EARNINGS EXTRAPOLATION AND PREDICTABLE STOCK MARKET RETURNS*

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Abstract

The U.S. stock market's return during the first month of a quarter correlates strongly with returns in future months, but the correlation is negative if the future month is the first month of a quarter, and positive if it is not. These effects offset, leaving the market return with its weak unconditional predictive ability known to the literature. The pattern accords with a model in which investors extrapolate announced earnings to predict future earnings, not recognizing that earnings in the first month of a quarter are inherently less predictable than in other months. Survey data support this model, as does out-of-sample evidence across industries and international markets. These results challenge the Efficient Market Hypothesis and advance a novel mechanism of expectation formation.

Keywords: Announcements, Stock Returns, Behavioral Finance

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1 Introduction

Predicting stock market returns with past returns is famously difficult. Kendall and Hill (1953) and Fama (1965) documented decades ago that serial correlations in stock returns are close to zero. In his seminal work, Fama (1970) defines the weakest form of the Efficient Market Hypothesis as that prices reflect all information in past prices. This hypothesis appears to work especially well for the US aggregate market. Poterba and Summers (1988) show, for example, that monthly market returns in the US have a small, insignificant positive autocorrelation over a horizon of 12 months. The lack of correlation between past and future market returns in the US is not only a widely accepted statistical phenomenon, but also an emblem of market efficiency.

I document that the US market return in the first month of a quarter in fact strongly correlates with returns in future months, with the correlation being strongly negative if the *forecasted* month is the first month of a quarter (i.e. January, April, July, and October) and strongly positive if it is not. This result can be understood as a two-step refinement of regressing one month's return on past 12 months' return. The first step is to condition on the timing of the dependent variable. The market return in the first month of a quarter is strongly negatively predicted by the return in the preceding 12 months, whereas the returns in the second and third months of the quarter are strongly positively predicted by the past 12 months' return. This distinction is already strong, highly significant at the one percent level, but it becomes even stronger after taking the second step—refining the independent variable. Specifically, among any 12 consecutive months, exactly 4 are first months of a quarter, and these 4 months are especially useful for predicting future returns.

These first months of a quarter are special and important to investors because they contain fresh earnings news. This is due to the nature of the earnings cycle in the US. Take January as an example. At the end of the December, firms close their books for Q4, and they announce Q4 earnings in January, February, and March. January therefore contains the early earnings announcements and is the first time that investors learn about the economy's performance in Q4. February and March also contain a sizable fraction of earnings announcements, but by that time investors have already learned much about Q4. The first months of the quarters are famously known as the "earnings seasons" among practitioners and receive heightened attention. Throughout this paper, I refer to them as "newsy" months, as they produce fresh earnings news. I call the other 8 months "non-newsy" months.

I hypothesize that the above pattern of market return predictability arises from imperfectly rational investors who extrapolate newsy month earnings to predict earnings in future months but fail to account for the inherent variation of such predictability across these future months. Because earnings autocorrelate across multiple fiscal quarters, this practice of extrapolation is broadly correct. However, earnings announced in the newsy months are more difficult to predict than those announced in other months. This is because in the newsy months firms report on a new fiscal period, and these earnings naturally have lower correlation with past earnings. This lower correlation is the concrete meaning of fresh earnings news. On the other hand, earnings in the non-newsy months have higher correlation with the past. A rational investor should accordingly predict with a time-varying parameter. However, if the investor fails to recognize this variation and extrapolates with the average parameter value instead, then good news in the past predicts negative surprises in future newsy months and positive surprises in future non-newsy months. These predictable surprises then give rise to predictable return reversal (continuation) in newsy (non-newsy) months. Furthermore, even as investors naively extrapolate, their expectations will tend to shift more in newsy months, making the returns in those months especially useful in predicting future returns.

Having stated my hypothesis, I test its immediate predictions. I start by showing that the serial correlation structure of aggregate earnings, as measured by aggregate return on equity (ROE), is indeed significantly lower in the newsy months. This evidence substantiates one premise of my hypothesis. I then show with survey data from IBES that sell-side analysts indeed fail to account fully for this variation in earnings autocorrelation, consequently leaving different types of predictability in earnings surprises through the earnings cycle. This evidence is uniquely useful because survey data are direct measures of market expectations, albeit imperfect. Moreover, I show that the predictable reversals in aggregate market returns do not occur until the earnings seasons begin. This alignment in timing suggests that it is indeed the earnings seasons that drive the return predictability, as opposed to other quarterly fluctuations unrelated to earnings announcements.

The return predictability results of this paper are motivated by, but not constrained to, the time-series setting. In additional to predictions confirmed in the time series setting, my theory also makes predictions about cross sections. In particular, the imperfect extrapolation mechanism that I propose potentially applies to the cross sections of industries and countries. Motivated by these natural extensions, I uncover a similar return predictability pattern in the cross section of industry excess returns.[1] Continuation in the cross section of stock returns, as in Jegadeesh and Titman (1993), has also been extensively studied. Unlike the weak continuation found in the US aggregate market, momentum in excess stock returns is a much stronger and more robust effect (e.g., Asness et al. (2013)), and the industry component is shown to drive a large fraction of it (Moskowitz and Grinblatt (1999)). This paper shows that the strength of the continuation in the cross section of industry returns also varies over time. Similar to the results found in the aggregate market, industry momentum is strong in the non-newsy months but virtually non-existent in the newsy months. Moreover, this dynamic momentum pattern is very strong in industries with tightly connected fundamentals and

[1] It technically also exists in the cross section of stock returns. The effect however operates entirely through the industry components of these stock returns.

weak in loosely connected industries, as my theory predicts. Additionally, I find a similar pattern in country momentum (Moskowitz et al. (2012), Garg et al. (2021)), and in country-industry momentum. This consistency across multiple contexts is remarkable and not always seen in studies of return predictability. These cross-sectional results not only expand the scope of this paper, but also provide important out-of-sample evidence.[2]

I also note that it seems difficult to explain the return predictability results with a risk-based framework. Presumably, in such a framework, after a good newsy month the future newsy months would be safe, but the future non-newsy months would be risky. Moreover, expected market returns implied by my results are frequently negative, so consequently a risk-based explanation would imply that the stock market is frequently safer than cash. However, common macro-based risk measures such as the surplus consumption ratio (Campbell and Cochrane (1999)) do not vary strongly at the monthly frequency, and even if they do, they are unlikely to be able to make the stock market safer than cash. Therefore, the most natural explanation for the novel predictability documented in this paper involves investors who make mistake. Such an explanation likely resides in the area of behavioral finance.

Fama (1998) makes an important critique of behavioral finance, which is that in this literature, return reversal and continuation appear about equally frequently, and the evidence accords with the Efficient Market Hypothesis if viewed together. This paper provides a response to this critique by predicting when return continuation and reversal occur. The response is specific to the context of the earnings reporting cycle,

[2]The most common approach of out-of-sample analysis in the context of return predictability is that in Mclean and Pontiff (2016) and Hou et al. (2018), which look at a signal's performance after its publication. This is by definition not something that one can run at the time of publication. Another approach is that utilized by Jensen et al. (2021), which involves looking at a larger and significantly different dataset, such as one consisting of different countries. Here, I am taking this second approach. Incidentally, another concept of 'out-of-sample' involves removing look-ahead-bias in the parameter estimation process. This is a point made by Goyal and Welch (2008) and is especially relevant to time-series signals. I will address this important point later in my paper, but 'out-of-sample' has a different meaning in their context.

but the latter is an important and universal aspect of the financial market that leads to strong return predictability across multiple contexts. The evidence in this paper together speaks in favor of a novel mechanism of expectation formation, which features fundamentals extrapolation with a "representative parameter" in lieu of a correct, time-varying parameter.

The rest of this paper is structured as follows: Section 2 relates this paper to the existing literature. Section 3 describes my data. Section 4 demonstrates the key return predictability results in US market returns. Section 5 provides intuition behind those results, and it substantiates the intuition using fundamental data. Section 6 provides a simple stylized model with closed-form solutions that qualitatively illustrate the intuition in Section 5. Section 7 performs supplementary analyses to test my theory in further depth. Section 8 discusses alternative explanations. Section 9 concludes.

2 Related literature

This study relates to various ares of existing literature, beyond the branch that directly focuses on return autocorrelation. My theoretical framework relates to a large body of work in behavioral finance that focuses on the notions of under-, and over-reaction, which naturally lead to predictable return continuation and reversal. However, relatively few paper has a model that simultaneously features under- and over-reaction, both of which are necessary for my purpose. Such a framework would be useful, as it informs us under what circumstances should one observe under- rather than over-reaction. Barberis et al. (1998) is a prominent piece of early work that achieves this. Starting with an earnings process that follows a random walk, they show that if investors incorrectly believe that the autocorrelation structure of this earnings process is dynamic—specifically, that the structure follows a two-state regime-switching model featuring continuation and reversal—then they will overreact to news that seems to be in a sequence, and underreact to news that seems not. My framework uses the opposite mechanism as that in Barberis et al. (1998). In my model, the autocorrelation of earnings process is actually dynamic, but investors incorrectly believe it is constant.

It is worth noting that while the broader logic behind such a mechanism is relatively new in the literature, the paper is not alone in employing it. Specifically, Matthies (2018) finds that beliefs about covariance exhibit compression towards moderate values in the context of natural gas and electric futures, as well as macroeconomic forecasts. Wang (2020) documents autocorrelation compression in the context of the yield curve. Behind our papers is a particular bounded-rationality mechanism where investors' limited cognitive capacity prevents them from fully exploring the heterogeneity of a parameter, leading them to simply use a moderate representative value instead.

This paper contributes to the literature on fundamentals extrapolation (Lakonishok et al. (1994), Greenwood and Hanson (2013), Nagel and Xu (2019)). An important mechanism behind extrapolative practices is diagnostic expectations (Bordalo et al. (2019), Bordalo et al. (2020), Bordalo et al. (2021b)). Investors who form expectations diagnostically overestimate the probabilities of the states that have recently become more likely, resulting in overall over-extrapolation.[3] In my framework, the level of extrapolation is moderate and correct on average. However, the level is incorrect in a specific month, as the earnings announced in that month will have either higher or lower correlation with past earnings than expected. Under- and over-extrapolation coexist in my framework. They are just targeting earnings of different months.

This paper relates also to work on predictable yet eventually surprising fundamental changes, e.g. Hartzmark and Solomon (2013) and Chang et al. (2017). This line of works shows that events that discretely yet *predictably* break from the past, e.g. issuing of large dividends or having seasonally high earnings, can still surprise investors and

[3]Diagnostic expectation has a psychological root, e.g. Bordalo et al. (2021a).

lead to positive excess returns on the corresponding firms. Extending this intuition to the aggregate market, one can understand the earnings announcements early in the earnings reporting cycles as trend breaking events, as the announced earnings have discretely yet predictably lower correlation with past earnings. If investors also fail to anticipate this drop, we will observe reversals of aggregate returns in the newsy months. Hence, this line of literature is especially relevant to the reversal arm in the dynamic serial correlation of the stock returns.

A feature of my model is that investors do not fully appreciate the correlation between earnings revealed early and late in the earnings reporting cycle. Enke and Zimmermann (2017) show in an experimental setting that subjects fail to discount correlated news despite the simple setup and extensive instructions and control questions. Fedyk and Hodson (2019) document that old 'news' on Bloomberg terminals—especially ones that combine multiple sources and are not direct reprints—generates overreactions in the abnormal returns of the associated stocks that are corrected in the subsequent days. The continuation arm of my results shares this theme, even though my results are on the aggregate level and over a longer horizon (monthly).[4] It is worth noting that even though the literature of correlation neglect and predictable fundamentals can individually explain the continuation and reversal arms of the returns, having a single explanation, i.e. parameter moderation, for both arms still adds meaningfully to the behavioral finance literature.

This paper also falls into the broader literature that studies the interaction between earnings announcements and stock returns (e.g., Beaver (1968), Bernard and Thomas (1989), Bernard and Thomas (1990), Chen et al. (2020b), Johnson et al. (2020)). An important piece of recent work in this area is Savor and Wilson (2016), which focuses on weekly stock returns. The authors first confirm that stocks have high returns

[4] My framework and correlation neglect predict different forms of return reversal. This is discussed in more details in Appendix A.

on earnings announcement-week (as in Beaver (1968)), and additionally show that stocks that have high announcement-week returns in the past are likely to have high announcement-week returns in the future. Among other things, the authors also show that early announcers earn higher returns than late announcers, and firms that are expected to announce in the near-term future have higher betas with respect to the announcing portfolios. Overall, the authors make a convincing case that earnings announcements of individual firms resolve systematic risks that have implications for the broader market.

Instead of the risks and the mean (excess) returns associated with earnings announcements, my paper focuses on the under- and over-reaction that are potentially related to them, as well as the resulting lead-lag relation of stock returns. Also, instead of the returns of the portfolio that long the announcing firms and short the non-announcing firms, I focus on the aggregate market returns or the industry-level returns in excess of the market, neither of which strongly correlate with the spread between the announcing and non-announcing portfolios. In addition to these high level distinctions, specific differences in empirical results will be further discussed later in Section 8.

This paper also relates to the broad literature studying the seasonality of stock returns, documented by Heston and Sadka (2008) and extended by Keloharju et al. (2016). This literature also studies the autocorrelation of stock returns, and makes the point that full-year lags have especially strong predictive power, which is a distinction of the *independent* variable. The main point of my paper, however, is that the predictive power of past returns is different according to the timing of the *dependent* variable. Philosophically, Heston and Sadka (2008) and Keloharju et al. (2016) are consistent with the notion of stationarity of stock returns, while my paper challenges it—specifically, the notion that the autocorrelation coefficients depend on displacement and not time. Again, specific distinctions will be further discussed in Section 8.

The portion of this paper studying the industry level returns relates to a large accounting literature studying the information transfer within industry. Foster (1981) first documented that earnings announcements have strong impact on stock prices of other firms in the same industry. Clinch and Sinclair (1987) confirm and extend this result on a sample of Australian firms; Han and Wild (1990) and Hann et al. (2019) confirm similar results using alternative measures of information; Han et al. (1989) and Brochet et al. (2018) do so with alternative announcements. Related, the literature has also documented that such learning is often imperfect and lead to predictable errors: Ramnath (2002) documents that news announced by the first announcer in the industry positively predicts surprises in subsequent announcements in the same industry, and argues that investors underreact to these first announcements; Thomas and Zhang (2008) confirm this finding, but additionally point out that within the same industry, the late announcers' excess returns during early announcers' announcements negatively predict these late announcers' own announcement excess returns. This suggests that investors overreact to these early announcements.[5][6] My paper differs from this literature on several aspects: It focuses on industry level excess returns as opposed to stock level in the context of both the independent and the dependent variables. Also, the frequency I focus on is monthly, as opposed to daily. Lastly, I am interested in both intra-quarter and cross-quarter relations, as opposed to just the former. My paper therefore provides additional value to the accounting literature.

[5] The two seemingly contradictory results both exist and are in fact quite robust in my replication. Their appearance of conflict highlights the imprecision in using under/overreaction to describe return predictability patterns. The two patterns can naturally be explained together with one story, which is that investors correctly extrapolate information from these early announcers, but fail to distinguish between industry level information, which they should extrapolate, and idiosyncratic information, which thy should not.

[6] Figure 1 of Thomas and Zhang (2008) cleanly summarizes the variety of predictability in this space.

3 Data

In terms of data sources, in the US, my return data come from CRSP, accounting data come from Compustat North America, and EPS forecast data come from IBES Detail History (adjusted). These are common data sources used by a large number of studies. There are two main sources of earnings announcement dates in the US: Compustat and IBES. Both data sources have been individually used in major studies. These announcement days often disagree, though the disagreements are usually small and are mostly concentrated before December 1994 (see Dellavigna and Pollet (2009), for instance, for a discussion). For my purpose, this source of discrepancy is unlikely to make a difference, but out of an abundance of caution, I implement the algorithm in Dellavigna and Pollet (2009), which combines the Compustat and the IBES announcement dates to form the best estimate of the actual announcement dates.[7] In the event that the adjusted announcement date is the same as the IBES announcement date, I also shift the date to the next trading date if the IBES announcement time is after the market closure. This follows Johnson and So (2018a), who implement the same algorithm.

Outside US, my stock level return data mainly come from Compustat Global. The only exceptions are Canadian data, which come from Compustat North America. My country level return data come from Global Financial Data (GFD). The reason why I use two different data sources of returns is that GFD provides country level return data with longer history, and Compustat provides the stock level data that I need for industry level studies. Compared to those focusing on the US market, studies employing global accounting data and global earnings announcement dates are in smaller numbers. However, there are still many prominent papers (e.g. Asness et al. (2019),

[7]The algorithm is effectively 1) when the two sources differ use the earlier date and 2) when they agree and the date is before Jan 1, 1990 shift the day to the previous trading date. Please see Dellavigna and Pollet (2009) for further details.

Jensen et al. (2021)), from which two data sources emerge: Compustat Global and Thomson Reuters Worldscope. I compared the two data sources. Both of them have good coverage of annual accounting data, but Worldscope provides substantially better coverage of quarterly and semi-annual accounting data than Compustat Global. Also, Worldscope records about 2 times as many earnings announcements. These two factors are especially important for my purpose. I therefore use Worldscope for my study. I use exchange rate data from Bloomberg to convert foreign currency denominated accounting data and stock returns into US dollar denominated ones.

In terms of specific variables used, in the US, I use 'value-weighted average return' (vwretd) to represent aggregate market returns, and SIC code to represent industries. I use 'Report Date of Quarterly Earnings' (rdq from Compustat) and 'Announcement Date, Actual' (anndats_act from IBES) for earnings announcement dates, 'Common/Ordinary Equity–Total' (ceqq) for book value of equity, and 'Income Before Extraordinary Items' (ibq) for earnings. Globally, I use item 5905 from Worldscope for earnings announcement dates, item 1551 for earnings, and item 7220 for book value of equity.[8]

4 Predicting the US aggregate market returns

In this section, I first describe the earnings reporting cycle in the US and then demonstrate that the serial correlation in the US aggregate market returns varies strongly within this cycle. For ease of expression, I first define three groups of months: "Group 1" contains January, April, July, and October, "Group 2" February, May, August, and November, and "Group 3" March, June, September, and December. They are the first, second, and the third months of quarters, respectively. In the US, I will call group 1

[8] It is useful to note that the data are obtained by directly querying the 'wsddata' and 'wsndata' tables of Worldscope. Using the Wharton Research Data Services' web query forms to download the data might result in incorrect exclusion of semi-annual accounting data (those keyed with freq of 'S').

months the "newsy" months. The reason that they are called newsy is they are when *fresh* news on firm earnings comes out *intensively*. The news is fresh because group 1 months immediately follow the end of the fiscal quarters, the majority of which are aligned with the calendar quarters. This is demonstrated in Table 1, which shows that in the US, about 85% of fiscal quarters end in the group 3 months. Moreover, Table 2 shows that in the US, about half of the firms announce within one month after the end of a fiscal period. In fact, among all of the three types of months, most firms announce in group 1 months. Therefore, group 1 months are when fresh news is reported intensively. The two features of freshness and intensity are the concrete meanings of the word "newsy." These newsy months largely correspond to the so-called 'earnings seasons', which is a term frequently used by practitioners. The bottom line is that in terms of the earnings news, in the US, group 1 months are the information-relevant months.

Having understood why these group 1 months are special, we look at Table 3, which reports results of the following monthly time-series regression that predicts the aggregate US stock market return: $mkt_t = \alpha + \sum_{j=1}^{4} \beta_j mkt_{nm(t,j)} + \epsilon_t$. Here $mkt_{nm(t,j)}$ is the j th "newsy" month return strictly before the month t. Unless otherwise noted, returns on those newsy months are put on the right-hand side of the regressions throughout my empirical analyses. Figure 1 thoroughly illustrates how lagging is done on the regression: Suppose the dependent variable is the return of November, then lag 1 newsy month (abbrv. lag 1nm) return is that of October, lag 2nm return is that of July and so on. As the dependent variable moves forward to December and January of the next year, the lagged newsy month returns on the right-hand side stay the same. However, when the dependent variable becomes the return of February, the lag 1nm return will move forward by three months to January, as that is the most recent newsy month strictly before February.

