earnings surprises are determined as the difference between actual quarterly earnings per share and the individual analyst's latest forecasts of earnings per share before the quarterly earnings announcement, both determined using the I/B/E/S unadjusted detail files; see Figure 1 for a timeline explaining the measurement of this variable;
$Pess\_combined_{t-1}$	Sum of $Pess\_consensus_{t-1}$ and $Pess\_individual_{t-1}$;
Outcome variables:	
$Surprise_t$	Earnings surprise in announcement month *t*, measured as the difference between actual quarterly earnings per share and the mean of individual analysts' latest forecasts of earnings per share before the quarterly earnings announcement, both determined using the I/B/E/S unadjusted detail files, scaled by the stock price at the end of the announced fiscal quarter (CRSP variable PRC), multiplied by 100;
$Nonneg_t$	Indicator variable set equal to 1 if the firm's earnings surprise in announcement month *t* is non-negative, 0 otherwise, where earnings surprise is determined as the difference between actual quarterly earnings per share and the mean of individual analysts' latest forecasts of earnings per share before the quarterly earnings announcement, both determined using the I/B/E/S unadjusted detail files;
$Return_t$	Raw monthly stock return including distributions obtained from CRSP in month *t*, multiplied by 100 (CRSP variable RET);
$BHAR_t[0,2]$	Buy-and-hold size-adjusted return measured from day 0 through day +2 relative to the quarterly earnings announcement date, multiplied by 100, where size-adjustments are based on NYSE/AMEX/NASDAQ cutoffs (CRSP file "erdport1");
Control variables:	
$Size_{t-1}$	Market capitalization at the end of month *t-1* (CRSP variables SHROUT * PRC);
$Book\text{-}to\text{-}market_{t-1}$	Book-to-market ratio computed based on book value of common equity (Compustat Fundamentals Annual data item CEQ) from the most recent fiscal year scaled by market capitalization (CRSP); accounting data from Compustat are assumed to be available four months after a firm's fiscal year end and observations with negative book values of equity are excluded;
$Return_{t-1}$	Raw return in month *t-1* (CRSP);
$Return_{t-12,t-2}$	Buy-and-hold return over the 11-month period ending before the beginning of the previous month (CRSP);

Idiosyncratic volatility$_{t-1}$	Standard deviation of residuals obtained from market model estimations over the previous 60 months, with a minimum of 12 months required (CRSP);
Institutional ownership$_{t-1}$	Fraction of shares held by institutional investors at the end of the most recently finished calendar quarter (Thomson Reuters Institutional (13f) Holdings);
Analyst following$_{t-1}$	Number of analysts with an outstanding forecast of one-quarter-ahead (I/B/E/S fiscal period indicator 6) earnings per share in month *t-1* from the I/B/E/S unadjusted summary files;
Asset growth$_{t-1}$	Annual percentage growth rate in total assets from Compustat for the most recently completed fiscal year (AT);
Operating profitability$_{t-1}$	Firm operating profitability following Ball et al. (2015), based on annual accounting data from Compustat and defined as total revenues (REVT) minus cost of goods sold (COGS) minus SG&A expense (XSGA) adjusted for R&D expense (XRD), scaled by total assets (AT);
$\Delta QEARN_{t-1}$	The most recently announced quarterly earnings (Compustat Fundamentals Quarterly data item IBQ) minus earnings of the same fiscal quarter one year earlier, scaled by lagged assets (ATQ);
$Q_{-\tau}$ earnings surprise$_{t-1}$	The previously announced earnings surprise for quarter q-τ, where $\tau \in \{1, \ldots, 4\}$, where earnings surprise is determined as the difference between actual quarterly earnings per share and the mean of individual analysts' latest forecasts of earnings per share before the quarterly earnings announcements, both determined using the I/B/E/S unadjusted detail files and rounded to cents per share, scaled by the stock price at the end of fiscal quarter q-τ (CRSP variable PRC);
Pess_consensus#q$_{t-1}$	Fraction of the firm's most recent # quarterly earnings announcements ($\# \in \{1,4,8,12\}$) for which the consensus analyst forecast resulted in a positive earnings surprise (the consensus forecast was pessimistic) instead of a negative earnings surprise (the consensus forecast was optimistic), ignoring all earnings surprises of $0.00 per share, where earnings surprises are determined as the difference between actual quarterly earnings per share and the mean of individual analysts' latest forecasts of earnings per share before the quarterly earnings announcement, both determined using the I/B/E/S unadjusted detail files; for $\# = 12$ the variable is equal to *Pess_consensus$_{t-1}$*;
Pess_consensus_LT$_{t-1}$	Same as *Pess_consensus$_{t-1}$*, but now calculated based on analysts' latest forecasts of quarter *q* earnings per share issued before the *q-1* earnings announcement (i.e., two-quarter-ahead forecasts);
Pess_individual_LT$_{t-1}$	Same as *Pess_individual$_{t-1}$*, but now calculated based on analysts' latest forecasts of quarter *q* earnings per share issued before the *q-1* earnings announcement (i.e., two-quarter-ahead forecasts);

