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Expectations Management and Stock Returns

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We establish a link between firms managing investors' performance expectations, earnings announcement premiums, and cyclical patterns (i.e., seasonalities) in returns. Firms that are more likely to manage expectations toward beatable levels predictably earn lower returns before, and higher returns during, their earnings announcements. This pattern repeats across firms' fiscal quarters, suggesting firms manufacture positive "surprises" by negatively biasing investors' expectations ahead of announcing earnings. We corroborate these findings using non-price-based outcomes indicative of expectations management. Together, our findings are consistent with the pressure for firms to meet earnings targets shaping the cross-section of firms' stock returns. (*JEL* G10, G11, G12, G14, M40, M41)

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This study examines the link between firms' incentives to manage earnings expectations toward beatable levels and predictable patterns in the cross-section of monthly stock returns. We do so by introducing a simple proxy for firms' incentives to manage expectations based on widely observable firm characteristics, which we show has strong predictive power for two economically large asset pricing patterns: earnings announcement premiums and return seasonalities. In addition to offering a new explanation for these

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patterns, our evidence contributes to the literature examining the interactions between investors, firms, and informational intermediaries. Specifically, our evidence suggests that expectations management elicits predictable biases and reversals in investors' expectations, which influences the dynamics of market prices relative to earnings announcements.

Over the past few decades, a substantial literature has documented and studied the prevalence of earnings announcement premiums, which is the tendency for firms to earn abnormally high returns during their earnings announcements (e.g., Frazzini and Lamont 2007; Barber et al. 2013; Hartzmark and Solomon 2018). Related studies provide evidence of broader return seasonalities, which refers to cyclical return patterns that repeat at predictable intervals, similar to seasons in weather (e.g., Heston and Sadka 2008; Keloharju et al. 2016).

Over roughly the same time frame, a parallel but separate literature shows that firms regularly engage in expectations management by walking down preannouncement earnings expectations in hopes of conveying upbeat news during earnings announcements. A central inference among these studies is that firms' executives face both long-term and short-term incentives to manage expectations. The long-term incentives mainly relate to executives' reputational capital and career outcomes. Specifically, both survey evidence (Graham et al. 2005) and CEO retention data (Puffer and Weintrop 1991) indicate that successfully managing expectations improves executives' longer-term career trajectory. By contrast, the shorter-term incentives stem from the negative price reaction that accompanies missing earnings targets, which elicits negative press at times when investor attention is likely to be heightened, weakened relationships with institutional investors, and increased litigation risk (e.g., Barth et al. 1999; Bartov et al. 2002; Kasznik and McNichols 2002; Richardson et al. 2004; Bradshaw et al. 2016).

The central goal of this study is to establish expectations management as a contributing factor to the prevalence of both earnings announcement premiums and return seasonalities. Whereas prior research studies these asset pricing regularities and expectations management separately, our innovation is to study them jointly. The idea that expectations management contributes to earnings announcement premiums and return seasonalities is bolstered by the attributes they share. The potential for expectations management to explain announcement premiums is perhaps most intuitive because both phenomena engender predictable upward revisions in investors' perceptions of firm value (proxied by earnings surprises and stock returns) that anchor on earnings announcements. Similarly, return seasonalities and expectations management—when repeated across firms' fiscal reporting periods—both engender cyclical patterns in the revision of investors' beliefs (proxied by earnings forecast revisions and stock returns) that recur at predictable horizons. Prior research on expectations management has tended to focus on its determinants and the channels through which it is achieved or its relation with

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contemporaneous quarterly stock returns and/or valuations. For example, one strand of research shows firms that successfully managed and beat analysts' earnings expectations earn higher full-quarter stock returns and receive higher valuation multiples incremental to the change in firms' earnings (e.g., Barth et al. 1999; Bartov et al. 2002; Kasznik and McNichols 2002). Relative to this research, we contribute by developing an ex ante proxy for expectations management incentives, which we show has strong forecasting power for future returns. Our study also relates to Veenman and Verwijmeren (2018), which shows some analysts are persistently pessimistic in their earnings forecasts, and investors fail to fully price in this pessimism, leading to predictable returns concentrated at earnings announcements. Our study complements and extends these prior studies by exploring expectations management as a potential reason for cross-sectional differences in analyst pessimism. Moreover, unlike any existing work we are aware of, we study the effects of expectations management on return patterns that oscillate throughout the quarter, rather than just around earnings announcements, yielding a new explanation for two economically large empirical asset pricing patterns.

Firms' expectations management incentives are challenging to use in asset pricing tests because they are not directly observable and are likely time varying. We address this measurement problem by developing a novel and simple ex ante proxy for firms' incentives to manage expectations, which we show offers strong predictive power for earnings news and returns. Our proxy uses principal component analysis to summarize several factors from prior research indicative of firms' incentives to manage expectations. We incorporate three groups of factors that we refer to as (1) "attention," reflecting a greater focus toward firms' earnings announcements (2) "pressure," reflecting unsustainable growth expectations, and (3) "relevance," reflecting the sensitivity of prices to earnings news. To maximize our sample, we prioritize proxies that are parsimonious and widely available. As detailed in Section 1, we proxy for attention using firms' analyst coverage and institutional ownership; pressure using firms' trailing sales growth; and relevance using the solvency metric from Altman (1968) to capture the responsiveness of prices to earnings news.

Our main tests examine whether our proxy for expectations management incentives, which we refer to as *EMI*, contains predictive power for returns relative to earnings announcement months. Most studies involving firms' earnings news and return predictability show a unidirectional effect whereby returns concentrate at earnings announcements but continue in the same direction in nonannouncement periods (Engelberg et al. 2018). By contrast, we hypothesize that firms engaging in expectations management initially bias investors' preannouncement expectations downward and that market prices later correct upward at the time of the announcement. Thus, we predict that returns of high *EMI* firms follow a "V-shaped" pattern where they *underperform* prior to earnings announcements but *outperform* during announcement periods. Return predictability that changes signs in this way in event time around

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earnings announcements is, to our knowledge, unique in the literature and challenging to explain as compensation for risk. To test these predictions, we study a sample of roughly 320,000 total quarterly earnings announcements from 1985 through 2015, which corresponds to a broad cross-section of approximately 850 firms expected to announce earnings each month or 2,500 firms per quarter. This illustrates an important appeal of our composite proxy, that it is broadly applicable and thus delivers a large sample necessary for studying the cross-section of returns.

Our first main tests show that firms with "stronger" incentives to manage expectations (i.e., high *EMI* firms) tend to outperform firms with "weaker" incentives (i.e., low *EMI* firms) by roughly 64 basis points (bps) in expected announcement months using equal-weighted returns (t-statistic = 4.03) and 80 bps using value-weighted returns (t-statistic = 3.49). These return patterns are striking in their magnitude and consistency across equal- and value-weighting, suggesting expectations management is associated with a predictable and economically large source of cross-sectional variation in monthly announcement returns.

A key inference from our paper is that expectations management represents an important, and previously unexplored, source of variation in monthly earnings announcement premiums. Specifically, our tests show announcement premiums predictably increase in magnitude and significance across *EMI* portfolios. Moreover, announcement premiums are concentrated among high *EMI* firms and, conversely, insignificant among low *EMI* firms. The predictive link between *EMI* and announcement returns is also distinct from standard asset pricing factors, complementary to the volume effect in Frazzini and Lamont (2007) and idiosyncratic risk effect in Barber et al. (2013), and inconsistent with risk-based explanations centered on aggregate earnings growth. Our findings are also robust to controls for well-known return predictors, including an expansive set of 94 variables from Green et al. (2017).

In our second main tests, we show that although high *EMI* firms outperform during their expected announcement month, they also significantly *underperform* by approximately 50 bps in the month prior to announcing earnings. This predictable "V-shaped" pattern is difficult to reconcile with standard risk-based explanations that would require risk premiums to reverse signs sharply in firms' event-time returns. Instead, the V-shaped return pattern appears consistent with high *EMI* firms walking down investors' preannouncement expectations to generate positive surprises coinciding with their announcements.

The V-shaped return pattern we document also points to expectations management as a potential source of return seasonalities across firms' fiscal quarters. To the extent firms repeat cycles of expectations management across their fiscal quarters, we predict a positive correlation between firms' month M returns and their returns "synced" within the 3-month quarterly reporting cycle (i.e., M-3,-6,-9,-12) because firms are more likely engaging in similar

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behavior (e.g., repeating walkdown behavior). Conversely, we predict a negative correlation with "nonsynced" returns (i.e., M-2,-4,-5,-7,-8,-10,-11) because firms are more likely engaging in offsetting behavior (e.g., walking down vs. positively surprising).

Consistent with our predictions, we find significant returns to a calendar-time seasonality strategy that sorts firms by differences in their synced versus nonsynced lagged month returns, particularly among high *EMI* firms. Strategy returns are not only economically significant at roughly 50 bps per month among high *EMI* firms (t-statistic = 3.17) but also hold incrementally to the predictive link between *EMI* and earnings announcement premiums. The joint predictive power of *EMI* for both announcement premiums and quarterly return seasonalities is a key result in our paper and consistent with our central thesis that cycles of managing expectations simultaneously contribute to both asset pricing regularities.

In the second half of the paper, we conduct a variety of validation tests that link *EMI* to several non-price-based outcomes that intuitively reflect expectations management, but are also unlikely to reflect priced risks. We first verify that high *EMI* firms are more likely to report positive surprises (i.e., earnings that exceed analysts' forecasts).

Perhaps more surprisingly, we show high *EMI* firms are more likely to exceed analysts' forecasts despite also being more likely to report year-over-year *decreases* in their earnings. The mismatch in these results is likely puzzling in the absence of expectations management because it would require that analysts overreact to contemporaneous declines in firms' earnings, despite evidence the opposite is true on average (e.g., Dechow and Sloan 1997). Instead, these findings suggest high *EMI* firms manage expectations to soften the impact of reporting declining performance (see the appendix for a motivating example from Citigroup). A critical piece of evidence is that *EMI* also predicts a sharp discontinuity in the distribution of analyst-based surprises around zero. Specifically, the imbalance of small positive, compared to small negative, surprises increases monotonically across *EMI* quintiles. This evidence is unlikely to be explained by firms' risk exposure or the difficulty of forecasting earnings because narrow beats and misses are defined in tight symmetric windows surrounding reported earnings. We also show high *EMI* firms experience steeper walkdowns in analysts' preannouncement forecasts, particularly in the weeks leading up to the announcement, which overlaps with the window when high *EMI* firms predictably earn lower returns.

We also study the actions firms undertake to manage expectations by examining their communications with analysts and investors. We show high *EMI* firms are more likely to issue "low-ball" earnings guidance that falls below reported earnings, consistent with firms attempting to negatively bias preannouncement expectations. Additionally, we show the prevalence of positive surprises grew faster for high *EMI* firms compared to low *EMI* firms over our sample period. These results suggest that even as investors observe and

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presumably learn from past earnings announcements, high *EMI* firms became more adept at managing expectations over time, which likely raised learning costs for investors by weakening the predictive link between high *EMI* firms' past and future average behavior.

Finally, the V-shaped return pattern we document suggests that insiders at some firms may be incentivized to opportunistically time their trades around the return cycle that their own firm helps elicit. Using measures of opportunistic trading behavior derived from Cohen et al. (2012) and Ali and Hirshleifer (2017), we show insiders at high *EMI* firms abnormally shift their trades toward buys prior to announcements when prices to tend to be low, and toward sells afterward when prices to tend to be high. This pattern of insider trading for high versus low *EMI* firms is new to the literature and points to a novel incentive for firms to manage expectations that complements explanations from prior research.

The primary contribution of this paper is in establishing conceptual and empirical links between expectations management, announcement premiums, and return seasonalities. Market commentators, regulators, and the financial press commonly echo prior research on expectations management, which portrays the practice as a pervasive feature of modern capital markets. Despite this pervasiveness, expectations management has largely escaped the domain of academic finance. Our study seeks to bridge this gap and, in doing so, provides a novel insight into the prevalence of two economically large asset pricing patterns.

1. Empirical Tests

1.1 Data

We obtain data for measuring firms' expectations management incentives from standard academic databases. Analyst coverage data come from the IBES unadjusted consensus file, price and return data from the monthly CRSP file, financial statement data from Compustat, and institutional ownership data from Thomson Reuters 13F filings. To focus our analysis on larger and more liquid firms, we exclude firms in the lowest NYSE size decile, and those with CRSP share codes other than 10 or 11 or a share price of less than $1, although our results do not appear sensitive to these requirements. The final sample for our main analyses consists of 320,171 firm-quarters spanning the 31-year window from 1985 through 2015.

1.2 Proxying for firms' expectations management incentives

Our study builds on a substantial body of research showing firms engage in expectations management to increase the likelihood of exceeding analysts' forecasts (e.g., Barth et al. 1999; Bartov et al. 2002; Matsumoto 2002; Richardson et al. 2004; Bernhardt and Campello 2007). Our study is distinct from these prior studies in that our tests establish predictive patterns in future

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returns, rather than associations with contemporaneous prices or revisions in analysts' forecasts. This innovation allows us to study whether managers elicit predictable errors in investors' expectations of earnings and, in doing so, link expectations management to earnings announcement premiums as well as return seasonalities.

Our main analyses focus on monthly returns for at least two reasons. First, the use of monthly returns more closely aligns our analysis with the bulk of studies in finance regarding earnings announcement premiums and return seasonalities. Second, Johnson and So (2018a) advocate the use of monthly earnings announcement returns to mitigate the influence of trading frictions on researchers' inferences. However, we supplement our monthly tests using daily returns, which reinforce and extend our main inferences. A key challenge in our study that has likely hampered prior research on expectations management is the need for ex ante measures that facilitate large sample asset pricing tests. Our main analyses rely on a summary metric that is broadly applicable and parsimonious, similar in spirit to the composite investor sentiment proxy from Baker and Wurgler (2006).[1] To organize the construction of our composite proxy, we conjecture that firms' incentives to manage expectations are likely driven by three broad categories of factors that we refer to as "attention," "pressure," and "relevance."

The "attention" component refers to the extent of external monitoring of firms' earnings. We expect firms face greater incentives to manage expectations when their reported results are more likely to garner attention from analysts and influence their standing with institutional investors (e.g., Bushee 1998; Hotchkiss and Strickland 2003; He and Tian 2013; Hilary and Hsu 2013; Bradshaw et al. 2016). Accordingly, we proxy for the attention paid to a firm's earnings announcement via the number of analysts providing annual forecasts and the percentage of shares outstanding held by institutional investors. The second component, "pressure," refers to the extent firms face unsustainable growth expectations. Several studies show investors tend to overextrapolate past growth and that firms face significant price drops when reporting breaks in growth (Lakonishok et al. 1994; Barth et al. 1999; Kasznik and McNichols 2002). Together, these studies suggest firms face greater incentives to manage expectations following stretches of high growth as a means to soften the impact of reporting declining financial performance. We proxy for unsustainable growth expectations using firms' 5-year trailing seasonally adjusted sales growth, as implemented in Lakonishok et al. (1994).[2] Our final component, "relevance," refers to the sensitivity of firms' equity prices to earnings news.

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[1] In Section 2.5, we corroborate our main results using an alternative proxy that we derive by summarizing factors associated with meeting-or-beating expectations in Matsumoto (2002). We use this approach as an alternative rather than as our main measure, in part, because some of the inputs in Matsumoto (2002) are binary leading to discontinuities in the distribution of firms across portfolios.

[2] The Online Appendix shows that the use of earnings growth in place of sales growth yields similar results. We omit earnings growth to avoid complications when earnings are negative. Similarly, the use of internally funded

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Prior research shows earnings news has a stronger association with stock prices for solvent firms, and weaker for distressed firms, due to the liquidation option of equity (e.g., Dhaliwal and Reynolds 1994; Hayn 1995; Matsumoto 2002). These studies show that transitory earnings information is, on average, less relevant among near-insolvent firms because shareholders can opt to liquidate the firm for its assets rather than risk incurring further losses. As a result, we expect that expectations management incentives are pronounced among more solvent firms due to a higher sensitivity to earnings surprises.

We proxy for firms' solvency using the Altman z-score from Altman (1968), with higher values identifying more solvent (i.e., less-distressed) firms. We rely on firms' z-score to capture distress, rather than alternative measures, such as credit ratings or historical prevalence of losses, to maximize the coverage of our main sample. However, in tests tabulated in our Online Appendix, we show that our results do not appear sensitive to alternative relevance proxies to capture firms' sensitivity to earnings news.