Having clarified the specifics of the regressions we move on to the results. Column

1 of Table 3 confirms the conventional view that the aggregate stock market exhibits only weak momentum with a look-back window of one year. Column 2 does the same regression, but only on the 1/3 of the sample where the dependent variables are returns of the newsy months. This column shows that in newsy months, returns are decidedly negatively correlated with past newsy month returns. Column 3 does the regression for the rest of the sample, where the dependent variables are returns of non-newsy months. In those months, returns are positively correlated with past newsy month returns. However, on average they cancel each other out, resulting in the weak unconditional predictive coefficients shown in column 1.

The main empirical finding of this paper is that the serial predictive relation in stock returns varies by the timing of the dependent variable. Column 4 delivers this main point by showing the difference in the coefficients of columns 2 and 3. While the differences are not monotonic with lags, they are clearly all negative, and overall the effect is stronger the smaller the lag. To evaluate the strength of the effect in different contexts, such as different historical periods, it is useful to have one coefficient instead of four. Throughout the empirical section, I use the sum of the first four lags, or $\sum_{j=1}^{4} mkt_{nm(t,j)}$, as the flagship signal. Since four lags correspond to the typical one-year look-back window of the various price momentum strategies, when I get to the cross section this choice will enable me to benchmark against those strategies and speak to when they work and don't work.

Table 4 focuses on the following regression: $mkt_t = \alpha + \beta \sum_{j=1}^{4} mkt_{nm(t,j)} + \epsilon_t$. Here $\sum_{j=1}^{4} mkt_{nm(t,j)}$ is the sum of the lag 1 to lag 4 newsy month returns, the said flagship signal. Its coefficient here roughly corresponds to the average of the first four coefficients[9] in Table 3. Column 1 shows the weak unconditional time-series momentum, pushed over the p-value cutoff of 5% by putting only the newsy month returns on the right-hand side (regressing on the past 12-month return will result in a t-stat of 0.60).

[9]This approximate relation works for returns but not in general.

Column 2 and 3 are the subsamples for newsy months and non-newsy months returns. Again we see strong negative predictive coefficients in newsy months and strong positive coefficients in non-newsy months. The difference in the coefficients, -0.232, is shown in the interaction term of column 4 with a t-stat of -4.93. These two values indicate that in the full CRSP sample of 1926-2021, the serial predictive relation of the US aggregate market return is strongly time varying. Columns 5-7 show that these results are strong in the post-WWII period, first half, and second half of the sample, though the effect is stronger in the first half of the sample.

Figure 2 compactly represents the results above. The red bars from left to right show that market returns during past newsy months negatively predict returns in future newsy months. The blue bars show that the relation flips if it is the non-newsy months that are being predicted.

It is worth noting that because the predictor in the regression consists of newsy month returns, when the dependent variable is newsy, it is further away from the predictor in terms of calendar time. In column 2 of Table 4, the predictor is on average 7.5 calendar months away from the dependent variable. In column 3, the distance is only 6 calendar months away. If return autocorrelation is greater the smaller the calendar lags, then the difference of 1.5 months can potentially contribute the difference between column 2 and 3 of Table 4.

To investigate the impact of calendar month lags on return autocorrelation, I perform a multiple regression of monthly aggregate market returns on its 12 calendar month lags. Figure 3 plots the resulting autoregressive coefficients. Notice that the fitted line across the lags is almost horizontal, with a slope of -0.00062. This shows that within the horizon of 12 calendar months—which is what is relevant for our regressions in Table 4, there is little relation between the calendar lag and autocorrelation. A slope of -0.00062 per lag, combined with a total difference of $1.5 \times 4 = 6$ calendar month lags, produces a product of -0.004. This is substantially smaller than the difference of

-0.232 shown in column 4 of Table 4.

Even though there isn't an appreciable association between return autocorrelation and calendar month lags, Figure 3 does show a positive autoregressive coefficient of 0.11 for the very first lag. This coefficient is in fact significant at the conventional 5% level. One may then worry that perhaps this first lag in itself drives the results in Table 4. To investigate whether this is the case, I run 10,000 simulations of AR(1) process with the autocorrelation being 0.11, and then run the regressions in Table 4 on each set of simulated sample of 1,136 monthly observations. Table 5 juxtaposes regressions done on real data with those done on simulated data. Column 1-3 are regression results on real data. Column 4-6 report averages of 10,000 regression coefficients, each of which is computed on a simulated sample. Column 1 repeats the previously shown main result, featuring a highly significantly negative coefficient of -0.232 on the interaction term. Column 4 is the corresponding regression done on simulated data. Here we instead observe a much smaller coefficient of -0.019 that is also not anywhere close to significance on samples of the same size. This evidence suggests that the difference in calendar lags does not drive my results.

One may still be curious on how the regressions behave if we simply use trailing 12 month returns as predictors, which holds the calendar lag constant, as opposed to trailing four newsy month returns, which do not. Column 2 of Table 5 does exactly that. Here we see that the results remain highly significant at 1% level,[10] even though less significant than those in column 1. Column 3 breaks down the trailing 12 month returns into the trailing 4 newsy month and the trailing 8 non-newsy month return. It shows that while market return's correlation with the past returns are generally lower when the dependent variable is newsy, from the perspective of independent variable, past newsy months are mainly responsible for this dynamic predictive relation. The

[10] It is worth mentioning the results in later sections also remain significant if we use trailing 12 month returns.

interaction term for the non-newsy months also gets a negative coefficient of -0.031, which means that similar dynamic predictability pattern also exists with respect to past non-newsy months. This relation, however, is weak. Consequently, the specification in column 2 behaves like column 1, except with more noise in the predictor. As we will see in the following sections, the proposed explanation for this pattern naturally applies better to the newsy months.

Lastly, one may wonder if this predictability can be profitably translated into a trading strategy that is implementable in real time. This is indeed a concern especially relevant for time series predictors. In fact, Goyal and Welch (2008) show that certain predictors of aggregate market return appear to work with full-sample information, but fail when implemented with information available in real time. In Appendix C, I construct a real-time, beta-neutral strategy based on the return predictability result documented in this section, and show that it leads to a information ratio of 0.44. This is about the same as the Sharpe ratio on aggregate market itself, and the trading strategy does not load on the market. The strategy's CAPM and Fama-French-Carhart four factor alphas are about 9% per annum. The results in Appendix C show that the predictability pattern documented in this paper can indeed be profitability translated into a trading strategy.

5 Intuition and earnings predictability

5.1 Intuition

In the past section, we saw that aggregate stock market returns in newsy months have lower correlation with past returns, and those in non-newsy months have higher correlation with past returns. This difference in correlation exists in multiple newsy month lags. In this section, I first provide intuitions on the reasons underlying this return predictability pattern, and then substantiate the premises behind these intuitions with fundamentals data.

Consider the following narrative: suppose investors forecast earnings outcome in the upcoming months based on past earnings. To fix idea, suppose that they have just observed positive earnings news in April from the announcing firms, and are (re)assessing their forecasts in May, June, and July. Because earnings are positively autocorrelated—which we will show in the next subsection—investors correctly think that earnings in the upcoming months are also good. In fact, earnings announced in May and June are *especially* likely to be good. This is because the announcing firms in those months are also announcing on Q1—perhaps Q1 is just a good quarter for everyone.

However, in July, earnings of Q2, a different fiscal quarter, will be announced. Since earnings are positively autocorrelated across multiple fiscal quarters, the numbers in July are still likely good, as Q2 and Q1 are only one fiscal quarter apart. However, earnings announced in May and June are *zero* fiscal quarter apart from that in April. Therefore, compared to those in May and June, earnings in July are less likely to resemble that in April. If investors fail to fully anticipate this *discrete* drop in earnings similarity, they will be disappointed in July. On the other hand, if they do not fully realize that the earnings in May and June are going to be especially good, they will be positively surprised in those months.[11]

To see why multiple lags can be significant in column 4 of Table 3, notice that if investors only forecast earnings in the next 3 months, then only one newsy month lag should be operative. If investors forecast more months ahead, say 6, then good news

[11]Thomson Reuters, which operates the IBES system, organize earnings forecasts with the 'FQx' labels, where FQ1 represents the closet fiscal quarter in the future for which the earnings have not been announced. FQ2 represents the 2nd closet fiscal quarter, and so forth. After an early announcer announce, say, in April, its next quarter earning—which is likely to be announced in July—will take the label FQ1. Notice earnings that will be announced in May and June also have the label FQ1. Those who participate in the Thomson Reuters' system and also use the result of this announcement to inform their future forecasts can potentially be nudged to think of May, June, and July together by this shared label.

back in January would have led to higher earnings expectations in May, June, and July—assuming that these initial reactions are not fully reversed before these target months.[12] These higher expectations are again correct in direction as earnings in May and June is only 1 fiscal quarter apart from that in January. In July, the distance becomes 2 fiscal quarters. If investors again treat this discrete drop in similarity as gradual, then good news in January would also correspond to positive surprises in May and June, and disappointment in July.

The story above narrates from the perspective of a given forecasting month. Pivoting to a given target month, the equivalent intuition is that aggregate earnings announced in the newsy months naturally have lower correlation with past earnings, since announcers in those months are announcing on a new fiscal quarter. This makes the earnings in newsy months further away from past earnings in terms of fiscal time, holding constant the distance in calendar time.[13] On the other hand, earnings in non-newsy months have higher correlation with past earnings. Consider investors who forecast next-month earnings using past earnings: If they treat the next month as an average month, i.e., they do not sufficiently distinguish whether the next month is newsy or non-newsy, then when past earnings have been good, in the upcoming newsy months the investors are likely to be disappointed, and in the upcoming non-newsy months they are likely to see positive surprises.

The behavior that I propose above can be compactly described as fundamentals extrapolation with a representative parameter. In the language of under- and over-

[12]This is an important assumption with an implication that I will verify with survey data: initial surprises should correspond to predictable surprises in the target months, as opposed to be fully corrected before the target months.

[13]The distinction between fiscal and calendar time is illustrated in Figure 4. For example, focusing on news in the lag 1 calendar quarter: when the forecasted month is group 1, the average fiscal time between the news in the forecasted month and that in the past calendar quarter is 1 fiscal quarter. When the forecasted month is group 2, the average distance shortens to 2/3 fiscal quarter, and for group 3 it is only 1/3 fiscal quarter. Note this relation holds for more than one lagged calendar quarter. The overarching message is that when investors are trying to forecast the earnings in the upcoming months, past information is more/less timely the later/earlier in the earnings reporting cycle.

reaction, this behavior implies that investors overreact when forecasting the earnings announced in future newsy months, and underreact when forecasting future non-newsy months earnings. Additionally, those newsy months are very natural time for investors to revise their forecasts of future earnings. Hence, the initial mis-reactions are likely more concentrated in the newsy months themselves. As the forecasted earnings are later announced, the initial misreactions get corrected, and return continuation and reversal emerge. Not only do the newsy (non-newsy) month returns correlate negatively (positively) with past returns in general, they correlate especially negatively (positively) with past newsy-month returns. This mis-reaction concentration feature does not endogenously arise from my framework of representative parameter. It is nonetheless an intuitive feature that the return data speak in favor of. I discuss how to formally incorporate this feature in the modeling section.

5.2 US fundamental news in calendar time

In this subsection we map the intuition in the previous subsection to fundamental data, and show that earnings announced early in the reporting cycle indeed have lower correlation with past earnings.

First, I need a measure of the previously mentioned "earnings" for a given month, and ideally without using return information: It would be the most helpful to explain the pattern in stock returns without using stock returns. The measure I choose is aggregate return on equity (ROE), which is aggregate quarterly earnings divided by aggregate book value of equity on the universe of stocks that announce in a given month. Notice that aggregate earnings themselves are non-stationary, and need to be scaled by something. I follow Vuolteenaho (2002) to use book value of equity, which could be thought of as a smoothed earnings measure over a long look-back window. This is because of the "clean accounting assumption," which holds reasonably well in reality (Campbell (2017)). This measure echoes with the literature studying aggregate earnings (e.g. Ball et al. (2009), Patatoukas (2014), Ball and Sadka (2015), Hann et al. (2020)), which shows that aggregate earnings convey important information for the economy. Overall, ROE is a simple and reasonable manifestation of earnings, with which I can quantitatively illustrate the intuition in the previous section.

Having picked the specific earnings measure, I construct this measure for each calendar month among all the firms that announce in the month. Column 1 of Table 6 performs a simple regression of aggregate ROE on the sum of aggregate ROE over the past months, and the result is simple and easy to interpret: the coefficient is significantly positive, indicating it is indeed reasonable for investors to extrapolate past earnings to forecast the future. However, columns 2-3 show that there are important complications underneath this simple result, which is that this extrapolation works substantially less well when the forecasted month is newsy, and that it works much better when the forecasted month is non-newsy. Column 4 demonstrates that this difference is statistically significant. Panel A performs the regressions only on firms with fiscal quarters aligned with calendar quarters and also timely reporting. This may lead to the concern that this does not represent the real experience of investors, who observe all announcements of all firms. Panel B-D include these other firms and show that the result is qualitatively similar.

What if the investors do not consider the complications in column 2-4, and use only the simple and static results in column 1? In that case, when past earnings are good, you would see negative surprises in upcoming newsy months; in the non-newsy months you would see positive surprises. When forecasting earnings of these newsy months you overreacted in the past; in forecasting these non-newsy month earnings you underreacted in the past.

Notice it is not quite accurate to simply say that people underreact to news in the newsy months. If return continues over some horizons after the newsy months, one can characterize investors' initial reactions in the newsy months as underreactions. This indeed seems to be the case if one look at horizons that are less than two months, but in the third month the return reverses and the overall continuation weakens substantially. Besides, the main point of this paper is the *difference* in the return serial correlations between newsy and non-newsy months, not the sum.

It is more accurate to say that reactions to news in newsy months contain both under- and overreactions. Specifically, reactions to news about future newsy months are overreactions, and will be met with surprises in the opposite direction in future newsy months. On the other hand, reactions to news about future non-newsy months are underreactions, and will be met with surprises in the same direction in future non-newsy months. Notice this is not a simple underreaction or overreaction story, but instead is a framework featuring one mechanism of imperfect extrapolation, from which both under- and over-reaction arise.[14]

6 Stylized model

In this section I build a stylized model to formalized the intuition stated in earlier sections. I present the simplest model that gets to the most important feature of the data which is that newsy month returns are being more negatively predicted by past returns, relative to the non-newsy month returns. A feature of the data that I leave out of the model is that the newsy month returns themselves are responsible for positively and negatively predicting future returns. I discuss how to modify the model to incorporate this feature at the end of the section. The model is inspired by Guo and Wachter (2019). Consider an infinite-horizon discrete-time economy with risk-neutral investors. Let D_t denote the aggregate dividend at time t, and $d_t = \log D_t$. Define $\Delta d_t = d_t - b_{t-1} = d_t - (1-\rho)(\sum_{i=0}^{\infty} \rho^i d_{t-1-i})$. Here, b_{t-1} is an exponentially

[14]This is also distinctive from a story of correlation neglect, which states that the overreaction is in the second months of the quarters. The distinction is carefully discussed in Appendix A. Evidence supporting correlation neglect is documented in Table A1.

weighted moving average of past dividends. Assuming a stable payout ratio, dividend and earnings will be tightly related. b_{t-1} then resembles a scaled version of book value of equity, which is an accumulation of past retained earnings. The measure Δd_t then mimics the ROE measure that I used in my previous analyses. While the relation is not exact and involves major simplifying assumptions, this setup does lead to a simple, closed-form solution. I choose this setup to balance the simplicity in the model and the connection with my empirical analyses.[15]

Consider investors in month $t-j$ who have just observed Δd_{t-j}. They, being reasonably extrapolative, make an adjustment of $m\delta^{j+1}\Delta d_{t-j}$ on their forecast of Δd_{t+1}. Here m represents the degree of extrapolation, and δ^{j+1} the decay over time. Then, assuming the changes made in each month are additive, it follows that investors' forecast for Δd_{t+1} is $m\sum_{j=0}^{\infty}\delta^j\Delta d_{t-j}$ at the end of month t. Formally, let the investors believe:

$$\Delta d_{t+1} = m\sum_{j=0}^{\infty}\delta^j\Delta d_{t-j} + u_{t+1} \tag{1}$$

$$u_t \overset{iid}{\sim} N(0,\sigma_u), \quad \forall t \tag{2}$$

And more generally, for all $i \geq 1$:

$$\Delta d_{t+i} = m\sum_{j=0}^{\infty}\delta^j\Delta d_{t+i-1-j} + u_{t+i} \tag{3}$$

$$u_t \overset{iid}{\sim} N(0,\sigma_u), \quad \forall t \tag{4}$$

In other words, the investors extrapolate an exponentially weighted moving average (EWMA) of past cash flow growth. The decay parameter in the EWMA δ and the

[15] A simpler way to model this is to let $\Delta d_t = d_t - d_{t-1}$, or period over period dividend growth. This is in fact a special case of my setup where ρ equals 0. It leads to an even simpler model with fewer state variables, and conveys very similar intuitions. The measure is however different from what I use in the empirical section. Another way of modeling this is to literally model book value of equity as the sum of past retained earnings. This approach does not lead to closed-form solutions.

degree of extrapolation m lie between 0 and 1. Denote $x_t = \sum_{j=0}^{\infty} \delta^j \Delta d_{t-j}$, so that investors expect $\Delta d_{t+1} = m x_t + u_{t+1}$. Notice x_{t+1} can be recursively written as:

$$x_{t+1} = \Delta d_{t+1} + \delta x_t \tag{5}$$

This recursive relation does not involve the investors' beliefs yet. Now given the investors' beliefs of future cash flow growth, it follows that they believe the following process of x going forward:

$$\begin{aligned} x_{t+1} &= \Delta d_{t+1} + \delta x_t & (6) \\ &= m x_t + u_{t+1} + \delta x_t & (7) \\ &= (m + \delta) x_t + u_{t+1} & (8) \end{aligned}$$

A similar relation applies beyond period $t + 1$. Notice $m + \delta$ needs to be less than 1 for the process of x_t to be stationary in the investors' minds.

While the investors use a constant extrapolation parameter m in their beliefs, in reality the process is driven by a dynamic parameter that takes values h and l in alternating periods, where $l < m < h$:

$$\Delta d_{t+1} = \begin{cases} h x_t + u_{t+1}, & \text{where } t \text{ is even} \\ l x_t + u_{t+1}, & \text{where } t \text{ is odd} \end{cases}$$

This reduced-form setup maps to the empirical ROE dynamics described in previous sections. While such dynamics are caused by heterogeneity in reporting lag among firms that share a persistent time component in earnings, I do not model this particular mechanism.[16] Given this cash flow process in reality, x_{t+1} actually follows the process:

$$x_{t+1} = \delta x_t + \Delta d_{t+1} = \begin{cases} (h+\delta)x_t + u_{t+1}, \text{ where } t \text{ is even} \\ (l+\delta)x_t + u_{t+1}, \text{ where } t \text{ is odd} \end{cases}$$

Having set up the investors' beliefs and how they deviate from reality, I now compute the equilibrium valuation ratio, which requires solely the beliefs, and the equilibrium equity returns, which require both the beliefs and the reality. Denote the current dividend on the aggregate market D_t. Let P_{nt} be the price of an equity strip that expires n periods away. Define:

$$F_n(x_t) = \frac{P_{nt}}{D_t} \tag{9}$$

We now show that $F_n(x_t)$ is indeed a function of x_t, our state variable representing past cash flow growth. Notice $F_n(x_t)$ must satisfy the following recursive relation:

$$F_n(x_t) = E_t[rF_{n-1}(x_{t+1})\frac{D_{t+1}}{D_t}] \tag{10}$$

Where r is the time discounting parameter of the investors. Conjecture $F_n(x_t) = e^{a_n+b_nx_t+c_n\Delta d_t}$. Notice the relation $d_{t+1} - d_t = \Delta d_{t+1} - \rho\Delta d_t$. This is key to a simple solution in closed form. Substitute the conjecture back into equation 10 and take the log of both sides:

$$a_n+b_nx_t+c_n\Delta d_t = \log r+a_{n-1}+(b_{n-1}(m+\delta)+(c_{n-1}+1)m)x_t-\rho\Delta d_t+\frac{1}{2}(b_{n-1}+c_{n-1}+1)^2\sigma_u^2 \tag{11}$$

[16] In an alternative version of the model, I model the underlying quarterly earnings as a persistent process and monthly earnings as quarterly earnings broken with randomness. This more realistic approach delivers similar intuition as my baseline model, but not closed-from solution.