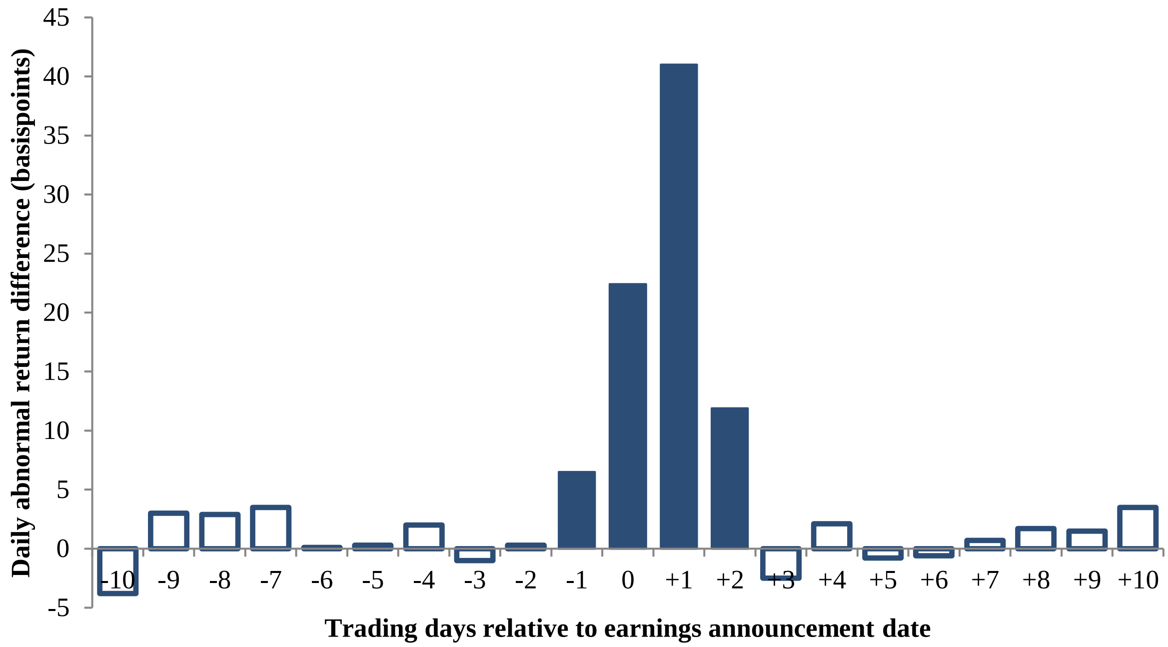
FIGURE 1

Timeline Explaining Measurement of Prior Individual Analyst Forecast Pessimism Scores



Timeline illustrating the measurement of prior individual analyst forecast pessimism scores using a hypothetical firm that announces quarterly earnings in October 2015. During the twelve months before portfolio-formation month *it-1* (September 2014 through August 2015), the quarterly forecast errors of each analyst $j \in \{1, \ldots, J\}$ that contributes to the *it-1* consensus are identified based on the earnings announcements of all firms covered by the analyst. Forecast errors are defined as a firm's actual earnings per share minus the individual analysts' latest forecast before the earnings announcement, rounded to cents per share. Each individual forecast error is categorized as pessimistic (optimistic) if the forecast error is positive (negative), ignoring all forecast errors of \$0.00 per share. Based on this categorization, average pessimism is determined for each individual analyst based on all non-zero forecast errors identified in the twelve-month period. The median number of prior non-zero forecast errors used to compute the individual analyst pessimism score is 28 (interquartile range 11–46). Next, the individual analyst pessimism scores are aggregated to a firm-specific score based on the *J* analysts in the firm-month *it-1* consensus forecast ($Pess\_individual_{it-1}$). A one-month lag is used between the calculation of past forecast pessimism scores and the observation of earnings surprises and returns to allow for sufficient time between the observation of prior earnings announcements (which reveal the analysts' ex-post pessimism versus optimism) and portfolio formation in month *it-1*.

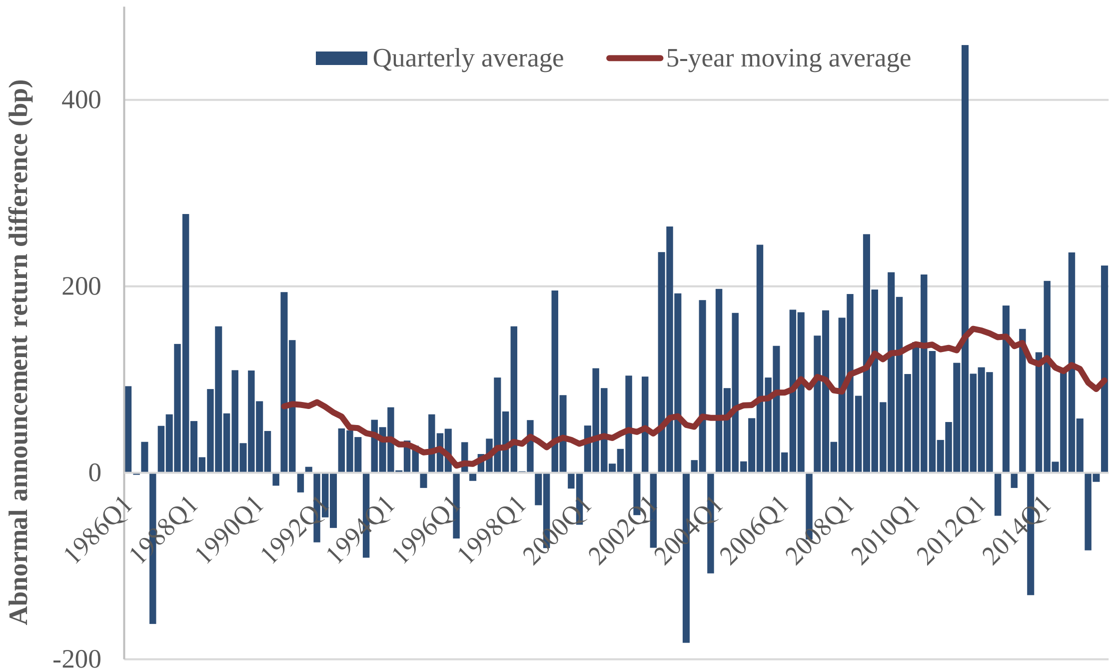
FIGURE 2
Abnormal Return Differences for Different Days around Earnings Announcement



