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Aggregate earnings and stock market returns: The good, the bad, and the state-dependent

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ABSTRACT

Prior research documents a negative aggregate earnings-returns relation. In contrast, we posit that the sign of the relation varies, depending upon the macroeconomic and financial market conditions that exist in the earnings announcement quarter. We argue that the existing macroeconomic and financial market conditions influence market participants' frame of reference, which in turn affects whether they interpret aggregate earnings surprises to be informative about the expected inflation component of the discount rate, the market risk premium component of the discount rate, or aggregate future cash flows. Consistent with this, we find that the sign of the aggregate earnings-returns relation changes numerous times across our sample period. We also find that market participants interpret aggregate earnings to be informative about changes in expected inflation (market risk premium) when the sign of the aggregate earnings-returns relation is negative (positive). Finally, we identify macroeconomic and financial market conditions under which the aggregate earnings-returns relation is more (less) likely to be negative (positive).

1. Introduction

The link between stock prices and corporate earnings is a fundamental issue of interest to accounting and finance academics, financial intermediaries (such as financial analysts), and investors. A recent stream of research examines the relation between changes in earnings and stock prices at the aggregate level (see, e.g., Kothari et al., 2006; Hirshleifer et al., 2009; Cready and Gurun, 2010), and there have been calls for further research in this area (Ball and Sadka, 2015). Consistent with the market value of equity being equal to the present value of expected cash flows, market participants could interpret aggregate earnings surprises as being informative about one or more of the following items: (1) aggregate future cash flows, (2) the market risk premium component of the discount rate, or (3) the expected inflation rate component of the discount rate (Shivakumar 2007). The first two items imply a positive aggregate earnings-returns relation while the third implies a negative relation (Shivakumar 2007). The aggregate level studies (e.g., Kothari et al., 2006; Hirshleifer et al., 2009; Cready and Gurun, 2010) find, on average, a negative relation between unexpected changes in aggregate earnings (hereafter, aggregate earnings surprises) and market returns, suggesting that market participants interpret aggregate earnings surprises as being informative primarily about changes in the expected inflation rate.[1]

Prior aggregate earnings-returns research adopts a static perspective, implicitly assuming that the sign of the relation is constant across time. In contrast, we posit that the sign of the aggregate earnings-returns relation varies, depending upon the macroeconomic and financial market conditions that exist at the time earnings are announced. There are two reasons for why the sign of the aggregate earnings-returns relation could vary as macroeconomic and financial market conditions change: (1) the underlying statistical properties of aggregate earnings vary as macroeconomic and financial market conditions change or (2) the underlying statistical properties remain constant, but the way in which market participants interpret aggregate earnings surprises varies as macroeconomic and financial market conditions change. Given that changes in the underlying statistical properties of aggregate earnings should be driven primarily by changes in how earnings are measured—which in turn are driven primarily by changes in accounting standards, the first reason seems implausible. Accordingly, we focus on the second reason.[2]

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[1] These studies examine the United States. He and Hu (2014) examine non-U.S. markets and find a positive aggregate earnings-returns relation for some non-U.S. markets. Our focus is solely the U.S.

[2] Changes in accounting standards that have a significant effect on how earnings are measured occur infrequently. However, we recognize that during our sample

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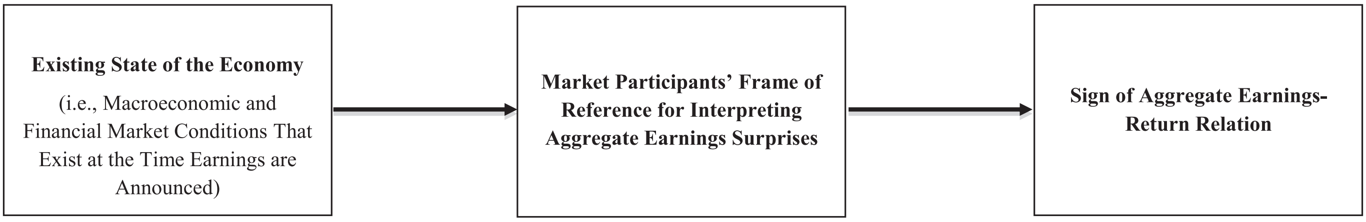

Fig. 1. Proposed conceptual link between existing macroeconomic and financial market conditions and the sign of the aggregate earnings-returns relation.

Fig. 1 illustrates the proposed conceptual link between existing macroeconomic and financial market conditions and the sign of the aggregate earnings-returns relation. Existing macroeconomic and financial market conditions determine the current state of the economy. We assume that the existing economic state influences market participants' frame of reference, and their frame of reference then affects whether they interpret aggregate earnings surprises to be informative about the expected inflation component of the discount rate, the market risk premium component of the discount rate, or aggregate future cash flows. In those periods where market participants' interpret aggregate earnings to be informative about expected inflation, the aggregate earnings-returns relation will be negative. In contrast, in those periods where they interpret aggregate earnings to be informative about either the market risk premium or aggregate future cash flows, the aggregate earnings-returns relation will be positive.

Two streams of research, when considered together, underlie our conceptual framework. The first suggests that aggregate earnings surprises are a proxy for the systematic component of an individual firm's earnings surprise (Kothari et al., 2006; Hirshleifer et al., 2009; Cready and Gurun, 2010), and that the systematic component is a signal about new macroeconomic news (Lamont, 1998; Ball et al., 2009). Thus, we posit that aggregate earnings surprises convey macroeconomic news. The second stream of research documents that individuals' interpretation of information depends upon the knowledge structures that are active at the time they receive the information (Higgins and King, 1981; Wyer and Srull, 1981). The environment or context in which the information is received can make certain knowledge structures more accessible, and thus affect how individuals interpret that information. As Dutta and Trueman (2002, 75) note, "While facts are objective, their interpretation is dependent upon investors' assessments of the environment … which generated those facts." Put simply, the same individual placed in different environments could interpret the same information differently in those two environments solely because the environments create different frames of reference through which the individual interprets the information. Studies in accounting, economics, and finance report results consistent with the environment or context affecting information interpretation (see, e.g., McQueen and Roley, 1993; Amer et al., 1995; Boyd et al., 2005; Andersen et al., 2007; Koh et al., 2008; Gilbert, 2011). Building on these two streams of research, we posit that market participants' interpretation of the macroeconomic news contained in aggregate earnings surprises depends upon the context—such as the macroeconomic and financial market conditions—that exists at the time earnings are announced.

If the effects of macroeconomic and financial market conditions on market participants' interpretations were known ex ante, a natural way to address our research question would be to test whether the sign of the aggregate earnings-returns relation varies in a manner consistent with ex ante expectations. However, the effects are not known ex ante, so this approach is not feasible. Instead, we use a backward inference approach, addressing the three components of our conceptual framework (see Fig. 1) in reverse order. Consistent with this, we decompose our overall research question into three separate questions: (1) Is the sign of the aggregate earnings-returns relation constant, or does it vary across time? (2) What do market participants interpret aggregate earnings surprises to be informative about (i.e., expected inflation, market risk premium, or aggregate future cash flows) when the aggregate earnings-returns relation is positive versus when it is negative? (3) Are the prevailing macroeconomic and financial market conditions different when the aggregate earnings-returns relation is positive versus when it is negative?

To assess whether the sign of the aggregate earnings-returns relation varies across time, we use a Markov-switching regression framework. In our context, this model allows—but does not require—the sign of the aggregate earnings-returns relation to differ across different endogenously determined unobservable states, where the Markov chain governs the evolution of the state variable.[3] The ability to determine endogenously the unobservable states is particularly important in our setting because the effects of macroeconomic and financial market conditions are not known ex ante. Our Markov-switching model identifies two states (which we label state 1 and state 2), with the states having opposite signs for the aggregate earnings-returns relation. The relation is negative in state 1 versus positive in state 2. As shown in Fig. 2, the sign of the aggregate earnings-returns relation changes numerous times across our sample period. The effects in both states are statistically and economically significant, and are robust to alternative measures of both market returns and aggregate earnings surprises.[4]

Consistent with our conceptual framework, the different signs of the aggregate earnings-returns relation in state 1 versus in state 2 suggest that market participants' interpretation of aggregate earnings surprises differs across the two states. However, the different signs do not reveal what market participants are interpreting those surprises to be informative about in each state. To assess this, we decompose unexpected market returns into their aggregate cash-flow and discount-rate news components (Campbell and Vuolteenaho, 2004) and examine the relation between each component and aggregate earnings surprises in each state. We find that aggregate earnings surprises are not associated with cash-flow news in either state, but they are associated with discount-rate news in both states. However, the sign of the association differs across the two states: positive in state 1 versus negative in state 2.

period, there were some significant changes in how earnings are measured (e.g., goodwill accounting). In Section 3 we consider the potential effect of these changes.

3 Markov-switching models have been used in a variety of empirical applications. Examples include asset pricing (Ang and Bekaert, 2002b,c; Bansal and Zhou, 2002; Baele et al., 2010), business cycle modeling (Hamilton, 1989; Chauvet and Hamilton, 2006), fiscal and monetary policy modeling (Chung et al., 2007; Davig and Leeper, 2007), and portfolio selection (Ang and Bekaert, 2002a; Ang and Chen, 2002; Guidolin and Timmermann, 2007).

4 We also considered models with more than two states. However, the two-state model outperforms these other models. As a result, we focus on the two-state model. Also, as discussed more fully in footnote 9, the results from an alternative approach to the Markov-switching regression framework are also consistent with the sign of the aggregate earnings-returns relation not being constant.

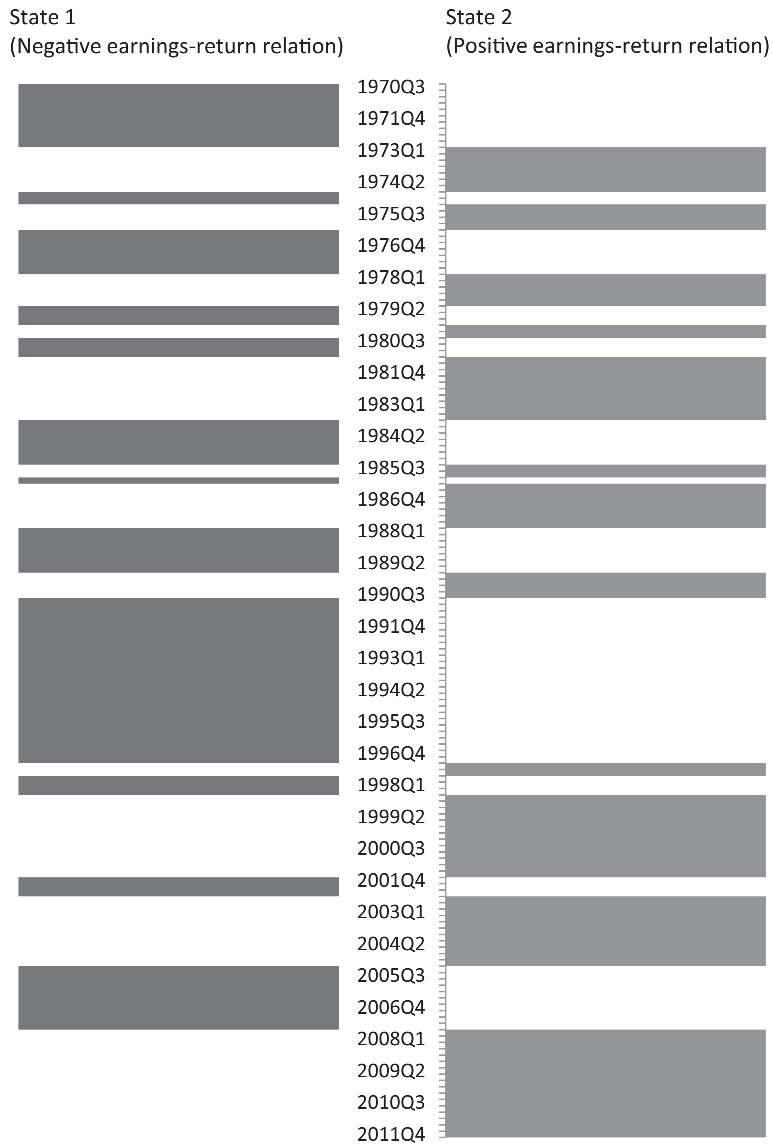

Fig. 2. Pattern of states and sign of aggregate earnings-returns relation across sample period.

Results from several additional analyses using alternative measures of cash-flow news and discount-rate news support the conclusion that in both states, market participants interpret aggregate earnings surprises to be informative about discount-rate news, but not about aggregate cash-flow news.[5]

The different signs for the association between aggregate earnings surprises and discount-rate news in state 1 versus in state 2 imply that market participants interpret aggregate earnings surprises to be informative about different components of the discount rate in state 1 versus in state 2. For state 1, the positive association between aggregate earnings surprises and discount rate news implies that in this state, market participants interpret aggregate earnings surprises to be informative about changes in the risk-free rate and, in particular, changes in the expected inflation rate (Kothari et al., 2006; Cready and Gurun, 2010). In contrast, for state 2, the negative association between aggregate earnings surprises and discount rate news is consistent with the risk premium being countercyclical; that is, the market risk premium is high (low) when macroeconomic conditions are weak (strong) (Campbell and Cochrane, 1999; Chan and Kogan, 2002). The latter result suggests that in state 2, market participants interpret aggregate earnings surprises to be informative about changes in the market risk premium. Consistent with the above arguments, we find a positive association in state 1—but not in state 2—between aggregate earnings surprises and multiple proxies for changes in the risk-free rate, in particular changes in the expected inflation rate. Further, we find a negative association in state 2—but not in state 1—between aggregate earnings surprises and multiple proxies for changes in the market risk premium. These results suggest that in state 1, market participants interpret aggregate earnings surprises to be informative primarily about changes in the expected inflation rate, whereas in state 2, market participants interpret such surprises to be informative primarily about changes in the market risk premium.