Which leads to the following recursive relation for a_n, b_n, and c_n:

$$
\begin{aligned}
a_n &= a_{n-1} + \log r + \frac{1}{2}(b_{n-1} + c_{n-1} + 1)^2 \sigma_u^2 \qquad (12) \\
b_n &= b_{n-1}(m + \delta) + m(1 + c_{n-1}) \qquad (13) \\
c_n &= -\rho \qquad (14)
\end{aligned}
$$

Notice equation 14 along with the boundary condition of $b_0 = 0$ implies the solution:

$$b_n = \frac{1 - (m + \delta)^n}{1 - m - \delta} m(1 - \rho) \qquad (15)$$

And a_n can be pinned down accordingly. Notice the sequence of b_n is a positive, increasing sequence that approach a potentially large limit $\frac{m(1-\rho)}{1-m-\delta}$. Intuitively speaking, when x_t is high, dividends growth is expected to be high in the future, and therefore current valuation is high.[17]

Having solved for the valuation ratios of an equity strip that expires n periods away, we bring in the actual cash flow process to compute its return $R_{n,t+1}$. For even t, notice the log return needs to follow:

$$
\begin{aligned}
\log(1 + R_{n,t+1}) &= \log(\frac{F_{n-1}(x_{t+1})}{F_n(x_t)} \frac{D_{t+1}}{D_t}) \\
&= a_{n-1} - a_n + b_{n-1} x_{t+1} - b_n x_t + c_{n-1} \Delta d_{t+1} - c_n \Delta d_t \\
&\quad + \Delta d_{t+1} - \rho \Delta d_t \\
&= a_{n-1} - a_n + b_{n-1}((h + \delta) x_t + u_{t+1}) - b_n x_t + (c_{n-1} + 1)(h x_t + u_{t+1}) \\
&= a_{n-1} - a_n + (h - m)(b_{n-1} + (1 - \rho)) x_t + (b_{n-1} + (1 - \rho)) u_{t+1}
\end{aligned}
$$

[17] The loading on Δd_t is $-\rho$ because there is a reversal effect, which can be understood by considering the extreme case of $\rho = 1$. In that case, Δd_t equals d_t, and this means that investors expect the *level* of the dividend to mean revert. Hence high dividend implies low dividend growth in the future, and thereby leads to low current valuation. Notice the loading $-\rho$ does not change with n and the coefficients b_n can eventually have a much larger effect.

Similarly, for odd t, we have:

$$\log(1 + R_{n,t+1}) = a_{n-1} - a_n + (l - m)(b_{n-1} + (1 - \rho))x_t + (b_{n-1} + (1 - \rho))u_{t+1}$$

Two points are worth noting: First, in returns there is an unpredictable component $(b_{n-1} + (1 - \rho))u_{t+1}$ that is completely driven by the unpredictable component in cash flow growth. Cash flow growth therefore correlates positively with contemporaneous returns. Since returns are largely unpredictable, this component accounts for most of their variation. Second, there is a predictable component that takes alternate signs. Hence, in the months where cash flow growth has high/low correlation with past growth, as represented by x_t, past cash flow growth positively/negatively forecasts the return. Given the contemporaneous correlation between return and cash flow growth, past returns would also positively/negatively forecast current return in the high/low correlation months.

Notice that this simple model has a few counterfactual aspects. First, it predicts that returns and cash flow surprises are very highly correlated. In the data they are only weakly positively correlated. This is because investors extrapolate the entirety of Δd_t, which then feeds into x_t and drives valuation and return. A more realistic framework would feature investors who understand that part of the realized cash flow is purely transitory and correctly leave them out of the state variable x_t. I write down such a model in Appendix B.1.

Second, the baseline model predicts that all past returns—whether they are newsy month returns or not—negatively predict future newsy month returns and positively predict non-newsy month returns. In the data this distinction is much stronger when past newsy month returns are used to forecast future returns. Notice in Table 3 and 4 only the newsy month returns are used on the right-hand-side of the regressions. This feature can be incorporated by letting the Δd_t in the l realization periods go into

x_t with higher weights. The economic meaning of this modification is that investors perform especially intensive expectation formation in earnings seasons. While this may be an intuitive premise, it is a feature that does not arise naturally from the model but rather needs to be added. A version of this model that incorporates this feature is written down in Appendix B.2.

7 Additional tests

7.1 First week of the quarter and first quarter of the year

In this subsection I present further evidence on the relation between the predictability pattern of aggregate market returns and the earnings reporting cycle.

First, in my previous analysis I focused on monthly stock returns, and therefore used the concept of newsy months. However, the period of intensive earnings reporting, or the earnings season, does not start immediately on the first day of the newsy months. In fact, among firms with fiscal periods aligned with calendar quarters, only 0.27% of their earnings announcements occur within the first week (more precisely, the first 5 trading days) of the quarter. This is an order of magnitude lower than what an average week contains, which is about 8% of the announcements. In contrast, the second week in each quarter sees 2.93% of the announcements, which is on the same order of magnitude as an average week. The reversal of market returns—if indeed arising from these earnings announcements—should not exist in the first week of the newsy months.

The left panel of Table 7 shows that this prediction is exactly true. While we have seen that past newsy month returns negatively predicts the next newsy month return (reproduced in column 1), the coefficient is close to zero in the first week of a newsy month. This weak coefficient is shown in column 2. Consequently, excluding the first week of the newsy months makes the reversal effect even stronger, as is in column 3.

The right panel of Table 7 shows that analogous patterns exist in other countries according to their own earnings seasons. For each country, I determine the pre-season period in the first months of the quarters by calculating the 0.5 percentile value of the reporting lag for that country. This value is then rounded down to the closet trading week to arrive at the length of the pre-season. For US, because the reporting is fast, this value converts to one trading week, which is the length used in the US analysis above. For the other countries reporting is slower, and the pre-season periods are often longer, ranging from 1 to 3 weeks. Column 5 shows that the market returns of these countries also do not reverse in their corresponding pre-season periods. In contrast, column 6 shows that the reversal is quite strong immediately outside these pre-season periods. This foreshadows the reversal arm of my global sample results, which I will demonstrate in more details in Section 7.3.2. Overall, Table 7 shows that the dynamic serial predictive relation in stock returns is indeed tied to the earnings seasons. This piece of evidence speaks in favor of stories involving these earnings reporting cycles and against those built upon other unrelated quarterly fluctuations.

In addition to the first week of each quarter, in the first quarter of each year we may also expect a weaker pattern of dynamic serial correlation of returns. The reasons are two-folded. First, in Q1 earnings reporting is substantially slower. The median reporting lag in the first quarter of the US is 41 days, while that for the other 3 quarters is 30 days. This is because firms need to additionally conduct 10-K filing in Q1, which takes resources that could otherwise be used for earnings announcements. Hence, January is less newsy than the other 3 newsy months. Second, in Q1 there are widespread tax related trading, which can potentially add unrelated movements to aggregate returns. Both reasons can lead to a weaker effect in Q1 than in the other 3 quarters. Table 8 shows that this is true. Comparing column 1-3 to 4-6, we see that in Q1 both the positive and negative arms of return predictability are weaker.

7.2 Evidence from survey data

In this subsection I test my theory with survey data from IBES. In the model, investors overreact when predicting earnings in the upcoming newsy months, and underreact when predicting those in the upcoming non-newsy months. It therefore has a key prediction, which is that past earnings surprises positively predict surprises in the upcoming non-newsy months, and negatively predict those in the upcoming newsy months.

To test this prediction, I use EPS estimates from IBES Detail History. IBES Summary History conveniently provides firm level consensus estimates, which are IBES's flagship product. However, it cannot be used in this particular case because these consensuses are struck in the middle of the month per Thomson Reuters' production cycle.[18] Since I use calendar month returns, I compute analogous consensus estimates at month ends, so that earnings surprises in a given calendar month can be measured relative to them.[19]

At the end of each month, each firm's consensus EPS estimate for a given fiscal period is computed as the median of the estimates that are issued in the past 180 days relative to the forecast date. For each analyst, only the most recent estimate is included in this calculation. This horizon is chosen to reflect the methodology with which the IBES consensus is computed.[20] The results of the analysis are qualitatively the same with a wide range of look-back windows.

A firm's earnings surprise in the announcing month is the announced earnings per share subtract its consensus forecast at the end of the previous month, and then divide by its stock price at the previous month end. I am adopting price as the scaling

[18]Specifically the Thursday before the third Friday of every month.

[19]Incidentally, the most frequently cited issue with IBES Summary—the practice of crude rounding combined with splits (Payne and Thomas (2003))—is not necessarily a grave concern for our purpose as we are looking at the aggregate data, and rounding errors cancel with each other if aggregated across many firms.

[20]This is according to the user manual of IBES.

variable as opposed to book value per share to align with the standard practice in the literature that studies earnings surprises (e.g. Hartzmark and Shue (2018)). The results are very similar if I instead use book value of equity per share. For each earnings announcement that occurs in month t, I aggregate their surprise measures with market cap weight to form the aggregate earnings surprise in month t, or Sup_t. I then run time-series predictive auto-regressions on Sup_t, and importantly, I separate the sample by whether the dependent variable is a newsy month, and examine whether the predictive coefficients differ in the two sub-samples.

Table 9 shows that we indeed observe a significantly lower predictive coefficient when the dependent variable is newsy. Column 1 shows that past surprises strongly positively predict the eventual aggregate earnings surprise on average. Column 2 shows that this predictive relation is less positive in the newsy months. Column 3 shows that it is much stronger in the non-newsy months. Column 4 shows that this difference between newsy and non-newsy months is statistically significant. Column 5 shows that this difference is especially strong if we use surprises in newsy months in the past to predict future aggregate earnings surprises. These significant differences are consistent with the key prediction of the model.

However, if the model is taken to be a literal model of survey data, we should not just expect a substantially weaker coefficient in column 2—we should see a negative coefficient, like in the regressions with aggregate market returns. We do not see this negative coefficient, because the overall underreaction among the analysts, reflected by a strongly positive coefficient in column 1, is an aspect that does not translate into market returns—the aggregate market returns in the US are only very weakly positively autocorrelated overall. This discrepancy suggests that the latency in the survey expectations is not completely present in the actual expectations of the market, and it is the latter that I model. A more realistic representation of survey expectation is perhaps an average between the timely market expectation and a smoothed measure of past expectations. In the wake of this modification, my model would generate this overall underreaction in the survey data. It would still predict that this underreaction is weaker in the newsy month, and Table 9 shows that this key prediction holds true.

7.3 Cross sectional analysis

7.3.1 US cross section of industries

The main intuition behind the theory is the follows: if a group of stocks are 1) tightly and obviously connected in fundamentals, so that investors actively learn one stock's information from other another stock's announcement and 2) sizable in number, so that the group as a whole reports progressively along the earnings reporting cycle, then earnings announced in the newsy months will correlate much less strongly with past news, compared to earnings announced in the non-newsy months. Failure to see this time-varying serial correlation structure of earnings will lead to the dynamic return predictability pattern shown above.

While it is very natural to apply this story first to all stocks in the US economy, it should additionally apply to the cross section of industry-level stock returns. Two random stocks in each industry of a country are more connected with each other than two random stocks drawn from the same country. An industry is therefore a smaller economy except better connected. As discussed in Section 1, extensive intra-industry information transfer during earnings announcements is well documented by the accounting literature (e.g. Foster (1981)). In this section, I test whether industry excess returns, or industry returns subtracting the aggregate market returns, exhibit a dynamic serial predictive relation similar to that in the aggregate market returns.

Table 10 shows the regression results of industry excess returns on past newsy month industry excess returns. While the structure of this table looks similar to that of Table 3, it differs in two aspects: First, Table 10 is on an industry-month panel instead of a monthly time series. Second, Table 10 uses industry excess returns as opposed to the aggregate market returns. What is used in Table 3 is what is being subtracted from the dependent and independent variables in Table 10.

Stocks data are taken from CRSP. In each cross section, I drop the small stocks, defined as those with market cap below the 10th percentile of the NYSE universe. Industry-level returns are market cap-weighted averages. All regressions in Table 10 require that there be at least 20 stocks in the industry-month. This filter is applied because the theory requires a sizable group of stocks to be in an industry. I use the stock's issuing company's four-digit SIC code as the industry classification variable, and drop observations with a missing SIC code, or a code of 9910, 9990, and 9999, which represent unclassified. The empirical results remain significant if smaller cutoffs are chosen, even though they become weaker. This is discussed later in the section.

Column 1 shows that within a look-back window of about a year, or the first four lags, the cross section of industry stock returns exhibits positive price momentum on average. This contrasts the tenuous momentum effect found on the US aggregate market. Similar to the results on the aggregate market, this momentum effect is entirely concentrated in the non-newsy months, and even flips sign in the newsy months. This is shown in columns 2 and 3. Column 4 shows the difference between the coefficients in the newsy months and non-newsy months, and they are overall negative within four lags, as predicted.

While the four-digit SIC code is a commonly used, natural industry classification variable, the first two and three digits represent less granular "industry" classification, known as "major group" and "industry group". Table 11 examines whether the return predictability pattern is robust to the choice of the industry classification variable. Here I switch to the sum of the first four lags, as before. Across Panel A to C, the serial predictive relation of industry excess returns is strongly different across newsy and non-newsy months. Hence, this pattern is not sensitive to the specific level of the industry classification. Unless otherwise noted, I use the four-digit SIC code to represent industries.

Analogous to what is done in the time series section, Table 12 additionally verifies this time-varying predictive relation of industry level excess ROE with a monthly panel regression. As before, we see that past earnings predict future newsy month earnings significantly less well, compared to future non-newsy month earnings. This difference appears statistically stronger than the time-series one in Table 6, likely due to the large number of industries that provide richer variations in earnings and substantially more observations.

Cross sectional variation across industries provides us with an interesting testing ground of our proposed theory. At the beginning of the section, I mentioned that my story applies to groups of stocks that are sizable in number, and are tightly connected in fundamentals. These lead to testable predictions, which are examined by Table 13. Column 1 and 2 run this test on directly measured cash flow connectivity. I compute covariance of normalized excess ROE for each pair of stocks in the same industry-quarter, compute the within industry average (weighted by the geometric average of the market capitalization of the pair of stocks), and then take the trailing four quarter average for each industry. Each cross section is then split between high connectivity industries and low connectivity ones. Column 1 and 2 show that the dynamic return predictability pattern in industry level excess returns is indeed stronger on the highly connected industries, and weak on the low connectivity ones. Chen et al. (2020a) documented a financial contagion effect that leads to large cash flow comovements within industries. They documented that such effect is larger on industries that 1) have higher entry barrier and 2) are more balanced between financially strong and weak firms. Column 3-6 run the tests on the corresponding subsamples, and found that the effect is indeed stronger on the more balanced and the harder-to-enter industries. The last two columns run the regression separately on industries with a smaller and a larger number of constituents. They show that the effect is larger on those larger industries, as predicted.

Table 14 further demonstrates the importance of connected fundamentals by conducting placebo tests on superficial and fake "industries", where no such connection exists. Column 1 performs the regression on an industry consisting of stocks with SIC codes of 9910, 9990, 9999, and missing values, which all represent unclassified. Despite the shared SIC code values, the stocks are not actually similar to each others. Here, we see no effect, as expected. Column 2 assigns stocks to "industries" based on randomly generated "SIC codes". Here we again see no effect, unsurprisingly.

A potential confounding effect to heterogeneity analyses of return predictability in general is that return predictability is naturally more concentrated on "inefficient" stocks and industries, such as those with low market capitalization, price, and volume, because it is harder for arbitrageurs to take advantage of return predictability on these stocks. While there is no consensus on how this notion of inefficiency should be measured, market capitalization is a good place to start. It is worth noting that among the sorting variables I use, within industry cash flow connectivity and balance are not obviously related to industry capitalization. Entry cost and number of industry constituents are in fact positively related to industry capitalization, and the inefficiency story alone predicts *smaller* effects on the harder-to-enter and the larger industries, which is the opposite of what my theory predicts and the opposite of what the data shows. The tests run in Table 13 are sharp tests, in that the predicted empirical pattern is unlikely to rise from this other effect of heterogeneous "inefficiency".

Throughout the paper, I have been using the notions of 'newsy' and 'non-newsy' months, which reflect a binary approach. In Section 7.1, we saw that this binary approach is sometimes insufficient. Specifically, in the first quarter the reporting is substantially slower, and consequently January is less newsy than the April, July, and October. I then showed that the reversal in January and the continuation in February and March are less strong, and this is consistent with the notion that January is less newsy and February and March are newsier. This illustrates the potential usefulness of a quantitative measure of 'newsyness', according to which one can form testable predictions like this in a more general and systematic way.

The major source of time series variation in newsyness is the Q1 effect, which is already explored in Table 8.[21] However, the cross industry setting provides interesting heterogeneity in 1) reporting lags and 2) fiscal period end time. Concretely, if an industry consistently reports slowly, then for that industry, the first months of the quarters should be less newsy, and the second and third months newsier. If an industry has a sizable fraction of the firms ending their fiscal quarter with the first month of each quarter, then for that industry the *second* months of the quarters can potentially contain more announcers with fresh news, and hence become newsier. Below, I develop a method to quantify the newsyness of a month and then run tests on the constructed measures.

I model the unit newsyness of each earnings announcement as exponentially declining in reporting lag, with various half-lives. Specifically, let the lag be x days, then $unit\_newsy(x) = 0.5^{\frac{x}{HL}}$, where HL is the half-life parameter. For each month-reporting lag, I compute the product of this unit newsyness measure and the percentage of earnings announcements with this lag, which is the number of earnings announcements with the lag, divided by the total number of announcements this quarter. I then aggregate the product to the month level. Overall, if a month contains announcements with shorter reporting lags, it will be newsier. If a month contains more earnings announcements, it will be newsier. Lastly, I rescale to sum to 1 per quarter, and average historical newsyness to the month of the year level. In doing so, I use only data

[21] Another thing is the earnings announcements have become a few days slower in the last two decades, potentially due to the Sarbanes–Oxley Act of 2002. The change is too small to have an appreciable effect in my later analyses. The sample is also not quite long enough to establish a clear effect.

available in real time. Specifically, I use the expanding window averages.

To illustrate the effect of the half life parameter, Table 15 tablulates the Q2 newsyness on the US aggregate economy for the last cross section, i.e. it uses all historical data. From the left to right, the half life in the measure increases from one day to sixty days. When the half life is small, the newsyness vector is effectively (1, 0, 0), which is my original binary approach which sets April as newsy and May/June as non-newsy. As the half life increases, the vector becomes closer to (0.5, 0.5, 0), which is roughly the fractions of earnings announcements within those months. This is because that as the half-life increases, early and late announcers are being weighted increasingly equally.

Previously, I run the regression $exret_{i,t} = \alpha + \beta_1 \sum_{j=1}^{4} exret_{i,nm(t,j)} + \beta_2 (\sum_{j=1}^{4} exret_{i,nm(t,j)} \times I_t^{nm}) + \beta_3 I_t^{nm} + \epsilon_{i,t}$. Here $exret_{i,t}$ is the value weighted return of industry i in month t in excess of the market. $exret_{i,nm(t,j)}$ is the value weighted average excess return of industry i in the jth newsy month before month t. Importantly, I_t^{nm} is a dummy variable indicating whether month t is newsy. I incorporate the said quantitative measure in this regression in two ways. First, I replace I_t^{nm} with the quantitative newsyness measure New_t. A newsyness value of 1 predicts strong reversal as before, while a moderate value of 0.8 predicts weaker reversal in month t. Second, I replace $\sum_{j=1}^{4} exret_{i,nm(t,j)}$, which is the sum of the previous four newsy months, with $exret12_{i,t}^{nw} = \sum_{j=1}^{12} exret_{i,t-j} \cdot New_{i,t-j}$, which is a weighted average of past 12 monthly excess return of industry i, with newsier months carrying higher weights.

Panel A of Table 16 shows the results with half lives of 3, 4, and 5 days. The effect is strong under a wider range of half lives, but these are roughly where the effect is the most pronounced. It is worth noting that these half lives are kept the same across industries to enforce discipline in this exercise and avoid excessive data mining. These half lives will also be used in exercises across countries and country-industries. Overall, we see that both the continuation term and the reversal term are stronger than under the binary specification.[22] This exercise is not only a way to obtain higher statistical power, but also a meaningful auxiliary test that takes advantage of the heterogeneity across industries.