To compute our composite expectations management score, *EMI*, we separately rank all expected announcers within a given month into percentiles, ranging from zero to one, for each of the four firm-level attributes discussed above. We use cross-sectional percentiles to facilitate the aggregation of several variables with differing scales and to mitigate the influence of outliers when summarizing the data. As in Baker and Wurgler (2006), we use principal component analysis (PCA) as a convenient way to summarize the variation in our four input variables and to facilitate standard asset pricing tests based on a single sorting variable. More specifically, we use the first principal component of the inputs as our composite incentive proxy, which we refer to as *EMI*. Notationally, letting $\mathbb{Z}_{i,m}$ denote the set of four (centered) characteristics discussed above, we implement our composite incentive proxy each calendar month as follows:

$$EMI_{i,m} = \mathbf{a}'\mathbb{Z}_{i,m} = a_1 Z^{(1)}_{i,m} + a_2 Z^{(2)}_{i,m} + a_3 Z^{(3)}_{i,m} + a_4 Z^{(4)}_{i,m} \tag{1}$$

where the subscripts correspond to firm i and expected announcement month m and the superscripts denote the four input variables. The values of a_p applied to each attribute reflect the monthly weightings from the principal component analysis, which we summarize below, that best explain the total variation in the four input variables.

To mitigate concerns that our broader inferences are specific to the implementation of our composite proxy expressed in Equation (1), we implement several alternative proxies that take different approaches. For example, we show in the Online Appendix our results are robust to using simple averages of the input variables instead of PCA, taking the product of the input

sales growth in place of raw sales growth, as discussed and implemented in Daniel and Titman (2006), yields similar results. We rely on raw sales growth in our main tests for parsimony.

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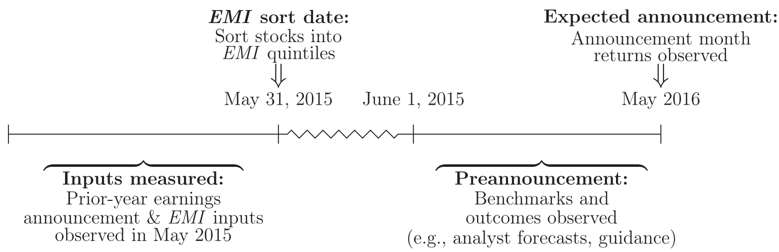
variables to capture interaction effects, variations of our input variables, and other alternative functional forms. We also show in the Online Appendix the attention, pressure, and relevance components of *EMI* each individually predict announcement-month returns, though with more noise than our composite measure, and that the attention component is the strongest individual predictor.[3]

To forecast announcement returns, we estimate firms' expected announcement month using their announcement dates from the prior year. Throughout the paper, we use the notation M to refer to a given month in calendar-time and T to refer to a given month in event-time relative to firms' expected announcement. Thus, the notation $M{=}T$ refers to analyses conducted in the calendar month coinciding with firms' expected earnings announcement, whereas $M{=}T-1$ refers to preannouncement analyses conducted in the calendar month immediately prior to firms' expected announcement.

In all of our return tests, we do not condition ex post on whether a firm has an earnings announcement in month M, but simply predict that a firm will have an announcement in month M if it had an announcement in month M-12. This approach prevents look-ahead biases driven by firms strategically timing their announcements based on the nature of their earnings news (e.g., Johnson and So 2018b).

To illustrate our empirical design, the diagram below provides a time line of our main analyses that use ex ante incentive proxies to forecast firms' earnings surprises and returns while avoiding the influence of look-ahead bias. To make the time line concrete, we focus it on a firm that announced earnings in May of 2015 such that they are expected to announce earnings again in May of 2016.



In the example above, we use inputs observable in May 2015 to forecast outcomes during firms' expected announcement month (May 2016) and preannouncement months (March and April 2016), which aligns with the 12-month data lag used in Chang et al. (2017). Panel A of Table 1 contains the time-series average observation counts and input characteristics across

[3] Our finding that the attention component offers the most forecasting power for returns relates to evidence in Linnainmaa and Zhang (2019) that firms with high analyst coverage tend to underperform prior to their earnings announcement month. Our study differs by focusing on expectations management as an economic rationale for intraquarter return patterns, as well as return seasonalities, which we also corroborate using non-price-based measures of biases in investors' expectations.

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Table 1
Descriptive statistics

A. Averages by expectations management incentives quintiles

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)
OBS	171.7	172.2	172.1	172.1	172.5
EMI	−1.293	−0.713	−0.082	0.635	1.443
Analyst coverage (COV)	0.154	0.824	2.299	4.832	9.832
Inst ownership (INST)	0.043	0.175	0.369	0.517	0.682
Sales growth (SG)	−0.663	1.009	0.985	1.308	2.466
Altman's z (ALT)	1.535	4.368	4.211	4.015	5.422
log(Market capitalization)	11.888	11.754	11.977	12.807	13.904
log(Book-to-market)	0.531	0.499	0.510	0.470	0.366
Return volatility	14.337	13.397	12.359	11.105	10.280
Return momentum	0.003	0.029	0.039	0.024	0.008
Share turnover	1.090	1.025	1.075	1.306	1.930
Relative spreads	0.038	0.034	0.030	0.022	0.013

B. Correlations between EMI inputs

	(1)	(2)	(3)	(4)	(5)
(1) EMI		0.880	0.864	0.319	0.371
(2) Analyst coverage	0.846		0.675	0.160	0.141
(3) Inst ownership	0.868	0.675		0.077	0.142
(4) Sales growth	0.323	0.160	0.077		0.117
(5) Altman's z	0.383	0.141	0.142	0.117	

C. Time-series statistics for first principal component

	Mean	Median	SD
Eigenvalue	1.783	1.805	0.115
Total variance explained (%)	44.736	45.116	2.403
Weighting for analyst coverage (COV)	0.484	0.494	0.069
Weighting for inst ownership (INST)	0.486	0.485	0.027
Weighting for sales growth (SG)	0.180	0.180	0.070
Weighting for Altman's z (ALT)	0.210	0.209	0.083

Panel A presents monthly time-series averages of the variables used to construct expectations management incentives (*EMI*) as well as firm characteristics across *EMI* quintiles. *EMI* is a composite proxy for firms' expectations management incentives, as outlined in Equation (1) and discussed in Section 1, where higher values indicate greater incentives to report positive earnings surprises. *Analyst coverage* is the number of analysts covering a firm. *Inst ownership* is the percentage of shares held by institutions. *Sales growth* is defined as the 5-year sales growth by multiplying the most recent growth by 5, the second to most recent by 4, and so on (as in Lakonishok et al. 1994). *Altman's z* is the distress risk measure based on Altman (1968). Panel B contains time-series averages of firm characteristics across *EMI* quintiles. *log(Market capitalization)* is log of one plus market capitalization. *log(book-to-market)* is log of one plus a firm's book-to-market ratio. *Return volatility* is defined as the standard deviation of monthly returns over the 12 months ending in month T-1. *Return momentum* is market-adjusted cumulative returns over the 12 months ending in month T-1. *Share turnover* is the mean of volume divided by shares outstanding over the 12 months ending in month T-1. *Relative Spreads* is the mean bid-ask spread over the 12 months ending in month T-1. T is the expected announcement month. Panel B presents the Pearson (Spearman) correlations of the four inputs used to construct *EMI* above (below) the diagonal. Panel C reports time-series summary statistics for the first principal components eigenvalue, the fraction of total variance in the data explained by the first principal component factor *EMI*, and each input variable's weighting. The sample consists of 320,171 firm-quarter observations spanning 1985 through 2015.

EMI quintiles. The observation counts show approximately 170 firms in each quintile, indicating that *EMI* is observable for a broad sample of roughly 850 expected announcers per calendar month. Panel A also provides average values of the four input characteristics and shows that each is generally increasing across *EMI* quintiles. The bottom half of panel A presents time-series averages

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of firm characteristics across *EMI* quintiles. Firms' size and book-to-market ratio are measured in the month prior to firms' expected announcement month (i.e., T-1), whereas volatility, momentum, turnover, and relative spreads are measured over the 12 months ending in T-1. While firm size and share turnover are positively related to *EMI*, firms' book-to-market ratio, volatility, and spreads are negatively related to *EMI*. These results indicate that high *EMI* firms tend to be more established, liquid firms with lower volatility, and higher valuations.

Panel B of Table 1 confirms that all four input variables are positively correlated with each other as well as *EMI*, which is helpful because we expect that each dimension works in tandem to increase firms' expectations management incentives. For example, firms that face unsustainable growth expectations may refrain from expectations management if there are no analysts providing earnings forecasts to evaluate the nature of their earnings news.

Panel C of Table 1 presents time-series averages of the results from estimating *EMI* each calendar month as the first principal component of the four input variables. The first row shows that the first principal component satisfies the Kaiser criterion of having an Eigenvalue above one.[4] The second row of panel C shows that, on average, *EMI* accounts for 44.7% of the total sample variance. The bottom rows of panel C contain the individual loadings, a_p, for each input variable as expressed in Equation (1). The loadings align with the evidence in panel B that *EMI* is most strongly correlated with analyst coverage and institutional ownership.

1.3 Expectations management and announcement-month returns

Table 2 contains the first main result of our paper. Specifically, the table establishes a strong predictive link between expectations management incentives, *EMI*, and firms' average raw returns in their expected announcement month, where we adjust for delisting returns following the approach in Shumway (1997). Corresponding t-statistics, shown in parentheses, are based on the time-series distribution of monthly returns.

Panel A shows that firms in the highest quintile of *EMI* outperform those in the lowest quintile by 88 bps per month on an equal-weighted basis (t-statistic = 4.59), which annualizes to approximately 10.6%. It is interesting to note, however, that the large equal-weighted spread appears to be in part driven by the unusually poor performance of low *EMI* firms. Although our hypotheses predict that low *EMI* firms underperform high *EMI* firms in announcement months because they have the weakest incentives to manage expectations, it would be problematic if all of the return spread was driven by low *EMI* firms that presumably do not take actions to manipulate market expectations upward.

[4] We rely on the first principal component to facilitate standard asset pricing tests based on a single sorting variable. The inclusion of higher-order components as controls does not materially affect our main inferences (results untabulated).

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Table 2
Monthly average returns

A. Average announcement-month raw returns

	EMI quintiles					
	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	High - Low
Equal weighted	0.794	1.320	1.427	1.726	1.674	0.880
	(2.42)	(4.08)	(4.57)	(5.73)	(5.47)	(4.59)
Value weighted	0.957	1.115	1.325	1.545	1.599	0.643
	(3.42)	(3.44)	(4.16)	(6.21)	(5.97)	(3.02)

B. Average announcement-month char-adjusted returns

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	High - Low
Equal weighted	−0.052	0.401	0.394	0.678	0.587	0.640
	(−0.43)	(4.08)	(4.30)	(8.53)	(5.75)	(4.03)
Value weighted	−0.213	0.181	0.194	0.413	0.589	0.801
	(−1.11)	(0.90)	(1.11)	(3.24)	(4.15)	(3.49)

C. Fama-MacBeth regressions of announcement returns

	Pooled sample				Subsamples		Subsamples	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EMI	0.301***	0.378***	0.350***	0.299***	0.160*	0.439***	0.243***	0.388***
	(4.31)	(5.51)	(5.15)	(4.36)	(1.79)	(4.42)	(2.69)	(3.76)
SIZE	–	−0.194**	−0.198**	−0.211**	−0.112	−0.311**	−0.190*	−0.217*
	–	(−2.30)	(−2.37)	(−2.47)	(−0.95)	(−2.54)	(−1.67)	(−1.67)
LBM	–	0.254***	0.249***	0.255***	0.142	0.370***	0.196*	0.339**
	–	(2.97)	(2.96)	(3.04)	(1.30)	(2.93)	(1.94)	(2.39)
MOMEN	–	0.384***	0.349***	0.337***	0.613***	0.057	0.610***	−0.078
	–	(3.72)	(3.41)	(3.32)	(7.28)	(0.33)	(5.90)	(−0.43)
VLTY	–	−0.119	−0.083	−0.072	−0.098	−0.045	−0.138	0.040
	–	(−1.01)	(−0.71)	(−0.60)	(−0.70)	(−0.23)	(−0.99)	(0.19)
TURN	–	−0.242***	−0.242***	−0.261***	−0.114	−0.409***	−0.182	−0.393***
	–	(−2.72)	(−2.72)	(−2.99)	(−0.90)	(−3.56)	(−1.45)	(−3.55)
log(COV)	–	0.077	0.061	0.079	0.151*	0.006	0.151**	−0.048
	–	(1.18)	(0.93)	(1.20)	(1.87)	(0.06)	(2.05)	(−0.40)
RET(-1)	–	−0.716***	−0.731***	−0.720***	−0.779***	−0.660***	−0.852***	−0.532***
	–	(−6.23)	(−6.32)	(−6.26)	(−6.47)	(−3.35)	(−6.22)	(−2.72)
Δ*EPS*	–	–	−0.420***	−0.415***	−0.475***	−0.354***	−0.505***	−0.274**
	–	–	(−7.17)	(−7.00)	(−7.73)	(−3.51)	(−8.42)	(−2.43)
ACC	–	–	0.203***	0.204***	0.226***	0.182*	0.210***	0.199*
	–	–	(3.20)	(3.27)	(3.02)	(1.83)	(2.90)	(1.79)
VCR	–	–	–	0.188***	0.167***	0.209***	0.166***	0.224***
	–	–	–	(4.14)	(2.82)	(3.03)	(3.09)	(2.84)
IVOL	–	–	–	0.502***	0.588***	0.416***	0.528***	0.476***
	–	–	–	(5.78)	(5.84)	(2.94)	(5.31)	(3.03)
Intercept	1.389***	1.392***	1.406***	1.405***	1.470***	1.339**	1.385***	1.480**
	(4.06)	(4.06)	(4.10)	(4.10)	(3.45)	(2.48)	(3.44)	(2.46)
R^2 (%)	0.554	6.402	7.300	8.301	7.565	9.045	8.209	8.432
Sample:	All	All	All	All	Pre-RFD	Post-RFD	Pre-GS	Post-GS

(Continued)

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Table 2
(Continued)

D. Fama-MacBeth regressions of announcement returns with GHZ controls

	(1)	(2)	(3)
EMI	0.297***	0.328***	0.256***
	(4.62)	(5.88)	(5.12)
GHZ controls	*agr, chatoia, chcsho, chinv ear, egr, grcapx, grltnoa, invest, nincr, pchsale_pc, sue,*	*cash, chnanalyst, ear, mom1m, nincr, rd_mve, retvol, std_turn, turn,*	*absacc, acc, aeavol, age, agr, baspread, beta, bm, bm_ia, cash, cashdebt, cashpr, cfp, cfp_ia, chatoia, chcsho, chempia, chfeps, chinv, chmom, chnanalyst, chpmia, chtx, convind, currat, depr, disp, divi, divo, cinvest, egr, ep, fgr5yr, gma, grcapx, dy, ear, grltnoa, herf, hire, idiovol, ill, indmom, invest, IPO, lev, mom12m, mom1m, mom36m, ms, mve, mve_ia, nanalyst, nincr, operprof, orgcap, pchcapx_ia, pchcurrat, pchdepr, pchgm_pchsale, pchsale_pchinvt, pchsale_pchrect, pchsale_pchxsga, pchsaleinv, pctacc, pricedelay, ps, rd, rd_mve, rd_sale, realestate, retvol, roaq, roavol, roeq, roic, rsup, salecash, saleinv, salerec, secured, securedind, sfe, sgr, sin, sp, std_dolvol, std_turn, stdcf, sue, tang, tb, turn, zerotrade*
R^2 (%)	4.381	5.774	27.742

Panel A presents equal- and value-weighted average announcement-month returns across expectations management incentive (*EMI*) quintiles. Returns are measured in the expected announcement month T, where *EMI* is calculated and assigned into quintiles in month T-12. *EMI* is a composite proxy for firms' expectations management incentives, as outlined in Equation (1) and discussed in Section 1, where higher values indicate greater incentives to report positive earnings surprises. Panel B presents equal- and value-weighted characteristic-adjusted average announcement returns across *EMI* quintiles. Characteristic-adjusted returns have subtracted from them the returns of a matching portfolio of firms sorted on market capitalization, book-to-market ratio, and momentum, as in Daniel et al. (1997). Panel C presents results from monthly Fama-MacBeth regressions of raw announcement-month returns on *EMI* and additional controls. Columns 5 and 6 split the sample before and after Regulation Fair Disclosure (RFD) in August 2000, and Columns 7 and 8 split the sample before and after the Global Research Analyst Settlement in April 2003. To facilitate interpretation, we standardize all independent variables in this regression each month to have a zero mean and unit standard deviation. The regressions control for firm's log market capitalization (*SIZE*), log of one plus a firm's book-to-market ratio (*LBM*), and lagged 12-month momentum (*MOMEN*) and share turnover (*TURN*). *VLTY* is defined as the standard deviation of monthly returns over the 12 months ending in month M. *RET(-1)* is defined as raw monthly return in month M-1. *log(COV)* is defined as log of one plus the number of analysts covering a firm. Δ*EPS* is change in earnings per share scaled by lagged total assets per share. *ACC* is the difference between net income and cash flows from operations scaled by lagged total assets per share. *VCR* is based on the *Volume concentration ratio* from Frazzini and Lamont (2007) defined as volume on the previous 16 announcement months divided by the total volume in the previous 48 months. The ratio is lagged 3 months prior to a firm's expected announcement month. *IVOL* is the abnormal idiosyncratic volatility measure from Barber et al. (2013). Panel D presents results from monthly Fama-MacBeth regressions of raw announcement returns on *EMI* and characteristics discussed and generously provided by Green et al. (2017) (GHZ). *GHZ Controls* lists the characteristics used in each model. Missing characteristic observations are set to the zero mean of the characteristic in that month after nonmissing values have been standardized to have a zero mean and unit standard deviation. We refer interested readers to Green et al. (2017) for definitions of each characteristic. The sample consists of 320,171 firm-quarter observations spanning 1985 through 2015. The parentheses contain t-statistics calculated using the monthly time-series distribution for panels A and B. For panel C and D parentheses contain t-statistics from the Fama-MacBeth regressions after Newey-West adjustments for autocorrelation up to 10 lags. *p <.1; **p <.05; ***p <.01.