Cross-sectional regression coefficients for *Pess_combined*$_{t-1}$ obtained from the regressions in Table 5, estimated separately using the size-adjusted returns for each trading day in the [-10,+10] window around the earnings announcement date as dependent variable. The cross-sectional regression coefficient measures the difference in daily abnormal returns between firms with high (monthly quintile 5) and low (monthly quintile 1) combined pessimism scores (*Pess_combined*$_{t-1}$), incremental to the other return predictive signals used in Table 5. Coefficients are multiplied by 100 to reflect abnormal return differences in basis points on the vertical axis (bp). Filled (unfilled) bars reflect return differences significantly (not significantly) different from zero at $p<0.05$. Table 1 presents the sample selection details. Appendix A provides details on the measurement of *Pess_combined*$_{t-1}$ and its components *Pess_consensus*$_{t-1}$ and *Pess_individual*$_{t-1}$.

FIGURE 3

Trends in Announcement Return Differences Based on Combined Pessimism Measure



The bars capture the quarterly averages of the cross-sectional regression coefficients for *Pess_combined*$_{t-1}$ obtained from the regressions in Table 5 using earnings announcement date abnormal returns (*BHAR*$_t$[0,2]) as dependent variable. The cross-sectional regression coefficient measures the difference in announcement returns between firms with high (monthly quintile 5) and low (monthly quintile 1) combined pessimism scores (*Pess_combined*$_{t-1}$), incremental to the other return predictive signals used in Table 5. The solid line captures the five-year moving average of the monthly cross-sectional regression estimates, starting the first month with 60 monthly coefficient estimates available for our sample (December 1990). Coefficients are multiplied by 100 to reflect abnormal return differences in basis points (bp) on the vertical axis. Table 1 presents the sample selection details. Appendix A provides details on the measurement of *Pess_combined*$_{t-1}$ and its components *Pess_consensus*$_{t-1}$ and *Pess_individual*$_{t-1}$.

TABLE 1
Sample Selection Details

Description	Observations	Securities
Security-month observations in CRSP during 1986-2015 of firms with ordinary shares listed on NYSE, AMEX, or NASDAQ and non-missing return data	1,943,650	18,613
- Stock price below $5	-527,120	-2,038
- Less than two analysts in I/B/E/S forecasting quarterly earnings	-604,591	-5,727
- No earnings announcement data available	-7,780	-207
- Less than four previous quarterly earnings surprises available	-72,540	-1,506
- All four previous quarterly earnings surprises equal to $0.00 per share	-2,791	-7
- Insufficient data to compute individual analyst pessimism measure	-2,091	-15
- Data on control variables not available	-56,472	-924
Full sample of security-month observations	670,265	8,189
- Of which earnings announcement months:	225,283	[33.6%]
Sample with ex-post earnings surprise data (Table 4)	224,048	
Sample with ex-post earnings announcement return data (Table 5, cols. 3 and 4)	224,145	

Security-month observations are obtained from the CRSP monthly stock file. Listing on NYSE, AMEX, or NASDAQ is identified by CRSP's historical exchange identifier (EXCHCD equals 1, 2, or 3). Ordinary shares are identified based on CRSP's share code (SHRCD equals 10 or 11). Security-month observations are merged with the I/B/E/S unadjusted historical summary file based on CUSIP. If a security changes CUSIP over time, CRSP's historical CUSIP code (NCUSIP) is used instead of the header CUSIP. Earnings announcement (EA) months are months in which the firm announces quarterly earnings, identified based on Compustat and I/B/E/S using the procedure outlined in Dellavigna and Pollet (2009). In the initial selection of 225,283 observations, we require only monthly return data in month *t* and test and control variable information measured before month *t*. In Table 4 the analyses are additionally restricted to those observations for which ex-post earnings surprises could be calculated. Analyses based on announcement date returns (e.g., Table 5, cols. 3 and 4) are additionally restricted to those observations where ex-post size-adjusted returns could be calculated around the earnings announcement date.

TABLE 2

Descriptive Statistics

Panel A: Summary Statistics on Test and Control Variables

	Average distributional characteristic across 360 months in sample:				
	Mean	St. dev.	Q1	Median	Q3
$Pess\_consensus_{t-1}$	0.575	0.223	0.419	0.583	0.737
$Pess\_individual_{t-1}$	0.587	0.089	0.529	0.589	0.649
Size$_{t-1}$	3,456	8,185	321	839	2,558
Book-to-market$_{t-1}$	0.527	0.352	0.275	0.455	0.687
Return$_{t-1}$	0.010	0.099	-0.049	0.006	0.064
Return$_{t-12,t-2}$	0.172	0.423	-0.093	0.105	0.346
Idiosyncratic volatility$_{t-1}$	0.110	0.047	0.076	0.101	0.136
Institutional ownership$_{t-1}$	0.583	0.206	0.441	0.604	0.742
Analyst following$_{t-1}$	7.423	5.286	3.385	5.779	10.006
Asset growth$_{t-1}$	0.196	0.348	0.019	0.104	0.244
Operating profitability$_{t-1}$	0.158	0.103	0.090	0.149	0.214
$\Delta QEARN_{t-1}$	0.000	0.024	-0.004	0.001	0.006
Q_{-1} *earnings surprise*$_{t-1}$	-0.001	0.007	-0.002	0.000	0.002
Q_{-2} *earnings surprise*$_{t-1}$	-0.001	0.007	-0.002	0.000	0.002
Q_{-3} *earnings surprise*$_{t-1}$	-0.001	0.007	-0.002	0.000	0.002
Q_{-4} *earnings surprise*$_{t-1}$	-0.001	0.007	-0.002	0.000	0.002