7.3.2 Global aggregate markets

Global earnings reporting cycle Having described the results in the US, we move to the global data. In addition to new data on stock returns, other countries have different earnings reporting cycles from the US and therefore can potentially provide meaningful out-of-sample tests of the theory. At least two sources of variations in the earnings reporting cycles appear of interest. First, variation in reporting frequency, specifically, a number of major countries require firms to report semi-annually instead of quarterly. Second, variation in reporting lag, specifically, all major countries report substantially slowlier than the US.

To look into the variations, I collect interim earnings announcement date, earnings, and book value of equity from Worldscope. Even though this data source has substantially better coverage of interim accounting data than Compustat Global, the data start only in 1990s, and the coverage does not stabilize until 1998. This is substantially shorter history relative to the quarterly accounting data in the US, where stable coverage begins in 1971. Perhaps this is in part why studies on the US market is more abundant. I nonetheless draw lessons from this international dataset, as some patterns can be sufficiently clear even on a short sample of 20 years.

In terms of the variation in reporting frequency, a country level tabulation exercise on fiscal periods' end months reveals that in those countries requiring semi-annual

[22] Since it is important that we do not invoke look-ahead bias in our quantitative newsyness measure, the exercise is done on the post-1973 sample, where the earnings announcement dates are available. The improvement is clear in spite of the smaller, post-1973 sample, where industry momentum is in fact a little weaker overall. This is possible because after 1973 we still have about 50 years of data, and the effect of correctly setting the newsyness for each month across different industries greatly outweighs the effect of a smaller sample.

reporting, comparable numbers of firms have Mar/Sep and Jun/Dec fiscal periods end. Hence, the entire country still operates on a quarterly calendar, and first months of each quarters are still the earliest time for the freshest news to come out. The theory therefore applies to those countries as well.[23]

Regarding the variation in reporting lags, first, the right panel of Table 1 shows that the fiscal quarters are also well aligned with the calendar quarters in the global sample. Hence, news in group 1 months remains the freshest in the global data. However, the reporting intensity is very different and can be used to generate some heterogeneity in the right-hand-side variables in the global analysis. Table 17 shows that relative to the US, a much smaller fraction of the firms announce in the group 1 months in the global sample. In contrast, group 2 months contain the largest fraction of announcing firms—about 60%. Globally, it seems that both group 1 and group 2 months are viable candidates for newsy months, as the former provide the freshest news and the latter come with the most intensive reporting. Group 3 months, however, do not fall in either category. In fact, the average reporting lag in the US is 37 days, which is a little longer than one month; that for the international sample is 55 days, which is about two months.[24] In other words, globally group 1 combined with group 2 months roughly constitute the first half of the earnings reporting cycles. To enforce consistency across the US and the global analysis, I set the newsy "months" to be the combined periods of group 1 and group 2 months in the global data. For example, April and May combined is considered to be a newsy 'month' in the global data.[25]

[23]The only exception here is Australia, where Jun/Dec fiscal periods are overwhelmingly more common. However, overall country level momentum is weak in Australia, and it is hard to say that the small reversal we see in Jan/Feb and Jul/Aug is lending support to my theory. I nonetheless keep the country in my sample, since there is still a non-trivial portion of firms with Mar/Sep fiscal periods.

[24]Both numbers exclude cases where the lag exceeds 182 days. These cases have heightened probability of data errors. They are rare anyway.

[25]Finland is the only country other than the US to have an average reporting lag of less than 6 weeks. Setting group 2 months as non-newsy for Finland and newsy for all other non-US countries indeed leads to slightly stronger results, but since this logic turns on for only one country it is too sparse a source of variation. For the sake of simplicity I do not do this in my baseline analyses. Rather,

It is important to note while the practice of setting 'newsy' months based on aggregate data is similar to what I did in the US, doing so on the global sample involves a stronger assumption. In both the US and the global sample, the return data start substantially earlier than the accounting data from which the newsy months are inferred. However, the history of accounting data is much longer in the US, and it can be seen that over the course of this longer history the aggregate reporting cycle remained stable, and in fact was a few days faster in the earlier decades. Also, it is clearly documented that quarterly reporting has been present in the US even years before 1926 thanks to the requirements of the NYSE (Kraft et al. (2017)). Outside the US similar evidence is less easy to find systematically in one place,[26] even though country-by-country research clearly shows that regular financial reporting has been on going decades before the inception of the Worldscope data, at least for financially developed nations like UK, Japan, France, and Australia.

Given these contexts, while I still use return data before 1990s in my global tests, I focus on the financially developed countries, where financial regulation is sounder and has longer history. The list of developed markets that I use follows that in Asness et al. (2019) and consists of the developed markets classified by Morgan Stanley Capital International (MSCI). Also, on this long sample of returns I only use the simplest and most obvious message from the global earnings announcement data, specifically which months are the newsy months. Analyses that take advantage of finer variations in the earnings reporting cycles across countries are done on the post-1998 sample, and are implemented so that the independent variable does not incur any look-ahead bias, similar to what was done for the US industries. Even with these practices, one should perhaps place more focus the post-war and the post-1974 results for the global sample,

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I more thoroughly utilize the variation in reporting lags across countries in the form of quantitative newsyness in later analyses.

[26]It is very easy to find each country's current reporting convention, but that can be seen in the accounting data anyway.

and interpret the pre-1974 results with more caution.

Global fundamental news On the global panel of countries, analysis of the earnings predictability supports the newsy status of group 2 months in the global data. Table 18 does similar regressions to those in Table 6, except it is now at a country-month level. Because an average country has much smaller sample size than the US, the country-month level ROE is winsorized at the 10th and the 90th percentiles of each cross section to limit the impacts of the outliers caused by low aggregate book values of equity.[27] The regressions are weighted by aggregate book value of equity of the country-month divided by the total book value of the year. This regression weight mimics that in Hartzmark and Shue (2018). It overweights large country-months and at the same time does not mechanically overweight more recent cross sections. Overall, Table 18 shows similar results to those in Table 6, which is past earnings predicts future earnings substantially less well in the newsy months, which are now first and the second months of each quarters. The results are again robust to the inclusion of firms that have fiscal quarters unaligned with calendar quarters and those reporting late.

Return predictability Having described the earnings-related information globally, I move to the return predictability results. My country-level market returns come from Global Financial Data (GFD). Returns are all in US dollar. A number of return series go back further than 1926, but in this analysis I cut the sample at 1926 to be consistent with the US results.[28] Of course, if the data for a certain country do not go back further than 1926, the truncation is not operative for that country.

[27] These rather deep winsorization bounds are necessitated by the small cross sections early in the sample: those are precisely where the raw ROE values are extreme (due to small number of stocks in the aggregation), and the cross section sizes are less than 20 countries—which means winsorzation at the 5th and 95th percentiles makes no difference.

[28] After deleting some obviously problematic data in the UK in the 1600s and 1700s, inclusion of those early samples makes the results stronger.

To start, Table 19 runs analogous regressions as those in Table 4, except they are now on a panel of country level aggregate returns, and that the newsy months now include both the first and the second months of each calendar quarter. In column 1, we observe an unconditional momentum effect. This reflects country-level momentum in Moskowitz et al. (2012), which is in fact stronger in more recent periods. Columns 2 and 3 then show that this component is much stronger in the non-newsy months, here meaning the third months of the quarters. The results are robust in the post-war and the post-1974 sample. The result is very weak in the first half of the sample, however, perhaps reflecting the smaller sample size before 1974.

Since aggregate returns in other countries are going to be positively related to the US market return contemporaneously, to observe the additional effect more cleanly, I remove each country's loading on the US market return according to their US return betas. I estimate the betas on a rolling 24 month basis up to one month before the dependent variable month, so that the beta does not contain any look-ahead bias, and the dependent variable corresponds to positions implementable in real time. The results are in Table 20, and they convey similar messages as those in Table 19.

In panel B of Table 16, I conduct an exercise involving quantitative newsyness, as in the cross section of US industries. Here the analysis starts only in 2000, which leads to a very small sample size. On this small sample, we do observe marginally significant results, and somewhat larger effect. However, because of the small sample size one needs to interpret these results with caution.

7.3.3 Global cross sections of industries

Similar to the analyses for the US, I look at the cross sections of country-industry returns in excess of the corresponding country-level returns. Returns are mostly taken from Compustat Global, augmented with the Canadian stocks from Compustat North America. To be consistent with the global aggregate market results, I constrain the sample to the same list of countries in the previous section. Returns are winsorized at the 0.5 and the 99.5 percentiles each cross section to limit the impact of absurdly large values which are likely erroneous.[29] All returns are in USD. In each country-month, 10% of the smallest stocks are dropped, after which the returns are aggregated to the industry and market level using market cap weight. The difference of those two returns are then taken to arrive at the excess returns that I use. Here, I again require each country-industry to have at least 20 stocks, consistent with the rest of the paper.

Table 22 shows similar patterns to those found in Table 11: Country-industries exhibit momentum only in the non-newsy months. The results do not seem to be sensitive to the particular choice of industry variable. Table 21 is the companion results from earnings. It again demonstrates the strong variation in earnings' correlation with the past earnings. Like those in the US, the cross sectional piece of the earnings regression produce statistically stronger difference than the time series piece. Despite the very short sample that start in 1998, the difference is quite significantly established, thanks to the large number of industries that provides rich cross sectional variation in the data.

In panel C of Table 16, I again conduct an exercise involving quantitative newsyness as before. Here the analysis again starts only in 2000, which again leads to a small sample size, even though the cross sections of industries help to improve things relative to the analyses on global market excess returns. We observe improvements and results significant at the traditional level. Because of the small sample size we again need to interpret these results with caution.

[29] This step may appear non-standard from the perspective of the US sample, but the reason is that CRSP's pricing data quality is unusually good. On a global sample the winsorization step or operations that achieve similar ends are unavoidable. See, for instance, Jensen et al. (2021)

8 Alternative explanations

Firms endogenously changing their reporting latency A large literature in accounting examines the relation between the timing of firms' earnings announcements and the news they convey. A clear empirical pattern that emerges is that early announcers tend to announce better news than late announcers (e.g. Kross (1981), Kross and Schroeder (1984), Chambers and Penman (1984), Johnson and So (2018b), Noh et al. (2021)). The literature has also extensively studied the reasons behind this pattern, and has partially attributed it to firms' endogenous choices of reporting lag. For instance, deHaan et al. (2015) argue that firms delay earnings announcements with bad results to avoid the early portion of the earnings reporting cycle which receives heightened attention. Givoly and Palmon (1982) argue that they do so to buy time so that they can manipulate their accounting results.

However, it is not clear how this empirical regularity alone speaks to my results. Overall, they imply that early announcers announce better results than late announcers. If investors fail to anticipate that, then early announcers will have higher earnings surprises and higher announcement excess returns. It is not clear why it would cause the market return early in the announcement cycle to positively correlate with that late in the earnings reporting cycle. If anything, exogenous variation in the intensity of this self-selection effect seems to lead to a negative correlation of early announcement returns and late announcement returns within quarter, as bad announcers being moved out of the newsy months makes the newsy months look better and the subsequent non-newsy months look worse than they otherwise would do. And even then it is not clear why this return predictability pattern would extend across quarters.

Predictability reflecting predictable resolution of risks The most important set of explanations for return predictability come from predictable resolution of risks, which leads to high expected returns, as well as going through predictably low risk periods, which leads to low expected returns. The type of variation in risks that is necessary to explain my time series results is that after a good newsy month, the stock market is very risky in the upcoming non-newsy months, and very safe in the upcoming newsy months. This requires the risk of the market to vary at the monthly frequency. The variation needs to have a dependency up to four quarters away, and it needs to have a mixture of positive and negative dependence on the past, with the sign of the dependence going from positive to negative, and then back to positive, and so on.

Standard asset pricing models such as habit, long-run risk, disaster, and intermediary-based asset pricing all involve risks that should be fairly persistent at the monthly frequency. Even if they do vary, it is unlikely that the variation would cause its dependency on the past to take alternate signs across months. So it does not appear appropriate to use them to explain my predictability pattern. A potentially more hopeful candidate is those exploring the risk resolution that are associated with earnings announcements. Empirically, Savor and Wilson (2016) show that early announcers earn higher excess returns than later announcers, which is indeed consistent with the overall importance of the earnings season. This, however, does not explain why current earnings season being good makes future earnings seasons safer and future months out of earnings seasons riskier. The authors also show that stocks with high past announcement return in excess of the market earn higher returns during their upcoming announcement weeks than those with low past announcement excess returns. The authors argue that this shows that the level of risks resolved by a given stock's earnings announcement is persistent. The authors also show that earnings announcement dates are highly stable, and therefore firms that have announced in January are likely to announce in April. Combining these two pieces of information, it may seem that returns 3/6/9/12 months ago might be influencing part of my cross sectional results. However, apart from the difference in return frequency (monthly versus weekly) and cross sectional unit (industry/aggregate versus stock), observe that the excess returns 3/6/9/12 months ago are used only when the dependent variables are the newsy months, which is a sub-sample where the coefficient in my regression is low, not high.

Loading on the seasonality effect My cross sectional results might seem related to those in Heston and Sadka (2008) and Keloharju et al. (2016), who show that the full-year lags, i.e., the 12, 24, 36, etc. monthly lags have unusually high predictive coefficients on stock-level excess returns. Since their signals have no time-series variation (i.e. stock returns in excess of the market have zero mean cross section by cross section), the results cannot be related to my time-series results. However, could they explain my industry level results? Full-year lags are indeed used in some of my regression results. Specifically, they are part of the RHS when the dependent variable are the group 1 months, like in column 2 of Table 10. However, observe that the point of my paper is that in group 1 months the return predictive coefficients are unusually low, exactly the opposite of the points made in the return seasonality literature. In other words, my results exist in spite of the loading on return seasonality, not because of it.

Fluke driven by a small number of outliers One may worry that the time-series result is driven by a handful of outliers, and is therefore not very robust. To mitigate this concern, I perform the regression in Table 4 by decades, and report the results in Table 23. A few things come out of this exercise. First, the pattern is very strong in the pre-1940 era, which can already been inferred from the post-war column of Table 4. Second, in each and every decade, the coefficient on the interacted term is negative and economically sizable. This shows that the effect is in fact quite robust across time and not solely driven by short episode like the pre-1940 era. Lastly, we see that this effect is by no means dwindling over time. In fact, in recent decades the dynamic serial correlation pattern of the US market return is stronger. This shows that this effect is not just a piece of history, but rather an ongoing phenomenon.

Driven by look-ahead bias in estimated coefficient Past research has cast doubts especially on the practicality of time-series strategies in the stock market. Specifically, Goyal and Welch (2008) show that in forecasting future stock market returns, predictors combined with expanding window coefficients extracted without look-ahead bias fail to outperform the expanding window mean of past market returns. While Campbell and Thompson (2008) quickly show that imposing some simple and reasonable constraints on the regression estimation process will make the predictor-based approach clearly superior, it is nonetheless useful to make sure that the predictor in this paper can generate positive R^2 without involving coefficients estimated with look-ahead bias.

To investigate the R^2 generated with no look-ahead bias coefficients, I extend the CRSP aggregate market return series to 1871 using GFD data. I take valuation ratios data from Robert Shiller's website, and construct payout ratios and ROE series with data from Amit Goyal's website. These are used to generate the long-run return forecasts as in Campbell and Thompson (2008). While the estimation sample go back to 1872, the R^2 are evaluated starting from 1926, consistent with what is done in Campbell and Thompson (2008).

The monthly R^2 generated by various estimation methods are reported in Table 24. Coefficients are either constrained to be 1 or generated with simple expanding-window OLS estimations. No shrinkage procedure is applied at all. In method 1, we see that even the most naive method—combining signal with regression coefficients of returns on past signals and a freely estimated constant—generates an R^2 of 3.65%. This positive R^2 along with those generated with methods 2-7, should mitigate the concern that the strategy implied by the time-series results in this paper could not have been profitably employed.

It is important to realize that section is about the implementation of the coefficient estimation procedure. It makes no statement on how much of these return predictability results will continue to exist in the future. Recent works explicitly making those statements include Mclean and Pontiff (2016) and Hou et al. (2018).

9 Conclusion

Contrary to prior beliefs, monthly stock market returns in the US can in fact be predicted with past returns. Specifically, the U.S. stock market's return during the first month of a quarter correlates strongly with returns in future months, but the correlation is negative if the future month is the first month of a quarter, and positive if it is not. I show that these first months of a quarter are 'newsy' because they contain fresh earnings news, and argue that the return predictability pattern arises because investors extrapolate these newsy month earnings to predict future earnings, but did not recognize that earnings in future newsy months are inherently less predictable. Survey data support this explanation, as does out-of-sample evidence across industries and international markets. This paper seriously challenge the Efficient Market Hypothesis by documenting a strong and consistent form of return predictability. Behind this return predictability result is a novel mechanism of expectation formation, which features fundamentals extrapolation with a representative parameter.

References

Abel, A. (1990). Asset Prices Under Habit Formation And Catching Up With The Joneses. *American Economic Review*, 80:38–42.

Asness, C. S., Frazzini, A., and Pedersen, L. H. (2019). Quality minus junk. *Review of Accounting Studies*, 24(1):34–112.

Asness, C. S., Moskowitz, T. J., and Pedersen, L. H. (2013). Value and Momentum Everywhere. *The Journal of Finance*, 68(3):929–985.

Ball, R. and Sadka, G. (2015). Aggregate earnings and why they matter. *Journal of Accounting Literature*, 34:39–57.

Ball, R., Sadka, G., and Sadka, R. (2009). Aggregate Earnings and Asset Prices. *Journal of Accounting Research*, 47(5):1097–1133.

Bansal, R. and Yaron, A. (2004). Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles. *The Journal of Finance*, 59(4):1481–1509.

Barberis, N., Shleifer, A., and Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, 49(3):307–343.

Barro, R. J. (2006). Rare Disasters and Asset Markets in the Twentieth Century*. *The Quarterly Journal of Economics*, 121(3):823–866.

Beaver, W. H. (1968). The Information Content of Annual Earnings Announcements. *Journal of Accounting Research*, 6:67–92.

Bernard, V. L. and Thomas, J. K. (1989). Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium? *Journal of Accounting Research*, 27:1–36.

Bernard, V. L. and Thomas, J. K. (1990). Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics*, 13(4):305–340.

Bordalo, P., Coffman, K., Gennaioli, N., Schwerter, F., and Shleifer, A. (2021a). Memory and Representativeness.

Bordalo, P., Gennaioli, N., Kwon, S. Y., and Shleifer, A. (2021b). Diagnostic Bubbles. *Journal of Financial Economics*, 141(3).

Bordalo, P., Gennaioli, N., LaPorta, R., and Shleifer, A. (2019). Diagnostic Expectations and Stock Returns. *Journal of Finance*, 74(6):2839–2874.

Bordalo, P., Gennaioli, N., Ma, Y., and Shleifer, A. (2020). Overreaction in Macroeconomic Expectations.

Brochet, F., Kolev, K., and Lerman, A. (2018). Information transfer and conference calls. *Review of Accounting Studies*, 23(3):907–957.

Campbell, J. (2017). *Financial Decisions and Markets: A Course in Asset Pricing*. Princeton University Press.

Campbell, J. and Thompson, S. B. (2008). Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average? *Review of Financial Studies*, 21(4):1509–1531.

Campbell, J. Y. and Cochrane, J. H. (1999). By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior. *Journal of Political Economy*, 107(2):205–251. Publisher: The University of Chicago Press.

Chambers, A. and Penman, S. (1984). Timeliness of Reporting and the Stock-Price Reaction to Earnings Announcements. *Journal of Accounting Research*, 22(1):21–47.

Chang, T. Y., Hartzmark, S. M., Solomon, D. H., and Soltes, E. F. (2017). Being Surprised by the Unsurprising: Earnings Seasonality and Stock Returns. *Review of Financial Studies*, 30(1):281–323.

Chen, H., Dou, W., Guo, H., and Ji, Y. (2020a). Feedback and Contagion through Distressed Competition. SSRN Scholarly Paper ID 3513296, Social Science Research Network, Rochester, NY.

Chen, Y., Cohen, R. B., and Wang, Z. K. (2020b). Famous Firms, Earnings Clusters, and the Stock Market. SSRN Scholarly Paper ID 3685452, Social Science Research Network, Rochester, NY.