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Panel A of Table 2 also shows, however, the unusual underperformance of low *EMI* firms disappears when returns are value weighted. Specifically, the second line of panel A shows that high *EMI* firms outperform low *EMI* firms in announcement months by 64 bps per month (t-statistic = 3.02) despite no dramatic underperformance among low *EMI* firms. These results indicate the low equal-weighted returns in the lowest quintile are driven by the poor performance of smaller firms, though later tests show this effect is also not robust.[5]

Panel B of Table 2 shows the strong positive relation between *EMI* and announcement returns continues to hold when returns are characteristically adjusted based on firm size, book-to-market ratio, and momentum, following Daniel et al. (1997). With these adjustments, firms in the highest quintile of *EMI* outperform those in the lowest quintile by 64 bps per month on an equal-weighted basis (t-statistic = 4.03), and by 80 bps per month on a value-weighted basis (t-statistic = 3.49), mitigating concerns our results simply reflect differential exposure to firms' size, glamour, or past performance profile. Panel C of Table 2 uses Fama-MacBeth regressions to establish the incremental predictive power of *EMI* relative to other signals known to explain the cross-section of returns including firm size, book-to-market ratio, momentum, volatility, turnover, 1-month-lagged returns, scaled changes in EPS, accruals, and standard analyst coverage proxies as studied in Lee and So (2017). To facilitate interpretation, we standardized all the independent variables (but not returns) each month to have a zero mean and unit standard deviation. A 1-standard-deviation increase in *EMI* translates into an average return spread ranging from 30 to 42 bps, with corresponding t-statistics ranging from 4.31 to 7.89. Frazzini and Lamont (2007) provide evidence that earnings announcement premiums are driven by increased attention from retail investors who are more likely to buy than sell shares. Frazzini and Lamont (2007) proxy for attention using abnormal trading volume and show that announcement premiums are concentrated in firms with a higher ratio of trading volume in earnings announcement months compared to nonannouncement months.

Our findings are conceptually related to those in Frazzini and Lamont (2007) because a component of our composite proxy is the attention that market participants place on firms' earnings. To distinguish our findings, we add the volume-concentration ratio (*VCR*) measure used in their main tests as an additional predictor of announcement-month returns. Column 6 of panel C confirms *VCR* positively predicts announcement returns but also shows that its inclusion has little effect on the predictive power of *EMI*, suggesting that expectations management reflects a distinct driver of the earnings announcement premium.

[5] We return to this issue in our discussion of Tables 4, 5, and 6, which show the unexpected pattern in equal-weighted returns is statistically insignificant in many alternative specifications and when standard control variables are included.

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Barber et al. (2013) provide evidence that earnings announcement premiums are higher when idiosyncratic volatility rises more during earnings announcement months. To distinguish our findings, we add as an additional predictor idiosyncratic volatility over the 3-day earnings announcement windows relative to the rest of the quarter (*IVOL*, see Barber et al. 2013 for details). We replicate the positive relation between *IVOL* and announcement-month returns documented in Barber et al. (2013) and find that our *EMI* measure remains an incrementally significant predictor. This suggests that the idiosyncratic volatility story from Barber et al. (2013) and our expectations management story offer complementary explanations for the earnings announcement premium.

Although our study focuses on U.S. markets, prior evidence suggests firms face similar expectations management incentives abroad. For example, analysts make earnings forecasts for firms in 94 unique countries on IBES. Beckers et al. (2004) show analysts' forecasts decline in European markets as the announcement approaches, indicating a similar walkdown occurs as in U.S. markets. Kato et al. (2009) shows that in Japan, where managers are required to publicly report earnings guidance, managers' earnings guidance also becomes predictably more pessimistic when approaching the announcement, consistent with the general walkdown pattern documented in U.S. markets.

Black and Carnes (2006) show average preannouncement forecasts are pessimistic more than half the time in all 13 Asia-Pacific countries they study. These findings align well with evidence in Barber et al. (2013) of a significant earnings announcement premium in many countries around the world.

The last four columns of panel C show our findings hold both before and after the enactment of Regulation Fair Disclosure (RFD) in August 2000, and the Global Analyst Research Settlement (GS) in April 2003. The robustness of our findings post-RFD is consistent with the example in the appendix, which emphasizes that firms can influence analysts' forecasts without violating SEC regulations or issuing new disclosures, by selectively directing analysts' attention to previously issued statements that convey their intended message. Even after Reg FD, firms are, for example, allowed to reiterate or emphasize previously issued public reports or opinions that help elicit pessimism from analysts (see Brown et al. 2015 for details and the appendix for an example). Related evidence in Barber et al. (2006) and Kadan et al. (2008) suggests Global Settlement reduced optimistic analyst buy-sell recommendations. The robustness of our findings pre- and post-GS suggests the move toward reducing excessive optimism may have spurred analysts to be more responsive to warnings and negative guidance from management, which could facilitate walkdown behavior.[6] Readers may be initially concerned that our results reflect the use of past sales growth in calculating *EMI*. However,

[6] A complementary explanation we explore in Section 2.2 is that firms have become more adept at managing expectations over time.

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Lakonishok et al. (1994) and Dechow and Sloan (1997) show that past sales growth negatively predicts future returns because investors tend to over-extrapolate past trends. The fact that high *EMI* firms tend to have higher past sales growth, therefore, makes the positive link between *EMI* and announcement returns more surprising.

Panel D of Table 2 also features Fama-MacBeth regressions that control for an expansive list of 94 return prediction variables used in Green et al. (2017). The first column controls for the 12 variables from Green et al. (2017) that contain significant univariate predictive power; the second column controls for the 9 variables that incrementally predict in their multivariate tests; and the final column contains all 94 variables that they consider. Across all three specifications, *EMI* retains predictive power for returns with similar magnitude and significance as in our pooled analysis in Column 6 of panel C.

Related evidence in the top panel of Figure 1 presents average monthly raw returns to our long-short *EMI* strategy for each year in the sample window. We find equal-weighted (value-weighted) strategy returns are positive in 23 (22) of the 31 years within our 1985–2015 sample window, indicating our findings are not driven by a small subset of years. We also find no apparent underperformance in market down years, such as 2008. Savor and Wilson (2016) offer a potential risk-based explanation for these findings. The authors model firms' expected returns during earnings announcements as compensation for the extent to which their earnings news signals macroeconomic growth. Empirically, Savor and Wilson (2016) show that earnings announcement premiums are positively related to future aggregate earnings growth. Panel B of Figure 1 explores this potential explanation. The panel contains average monthly *EMI* strategy returns after partitioning our sample into three subsamples of years based on their corresponding level of future seasonally adjusted growth in aggregate earnings as measured in Savor and Wilson (2016).

Under a risk-based explanation for our findings, the earnings news of high *EMI* firms is informative of macroeconomic growth and, thus, the monthly *EMI* return spread should be strongest (weakest) at times when future macroeconomic earnings are growing (contracting). If anything, panel B of Figure 1 shows the opposite holds empirically. Specifically, we find a weak negative relation between macroeconomic earnings growth and the *EMI* return spread. These results suggest our findings are unlikely to be explained by the nondiversifiable risk explanation of announcement premiums in Savor and Wilson (2016).

To further mitigate risk-based explanations for our findings, Table 3 reports *EMI* return spreads during firms' expected announcement month when controlling for each portfolio's exposure to standard monthly asset pricing factors. The reported alphas in panels A and B correspond to the intercept from a monthly time-series regression of the portfolio's returns regressed on the contemporaneous excess market return (*MKTRF*) as well as factors based on size, book-to-market ratio, and momentum (*SMB*, *HML*, and

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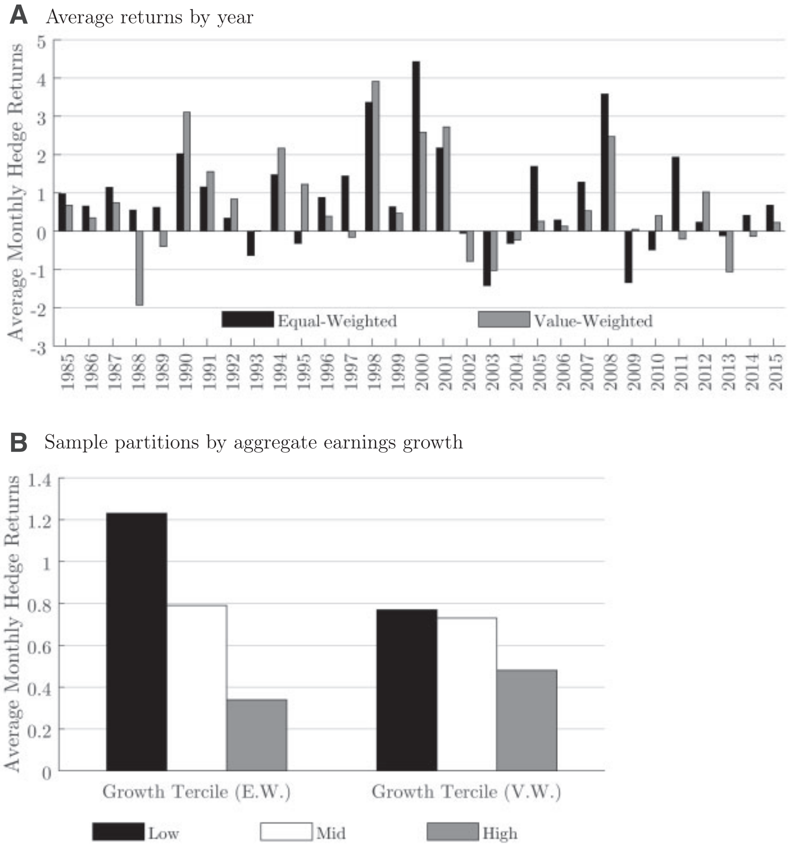

Figure 1
Time series of returns
Panel A plots equal- (value-)weighted average monthly long-short portfolio returns in blue (red) bars across high versus low *EMI* quintiles for each year in our 1985–2015 sample. Returns are measured in in the expected announcement month T, where *EMI* is calculated and assigned into quintiles in month T-12. *EMI* is a composite proxy for firms' expectations management incentives, as outlined in Equation (1) and discussed in Section 1, where higher values indicate greater incentives to report positive earnings surprises. Panel B plots quarterly averages of monthly strategy returns, with each month's return weighted by the number of announcements that month, across sample partitions of macroeconomic growth as measured in Savor and Wilson (2016). Specifically, we partition our sample across different calendar quarters into three subsamples based on their corresponding level of future seasonally adjusted growth in aggregate earnings scaled by total market equity of all firms in the sample. E.W. (V.W.) denotes equal- (value-) weighted average monthly long-short portfolio returns. The sample consists of 320,171 firm-quarter observations spanning 1985 through 2015.

UMD). Additionally, to mitigate concerns that our findings reflect exposure to announcement risk premiums, the analyses in panels C and D include a monthly earnings announcement risk factor (*EARF*), the return spread between announcers and nonannouncers, as implemented in Chang et al. (2017). Panels A and B show the alphas corresponding to the *EMI* strategy are both economically and statistically significant with an equal-weighted alpha of 81

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Table 3
Announcement-month portfolio alphas

A. Equal-weighted alphas in month M=T

	ALPHA	*MKTRF*	*SMB*	*HML*	*UMD*
Q5 (High)	0.714	1.068	0.535	0.067	−0.161
	(5.99)	(38.70)	(13.76)	(1.55)	(−6.22)
Q4	0.771	1.011	0.754	0.221	−0.178
	(7.62)	(43.14)	(22.84)	(6.02)	(−8.09)
Q3	0.489	0.968	0.920	0.250	−0.181
	(4.24)	(36.22)	(24.45)	(5.98)	(−7.22)
Q2	0.422	0.983	0.885	0.176	−0.238
	(3.18)	(31.93)	(20.40)	(3.64)	(−8.23)
Q1 (Low)	−0.096	0.972	0.886	0.206	−0.250
	(−0.64)	(28.06)	(18.16)	(3.79)	(−7.68)
High - low	0.810	0.095	−0.351	−0.139	0.089
t-statistic	(4.27)	(2.17)	(−5.67)	(−2.01)	(2.15)

B. Value-weighted alphas in month M=T

	ALPHA	*MKTRF*	*SMB*	*HML*	*UMD*
Q5 (High)	0.666	0.980	0.064	−0.210	0.031
	(5.26)	(33.40)	(1.55)	(−4.57)	(1.11)
Q4	0.627	0.886	0.213	−0.020	0.032
	(4.78)	(29.18)	(4.98)	(−0.41)	(1.11)
Q3	0.287	1.010	0.395	−0.195	0.134
	(1.53)	(23.25)	(6.45)	(−2.87)	(3.28)
Q2	0.062	1.097	0.150	−0.201	0.087
	(0.33)	(24.89)	(2.41)	(−2.91)	(2.10)
Q1 (Low)	−0.046	0.976	0.206	0.161	0.013
	(−0.28)	(25.30)	(3.79)	(2.67)	(0.35)
High - low	0.713	0.004	−0.142	−0.371	0.018
t-statistic	(3.33)	(0.09)	(−2.03)	(−4.78)	(0.39)

(Continued)

bps (t-statistic = 4.27) and value-weighted alpha of 71 bps (t-statistic = 3.33). Moreover, panels C and D show the documented alphas remain significant after adjusting for the announcement risk factor, *EARF*, yielding an equal-weighted alpha of 65 bps (t-statistic = 3.26) and value-weighted alpha of 61 bps (t-statistic = 2.72).

To place the Table 3 results in context, our four-factor value-weighted alpha of 71 bps implies an approximate annualized return of 8.5%. This magnitude is comparable to the 7.2% annualized earnings announcement premium documented in Barber et al. (2013), which relies on an international sample, and the 9.9% annualized announcement premium documented in Savor and Wilson (2016), which relies on weekly rebalanced portfolios.