The results for our second research question suggest that market participants have a different frame of reference for interpret-

[5] These results should not be interpreted as aggregate cash flows being unimportant to the market. Rather, our results suggest that if aggregate cash flows are important, the market is obtaining information about aggregate cash flows from sources other than aggregate earnings surprises (e.g., from macroeconomic announcements).

ing aggregate earnings surprises in state 1 (when the aggregate earnings-returns relation is negative) than they do in state 2 (when the relation is positive). Consistent with our conceptual framework, this difference suggests that state 1 and state 2 reflect different states of the economy. Accordingly, we examine whether macroeconomic and financial market conditions are different when the earnings announcement quarter occurs during state 1 versus when it occurs during state 2. We consider two models—one based on real economy and monetary indicators and one based on financial market indicators—and assess which indicators are useful for predicting whether the economy in the earnings announcement quarter is in state 1 or state 2.[6] Overall, our results suggest that the likelihood of the economy being in state 1 (state 2) associates positively (negatively) with expectations of (1) higher inflation, in particular an expected increase in the consumer price index or a tightening of the Federal Reserve's monetary policy, (2) an improvement in macroeconomic conditions, in particular an increase in housing starts or a decrease in unemployment, and (3) an improvement in financial market conditions, in particular a lower default spread or an improvement in the Chicago Federal Reserve's National Financial Conditions Index.

Taken together, the results from our backward inference approach suggest the following. Selected macroeconomic and financial market conditions that exist in the earnings announcement quarter create a frame of reference for how market participants interpret aggregate earnings surprises. When inflation is high and/or macroeconomic conditions are improving (i.e. state 1), market participants' frame of reference focuses on future inflation. This frame of reference results in them interpreting aggregate earnings surprises primarily as additional evidence about future inflation. Specifically, market participants interpret positive (negative) aggregate earnings surprises as confirmatory (disconfirmatory) evidence about higher future inflation, resulting in a higher (lower) discount rate, lower (higher) stock prices, and thus a negative aggregate earnings-returns relation. In contrast, when macroeconomic conditions are worsening (i.e., state 2), market participants' frame of reference focuses on financial distress. This frame of reference results in them interpreting aggregate earnings surprises primarily as additional evidence about market risk, which is reflected in the market risk premium. Specifically, market participants interpret negative (positive) aggregate earnings surprises as confirmatory (disconfirmatory) evidence about greater future risk of financial distress, resulting in a higher (lower) discount rate, lower (higher) stock prices, and thus a positive aggregate earnings-returns relation.

Our paper contributes to the growing stream of research that examines the relation between aggregate earnings surprises and market returns. Prior studies consistently document a negative aggregate earnings-returns relation (e.g., Kothari et al., 2006; Hirshleifer et al., 2009; Cready and Gurun, 2010). While we also find a negative relation in some periods, we document that the sign of the relation is not static, with the sign positive in some periods and negative in others depending upon the macroeconomic and financial market conditions that exist at the time earnings are announced. Our results suggest that in certain time periods market participants interpret aggregate earnings surprises to be informative about changes in expected inflation, resulting in a negative aggregate earnings-returns relation, and in other time periods they interpret aggregate earnings surprises to be informative about changes in the market risk premium, resulting in a positive aggregate earnings-returns relation.

[6] We use separate models for real economy and monetary indicators versus financial market indicators due to differences in data availability.

We also contribute to research that examines the role of the environment or context in information interpretation (e.g., Boyd et al., 2005; Andersen et al., 2007; Koh et al., 2008; Gilbert, 2011). Our results suggest that market participants are more likely to interpret aggregate earnings surprises as being informative about expected inflation (and less likely to be informative about the market risk premium) when market participants expect (1) a higher inflationary environment, (2) an improvement in macroeconomic conditions, and/or (3) an improvement in financial market conditions. Overall, our results are consistent with the existing macroeconomic and financial market conditions affecting market participants' frames of reference, which in turn affect whether they interpret aggregate earnings to be informative about expected inflation versus about the market risk premium.

The remainder of the paper is organized as follows. Section 2 describes the data and reports summary statistics. In Section 3 we examine whether the aggregate earnings-returns relation varies across time. In Section 4 we examine what market participants interpret aggregate earnings surprises to be informative about when the aggregate earnings-returns relation is negative versus when it is positive. In Section 5 we identify the macroeconomic and financial market indicators that help predict whether the economy is in state 1 or state 2 during the earnings announcement quarter. We summarize our findings and conclude in Section 6.

2. Data

2.1. Sample and aggregate earnings surprise

Our sample consists of the quarterly earnings announcements from the first quarter of 1970 to the fourth quarter of 2011 for all firms in the quarterly Compustat database. Consistent with Kothari et al., (2006), our sample period starts in 1970 because Compustat coverage of quarterly items is limited prior to that year.

We use a three-step process to estimate the aggregate earnings surprise for earnings announced in quarter *t*, $AGG\_UE\_AR(1)_t$. We first calculate the earnings surprise for the earnings that firm *i* announced in quarter *t*, UE_{it}, as:

$$UE_{it} = (EPS_{it} - EPS_{it-4})/P_{it}, \tag{1}$$

where EPS_{it} and EPS_{it-4} are the earnings per share that firm *i* announced in quarter *t* and quarter $t-4$, respectively (Kothari et al., 2006; Livnat and Mendenhall, 2006), and P_{it} is firm *i*'s share price at the beginning of quarter *t* (Livnat and Mendenhall, 2006). Following Kothari et al., (2006), we exclude all firm-quarters whose fiscal and calendar quarters do not match and all firm-quarters where UE_{it} is in the top or bottom 0.5% for that quarter. We also exclude all firm-quarters whose share price at the start of quarter *t* is less than $1 to mitigate the effect of stale share prices.

In the second step, we estimate the change in aggregate earnings, AGG_UE_t, as the cross-sectional mean of the individual earnings surprises from the *N* firms that announce their earnings in quarter *t*:

$$AGG\_UE_t = \frac{1}{N}\sum_{i=1}^{N} UE_{it}, \tag{2}$$

Prior research suggests that AGG_UE_t may not properly reflect aggregate earnings surprise due to serial correlation (Kothari et al., 2006; Sadka and Sadka, 2009). If we do not remove the predictable component, the contemporaneous relation between aggregate earnings changes and market returns may simply reflect the effect of aggregate earnings changes from the previous quarter on the expected market returns (Sadka and Sadka, 2009). Thus, in the third step, we assess and adjust for serial correlation in *AGG_UE*

Table 1
Serial correlation of aggregate earnings changes.

Panel A: Serial Correlation of aggregate earnings changes

	Simple correlations			Partial correlations		
Lag	Slope	t-statistic	Adjusted R^2	Slope	t-statistic	Adjusted R^2
1	0.53	8.02***	0.28	0.52	6.61***	0.32
2	0.29	3.82***	0.08	0.10	1.18	
3	0.05	0.64	0.00	-0.03	−0.29	
4	−0.20	−2.61**	0.04	−0.31	−3.60***	
5	−0.15	−1.86*	0.02	0.13	1.59	

Panel B: Forecasting performance of different time series models applied to aggregate earnings changes

Model	Bayesian Information Criterion	Mean absolute error	Root mean squared error
AR(0)	−5.796	0.0086	0.0172
AR(1)	−6.096	0.0069	0.0167
AR(2)	−6.060	0.0074	0.0178
AR(3)	−6.044	0.0077	0.0183
AR(4)	−6.072	0.0078	0.0189
AR(5)	−6.051	0.0083	0.0199

Panel A reports serial correlations of the change in aggregate earnings. Panel B reports forecasting performance of different time series models applied to changes in aggregate earnings.
The change in aggregate earnings for quarter t is calculated as the equally weighted mean of individual firms' changes in earnings for quarter t. An individual firm's change in earnings for quarter t is calculated as the difference between earnings per share that the firm announced in quarters t and $t-4$, scaled by the firm's share price at the start of quarter t. Earnings per share are before extraordinary items.
The earnings sample consists of firm-quarters with a March, June, September, or December fiscal-quarter end and with earnings, share-price data, and earnings-announcement dates available on Compustat in the period of 1970–2011. We exclude those firm-quarters where the firm's earnings surprise is in the top or bottom 0.5% of earnings surprises for that quarter. We also exclude all firm-quarters where the firm's share price at the start of the quarter is less than \$1. The requisite data are obtained from CRSP and COMPUSTAT databases. Significance levels of 1%, 5%, and 10% (two-tailed) are denoted by ***, **, and *, respectively. Lower values of the Bayesian Information Criterion indicate a better model.

so that we capture the news contained in aggregate earnings *surprises*.

To identify the appropriate model for removing the serial correlation in *AGG_UE*, we conduct two tests. In the first, we assess the in-sample significance of simple and partial autocorrelations for lags 1 to 5. We estimate the autocorrelations using the following models:

$$AGG\_UE_t = \alpha_n + \beta_n AGG\_UE_{t-n} + \varepsilon_t, \, for n = [1, 5], \quad \text{and} \tag{3}$$

$$AGG\_UE_t = \alpha + \sum_{n=1}^{5} \beta_n AGG\_UE_{t-n} + \varepsilon_t, \tag{4}$$

where $AGG\_UE_{\text{t-n}}$ is the change in aggregate earnings lagged n quarters for $n = 1, 2\ldots5$. Panel A of Table 1 reports the estimates of the autocorrelations. The changes in aggregate earnings surprises exhibit a substantial persistence for both the first and fourth lags, as evidenced by the significant first- and fourth-order partial autocorrelations (smallest t-statistic = −3.60, p-value < 0.01, two-tail). The estimated partial autocorrelations at the second, third, and fifth lags are not significant (largest t-statistic = 1.59, p-value > 0.11, two-tail). These results suggest AR(1) or AR(4) as possible model specifications.

In-sample significance of forecasting variables does not imply incremental forecasting ability out of sample (Swanson 1998; Giacomini and Rossi, 2006). Thus, in our second test, we follow prior research and examine a model's out-of-sample forecasting ability. We consider the following model specifications for the aggregate earnings changes: AR(0) (i.e., seasonal random walk for the aggregate earnings levels), AR(1), AR(2), AR(3), AR(4), and AR(5). For each model, we construct a one-step ahead forecast of the aggregate earnings changes using an expanding estimation window approach (Pesaran and Timmerman, 1995) and then assess the out-of-sample performance using two criteria: (1) mean absolute forecasting error and (2) root mean squared forecasting error. The results are reported in Panel B of Table 1. The AR(1) model specification outperforms the other five specifications.

Taken together, the results from the two tests suggest that the first-order AR(1) model captures most of the serial dependence in *AGG_UE*, consistent with the conclusions of Kothari et al. (2006). Accordingly, we account for serial dependence using $AGG\_UE\_AR(1)_{\text{t}}$ as our estimate of aggregate earnings surprises in the tests reported in Section 3 and later. Consistent with Kothari et al. (2006), $AGG\_UE\_AR(1)_{\text{t}}$ is the forecast error from the AR(1) model fitted to the time series of *AGG_UE*.

2.2. Descriptive statistics

Table 2 presents selected descriptive statistics. The mean number of firms per quarter is 3977 with a mean market capitalization and mean book-to-market (B/M) ratio of \$1848.3 million and 0.80, respectively. The mean change in aggregate earnings, *AGG_UE*, is 0.21% of share price. To provide further insight into *AGG_UE*, we compute it both for firms ranked by size and by book-to-market ratio. Specifically, for each quarter t, we rank all firms based on their market capitalization (B/M ratio) at the beginning of quarter t and then estimate *AGG_UE* for the firms in the lowest quintile and highest quintile, yielding small-cap (low-B/M) and large-cap (high-B/M) firms, respectively. For market capitalization, *AGG_UE* has a mean (standard deviation) of −0.08% (2.34%) of share price for small-cap firms versus 0.12% (0.69%) for large-cap firms. For the B/M ratio, *AGG_UE* has a mean (standard deviation) of 0.11% (0.55%) of share price for low-B/M firms versus −0.93% (3.55%) for high-BM firms. Additional (untabulated) analysis suggests that the

Table 2
Descriptive statistics.

Variable	Mean	Std. Dev.	25%	Median	75%
Number of firms	3977	1620	2087	3511	5660
Firm size ($US million)	1848.3	10,405.1	37.66	145.12	677.53
B/M ratio	0.80	18.90	0.36	0.62	0.98
AGG_UE: all sample	0.21	1.31	−0.55	0.00	0.25
AGG_UE: small stocks	−0.08	2.34	−0.77	0.04	0.75
AGG_UE: large stocks	0.12	0.69	−0.08	0.17	0.43
AGG_UE: low-B/M stocks	0.11	0.55	−0.08	0.12	0.37
AGG_UE: high-B/M stocks	−0.93	3.55	−1.46	−0.19	0.38
AGG_UE_AR(1)	0.00	1.11	−0.26	0.00	0.20
Market return	2.79	9.13	−1.52	3.70	8.45

This table reports selected descriptive statistics of our sample. The sample consists of firm-quarters with a March, June, September, or December fiscal-quarter end and with earnings, share-price data, and earnings-announcement dates available on COMPUSTAT in the period of 1970–2011. We exclude those firm-quarters where the firm's earnings surprise is in the top or bottom 0.5% of earnings surprises for that quarter. We also exclude all firm-quarters where the firm's share price at the start of the quarter is less than $1.
Firm size is the market value at the start of the quarter in which the firm announces its earnings. The B/M ratio is the book value of equity divided by market value at the start of the announcement quarter. AGG_UE_t is the change in aggregate earnings for quarter t, calculated as the equally weighted mean of individual firms' changes in earnings for quarter t. An individual firm's change in earnings for quarter t is calculated as the difference between earnings per share that the firm announced in quarters t and $t-4$, scaled by the firm's share price at the start of quarter t. Earnings per share are before extraordinary items. 'Small stocks' and 'Large stocks' are the bottom and top quintiles of stocks ranked by market value. 'Low B/M stocks' and 'High B/M stocks' are the bottom and top quintiles of stocks ranked by book-to-market ratio. $AGG\_UE\_AR(1)_t$ is the aggregate earnings surprise, measured as the forecast error from the AR(1) model fitted to the time series of AGG_UE_t. Market return is the quarterly return in the announcement quarter on the value-weighted CRSP portfolio. The requisite data are obtained from CRSP and Compustat databases. All reported figures, other than number of firms, firm size, and B/M ratio, are percentages.

negative mean for both small-cap firms and low-BM firms is due primarily to the financial crisis that began in 2008.[7]

Mean aggregate earnings surprise, *AGG_UE_AR(1)*, is 0.00, and its standard deviation is 1.11. The mean quarterly return on the CRSP value-weighted index is 2.79% and its standard deviation is 9.13%.