Panel B: Correlations Table

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.
1.	*Pess_consensus*$_{t-1}$		0.344	0.184	-0.176	0.014	0.148	-0.026	0.121	0.175	0.144	0.216	0.121	0.313	0.345	0.365	0.374
2.	*Pess_individual*$_{t-1}$	0.342		0.174	-0.132	0.010	0.141	0.000	0.140	0.176	0.037	0.147	0.160	0.230	0.215	0.202	0.165
3.	*Size*$_{t-1}$	0.090	0.096		-0.306	0.057	0.170	-0.488	0.275	0.667	0.001	0.134	0.043	0.057	0.045	0.049	0.036
4.	*Book-to-market*$_{t-1}$	-0.172	-0.124	-0.167		-0.112	-0.375	-0.074	-0.021	-0.227	-0.209	-0.447	-0.153	-0.085	-0.074	-0.065	-0.046
5.	*Return*$_{t-1}$	0.004	0.003	0.014	-0.111		0.006	-0.005	-0.024	-0.006	-0.017	0.009	0.031	0.023	0.017	0.014	0.008
6.	*Return*$_{t-12,t-2}$	0.123	0.122	0.040	-0.349	0.009		-0.021	0.011	0.002	-0.029	0.053	0.362	0.241	0.214	0.169	0.084
7.	*Idiosyncratic volatility*$_{t-1}$	-0.028	-0.006	-0.278	-0.056	0.025	0.105		-0.073	-0.178	0.147	0.039	0.028	0.019	0.022	0.021	0.026
8.	*Institutional ownership*$_{t-1}$	0.126	0.152	0.038	-0.031	-0.036	-0.008	-0.121		0.310	-0.024	0.120	0.014	0.027	0.030	0.034	0.034
9.	*Analyst following*$_{t-1}$	0.151	0.167	0.547	-0.203	-0.014	-0.020	-0.172	0.262		0.089	0.178	-0.006	0.023	0.022	0.025	0.026
10.	*Asset growth*$_{t-1}$	0.085	0.014	-0.019	-0.134	-0.021	-0.019	0.218	-0.039	0.037		0.125	-0.009	-0.028	-0.011	0.024	0.051
11.	*Operating profitability*$_{t-1}$	0.219	0.146	0.101	-0.385	-0.001	0.049	0.025	0.117	0.190	0.023		-0.012	0.016	0.038	0.066	0.094
12.	$\Delta QEARN_{t-1}$	0.063	0.103	0.021	-0.171	0.012	0.249	-0.010	0.010	0.004	-0.034	0.002		0.364	0.225	0.165	0.093
13.	*Q*$_{-1}$ *earnings surprise*$_{t-1}$	0.239	0.177	0.032	-0.149	0.010	0.189	-0.027	0.032	0.037	-0.010	0.050	0.341		0.233	0.140	0.104
14.	*Q*$_{-2}$ *earnings surprise*$_{t-1}$	0.257	0.166	0.034	-0.141	0.007	0.163	-0.043	0.041	0.046	0.002	0.076	0.182	0.226		0.224	0.134
15.	*Q*$_{-3}$ *earnings surprise*$_{t-1}$	0.271	0.156	0.033	-0.120	0.000	0.130	-0.038	0.041	0.044	0.025	0.097	0.114	0.141	0.229		0.221
16.	*Q*$_{-4}$ *earnings surprise*$_{t-1}$	0.278	0.128	0.029	-0.100	-0.004	0.060	-0.037	0.042	0.040	0.041	0.122	0.039	0.106	0.150	0.216	

Panel A presents descriptive statistics on our test variables (*Pess_consensus*$_{t-1}$ and *Pess_individual*$_{t-1}$) and control variables. For consistency with the estimation of monthly portfolio returns and monthly cross-sectional regressions, the distributional characteristics (mean, standard deviation, first quartile, median, and third quartile) are based on averages calculated across the 360 months in our sample. Panel B presents average monthly Spearman (Pearson) correlations displayed above (below) the diagonal. All continuous variables are winsorized to the 1st and 99th percentiles of their distributions. See Table 1 for sample selection details and Appendix A for detailed variable definitions.

TABLE 3
Portfolio Tests of Earnings Surprises and Return Predictability

Panel A: Predictability of Earnings Surprise Signs and Returns Based on Prior Consensus Pessimism

			All months	EA=0	EA=1	
	$Pess\_consensus_{t-1}$	$Nonneg_t$	$Return_t$	$Return_t$	$Return_t$	$BHAR_t$[0,2]
Q1 (low)	0.270	0.506	0.746	0.556	0.940	-0.123
Q2	0.476	0.580	0.955	0.681	1.313	0.013
Q3	0.604	0.627	1.115	0.831	1.623	0.180
Q4	0.726	0.670	1.149	0.840	1.706	0.251
Q5 (high)	0.891	0.743	1.229	0.971	1.752	0.373
Q5–Q1	0.621	0.236	0.483	0.415	0.812	0.495
t-statistic	[146.23***]	[28.48]***	[5.41]***	[4.56]***	[5.04]***	[5.49]***

Panel B: Predictability of Earnings Surprise Signs and Returns Based on Prior Individual Pessimism