In addition to establishing a strong cross-sectional link between *EMI* and firms' expected announcement returns, a key result from Table 3 is that conditional earnings announcement premiums are predictably absent among low *EMI* firms despite also bearing exposure to potential announcement risks. For example, panels B and D show that value-weighted announcement-month alphas are only statistically significant among the top-two *EMI* quintiles. Moreover, monthly alphas predictably increase in both economic and statistical significance across *EMI* portfolios, which is consistent with our central

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Table 3
(Continued)

C. Equal-weighted alphas in month M=T

	ALPHA	*MKTRF*	*SMB*	*HML*	*UMD*	*EARF*
Q5 (High)	0.408	1.103	0.156	−0.103	−0.158	0.653
	(3.55)	(43.05)	(2.71)	(−2.32)	(−6.65)	(8.43)
Q4	0.521	1.040	0.443	0.081	−0.176	0.534
	(5.30)	(47.45)	(9.04)	(2.14)	(−8.64)	(8.07)
Q3	0.258	0.994	0.634	0.121	−0.179	0.494
	(2.24)	(38.64)	(11.00)	(2.72)	(−7.50)	(6.35)
Q2	0.314	0.996	0.750	0.115	−0.237	0.232
	(2.26)	(32.13)	(10.81)	(2.14)	(−8.25)	(2.48)
Q1 (Low)	−0.238	0.989	0.710	0.127	−0.249	0.303
	(−1.53)	(28.43)	(9.13)	(2.10)	(−7.71)	(2.88)
High - low	0.646	0.114	−0.555	−0.230	0.091	0.350
t-statistic	(3.26)	(2.58)	(−5.60)	(−3.00)	(2.21)	(2.62)

D. Value-weighted alphas in month M=T

	ALPHA	*MKTRF*	*SMB*	*HML*	*UMD*	*EARF*
Q5 (High)	0.485	1.001	−0.161	−0.311	0.033	0.388
	(3.72)	(34.50)	(−2.49)	(−6.19)	(1.21)	(4.42)
Q4	0.432	0.909	−0.030	−0.129	0.034	0.418
	(3.21)	(30.33)	(−0.45)	(−2.47)	(1.21)	(4.62)
Q3	0.137	1.027	0.208	−0.279	0.136	0.321
	(0.70)	(23.49)	(2.13)	(−3.67)	(3.34)	(2.43)
Q2	0.046	1.099	0.130	−0.210	0.087	0.035
	(0.23)	(24.58)	(1.29)	(−2.70)	(2.10)	(0.26)
Q1 (Low)	−0.129	0.985	0.103	0.115	0.013	0.176
	(−0.74)	(25.25)	(1.18)	(1.70)	(0.37)	(1.50)
High - low	0.614	0.016	−0.265	−0.426	0.019	0.211
t-statistic	(2.72)	(0.31)	(−2.36)	(−4.90)	(0.41)	(1.39)

Panels A and B (C and D) present equal- and value-weighted 4-factor (5-factor) portfolio alphas in the expected announcement month T. Expectations management incentives (EMI) quintiles; corresponding t-statistics are in parentheses. *EMI* is calculated and assigned into quintiles in month T-12. *ALPHA* is the intercept from a regression of raw returns minus the risk-free rate, regressed on the contemporaneous excess market return (*MKTRF*); two Fama-French factors (*SMB* and *HML*); the momentum factor (*UMD*); and the announcement risk factor (*EARF*), defined as the value-weighted return spread between expected announcers and nonannouncers. *EMI* is a composite proxy for firms' expectations management incentives, as outlined in Equation (1) and discussed in Section 1, where higher values indicate greater incentives to report positive earnings surprises. The sample consists of 320,171 firm-quarter observations spanning 1985 through 2015.

thesis that expectations management contributes to the prevalence of monthly earnings announcement premiums.

A natural extension of our results so far is to examine whether our findings are predictably concentrated among high uncertainty firms, which likely have greater latitude to shift investors' expectations (Bradshaw et al. 2016). To explore this possibility, panel A of Figure 2 contains both equal- and value-weighted announcement returns independently double-sorted by *EMI* and two firm-level proxies for uncertainty: firm age (AGE), measured as the number of months since the firm first appeared in CRSP, and return volatility (VLTY). These tests show that strategy returns are intuitively concentrated among newly listed and high uncertainty firms, suggesting that expectations management is

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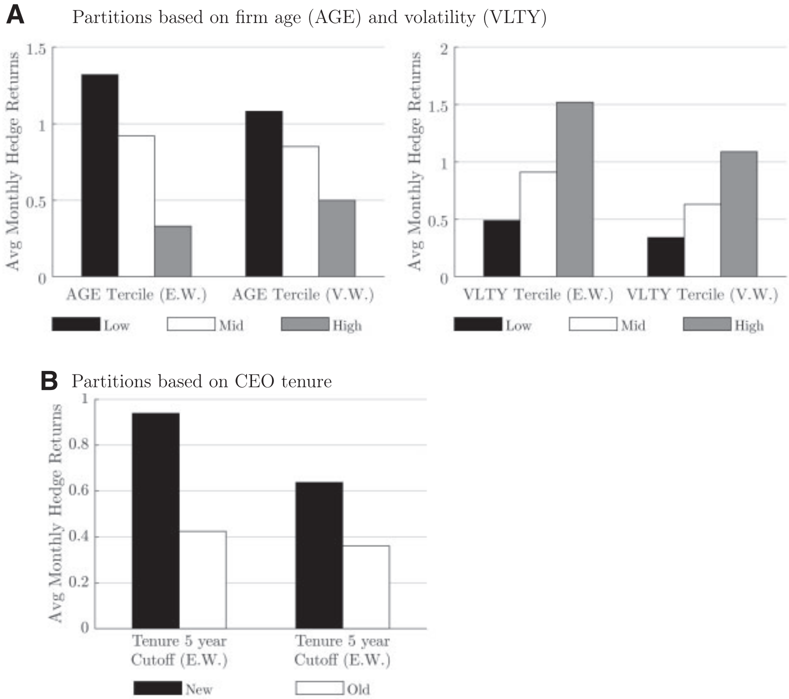

Figure 2
***EMI* strategy returns, uncertainty, and CEO characteristics**
The charts above present equal- and value-weighted *EMI* strategy (High EMI-Low EMI) raw announcement returns independently double-sorted across firm-characteristic terciles. Returns are measured in the expected announcement month T, where *EMI* is calculated and assigned into quintiles in month T-12. *EMI* is a composite proxy for firms' expectations management incentives, as outlined in Equation (1) and discussed in Section 1, where higher values indicate greater incentives to report positive earnings surprises. Panel A sorts firms by *AGE*, defined as the number of months since the firm first appeared in CRSP, and *VLTY*, defined as the standard deviation of monthly returns measured over the 12 months ending in T-12. We assign firms to AGE and VLTY terciles each calendar quarter using the distributional cutoffs from the prior calendar quarter. Panel B sorts firms by CEO *Tenure*, defined as the number of years in which the current CEO has held his office. We assign firms based on CEO's with *Tenure* greater than or less than 5 years (excluding firms whose IPO occurred within the last 5 years). The sample consists of 320,171 firm-quarter observations for panel A spanning 1985 through 2015 and 109,739 firm-quarter observations for panel B spanning 1993 through 2015.

most effective among younger firms and when investors are less certain about firms' performance prospects.[7]

Another potential source of uncertainty is a new CEO that may change the firm's strategic or financial policies. New CEOs may also have stronger incentives for expectations management as a means of signalling their competence to the board and the broader market for CEOs, as suggested in Graham et al. (2005). For both these reasons, we expect and empirically confirm

[7] In Section 2.2, we also explore the role of learning on behalf of both investors and firms.

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in panel B of Figure 2 that *EMI* strategy returns are pronounced in firms with CEOs appointed within the last 5 years.[8]

In additional tests presented in the Online Appendix, we show the average return spread across *EMI* quintiles in announcement months remains statistically and economically significant among large firms but is stronger among small firms. We also show our results are stronger among firms with low per-share prices, consistent with the evidence in Cheong and Thomas (2017) that while low per-share price firms have smaller walkdowns in dollar terms, they have larger walkdowns as a fraction of firm value.

1.4 Walking down expectations: Evidence from preannouncement returns

A distinguishing feature of our study, relative to studies on investor underreaction, is that we hypothesize firms contribute to mispricing by downwardly biasing investors' preannouncement expectations, and that market prices later correct upward at the time of the announcement. Thus, rather than an initial underreaction and subsequent drift in the same direction, we expect that expectations management yields a "V-shaped" return pattern that reverses sign in the months prior to, versus during, firms' earnings announcements.

Specifically, to the extent that firms contribute to mispricing by predictably walking down investors' expectations ahead of their announcements, we predict firms with stronger incentives will *underperform* firms with weaker incentives in the preannouncement period. We test this prediction in panels A and B of Table 4 by studying returns in the calendar month prior to a firm's expected announcement (i.e., when $M = T$-1).

Consistent with our prediction, Table 4 shows high *EMI* firms on average underperform low *EMI* firms in the month prior to announcing earnings in terms of raw, characteristic-adjusted, and factor-adjusted returns. For equal-weighted raw returns, a large part of this difference is driven by firms in Q5 underperforming relative to other *EMI* quintiles. However, the negative relation between *EMI* and returns is stronger and more evenly spread across the *EMI* distribution for all other approaches estimated in Table 4, suggesting the equal-weighted raw return pattern is driven by differential risk exposures among small cap firms. Related evidence in Figure 3 presents the spread in factor-adjusted alphas in event-time leading up to the expected announcement month, where colored bars indicate significance at the 5% level. The graphs visually demonstrate the striking V-shaped pattern in firms' event-time returns for high versus low *EMI* portfolios. To provide more granular detail, Figure 4 contains the spread in daily returns across high versus low *EMI* firms, plotted relative to firms' expected announcement date in panel A and actual announcement date

[8] To distinguish the results of these tests from the firm-age-based results in panel A, we exclude firms with less than 5 years since their initial public offering (IPO). Our results, however, do not appear sensitive to this choice.

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Table 4
Preannouncement portfolio returns

A. Preannouncement raw returns (M=T-1)

	EMI quintiles					
	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	High - Low
Equal weighted	1.128	1.167	1.268	1.164	0.798	−0.330
	(3.22)	(3.77)	(4.20)	(3.85)	(2.57)	(−1.65)
Value weighted	2.153	1.634	1.878	1.910	1.440	−0.713
	(6.86)	(5.53)	(6.25)	(7.04)	(5.21)	(−3.34)
B. Preannouncement char-adjusted returns (M=T-1)						
Equal weighted	0.201	0.125	0.164	0.135	−0.167	−0.368
	(1.71)	(1.31)	(2.20)	(1.75)	(−1.70)	(−2.52)
Value weighted	0.945	0.785	0.579	0.767	0.467	−0.478
	(4.09)	(4.65)	(4.06)	(4.72)	(3.66)	(−2.06)
C. Preannouncement alphas (M=T-1)						
Equal weighted	0.368	0.240	0.141	0.079	−0.292	−0.660
	(2.12)	(2.01)	(1.30)	(0.84)	(−2.67)	(−3.27)
Value weighted	0.290	−0.195	−0.141	0.092	−0.137	−0.426
	(1.59)	(−1.16)	(−0.84)	(0.73)	(−1.30)	(−2.07)

Panel A presents equal- and value-weighted average preannouncement month T-1 returns across Expectations Management Incentive (*EMI*) quintiles, where T denotes firms' expected announcement month. Expectations Management Incentives *(EMI)* quintiles; corresponding t-statistics are in parentheses. *EMI* is calculated and assigned into quintiles in month T-12. *EMI* is a composite proxy for firms' expectations management incentives, as outlined in Equation (1) and discussed in Section 1, where higher values indicate greater incentives to report positive earnings surprises. Panel B presents equal- and value-weighted characteristic-adjusted average announcement returns across *EMI* quintiles. Characteristic-adjusted returns have subtracted from them the returns of a matching portfolio of firms sorted on market capitalization, book-to-market ratio, and momentum, as in Daniel et al. (1997). Panel C presents equal- and value-weighted portfolio alphas. Alpha is the intercept from a regression of raw returns minus the risk-free rate, regressed on the contemporaneous excess market return (*MKTRF*); two Fama-French factors (*SMB* and *HML*); the momentum factor (*UMD*); and the announcement risk factor (*EARF*), defined as the value-weighted return spread between expected announcers and nonannouncers. The sample consists of 320,171 firm-quarter observations spanning 1985 through 2015.

in panel B. The window from days -10 to +10 centers on the announcement date and approximately corresponds to firms' announcement month.

Both panels in Figure 4 show high *EMI* firms underperform low *EMI* firms prior to their announcements. Consistent with our earlier results based on monthly returns, our daily return plots show the underperformance of high *EMI* firms is pronounced in the approximate preannouncement month from days -30 to -11. Figure 4 also reinforces our finding that high *EMI* firms earn higher excess returns during announcement months.

The use of firms' actual earnings announcement date as the focal point in panel B of Figure 4 helps emphasize that the outperformance of high *EMI* firms concentrates in short-windows surrounding the release of earnings news. As we show in more detail below, this outperformance coincides with high *EMI* firms reporting earnings that exceed consensus forecasts, on average. Together, these results are consistent with high *EMI* firms walking down investors' expectations ahead of announcing earnings and, in doing so, manufacturing positive surprises coinciding with their earnings announcements.

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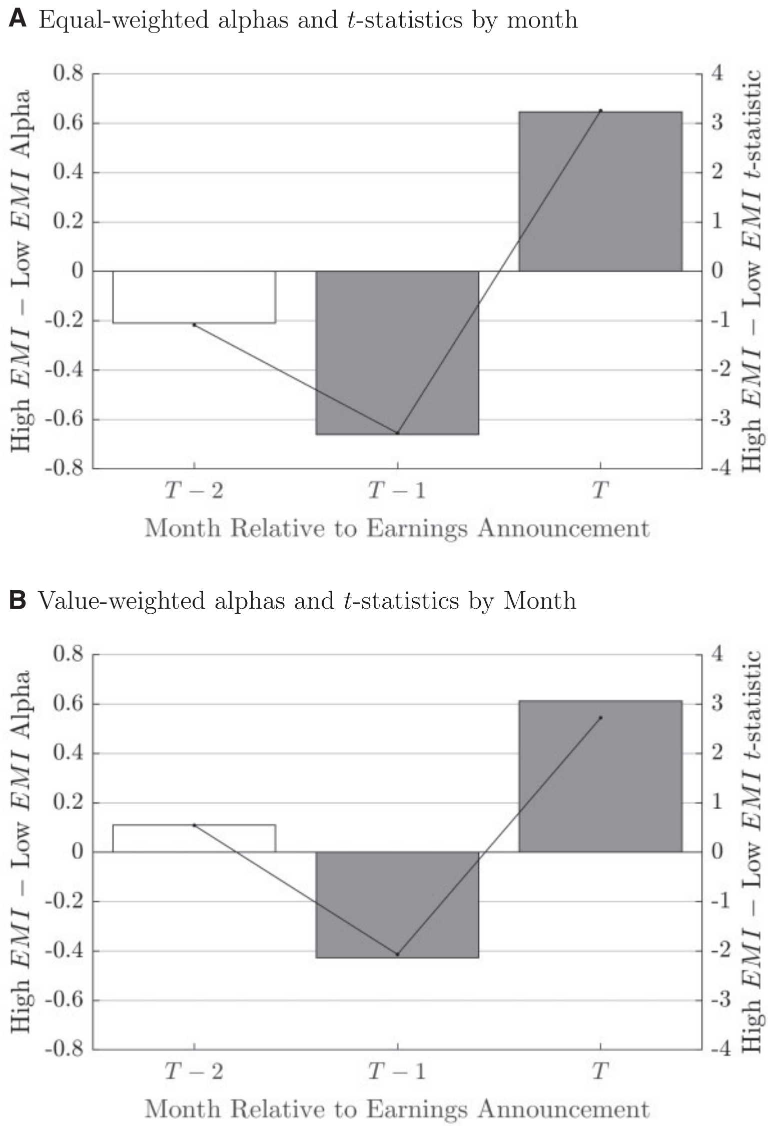

Figure 3
Monthly returns and t-statistics in event time
The charts above present equal-weighted (panel A) and value-weighted (panel B) difference in event-time returns across *EMI* portfolios (High *EMI* - Low *EMI*) *ALPHA*s (bar graphs) and corresponding t-statistics (line graphs). Colored bars indicate that the reported strategy return is significant at the 5% level. *EMI* is calculated and assigned into quintiles in month T-12 and future returns are measured from months T-2 through T where T is the expected announcement month. *EMI* is a composite proxy for firms' expectations management incentives, as outlined in Equation (1) and discussed in Section 1, where higher values indicate greater incentives to report positive earnings surprises. *ALPHA* is the intercept from a regression of raw returns minus the risk-free rate, regressed on the contemporaneous excess market return (*MKTRF*); two Fama-French factors (*SMB* and *HML*); the momentum factor (*UMD*); and the announcement risk factor (*EARF*), defined as the value-weighted return spread between expected announcers and nonannouncers. The sample consists of 320,171 firm-quarter observations spanning 1985 through 2015.