Clinch, G. J. and Sinclair, N. A. (1987). Intra-industry information releases: A recursive systems approach. *Journal of Accounting and Economics*, 9(1):89–106.

Constantinides, G. M. (1990). Habit Formation: A Resolution of the Equity Premium Puzzle. *Journal of Political Economy*, 98(3):519–543.

deHaan, E., Shevlin, T., and Thornock, J. (2015). Market (in)attention and the strategic scheduling and timing of earnings announcements. *Journal of Accounting and Economics*, 60(1):36–55.

Dellavigna, S. and Pollet, J. M. (2009). Investor Inattention and Friday Earnings Announcements. *The Journal of Finance*, 64(2):709–749.

Enke, B. and Zimmermann, F. (2017). Correlation Neglect in Belief Formation. *The Review of Economic Studies*.

Fama, E. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics*, 49(3):283–306.

Fama, E. F. (1965). The Behavior of Stock-Market Prices. *The Journal of Business*, 38(1):34–105.

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 25(2):383–417.

Fama, E. F. and MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, 81(3):607–636. Publisher: University of Chicago Press.

Fedyk, A. and Hodson, J. (2019). When Can the Market Identify Old News? SSRN Scholarly Paper ID 2433234, Social Science Research Network, Rochester, NY.

Foster, G. (1981). Intra-industry information transfers associated with earnings releases. *Journal of Accounting and Economics*, 3(3):201–232.

Gabaix (2012). Variable Rare Disasters: An Exactly Solved Framework for Ten Puzzles in Macro-Finance. *Quarterly Journal of Economics*, 127(2):645–700.

Garg, A., Goulding, C. L., Harvey, C. R., and Mazzoleni, M. (2021). Momentum Turning Points. SSRN Scholarly Paper ID 3489539, Social Science Research Network, Rochester, NY.

Givoly, D. and Palmon, D. (1982). Timeliness of Annual Earnings Announcements: Some Empirical Evidence. *The Accounting Review*, 57(3):486–508.

Goyal, A. and Welch, I. (2008). A Comprehensive Look at The Empirical Performance of Equity Premium Prediction. *The Review of Financial Studies*, 21(4):1455–1508.

Greenwood, R. and Hanson, S. G. (2013). Issuer Quality and Corporate Bond Returns. *The Review of Financial Studies*, 26(6):1483–1525.

Guo, H. and Wachter, J. A. (2019). 'Superstitious' Investors. SSRN Scholarly Paper ID 3245298, Social Science Research Network, Rochester, NY.

Han, J. C. Y. and Wild, J. J. (1990). Unexpected Earnings and Intraindustry Information Transfers: Further Evidence. *Journal of Accounting Research*, 28(1):211–219.

Han, J. C. Y., Wild, J. J., and Ramesh, K. (1989). Managers' earnings forecasts and intra-industry information transfers. *Journal of Accounting and Economics*, 11(1):3–33.

Hann, R. N., Kim, H., and Zheng, Y. (2019). Intra-Industry Information Transfers: Evidence from Changes in Implied Volatility around Earnings Announcements. SSRN Scholarly Paper ID 3173754, Social Science Research Network, Rochester, NY.

Hann, R. N., Li, C., and Ogneva, M. (2020). Another Look at the Macroeconomic Information Content of Aggregate Earnings: Evidence from the Labor Market. *The Accounting Review*, 96(2):365–390.

Hartzmark, S. M. and Shue, K. (2018). A Tough Act to Follow: Contrast Effects in Financial Markets. *The Journal of Finance*, 73(4):1567–1613.

Hartzmark, S. M. and Solomon, D. H. (2013). The dividend month premium. *Journal of Financial Economics*, 109(3):640–660.

Heston, S. L. and Sadka, R. (2008). Seasonality in the cross-section of stock returns. *Journal of Financial Economics*, 87(2):418–445.

Hou, K., Xue, C., and Zhang, L. (2018). Replicating Anomalies. *The Review of Financial Studies*.

Jegadeesh, N. and Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*, 48(1):65–91.

Jensen, T. I., Kelly, B. T., and Pedersen, L. H. (2021). Is There a Replication Crisis in Finance? SSRN Scholarly Paper ID 3774514, Social Science Research Network, Rochester, NY.

Johnson, T. L., Kim, J., and So, E. C. (2020). Expectations Management and Stock Returns. *The Review of Financial Studies*, 33(10):4580–4626.

Johnson, T. L. and So, E. C. (2018a). Asymmetric Trading Costs Prior to Earnings Announcements: Implications for Price Discovery and Returns. *Journal of Accounting Research*, 56(1):217–263.

Johnson, T. L. and So, E. C. (2018b). Time Will Tell: Information in the Timing of Scheduled Earnings News. *Journal of Financial and Quantitative Analysis*, 53(6):2431–2464.

Keloharju, M., Linnainmaa, J. T., and Nyberg, P. (2016). Return Seasonalities. *The Journal of Finance*, 71(4):1557–1590.

Kendall, M. G. and Hill, A. B. (1953). The Analysis of Economic Time-Series-Part I: Prices. *Journal of the Royal Statistical Society. Series A (General)*, 116(1):11–34.

Kraft, A. G., Vashishtha, R., and Venkatachalam, M. (2017). Frequent Financial Reporting and Managerial Myopia. *The Accounting Review*, 93(2):249–275.

Kross, W. (1981). Earnings and announcement time lags. *Journal of Business Research*, 9(3):267–281.

Kross, W. and Schroeder, D. A. (1984). An Empirical Investigation of the Effect of Quarterly Earnings Announcement Timing on Stock Returns. *Journal of Accounting Research*, 22(1):153–176.

Lakonishok, J., Shleifer, A., and Vishny, R. W. (1994). Contrarian Investment, Extrapolation, and Risk. *The Journal of Finance*, 49(5):1541–1578.

Matthies, B. (2018). Biases in the Perception of Covariance. SSRN Scholarly Paper ID 3223227, Social Science Research Network, Rochester, NY.

Mclean, R. D. and Pontiff, J. (2016). Does Academic Research Destroy Stock Return Predictability? *The Journal of Finance*, 71(1):5–32.

Mehra, R. and Prescott, E. C. (1985). The equity premium: A puzzle. *Journal of Monetary Economics*, 15(2):145–161.

Moskowitz, T. J. and Grinblatt, M. (1999). Do Industries Explain Momentum? *The Journal of Finance*, 54(4):1249–1290.

Moskowitz, T. J., Ooi, Y. H., and Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics*, 104(2):228–250.

Nagel, S. and Xu, Z. (2019). Asset Pricing with Fading Memory. Working Paper 26255, National Bureau of Economic Research. Series: Working Paper Series.

Noh, S., So, E. C., and Verdi, R. S. (2021). Calendar rotations: A new approach for studying the impact of timing using earnings announcements. *Journal of Financial Economics*, 140(3):865–893.

Patatoukas, P. N. (2014). Detecting news in aggregate accounting earnings: implications for stock market valuation. *Review of Accounting Studies*, 19(1):134–160.

Payne, J. L. and Thomas, W. B. (2003). The Implications of Using Stock-Split Adjusted I/B/E/S Data in Empirical Research. *The Accounting Review*, 78(4):1049–1067.

Poterba, J. M. and Summers, L. H. (1988). Mean reversion in stock prices: Evidence and Implications. *Journal of Financial Economics*, 22(1):27–59.

Ramnath, S. (2002). Investor and Analyst Reactions to Earnings Announcements of Related Firms: An Empirical Analysis. *Journal of Accounting Research*, 40(5):1351–1376.

Rietz, T. A. (1988). The equity risk premium a solution. *Journal of Monetary Economics*, 22(1):117–131.

Savor, P. and Wilson, M. (2016). Earnings Announcements and Systematic Risk. *The Journal of Finance*, 71(1):83–138.

Thomas, J. and Zhang, F. (2008). Overreaction to Intra-industry Information Transfers? *Journal of Accounting Research*, 46(4):909–940.

Vuolteenaho, T. (2002). What Drives Firm-Level Stock Returns? *The Journal of Finance*, 57(1):233–264.

Wachter, J. A. (2013). Can Time-Varying Risk of Rare Disasters Explain Aggregate Stock Market Volatility? *The Journal of Finance*, 68(3):987–1035.

Wang, C. (2020). Under- and Over-Reaction in Yield Curve Expectations. SSRN Scholarly Paper ID 3487602, Social Science Research Network, Rochester, NY.

Table 1

Company-fiscal period count by fiscal period end month

	US		Global	
	Count	Percent	Count	Percent
Group 1: Jan/Apr/Jul/Oct	78,747	8.85	56,951	5.74
Group 2: Feb/May/Aug/Nov	49,385	5.55	64,303	6.49
Group 3: Mar/Jun/Sep/Dec	761,310	85.59	870,263	87.77
Total	889,442	100.00	991,517	100.00

The table tabulates the number of company-quarter by 3 groups, where the groups are determined by the fiscal quarter end month, specifically its remainder when divided by 3. First two columns contain count and percentage on the full sample of US companies. The next two columns do the same tabulation on the full sample of global companies. For the US sample, data are quarterly from 1971 to 2021. For the global sample, data are quarterly and semi-annually from 1998 to 2021.

Table 2

US company-quarter count by reporting month

	Both filters		Rpt Lag <= 92		Group 3 FQ end		No filter	
	Count	Pct	Count	Pct	Count	Pct	Count	Pct
Group 1: Jan/Apr/Jul/Oct	345,986	46.47	375,787	43.24	357,265	46.93	387,466	43.56
Group 2: Feb/May/Aug/Nov	344,666	46.30	380,792	43.81	348,118	45.73	385,806	43.38
Group 3: Mar/Jun/Sep/Dec	53,830	7.23	112,594	12.95	55,927	7.35	116,170	13.06
Total	744,482	100.00	869,173	100.00	761,310	100.00	889,442	100.00

The table tabulates the number of company-quarter by 3 groups, where the groups are determined by the reporting month, specifically its remainder when divided by 3. If a company reports earnings for a given fiscal quarter in October, this company-quarter belongs to group 1, as $10 \equiv 1 \mod 3$. First two columns contain count and percentage on the sample where 1) reporting within 92 days and 2) aligned with calendar quarters. The next two columns do the same tabulation with only the first filter. The next two columns apply only the second filter. The last two columns apply no filter. Data are quarterly from 1971 to 2021.

Table 3

Lead-lag relations of US monthly market returns

	(1)	(2)	(3)	(4)
	All	NM	Non-NM	Difference
$mkt_{nm(t,1)}$	0.090*	-0.168**	0.219***	-0.388***
	[1.73]	[-2.32]	[3.92]	[-4.23]
$mkt_{nm(t,2)}$	0.014	-0.177***	0.109**	-0.287***
	[0.34]	[-2.85]	[2.29]	[-3.66]
$mkt_{nm(t,3)}$	0.069	0.041	0.083**	-0.042
	[1.55]	[0.44]	[2.07]	[-0.41]
$mkt_{nm(t,4)}$	0.027	-0.086	0.084**	-0.169**
	[0.69]	[-1.26]	[2.09]	[-2.14]
$const$	0.007***	0.017***	0.002	0.015***
	[3.40]	[4.77]	[0.86]	[3.53]
N	1,136	378	758	1,136
R-sq	0.013	0.064	0.072	0.070

Column 1 of this table reports results from the following monthly time-series regression: $mkt_t = \alpha + \sum_{j=1}^{4} \beta_j mkt_{nm(t,j)} + \epsilon_t$. Here mkt_t is the US aggregate market return in month t, and $mkt_{nm(t,j)}$ is the return in the jth newsy month (Jan, Apr, Jul, Oct) preceding month t. Column 2 reports the same regression on the subsample where the dependent variable is returns of the newsy months. Column 3 is for the non-newsy months. Column 4 reports the difference between the coefficients in column 2 and 3, extracted from this regression $mkt_t = \alpha + \sum_{j=1}^{4} \beta_j mkt_{nm(t,j)} + \sum_{j=1}^{4} \gamma_j mkt_{nm(t,j)} \times I_t^{nm} + \delta I_t^{nm} + \epsilon_t$, where I_t^{nm} is a dummy variable taking the value of 1 when month t is newsy. Data are monthly from 1926 to 2021. T-statistics computed with White standard errors are reported in square brackets.

Table 4

Lead-lag relations of US monthly market returns, across subsamples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	NM	Non-NM	All	Post-WW2	First Half	Second Half
$\sum_{j=1}^{4} mkt_{nm(t,j)}$	0.052**	-0.103***	0.129***	0.129***	0.082***	0.162***	0.090***
	[2.04]	[-2.67]	[4.76]	[4.76]	[3.59]	[3.86]	[3.17]
$\sum_{j=1}^{4} mkt_{nm(t,j)} \times I_t^{nm}$				-0.232***	-0.157***	-0.279***	-0.176***
				[-4.93]	[-3.51]	[-3.96]	[-3.09]
I_t^{nm}				0.016***	0.011***	0.019***	0.012**
				[3.51]	[2.68]	[2.68]	[2.26]
const	0.007***	0.017***	0.002	0.002	0.005**	-0.001	0.005
	[3.30]	[4.60]	[0.74]	[0.74]	[2.16]	[-0.19]	[1.56]
N	1,136	378	758	1,136	893	567	569
R-sq	0.008	0.029	0.057	0.047	0.026	0.061	0.032

Column 1 of this table reports results from the following monthly time-series regression: $mkt_t = \alpha + \beta \sum_{j=1}^{4} mkt_{nm(t,j)} + \epsilon_t$. Here mkt_t is the US aggregate market return in month t, and $mkt_{nm(t,j)}$ is the return in the jth newsy month (Jan, Apr, Jul, Oct) preceding month t. Column 2 reports the same regression as in 1, but on the subsample where the dependent variable is returns of the newsy months. Column 3 is for the non-newsy months. Column 4 reports the results of $mkt_t = \alpha + \beta_1 \sum_{j=1}^{4} mkt_{nm(t,j)} + \beta_2 (\sum_{j=1}^{4} mkt_{nm(t,j)}) \times I_t^{nm} + \beta_3 I_t^{nm} + \epsilon_t$, where I_t^{nm} is a dummy variable taking the value of 1 when month t is newsy. Column 5-7 report results for the regression in column 4 on the subsamples of the post-WW2 period (1947-2021), the first half (1926-1973), and the second half (1974-2021). T-statistics computed with White standard errors are reported in square brackets.

Table 5

Lead-lag relations of US monthly market returns, actual vs simulated data

	Actual			Simulated		
	(1)	(2)	(3)	(4)	(5)	(6)
$\sum_{j=1}^{4} mkt_{nm(t,j)}$	0.129***		0.128***	0.015		0.014
	[4.76]		[4.43]	[0.75]		[0.71]
$\sum_{j=1}^{4} mkt_{nm(t,j)} \times I_t^{nm}$	-0.232***		-0.216***	-0.019		-0.023
	[-4.93]		[-5.01]	[-0.62]		[-0.69]
$\sum_{j=1}^{12} mkt_{t-j}$		0.042**			0.007	
		[2.39]			[0.71]	
$\sum_{j=1}^{12} mkt_{t-j} \times I_t^{nm}$		-0.090***			0.000	
		[-2.77]			[-0.01]	
$\sum_{j=1}^{8} mkt_{nnm(t,j)}$			0.004			0.003
			[0.15]			[0.21]
$\sum_{j=1}^{8} mkt_{nnm(t,j)} \times I_t^{nm}$			-0.031			0.011
			[-0.69]			[0.51]
N	1,136	1,134	1,134	1,136	1,134	1,134
R-sq	0.047	0.028	0.049	0.003	0.003	0.006

Column 1-3 are on actual data. Column 4-6 perform the same set of regressions on simulated data. Column 1 of this table reports results from the following monthly time-series regression: $mkt_t = \alpha + \beta_1 \sum_{j=1}^{4} mkt_{nm(t,j)} + \beta_2(\sum_{j=1}^{4} mkt_{nm(t,j)}) \times I_t^{nm} + \beta_3 I_t^{nm} + \epsilon_t$. Here mkt_t is the US aggregate market return in month t, $mkt_{nm(t,j)}$ is the return in the jth newsy month (Jan, Apr, Jul, Oct) preceding the month t, and I_t^{nm} is a dummy variable taking the value of 1 when month t is newsy. Column 2 reports results of the following regression: $mkt_t = \alpha + \beta_1 \sum_{j=1}^{12} mkt_{t-j} + \beta_2(\sum_{j=1}^{12} mkt_{t-j}) \times I_t^{nm} + \beta_3 I_t^{nm} + \epsilon_t$. Here mkt_{t-j} is the aggregate market returns j calendar months before month t. Column 3 is the regression in column 1 with two additional independent variables $\sum_{j=1}^{8} mkt_{nnm(t,j)}$ and $(\sum_{j=1}^{8} mkt_{nnm(t,j)}) \times I_t^{nm}$. Here, $mkt_{nnm(t,j)}$ is the US aggregate market return in the jth non-newsy month preceding the month t. Data are monthly from 1926 to 2021. Column 4-6 report results from the same regressions as in column 1-3 respectively, except here they are done on simulated AR(1) times series with the first order autocorrelation of 0.11. The regression coefficients in column 4-6 are average of the 10,000 coefficients each computed from a separate simulation. For column 1-3, t-statistics computed with White standard errors are reported in square brackets. For column 4-6, standard errors are standard deviations of coefficients across simulations, and the corresponding t-statistics are reported in square brackets.

Table 6
Lead-lag relations of US monthly earnings

	(1)	(2)	(3)	(4)
	All	NM	Non-NM	Difference
Panel A: Report Lag $\leq$ 92 & Group 3 Month FQ end				
$\sum_{j=1}^{12} roe_{t-j}$	0.051***	0.027***	0.064***	-0.036***
	[5.30]	[3.96]	[5.81]	[-3.57]
N	587	196	391	587
Panel B: Report Lag $\leq$ 92				
$\sum_{j=1}^{12} roe_{t-j}$	0.060***	0.041***	0.070***	-0.029***
	[5.32]	[4.56]	[5.97]	[-3.31]
N	587	196	391	587
Panel C: Group 3 Month FQ end				
$\sum_{j=1}^{12} roe_{t-j}$	0.053***	0.025***	0.067***	-0.043***
	[5.58]	[3.71]	[6.46]	[-4.17]
N	587	196	391	587
Panel D: No filter				
$\sum_{j=1}^{12} roe_{t-j}$	0.060***	0.040***	0.071***	-0.032***
	[5.24]	[4.63]	[5.76]	[-3.32]
N	587	196	391	587

Column 1 of this table reports results from the following monthly time-series regressions: $roe_t = \alpha + \beta \sum_{j=1}^{12} roe_{t-j} + \epsilon_t$. Here roe_t is the aggregate roe, or the aggregate net income before extraordinary items divided by aggregate book value of equity, of firms announcing their earnings in month t. Column 2 and 3 report results from the same regression except on the subsample where the dependent variables are newsy and non-newsy month returns, respectively. Column 4 reports the difference between column 2 and 3. Panel A aggregates ROE only on firm-quarters that are 1) reporting within 92 days and 2) aligned with calendar quarters. Panel B applies only the first filter; panel C only the second; panel D none. Data are monthly from 1971 to 2021. T-statistics computed with Newey-West standard errors are reported in square brackets.