3. Test of the sign of the aggregate earnings-return relation

3.1. Baseline model

We posit that the sign of the aggregate earnings-returns relation can be positive or negative, with the sign dependent upon the macroeconomic and financial market conditions that exist at the time earnings are announced. Recall that we decompose this overall research question into three separate questions. In this section, we address the first question: Is the sign of the aggregate earnings-returns relation constant, or does it vary across time?

A common approach for examining the aggregate earnings-returns relation is simple linear regression (e.g., Kothari et al., 2006; Hirshleifer et al., 2009; Cready and Gurun, 2010). This approach implicitly assumes that the sign of the aggregate earnings-returns relation is constant within the sample. Given that we expect the sign to vary, using simple linear regression would require an ex ante partitioning of our sample into two sub-samples—one where we expect the sign of the aggregate earnings-returns relation to be positive and one where we expect the sign to be negative—and then separately testing the two sub-samples. However, this partitioning is not feasible because it requires ex ante knowledge of how macroeconomic and financial market conditions affect market participants' interpretation of aggregate earnings surprises (i.e., their frames of reference), and thus the sign of the aggregate earnings-returns relation.

Instead, we use the Markov switching regression framework to assess whether the sign of the aggregate earnings-returns relation varies across time. In our context, this model allows—but does not require—the aggregate earnings-returns relation to differ across unobservable states (i.e., different interpretations of aggregate earnings surprises). Applying this framework requires that we specify ex ante the number of unobservable states. However, the states are unobservable, so knowing ex ante the number of states to specify is problematic. Because of this, we consider models with one state, two states, three states, and four states. Intuitively, for the number of states specified, the Markov switching regression framework determines both when each state occurs and the sign—as well as the magnitude—of the coefficient of the aggregate earnings-returns relation in each state. In the analyses that follow, we focus on the two-state model because results (untabulated) indicate that it outperforms the other models.[8]

Eq. (5) presents our Markov switching regression. The dependent variable, R_t, is the total return on the CRSP value-weighted market index in quarter t. $AGG\_UE\_AR(1)_t$ is the aggregate quarterly earnings surprise for the earnings announced in quarter t, as previously described.

$$R_t = \alpha(S_t) + \beta(S_t) AGG\_UE\_AR(1)_t + \varepsilon_t. \tag{5}$$

The Markov switching regression framework assumes that the model parameters—$\alpha(S_t)$ and $\beta(S_t)$—depend upon an endogenously determined, unobservable state variable, S_t, where $\varepsilon_t \sim N(0,\sigma^2(S_t))$. Specifically, the Markov switching regression framework endogenously determines whether α, β, and/or σ vary across the two

[7] This observation is consistent with prior studies that show small-cap and value (i.e., high-B/M) firms are more exposed to macroeconomic shocks (see, e.g., Hahn and Lee 2006; Petkova 2006; Cenesizoglu, 2011). For 2009, mean *AGG_UE* is -6.8% versus -2.2% for small-cap versus large-cap firms and -1.1% versus -13.5% for low-B/M firms versus high-B/M firms.

[8] To assess which model performs best, we use the Bayesian Information Criterion (Schwarz, 1978; Kass and Raftery, 1995).

unobservable states, where a Markov chain (discussed below) governs the time-evolution of the unobservable states. Thus, this approach allows us to assess both (1) whether the sign of the aggregate earnings-returns relation differs across the two states and (2) if it does, how many times the sign changes and when those changes occur.

The transition probabilities matrix, Π, for the two-state Markov chain that governs the time-evolution of the unobservable state variable, S_t is:

$$\prod = \begin{bmatrix} P_{11}P_{12} \\ P_{21}P_{22} \end{bmatrix}. \tag{5.1}$$

where $P_{ij} = \Pr(S_t = j|S_{t-1} = i)$ for $i = 1, 2$ and $j = 1, 2$.

Define ψ_{t-1} as the information set $\{R_{t-1}, R_{t-2}, \ldots; AGG\_UE\_AR(1)_t, AGG\_UE\_AR(1)_{t-1}, \ldots\}$. The parameter vector $\theta = [\alpha(S_t = 1), \alpha(S_t = 2), \beta(S_t = 1), \beta(S_t = 2), \sigma(S_t = 1), \sigma(S_t = 2), P_{11}, P_{22}]$ is estimated using maximum likelihood. Specifically,

$$\theta = \arg\max \sum_{t=1}^{T} \ln\{f(R_t|\psi_{t-1}), \tag{5.2}$$

where $f(R_t|\ \psi_{t-1})$ is given by the following expression:

$$f(R_t|\psi_{t-1}) = \sum_{j=1}^{2}\sum_{i=1}^{2} f(R_t|S_t = j, \psi_{t-1})P_{ij} \Pr(S_{t-1} = i|\psi_{t-1}), \tag{5.3}$$

where $\Pr(S_{t-1} = i|\psi_{t-1})$ is a filtered probability computed using a recursive filter (Hamilton, 1994; Kim and Nelson, 1999). Given the Gaussian error term, ε_t, the conditional density $f(R_t|S_t = j, \psi_{t-1})$ is:

$$f(R_t|S_t = j, \psi_{t-1}) = \frac{1}{\sqrt{2\pi}\sigma(S_t = j)} \exp\left\{\frac{z_t^2(S_t = j)}{2}\right\}, \tag{5.4}$$

where:

$$z_t(S_t = j) = \frac{R_t - \alpha(S_t = j) - \beta(S_t = j)AGG\_UE\_AR(1)_t}{\sigma(S_t = j))} \tag{5.5}$$

The estimation proceeds by maximizing the likelihood function, constructed using an iterative algorithm provided by Hamilton (1994). The results are presented in Table 3. The estimate of β is negative and significant in state 1 (z-statistic $= -9.23$, p-value < 0.01) versus positive and significant in state 2 (z-statistic $= 2.41$, p-value $= 0.02$). These results are consistent with the sign of β—and thus the sign of the aggregate earnings-returns relation—being different in the two states, suggesting that the sign varies across time.[9]

The aggregate earnings-returns relation is also economically meaningful in both states. The estimated standard deviation of *AGG_UE_AR(1)* is 0.49% in state 1 and 1.50% in state 2. Accordingly, a two-standard-deviation positive shock to the aggregate earnings surprise results in an 8.6% *decrease* in aggregate stock prices in state 1 versus a 5.7% *increase* in aggregate stock prices in state 2. To further assess economic significance, we also examine the explanatory power of our model—where α, β, and σ are allowed to vary across the two states—versus a model where β is restricted to be the same in the two states, but α and σ are still allowed to vary. The pseudo R^2 (Nagelkerke, 1991) for our model is 0.218 versus only 0.108 for the restricted model. Thus, allowing the aggregate earnings-returns relation to vary across the two states doubles the model's explanatory power.

Table 3
A switching-regimes regression of market returns on aggregate earnings surprises.

	Inferred state 1		Inferred state 2	
Variable	Coefficient	z-statistic	Coefficient	z-statistic
Constant	0.039	6.58***	0.017	1.54
AGG_UE_AR(1)	−8.81	−9.23***	1.81	2.41**
Sigma^2	0.001	3.33***	0.01	8.33***
Probability	0.77	19.25***	0.83	11.85***
N	166			
Log-likelihood	185.51			
Pseudo-R^2	0.218			

This table reports the results of regressing stock market returns on aggregate earnings surprises where the market response is allowed to vary endogenously depending on an unobservable state, and a Markov chain governs the time-evolution of the unobservable state. The estimated model is:
$R_t = \alpha(S_t) + \beta(S_t)AGG\_UE\_AR(1)_t + \varepsilon_t$.
The sample consists of firm-quarters with a March, June, September, or December fiscal-quarter end and with earnings, share-price data, and earnings-announcement dates available on Compustat in the period of 1970–2011. We exclude those firm-quarters where the firm's earnings surprise is in the top or bottom 0.5% of earnings surprises for that quarter. We also exclude all firm-quarters where the firm's share price at the start of the quarter is less than $1. R_t, is the return in quarter t, the earnings announcement quarter, on the value-weighted CRSP market index. $AGG\_UE\_AR(1)_t$ is the aggregate earnings surprise, measured as the forecast error from the AR(1) model fitted to the time series of *AGG_UE*. AGG_UE_t is the change in aggregate earnings for quarter t, calculated as the equally weighted mean of individual firms' changes in earnings for quarter t. An individual firm's change in earnings for quarter t is calculated as the difference between earnings per share that the firm announced in quarters t and $t-4$, scaled by the firm's share price at the start of quarter t. Earnings per share are before extraordinary items. S_t is an unobservable state variable governed by a Markov chain, where $\varepsilon_t \sim N(0,\sigma^2(S_t))$. The estimation proceeds by maximizing the likelihood function, constructed using an iterative algorithm provided by Hamilton (1994). Significance levels of 1%, 5%, and 10% (two-tailed) are denoted by ***, **, and *, respectively.

To determine how many times the sign of the aggregate earnings-returns relation changes in our sample, as well as when the changes occur, we create a time-plot of the smoothed probability of state 1 (see Fig. 3).[10] Following common practice, we classify period t as being in state 1 (2) when the smoothed probability of the period being in state 1 is greater (less) than 0.5. Thus, period t is in state 1 (2) when the line in Fig. 3 is above (below) 0.5. Recall that the sign of the aggregate earnings-returns relation is negative in state 1 versus positive in state 2. Fig. 3 reveals numerous shifts between state 1 and state 2 over our sample period, and thus also numerous shifts in the sign of the aggregate earnings-returns relation.

The pattern of state 1 versus state 2 in Fig. 3 helps explain the negative aggregate earnings-returns relation reported in prior studies. For example, while both state 1 and state 2 occur during the 1970–2000 sample period used by Kothari et al. (2006), state 1 (when the aggregate earnings-returns relation is negative) dominates their sample period. More generally, the estimate of β is approximately 4.5 times larger in state 1 than in state 2. However, the expected durations of state 1 and state 2, measured as $1 + [P_{jj}/(1 - P_{jj})]$, are similar at 4.34 and 5.88 quarters, respectively. Taken together, these results suggest that one is more likely to find

[9] As an alternative to the Markov switching framework, we partition our sample period into eight arbitrary subperiods of approximately equal length and then estimate the following model for each sub-period.
$R_{t+k} = \alpha + \beta AGG\_UE\_AR(1)_t + \varepsilon_{t+k}$
Note that the time periods are determined arbitrarily, and thus a given period may contain both state 1 and state 2. The estimate (untabulated) of β is negative and significant in the periods 1970-1975 and 1991-1995, positive and significant in the period 2006-2011, and not significant in the remaining periods 1976-1980, 1981-1985, 1986-1990, 1996-2000, and 2001-2005. Overall, this analysis provides additional support—albeit weaker due to the arbitrary determination of periods—that the aggregate earnings-returns relation varies across time.

[10] A smoothed probability is the probability of an unobservable event occurring in period t, calculated using information from the entire sample period, not just the information available prior to period t. Thus, for our setting, the smoothed probability that the market is in state 1 in period t is based on the information for our entire 1970-2011 sample period. We calculate the smoothed probabilities using the algorithm proposed by Kim (1994).

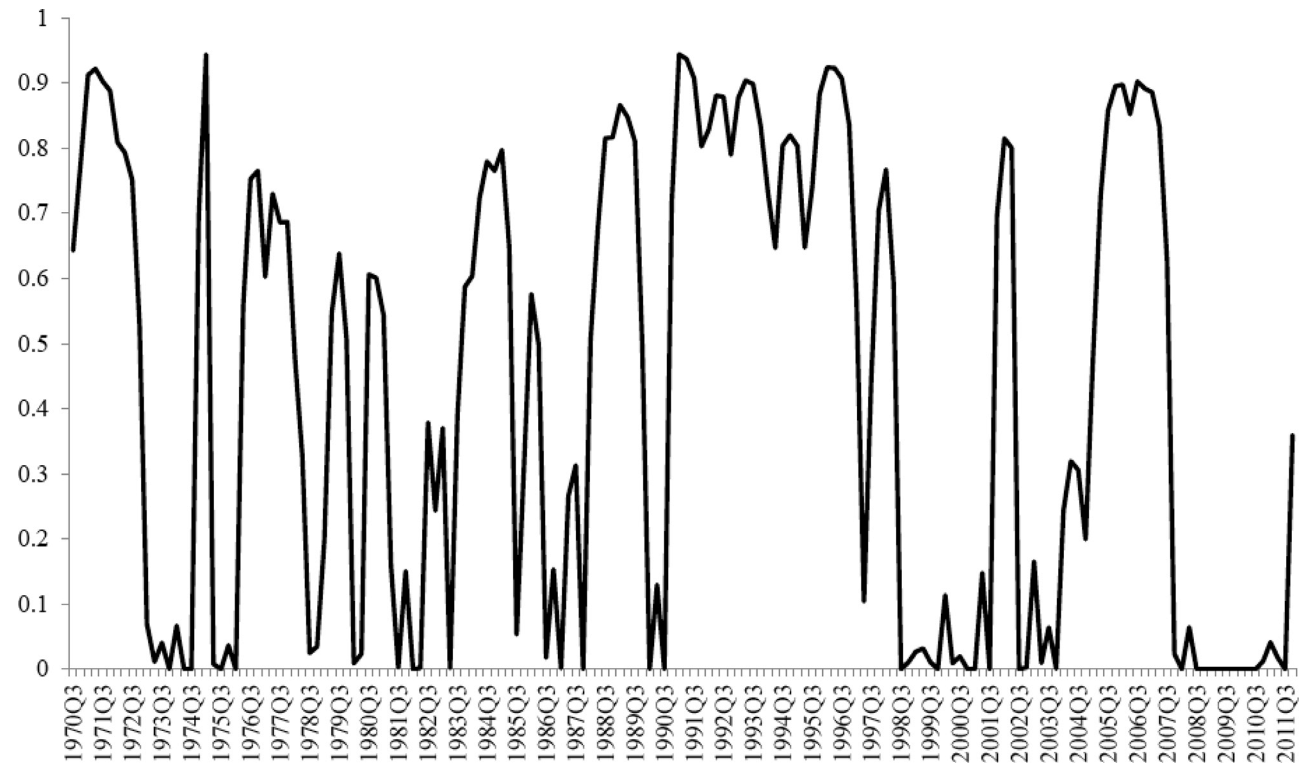

Fig. 3. Smoothed probabilities of state 1.

a negative aggregate earnings-returns relation, as prior research has shown, if one does not separate the sample period into state 1 versus state 2.