			All months	EA=0	EA=1	
	$Pess\_individual_{t-1}$	$Nonneg_t$	$Return_t$	$Return_t$	$Return_t$	$BHAR_t$[0,2]
Q1 (low)	0.460	0.516	0.829	0.591	1.023	-0.081
Q2	0.542	0.578	0.995	0.734	1.287	0.025
Q3	0.590	0.617	1.052	0.820	1.280	0.033
Q4	0.636	0.663	1.124	0.834	1.708	0.313
Q5 (high)	0.709	0.713	1.153	0.857	1.823	0.324
Q5–Q1	0.249	0.197	0.324	0.266	0.801	0.405
t-statistic	[80.16***]	[20.36]***	[2.28]**	[1.73]*	[4.37]***	[4.70]***

Panel C: Factor Exposure Tests for Earnings Announcement Month Portfolio Returns

$Pess\_consensus_{t-1}$		Alpha	$MKTRF_t$	SMB_t	HML_t	UMD_t	Adj. R^2	No. obs.
EW	Q5–Q1	0.896	-0.019	-0.290	-0.206	-0.018	0.072	360
	t-statistic	(5.29)***	(-0.34)	(-2.68)***	(-2.44)**	(-0.34)		
VW	Q5–Q1	0.413	-0.074	-0.242	-0.195	0.098	0.035	360
	t-statistic	(1.72)*	(-1.00)	(-1.73)*	(-1.53)	(1.80)*		
$Pess\_individual_{t-1}$		Alpha	$MKTRF_t$	SMB_t	HML_t	UMD_t	Adj. R^2	No. obs.
EW	Q5–Q1	0.798	0.062	-0.222	-0.301	0.062	0.071	360
	t-statistic	(3.96)***	(0.83)	(-1.62)	(-2.83)***	(0.90)		
VW	Q5–Q1	0.806	-0.067	-0.087	-0.471	0.245	0.120	360
	t-statistic	(3.21)***	(-0.75)	(-0.53)	(-3.74)***	(3.75)***		

Descriptive statistics for quintile portfolios formed before each of the 360 months in the sample based on measures of prior analyst forecast pessimism. Panels A and B present averages of the 360 monthly means of the frequency of non-negative future earnings surprises (*Nonneg*), monthly returns (*Return*), and earnings announcement date abnormal returns (*BHAR*[0,2]). Average monthly returns are presented separately for all months, months without earnings announcement (EA=0), and months with an earnings announcement (EA=1), respectively. Panel C presents results from calendar-time portfolio regressions of the Fama and French (1993) three-factor model augmented with momentum (Carhart 1997), where firms are assigned to quintile portfolios based on the respective pessimism measures at the end of the month before their earnings announcement. Intercepts ("alphas") capture abnormal returns. Value-weighted (VW) portfolio returns are determined by weighting individual stock returns by the end-of-month-*t-1* market capitalizations. See Table 1 for sample selection details and Appendix A for detailed variable definitions. Standard errors are adjusted for autocorrelation based on Newey-West using five lags. ***, **, and * reflect statistical significance at the level of 0.01, 0.05, and 0.10, respectively.

TABLE 4

Cross-Sectional Regressions of Earnings Surprise Outcomes on Pessimism Measures

Dependent variable:	*Surprise$_t$*	*Surprise$_t$*	*Nonneg$_t$*	*Nonneg$_t$*	Marginal effect:
Pess_consensus$_{t-1}$	0.030 (3.07)***		0.511 (11.78)***		
Pess_individual$_{t-1}$	0.055 (4.27)***		0.449 (10.75)***		
Pess_combined$_{t-1}$		0.063 (5.06)***		0.761 (14.05)***	0.162
Size$_{t-1}$	0.013 (0.93)	0.016 (1.10)	-0.090 (-2.00)**	-0.077 (-1.68)*	-0.015
Book-to-market$_{t-1}$	-0.134 (-6.32)***	-0.133 (-6.21)***	-0.210 (-5.42)***	-0.206 (-5.30)***	-0.044
Return$_{t-1}$	0.158 (12.69)***	0.159 (12.46)***	0.481 (15.92)***	0.476 (16.02)***	0.107
Return$_{t-12,t-2}$	0.105 (9.01)***	0.104 (8.99)***	0.398 (9.40)***	0.392 (9.12)***	0.086
Idiosyncratic volatility$_{t-1}$	-0.127 (-9.77)***	-0.124 (-9.42)***	-0.055 (-1.36)	-0.038 (-0.93)	-0.008
Institutional ownership$_{t-1}$	0.029 (3.32)***	0.033 (3.73)***	0.142 (5.29)***	0.149 (5.63)***	0.031
Analyst following$_{t-1}$	0.018 (1.69)*	0.019 (1.74)*	0.204 (5.09)***	0.214 (5.24)***	0.045
Asset growth$_{t-1}$	-0.033 (-3.28)***	-0.035 (-3.50)***	-0.065 (-2.44)**	-0.073 (-2.80)***	-0.016
Operating profitability$_{t-1}$	0.031 (2.26)**	0.036 (2.57)**	0.037 (1.03)	0.055 (1.57)	0.011
ΔQEARN$_{t-1}$	0.038 (3.63)***	0.040 (3.75)***	0.108 (3.69)***	0.115 (4.02)***	0.026
Q_{-1} earnings surprise$_{t-1}$	0.280 (17.62)***	0.281 (17.83)***	0.611 (19.86)***	0.613 (20.25)***	0.136
Q_{-2} earnings surprise$_{t-1}$	0.114 (10.44)***	0.114 (10.66)***	0.133 (4.99)***	0.132 (4.93)***	0.029
Q_{-3} earnings surprise$_{t-1}$	0.054 (5.09)***	0.054 (5.00)***	0.046 (1.56)	0.043 (1.46)	0.009
Q_{-4} earnings surprise$_{t-1}$	0.094 (9.20)***	0.092 (8.94)***	0.115 (3.87)***	0.095 (3.05)***	0.021
n (firm-months)	224,048	224,048	224,048	224,048	
n (months)	360	360	360	360	
Average adjusted | pseudo R^2	0.077	0.076	0.102	0.098	