Table 7

No reversal in the pre-season portion of the newsy months

	US			Global		
	(1)	(2)	(3)	(4)	(5)	(6)
	mkt_t	mkt_t^{FW}	mkt_t^{ExclFW}	$mkt_{c,t}$	$mkt_{c,t}^{PS}$	$mkt_{c,t}^{ExclPS}$
$\sum_{j=1}^{4} mkt_{nm(t,j)}$	-0.103***	0.019	-0.120***	-0.029	0.011	-0.040**
	[-2.67]	[1.03]	[-2.92]	[-1.07]	[0.76]	[-2.29]
const	0.017***	0.005***	0.012***	0.017***	0.008***	0.009***
	[4.60]	[3.35]	[3.38]	[3.21]	[2.66]	[2.72]
N	378	378	378	2,305	2,305	2,305
R-sq	0.029	0.005	0.047	0.006	0.002	0.022

Column 1 of this table reports results from the following monthly time-series regression: $mkt_t = \alpha + \beta \sum_{j=1}^{4} mkt_{nm(t,j)} + \epsilon_t$, on the subsample where the dependent variable is the first month of a quarter, or Jan, Apr, Jul, Oct. Here mkt_t the market return in month t, and $mkt_{nm(t,j)}$ is the market return in the jth newsy month preceding month t. Column 2 replaces the dependent variable with mkt_t^{FW}, which is the aggregate market return in the first five trading days in month t. Column 3 has the dependent variable mkt_t^{ExclFW}, which is the aggregate market return in month t excluding the first five trading days. Column 4 does the regression $mkt_{c,t} = \alpha + \beta \sum_{j=1}^{4} mkt_{c,nm(t,j)} + \epsilon_{c,t}$, again on cases where month t are the first months of the quarters. Here $mkt_{c,t}$ is the aggregate market return in month t for country c, and $mkt_{c,nm(t,j)}$ is the aggregate market return in the jth newsy "month" (Jan+Feb, Apr+May, Jul+Aug, Oct+Nov) preceding the month t for country c. Column 5 replaces the dependent variable with $mkt_{c,t}^{PS}$, the pre-earnings season returns. They are returns in the first 5, 10, or 15 trading day of the month, depending on country c's reporting speed. Column 6 changes the dependent variable to $mkt_{c,t}^{ExclPS}$, which equals $mkt_{c,t} - mkt_{c,t}^{PS}$. For the US sample, data are monthly from 1926 to 2021. For the global sample, data are monthly from 1964 to 2021. This shorter sample is due to the availability of the daily return data. T-statistics computed with White standard errors are reported in square brackets for column 1-3. Columns 4-6 use standard errors clustered at the monthly level.

Table 8

Weak dynamic autocorrelation in Q1

	Q2, Q3, and Q4			Q1		
	(1)	(2)	(3)	(4)	(5)	(6)
	Group 1	Group 2	Group 3	Jan	Feb	Mar
$\sum_{j=1}^{4} mkt_{nm(t,j)}$	-0.125***	0.173***	0.121***	-0.024	0.056	0.084
	[-2.83]	[3.67]	[2.95]	[-0.35]	[1.07]	[1.14]
const	0.017***	0.003	0.000	0.016***	0.003	0.002
	[3.79]	[0.69]	[0.10]	[2.88]	[0.58]	[0.33]
N	283	284	284	95	95	95
R-sq	0.040	0.088	0.054	0.002	0.015	0.023

This table reports results from the following monthly time-series regression: $mkt_t = \alpha + \beta \sum_{j=1}^{4} mkt_{nm(t,j)} + \epsilon_t$. Here mkt_t is the US aggregate market return in month t, and $mkt_{nm(t,j)}$ is the return in the jth newsy month (Jan, Apr, Jul, Oct) preceding month t. Column 1-3 are where the dependent variables are group 1-3 months outside the first quarter. Column 4-6 are where the dependent variables are returns of January, February, and March. Data are monthly from 1926 to 2021. T-statistics computed with White standard errors are reported in square brackets.

Table 9
Survey evidence from IBES

	(1) All	(2) NM	(3) Non-NM	(4) All	(5) All
$\sum_{j=1}^{12} Sup_{t-j}$	0.061***	0.049***	0.068***	0.068***	
	[8.54]	[4.82]	[9.96]	[9.95]	
$\sum_{j=1}^{12} Sup_{t-j} \times I_t^{nm}$				-0.019**	
				[-2.18]	
$\sum_{j=1}^{4} Sup_{nm(t,j)}$					0.584***
					[3.12]
$\sum_{j=1}^{4} Sup_{nm(t,j)} \times I_t^{nm}$					-0.064**
					[-2.26]
I_t^{nm}				0.001***	0.001***
				[7.71]	[6.12]
const	-0.000	0.000***	-0.000***	-0.000***	-0.001***
	[-1.08]	[3.62]	[-3.90]	[-3.87]	[-5.91]
N	419	140	279	419	419

Column 1 of this table reports results from the following monthly time-series regression: $Sup_t = \alpha + \beta \sum_{j=1}^{12} Sup_{t-j} + \epsilon_t$. Here Sup_t is the aggregate earnings surprise in month t, which is market cap weighted average of firm level earnings surprises of all firms announcing in month t. The firm level earnings surprises are computed as the difference between realized EPS and expected EPS divided by the firm's stock price at the end of the previous month. Column 2 reports the same regression as in 1, but on the subsample where the dependent variable is aggregate surprises of the newsy months. Column 3 is for the non-newsy months. Column 4 reports the difference between the coefficients in column 2 and 3, extracted from a regression with additional interaction terms to I_t^{nm}, which is a dummy variable taking value 1 if month t is newsy. Column 5 performs the same regression as in column 4, except additionally confine the surprises on the right-hand-side to be those in newsy months. Data are monthly from 1985 to 2021. T-statistics computed with Newey-West standard errors are reported in square brackets.

Table 10

Lead-lag relations of monthly excess industry returns in the US

	(1) All	(2) NM	(3) Non-NM	(4) Difference
$exret_{i,nm(t,1)}$	0.023	-0.036	0.052**	-0.087**
	[1.23]	[-1.40]	[2.14]	[-2.49]
$exret_{i,nm(t,2)}$	-0.004	-0.024	0.005	-0.029
	[-0.28]	[-0.90]	[0.29]	[-0.90]
$exret_{i,nm(t,3)}$	0.024	-0.012	0.042**	-0.054
	[1.47]	[-0.42]	[2.17]	[-1.56]
$exret_{i,nm(t,4)}$	0.036**	0.004	0.052**	-0.048
	[2.21]	[0.15]	[2.48]	[-1.51]
$const$	-0.001	0.001	-0.001***	0.002***
	[-1.48]	[1.44]	[-3.10]	[2.83]
N	19,108	6,353	12,755	19,108
R-sq	0.003	0.002	0.009	0.006

Column 1 of this table reports results from the following industry-month level panel regression: $exret_{i,t} = \alpha + \sum_{j=1}^{4} \beta_j exret_{i,nm(t,j)} + \epsilon_{i,t}$. Here $exret_{i,t}$ is the value weighted average return of industry i in excess of the market in month t, and $exret_{i,nm(t,j)}$ is the excess return in the jth newsy month (Jan, Apr, Jul, Oct) preceding month t. The industry is defined by the firm's 4-digit SIC code. Column 2 reports the same regression on the subsample where the dependent variable is returns of the newsy months. Column 3 is for the non-newsy months. Column 4 reports the difference between the coefficients in column 2 and 3, extracted from this regression $exret_{i,t} = \alpha + \sum_{j=1}^{4} \beta_j exret_{i,nm(t,j)} + \sum_{j=1}^{4} \gamma_j exret_{i,nm(t,j)} \times I_t^{nm} + \delta I_t^{nm} + \epsilon_{i,t}$, where I_t^{nm} is a dummy variable taking the value of 1 when month t is newsy. Regressions are weighted by the market cap of industry i as of the month $t-1$, normalized by the total market cap in the cross section. 20 stocks are required in each month-industry. Data are monthly from 1926 to 2021. T-statistics computed with clustered standard errors by month are reported in square brackets.

Table 11

Lead-lag relations of monthly excess industry returns in US, by different industry measures

	(1) All	(2) NM	(3) Non-NM	(4) Difference
Panel A: SIC Major Group				
$\sum_{j=1}^{4} exret_{i,nm(t,j)}$	0.021***	-0.012	0.038***	-0.050***
	[2.89]	[-0.96]	[4.35]	[-3.26]
N	28,028	9,327	18,701	28,028
R-sq	0.002	0.001	0.007	0.004
Panel B: SIC Industry Group				
$\sum_{j=1}^{4} exret_{i,nm(t,j)}$	0.020***	-0.008	0.034***	-0.041***
	[2.76]	[-0.64]	[3.81]	[-2.78]
N	24,082	8,037	16,045	24,082
R-sq	0.002	0.000	0.005	0.004
Panel C: SIC Industry				
$\sum_{j=1}^{4} exret_{i,nm(t,j)}$	0.020**	-0.017	0.038***	-0.055***
	[2.51]	[-1.39]	[3.84]	[-3.50]
N	19,108	6,353	12,755	19,108
R-sq	0.002	0.001	0.007	0.005

Column 1 of this table reports results from the following industry-month level panel regression: $exret_{i,t} = \alpha + \beta \sum_{j=1}^{4} exret_{i,nm(t,j)} + \epsilon_{i,t}$. Here $exret_{i,t}$ is the value weighted average return of industry i in excess of the market in month t, and $exret_{i,nm(t,j)}$ is the excess return in the jth newsy month (Jan, Apr, Jul, Oct) preceding month t. Column 2 reports the same regression on the subsample where the dependent variable are returns of the newsy months. Column 3 is for the non-newsy months. Column 4 reports the difference between the coefficients in column 2 and 3, extracted from this regression $exret_{i,t} = \alpha + \beta \sum_{j=1}^{4} exret_{i,nm(t,j)} + \gamma \sum_{j=1}^{4} exret_{i,nm(t,j)} \times I_t^{nm} + \delta I_t^{nm} + \epsilon_{i,t}$, where I_t^{nm} is a dummy variable taking the value of 1 when month t is newsy. Panel A to C differ only in the industry variable used. Regressions are weighted by the market cap of industry i as of the month $t-1$, normalized by the total market cap of each cross section. 20 stocks are required in each month-industry. Data are monthly from 1926 to 2021. T-statistics computed with clustered standard errors by month are reported in square brackets.

Table 12

Lead-lag relations of monthly excess industry earnings in US

	(1) All	(2) NM	(3) Non-NM	(4) Difference
Panel A: Report Lag $\leq$ 92 & Group 3 Month FQ end				
$\sum_{j=1}^{12} exroe_{i,t-j}$	0.027***	0.016***	0.054***	-0.037***
	[7.03]	[4.51]	[10.57]	[-6.96]
N	18,462	6,958	11,504	18,462
R-sq	0.090	0.060	0.169	0.125
Panel B: Report Lag $\leq$ 92				
$\sum_{j=1}^{12} exroe_{i,t-j}$	0.044***	0.033***	0.064***	-0.031***
	[11.53]	[6.81]	[13.82]	[-4.75]
N	24,835	8,683	16,152	24,835
R-sq	0.148	0.125	0.194	0.165
Panel C: Group 3 Month FQ end				
$\sum_{j=1}^{12} exroe_{i,t-j}$	0.027***	0.017***	0.053***	-0.036***
	[7.13]	[4.87]	[10.18]	[-6.82]
N	19,206	7,215	11,991	19,206
R-sq	0.096	0.068	0.171	0.129
Panel D: No filter				
$\sum_{j=1}^{12} exroe_{i,t-j}$	0.043***	0.033***	0.061***	-0.029***
	[11.26]	[7.00]	[12.73]	[-4.50]
N	25,812	9,015	16,797	25,812
R-sq	0.148	0.129	0.188	0.163

Column 1 of this table reports results from the following industry-month level panel regression: $exroe_{i,t} = \alpha + \beta \sum_{j=1}^{12} exroe_{i,t-j} + \epsilon_t$. Here $exroe_{i,t} = roe_{i,t} - roe_t$, where $roe_{i,t}$ is the roe aggregated for industry i among all of its announcers in month t, or the aggregate net income before extraordinary items divided by aggregate book value of equity, and roe_t is the aggregate roe on all firms announcing in month t. The ROE is then winsorized at the 10th and the 90th percentiles of each cross section to limit the impact of extreme data. It is filled with a neutral value of zero when missing as part of the independent variable, but kept missing when used individually as the dependent variable. Column 2 and 3 report results from the same regression except on the subsample where the dependent variables are newsy and non-newsy month returns, respectively. Column 4 reports the difference between column 2 and 3. Panel A aggregates ROE only on firm-quarters that are 1) reporting within 92 days and 2) aligned with calendar quarters. Panel B applies only the first filter; panel C only the second; panel D none. The regressions are weighted by aggregate book value of equity of the industry-month divided by the total book value of the year. 20 stocks are required for each industry-quarter. Data are monthly from 1971 to 2021. T-statistics computed with standard errors double clustered at the month, industry level are reported in square brackets.

Table 13

Heterogeneous effect across industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	connectivity		entry cost		balance		size	
	low	high	low	high	low	high	small	large
$\sum_{j=1}^{4} exret_{i,nm(t,j)}$	0.041**	0.057***	0.047**	0.058***	0.043*	0.063***	0.018***	0.030***
	[2.35]	[2.85]	[2.02]	[3.00]	[1.95]	[3.40]	[3.30]	[4.57]
$\sum_{j=1}^{4} exret_{i,nm(t,j)} \times I_t^{nm}$	-0.039	-0.134***	-0.040	-0.115***	-0.041	-0.123***	-0.016	-0.031***
	[-1.28]	[-4.03]	[-1.05]	[-3.31]	[-1.00]	[-3.81]	[-1.61]	[-2.84]
N	7,571	7,290	5,376	4,899	4,830	5,390	250,034	183,316
R-sq	0.004	0.013	0.005	0.011	0.004	0.013	0.002	0.002

This table reports results on the following industry-month level panel regression: $exret_{i,t} = \alpha + \beta_1 \sum_{j=1}^{4} exret_{i,nm(t,j)} + \beta_2(\sum_{j=1}^{4} exret_{i,nm(t,j)} \times I_t^{nm}) + \beta_3 I_t^{nm} + \epsilon_{i,t}$. Here $exret_{i,t}$ is the value weighted return of industry i in excess of the market in month t, $exret_{i,nm(t,j)}$ is excess return in the jth newsy month (Jan, Apr, Jul, Oct) preceding month t, and I_t^{nm} is a dummy variable indicating whether month t is newsy. Column (1) and (2) perform the regression on the subsamples where the within industry ROE connectivity is respectively low and high. Column (3) and (4) perform a similar exercise on low and high entry cost industries. Column (5) and (6) are on unbalanced and balanced industries. Column (7) and (8) are on industries with a small and larger number of stocks. 20 stocks are required in each industry-month, except for the last two columns, where no size filter is applied. Data are monthly from 1971 to 2021 for columns 1-6, and from 1926 to 2021 for columns 7-8. T-stats computed with standard errors clustered at the month level are reported in square brackets.

Table 14

Placebo test: no effect on fake 'industries'

	(1)	(2)
	unclassified	random
$\sum_{j=1}^{4} exret_{i,nm(t,j)}$	-0.028	-0.003
	[-0.77]	[-0.49]
$\sum_{j=1}^{4} exret_{i,nm(t,j)} \times I_t^{nm}$	0.065	0.005
	[0.98]	[0.47]
N	256	30,704
R-sq	0.010	0.000

This table reports results on the following 'industry'-month level panel regression: $exret_{i,t} = \alpha + \beta_1 \sum_{j=1}^{4} exret_{i,nm(t,j)} + \beta_2(\sum_{j=1}^{4} exret_{i,nm(t,j)} \times I_t^{nm}) + \beta_3 I_t^{nm} + \epsilon_{i,t}$. Here $exret_{i,t}$ is the value weighted return of industry i in excess of the market in month t, $exret_{i,nm(t,j)}$ is excess return in the jth newsy month (Jan, Apr, Jul, Oct) preceding month t, and I_t^{nm} is a dummy variable indicating whether month t is newsy. Column (1) performs the regression on the 'industry' consisting of stocks with SIC codes of 9910, 9990, 9999—which represent unclassified—and missing SIC code. Column 2 does the regression on the 'industries' represented by randomly generated SIC codes that takes on 30 values with equal probability. Data are from 1972 to 2021 for column 1, and from 1926 to 2021 for column 2. 20 stocks are required in each industry-month. T-stats computed with standard errors clustered at the month level are reported in square brackets.

Table 15

Newsyness of Q2 in US across various half lives

	1	2	3	4	5	6	7	14	30	60
Apr	0.92	0.97	0.95	0.92	0.88	0.85	0.82	0.70	0.62	0.58
May	0.06	0.02	0.04	0.08	0.11	0.15	0.18	0.30	0.38	0.41
Jun	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01

This table shows the value of quantitative newsyness of Q2 with various of half-life values for the aggregate market as of 2021.

Table 16

Quantitative newsyness and performance

	(1)	(2)	(3)	(4)
	Discrete	3-day	4-day	5-day
Panel A: US Industries excess returns				
β_1	0.042***	0.058***	0.062***	0.066***
	[3.84]	[3.70]	[3.68]	[3.68]
β_2	-0.061***	-0.125***	-0.133***	-0.142***
	[-3.50]	[-4.39]	[-4.30]	[-4.25]
N	19,108	14,748	14,748	14,748
R-sq	0.005	0.009	0.009	0.009
Panel B: Country excess returns				
β_1	0.087***	0.038	0.052*	0.064**
	[3.90]	[1.53]	[1.90]	[2.18]
β_2	-0.063**	-0.070*	-0.090*	-0.103*
	[-2.14]	[-1.73]	[-1.91]	[-1.91]
N	19,062	5,570	5,570	,5570
R-sq	0.004	0.007	0.007	0.007
Panel C: Country-Industries excess returns				
β_1	0.046*	0.038**	0.042**	0.045**
	[1.74]	[2.27]	[2.29]	[2.31]
β_2	-0.068**	-0.071**	-0.078**	-0.083**
	[-2.17]	[-2.09]	[-2.04]	[-2.01]
N	28,624	10,391	10,391	10,391
R-sq	0.004	0.004	0.004	0.004

In panel A, column 2-4 run the following industry-month level panel regressions with 3, 4, and 5 day half-lives $exret_{i,t} = \alpha + \beta_1 exret12^{nw}_{i,t} + \beta_2 exret12^{nw}_{i,t} \times New_{i,t} + \beta_3 New_{i,t} + \epsilon_{i,t}$. Here $exret_{i,t}$ is market cap weighted return of industry i in excess of the market in month t. $New_{i,t}$ is the newsyness for industry i in month t, and $exret12^{nw}_{i,t} = \sum_{j=1}^{12} exret_{i,t-j} \cdot New_{i,t-j}$ is the average excess return for industry i over the past 12 months, weighted by each month's newsyness. Column 1 is the version of the regression with discrete, binary newsyness, except the independent variable is scaled to have the same dispersion as $exret12^{nw}_{i,t}$ with 4-day half-life, so that the coefficients are roughly comparable across columns. Panel B and C are analogous exercises with country level excess returns and country-industry level excess returns. In panel A and C the regressions are weighted by the industry's market cap normalized by the cross section's total market cap. Panel B uses equal weight. For column 2-4, data are monthly from 1973 to 2021 in panel A and 2000 to 2021 in B and C. The later starting dates arises from the computation of the quantitative newsyness measures. T-statistics computed with standard errors clustered at the month level are reported in square brackets.

Table 17

Global company-fiscal period count by reporting month group

	Both filters		Rpt Lag <= 183		Group 3 FQ end		No filter	
	Count	Pct	Count	Pct	Count	Pct	Count	Pct
Group 1: Jan/Apr/Jul/Oct	168,568	19.76	222,976	22.94	173,502	19.94	228,720	23.07
Group 2: Feb/May/Aug/Nov	534,837	62.70	550,727	56.66	542,855	62.38	559,349	56.41
Group 3: Mar/Jun/Sep/Dec	149,654	17.54	198,271	20.40	153,906	17.68	203,448	20.52
Total	853,059	100	971,974	100.00	870,263	100.00	991,517	100.00

The table tabulates the number of company-quarter by 3 groups, where the groups are determined by the remainder of the reporting month divided by 3. If a company reports earnings for a given fiscal quarter in October, this company-quarter belongs to group 1, as $10 \equiv 1 \mod 3$. First two columns contain count and percentage on the sample where 1) reporting within 183 days and 2) aligned with calendar quarters. The next two columns do the same tabulation with only the first filter. The next two columns apply only the second filter. The last two columns apply no filter. Data are quarterly and semi-annually from 1998 to 2021.