3.2. Robustness tests

3.2.1. Accuracy of model in assigning latent states

The smoothed probabilities depicted in Fig. 3, which we use to identify the unobservable states 1 and 2, were estimated using the results from the Markov switching regression. To verify that the smoothed probabilities reflect those periods where the aggregate earnings-returns relation is negative (i.e., state 1) versus positive (i.e., state 2), we conduct two tests. In the first, we examine the robustness of the Markov-switching model under the null of there being only one state. In the second test, we examine the robustness of the Markov-switching model under the null that the sign of the aggregate earnings-returns relation varies based on the two-state Markov chain (as in our analytical model).

In the first test, we use the smoothed probabilities to partition our sample period into state 1 and state 2 sub-samples and then we estimate the Markov-switching model separately for the state 1 and state 2 sub-samples. The (untabulated) results indicate that when estimated using the state 1 (state 2) sub-sample, the Markov-switching model assigns 98% (94%) of the observations to state 1 (state 2). In additional analysis, we examine the estimated parameters of the transition probability matrices for the state 1 sub-sample and the state 2 sub-sample. When estimated using the state 1 (state 2) sub-sample, the results indicate that P_{11} (P_{22})—the probability of remaining in state 1 (state 2) conditional on already being in state 1 (state 2)—is equal to, or is very close to, 1. These results are consistent with the notion that within the state 1 (state 2) sub-sample, there is a single state and the sign of the aggregate earnings-market returns relation is constant in that state.[11]

In the second test, we conduct a small-scale simulation study. Each simulation involves three steps. First, we simulate the time series of latent Markov states based on the estimates of the diagonal elements of the transition probabilities from the Markov-switching model (i.e., the Probability row in Table 3). Second, we use regression estimates of the Markov-switching model to simulate a time series of pseudo market returns, constructed under the assumption that the aggregate earnings-returns relation follows a two-state Markov-switching regression. Specifically, we generate a time series of pseudo market returns using (1) the time series data of the actual aggregate earnings surprises and (2) the set of regression coefficients that correspond to the simulated state from step 1. With respect to the latter, if in time t the simulated state is state 1 (2), the set of regression coefficients are the coefficient estimates that correspond to state 1 (2) in Table 3. Third, we fit the Markov-switching model to the simulated series of market returns and aggregate earnings surprises, and calculate the proportion of observations correctly assigned to state 1 and state 2 by the model (which we refer to as a “hit rate”). We repeat these simulations 1000 times. The median hit rate for the Markov-switching model is 81%. For comparison, the median hit rate estimated using a naïve benchmark approach, where each observation is randomly allocated to either state 1 or state 2, is only 21%. The results of our two tests provide confidence that the Markov switching regression accurately identifies the periods where the aggregate earnings-returns relation is negative versus positive.[12]

[11] Note that when estimating the Markov-switching model for our entire sample period (as opposed to estimating it separately for state 1 and state 2), P_{11} and P_{22} are both significantly less than 1. This is consistent with the notion of switching from state 1 to state 2 (and vice versa), and thus the sign of the aggregate earnings-market returns relation switching.

[12] The two approaches for testing assignment accuracy both rely solely upon the Markov-switching model. As an alternative, we first use the Markov-switching model to partition our overall sample into state 1 and state 2 sub-samples and then use simple linear regression to assess the assignment accuracy for each sub-sample. Specifically, we regress market returns on *AGG_UE_AR(1)* separately for each sub-sample. The coefficient (untabulated) is negative and significant for the state 1 sub-sample (t-statistic = -11.66, p-value < 0.01) versus positive and significant for

3.2.2. Change in the statistical properties of aggregate earnings surprises

As discussed earlier, the change in the sign of the aggregate earnings-return relation could also reflect a shift in the underlying statistical properties of aggregate earnings surprises. Although the multiple changes in the sign depicted in Fig. 3 are inconsistent with this view, for completeness, we conduct three supplemental tests to rule out this alternative explanation.

In the first test, we examine whether the distribution of aggregates earnings surprises differs across state 1 and state 2, using the Kolmogorov-Smirnov test. The results (untabulated) provide no evidence that the underlying statistical distribution of aggregates earnings surprises differs across state 1 and state 2 (K-S statistic = 0.15; p-value = 0.25).

In the two remaining tests, we consider two specific potential changes in the statistical properties of aggregate earnings surprises: (1) change in how earnings are measured (e.g., due to a new accounting standard) and (2) change in the predictability of aggregate earnings. With respect to the first issue, we consider two changes in the measurement of earnings. The first is the change in goodwill accounting under *Statement of Financial Accounting Standards* 142 around 2001. Sadka and Sadka (2009) suggest that this change affected the aggregate earnings-return relation. The second change we consider is the increased use of fair value accounting. To investigate whether either of these changes drives our results, we re-estimate Eq. (5) using alternative measures of aggregate earnings surprises. We use two different measures of aggregate earnings surprises to test goodwill: (1) aggregate earnings surprises using net income before the effects of goodwill impairment, and (2) aggregate earnings surprises using net income from only those firms that do not report any goodwill (according to Compustat) in any quarter during the entire 1970–2011 sample period.[13] We also use two different measures of aggregate earnings surprises to test fair value accounting: (1) aggregate earnings surprises using net income from only nonfinancial firms, and (2) aggregate earnings surprises using net income from only those firms that do not report any fair value assets or liabilities (according to Compustat) in any quarter during the entire 1970–2011 sample period. For each of these four alternative measures, the results (untabulated) are qualitatively similar to the results reported in Table 3. Thus, we find no evidence to suggest that either the change in goodwill accounting or the increased use of fair value accounting explains the observed changes in the sign of the aggregate earnings-return relation.

Recall that we apply an AR(1) model to aggregate earnings changes to calculate our measure of the aggregate earnings surprise. If the predictability of aggregate earnings changed over time, this would cause misspecification in our AR(1) model, and by extension, in our measure of the aggregate earnings surprise. To address this potential concern, we test for a structural break in the autoregressive term of aggregate earnings changes at any point of time in our sample period, using an endogenous structural break test (Andrews, 1993). The results (untabulated) provide no support for a structural break in the persistence of aggregate earnings changes. Thus, we find no evidence that the predictability of aggregate earnings changed during our sample period.

3.2.3. Controlling for potential correlated omitted variable

Another potential explanation for the change in the sign of the aggregate earnings-return relation is a correlated omitted variable. In our context, it is possible that the observed change in sign is due to investors directly trading on new financial or macroeconomic information, which in turn is correlated with aggregate earnings surprises.

To examine this issue, we conduct two tests. In the first, we examine pairwise correlation coefficients between aggregate earnings surprises and the news component of each of the following macroeconomic or financial market indicators: (1) growth in GDP, (2) unemployment rate, (3) growth in new housing starts, (4) term-spread, and (5) Federal funds rate. To estimate the news component of each indicator, we fit a first-order VAR to these indicators and take VAR residuals as the news components (Petkova, 2006). The (untabulated) results indicate that aggregate earnings surprises are associated negatively with the news about unemployment (t-statistic = −2.289, p-value = 0.02). The remaining coefficients are not significant.

In the second test, we examine whether the change in the sign of the aggregate earnings-returns relation holds after including all the news components for the five macroeconomic and financial indicators in our switching regression, Eq. (5). The (untabulated) results show that after controlling for the five sources of macroeconomic and financial market news, the coefficient for the aggregate earnings surprise remains negative and significant in State 1 (p-value < 0.01) and positive and significant in State 2 (p-value = 0.05).[14]

The results of our two tests provide confidence that the documented change in the sign of the aggregate earnings surprise-returns relation is not due to macroeconomic and financial market news being omitted correlated variables.

3.2.4. . Alternative measures of aggregate earnings surprises

The results in Table 1 indicate that in our context, the AR(1) model is a robust and parsimonious model for forecasting changes in aggregate earnings. However, the results also provide some in-sample evidence of higher order serial correlation in changes in aggregate earnings. Thus, for completeness, we re-estimate Eq. (5) (i.e., our baseline switching regime model) twice, once with aggregate earnings surprises calculated using an AR(4) model and once with aggregate earnings surprises calculated using an AR(5) model. The results (untabulated) are qualitatively similar to the results generated using an AR(1) model.

The results presented above are based on aggregate earnings surprises constructed using only lagged changes in aggregate earnings as forecasting variables. It is possible that past market returns may also be useful for forecasting changes in aggregate earnings. Accordingly, for completeness, we construct two alternative measures of aggregate earnings surprises. The first (second) is constructed by supplementing our AR(1) forecasting model with lagged stock market returns for the prior four (five) quarters. We re-estimate Eq. (5) separately for each alternative measure of aggregate earnings surprises. The results (untabulated) are qualita-

the state 2 sub-sample (t-statistic = 2.40, p-value < 0.02). Further, the magnitudes of the coefficients are consistent with the magnitudes reported in Table 3 from the Markov switching regression. These results provide further evidence that the Markov-switching model accurately identifies latent states.

[13] If the difference reported in Table 3 in the sign of β across state 1 and state 2 is due solely to a one-time structural shift due to the change in goodwill accounting, we should observe in Figure 3 only a single spike at the time of the structural shift (Fruhwirth-Schnatter, 2006). Specifically, the smoothed probability of state 1 would be close to one prior to 2001 and then drop to zero at the shift and remain there. For completeness, we constructed a small-scale simulation where the returns under the null were generated assuming a one-time structural shift in 2001 in the aggregate earnings-returns relation. The results (untabulated) confirm that if there had been a single shift in 2001, the model is capable of detecting it.

[14] As an alternative approach to estimating the news components, we use the difference between the value of the indicator and its consensus forecast obtained from Federal Reserve Bank of Philadelphia Survey of Professional Forecasters. These consensus forecasts are available only for the three macroeconomic indicators: (1) growth in GDP, (2) unemployment rate, and (3) growth in new housing starts. The results for both tests using this alternative approach are qualitatively similar to the results using the VAR residuals as the news components.

tively similar to the results generated using our base AR(1) forecasting model.

4. Interpretation of aggregate earnings surprises in state 1 versus state 2

We posit that the sign of the aggregate earnings-returns relation can be positive or negative, with the sign dependent upon the macroeconomic and financial market conditions that exist at the time earnings are announced. The results in Section 3 provide evidence consistent with the first condition necessary to support our expectation: the sign of the aggregate earnings-returns relation varies across time. Consistent with our conceptual framework, this variation in the sign suggests that market participants interpret aggregate earnings surprises to be informative about something different in state 1 from that in state 2. In this section, we examine how their interpretations differ in the two states.

4.1. Aggregate earnings, cash Flow, and discount-rate components of market return

Let r_t be the unexpected market return in quarter *t*. The market value of equity is equal to the present value of expected future cash flows. This suggests that market participants interpret aggregate earnings surprises to be informative primarily about future cash flows or about the discount rate. Consistent with this, we decompose r_t into the news the market obtained in quarter *t* about (1) cash flows, NCF_t and (2) the discount rate, NDR_t (Campbell and Vuolteenaho, 2004). We estimate the cash-flow and discount-rate components of r_t using the decomposition developed by Campbell and Vuolteenaho (2004), which has been widely used in prior research (e.g., Bernanke and Kuttner, 2005; Hecht and Vuolteenaho, 2006; Campbell et al., 2010).

We separately regress NCF_t and NDR_t on $AGG\_UE\_AR(1)_t$, using the following models:

$$NCF_t = \alpha_{NCF} + \beta_{NCF} AGG\_UE\_AR(1)_t + \varepsilon_t, \quad \text{and} \tag{6}$$

$$NDR_t = \alpha_{NDR} + \beta_{NDR} AGG\_UE\_AR(1)_t + \varepsilon_t. \tag{7}$$

Each model is estimated twice: (1) once for the periods classified as state 1 and (2) once for the periods classified as state 2, where the states are classified based on smoothed probabilities.

Campbell and Vuolteenaho (2004) show that the excess of NCF_t over NDR_t approximates the unexpected market return, r_t. It follows that cov(r_t, $AGG\_UE\_AR(1)_t$)—the covariance of the unexpected market return in quarter *t* and the aggregate earnings surprise from earnings announced in quarter *t*—is a function of the covariance of $AGG\_UE\_AR(1)_t$ with NCF_t and NDR_t, respectively (Kothari et al., 2006; Cready and Gurun, 2010).[15]

The results reported in Section 3 suggest that cov(r_t, $AGG\_UE\_AR(1)_t$) is negative in state 1, but positive in state 2. Consistent with the conclusions of Kothari et al. (2006) and Cready and Gurun (2010), the negative covariance in state 1 implies that aggregate earnings surprises are positively associated with—and thus market participants interpret aggregate earnings surprises to be informative primarily about—the discount rate. We therefore expect that in state 1, β_{NDR} will be positive and β_{NCF} will not be significant. The positive covariance in state 2 suggests that market participants interpret aggregate earnings surprises to be informative about either (1) future aggregate cash flows or (2) the discount rate, where the discount rate is countercyclical (Fama and French, 1989; Campbell and Cochrane, 1999; Chan and Kogan, 2002) and thus is associated negatively with aggregate earnings surprises. If the first scenario is valid, we expect that in state 2, β_{NCF} will be positive and β_{NDR} will not be significant. Alternatively, if the second scenario is valid, we expect β_{NDR} will be negative and β_{NCF} will not be significant.

The results are reported in Panel A of Table 4. First consider state 1. The estimate of β_{NDR} is positive and significant (t-statistic = 8.14, p-value < 0.01) while β_{NCF} is not significant (t-statistic = −1.21, p-value = 0.23). Now consider state 2. The estimate of β_{NDR} is negative and significant (t-statistic = −2.32, p-value = 0.02) while β_{NCF} is not significant (t-statistic = 1.37, p-value = 0.18). These results are consistent with our previous findings of a negative (positive) aggregate earnings-returns relation in state 1 (2). Further, these results suggest that market participants interpret aggregate earnings surprises to be informative about the discount rate in both state 1 and state 2, but the association between aggregate earnings surprises and the discount rate is positive in state 1 versus negative in state 2.