Average estimates obtained from Fama and MacBeth (1973) monthly cross-sectional OLS and logit regressions of signed earnings surprises (*Surprise*) and non-negative earnings surprise incidence (*Nonneg*), respectively, on ex-ante variables. All variables are defined as in Appendix A, but transformed into monthly quintile ranks and scaled between 0 and 1. Regression intercepts are included but not tabulated. Standard errors of the coefficient estimates are adjusted for autocorrelation based on Newey-West using five lags, *t*-statistics are presented in parentheses. ***, **, and * reflect statistical significance at the level of 0.01, 0.05, and 0.10, respectively. Marginal effects reflect the difference in probability of observing a non-negative earnings surprise in month *t* between observations in highest and lowest quintile of the variable, holding all other variables constant at their means, calculated for each monthly logit regression and averaged across the 360 months.

TABLE 5

Cross-Sectional Return Regressions

Dependent variable:	*Return$_t$*	*Return$_t$*	*BHAR$_t$*[0,2]	*BHAR$_t$*[0,2]
Pess_consensus$_{t-1}$	0.552 (3.41)***		0.593 (6.66)***	
Pess_individual$_{t-1}$	0.543 (3.09)***		0.323 (3.53)***	
Pess_combined$_{t-1}$		0.793 (4.90)***		0.741 (7.76)***
Size$_{t-1}$	-0.368 (-1.28)	-0.335 (-1.19)	-0.228 (-1.66)*	-0.207 (-1.54)
Book-to-market$_{t-1}$	0.821 (3.24)***	0.790 (3.13)***	0.367 (3.08)***	0.360 (3.02)***
Return$_{t-1}$	-1.194 (-5.27)***	-1.206 (-5.36)***	-0.070 (-0.59)	-0.083 (-0.70)
Return$_{t-12,t-2}$	0.974 (3.32)***	0.957 (3.22)***	0.473 (4.49)***	0.467 (4.37)***
Idiosyncratic volatility$_{t-1}$	-0.101 (-0.30)	-0.070 (-0.21)	-0.441 (-3.57)***	-0.425 (-3.54)***
Institutional ownership$_{t-1}$	-0.793 (-5.54)***	-0.764 (-5.39)***	-0.194 (-2.27)**	-0.175 (-2.05)**
Analyst following$_{t-1}$	0.621 (2.91)***	0.600 (2.92)***	0.158 (1.36)	0.152 (1.33)
Asset growth$_{t-1}$	-0.353 (-2.44)**	-0.369 (-2.56)**	-0.199 (-2.33)**	-0.191 (-2.28)**
Operating profitability$_{t-1}$	0.804 (3.37)***	0.814 (3.51)***	0.136 (0.96)	0.153 (1.12)
ΔQEARN$_{t-1}$	0.446 (2.76)***	0.467 (2.93)***	-0.037 (-0.40)	-0.025 (-0.26)
Q_{-1} earnings surprise$_{t-1}$	-0.110 (-0.72)	-0.068 (-0.46)	-0.264 (-2.70)***	-0.253 (-2.65)***
Q_{-2} earnings surprise$_{t-1}$	0.243 (1.86)*	0.238 (1.81)*	0.128 (1.64)	0.126 (1.60)
Q_{-3} earnings surprise$_{t-1}$	0.126 (0.84)	0.131 (0.89)	0.011 (0.14)	0.020 (0.25)
Q_{-4} earnings surprise$_{t-1}$	-0.193 (-1.49)	-0.192 (-1.52)	-0.245 (-3.30)***	-0.244 (-3.31)***
n (firm-months)	225,283	225,283	224,145	224,145
n (months)	360	360	360	360
Average adj. R^2	0.067	0.065	0.014	0.015

Average estimates obtained from Fama and MacBeth (1973) monthly cross-sectional regressions of returns in earnings announcement months on ex-ante variables. Returns are measured as the monthly returns in earnings announcement months (*Return*) and earnings announcement date returns (*BHAR*[0,2]), respectively. All variables are defined as in Appendix A, but transformed into monthly quintile ranks and scaled between 0 and 1. Regression intercepts are included but not tabulated. Standard errors of the coefficient estimates are adjusted for autocorrelation based on Newey-West using five lags, *t*-statistics are presented in parentheses. ***, **, and * reflect statistical significance at the level of 0.01, 0.05, and 0.10, respectively.

TABLE 6

Complexity of Pessimism Measures and Announcement Return Predictability

Panel A: Length of Time Series of Prior Consensus Pessimism and Announcement Return Predictability

Dependent variable:	$BHAR_t[0,2]$	$BHAR_t[0,2]$	$BHAR_t[0,2]$	$BHAR_t[0,2]$
$Pess\_consensus1q_{t-1}$	0.255 (1.91)*			
$Pess\_consensus4q_{t-1}$		0.219 (1.92)*		
$Pess\_consensus8q_{t-1}$			0.440 (4.93)***	
$Pess\_consensus12q_{t-1}$				0.593 (6.66)***
$Pess\_individual_{t-1}$	0.402 (4.03)***	0.394 (4.21)***	0.352 (3.76)***	0.323 (3.53)***
Control variables	Included	Included	Included	Included
n (firm-months)	197,070	224,145	224,145	224,145
n (months)	360	360	360	360
Average adj. R^2	0.017	0.014	0.014	0.014

Panel B: Complexity of Individual Forecast Pessimism Measure and Announcement Return Predictability