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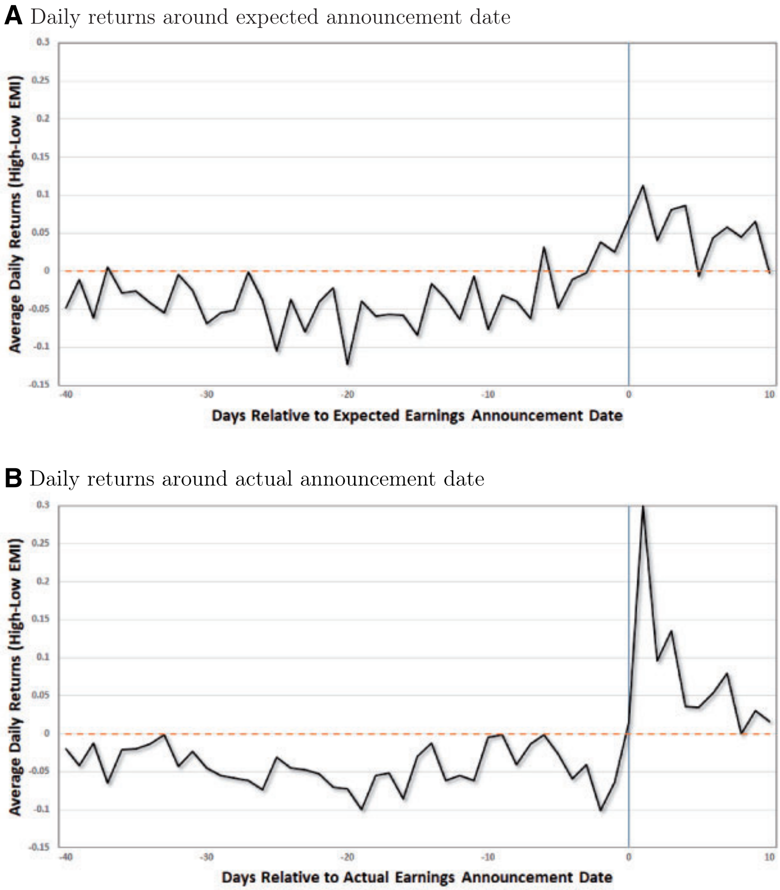

Figure 4
Daily returns in event time
The charts above present the equal-weighted daily market adjusted returns for the difference portfolio (High *EMI* - Low *EMI*) around the expected announcement date (panel A) and actual announcement date (panel B). *EMI* is calculated and assigned into quintiles in month T-12, where T is the expected announcement month. *EMI* is a composite proxy for firms' expectations management incentives, as outlined in Equation (1) and discussed in Section 1, where higher values indicate greater incentives to report positive earnings surprises. Daily market-adjusted returns are defined as the daily raw return minus the CRSP equal-weighted index return. The sample consists of 320,171 firm-quarter observations spanning 1985 through 2015.

The V-shaped patterns shown in Figures 3 and 4 also raise the bar for what a risk-based explanation for our findings would require. A risk-based explanation would need to explain why high *EMI* firms earn a risk premium during announcement months T, but the premiums is predictably absent and/or flips signs prior to announcing earnings in T-2 and T-1. Moreover, risk-based explanations would need to explain why the preannouncement underperformance is predictable despite these dates being known at least a

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year out, and firms releasing the majority of earnings news prior to their announcements (Ball and Shivakumar 2008).

Next, we combine our announcement-month results with our preannouncement results to illustrate how the V-shaped return pattern shown in Figures 3 and 4 varies with *EMI*. We do so using a trading strategy that aligns the preannouncement underperformance and announcement-month outperformance of high *EMI* firms in calendar time. Specifically, at the conclusion of calendar month M-1, we initiate long positions in firms expected to announce earnings in month M (i.e., those with M=T) and short positions in firms expected to announce in month M+1 (i.e., those with M=T-1). Our story predicts this strategy will perform well among high *EMI* firms due to their expectations management incentives resulting in a V-shaped return pattern, and earn no abnormal returns among low *EMI* firms due to the absence of expectations management.

Panel A of Table 5 shows that this strategy yields a highly significant value-weighted factor-adjusted alpha of about 82 bps (t-statistic = 5.12) when trading only among high *EMI* firms. Furthermore, consistent with our prediction, this strategy's alpha is statistically insignificant among the lowest *EMI* quintile and monotonically increasing in *EMI*.[9] The difference between high and low *EMI* quintiles, representing a combined strategy that is long the V-shaped strategy among high *EMI* firms and short the same strategy among low *EMI* firms, yields a value-weighted alpha of 116 bps (t-statistic = 4.38).

Thus, a simple utilization of the V-shaped return pattern shown in Figure 3 significantly improves the risk-reward tradeoff for *EMI*-based strategies, resulting in t-statistics above the thresholds set in Harvey et al. (2016) and almost no measurable risk factor exposure. These results also cast significant doubt on risk-based explanations for our main findings because the combined strategy not only mechanically neutralizes exposure to static sources of risk (e.g., risk premiums for certain industries) but also yields superior returns, while bearing no exposure to dynamic sources of risk as proxied by standard monthly asset pricing factors. The combined strategies in panel A of Table 5 are closely related to the earnings announcement premium (EAP) strategy from prior literature that forms long positions in announcing firms and short positions in all other firms. Similar to panel A, the results in panel B show a large positive EAP strategy alpha among high *EMI* firms, a near-zero alpha among low *EMI* firms, and monotonically increasing alphas across *EMI* quintiles. Taken together, the evidence in Table 5 indicates the earnings announcement premium documented in prior research is not a general phenomenon pertaining

9 We use equal-weighted returns results in larger t-statistics for high *EMI* strategy alphas and marginally significant negative alphas for the lowest *EMI* quintile. As detailed in the Online Appendix, these negative alphas are very sensitive to changes in the specification and disappear with value weighting, suggesting they are driven by the same underperformance of small-cap firms documented in Table 3.

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Table 5
Combined strategy alphas and factor loadings

A. Long $\boldsymbol{M=T}$*, short* $\boldsymbol{M=T-1}$ *strategy*

	ALPHA	*MKTRF*	*SMB*	*HML*	*UMD*
Q5 (High)	0.817	−0.055	−0.063	0.038	0.076
	(5.12)	(−1.48)	(−1.20)	(0.66)	(2.20)
Q4	0.573	−0.042	−0.070	−0.090	−0.046
	(3.14)	(−0.98)	(−1.17)	(−1.36)	(−1.17)
Q3	0.389	−0.027	0.106	−0.156	0.082
	(1.53)	(−0.45)	(1.28)	(−1.69)	(1.49)
Q2	0.238	0.067	−0.023	−0.128	0.126
	(0.94)	(1.14)	(−0.28)	(−1.39)	(2.29)
Q1 (low)	−0.343	−0.009	0.021	0.080	0.110
	(−1.52)	(−0.16)	(0.28)	(0.97)	(2.23)
High - low	1.160	−0.046	−0.083	−0.041	−0.033
t-statistic	(4.38)	(−0.75)	(−0.97)	(−0.43)	(−0.58)

B. EAP strategy

	ALPHA	*MKTRF*	*SMB*	*HML*	*UMD*
Q5 (High)	0.731	−0.067	−0.004	−0.029	0.073
	(5.14)	(−2.03)	(−0.10)	(−0.57)	(2.36)
Q4	0.621	−0.014	−0.107	−0.091	−0.026
	(3.96)	(−0.39)	(−2.08)	(−1.59)	(−0.75)
Q3	0.282	−0.021	0.111	−0.112	0.138
	(1.23)	(−0.39)	(1.48)	(−1.35)	(2.78)
Q2	0.184	0.100	−0.047	−0.058	0.158
	(0.81)	(1.89)	(−0.64)	(−0.70)	(3.18)
Q1 (low)	−0.087	0.041	0.030	0.061	0.059
	(−0.45)	(0.91)	(0.47)	(0.86)	(1.40)
High - low	0.817	−0.107	−0.034	−0.090	0.014
t-statistic	(3.53)	(−2.01)	(−0.45)	(−1.07)	(0.28)

Panels A and B present alphas and factor loadings for value-weighted strategies combining announcing firms and nonannouncing firms across quintiles of *EMI*. In panel A, we form a portfolio with long positions in all firms for which M=T and short positions in all firms for which M=T-1, where *M* denotes the calendar month and *T* denotes firms' expected announcement month. In panel B, we form a portfolio with long positions in all firms for which M=T and short positions in all other firms, the standard earnings announcement premium (EAP) strategy. We compute strategy returns within each quintile of expectations management incentives (*EMI*), a composite proxy for firms' expectations management incentives, as outlined in Equation (1) and discussed in Section 1, where higher values indicate greater incentives to report positive earnings surprises. We also compute the difference between strategy returns in the highest and lowest *EMI* quintiles, which can be interpreted as a combined strategy that is long high *EMI* announcers and low *EMI* nonannouncers, and short high *EMI* nonannouncers and low *EMI* announcers. *ALPHA* is the intercept from a regression of raw returns minus the risk-free rate, regressed on the contemporaneous excess market return (*MKTRF*); two Fama-French factors (*SMB* and *HML*); and the momentum factor. *t*-statistics are in parentheses. The sample consists of 320,171 firm-quarter observations spanning 1985 through 2015.

to all firms, and is instead concentrated among high *EMI* firms that generate a V-shaped cycle in quarterly returns via expectations management.

1.5 Seasonalities in returns

In this section, we examine the link between expectations management and quarterly seasonalities in returns documented in prior research (e.g., Heston and Sadka 2008; Keloharju et al. 2016). Heston and Sadka (2008) show that stocks tend to have high (or low) returns every year in the same calendar month. They rule out recurring firm events, such as earnings announcements, as an explanation for these seasonalities by showing that the seasonality result persists even after dropping months with earnings announcements. We argue this,

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however, does not rule out expectations management as a contributing factor to return seasonalities because expectations management generates repeated return patterns not only in announcement months but also in nonevent months. Specifically, we predict expectations management leads stock returns to be more-positively correlated with returns in past months that are synced in the earnings cycle (3, 6, 9, and 12 months prior) than returns in nonsynced months (2, 4, 5, 7, 8, 10, and 11 months prior).[10] This prediction implies that the extent of return seasonalities, measured by the difference in predictive value of synced and nonsynced past returns, is increasing in *EMI*, and that this effect is distinct from the relation between EMI and earnings announcement premiums.

In Table 6, we explore our predictions via Fama-MacBeth regressions of monthly returns on the spread in firms' cumulative returns in months synced within their reporting cycle versus their returns in nonsynced months. To conduct these tests, we assign firms to deciles based on the spread in their synced versus nonsynced returns, denoted *Synced vs. nonsynced spread*. To test how seasonalities vary with expectations management incentives, we also interact *Synced vs. nonsynced spread* with two indicator variables, *High EMI* and *Mid-EMI*, which denote firms in the top-two terciles, respectively. We measure a firm's returns in month M and pair it with the firm's average value of *EMI* over the calendar year ending prior to month M. Because our seasonality tests are based on calendar-time analyses, the resultant sample used in Table 6 is considerably larger than in our main analyses used thus far, yielding a total of 947,471 firm-month observations.

Consistent with our main predictions, Columns 1 through 3 of Table 6 show that our seasonality decile strategy yields an abnormal return of approximately 30 bps per month (t-statistic = 3.43), and that this pattern appears primarily driven by firms with stronger incentives to manage expectations. Specifically, the interaction terms in Column 2 show strategy returns rise to roughly 50 bps (t-statistic = 3.30) among high *EMI* firms, but are statistically and economically insignificant among low *EMI* firms.[11]

Table 6 also confirms our earlier results that earnings announcement premiums are concentrated among high *EMI* firms and incremental to the seasonality effect. Specifically, the interaction effect between our announcement-month indicator, *EA Month*, and *High EMI* indicates the average announcement premiums reaches 72 bps per month (t-statistic = 7.02) among high *EMI* tercile firms. Conversely, announcement premiums appear absent among low *EMI* firms, as predicted by our story and illustrated using time-series

[10] We intentionally omit returns in the prior month to avoid confounding our results with short-term return reversals in adjacent months.

[11] In untabulated results, we find materially similarly results when omitting 12-month ago returns from the calculation of *Synced-Nonsynced Spread* and when directly including the returns as a control.

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Table 6
Calendar-time seasonality strategy

	Pooled sample			Partitioned subsamples		
	(1)	(2)	(3)	(4)	(5)	(6)
Synced vs. nonsynced spread	0.303***	0.081	0.082	0.053	0.096	0.053
	(3.43)	(0.68)	(0.69)	(0.29)	(0.53)	(0.31)
Synced vs. nonsynced spread X High EMI	–	0.475***	0.455***	0.596***	0.399*	0.417*
	–	(3.30)	(3.17)	(2.87)	(1.83)	(1.73)
Synced vs. nonsynced spread X Mid-EMI	–	0.172	0.175	0.348	0.006	0.216
	–	(1.33)	(1.35)	(1.49)	(0.03)	(1.04)
EA month	0.382***	0.367***	−0.024	−0.127	0.022	−0.092
	(7.78)	(7.58)	(−0.28)	(−0.72)	(0.15)	(−0.64)
EA month X High EMI	–	–	0.715***	0.766***	0.651***	0.743***
	–	–	(7.02)	(4.11)	(3.65)	(3.87)
EA month X Mid-EMI	–	–	0.411***	0.446**	0.330*	0.548***
	–	–	(3.99)	(2.12)	(1.83)	(2.97)
High EMI	–	0.294***	0.107	−0.065	0.093	0.361**
	–	(2.93)	(1.02)	(−0.53)	(0.62)	(2.19)
Mid-EMI	–	0.227***	0.108	−0.049	0.330**	0.098
	–	(2.64)	(1.21)	(−0.35)	(2.27)	(0.76)
SIZE	−0.097	−0.164**	−0.161**	−0.173**	−0.138*	−0.298***
	(−1.31)	(−2.21)	(−2.18)	(−2.46)	(−1.71)	(−3.03)
LBM	0.154***	0.146***	0.145***	−0.014	0.088	0.245***
	(3.02)	(2.88)	(2.87)	(−0.23)	(1.58)	(3.87)
MOMEN	0.367***	0.377***	0.376***	0.278***	0.377***	0.451***
	(5.05)	(5.19)	(5.16)	(2.70)	(4.23)	(6.30)
VLTY	−0.086	−0.067	−0.070	0.114	−0.106	−0.117
	(−1.13)	(−0.88)	(−0.92)	(0.98)	(−1.24)	(−1.53)
TURN	−0.140*	−0.168**	−0.168**	−0.092	−0.130	−0.198**
	(−1.78)	(−2.17)	(−2.16)	(−1.02)	(−1.44)	(−2.26)
RET(-1)	−0.426***	−0.428***	−0.428***	−0.379***	−0.478***	−0.407***
	(−6.05)	(−6.10)	(−6.11)	(−4.26)	(−6.49)	(−5.23)
Intercept	0.846***	0.676**	0.780***	1.033***	0.720**	0.651**
	(2.80)	(2.27)	(2.61)	(3.17)	(2.34)	(2.02)
R^2 (%)	4.577	4.886	4.976	8.591	6.350	5.388
Sample	All	All	All	High REG	Mid REG	Low REG
Observations	947,471	947,471	947,471	336,023	289,858	321,590

This table contains results from monthly Fama-MacBeth regressions of raw calendar-month returns on *Synced vs. nonsynced spread*, *EMI*, and additional controls. *Synced vs. nonsynced spread* is defined as the decile assignment, ranging from zero to one, based on the difference in firms' cumulative returns in synced (M-3, M-6, M-9, M-12) and nonsynced (M-2, M-4, M-5, M-7, M-8, M-10, M-11) month returns. *EMI* is our composite proxy for firms' expectations management incentives, as outlined in Equation (1) and discussed in Section 1, where higher values indicate greater incentives to report positive earnings surprises. *High EMI* (*Mid-EMI*) is a dummy variable that equals one for firms in the highest (middle) tercile of *EMI* within a given month. *EA month* is a dummy variable for firms' expected announcement month. We measure a firm's returns in month M and pair it with the firm's average value of *EMI* over the calendar year ending prior to month M. We also require that a firm have nonmissing return data for each of the 12 months ending in M-1. The regressions include controls for firm's log market capitalization (*SIZE*), log of one plus a firm's book-to-market ratio (*LBM*), lagged 12-month momentum (*MOMEN*), and share turnover (*TURN*). *VLTY* is defined as the standard deviation of monthly returns over the 12 months ending in month M, and *RET(-1)* is defined as raw return in month M-1. All control variables are standardized each month to have a zero mean and unit standard deviation. The regressions in Columns 4 and 5 split the sample based on the regularity with which firms announce earnings at 3-month intervals. Specifically, the sample is partitioned into terciles of the standard deviation of the number of months between quarterly earnings announcements (High REG, Mid REG, and Low REG), where standard deviations are measured over the 5 years prior to month M, and lower standard deviations indicate higher regularity. Parentheses contain t-statistics from the Fama-MacBeth regressions after Newey-West adjustments for autocorrelation up to 10 lags. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

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tests in Table 5.[12] These findings are consistent with our central thesis that cycles of managing expectations simultaneously contribute to both asset pricing regularities.