Table 18

Lead-lag relations of monthly earnings in other countries

	(1) All	(2) NM	(3) Non-NM	(4) Difference
Panel A: Report Lag ≤ 183 & Group 3 Month FQ end				
$\sum_{j=1}^{12} roe_{c,t-j}$	0.015***	0.013***	0.043***	-0.031**
	[4.08]	[3.65]	[3.52]	[-2.39]
N	5,369	3,654	1,715	5,369
R-sq	0.048	0.046	0.096	0.060
Panel B: Report Lag ≤ 183				
$\sum_{j=1}^{12} roe_{c,t-j}$	0.012*	0.010*	0.041***	-0.031**
	[1.78]	[1.70]	[3.11]	[-2.15]
N	5,452	3,664	1,788	5,452
R-sq	0.052	0.044	0.170	0.072
Panel C: Group 3 Month FQ end				
$\sum_{j=1}^{12} roe_{c,t-j}$	0.013***	0.012***	0.042***	-0.031**
	[3.90]	[3.45]	[3.56]	[-2.50]
N	5,382	3,659	1,723	5,382
R-sq	0.042	0.040	0.094	0.055
Panel D: No filter				
$\sum_{j=1}^{12} roe_{c,t-j}$	0.012*	0.010*	0.041***	-0.031**
	[1.78]	[1.70]	[3.16]	[-2.18]
N	5,457	3,666	1,791	5,457
R-sq	0.049	0.042	0.159	0.068

Column 1 of this table reports results from the following country-month level panel regressions: $roe_{c,t} = \alpha + \beta \sum_{j=1}^{12} roe_{c,t-j} + \epsilon_{c,t}$. Here $roe_{c,t}$ is the aggregate roe, or the aggregate net income before extraordinary items divided by aggregate book value of equity, of firms reporting their earnings in month t. It is then winsorized at the 10th and the 90th percentiles per cross section. It is filled with a neutral value of zero when missing as part of the independent variable, but kept missing when used individually as the dependent variable. Column 2 and 3 report results from the same regression except on the subsample where the dependent variables are newsy and non-newsy month returns, respectively. Column 4 reports the difference between column 2 and 3. Panel A aggregates ROE only on firm-quarters that are 1) aligned with calendar quarters and 2) reporting within 183 days. Panel B applies only the first filter; panel C only the second; panel D none. The regressions are weighted by aggregate book value of equity of the country-month divided by the total book value of the year. Data are monthly from 1998 to 2021. T-statistics computed with standard errors double clustered at the month, country level are reported in square brackets.

Table 19

Lead-lag relations of monthly market returns in other countries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	NM	Non-NM	All	Post-WW2	First-Half	Second-Half
$\sum_{j=1}^{4} mkt_{c,nm(t,j)}$	0.010	-0.003	0.037***	0.037***	0.038**	0.025*	0.043**
	[1.21]	[-0.30]	[2.77]	[2.78]	[2.55]	[1.72]	[2.28]
$\sum_{j=1}^{4} mkt_{c,nm(t,j)} \times I_t^{nm}$				-0.040**	-0.041**	-0.023	-0.049**
				[-2.36]	[-2.15]	[-1.25]	[-2.03]
I_t^{nm}				0.007*	0.007	0.006*	0.007
				[1.84]	[1.61]	[1.93]	[1.26]
$const$	0.009***	0.011***	0.004	0.004	0.005	0.004	0.004
	[5.10]	[5.23]	[1.47]	[1.47]	[1.40]	[1.45]	[1.05]
N	19,477	12,980	6,497	19,477	16,665	7,201	12,276
R-sq	0.001	0.000	0.012	0.004	0.005	0.003	0.006

Column 1 of this table reports results from the following country-month panel regressions: $mkt_{c,t} = \alpha + \beta \sum_{j=1}^{4} mkt_{c,nm(t,j)} + \epsilon_{c,t}$. Here $mkt_{c,t}$ is the aggregate market return in month t for country c, and $mkt_{nm(t,j)}$ is the aggregate market return in the jth newsy "month" (Jan+Feb, Apr+May, Jul+Aug, Oct+Nov) preceding month t for country c. Column 2 reports the same regression as in 1, but on the subsample where the dependent variable is returns of the newsy months. Column 3 is for the non-newsy months. Column 4 reports the difference between the coefficients in column 2 and 3, extracted from a regression with additional interaction terms to I_t^{nm}, a dummy variable taking value 1 if month t is newsy. Column 5-7 report results for the regression in column 4 on the subsamples of the post-WW2 period (1947-2021), the first half (1926-1973), and the second half (1974-2021). Data are monthly from 1926 to 2021 for column 1-4. T-statistics computed with clustered standard errors by month are reported in square brackets.

Table 20

Lead-lag relations of monthly market excess returns in other countries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	NM	Non-NM	All	Post-war	First-Half	Second-Half
$\sum_{j=1}^{4} exmkt_{c,nm(t,j)}$	0.018***	0.009	0.035***	0.035***	0.038***	0.016	0.050***
	[2.99]	[1.23]	[3.90]	[3.90]	[3.85]	[1.19]	[4.13]
$\sum_{j=1}^{4} exmkt_{c,nm(t,j)} \times I_t^{nm}$				-0.025**	-0.029**	-0.006	-0.043***
				[-2.14]	[-2.22]	[-0.34]	[-2.81]
I_t^{nm}				0.002	0.002	0.004	0.001
				[1.00]	[0.99]	[1.29]	[0.25]
const	0.002*	0.002**	0.000	0.000	0.000	0.002	0.000
	[1.88]	[2.14]	[0.26]	[0.27]	[0.09]	[0.81]	[0.06]
N	19,062	12,692	6,370	19,062	16,444	6,899	12,163
R-sq	0.003	0.001	0.011	0.004	0.005	0.002	0.007

Column 1 of this table reports results from the following country-month panel regressions: $exmkt_{c,t} = \alpha + \beta \sum_{j=1}^{4} exmkt_{c,nm(t,j)} + \epsilon_{c,t}$. Here $exmkt_{c,t} = mkt_{c,t} - \hat{\beta}_{c,t-1}^{US} mkt_{US,t} - (1 - \hat{\beta}_{c,t-1}^{US}) rf_{t-1}$. It is the aggregate market return in month t for country c subtract the US market return in month t multiplied by country's loading on the US return, which is estimated on a rolling 24 months basis, and then subtract 1 minus this beta times the risk free rate. This corresponds to a long-short portfolio return. Notice this beta estimate is available at the end of month $t-1$. $mkt_{nm(t,j)}$ is the aggregate market return in the jth newsy "month" (Jan+Feb, Apr+May, Jul+Aug, Oct+Nov) preceding month t for country c. Column 2 reports the same regression as in 1, but on the subsample where the dependent variable is returns of the newsy months. Column 3 is for the non-newsy months. Column 4 reports the difference between the coefficients in column 2 and 3, extracted from a regression with additional interaction terms to I_t^{nm}, a dummy variable taking value 1 if month t is newsy. Column 5-7 report results for the regression in column 4 on the subsamples of the post war period (1947-2021), the first half (1926-1973), and the second half (1974-2021). Data are monthly from 1926 to 2021 for column 1-4. T-statistics computed with clustered standard errors by month are reported in square brackets.

Table 21

Lead-lag relations of monthly industry excess earnings in other countries

	(1) All	(2) NM	(3) Non-NM	(4) Difference
Panel A: Report Lag $\leq$ 183 & Group 3 Month FQ end				
$\sum_{j=1}^{12} exroe_{c,i,t-j}$	0.023***	0.019***	0.073***	-0.054***
	[4.68]	[4.11]	[7.64]	[-5.17]
N	13,311	10,268	3,043	13,311
R-sq	0.055	0.046	0.167	0.078
Panel B: Report Lag $\leq$ 183				
$\sum_{j=1}^{12} exroe_{c,i,t-j}$	0.037***	0.031***	0.077***	-0.046***
	[13.37]	[11.57]	[11.09]	[-6.24]
N	17,737	12,315	5,422	17,737
R-sq	0.098	0.081	0.222	0.116
Panel C: Group 3 Month FQ end				
$\sum_{j=1}^{12} exroe_{c,i,t-j}$	0.023***	0.019***	0.070***	-0.051***
	[4.79]	[4.23]	[7.96]	[-5.22]
N	13,740	10,582	3,158	13,740
R-sq	0.055	0.047	0.153	0.077
Panel D: No filter				
$\sum_{j=1}^{12} exroe_{c,i,t-j}$	0.036***	0.031***	0.075***	-0.044***
	[13.90]	[12.01]	[10.80]	[-5.96]
N	18,244	12,678	5,566	18,244
R-sq	0.098	0.082	0.214	0.114

Column 1 of this table reports results from the following country-industry-month level panel regressions: $exroe_{c,i,t} = \alpha + \beta \sum_{j=1}^{12} exroe_{c,i,t-j} + \epsilon_{c,i,t}$. Here $exroe_{c,i,t} = roe_{c,i,t} - roe_{c,t}$, where $roe_{c,i,t}$ is the roe of industry i of country c in month t, or the aggregate net income before extraordinary items divided by aggregate book value of equity, of firms of industry i in country c reporting their earnings in month t, and $roe_{c,t}$ is the country-month aggregate roe. It is then winsorized at the 10th and the 90th percentiles per cross section. It is filled with a neutral value of zero when missing as part of the independent variable, but kept missing when used individually as the dependent variable. Column 2 and 3 report results from the same regression except on the subsample where the dependent variables are newsy and non-newsy month returns, respectively. Column 4 reports the difference between column 2 and 3. Panel A aggregates ROE only on firm-quarters that are 1) aligned with calendar quarters and 2) reporting within 183 days. Panel B applies only the first filter; panel C only the second; panel D none. The regressions are weighted by aggregate book value of equity of the country-month divided by the total book value of the year. 20 stocks are required for each country-industry-quarter. Data are monthly from 1998 to 2021. T-statistics computed with standard errors double clustered at the month, country level are reported in square brackets.

Table 22

Lead-lag relations of monthly industry excess returns in other countries

	(1)	(2)	(3)	(4)
	All	NM	Non-NM	Difference
Panel A: SIC Major Group				
$\sum_{j=1}^{4} exret_{c,i,nm(t,j)}$	0.003	-0.007	0.024	-0.032*
	[0.38]	[-0.82]	[1.51]	[-1.72]
N	47,281	31,545	15,736	47,281
R-sq	0.000	0.000	0.005	0.002
Panel B: SIC Industry Group				
$\sum_{j=1}^{4} exret_{c,i,nm(t,j)}$	-0.000	-0.016	0.031*	-0.047**
	[-0.03]	[-1.59]	[1.74]	[-2.30]
N	34,383	22,925	11,458	34,383
R-sq	0.000	0.002	0.007	0.004
Panel C: SIC Industry				
$\sum_{j=1}^{4} exret_{c,i,nm(t,j)}$	0.000	-0.015	0.030*	-0.045**
	[0.04]	[-1.33]	[1.73]	[-2.18]
N	28,622	19,087	9,535	28,622
R-sq	0.000	0.002	0.007	0.004

Column 1 of this table reports results from the following country-industry-month panel regressions: $exret_{c,i,t} = \alpha + \beta \sum_{j=1}^{4} exret_{c,i,nm(t,j)} + \epsilon_{c,i,t}$. Here $exret_{c,i,t}$, is the value weighted average return of industry i in excess of the market of country c in month t, and $exret_{c,i,nm(t,j)}$ is the excess return in the jth newsy "month" (Jan+Feb, Apr+May, Jul+Aug, Oct+Nov) preceding the month t. Column 2 reports the same regression on the subsample where the dependent variable is returns of the newsy months. Column 3 is for the non-newsy months. Column 4 reports the difference between the coefficients in column 2 and 3, extracted from this regression $exret_{c,i,t} = \alpha + \beta \sum_{j=1}^{4} exret_{c,i,nm(t,j)} + \gamma \sum_{j=1}^{4} exret_{c,i,nm(t,j)} \times I_t^{nm} + \delta I_t^{nm} + \epsilon_{c,i,t}$, where I_t^{nm} is a dummy variable taking value 1 if month t is newsy. Panel A to C differ only in the industry variable used. Regressions are weighted by the market cap of industry i as of the month $t-1$, normalized by the total market cap of the cross section. 20 stocks are required in each month-country-industry. Data are monthly from 1986 to 2021. T-statistics computed with clustered standard errors by month are reported in square brackets.

Table 23

Lead-lag relations of monthly market returns in US, by decades

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	-1939	1940-49	1950-59	1960-69	1970-79	1980-89	1990-99	2000-09	2010-
$\sum_{j=1}^{4} mkt_{nm(t,j)}$	0.239***	0.041	0.107*	0.019	0.063	0.072	0.094	0.091	0.146**
	[3.88]	[0.52]	[1.81]	[0.28]	[1.37]	[1.52]	[0.89]	[1.41]	[2.19]
$\sum_{j=1}^{4} mkt_{nm(t,j)} \times I_t^{nm}$	-0.408***	-0.138	-0.100	-0.085	-0.117	-0.263**	-0.199	-0.209*	-0.291***
	[-3.76]	[-1.17]	[-1.05]	[-0.77]	[-1.05]	[-2.22]	[-1.45]	[-1.75]	[-2.80]
I_t^{nm}	0.037*	0.005	0.008	0.015	0.000	0.014	0.011	-0.000	0.036***
	[1.94]	[0.56]	[0.91]	[1.28]	[0.04]	[1.33]	[1.03]	[-0.03]	[3.12]
$const$	-0.011	0.008	0.006	0.003	0.007	0.009	0.009	0.001	-0.004
	[-1.23]	[1.47]	[1.11]	[0.43]	[1.42]	[1.44]	[1.05]	[0.28]	[-0.57]
N	159	120	120	120	120	120	120	120	137
R-sq	0.114	0.009	0.029	0.022	0.018	0.063	0.026	0.040	0.069

Column 1 of this table reports results from the following monthly time-series regressions: $mkt_t = \alpha + \beta_1 \sum_{j=1}^{4} mkt_{nm(t,j)} + \beta_2 \sum_{j=1}^{4} mkt_{nm(t,j)} \times I_t^{nm} + \beta_3 I_t^{nm} + \epsilon_t$. Here mkt_t is the US aggregate market return in month t, $mkt_{nm(t,j)}$ is the return in the jth newsy month (Jan, Apr, Jul, Oct) preceding month t, and I_t^{nm} is a dummy variable taking the value of 1 when month t is newsy. The regression is done on different subsamples across columns. T-statistics computed with White standard errors are reported in square brackets.

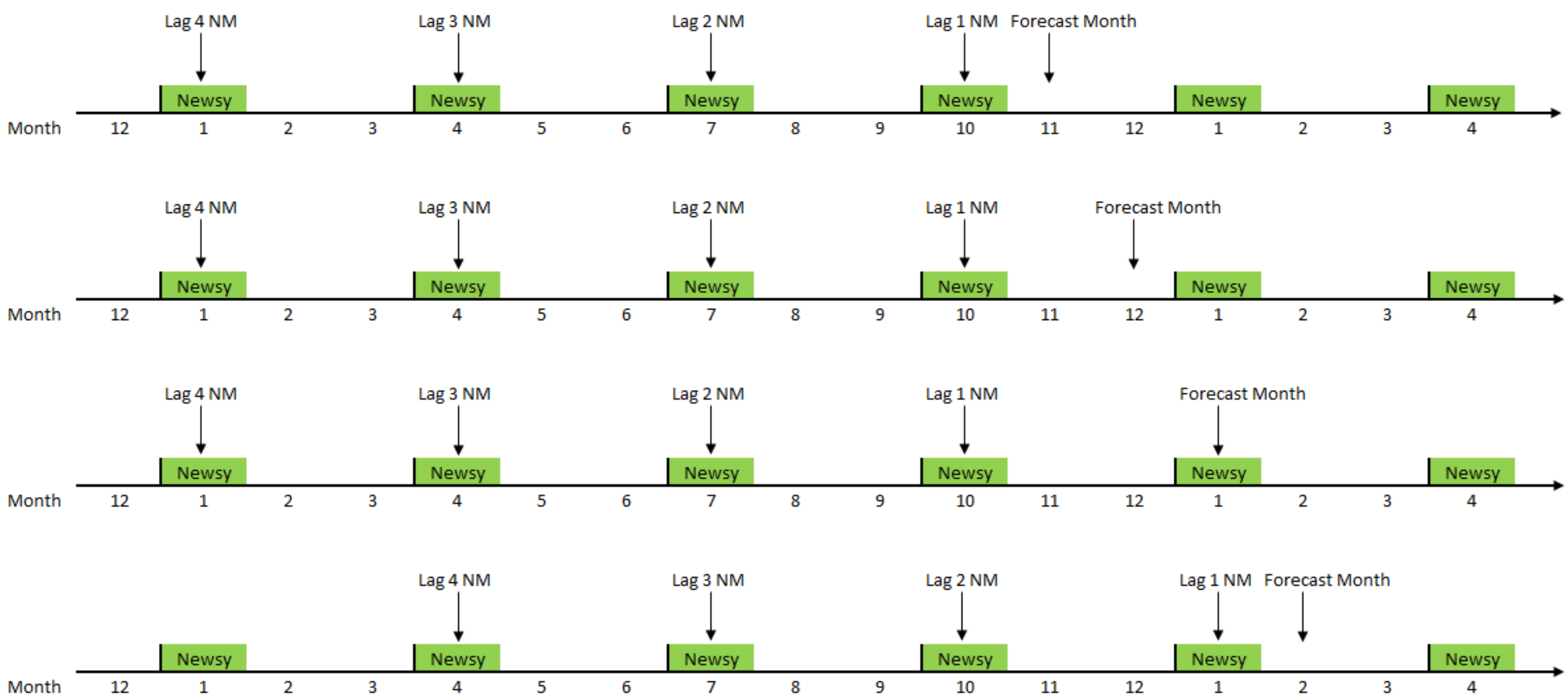
Table 24

Predicting US aggregate market returns with real time coefficients

Method	0	1	2	3	4	5	6	7
R^2	0.49%	3.72%	3.60%	3.68%	3.97%	3.77%	3.82%	4.30%

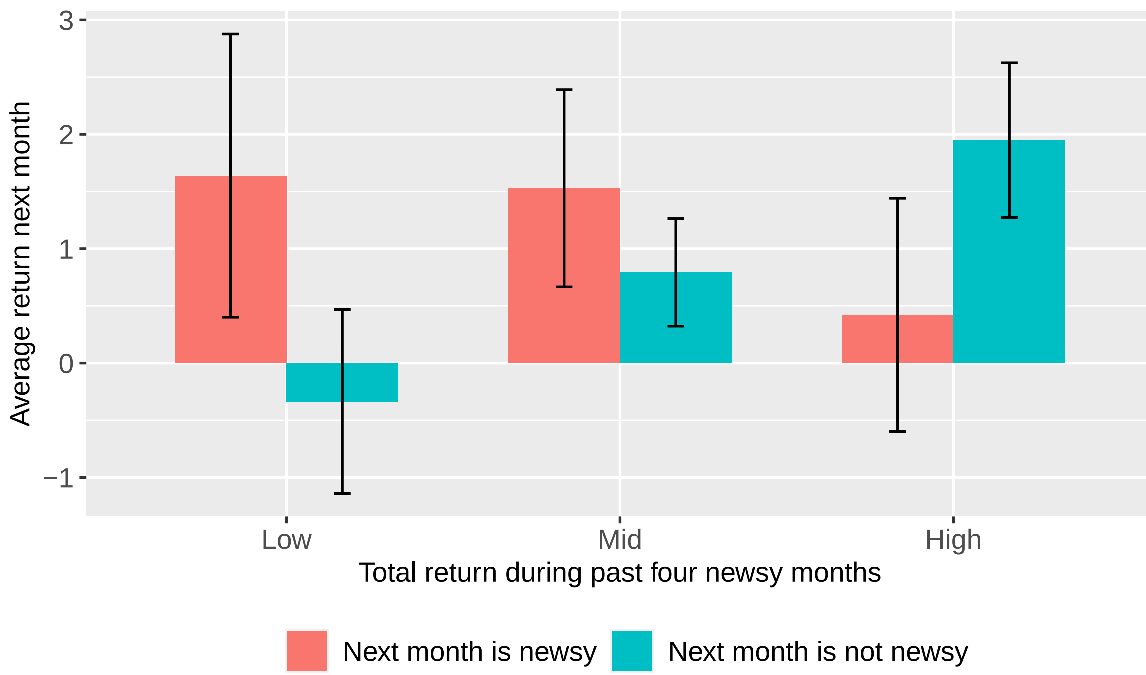
The R^2 in this table are calculated as $1-\frac{\sum_{t=1}^{n}(r_t-\hat{r}_t)^2}{\sum_{t=1}^{n}(r_t-\overline{r_t})^2}$, where $\overline{r_t}$ is the expanding window mean of past stock returns, and $\hat{r}_t$ is the forecast being evaluated. This R^2 is positive only when the forecast outperforms the expanding window mean of past stock returns. Method 0 comes solely from Campbell and Thompson (2008) and functions as a benchmark. It is the valuation constraint + growth specification with fixed coefficients. Simple average is taken from the Dividend/Price, Earnings/Price, and Book-to-market ratios based forecasts. Method 1 uses the signal that is simply the sum of past four newsy month returns. The coefficients are extracted from simple expanding-window OLS of past returns on past signals, separately for newsy and non-newsy month dependent variables. The signal used in method 2-7 is the sum of past four newsy month returns, subtracting its expanding window mean, and sign flipped if the dependent variable is a newsy month. Method 2 uses the same coefficient estimation method as in method 1. Methods 3 replace the constant terms with the expanding window means of past newsy and non-newsy month returns. Method 4 replace the constant terms with the forecast in method 0. Method 5-7 are method 2-4 with the coefficients estimated on the combined sample of newsy and non-newsy months. Data are monthly from 1926 to 2021.