	#Analysts		#Analysts-firms	
	High	Low	High	Low
Dependent variable:	$BHAR_t[0,2]$	$BHAR_t[0,2]$	$BHAR_t[0,2]$	$BHAR_t[0,2]$
$Pess\_individual_{t-1}$	0.478 (4.43)***	0.227 (1.62)	0.571 (4.91)***	0.168 (1.39)
Control variables	Included	Included	Included	Included
n (firm-months)	119,959	104,186	111,862	112,283
n (months)	360	360	360	360
Average adj. R^2	0.016	0.013	0.022	0.010

Average estimates obtained from Fama and MacBeth (1973) monthly cross-sectional regressions of returns on ex-ante variables, where returns are measured as the earnings announcement date returns (*BHAR*[0,2]). In Panel A, prior consensus forecast pessimism measures are calculated based on the previous one, four, eight, and twelve quarters, respectively. In Panel B, cross-sectional regressions are estimated separately for firm-month observations with high and low complexity of the individual forecast pessimism measure. High #Analysts captures observations where the number of analysts issuing a quarterly earnings forecast is at or above the monthly median, and Low #Analysts captures observations below the median. High #Analysts-firms captures observations where the number of data points (unique combinations of individual forecast errors for all firms covered by the individual analysts) entering the calculation of $Pess\_individual_{t-1}$ is above the monthly median, Low #Analysts-firms captures observations below the median. In Panel B, the set of control variables includes the consensus forecast pessimism measure calculated based on the previous twelve quarters. All variables are defined as in Appendix A. All variables except $Pess\_consensus1q_{t-1}$ are transformed into monthly quintile ranks and scaled between 0 and 1. Regression intercepts are included but not tabulated. Standard errors of the coefficient estimates are adjusted for autocorrelation based on Newey-West using five lags, *t*-statistics are presented in parentheses. ***, **, and * reflect statistical significance at the level of 0.01, 0.05, and 0.10, respectively.

TABLE 7

Pessimism Measures Based on Short- versus Long-Horizon Quarterly Forecasts

Panel A: Average Pessimism Scores for Short- versus Long-Horizon Forecasts

	Short-horizon forecasts		Long-horizon forecasts	
	$Pess\_consensus_{t-1}$	$Pess\_individual_{t-1}$	$Pess\_consensus\_LT_{t-1}$	$Pess\_individual\_LT_{t-1}$
Mean	0.561	0.575	0.435	0.429
Mean–0.5	0.061	0.075	-0.065	-0.071
t-statistic	[4.66]***	[6.00]***	[-6.96]***	[-6.98]***
Average pessimism (+) or optimism (–)?	Pessimism	Pessimism	Optimism	Optimism

Panel B: Differential Predictive Ability of Measures Based on Short- versus Long-Horizon Forecasts

Dependent variable:	$Nonneg_t$	$BHAR_t[0,2]$
Measures based on short-horizon forecasts:		
$Pess\_consensus_{t-1}$	0.567	0.526
	(11.35)***	(4.66)***
$Pess\_individual_{t-1}$	0.410	0.331
	(7.82)***	(2.66)***
Measures based on long-horizon forecasts:		
$Pess\_consensus\_LT_{t-1}$	-0.088	-0.114
	(-2.00)**	(-1.03)
$Pess\_individual\_LT_{t-1}$	-0.032	-0.117
	(-0.69)	(-0.91)
Control variables	Included	Included
n (firm-months)	222,338	222,420
n (months)	360	360
Average pseudo | adj. R^2	0.110	0.015

Panel A presents descriptive statistics on prior consensus and individual analyst forecast pessimism measures based on short- versus long-horizon forecasts. Short-horizon forecasts are analysts' latest forecasts issued before the current quarterly earnings announcement, while long-horizon forecasts are analysts' latest forecasts (of the same earnings) issued before the previous quarterly earnings announcement. At the time when actual earnings are announced, the median age of short-horizon (long-horizon) forecasts underlying the measures equals 74 (180) days. Average values greater (smaller) than 0.5 for the measures indicate analysts' prior forecasts are on average pessimistic (optimistic). Panel B presents average estimates obtained from Fama and MacBeth (1973) monthly cross-sectional regressions of non-negative earnings surprise incidence (*Nonneg*) and announcement returns (*BHAR*[0,2]) on the short- and long-horizon forecast pessimism measures and controls. All analyses in Panels A and B are based on the restriction that for each firm-quarter, both short- and long-horizon forecast data are available. All variables are defined as in Appendix A, but are transformed into monthly quintile ranks and scaled between 0 and 1 in Panel B. Regression intercepts are included but not tabulated. Standard errors of the coefficient estimates are adjusted for autocorrelation based on Newey-West using five lags, *t*-statistics are presented in parentheses. ***, **, and * reflect statistical significance at the level of 0.01, 0.05, and 0.10, respectively.