To the extent firms induce cyclical return correlations (i.e., seasonalities) by repeating cycles of expectations management across adjacent quarters, we also predict and find that our seasonality results are concentrated among firms that announce earnings at regular intervals. These tests are based on the idea that regular announcement timing makes it more likely that firms repeat their behavior at predictable 3-month intervals.

Columns 4 through 6 of Table 6 repeat our analysis across tercile sample partitions based on the historical standard deviation of months between firms' earnings announcements. Column 4 shows that strategy returns increase to roughly 60 bps (t-statistic = 2.87) among firms that regularly announce earnings at 3-month intervals.

Conversely, Columns 5 and 6 of Table 6 show that seasonality returns predictably attenuate in significance among firms that announce earnings at irregular intervals. The concentration of our results among regular announcers suggests the consistency of firms' announcement timing plays an intuitive role in eliciting seasonalities by making it more likely that firms cycle expectations management behavior at recurring intervals.

As a further illustration that expectations management affects return autocorrelation patterns, the Online Appendix also shows that past announcement-month returns are stronger predictors of future announcement returns among high *EMI* firms. Furthermore, we show that although high *EMI* firms have stronger positive autocorrleation in analyst-based earnings surprises, there is no difference in the autocorrelation of accounting-based earnings surprises, which is consistent with *EMI* more closely tracking expectations management behavior than earnings manipulation. Together, our results suggest that expectations management (an event-time phenomenon) offers significant explanatory power for return seasonalities (a calendar-time phenomenon). Whereas most prior research characterizes return seasonalities as puzzles and/or reflections of time-varying exposure to unobserved forms of priced risks, our findings point to expectations management as a distinct, and mutually nonexclusive, contributing factor.

2. Mechanism: Evidence of Expectations Management

Having established a robust link between *EMI* and firms' returns, in this section we examine predictable patterns in non-price-based outcomes that are intuitively correlated with firms engaging in expectations management, but are

[12] The insignificant announcement premium among low *EMI* firms we find in Table 6 further illustrates that the apparent underperformance of low *EMI* firms in announcement months suggested by the equal-weighted raw returns in Table 3 is not robust to alternative specifications and fails when standard control variables are included.

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also unlikely to reflect priced risks. This section also includes tests examining both how and why firms manage expectations.

2.1 Properties of earnings and analysts' forecasts

We begin this section by verifying that high *EMI* firms are more likely to report positive-analyst-based surprises. In doing so, we highlight a striking contrast in firms' analyst-based surprises and year-over-year changes in earnings across high versus low *EMI* firms.

Panel A of Table 7 presents year-over-year changes in quarterly earnings scaled by lagged assets per share, denoted ΔEPS, and analyst-based earnings surprises scaled by lagged assets per share, denoted *SURP*, across *EMI* quintiles. We find that high *EMI* firms report *negative* year-over-year average changes in quarterly profits, which may not be surprising given that high *EMI* firms tend to have higher past sales growth by construction, and prior research shows that extreme growth tends to predictably reverse (e.g., Lakonishok et al. 1994). A more surprising result is that high *EMI* firms are also more likely to report positive analyst-based surprises, despite reporting contemporaneous negative changes in profits.

The results in Table 7 are consistent with high *EMI* firms walking down analysts' expectations to beatable levels to soften the impact of reporting a decline in profitability, which qualitatively matches the Citigroup example detailed in the appendix. Additionally, panel A shows that high *EMI* firms tend to have more negative accrual components of earnings, suggesting that our composite proxy is more likely to reflect expectations management than firms manipulating accounting-based measures of profits.[13] Because media articles commonly characterize firms' earnings news based on the sign of their analyst-based surprises, we predict the positive relation between *EMI* and surprises are concentrated around zero. We explore this prediction in panel B using a series of binary variables defined relative to analysts' forecasts: *Meet* equals one when *SURP* equals zero; *NBEAT* equals one when *SURP* is greater than zero but less than 1%, indicating firms that narrowly beat analysts' forecasts; and *NMISS* equals one when *SURP* is less than zero but greater than -1%, indicating firms that narrowly missed analysts' forecasts. In panel C, we also consider unscaled earnings surprises based on a cutoff of 1 cent. Our main tests in Table 7 use the following difference-in-difference design to estimate the discontinuity of earnings surprises around zero across high versus low *EMI* firms:

$$\begin{aligned} \textit{D-I-D} \equiv & [\, Prob(NBEAT \mid HighEMI) - Prob(NMISS \mid HighEMI)\,] \\ & -[\, Prob(NBEAT \mid LowEMI) - Prob(NMISS \mid LowEMI)\,], \end{aligned} \tag{2}$$

[13] In the Online Appendix, we find a weakly negative relation between *EMI* and discretionary accruals from Jones (1991) and Dechow et al. (1995). One plausible explanation for the weak link between *EMI* and earnings management is that analysts are striking a balance between their role as external monitors and their incentives to curry favor with managers. In particular, analysts may be curbing managers from manipulating earnings, while appeasing them by providing more easily beatable earnings targets.

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Table 7
Earnings metrics

A. Earnings metrics by EMI portfolios

	Equal weighted				Value weighted			
	ΔEPS	*SURP*	*1(SURP>0)*	*ACC*	*ΔEPS*	*SURP*	*1(SURP>0)*	*ACC*
Q1 (Low)	0.459	−0.327	0.049	−1.894	0.289	−0.180	0.051	−3.483
Q2	−0.078	−0.254	0.145	−2.715	−0.107	−0.069	0.144	−4.781
Q3	−0.059	−0.166	0.288	−2.885	0.000	−0.029	0.347	−4.214
Q4	−0.083	−0.095	0.424	−3.621	−0.012	−0.004	0.494	−4.516
Q5 (high)	−0.219	−0.013	0.514	−4.722	−0.055	0.059	0.580	−5.964
High-low	−0.678	0.327	0.465	−2.829	−0.344	0.246	0.529	−2.481
p-value	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)

B. Differences in scaled surprises by EMI portfolio

	Meet	*NBEAT*	*NMISS*	*Level D-i-D*	*%D-i-D*
Q1 (Low)	0.009	0.009	0.006	0.003	0.149
Q2	0.027	0.031	0.020	0.012	0.194
Q3	0.050	0.077	0.046	0.031	0.196
Q4	0.082	0.151	0.084	0.068	0.252
Q5 (high)	0.117	0.217	0.125	0.092	0.296
High-low	0.108	0.209	0.119	0.090	0.208
p-value	(.00)	(.00)	(.00)	(.00)	(.00)

C. Differences in dollar surprises by EMI portfolio

	Meet	*NBEAT*	*NMISS*	*Level D-i-D*	*%D-i-D*
Q1 (Low)	0.023	0.014	0.010	0.004	0.151
Q2	0.039	0.024	0.015	0.008	0.215
Q3	0.053	0.034	0.021	0.013	0.222
Q4	0.067	0.051	0.032	0.019	0.211
Q5 (high)	0.103	0.094	0.059	0.035	0.275
High-low	0.080	0.081	0.049	0.031	0.135
p-value	(.00)	(.00)	(.00)	(.00)	(.00)

Panel A presents equal- and value-weighted time-series averages of analyst-based surprise (*SURP*) and change in earnings per share (Δ*EPS*) across expectations management incentives (*EMI*) quintiles. *EMI* is a composite proxy for firms' expectations management incentives, as outlined in Equation (1) and discussed in Section 1, where higher values indicate greater incentives to report positive earnings surprises. Δ*EPS* is defined as change in earnings per share scaled by lagged total assets per share. *SURP* is defined as the difference between actual earnings per share and the median analyst forecast of earnings per share divided by lagged total assets per share. *PSURP* is a dummy variable that equals one when *SURP* is positive. *ACC* is a measure of accruals defined as the difference between net income and cash flows from operations scaled by lagged total assets per share. Panels B and C present the distributions of time-series averages of analyst-based earnings surprise statistics across *(EMI)* quintiles. *Meet* equals one when *SURP* is zero. For panel B (C), *NBEAT* equals one when *SURP* is greater than zero but less than 1% (1 cent). *NMISS* equals one when *SURP* is less than zero but greater than -1% (-1 cent). *Level D-i-D* is defined as the difference between *NBEAT* and *NMISS*. *%D-i-D* is defined as the difference between *NBEAT* and *NMISS* divided by the sum of *NBEAT* and *NMISS*. The sample consists of 320,171 firm-quarter observations spanning 1985 through 2015. **p* <.1; ***p* <.05; ****p* <.01.

where higher values indicate that high *EMI* firms are more likely to narrowly beat expectations compared to narrowly miss. Panels B and C show that the difference-in-differences described in Equation (2) monotonically increase across *EMI* quintiles, consistent with *EMI* firms being more likely to narrowly beat than miss expectations.

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Table 7 also shows that high *EMI* firms are more likely to have smaller absolute analyst forecast errors (i.e., more narrow beats and misses), consistent with analysts more accurately forecasting the earnings of high *EMI* firms that tend to be larger and less volatile. To mitigate concerns that the Table 7 findings reflect variation in the difficulty of forecasting earnings, we compare the distributions of surprises in Figure 5 after scaling all firms' surprises by the standard deviation of surprises for their respective *EMI* quintile. This scaling makes the across-quintile differences in the distribution of earnings surprises easier to interpret by ensuring that each quintile has a distribution with a standard deviation of one. Figure 5 plots the differences in the scaled distributions across the highest and lowest *EMI* quintiles, showing a strong discontinuity in the distribution around zero. Specifically, high *EMI* firms are significantly more likely to come in above analysts' expectations compared to low *EMI* firms. Conversely, high *EMI* firms are significantly less likely to fall short of analysts' expectations compared to low *EMI* firms. The striking distributional asymmetry shown in Figure 5 also dissipates when moving further away from zero. This localized asymmetry in the distribution of surprises around zero is consistent with expectations management focusing primarily on whether firms beat expectations, rather than the magnitude of the positive surprise. We also conduct a placebo test by plotting the same differences in scaled distributions but for ΔEPS as implemented in panel A of Table 7. We find the reverse pattern holds, with high *EMI* firms more likely to have *declining* earnings relative to prior-year earnings, echoing the results in panel A of Table 7. These findings reinforce the view that *EMI* captures firms' incentives to specifically beat analysts' expectations, rather than general incentives to create positive news by beating some evaluation benchmark.

2.2 Learning

The results in Section 1 document *EMI* strategy returns that are persistent over our sample period. One potential explanation for this persistence discussed in Hartzmark and Solomon (2018) is that investors often make repeated mistakes even around recurring events. We hypothesize these repeated mistakes may allow firms to become more adept at managing expectations over time, increasing the frequency of positive surprises. This increase could hinder investors' learning by weakening the predictive power of past behavior and requiring investors estimate both the level of, and trend in, expectations management. To explore this possibility, Table 8 contains regressions where the dependent variable is an indicator for beating analysts' forecasts (i.e., *1(SURP>0)*).

To explore trends in firms' behavior, we include a new variable, $log(Time)$, which equals the log of the number of years between when our sample period began and the firm's earnings announcement. The positive coefficient on $log(Time)$ in Table 8 indicates the fraction of firms beating expectations increased over time, consistent with evidence in Veenman and Verwijmeren

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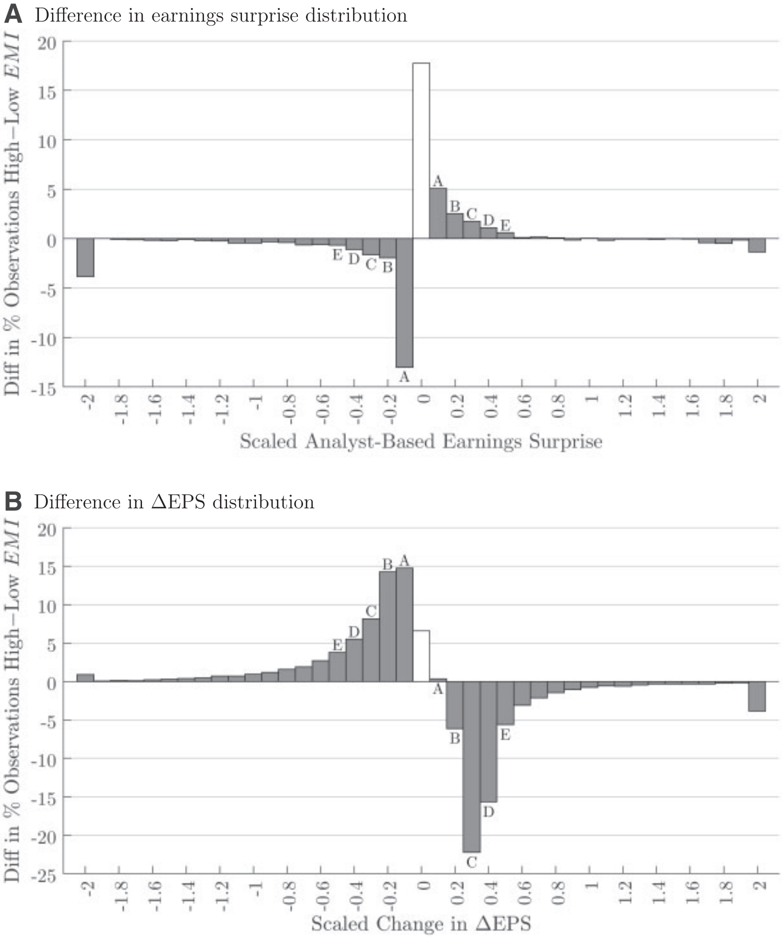

Figure 5
Difference in earnings surprise distribution
Panel A in the chart above presents differences in the scaled distributions of analyst-based earnings surprise, (*SURP*), and the scaled change in earnings per share (ΔEPS) across High *EMI* versus Low *EMI* firms. We scale all firms' *SURP* and ΔEPS by their respective standard deviations within *EMI* quintile, which makes across quintile differences in the distribution of earnings surprises easier to interpret by ensuring that each quintile has a distribution with a standard deviation of one. *SURP* is defined as the difference between actual earnings per share and the median analyst forecast of earnings per share divided by lagged total assets per share. ΔEPS is change in earnings per share scaled by lagged total assets per share. *EMI* is a composite proxy for firms' expectations management incentives, as outlined in Equation (1) and discussed in Section 1, where higher values indicate greater incentives to report positive earnings surprises. The capital letters denote symmetric intervals between positive and negative surprises to facilitate comparison. The sample consists of 176,264 firm-quarter observations spanning 1985 through 2015 with nonmissing analyst-based surprises.