Chen and Zhao (2009) argue that the variables used by Campbell and Vuolteenaho (2004) to estimate *NCF* and *NDR* have low predictive power, resulting in substantial measurement error.[16] To address this concern, we conduct three additional analyses. In the first, we supplement Campbell and Vuolteenaho's (2004) estimation approach with four variables shown in prior research to be predictive of future market returns. The variables are (1) the 12-month trailing price-to-dividend ratio (Campbell and Ammer, 1993), which is the level of the S&P 500 index at the end of quarter *t*, scaled by the sum of the monthly dividends over the previous 12 months for the firms in the S&P 500 index, (2) share of equity out of total new issues (Baker and Wurgler, 2000), which is the average ratio of the total market value of equity issued in quarter *t* over the sum of the total market values of equity and debt issued in quarter *t*, (3) default spread (Hahn and Lee, 2006; Petkova, 2006; Campbell, Polk, and Vuolteenaho, 2010), which is the difference at the end of quarter *t* between the yields on Moody's BBA versus AAA corporate bonds, and (4) the deviation from the long-run consumption-to-wealth ratio (Lettau and Ludvigson, 2001), which is the residual from the cointegration equation of consumption on quarter *t* income and aggregate wealth.[17] Due to data availability, we conduct this analysis for the period 1970 through the first quarter of 2008.

The results are reported in Panel B of Table 4. For state 1, the estimate of β_{NDR} is positive and significant (t-statistic = 4.56, p-value < 0.01) while β_{NCF} is not significant (t-statistic = −1.30, p-value = 0.19). For state 2, the estimate of β_{NDR} is negative and significant (t-statistic = −1.86, p-value = 0.06) while β_{NCF} is not significant (t-statistic = 0.52, p-value = 0.60). These results are qualitatively similar to the results reported in Panel A.

The analyses above are based on decomposing unexpected market returns into cash-flow news and discount-rate news. In our second robustness analysis, we use an alternative approach and decompose aggregate earnings surprises into aggregate cash flows surprises and aggregate accruals surprises. Hirshleifer et al. (2009) find that the documented negative aggregate earnings-returns relation is driven by aggregate accruals, suggesting that aggregate accruals are informative about the discount rate.

[15] Specifically, $r_t = NCF_t$ - NDR_t (Campbell and Vuolteenaho 2004), and cov(r_t, $AGG\_UE\_AR(1)_t$) = cov(NCF_t, $AGG\_UE\_AR(1)_t$) - cov(NDR_t, $AGG\_UE\_AR(1)_t$).

[16] For a counter-argument to Chen and Zhao (2009), see Engsted et al. (2012).

[17] The data to estimate the 12-month trailing dividend yield is from Robert Shiller's website: http://www.econ.yale.edu/~shiller/data.htm. The data to estimate the share of equity out of total new issues is from Jeffery Wurgler's website: http://people.stern.nyu.edu/jwurgler/. The data to estimate the default spread is from the Federal Reserve Bank of St. Louis website: http://research.stlouisfed.org/. The estimates of the deviation from the long-run consumption-to-wealth ratio are from Martin Lettau's website: http://faculty.haas.berkeley.edu/lettau/data_cay.html.

Table 4
Regressions of cash-flow (*NCF*) and discount-rate (*NDR*) news on aggregate earnings surprises in states 1 and 2.

	Inferred state 1				Inferred state 2			
	NCF		*NDR*		*NCF*		*NDR*	
Variable	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Panel A: Campbell and Vuolteenaho (2004) estimation approach								
Constant	−0.001	−0.026	−0.011	−2.59**	−0.006	−1.38	0.011	1.16
AGG_UE_AR(1)	−0.72	−1.21	6.96	8.14***	0.37	1.37	−1.53	−2.32**
N	82		82		84		84	
Adjusted R^2	0.006		0.446		0.01		0.05	
Panel B: Campbell and Vuolteenaho (2004) estimation approach, augmented with additional conditioning variables								
Constant	0.003	0.75	−0.001	−0.19	−0.003	−0.66	0.007	0.63
AGG_UE_AR(1)	−1.028	−1.30	5.05	4.56***	0.48	0.52	−4.27	−1.86*
N	82		82		69		69	
Adjusted R^2	0.008		0.196		−0.01		0.035	

This table reports the results of regressing cash-flow news and discount rate news, respectively, on aggregate earnings surprise in states 1 and 2, where the state is identified by the Markov-switching regimes model. We classify quarter *t* as state 1 (2) when the smoothed probability of the quarter being state 1 (2) is greater than 0.5. The estimated models for cash-flow news and discount rate news are:

$NCF_t = \alpha_{NCF} + \beta_{NCF} AGG\_UE\_AR(1)_t + \varepsilon_t$

$NDR_t = \alpha_{NDR} + \beta_{NDR} AGG\_UE\_AR(1)_t + \varepsilon_t$

The sample consists of firm-quarters with a March, June, September, or December fiscal-quarter end and with earnings, share-price data, and earnings-announcement dates available on Compustat in the period of 1970–2011. We exclude those firm-quarters where the firm's earnings surprise is in the top or bottom 0.5% of earnings surprises for that quarter. We also exclude all firm-quarters where the firm's share price at the start of the quarter is less than $1.

NCF_t (NDR_t) is the news that the market obtained in quarter *t*, the announcement quarter, about cash flows (discount rates), estimated using the approach of Campbell and Vuolteenaho (2004). The results in Panel A are based on the conditioning variables suggested by Campbell and Vuloteenaho (2004); the results in Panel B reflect additional conditioning variables used in prior research. $AGG\_UE\_AR(1)_t$ is the aggregate earnings surprise, measured as the forecast error from the AR(1) model fitted to the time series of *AGG_UE*. AGG_UE_t is the change in aggregate earnings for quarter *t*, calculated as the equally weighted mean of individual firms' changes in earnings for quarter *t*. An individual firm's change in earnings for quarter *t* is calculated as the difference between earnings per share that the firm announced in quarters *t* and *t*−4, scaled by the firm's share price at the start of quarter *t*. Earnings per share are before extraordinary items. Significance levels of 1%, 5%, and 10% (two-tailed) are denoted by ***, **, and *, respectively.

We estimate the aggregate cash-flow surprise, $AGG\_CF\_SURP_t$, and the aggregate accrual surprise, $AGG\_ACCR\_SURP_t$, as follows. We first estimate firm *i*'s cash-flow surprise, CF_{it}, (accrual surprise, $ACCR_{it}$) as the difference between its net operating cash flows (accruals) for quarter *t* versus quarter *t*−4, scaled by total assets at the end of quarter *t*−4. Accruals are the difference between income before extraordinary items and net operating cash flows (Ayers et al., 2006). We next aggregate the quarter *t* individual firm surprises, yielding AGG_CF_t and AGG_ACCR_t. For robustness, we use two approaches to address the serial correlation observed in both *AGG_CF* and *AGG_ACCR*. With the first approach, we separately estimate $AGG\_CF\_SURP_t$ and $AGG\_ACCR\_SURP_t$ as the forecast errors from the AR(1) model fitted to the respective time series of *AGG_CF* and *AGG_ACCR*. With the second approach, $AGG\_CF\_SURP_t$ and $AGG\_ACCR\_SURP_t$ are the residuals from the first-order VAR fitted to the time series of *AGG_CF* and *AGG_ACCR*. The latter approach allows for the possibility that investors use both aggregate cash flows and aggregate accruals to forecast future values of variables.

To examine the effect in each state of aggregate cash flows surprises and aggregate accruals surprises on market returns, we estimate the following model separately for state 1 and state 2:

$$R_t = \alpha + \beta AGG\_ACCR\_SURP_t + \lambda AGG\_CF\_SURP_t + \varepsilon_t. \tag{8}$$

The results for our AR(1) (VAR) specification are reported in Panel A (B) of Table 5. First consider state 1. For both specifications, the coefficient for the aggregate accruals surprise is negative and significant (smallest *t*-statistic = −4.87, *p*-value < 0.01) while the coefficient for aggregate cash flow surprise is not significant (largest *t*-statistic = −0.87, *p*-value = 0.38). Now consider state 2. For both specifications, the coefficient for the aggregate accruals surprise is positive and significant (smallest *t*-statistic = 2.18, *p*-value < 0.03) while the coefficient for aggregate cash flow surprise is not significant (largest *t*-statistic = 1.47, *p*-value = 0.14). These results are consistent with the change in the sign of the aggregate earnings-returns relation being driven by aggregate accruals. Coupled with the insignificant coefficient for aggregate cash flows surprise and Hirshleifer et al. (2009) results, the overall results in Table 5 provide further evidence that market participants interpret aggregate earnings surprises as being informative about discount rates in both state 1 and state 2.

In our third robustness analysis, we use the aggregate revision in analysts' median consensus cash-flow forecasts, $AGG\_REV\_FCF_t$, as a proxy for news about future cash flows, consistent with prior research (e.g., DeFond and Hung, 2003; McInnis and Collins, 2011). We conduct two regressions for each state. In the first, we regress aggregate cash-flow forecast revisions, *AGG_REV_FCF*, on aggregate earnings surprises, *AGG_UE_AR(1)*. In the second regression, we regress market returns on both aggregate cash-flow forecast revisions, *AGG_REV_FCF*, and aggregate earnings surprises, *AGG_UE_AR(1)*. If the positive aggregate earnings-returns relation observed in state 2 (as reported in Table 3) is due to market participants interpreting aggregate earnings surprises as being informative about cash-flow news, then we would expect to find the following for state 2: (1) in the first regression, a positive association between aggregate earnings surprises and aggregate cash-flow forecast revisions, and (2) in the second regression, a positive (insignificant) association between aggregate cash-flow forecast revisions (aggregate earnings surprises) and market returns.

Table 5
Test of information content of aggregate earnings surprises in states 1 and 2 using decomposition of aggregate earnings surprises into aggregate cash-flow and aggregate accrual components.

	Panel A: AR(1) specification				Panel B: VAR(1,1) specification			
	State 1		State 2		State 1		State 2	
Variable	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Constant	0.039	6.97***	0.011	0.68	0.041	6.95***	0.011	0.709
AGG_CF_AR(1)	−2.507	−0.87	5.764	1.33	−0.646	−0.24	6.556	1.47
AGG_ACCR_AR(1)	−12.05	−5.17***	6.030	2.18**	−10.95	−4.87***	6.669	2.18**
N	43		47		43		47	
Adjusted R^2	0.447		0.078		0.423		0.081	

This table reports the results of regressing market returns on the aggregate cash-flow and aggregate accrual surprises in states 1 and 2, where the state is identified by the Markov-switching regimes model. We classify quarter t as state 1 (2) when the smoothed probability of the quarter being state 1 (2) is greater than 0.5. The estimated models for cash-flow news and discount rate news are:

$R_t = \alpha + \beta AGG\_CF\_SURP_t + \lambda AGG\_ACCR\_SURP_t + \varepsilon_t$

The sample consists of firm-quarters with a March, June, September, or December fiscal-quarter end and with earnings, cash-flows and book values of assets available on Compustat in the period of 1989–2011. We exclude those firm-quarters where the individual firm's seasonally differenced (in absolute terms) operating cash-flows or accruals exceed total assets at the end of quarter t−4.

CF_{it} is firm i's cash-flow surprise, estimated as the difference between its quarter t versus quarter t−4 net operating cash flows, scaled by total assets at the end of quarter t−4. $ACCR_{it}$ is firm i's accrual surprise estimated as the difference between its quarter t versus quarter t−4 accruals, scaled by total assets at the end of quarter t−4. Accruals are the difference between income before extraordinary items and net operating cash flows (Ayers et al., 2006). AGG_CF_t and AGG_ACCR_t are the equally weighted cross-sectional means of CF_{it} and $ACCR_{it}$, respectively. In Panel A, $AGG\_CF\_SURP_t$ and $AGG\_ACCR\_SURP_t$ are the forecast errors from the AR(1) model fitted to the respective time series of *AGG_CF* and *AGG_ACCR*, respectively. In Panel B, $AGG\_CF\_SURP_t$ and $AGG\_ACCR\_SURP_t$ are the residuals from the first-order VAR fitted to the time series of *AGG_CF* and *AGG_ACCR*, respectively. Significance levels of 1%, 5%, and 10% (two-tailed) are denoted by ***, **, and *, respectively.

Table 6
Test of information content of aggregate earnings surprises in states 1 and 2 using aggregate revisions of analysts' cash-flow forecast revisions as a proxy for aggregate cash-flow news.

	Panel A: Cash-flow forecast revisions regressed on aggregate earnings surprises				Panel B: Market returns regressed on both cash-flow forecast revisions and aggregate earnings surprises			
	State 1		State 2		State 1		State 2	
Variable	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Constant	−0.002	−2.4**	−0.003	−2.39**	0.037	5.47***	0.022	1.24
AGG_UE_AR(1)	0.197	0.91	0.182	3.38***	−8.43	−6.04***	1.75	1.94*
AGG_REV_FCF					−0.84	−0.68	1.38	0.60
N	28		43		28		43	
Adjusted R^2	−0.007		0.198		0.582		0.099	

This table reports the results from two regressions. Panel A reports the results from regressing analysts' aggregate consensus cash-flow forecast revisions on aggregate earnings surprises while Panel B reports the results from regressing market returns on both analysts' aggregate consensus cash-flow forecast revisions and aggregate earnings surprises. The regressions are run separately for states 1 and 2 where the state is identified by the Markov-switching regimes model. The sample consists of firm-quarters with a March, June, September, or December fiscal-quarter end and with earnings, share-price data, and earnings-announcement dates available on Compustat, and the analyst cash-flow forecasts available on IBES in the period of 1994–2011. We exclude those firm-quarters where the firm's earnings surprise is in the top or bottom 0.5% of earnings surprises for that quarter. We also exclude all firm-quarters where the firm's share price at the start of the quarter is less than $1.