TABLE 8

Return Predictability and Firm Size

Panel A: Predictability of Returns across Firm Size Groups Based on Combined Pessimism Measure

Combined pessimism quintile	Fraction microcap	Fraction big	All	Microcap	All-but-micro	Big
			Alpha	Alpha	Alpha	Alpha
Q1 (low)	0.358	0.315	-0.131	-0.374	0.097	0.329
Q2	0.276	0.386	0.257	-0.431	0.179	0.435
Q3	0.238	0.433	0.446	0.545	0.462	0.441
Q4	0.189	0.487	0.866	1.349	0.809	0.746
Q5 (high)	0.158	0.527	0.817	0.969	0.853	0.856
Q5–Q1	-0.200	0.213	0.947	1.344	0.756	0.528
t-statistic	[-13.92]***	[16.53]***	[5.21]***	[3.76]***	[3.99]***	[2.13]**

Panel B: Predictability of Returns across Firm Size Groups Based on Consensus Pessimism Measure

Consensus pessimism quintile	Fraction microcap	Fraction big	All	Microcap	All-but-micro	Big
			Alpha	Alpha	Alpha	Alpha
Q1 (low)	0.344	0.328	-0.112	-0.550	0.104	0.296
Q2	0.269	0.393	0.293	-0.025	0.275	0.610
Q3	0.231	0.440	0.633	0.743	0.552	0.511
Q4	0.189	0.492	0.716	1.333	0.619	0.681
Q5 (high)	0.167	0.513	0.785	0.965	0.873	0.807
Q5–Q1	-0.177	0.185	0.896	1.515	0.769	0.511
t-statistic	[-13.19]***	[13.20]***	[5.29]***	[4.20]***	[4.45]***	[2.51]**

Panel C: Predictability of Returns across Firm Size Groups Based on Individual Pessimism Measure

Individual pessimism quintile	Fraction microcap	Fraction big	All	Microcap	All-but-micro	Big
			Alpha	Alpha	Alpha	Alpha
Q1 (low)	0.343	0.325	0.020	-0.167	0.097	0.185
Q2	0.260	0.409	0.246	0.133	0.243	0.345
Q3	0.227	0.443	0.297	0.426	0.480	0.686
Q4	0.205	0.474	0.733	0.698	0.717	0.662
Q5 (high)	0.183	0.497	0.818	0.958	0.856	0.951
Q5–Q1	-0.160	0.172	0.798	1.125	0.760	0.766
t-statistic	[-13.36]***	[16.42]***	[3.96]***	[2.97]***	[3.42]***	[2.87]***

Descriptive statistics and average returns for quintile portfolios formed in each of the 360 months in the sample based on the combined prior forecast pessimism measure ($Pess\_combined_{t-1}$) in Panel A, consensus pessimism measure ($Pess\_consensus_{t-1}$) in Panel B, and individual pessimism measure ($Pess\_individual_{t-1}$) in Panel C. Alphas are calendar-time portfolio regression intercepts obtained from estimation of the Fama and French (1993) three-factor model augmented with momentum (Carhart 1997), where firms are assigned to quintile portfolios at the end of the month before their earnings announcement. "Microcap" and "big" stocks are defined as in Fama and French (2008) based on the 20th and 50th NYSE percentile breakpoints, respectively. "All-but-micro" reflects the full sample of stocks except those designated as microcaps. Standard errors of the estimates are adjusted for autocorrelation based on Newey-West using five lags, *t*-statistics are presented in parentheses. ***, **, and * reflect statistical significance at the level of 0.01, 0.05, and 0.10, respectively.

TABLE 9

Evidence on Post-Earnings Announcement Drift (PEAD) in Sample

Panel A: Average Returns for Portfolios Formed on Recent Quarterly Earnings Surprises

Surprise quintile	All months Alpha	EA=0 Alpha	EA=1 Alpha	EA=1 $BHAR_t[0,2]$
Q1 (low)	-0.087	-0.370	0.318	0.094
Q2	-0.069	-0.325	0.284	0.102
Q3	0.089	-0.093	0.390	0.198
Q4	0.138	-0.166	0.541	0.228
Q5 (high)	0.197	-0.039	0.674	0.051
Q5–Q1	0.284	0.331	0.356	-0.043
t-statistic	[2.68]***	[2.78]***	[2.17]**	[-0.49]

Panel B: PEAD Tests for First Half of Sample Period (1986-2000)

Surprise quintile	All months Alpha	EA=0 Alpha	EA=1 Alpha	EA=1 $BHAR_t[0,2]$
Q1 (low)	-0.132	-0.487	0.398	-0.021
Q2	-0.116	-0.508	0.361	-0.016
Q3	0.092	-0.220	0.348	0.115
Q4	0.188	-0.179	0.657	0.229
Q5 (high)	0.530	0.241	1.150	0.260
Q5–Q1	0.662	0.728	0.752	0.281
t-statistic	[5.07]***	[3.99]***	[4.07]***	[2.72]***

Panel C: PEAD Tests for Second Half of Sample Period (2001-2015)

Surprise quintile	All months Alpha	EA=0 Alpha	EA=1 Alpha	EA=1 $BHAR_t[0,2]$
Q1 (low)	-0.005	-0.230	0.281	0.209
Q2	0.010	-0.128	0.277	0.220
Q3	0.086	-0.005	0.375	0.280
Q4	0.063	-0.170	0.346	0.227
Q5 (high)	-0.140	-0.291	0.214	-0.158
Q5–Q1	-0.093	-0.032	-0.005	-0.367
t-statistic	[-1.31]	[-0.70]	[-0.30]	[-3.15]***

Tests to contrast our main results with post-earnings announcement drift (PEAD) in the sample. Average returns for quintile portfolios formed in each of the 360 months in the sample based on the most recently announced quarterly earnings surprise (Q_{-1} *earnings surprise*$_{t-1}$). Alphas are calendar-time portfolio regression intercepts obtained from estimation of the Fama and French (1993) three-factor model augmented with momentum (Carhart 1997). *BHAR*[0,2] captures the size-adjusted earnings announcement date abnormal returns. Alphas are presented separately for all months in the sample, months without an earnings announcement (EA=0), and months with an earnings announcement (EA=1), respectively. Standard errors of the estimates are adjusted for autocorrelation based on Newey-West using five lags, *t*-statistics are presented in parentheses. ***, **, and * reflect statistical significance at the level of 0.01, 0.05, and 0.10, respectively.