(2018) that the prevalence of positive surprises has grown in recent years. Perhaps more interestingly, Table 8 also shows a positive and significant interaction term between $log(Time)$ and EMI, indicating the fraction of positive

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Table 8
Fraction of positive surprises over time by EMI

	(1)	(2)	(3)	(4)
log(Time)	0.171***	0.115***	0.171***	0.120***
	(16.15)	(7.76)	(16.16)	(8.02)
log(Time) X EMI	–	0.112***	–	0.102***
	–	(8.71)	–	(7.78)
EMI	0.612***	0.325***	0.572***	0.313***
	(46.91)	(11.41)	(43.23)	(10.78)
SIZE	–	–	0.090***	0.079***
	–	–	(11.31)	(10.64)
LBM	–	–	−0.022***	−0.026***
	–	–	(−3.83)	(−4.70)
MOMEN	–	–	0.126***	0.126***
	–	–	(27.60)	(28.03)
VLTY	–	–	0.018***	0.016***
	–	–	(2.92)	(2.62)
R^2(%)	28.008	28.413	29.623	29.958

This table contains results from pooled regressions of an indicator variable for positive analyst-based surprises, 1(SURP>0), on *log(Time)*, *EMI*, and controls. *log(Time)* measures the log of number of years since 1985, the beginning of our sample period. *EMI* is a composite proxy for firms' expectations management incentives, as outlined in Equation (1) and discussed in Section 1, where higher values indicate greater incentives to report positive earnings surprises. We measure analyst-based surprises as the difference between actual earnings per share and the median analyst forecast of earnings per share divided by lagged total assets per share. The regressions control for firm's log market capitalization (*SIZE*), log of one plus a firm's book-to-market ratio (*LBM*), and lagged 12-month momentum (*MOMEN*). *VLTY* is defined as the standard deviation of monthly returns over the 12 months ending in month M. All control variables, other than *log(Time)*, are assigned to quintile ranks each calendar quarter ranging from 0 to 1. The parentheses contain t-statistics clustered by firm and quarter. The sample consists of 320,171 firm-quarter observations spanning 1985 through 2015. *p <.1; **p <.05; ***p <.01.

surprises grew faster for high *EMI* firms compared to low *EMI* firms over our sample period. These results suggest that even as investors learn from the past behavior of high EMI firms, an increasing fraction of high EMI firms successfully managed expectations.[14] To complement our pooled analysis in Table 8, we also run analogous tests of learning at the firm level by computing the number of consecutive quarters each firm has been in the same *EMI* quintile. The results, presented in an Online Appendix, show the likelihood of a positive analyst-based surprise increases in the length of time a firm is in the highest *EMI* quintile, even after controlling for the level of *EMI*. Thus, similar to our pooled results from Table 8, the results of our firm-level tests in our Online Appendix suggest individual firms, particularly firms with persistently high incentives to manage expectations, became more adept at doing so over time, consistent with firms learning by doing.[15]

14 In untabulated results, we find no evidence of increased year-over-year changes in earnings (i.e., ΔEPS >0) for high versus low *EMI* firms over our sample period. These findings suggest our results reflect firms becoming more adept at managing expectations, rather than growth in the earnings of high *EMI* firms.

15 In the Online Appendix, we show the *EMI* return relation is largely unchanged even among firms who have been in the same *EMI* quintile for more than 3 years.

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Table 9
Communication with investors and analysts

	GUIDE		*Actual guide*		*Actual consensus*		*Walk down*	
EMI	0.016***	0.016***	0.450***	0.458***	0.235***	0.234***	0.755***	0.504**
	(6.95)	(6.87)	(4.12)	(4.17)	(3.03)	(2.97)	(3.76)	(2.52)
SIZE	0.021***	0.021***	−0.197***	−0.169***	−0.124**	−0.106*	−0.329***	−0.194***
	(10.18)	(10.15)	(−3.53)	(−2.89)	(−2.21)	(−1.82)	(−6.32)	(−3.29)
LBM	−0.003	−0.005	2.705***	2.780***	3.825***	3.826***	1.021***	−0.018
	(−0.79)	(−1.32)	(6.53)	(6.37)	(8.51)	(8.16)	(2.86)	(−0.05)
MOMEN	–	−0.003	–	0.084	–	−0.020	–	−2.405***
	–	(−1.55)	–	(0.68)	–	(−0.21)	–	(−7.72)
VLTY	–	−0.000*	–	0.016	–	0.010	–	0.059***
	–	(−1.92)	–	(1.20)	–	(1.01)	–	(3.01)
R^2(%)	2.280	2.290	2.695	2.732	7.946	7.966	0.739	1.155

This table contains results from regressing management forecast statistics on *EMI* and additional controls. *GUIDE* is defined as the frequency of guidance conditional on a firm issuing a guidance at least once. *Actual guide* is defined as the difference between actual earnings per share and management forecast of earnings per share scaled by lagged total assets per share. *Actual consensus* is defined as the difference between actual earnings per share and the analyst consensus forecast of earnings per share scaled by lagged total assets per share. *Walk down* is defined as the first available median analyst earnings forecast consensus minus the last available median analyst consensus for a given quarter prior to the expected earnings announcement date, divided by the first available median analyst consensus, multiplied by 100. The regressions control for firm's log market capitalization (*SIZE*), log of one plus a firm's book-to-market ratio (*LBM*), and lagged 12-month momentum (*MOMEN*). *VLTY* is defined as the standard deviation of monthly returns over the 12 months ending in month *M*. *EMI* is a composite proxy for firms' expectations management incentives, as outlined in Equation (1) and discussed in Section 1, where higher values indicate greater incentives to report positive earnings surprises. *EMI* is expressed in quintile ranks ranging from zero to one to facilitate economic interpretation. The sample consists of 23,037 firm-quarter observations spanning 1993 through 2015 for *GUIDE*, *Actual guide*, and *Actual consensus* and 117,102 firm-quarter observations spanning 1985 through 2015 for *Walk down*. * p <.1; ** p <.05; *** p <.01.

Together, the results in this section suggest firms may adapt or refine their strategies over time, which could increase the costs of investor learning. More generally, these results suggest the returns of some anomalies may persist, in part, because of firms' behavior changing over time, making investor learning a more gradual process.

2.3 Use of earnings guidance to manage expectations

Our next set of tests provide more direct evidence of firms engaging in expectations management by examining patterns in firms' earnings guidance from IBES. To capture expectations management ahead of firms' announcements, we examine patterns in firms' guidance in the 50-day window ending 5 days before their expected announcement dates. Table 9 contains regressions of several guidance metrics on *EMI*. The first two columns show high *EMI* firms are more likely to issue guidance prior to their announcements, consistent with high incentive firms more regularly communicating with investors.

The last four columns of Table 9 show that earnings guidance from high *EMI* firms is significantly more likely to be pessimistic relative to their subsequently reported earnings (i.e., reported EPS > guidance) as well as the prevailing consensus analyst forecast (i.e., consensus > guidance). Both results are consistent with prior evidence that firms use earnings guidance to manage expectations toward beatable levels ahead of their announcements

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(e.g., Cotter et al. 2006; Feng and McVay 2010). To the extent that firms issue low-ball earnings guidance, we expect to observe analysts' forecasts decline leading up to the announcement. Consistent with this prediction, the last two columns of Table 9 contain results from regressing the "walkdown" in analysts' earnings forecast on *EMI*, where *Walk Down* is defined as the percentage change in the median analyst consensus from the first to last earnings forecast of a given quarter prior to the expected earnings announcement date (multiplied by 100). Because *EMI* is expressed in quintiles ranging from zero to one, the positive *EMI* coefficient of 0.504 indicates that the spread in *Walk Down* across high and low *EMI* quintiles corresponds to an approximate a 23% increase in *Walk Down* relative to the 2.23% sample average of *Walk Down*.[16]

Related evidence in Figure 6 plots the weekly scaled analyst-based earnings surprises, *SURP*, leading up to the expected announcement week. *SURP* is defined as the difference between actual earnings per share and the median analyst forecast of earnings per share divided by lagged total assets per share. We scale all firms' *SURP* by the standard deviation of surprises for their respective *EMI* quintile, which makes across quintile differences easier to interpret by ensuring that each quintile has a standard deviation of one. Panel A of Figure 6 shows that analysts are more likely to negatively revise their preannouncement earnings forecasts for the difference portfolio (high *EMI* - low *EMI*). This is consistent with the evidence in Table 9 that firms tend to issue earnings guidance below the prevailing consensus. Moreover, this predictable "walkdown" pattern in analysts' forecasts is pronounced in the weeks leading up to the announcement, which overlaps with the event-time period when we observe high *EMI* firms predictably earning lower returns. Panel B of Figure 6 shows this walkdown pattern is mainly driven by high *EMI* firms, consistent with these results being driven by high *EMI* firms actively managing expectations.

2.4 Motivations for expectations management

Our results to this point show that expectations management affects stock prices, generating a quarterly return cycle for certain firms that helps explain variations in the earnings announcement premium and return seasonalities. In this subsection, we build on our return-based evidence by examining managers' incentives to manage expectations. In Table 10, we present evidence consistent with a novel motivation for expectations management related to insider trading that, to our knowledge, is new to the literature. Specifically, we predict insiders at high *EMI* firms opportunistically time their trades to profit from the V-shaped return pattern, which our results suggest their own firm facilitates via

[16] In untabulated tests, we find *Walk Down* is positively correlated with the amount of guidance offered. This is consistent with high *EMI* firms' guidance inducing the walkdown pattern. Moreover, our Online Appendix contains corroborating results using firm-initiated press releases from Ravenpack's News Analytics file. Specifically, we find high *EMI* firms are more likely to issue negatively toned press releases prior to announcing earnings.

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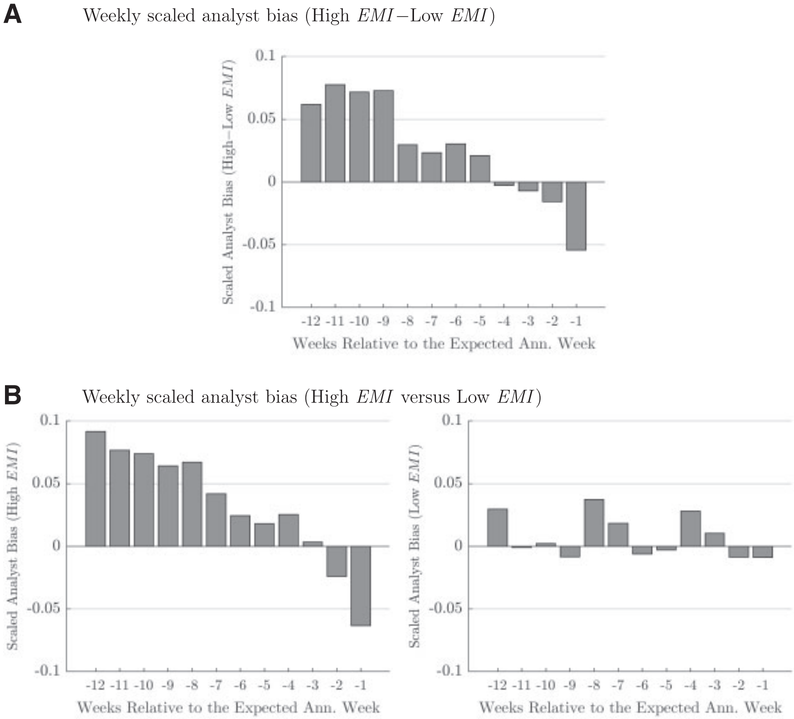

Figure 6
Weekly scaled analyst biases across high versus low *EMI* firms
The charts above present the weekly scaled analyst-based earnings surprise, (*SURP*), leading up to the expected announcement week *W* for the High *EMI* - Low *EMI* portfolio (panel A) and for High and Low *EMI* firms plotted separately (panel B). We scale all firms' surprises by the standard deviation of surprises for their respective *EMI* quintile, which makes across quintile differences easier to interpret by ensuring that each quintile has a distribution with a standard deviation of one. *SURP* is defined as the difference between actual earnings per share and the median analyst forecast of earnings per share divided by lagged total assets per share. *EMI* is a composite proxy for firms' expectations management incentives, as outlined in Equation (1) and discussed in Section 2, where higher values indicate greater incentives to report positive earnings surprises. The sample consists of 176,264 firm-quarter observations spanning 1985 through 2015 with nonmissing analyst-based surprises.

expectations management. Table 10 reports insider trading patterns as a function of *EMI* using two approaches. The first examines insider trades in the days immediately before and after earnings announcements, as suggested by Ali and Hirshleifer (2017). We measure buy-sell ratios as

$$\text{Buy-Sell Ratio} = \frac{B-S}{B+S}, \tag{3}$$

where B and S are the total number of insider buy and sell orders, respectively. We compute this ratio in the full quarter, preannouncement, and

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Table 10
Opportunistic insider trading

A. Pre- and post-announcement insider buy-sell ratios and EMI

	EMI quintiles						
	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	High - low	t-stat
Average	−12.37	−21.17	−29.95	−43.34	−55.16	−42.79	(−48.63)
Ab. pre-EA	7.99	14.51	20.18	29.25	36.38	28.39	(23.56)
Ab. post-EA	2.93	3.22	3.48	5.80	6.98	4.05	(5.63)
Pre − Post	5.06	11.29	16.70	23.45	29.40	24.33	(20.24)

B. Cohen et al. (2012) opportunism measure and EMI

Opportunisitic	All	−4.98	−6.29	−7.71	−11.96	−16.65	−11.67	(−18.75)
	Ab. M=T-1	1.31	2.54	3.04	5.19	7.30	5.99	(11.84)
	Ab. M=T	0.67	0.37	0.29	−0.19	−0.30	−0.97	(−2.12)
	Ab. M=T+1	−1.97	−2.90	−3.31	−4.97	−6.96	−4.99	(−10.75)
Routine	All	−1.17	−2.14	−3.44	−6.52	−10.63	−9.46	(−13.89)
	Ab. M=T-1	0.54	1.11	1.37	2.42	3.85	3.31	(8.65)
	Ab. M=T	−0.15	−0.15	0.43	−0.13	−1.01	−0.86	(−2.30)
	Ab. M=T+1	−0.39	−0.96	−1.80	−2.28	−2.83	−2.44	(−6.72)
Opp. − rout.	All	−3.61	−3.81	−3.96	−5.08	−5.67	−2.06	(−3.27)
	Ab. M=T-1	0.70	1.25	1.34	2.54	3.21	2.52	(5.45)
	Ab. M=T	0.78	0.49	0.06	−0.06	0.74	−0.04	(−0.09)
	Ab. M=T+1	−1.48	−1.74	−1.40	−2.48	−3.95	−2.47	(−5.24)

Panels A and B of this table present measures of opportunistic insider trading activity across quintiles of expectations management incentives (*EMI*). The first set of measures in panel A focus on trades by insiders in the preannouncement period (the 21 trading days ending 3 days prior to the expected announcement date) and the post-announcement period (the 21 trading days starting 3 days after the expected announcement date). For each window, we compute the buy-sell ratio, defined as the difference between the number of insider buys and sells dividend by the sum of buys and sells. We also compute the average value of this ratio throughout the entire quarter (Average) as a benchmark. Ab. pre-EA is the average preannouncement buy-sell ratio minus the full-quarter buy-sell ratio, whereas Ab. post-EAR is the average post-announcement buy-sell ratio minus the full-quarter buy-sell ratio. Pre − Post is the average difference between pre- and post-announcement buy-sell ratios. The second set of measures in panel B focus on monthly indicators for whether an insider initiates a buy or sell categorized as opportunistic or routine based on the Cohen et al. (2012) methodology. We present these averages for all months, and abnormal values within each calendar month relative to the expected announcement month (M=T), where we calculate abnormal values as the monthly raw values for the specified period minus the full quarter "All" values. *EMI* is a composite proxy for firms' expectations management incentives, as outlined in Equation (1) and discussed in Section 2, where higher values indicate greater incentives to report positive earnings surprises. Reported t-statistics are based on standard errors clustered at the firm and month levels. The sample consists of 138,617 firm-quarter observations in panel A and 113,088 firm-quarter observations in panel B, both of which span 1995 through 2015.

post-announcement periods.[17] We then compute abnormal buy-sell ratios by subtracting the full-quarter ratio from the pre- and post-announcement ratios.

Panel A of Table 10 shows that insiders at high *EMI* firms have abnormally high buy-sell ratios in the preannouncement period. The same panel also shows that a much weaker pattern holds in the post-announcement period. This discontinuity at the earnings announcement date suggests insiders at high *EMI* firms profit from depressed preannouncement prices and subsequent positive announcement returns that their own firm helps create. Specifically, our results

[17] The full quarter includes all insider trades in the 60 trading days ending 3 trading days prior to the scheduled earnings announcement date. The pre- and post-announcement periods include the 21 trading days ending 3 trading days prior to, and 3 trading days after, the expected announcement date. Data on insider transactions come from table 1 of the Thompson Reuters Insiders data set.

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suggest insiders at high EMI firms shift their normal trading pattern from sells to buys before announcements when prices are low, but not after.[18] Note that this does not necessarily indicate the same individual insiders buying before and selling immediately after the announcement, which would be a violation of the Short Swing Rule. Our buy-sell ratios aggregate across many insiders, so our results are likely driven by a different subset of insiders either buying before the announcement or selling after, but not engaging in both. We also study insider behavior at a monthly horizon using the Cohen et al. (2012) classification of insider trades as opportunistic or routine based on whether the same insider initiated a trade in the same direction during the same calendar month of the prior year. Panel B of Table 10 shows that, although opportunistic insider trades are more likely to be sells on average for high *EMI* firms, there is a cyclical pattern whereby their orders tilt more than usual toward buys in the month prior to an earnings announcement (T-1), and more toward sells in the month after (T+1). This cyclical pattern echoes the results in panel A with coarser time periods, indicating opportunistic insiders at high *EMI* firms exploit the return cycle caused by expectations management.