$AGG\_UE\_AR(1)_t$ is the aggregate earnings surprise, measured as the forecast error from the AR(1) model fitted to the time series of *AGG_UE*. AGG_UE_t is the change in aggregate earnings for quarter t, calculated as the equally weighted mean of individual firms' changes in earnings for quarter t. An individual firm's change in earnings for quarter t is calculated as the difference between earnings per share that the firm announced in quarters t and t−4, scaled by the firm's share price at the start of quarter t. Earnings per share are before extraordinary items. $AGG\_REV\_FCF_t$ is analysts' aggregate consensus cash-flow forecast revisions in quarter t. $AGG\_REV\_FCF_t$ is the average of the difference between FCF_{it} and FCF_{it-1}, scaled by P_{it-1}. FCF_{it} (FCF_{it-1}) is the analyst median consensus forecast as of the end (start) of quarter t of firm i's net operating cash flows per share for the fiscal year in which quarter t falls, and P_{it-1} is firm i's share price at the start of quarter t. Significance levels of 1%, 5%, and 10% (two-tailed) are denoted by ***, **, and *, respectively.

We calculate $AGG\_REV\_FCF_t$ as:

$$AGG\_REV\_FCF_t = \frac{1}{N}\sum_{i=1}^{N}\frac{(FCF_{it} - FCF_{it-1})}{P_{it}}, \quad (9)$$

where FCF_{it-1} (FCF_{it}) is the analyst median consensus forecast at the start (end) of quarter t of firm i's net operating cash flows per share for the fiscal year in which quarter t falls, and P_{it-1} is firm i's share price at the start of quarter t. Due to data availability, we conduct this analysis for the period 1994 through the fourth quarter of 2011.

The results are reported in Table 6. For the first regression, the coefficient for *AGG_UE_AR(1)* is positive and significant in state 2 (t-statistic = 3.38, p-value < 0.01).[18] For the second regression, the coefficient for *AGG_UE_AR(1)* is positive and significant in state 2 (t-statistic = 1.94, p-value < 0.06), whereas the coefficient for

[18] In contrast, the coefficient for *AGG_UE_AR(1)* is not significant in state 1 (t-statistic = 0.91, p-value = 0.37). The results across states 1 and 2 suggest that analysts' interpretations of what aggregate earnings surprises are informative about differ across the two states, complementing our earlier finding that the aggregate earnings-returns relation differs across the two states.

AGG_REV_FCF is not significant (t-statistic = 0.60, p-value = 0.56).[19] The results for state 2 suggest that while aggregate earnings surprises influence analysts' revisions of their cash flow forecasts, these revisions do not explain the positive aggregate earnings-returns relation that we observe in state 2.[20]

Collectively, the results from the three robustness analyses further confirm our initial conclusion that in both states, market participants interpret aggregate earnings surprises to be informative about changes in the discount rate. We find no evidence that aggregate earnings surprises affect aggregate market returns via a cash flow effect.

4.2. Aggregate earnings, interest rates, expected inflation, and market risk premium

The results in Section 4.1 suggest that while market participants interpret aggregate earnings surprises to be informative about changes in the discount rate in both state 1 and state 2, their interpretations focus on different discount rate components in state 1 versus state 2. In this section we examine what discount rate component market participants interpret aggregate earnings surprises to be informative about in state 1 versus in state 2.

Changes in the discount rate can be due to (1) changes in the risk-free rate, (2) changes in the risk premium, or (3) both (Campbell and Mei, 1993). The positive association in state 1 between aggregate earnings surprises and the discount rate is consistent with aggregate earnings surprises being associated positively with changes in the risk-free rate, as suggested by Kothari et al. (2006) and Cready and Gurun (2010). Accordingly, we expect that in state 1, aggregate earnings surprises will associate positively with changes in the risk-free rate. In contrast, the negative association in state 2 between aggregate earnings surprises and the discount rate is consistent with the risk premium being countercyclical (Campbell and Cochrane, 1999; Chan and Kogan, 2002). Accordingly, we expect in state 2 that aggregate earnings surprises will associate negatively with changes in the market risk premium.

We test these expectations regarding the associations between aggregate earnings surprises and changes in the risk-free rate or changes in the market risk premium using the following models:

$$\Delta RF\_RATE_t = \alpha + \beta AGG\_UE\_AR(1)_t + \varepsilon_t, \quad \text{and} \tag{10}$$

$$\Delta RISK_t = \alpha + \beta AGG\_UE\_AR(1)_t + \varepsilon_t. \tag{11}$$

Each model is estimated twice: (1) once for the periods classified as state 1 and (2) once for the periods classified as state 2.

For the first model, the dependent variable, ΔRF_RATE_t, is the change during quarter t in the risk-free rate. Prior research suggests that changes in the risk-free rate are driven primarily by changes in the inflation rate (Ang et al., 2008). Thus, one can interpret ΔRF_RATE_t as the revision during quarter t in the expected inflation rate. We use three alternative measures of the change in the risk-free rate: (1) the change during quarter t in the University of Michigan Inflation Expectation (MICH) index (Carroll, 2003; Branch, 2004, 2007), (2) the change during quarter t in the yield on 3-month Treasury Bills, and (3) the change during quarter t in the yield on 1-year Treasury Bills. The data for the MICH index are available from 1978 onward. Because 3-month and 1-year Treasury Bills are the most heavily traded 'on the run' bills (Gibbons and Ramaswamy, 1993), their quotes are likely to be current, and thus are likely to reflect any new information contained in aggregate earnings surprises. Changes in the yields on these securities exhibit significant serial correlation, so we use the forecast errors from their respective AR(4) models as the unexpected changes in yields.

For the second model, the dependent variable, $\Delta RISK_t$, is the change during quarter t in the market risk premium. We use three alternative measures of the risk premium: (1) the change in the CBOE implied volatility index (VIX), constructed from the S&P 100 options,[21] (2) the change in the survey-based risk-premium estimates reported by Graham and Harvey (2012) for their sample of surveyed CFOs, and (3) the change in the implied risk premium, estimated as the average difference between the implied cost of equity estimates for the firms in the S&P 500 index and the one-month T-bill (Li et al., 2013). The data for VIX are available from January 1990, the data for the second measure is for the period 2000–2010, and the data for the implied risk premium is available from January 1977. Similar to Treasury Bill yields, for both changes in VIX and changes in implied risk premium, we fit an AR(4) model to remove serial correlation observed in the data.

The results for these two analyses are reported in Table 7. Panel A (B) reports the results for the risk-free rate (market risk premium). For the risk-free rate, β is significant and positive in state 1 for all three measures (smallest t-statistic = 2.56, p-value < 0.02), but is not significant in state 2 for any of the measures (largest t-statistic = 1.09, p-value = 0.28). For market risk premium, β is negative and significant in state 2 for all three measures (smallest t-statistic = −2.46, p-value = 0.02) and is positive and significant in state 1 only for the implied risk premium (t-statistic = 1.86, p-value < 0.07). These results are generally consistent with market participants interpreting aggregate earnings surprises to be informative about changes in the risk-free rate—but not about the market risk premium—in state 1 versus about changes in the market risk premium—but not about the risk-free rate—in state 2.[22]

If these conclusions are valid, findings from prior research suggest that the effect of aggregate earnings surprises on the returns

[19] The largest Variance Inflation Factor is 1.28 in the state 2 regression, suggesting that the non-significant coefficient for *AGG_REV_FCF* is not due to multi-collinearity with *AGG_UE_AR(1)*.

[20] Patatoukas (2014) regresses market returns on proxies for aggregate earnings surprises and discount rates and finds a significant positive coefficient for his aggregate earnings surprises proxy. He interprets this positive coefficient as evidence that the market perceives aggregate earnings surprises to be informative about aggregate cash flows. Patatoukas bases this conclusion on a positive correlation between (1) changes in return on equity (ROE)—which is his proxy for aggregate earnings surprises—and (2) changes in aggregate revisions in analysts' one-year ahead ROE forecasts—which is his proxy for aggregate cash flow news. However, ROE is a noisy measure of aggregate earnings surprises because changes in ROE reflect changes in both earnings and equity. More importantly, revisions in one-year ahead ROE forecasts cannot be attributed solely to aggregate cash flow news because such revisions could be driven by revisions in (1) forecasted cash flows, (2) forecasted accruals, (3) forecasted equity, or (4) some combination of these items. Nonetheless, we attempt to reconcile our conclusion that aggregate cash flows do not explain the positive aggregate earnings-returns relation in state 2 with Patatoukas' conclusion that the market perceives aggregate earnings surprises to be informative about aggregate cash flows. Using Patatoukas' sample period, we replicate Patatoukas' regression three times, each time replacing his aggregate earnings surprises proxy (i.e., change in ROE) with an alternative measure: (1) the change in aggregate earnings, *AGG_UE* (see our Eq. 2), (2) our measure of aggregate earnings surprises, *AGG_UE_AR*(1), and (3) a direct measure of aggregate cash flow news: aggregate revisions in analysts' cash flow forecasts. We find consistent results (untabulated) for all three regressions. The discount rate proxies are significant and negatively associated with market returns. However, none of the alternative measures of aggregate earnings surprises are significant. These results provide additional support for our conclusion that aggregate cash flows do not explain the positive aggregate earnings-returns relation in state 2.

[21] Consistent with VIX reflecting investors' perception of market risk, prior studies find changes in VIX to be positively associated with future market returns (Giot, 2005; Guo and Whitelaw, 2006; Banerjee et al., 2007), expected risk premium (Graham and Harvey, 2012), as well as being able to provide superior out-of-sample forecasts of future realized volatility (Blair et al., 2001) compared to the volatility estimates constructed using historical prices.

[22] Recall that the expected durations of state 1 and state 2 are 4.34 and 5.88 quarters, respectively. These durations approximate the expected durations for high and low inflation states of the economy, respectively, based on the results reported by Amisano and Fagan (2010).

Table 7
Regressions of proxies for expected inflation rate and risk premium on aggregate earnings surprises in states 1 and 2.

PANEL A: Risk-free rate

	Inferred state 1						Inferred state 2					
	ΔMICH		ΔYIELD_3		ΔYIELD_12		ΔMICH		ΔYIELD_3		ΔYIELD_12	
Variable	Coeff.	t-statistic	Coeff.	t-statistic	Coeff.	t-statistic	Coeff.	t-statistic	Coeff.	t-statistic	Coeff.	t-statistic
Constant	−0.026	−0.36	0.11	1.21	0.077	0.74	0.009	0.11	−0.06	−0.44	−0.02	−0.16
AGG_UE_AR(1)	40.44	2.56**	51.10	2.75***	51.34	2.69**	5.75	1.09	9.01	0.97	9.21	1.01
N	63		82		82		72		84		84	
Adjusted R^2	0.075		0.072		0.082		0.003		0.000		0.000	

PANEL B: Market risk premium

	Inferred state 1						Inferred state 2					
	ΔVIX		ΔCFO		ΔIMPLIED		ΔVIX		ΔCFO		ΔIMPLIED	
Variable	Coeff.	t-statistic	Coeff.	t-statistic	Coeff.	t-statistic	Coeff.	t-statistic	Coeff.	t-statistic	Coeff.	t-statistic
Constant	−0.28	−0.54	−0.03	−0.24	−0.338	−2.32**	−0.004	−0.003	−0.015	−0.19	0.281	1.51
AGG_UE_AR(1)	74.16	0.58	−5.69	−0.28	59.22	1.86*	−157.74	−2.75***	−8.51	−2.46**	−28.47	−2.47**
N	40		13		63		43		26		72	
Adjusted R^2	−0.017		−0.083		0.038		0.134		0.136		0.067	

This table reports the results of regressing the changes in risk-free rate proxies and risk premium proxies, respectively, on aggregate earnings surprises in states 1 and 2, where the state is identified by the Markov-switching regimes model. We classify quarter t as state 1 (2) when the smoothed probability of the quarter being state 1 (2) is greater than 0.5. The estimated models for expected inflation rates and risk premiums are:
$\Delta RF\_RATE_t = \alpha + \beta AGG\_UE\_AR(1)_t + \varepsilon_t$
$\Delta RISK_t = \alpha + \beta AGG\_UE\_AR(1)_t + \varepsilon_t$
The sample consists of firm-quarters with a March, June, September, or December fiscal-quarter end and with earnings, share-price data, and earnings-announcement dates available on Compustat in the period of 1970–2011. We exclude those firm-quarters where the firm's earnings surprise is in the top or bottom 0.5% of earnings surprises for that quarter. We also exclude all firm-quarters where the firm's share price at the start of the quarter is less than $1.
$AGG\_UE\_AR(1)_t$ is the aggregate earnings surprise, measured as the forecast error from the AR(1) model fitted to the time series of *AGG_UE*. AGG_UE_t is the change in aggregate earnings for quarter t, calculated as the equally weighted mean of individual firms' changes in earnings for quarter t. An individual firm's change in earnings for quarter t is calculated as the difference between earnings per share that the firm announced in quarters t and t−4, scaled by the firm's share price at the start of quarter t. Earnings per share are before extraordinary items. ΔRF_RATE_t is the change during quarter t in the risk-free rate. Our three proxies for ΔRF_RATE_t are (1) $\Delta MICH_t$, (2) $\Delta YIELD\_3_t$, and (3) $\Delta YIELD\_12_t$ $\Delta MICH_t$ is the change during quarter t in the University of Michigan Inflation Expectation (MICH) index. $\Delta YIELD\_3_t$ ($\Delta YIELD\_12_t$) is the forecast errors from the AR(4) model of the change during quarter t in the yield on 3-month (12-month) Treasury Bills. $\Delta RISK_t$ is the change during quarter t in the market risk premium. Our three proxies for $\Delta RISK_t$ are (1) ΔVIX_t, (2) ΔCFO_t, and (3) $\Delta IMPLIED_t$. ΔVIX_t is the forecast errors from the AR(4) model of the change during quarter t in the CBOE implied volatility index (VIX), constructed from the S&P 100 options. ΔCFO_t is the change in the survey-based risk-premium estimates that Graham and Harvey (2012) report from their sample of surveyed CFOs. $\Delta IMPLIED_t$ is the forecast errors from the AR(4) model of the change during quarter t in the implied risk premium, estimated as the average difference between the implied cost of equity estimates for the firms in the S&P 500 index and the one month T-bill (Li et al., 2013). The data for VIX_t are available from January 1990, the data for ΔCFO_t is available for the period 2000–2010, and the data for $\Delta IMPLIED_t$ is available from January 1977. Significance levels of 1%, 5%, and 10% (two-tailed) are denoted by ***, **, and *, respectively.

of certain types of firms should differ in state 1 versus in state 2. Specifically, prior research finds that the share prices of small firms are more sensitive to changes in interest rates (i.e., risk-free rate) (Gertler and Gilchrist, 1994; Christiano et al., 1996; Perez-Quiros and Timmerman, 2000). Prior research also shows that the stocks of growth firms have higher equity duration (Dechow et al., 2004), which implies that the share prices of growth firms are more sensitive to changes in interest rates. Given our conclusion above that market participants interpret aggregate earnings surprises in state 1—but not in state 2—to be informative primarily about changes in the risk-free rate, it follows that in state 1—but not in state 2—the effect of aggregate earnings surprises on share prices will be greater for small-cap (growth) firms than for large-cap (value) firms.