In panel B, we conduct analogous tests for routine insider trades using the approach in Cohen et al. (2012). We find an economically weaker but still statistically significant cyclical pattern in routine trades. One possible explanation for this finding is that the cyclical return pattern repeats across years, and routine traders learn to profit from this cyclical pattern. However, a key finding is that the cyclicality of opportunistic trades is significantly greater than for routine trades as indicated by the results in in the row labeled "Opp.−Rout." Taken together, the results in Table 10 point to insider trading as a novel incentive for firms to manage expectations, and suggest that insiders at high *EMI* firms profit from its impact on returns by opportunistically timing their trades.

Our novel trading-based motivation for expectations management does not rule out other potential motivations suggested by prior research. One such motivation is that board members and the broader market for executives put more weight on beating expectations than downward forecast revisions in expectations, meaning lower earnings forecasts immediately prior to the announcement improve CEO performance evaluation (e.g., Puffer and Weintrop 1991; Matsumoto 2002; Graham et al. 2005). In the Online Appendix, we replicate this unconditional pattern and show it is stronger among high *EMI* firms. Our findings are thus consistent with variation in CEO career concerns also contributing to the incentive to manage expectations, particularly for high *EMI* firms. This pattern is also consistent with the evidence in Figure 2 that our

[18] In untabulated tests, we find that the combined profitability of pre- and post-announcement insider trades, as defined in Ali and Hirshleifer (2017), is higher among high *EMI* firms. This pattern arises because of insiders regularly selling at high *EMI* firms after positive earnings news. For parsimony and to avoid sample limitations associated with insider trading data, we exclude insider trading as an input to *EMI*.

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return-based results are stronger for CEOs with shorter tenures, for whom the turnover-earnings surprise relation is strongest (Dikolli et al. 2014).[19]

2.5 Robustness

In the final section of our paper, we show our main inferences are robust to alternative proxies for firms' expectations management incentives identified by prior research. Our first alternative measure relies on within-firm variation identified in Chang et al. (2017) corresponding to firms' fiscal quarters in which they have the historically highest concentration of total annual profits, such as ice cream companies during summer quarters. Chang et al. (2017) show firms tend to earn higher average returns when announcing earnings for high profit concentration quarters.

We conjecture that their profit concentration measure, denoted *EarnRank*, identifies the fiscal quarter most critical for evaluating a company's performance and prospects, and thus corresponds to periods during which firms face greater pressure to report positive news. For example, all else equal, we expect that an ice cream company's profits during the summer are likely a more-closely watched signal of managerial competence and the firms' ability to sustain its core business, compared to their profits during the winter. As in Chang et al. (2017), we calculate *EarnRank* as the average rank of a firm's earnings per share over the past five announcements from the same fiscal quarter, using the distribution of the firm's earnings over the past twenty quarters. Higher values of *EarnRank* indicate that a given firm is expected to announce earnings corresponding to fiscal periods representing a greater share of their annual profits.

Our second alternative measure aggregates several firm-characteristics identified in Matsumoto (2002) that are correlated with firms' tendency to meet-or-exceed analysts' forecasts. Matsumoto (2002) shows that firms are more likely to meet-or-exceed as those that have greater institutional ownership, growth expectations, and implicit claims on their assets, as well as among loss firms and those from more litigious industries.[20] Based on the findings in Matsumoto (2002), we create and use a second alternative proxy for firms'

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19 An additional potential incentive is based on prior evidence that firms' full-quarter stock returns are increasing in analyst-based earnings surprises even when controlling for the fundamental earnings news itself (see Kasznik and McNichols 2002, Bartov et al. 2002, Richardson et al. 2004, and Versano and Trueman 2017 for detailed explanations of why this could be the case.) In the Online Appendix, we find evidence that this relation does not vary with *EMI*, suggesting our findings are unlikely driven by differences in sensitivities of full quarter stock prices to expectations management across high versus low *EMI* firms.

20 Implicit Claims is the factor score from the principal component analysis of *DUR*, *R&D*, and *LABOR*, where *DUR* is a dummy variable indicating membership in durable goods (SIC codes 150–179, 245, 250–259, 283, 301, 324–399), *R&D* is the firms' R&D expenditures scaled by total assets, and *LABOR* is a measure of labor intensity defined as one minus PPE divided by total lagged gross assets. Similarly, high litigation risk industries are those with SIC codes in 2833–2836, 3570–3577, 7370–7374, 3600–3674, and 5200–5961.

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expectations management incentives that assigns higher values to firms that possess these five features.[21]

Because some of the inputs in Matsumoto (2002) are binary, we first transform the nonbinary variables to range from zero to one, such that the aggregation does not place undue weight on a specific input. The resultant composite proxy, which we denote *Matsumoto*, adds a score of one whenever a firm's institutional ownership, expected long-term growth, or implicit claims is above the median for all expected announcers in month M. Similarly, the *Matsumoto* metric increases by one when firms report consistent losses in each of the four most recent quarters and when operating in a high litigation risk industry.

To match our use of quintile portfolios in our main tests, we assign firms with *Matsumoto* scores of zero or one to the lowest quintile. Further, to forecast outcomes in month M, we assign firms to quintiles of *EarnRank* and *Matsumoto* in month M-12. Both alternative measures are positively correlated with *EMI*, displaying Spearman and Pearson correlations ranging from 0.10 to 0.33 (results untabulated), suggesting that the three proxies likely capture similar underlying constructs but are unlikely to be mechanically correlated.

Panel A of Table 11 shows that both alternative incentive proxies carry significant predictive power for firms' expected announcement-month returns. Specifically, the 64-bp value-weighted alpha (t-statistic = 2.83) corresponding to the long-short *EarnRank* strategy is a replication of the main result in Chang et al. (2017), indicating that investors appear positively surprised by earnings news in fiscal periods during which firms report a greater share of annual profits. Panel A also shows a similar predictive pattern in returns across *Matsumoto* portfolios. Specifically, the equal-weighted alpha for the long-short *Matsumoto* strategy is 101 bps (t-statistic = 3.97), which is a new result to the literature.

Panels B and C shows that firms with stronger incentives are also more likely to have positive analyst-based surprises, despite being also more likely to report a decline in profits. Similarly, these panels show that across both alternative proxies, firms with stronger expectations management incentives are 3 to 5 times more likely to narrowly beat analysts' forecasts, compared to narrowly miss. These findings mirror the results from our earlier tests that rely on *EMI* and further suggest that the evidence in Chang et al. (2017) that investors are "surprised by the unsurprising" is a reflection, in part, of firms being more likely to manufacture positive earnings surprises in high stakes periods.

Finally, in panels D and E, we illustrate how researchers can improve strategy returns by leveraging complementarities between *EMI* and our two alternative

[21] We refer interested readers to Matsumoto (2002) for the explanation of why the attributes identified in her study empirically predict a higher likelihood of positively surprising analysts. We extend Matsumoto (2002) by aggregating firm characteristics associated with meeting-or-beating into a summary measure and linking it to announcement returns. A key difference is that *EMI* utilizes variation in the intensity of analyst coverage, which we show is an important driver of variation in *EMI* and likely plays a central role in eliciting firms' incentives to manage expectations toward beatable levels.

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Table 11
Alternative proxies

A. Alternative strategy alphas

	ALPHA	*MKTRF*	*SMB*	*HML*	*UMD*
EarnRank (VW)	0.645	−0.173	−0.268	0.125	0.048
	(2.83)	(−3.22)	(−3.58)	(1.52)	(0.96)
EarnRank (EW)	0.315	−0.045	−0.411	0.325	0.222
	(1.96)	(−1.20)	(−7.79)	(5.61)	(6.35)
Matsumoto (VW)	0.363	0.261	0.377	−1.134	−0.160
	(1.05)	(3.21)	(3.33)	(−9.12)	(−2.13)
Matsumoto (EW)	1.012	0.107	0.357	−0.926	−0.093
	(3.97)	(1.78)	(4.27)	(−10.10)	(−1.67)

B. Earnings metrics by EarnRank portfolios

	ΔEPS	*SURP*	*Level D-i-D*	*%D-i-D*
Q1 (Low)	0.715	−0.157	0.023	0.184
Q2	0.134	−0.103	0.035	0.232
Q3	−0.055	−0.096	0.042	0.255
Q4	−0.252	−0.059	0.046	0.258
Q5 (High)	−0.481	−0.034	0.058	0.279
High-Low	−1.196	0.124	0.036	0.094
p-value	(.00)	(.00)	(.00)	(.00)

C. Earnings metrics by Matsumoto portfolios

Q1 (Low)	0.423	−0.200	0.014	0.111
Q2	0.157	−0.085	0.045	0.225
Q3	0.019	−0.057	0.048	0.241
Q4	−0.162	−0.050	0.064	0.295
Q5 (High)	−0.271	−0.043	0.072	0.342
High-low	−0.703	0.156	0.058	0.233
p-value	(.00)	(.00)	(.00)	(.00)

(Continued)

proxies. Specifically, the value-weighted *EMI* return spread in firms' expected announcement month is pronounced among firms within the highest terciles of *EarnRank* and *Matsumoto*. These complementarities provide further evidence that our proxies do not subsume each other and instead reinforce each other in predicting returns. Collectively, the evidence in Table 11 suggest the predictive link between firms' expectations management incentives and returns is quite general, and thus mitigates concerns that our broader inferences are driven by measurement choices specific to our composite proxy.

3. Conclusion

The central contribution of this paper is in establishing links between expectations management and two economically large return patterns: earnings announcement premiums and return seasonalities. Whereas prior research studies these broader phenomena separately, our innovation is to study them jointly. We do so by introducing simple proxies for firms' expectations

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Table 11
(Continued)

D. Complementarities between EMI and EarnRank in predicting returns

	EMI quintiles						
	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	High-Low	t-statistic
Low EarnRank	0.738	0.464	1.457	1.547	1.235	0.497	1.564
Mid	0.983	1.123	0.933	1.555	1.449	0.466	1.546
High EarnRank	1.004	1.318	1.436	1.691	1.835	0.831	2.884

E. Complementarities between EMI and Matsumoto in predicting returns

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	High-Low	t-statistic
Low Matsumoto	1.074	1.073	1.477	1.275	1.241	0.217	0.827
Mid	0.646	1.523	1.447	1.654	1.531	0.885	2.370
High Matsumoto	0.350	1.172	1.631	1.955	1.853	1.464	2.509

This table presents portfolio alphas, earnings metrics, and earnings surprise distributions across two alternative proxies for expectations management incentives: *EarnRank* as in Chang et al. (2017) and *Matsumoto* based on the findings of Matsumoto (2002). To calculate *EarnRank*, we rank the twenty quarters of past earnings data from largest to smallest. *EarnRank* is the average rank of the past five announcements from the same fiscal quarter, out of the twenty quarters, relative to the expected announcement month T. Firms are sorted into quintiles in month T-12 based on *EarnRank*. *Matsumoto* is a measure that receives a score whenever a firm's *Inst Own*, *ICLAIM*, or *LTG* is above the median in T-12 or when *LOSS* equals 1 or *LIT* equals 1. *Inst ownership* is the percentage of shares held by institutions. ICLAIM is the factor score from the principal component analysis of *DUR*, *R&D*, and *LABOR*, where *DUR* is a dummy variable indicating membership in durable goods (SIC codes 150–179, 245, 250–259, 283, 301, 324–399), *R&D* is R&D scaled by lagged total assets per share, and *LABOR* is a measure of labor intensity defined as one minus PPE divided by total lagged gross assets. *LTG* is the consensus long-term growth forecast. *LOSS* equals 1 if each of the four most recent quarters ending in T-12 realized a loss. *LIT* is a dummy variable indicating membership in high-risk industry (SIC codes 2833–2836, 3570–3577, 7370–7374, 3600–3674, 5200–5961). Firms with scores of 5 (0 or 1) are sorted into high (low) *Matsumoto* portfolios in month T-12. Panel A presents difference portfolio (high-low) equal- and value-weighted alphas and corresponding t-statistics for *EarnRank* and *Matsumoto* quintile portfolios. *ALPHA* is the intercept from a regression of raw returns minus the risk-free rate, regressed on the contemporaneous excess market return (*MKTRF*); two Fama-French factors (*SMB* and *HML*); and the momentum factor (*UMD*). Panels B and C present equal- and value-weighted time-series averages of change in earnings per share (ΔEPS) and analyst-based surprise (*SURP*), as well as *Level D-i-D*, defined as the difference between *NBEAT* and *NMISS* and *%D-i-D*, defined as the difference between *NBEAT* and *NMISS* divided by the sum of *NBEAT* and *NMISS* across *EarnRank* and *Matsumoto* quintiles. *SURP* is defined as the difference between actual earnings per share and the median analyst forecast of earnings per share divided by lagged total assets per share. ΔEPS is defined as change in earnings per share scaled by lagged total assets per share. *NBEAT* equals one when *SURP* is greater than zero but less than 1%. *NMISS* equals one when *SURP* is less than zero but greater than -1%. Panels D and E present value-weighted raw announcement returns independently double-sorted across the two alternative proxies *EarnRank* and *Matsumoto* with this paper's main proxy *EMI*. The sample consists of 320,171 firm-quarter observations spanning 1985 through 2015.

management incentives based on widely observable firm-characteristics, which we show offer strong predictive power for firms' earnings surprises and returns. We show that firms with stronger incentives display a predictable V-shaped pattern in their event-time returns, which is difficult to explain via risk-based explanations but consistent with firms lowering preannouncement expectations to manufacture positive earnings surprises in high attention periods. We also validate our incentive proxies by showing that firms with stronger incentives display several intuitive patterns that do not depend on market prices: they are more likely to narrowly beat analysts' expectations, issue low-ball earnings guidance, and experience steeper declines in analysts' preannouncement forecasts.

Taken together, our evidence suggests firms' incentives to convey upbeat earnings news help to explain the positive average return observed during their earnings announcements, as well as cyclical correlations in firms' returns

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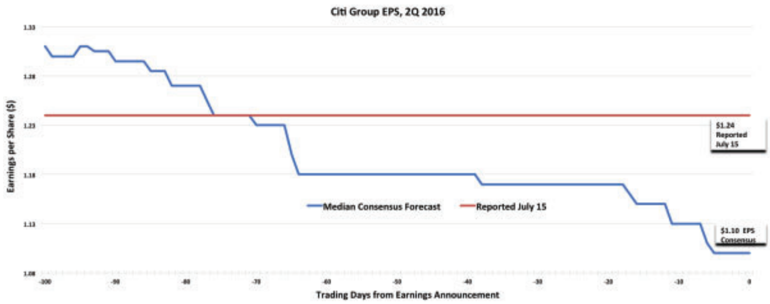
across their fiscal quarters. More broadly, our findings suggest that expectations management elicits predictable biases and reversals in investors' expectations, and thus provide a novel lens for studying the impact of investor attention, informational intermediaries, and firm behavior on the cross-section of returns.

Appendix Case Study: Citigroup

On July 15, 2016, Citigroup's share price rose by more than 2% despite announcing a 14% decline in year-over-year earnings. As shown in the exhibit below, this was made possible by a steady decline in analysts' consensus earnings forecasts leading up to the announcement, eventually falling below Citigroup's reported earnings by 14 cents per share.



In June 2016, the month prior to Citigroup's announcement, their shares fell by more than 9% coinciding with the sharp drop in analysts' earnings estimates as depicted above. In July 2016, Citigroup's share rose by more than 3% coinciding with media coverage of the announcement (see, e.g., Marino and Imbert 2016). How did Citigroup manage to positively "surprise" the market even when their profits were falling? According to the *Wall Street Journal*, when analysts called Citigroup's investor-relations department near the end of the second quarter, "they were referred to comments made by Chief Executive Michael Corbat at a June 2 investor conference... [that] the bank's second-quarter profits were likely to be 'roughly flat' compared with the first quarter when Citigroup earned $1.10 a share" (Gryta et al. 2016). This example illustrates that companies can exert influence on analysts without violating SEC regulations, or issuing new disclosures, by selectively directing attention to previously issued public statements that convey their intended message. Since 2012, Citigroup repeatedly registers in the highest quintile of firms' based on our composite proxy for firms' expectations management incentives.

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