To test these expectations, we use the 25 Fama-French portfolios, which are sorted on i = size (ME) and j = book-to-market (BE/ME) ratio.[23] We then regress—separately for state 1 and state 2—portfolio returns in quarter t, r_{ijt}, on the aggregate earnings surprises for earnings announced in quarter t, as:

$$r_{ijt} = \alpha_{i,j} + \beta_{ij} AGG\_UE\_AR(1)_t + \varepsilon_{ijt}. \tag{12}$$

[23] We obtained the data from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

The results for state 1 (2) are presented in Panel A (B) of Table 8. First consider state 1. Each individual β_{ij} is negative and significant (smallest t-statistic = −5.54, p-value < 0.01). These results are consistent with the overall state 1 results reported earlier in Table 3. Within each BE/ME quintile, not only is β_{ij} for the smallest ME portfolio significantly larger (in absolute terms) than for the largest ME portfolio (smallest t-statistic = −1.84, p-value < 0.07), but the magnitude of β_{ij} (in absolute terms) also generally decreases monotonically from the smallest to the largest ME portfolio. Similarly, within each ME quintile, the magnitude of β_{ij} (in absolute terms) generally decreases monotonically from growth firms to value firms. Further, within the three smallest ME quintiles, β_{ij} for the growth portfolio is significantly larger (in absolute terms) than for the value portfolio (smallest t-statistic = −1.82, p-value < 0.07).[24]

In contrast, for state 2, every β_{ij} is positive and all but three are significant at p < 0.10 (two-tail). These results are consistent with

[24] Sadka and Sadka (2009) argue that the negative aggregate earnings-returns relation is due to predictability in the changes in aggregate earnings. If this predictability is still present in our proxy for the aggregate earnings surprise, Sadka and Sadka's (2009) perspective suggests that the negative aggregate earnings-returns relation should be more pronounced for large capitalization stocks and value stocks. Our finding that the negative relation is more pronounced for small capitalization stocks and growth stocks is consistent with our proxy for the aggregate earnings surprise reflecting news about aggregate earnings.

Table 8
Regressions of size and book-to-market-sorted portfolio returns on aggregate earnings surprises in states 1 and 2.

	Book-to-Market											
	1 (GROWTH)		2		3		4		5 (VALUE)		GROWTH - VALUE	
Firm size	Coeff.	*t*-statistic	Coeff.	*t*-statistic	Coeff.	*t*-statistic	Coeff.	*t*-statistic	Coeff.	*t*-statistic	Coeff.	*t*-statistic
Panel A: State 1												
1 (SMALL)	−18.03	−8.49***	−14.77	−8.28***	−12.58	−7.54***	−10.75	−6.98***	−12.13	−6.76***	−5.95	−3.54***
2	−16.27	−9.35***	−13.78	−9.15***	−10.26	−9.46***	−10.51	−8.37***	−11.76	−8.41***	−4.50	−2.73***
3	−14.81	−9.47***	−12.12	−10.37***	−9.57	−8.93***	−10.15	−9.92***	−11.82	−9.47***	−2.99	−1.82*
4	−12.14	−9.43***	−10.50	−10.19***	−9.65	−10.02***	−9.74	−9.82***	−9.69	−7.36***	−2.44	−1.62
5 (LARGE)	−9.45	−8.99***	−7.13	−7.53***	−6.32	−6.76***	−7.90	−8.51***	−7.49	−5.54***	−1.96	−1.25
SMALL - LARGE	−8.63	−4.25***	−7.65	−4.07***	−6.26	−3.38***	−2.85	−1.84*	−4.64	−2.41**		
Panel B: State 2												
1 (SMALL)	2.39	1.72*	1.92	1.64	2.21	2.13**	2.55	2.60***	3.35	3.00***	−0.96	−1.47
2	2.23	1.82*	1.72	1.65*	2.16	2.29**	2.50	2.74***	3.46	3.67***	−1.23	−1.80*
3	2.01	1.78*	1.96	2.04**	1.85	2.15**	2.29	2.60***	2.55	2.73***	−0.54	−0.74
4	1.76	1.64	1.87	2.04**	2.33	2.69***	2.26	2.68***	3.27	3.57***	−1.51	−2.16**
5 (LARGE)	1.19	1.47	1.76	2.31**	1.83	2.57***	2.31	3.31***	2.33	3.11***	−1.13	−2.02***
SMALL - LARGE	1.20	1.33	0.17	0.25	0.38	0.62	0.25	0.42	1.03	1.54		

This table reports the estimates of the regressions of the size (ME) and book-to-market (BE/ME) sorted portfolio returns on the aggregate earnings surprises in states 1 and 2, where the state is identified by the Markov-switching regimes model. We classify quarter t as state 1 (2) when the smoothed probability of the quarter being state 1 (2) is greater than 0.5. The estimated model is:
$r_{ijt}=\alpha_{i,j}+\beta_{ij}AGG\_UE\_AR(1)_t+\varepsilon_{ijt}$
The sample consists of firm-quarters with a March, June, September, or December fiscal-quarter end and with earnings, share-price data, and earnings-announcement dates available on Compustat in the period of 1970–2011. We exclude those firm-quarters where the firm's earnings surprise is in the top or bottom 0.5% of earnings surprises for that quarter. We also exclude all firm-quarters where the firm's share price at the start of the quarter is less than $1.
$AGG\_UE\_AR(1)_t$ is the aggregate earnings surprise, measured as the forecast error from the AR(1) model fitted to the time series of *AGG_UE*. AGG_UE_t is the change in aggregate earnings for quarter t, calculated as the equally weighted mean of individual firms' changes in earnings for quarter t. An individual firm's change in earnings for quarter t is calculated as the difference between earnings per share that the firm announced in quarters t and t−4, scaled by the firm's share price at the start of quarter t. Earnings per share are before extraordinary items. $r_{ijt,}$ is the return during quarter t on the Fama-French ME(i) and BE/ME(j) sorted portfolio for i = small ME, large ME and j = low BE/ME, high BE/ME. Significance levels of 1%, 5%, and 10% (two-tailed) are denoted by ***, **, and *, respectively.

the overall state 2 results reported earlier in Table 3. In addition, the difference in β_{ij} for small versus large firms is not significant within any BE/ME quintile (largest t-statistic = 1.54, p-value = 0.12), and there is no discernable pattern in the magnitudes of β_{ij} within the different BE/ME quintiles. Similar to state 1, the difference in β_{ij} for growth versus value firms is significant within three ME quintiles (smallest t-statistic = −1.80, p-value < 0.08). However, unlike the results for growth versus value firms in state 1, (1) the significant difference between growth and value firms in state 2 is concentrated in the larger firm portfolios and (2) the magnitude of β_{ij} is larger for value firms than for growth firms.

Overall, the results reported in this section suggest that market participants interpret aggregate earnings surprises to be informative about a different component of the discount rate in state 1 than they do in state 2. Specifically, our results are consistent with market participants interpreting aggregate earnings surprises to be informative primarily about changes in the risk-free rate—but not about the market risk premium—in state 1 versus about changes in the market risk premium—but not about the risk-free rate—in state 2.

5. Macroeconomic and financial market predictors of states 1 and 2

We posit that the sign of the aggregate earnings-returns relation can be positive or negative, with the sign dependent upon the macroeconomic and financial market conditions that exist at the time earnings are announced. In Sections 3 and 4 we provide evidence consistent with the first two steps, respectively, of our backward inference approach. The last step is to examine whether state 1 and state 2 represent different states of the economy, and thus reflect different macroeconomic and financial market conditions. Accordingly, in this section, we examine whether the existing macroeconomic and financial market conditions are different in state 1 (when the aggregate earnings-returns relation is negative) than in state 2 (when the relation is positive). More specifically, we consider whether certain lagged macroeconomic or financial market indicators are useful for predicting whether the economy in the earnings announcement quarter is in state 1 or state 2. Using lagged indicators is consistent with our conceptual framework in that it ensures that the information set available to market participants is known prior to the earnings announcement quarter.[25][26]

We use the probit regression model in Eq. (13) to examine the predictive power of macroeconomic indicators.[27] The dependent variable, $STATE\_1_t$, is a dummy variable set equal to 1 if the smoothed probability of state 1 is greater than 0.5 in quarter t, and 0 otherwise.

$$\begin{aligned} STATE\_1_t = {} & \beta_0+\beta_1 INFL_{t-1}+\beta_2 FED_{t-1}+\beta_3 UNEMP_{t-1} \\ & +\beta_4 HOUSING_{t-1}+\beta_5 GOVEXP_{t-1}+\beta_6 GDP_{t-1} \\ & +\beta_7 RECESSION_{t-1}+\beta_8 CONFIDENCE_{t-1}+\varepsilon_t \end{aligned} \tag{13}$$

From prior research, we identify eight real and monetary macroeconomic indicators that may be useful for predicting whether the economy is in state 1 in quarter t (Pesaran and Timmerman, 1995; Hodrick and Prescot, 1997; Carlstrom and Fuerst, 2003; Peersman, 2005; Leamer, 2007; D'Agostino and Surico,

[25] The validity of the tests reported in this section depends upon the dependent variable being stationary. A visual inspection of the smoothed probabilities suggests that each state might be more persistent post-1990, suggesting that the smoothed probabilities may not be stationary. To examine this issue, we conduct two tests. The first examines whether there was a structural break in 1990 in the persistence of smoothed probabilities, and the second uses an endogenous structural break test (Andrews, 1993 to examine whether there was a structural shift at some unknown point of time during our sample period. For both tests, we use the following model specifications: AR(1), AR(2), AR(3), AR(4), and AR(5). The results (untabulated) from both tests provide no evidence of a structural break in the persistence of smoothed probabilities in 1990 or at any other point during our sample period.

[26] Both the latent states identified by our model and contemporaneous macroeconomic and financial market indicators are likely to be endogenously determined. Because of that, our results imply association and not necessarily causality.

[27] We examine separately the predictive power of macroeconomic indicators and financial market indicators due to different sample availability.

2012). The indicators are: (1) $INFL_{t-1}$, the forecasted inflation rate, estimated as the forecasted percentage change in the Consumer Price Index from quarter $t-1$ to quarter t,[28] (2) FED_{t-1}, a dummy variable set equal to 1 if the Federal Reserve raised the target interest rate in each of the four quarters preceding quarter t, (3) $UNEMP_{t-1}$, the implied forecasted change in the unemployment rate from quarter $t-1$ to quarter t, (4) $HOUSING_{t-1}$, the implied forecasted growth in housing starts from quarter $t-1$ to quarter t, (5) $GOVEXP_{t-1}$, the implied forecasted growth in real federal government consumption and gross investment from quarter $t-1$ to quarter t, (6) GDP_{t-1}, the implied forecasted growth in real seasonally-adjusted gross domestic product from quarter $t-1$ to quarter t, (7) $RECESSION_{t-1}$, a dummy variable equal to 1 if the NBER classified at least two months in quarter $t-1$ as being in recession, and (8) $CONFIDENCE_{t-1}$, the percentage change in the University of Michigan consumer confidence index from quarter $t-2$ to quarter $t-1$.[29] The data to test the model in Eq. (13) is available from the fourth quarter of 1982 to the third quarter of 2008.

The results are reported in Panel A of Table 9. The first specification is the benchmark model, which includes only the intercept. This model yields a naive within-sample benchmark estimate for state 1 of 0.57, which is the proportion of the Q4 1982–Q3 2008 sample period that is in state 1. Consequently, with a 0.5 success cutoff, the benchmark model correctly classifies 57% of the sample. The real/monetary predictor model correctly classifies 70% of the sample, an improvement of 13 percentage points over the benchmark model. The result from a likelihood-ratio (LR) test indicates that the real/monetary model significantly outperforms the benchmark model (statistic = 30.34, p-value < 0.01). Further, the result from a Hosmer-Lemeshow test (Hosmer and Lemeshow, 2000) indicates that the null hypothesis of the model being correctly specified is not rejected (H-L statistic = 11.91, p-value = 0.16).

Of the eight real economy and monetary indicators, four are significant. The coefficients for $INFL_{t-1}$ and FED_{t-1} are both positive and significant (smallest z-statistic = 2.61, p-value < 0.01). The former suggests that the economy is more likely to be in state 1 in quarter t when expectations in quarter $t-1$ are for higher inflation in quarter t, and the latter suggests the economy is more likely to be in state 1 in quarter t when the Federal Reserve has increased its target interest rate in quarter $t-1$ and in each of the three prior quarters. The Fed raises interest rates when the inflation rate is higher than the Fed's long-run target (Carlstrom and Fuerst, 2003). Taken together, the results for $INFL_{t-1}$ and FED_{t-1} suggest that the economy is more likely to be in state 1 when market participants expect a higher inflationary environment.

The coefficient for $UNEMP_{t-1}$ is negative and significant (z-statistic = −1.82, p-value < 0.07) while the coefficient for $HOUSING_{t-1}$ is positive and significant (z-statistic = 2.09, p-value < 0.04). The former suggests that the economy is less likely to be in state 1 in quarter t when unemployment is expected to increase from quarter $t-1$ to quarter t while the latter suggests that the economy is more likely to be in state 1 in quarter t when housing starts are expected to increase from quarter $t-1$ to quarter t. These results suggest that the economy is more likely to be in state 1 when market participants expect an improvement in macroeconomic conditions.

We now consider the predictive power of financial market indicators, using the probit regression model in Eq. (14). The dependent variable, $STATE\_1_t$, is the same as in Eq. (13).

$$\begin{aligned} STATE\_1_t = \beta_0 &+ \beta_1 TERM\_SPREAD_{t-1} + \beta_2 T-BILL_{t-1} \\ &+ \beta_3 DEFAULT\_SPREAD_{t-1} + \beta_4 NFCI_{t-1} \\ &+ \beta_5 VALUE\_SPREAD_{t-1} + \beta_6 VOLATILITY_{t-1} + \varepsilon_t \end{aligned} \tag{14}$$

From prior research, we identify six financial market indicators that may be useful for predicting whether the economy is in state 1 in quarter t (Estrella and Hardouvelis, 1991; Gertler et al., 1991; Kashyap et al., 1994; Campbell and Vuolteenaho, 2004; Estrella, 2005; Hahn and Lee, 2006; Petkova, 2006). These indicators are: (1) $TERM\_SPREAD_{t-1}$, the average difference between the 10-year and short-term US government bond yields throughout quarter $t-1$, (2) T_BILL_{t-1}, the average short-term interest rate throughout quarter $t-1$, (3) $DEFAULT\_SPREAD_{t-1}$, the average difference between the BAA and AAA-rated corporate bond yields throughout quarter $t-1$, (4) $NFCI_{t-1}$, the average financial market conditions throughout quarter $t-1$, as measured by The Chicago Federal Reserve's National Financial Conditions Index, (5) $VALUE\_SPREAD_{t-1}$, the average natural log of the ratio of the book-to-market ratios of small value firms to small growth firms, (6) $VOLATILITY_{t-1}$, market return volatility during quarter $t-1$, estimated as the annualized standard deviation of daily returns on the CRSP value-weighted market index in quarter $t-1$. The data to test the model in Eq. (15) is available from the second quarter of 1973 to the fourth quarter of 2011.

The results are reported in Panel B of Table 9. The benchmark model yields a naive within-sample benchmark estimate for state 1 of 0.465, which is the proportion of the Q2 1973–Q4 2011 sample period that is in state 1. Consequently, with a 0.5 success cutoff, the benchmark model correctly identifies 53.5% (i.e., 1 - 0.465) of the sample.[30] The financial market model correctly identifies 71.6% of the sample, an improvement of 18.1 percentage points over the benchmark model. The result from a likelihood-ratio (LR) test indicates that the financial market model significantly outperforms the benchmark model (statistic = 43.19, p-value < 0.01). Further, the result from a Hosmer-Lemeshow test indicates that the null hypothesis of the model being correctly specified is not rejected (H-L statistic = 9.47, p-value = 0.30).

Of the six financial market indicators, five are significant. The coefficients for $T\text{-}BILL_{t-1}$ and $TERM\_SPREAD_{t-1}$ are both positive and significant (smallest z-statistic = 2.84, p-value < 0.01). The former suggests that the economy is more likely to be in state 1 in quarter t when short-term interest rates were high in quarter $t-1$, and the latter suggests that the economy is more likely to be in state 1 in quarter t when the yield curve was steep in quarter $t-1$. Short-term interest rates and the slope of the yield curve have each been shown to be important predictors of future inflation (e.g., Fama, 1975; Estrella and Hardouvelis, 1991; Estrella, 2005). Thus, the results for these two indicators are consistent with the results reported earlier for $INFL_{t-1}$ and FED_{t-1} in that they suggest that the economy is more likely to be in state 1 when market participants expect a higher inflationary environment.

In contrast, the coefficients for $DEFAULT\_SPREAD_{t-1}$, $NFCI_{t-1}$, and $VALUE\_SPREAD_{t-1}$ are all negative and significant (smallest z-statistic = −1.83, p-value < 0.07). These results suggest that the economy is less likely to be in state 1 in quarter t when the following conditions existed in quarter $t-1$. First, the default spread was

[28] All forecasts are from the Survey of Professional Forecasters, available on the Federal Reserve Bank of Philadelphia website http://www.phil.frb.org/research-and-data/real-time-center/survey-of-professional-forecasters/. The survey provides the mean forecast for each macroeconomic indicator for the current quarter, as well as for each of the four successive quarters. For a given macroeconomic indicator, we calculate the implied forecasted growth rate for quarter t as follows: (Quarter t forecast – Quarter t-1 forecast)/Quarter t-1 forecast.

[29] For $CONFIDENCE_{t-1}$, we use the change from quarter t-2 to quarter t-1 because the data for quarter t are not available at the time earnings are announced in quarter t.

[30] The naive benchmark estimate for state 1 is less than the 0.5 success cutoff. Accordingly, each quarter is classified as state 2. Because the proportion of state 2 quarters in our sample is 53.5%, the benchmark model correctly identifies 53.5% of the sample.

Table 9
Probit regressions of likelihood of state 1 on real, monetary, and financial market predictors.

	Panel A: Real Economy and Monetary Indicators				Panel B: Financial Market Indicators			
	Benchmark Model		Predictor Model		Benchmark Model		Predictor Model	
	Coefficient	*z*-statistic	Coefficient	*z*-statistic	Coefficient	*z*-statistic	Coefficient	*z*-statistic
Constant	0.176	1.399	0.031	0.028	−0.089	−0.88	2.39	1.85
Real and monetary predictors								
INFL			0.44	2.72***				
FED			1.22	2.61***				
UNEMP			−5.11	−1.82*				
HOUSING			0.14	2.09**				
GOVEXP			−0.20	−0.89				
GDP			−1.82	−1.37				
RECESSION			1.12	1.48				
CONFIDENCE			0.02	1.43				
Financial market predictors								
TERM_SPREAD							0.48	2.84***
TBILL							0.27	3.47***
DEFAULT_SPREAD							−1.54	−3.54***
NFCI							−0.29	−1.83*
VALUE_SPREAD							−1.74	−2.04**
VOLATILITY							−2.08	−0.78
N		100		100	155			155
% Correct classifications		57.0		70.0	53.5			71.6
McFadden R^2				0.221				0.201
Likelihood ratio (LR) statistic				30.34***				43.19***
Hosmer-Lemeshow (H-L) statistic				11.91				9.47

This table reports the estimates of the two probit models given below. The first model is the real economy/monetary predictor model, and the second model is the financial markets predictor model.

$$STATE\_1_t = \beta_0 + \beta_1 INFL_{t-1} + \beta_2 FED_{t-1} + \beta_3 UNEMP_{t-1} + \beta_4 HOUSING_{t-1} + \beta_5 GOVEXP_{t-1} + \beta_6 GDP_{t-1} + \beta_7 RECESSION_{t-1} + \beta_8 CONFIDENCE_{t-1} + \varepsilon_t$$

$$STATE\_1_t = \beta_0 + \beta_1 TERM\_SPREAD_{t-1} + \beta_2 T-BILL_{t-1} + \beta_3 DEFAULT\_SPREAD_{t-1} + \beta_4 NFCI_{t-1} + \beta_5 VALUE\_SPREAD_{t-1} + \beta_6 VOLATILITY_{t-1} + \varepsilon_t$$

The sample consists of firm-quarters with a March, June, September, or December fiscal-quarter end and with earnings, share-price data, and earnings-announcement dates available on Compustat in the period of 1970–2011. We exclude those firm-quarters where the firm's earnings surprise is in the top or bottom 0.5% of earnings surprises for that quarter. We also exclude all firm-quarters where the firm's share price at the start of the quarter is less than $1.

$STATE\_1_t$ is a dummy variable that takes the value of 1 if at time *t* the smoothed probability of the economy being in state 1 is greater than 0.5 and 0 otherwise. The real economy/monetary predictor model includes the following variables: (1) $INFL_{t-1}$, the forecasted inflation rate, estimated as the forecasted percentage change in the Consumer Price Index from quarter $t-1$ to quarter *t*, (2) FED_{t-1}, a dummy variable set equal to 1 if the Federal Reserve raised the target interest rate in each of the four quarters preceding quarter *t*, (3) $UNEMP_{t-1}$, the implied forecasted change in the unemployment rate from quarter $t-1$ to quarter *t*, (4) $HOUSING_{t-1}$, the implied forecasted growth in housing starts from quarter $t-1$ to quarter *t*, (5) $GOVEXP_{t-1}$, the implied forecasted growth in real federal government consumption and gross investment from quarter $t-1$ to quarter *t*, (6) GDP_{t-1}, the implied forecasted growth in real seasonally-adjusted gross domestic product from quarter $t-1$ to quarter *t*, (7) $RECESSION_{t-1}$, a dummy variable equal to 1 if the NBER classified at least two months in quarter $t-1$ as being in recession, and (8) $CONFIDENCE_{t-1}$, the percentage change in the University of Michigan consumer confidence index from quarter $t-2$ to quarter $t-1$. The data to test the real/monetary predictor model is available from the fourth quarter of 1982 to the third quarter of 2008.

The financial market predictor model includes the following variables: (1) $TERM\_SPREAD_{t-1}$, the average difference between the 10-year and short-term US government bond yields throughout quarter $t-1$, (2) $T\text{-}BILL_{t-1}$, the average short-term interest rate throughout quarter $t-1$, (3) $DEFAULT\_SPREAD_{t-1}$, the average difference between the BAA and AAA-rated corporate bond yields throughout quarter $t-1$, (4) $NFCI_{t-1}$, the average financial market conditions throughout quarter $t-1$, as measured by The Chicago Federal Reserve's National Financial Conditions Index, (5) $VALUE\_SPREAD_{t-1}$, the average natural log of the ratio of the book-to-market ratios of small value firms to small growth firms, (6) $VOLATILITY_{t-1}$, market return volatility during quarter $t-1$, estimated as the annualized standard deviation of daily returns on the CRSP value-weighted market index in quarter $t-1$. The data to test the financial market predictor model is available from the second quarter of 1973 to the fourth quarter of 2011.

The proportion of correctly identified states is estimated relative to a 0.5 success cut-off. The Likelihood Ratio (*LR*) statistic is estimated as twice the difference between the log-likelihood of the unrestricted model and the benchmark model with the intercept only. Under the null hypothesis of having no predictive power, the *LR* statistic is distributed as a χ^2_m , with *m* being the number of predictor variables. The Hosmer-Lemeshow (H-L) test assesses whether the observed event rate matches the expected event rate in the identified subgroup of the model population. All *z*-statistics were calculated using Huber-White robust standard errors. Significance levels of 1%, 5%, and 10% (two-tailed) are denoted by ***, **, and *, respectively.

high. Default spreads reflect market expectations regarding future conditions in the credit market, in that higher default spreads are associated with worsening credit market conditions (e.g., Gertler et al., 1991; Kashyap et al., 1994). Second, the overall financial market conditions were weak given that higher values of *NFCI* indicate weaker market conditions. Third, the difference between the book-to-market ratios of small value firms versus small growth firms was high, which suggests that the value premium for small firms was high. Overall, the results for these three indicators suggest that the economy is less likely to be in state 1 when market participants expect higher market risk.

Collectively, the results reported in this section suggest that state 1 and state 2 represent different states of the economy. The results also suggest that real, monetary, and financial market indicators are useful for predicting whether the economy in the earnings announcement quarter is in state 1 or in state 2. Overall, the results suggest that the likelihood of the economy being in state 1—and thus the likelihood of market participants interpreting aggregate earnings surprises as being informative about changes in the expected inflation rate—associates positively with expectations of (1) a higher inflationary environment, (2) an improvement in macroeconomic conditions, and/or (3) lower market risk. In contrast, the likelihood of the economy being in state 2—and thus the likelihood of market participants interpreting aggregate earnings surprises as being informative about changes in the market risk premium—associates positively with expectations of (1) a lower inflationary environment, (2) worsening macroeconomic conditions, and/or (3) higher market risk.[31]

6. Summary and conclusions

Prior studies report a negative aggregate earnings-returns relation, concluding that aggregate earnings, on average, are associated positively with changes in the discount rate, and in particular changes in the expected inflation rate. In contrast, we propose a three-step conceptual framework, positing that the sign of the aggregate earnings-returns relation can be positive or negative, with the sign dependent upon the macroeconomic and financial market conditions that exist at the time earnings are announced. We examine each step in our conceptual framework separately. First, using a Markov-switching regression model we identify two states, with the states having opposite signs for the aggregate earnings-returns relation. Further, the sign of the relation changes numerous times over our sample period. Second, we find that market participants' interpretation of what aggregate earnings are informative about is different in the two states. Specifically, in the state where the aggregate earnings-returns relation is negative, our results suggest that market participants interpret aggregate earnings surprises to be informative about changes in the expected inflation rate; in contrast, in the state where the aggregate earnings-returns relation is positive, market participants interpret aggregate earnings surprises to be informative about changes in the market risk premium. We find no evidence in either state that market participants interpret aggregate earnings surprises to be informative about aggregate future cash flows. Finally, we identify real economy, monetary, and financial market indicators that are useful for predicting whether the economy in the earnings announcement quarter is in the negative relation state or in the positive relation state. We find that the likelihood of the economy being in the negative (positive) relation state associates positively (negatively) with expectations of a higher (lower) inflationary environment, improving (worsening) macroeconomic conditions, and/or lower (higher) market risk.

Collectively, our findings suggest that the aggregate earnings-returns relation is dynamic, with the sign dependent upon the macroeconomic and financial market conditions that exist in the earnings announcement quarter. Accordingly, understanding the association between stock market returns and aggregate earnings surprises requires an understanding of the underlying macroeconomic and financial market conditions that affect the way market participants perceive and interpret information about aggregate earnings.

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[31] We conduct two additional tests. In the first, we assess the out-of-sample predictive ability of both the real/monetary predictor model and the financial market predictor model using a rolling window estimation approach. The financial (real/monetary) predictor model outperforms the naive benchmark model by 20 (11) percentage points. In the second test, we replace the dependent binary variable in Equations (13) and (14) with the estimated smoothed probability of state 1 and estimate the models using least squares. The results (untabulated) are qualitatively similar to those reported.

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