Figure 1: Timing of independent and dependent variables in return forecasting regressions, US



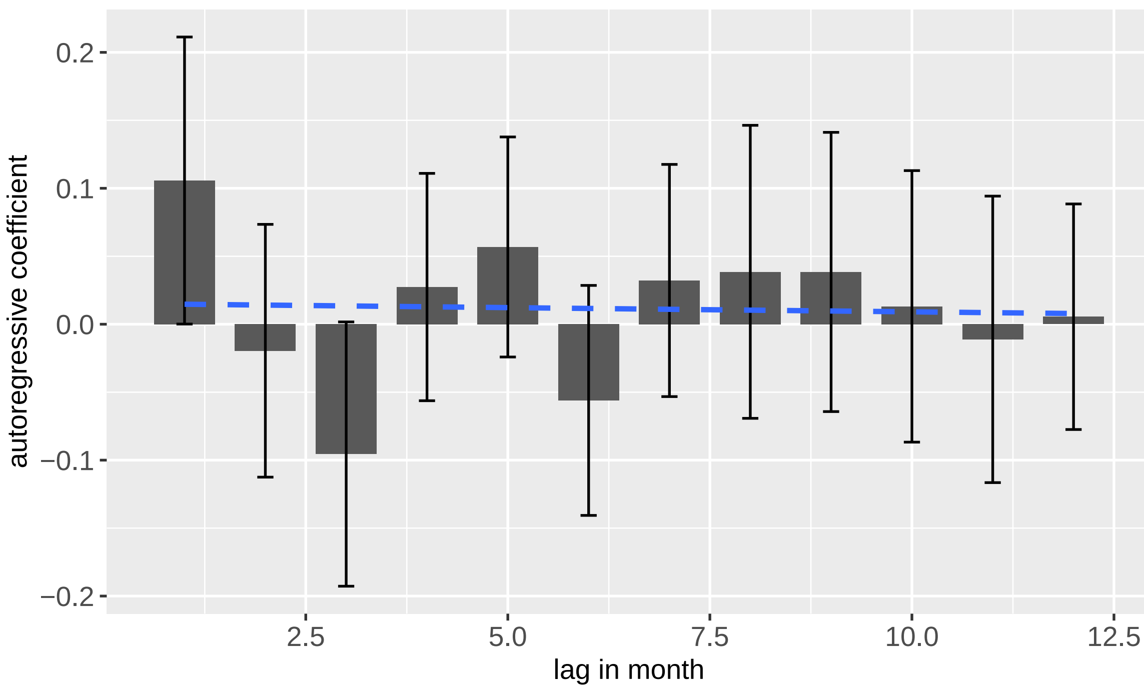
This figure shows how the independent variables in the US return forecasting regressions progress as the dependent variable move forward.

Figure 2: Next month's market returns vs past four newsy month returns, by whether the next month is newsy



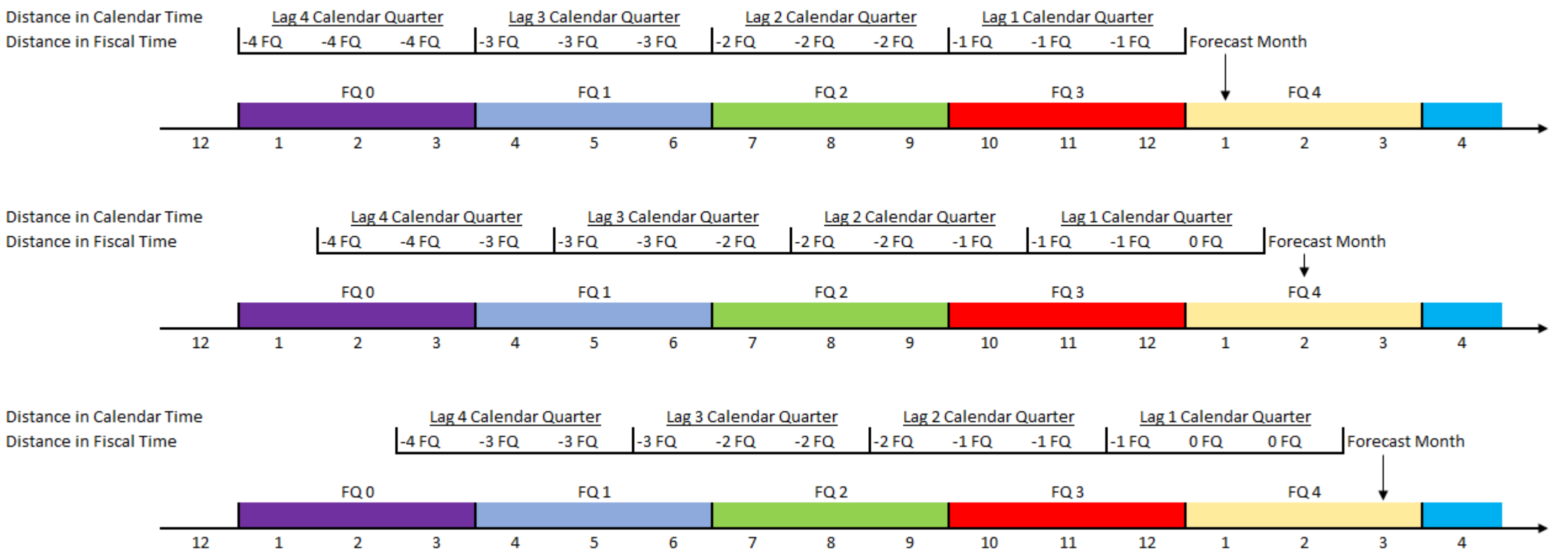
This figure plots mean of US monthly aggregate market returns in the next month against total returns during past four newsy months. The newsy months are the first months of the calendar quarters, namely January, April, July, and October. The sample is split based on whether the next month is newsy. Data are monthly from 1926 to 2021. One arm of the error bars represents 2 standard errors.

Figure 3: Autoregressive coefficients of US monthly aggregate market returns



This figure shows the autoregressive coefficients of US monthly aggregate market returns. The dotted line is a trend line on the coefficient values over lags. Data are monthly from 1926 to 2021. The error bars represented 2 standard errors.

Figure 4: Distance in calendar and fiscal time of lagged data in an earnings forecasting setting



This figure shows the dependent and independent variables used by a hypothetical investor trying to forecast the earnings in each calendar month using past earnings. It demonstrates that past earnings contained over the same look-back window in terms of calendar time are actually further away in terms of fiscal time—which is what determines the nature of the news—if the dependent variable is in a newsy month. Fiscal periods corresponding to earnings reported in each calendar month are labeled and color coded.

Appendix

A Correlation neglect and evidence

In short, the effect of correlation neglect says that if investors get two consecutive signals with the second being a thinly-veiled repetition of the first, agents then overreact to the second signal. This overreaction subsequently corrects itself. In the setting of the earnings reporting cycle, if we think of the first signal as aggregate earnings announced in the first month of quarter, and the second as that announced in the second month, correlation neglect then predicts that 1) the first month return positively predicts the second month return and 2) the second month return negatively predicts the return in the first month of the next quarter.

A major distinction between that and the main result documented in this paper are noteworthy: It is the *second* month return that negatively predicts future returns. The main result instead uses the first month return to negatively predict future returns. In other words, in the correlation neglect setting the second month is the time of overreaction. In the main result the first month contains both under and over-reaction.

Notice that correlation neglect does not explain why the first month return is positively predicting returns in the second and the third months of the next quarter and beyond. It also does not explain why the first month return is negatively predicting returns in the first month of the next quarter and beyond. Correlation neglect therefore differs from my story in two ways: it makes additional predictions, and at the same time does not make some predictions that my story makes. I therefore am documenting evidence in favor of correlation neglect in this appendix, so that the two effects can be separated and distinguished.

I document the evidence supporting correlation neglect in Table A1. Column 1 shows that aggregate market return in the second months of the quarters negatively predicts returns in the first month of the next calendar quarter. Column 2 shows that industry level return in excess of the market in the second month of the quarter negatively predicts the excess return in the first month of the next quarter and the quarter afterward. These are precisely what correlation neglect predicts.

An immediate next step prediction here is that this reversal is substantially stronger when the signals in the first month and the second month agreed. If one measure the degree of agreement using the product of the first and the second month returns this prediction does not pan out. It could be that we need a better measurement of agreement, however. Overall, the evidence here is interesting but we need more investigations to make a convincing case.

Table A1

Evidence supporting correlation neglect

	(1) market return	(2) industry exret
β_2	-0.275***	-0.110**
	[-3.05]	[-2.63]
β_5	0.040	-0.081**
	[0.73]	[-2.08]
β_8	0.140	-0.001
	[1.31]	[-0.02]
β_{11}	-0.072	0.041
	[-0.94]	[1.30]
N	378	6,131
R-sq	0.091	0.017

Column 1 shows results from the following monthly time-series regression: $mkt_t = \alpha + \beta_2 mkt_{t-2} + \beta_5 mkt_{t-5} + \beta_8 mkt_{t-8} + \beta_{11} mkt_{t-11} + \epsilon_t$, conditioning on month t is a newsy month. Here mkt_t is aggregate market return in month t, and mkt_{t-x} is aggregate market return x months before month t. It shows how the market returns in the newsy months are being predicted by past second months of the quarter. For instance, if the dependent variable is the return of October, the independent variables are returns of August, May, February, and November of the previous year. The second column does an analogous regression on an industry-month panel:$exret_{i,t} = \alpha + \beta_2 exret_{i,t-2} + \beta_5 exret_{i,t-5} + \beta_8 exret_{i,t-8} + \beta_{11} exret_{i,t-11} + \epsilon_{i,t}$. T-stats are reported in square brackets. Data are monthly from 1926 to 2021. In the first column, White standard errors are used to compute the t-stats. In the second column, standard errors clustered at the monthly level are used.

B Alternative versions of the models

B.1 Earnings surprises and returns

In the data, aggregate earnings surprises and aggregate market returns have only a small positive correlation around 0.1. Related, the correlation at the stock level is not too strong either. This pattern can potentially arise from investors' correct understanding that part of the cash flow surprise is temporary. The intuition can be reflected in my model, which I compactly summarize below. Let $\Delta d_{t+1} = d_{t+1} - b_t$, where $b_t = \sum_{j=0}^{\infty} \rho^j d_{t-j}$, as before.

Investors' beliefs:

$$
\begin{aligned}
\Delta d_{t+1} &= y_{t+1} + u_{t+1} \\
u_{t+1} &\overset{iid}{\sim} N(0, \sigma_u), \quad \forall t \\
y_{t+1} &= m x_t + v_{t+1} \\
x_t &= \sum_{j=0}^{\infty} \delta^j y_{t-j}
\end{aligned}
$$

Notice that investors correctly understand that u_t is purely temporary and does not impact future cash flow growth, even though it entered past cash flow growth. This leads to a two-state-variable solution for the valuation ratio as before:

$$
\frac{P_{nt}}{D_t} = e^{a_n + b_n x_t + c_n}
$$

where:

$$
\begin{aligned}
a_n &= a_{n-1} + \log r + \frac{(b_{n-1} + c_{n-1} + 1)^2}{2} \sigma_v^2 + \frac{(c_{n-1} + 1)^2}{2} \sigma_u^2 \\
b_n &= (m + \delta) b_{n-1} + (1 + c_{n-1}) m \\
c_n &= -\rho
\end{aligned}
$$

This set of valuation, combined with the realization of:

$$y_{t+1} = \begin{cases} hx_t + v_{t+1}, \text{ where } t \text{ is even} \\ lx_t + v_{t+1}, \text{ where } t \text{ is odd} \end{cases}$$

Leads to returns:

$$\begin{aligned} \log(1 + R_{n,t+1}) &= a_{n-1} - a_n + (h - m)(b_{n-1} + 1 - \rho)x_t + \\ &\quad b_{n-1}v_{t+1} + (1 - \rho)(v_{t+1} + u_{t+1}), \text{ where } t \text{ is even} \\ \log(1 + R_{n,t+1}) &= a_{n-1} - a_n + (h - m)(b_{n-1} + 1 - \rho)x_t + \\ &\quad b_{n-1}v_{t+1} + (1 - \rho)(v_{t+1} + u_{t+1}), \text{ where } t \text{ is odd} \end{aligned}$$

Notice that u_{t+1} and v_{t+1} equally enter Δd_{t+1}. However, due to the multiplier b_{n-1}, v_{t+1} is much more important than u_{t+1} as a component of the returns. This is because v_t enters x_t and thus influences valuation, while u_t does not.

B.2 Past cash flow growth unevenly enters valuation

We see that aggregate market returns in the newsy months are mainly responsible for predicting future returns. In our previous versions of the models, both kinds of past returns positively predict future non-newsy months returns, and negatively predict future newsy months returns. A potential explanation for this distinction from the independent variable's perspective is that investors re-form their earnings forecasts mainly around earnings seasons. The intuition can be added in my model, which I go over below. Let $\Delta d_{t+1} = d_{t+1} - b_t$, where $b_t = \sum_{j=0}^{\infty} \rho^j d_{t-j}$, as before.

Investors' beliefs:

$$\begin{aligned} \Delta d_{t+1} &= mx_t + u_{t+1} \\ u_{t+1} &\overset{iid}{\sim} N(0, \sigma_u), \quad \forall t \\ x_t &= \begin{cases} \sum_{j=0}^{\infty} \delta^j \Delta d_{t-2j} & \text{where } t \text{ is odd} \\ \sum_{j=0}^{\infty} \delta^j \Delta d_{t-2j-1} & \text{where } t \text{ is even} \end{cases} \end{aligned}$$

Notice only the odd period Δd_t enters x_t. This then leads to the following iteration rule:

$$x_t = \begin{cases} (m+\delta)x_{t-1} + u_t & \text{where } t \text{ is odd} \\ x_{t-1} & \text{where } t \text{ is even} \end{cases}$$

These together lead to a two-state-variable form for the valuation ratio as before, except that now there is a superscript indicating an additional dependence on whether t is even or odd:

$$\frac{P_{nt}}{D_t} = \begin{cases} e^{a_n^1 + b_n^1 x_t + c_n^1} & \text{where } t \text{ is odd} \\ e^{a_n^0 + b_n^0 x_t + c_n^0} & \text{where } t \text{ is even} \end{cases}$$

The iteration rules are:

$$\begin{aligned} a_n^1 &= a_{n-1}^0 + \log r + \frac{(c_{n-1}^0 + 1)^2}{2}\sigma_u^2 \\ b_n^1 &= b_{n-1}^0 + (1 + c_{n-1}^0)m \\ c_n^1 &= -\rho \end{aligned}$$

When t is even:

$$\begin{aligned} a_n^0 &= a_{n-1}^1 + \log r + \frac{(b_{n-1}^1 + c_{n-1}^1 + 1)^2}{2}\sigma_u^2 \\ b_n^0 &= (m+\delta)b_{n-1}^1 + (1 + c_{n-1}^1)m \\ c_n^0 &= -\rho \end{aligned}$$

Along with the initial condition that $a_0^1 = b_0^1 = c_0^1 = a_0^0 = b_0^0 = c_0^0 = 0$, all a, b, and c can be solved. In particular,

$$b_n^1 = \begin{cases} \frac{1-(m+\rho)^{\frac{n-1}{2}}}{1-m-\rho} 2m(1-\rho) + m(1-\rho) & \text{where } n \text{ is odd} \\ \frac{1-(m+\rho)^{\frac{n}{2}}}{1-m-\rho} 2m(1-\rho) & \text{where } n \text{ is even} \end{cases}$$

$$b_n^0 = \begin{cases} \frac{1-(m+\rho)^{\frac{n-1}{2}}}{1-m-\rho} 2m(1-\rho)(m+\delta) + m(1-\rho) & \text{where } n \text{ is odd} \\ \frac{1-(m+\rho)^{\frac{n}{2}}}{1-m-\rho} 2m(1-\rho) & \text{where } n \text{ is even} \end{cases}$$

These then lead to the following returns:

$$\log(1+R_{n,t+1}) = \begin{cases} a_{n-1}^0 - a_n^1 + (h-m)(1-\rho)x_t + (1-\rho)(u_{t+1}) & \text{where } t \text{ is odd} \\ a_{n-1}^1 - a_n^0 + (l-m)(b_{n-1}+1-\rho)x_t + (b_{n-1}+1-\rho)u_{t+1} & \text{where } t \text{ is even} \end{cases}$$

Notice the predictable component of stock returns depends on x_t as before. Because only the low realization periods, or newsy periods cash flow growth enters x_t, only returns in those periods will positively and negative predict future non-newsy and newsy periods returns, respectively.

C Trading strategies, Sharpe ratios, and alphas

C.1 Time series

I convert the return predictability patterns that I document into trading strategies implementable in real time. Coefficients obtained by regressing future returns on signals, like those documented in Table 4 and Table 11, are in principle returns to long short portfolios themselves (Fama and MacBeth (1973)).[30] Hence the results in this section is to some extent already implied by my return predicting results. However, the implied portfolios often have look-ahead bias in their weights and are technically not implementable in real time. Out of an abundance of caution, in this section I form portfolios with information available in real time, and compute its Sharpe ratio and multi-factor alphas.

Starting the aggregate market strategy, at the end of each month $t-1$ I take the total return of the aggregate market in the past four newsy months (potentially include month $t-1$), and compute the expanding window mean of this total return, which is its mean from the beginning of the sample to month $t-1$. I then take the difference between the total return and its expanding window mean, and flip sign if month t is newsy to arrive at the demeaned signal x_{t-1}. I then run a constrained time-series regression $mkt_t = \beta x_{t-1} + 1\,\overline{mkt}_{t-1} + \epsilon_t$, where mkt_t is the market return in month t, x_{t-1} is the said demeaned signal, and $\overline{mkt}_{t-1}$ is the expanding window mean of the market return up to month $t-1$. Notice the coefficient before $\overline{mkt}_{t-1}$ is constrained to be 1. Denote estimated coefficient β as c_t. The forecasted market return at the end of month t for month $t+1$ is then $c_t x_t + \overline{mkt}_t$. The portfolio weight in my strategy is $c_t x_t$, which roughly has a mean of zero over time. Lastly, the portfolio is scaled by a constant so that it has the same volatility as the aggregate market, which is 5.34% per month.[31] This is so that the portfolio's average return is in comparable unit as the

[30] Consider the simplest case where you do a cross sectional regression of returns on one signal and a constant. Denote the returns as the vector $(r_1, r_2, ..., r_n)$ and the signal $(x_1, x_2, ..., x_n)$. The coefficient on the signal is then $\frac{\sum_{i=1}^n (x_i-\overline{x})(r_i-\overline{r})}{\sum_{i=1}^n (x_i-\overline{x})^2} = \sum_{i=1}^n \frac{x_i-\overline{x}}{\sum_{i=1}^n (x_i-\overline{x})^2} r_i$, where $\overline{r}$ and $\overline{x}$ are the cross sectional means of r and x. Notice this coefficient value is the return to a portfolio of stocks, with the weight on stock i being $\frac{x_i-\overline{x}}{\sum_{i=1}^n (x_i-\overline{x})^2}$. Notice this weight sums to 0, and the portfolio is hence long short. Additionally, the weight ensures that the portfolio has unit exposure to the signal itself, i.e. $\sum_{i=1}^n \frac{x_i-\overline{x}}{\sum_{i=1}^n (x_i-\overline{x})^2} x_i = 1$, and therefore the scale of the portfolio is often not meaningful unless the signal is in interpretable unit. The Sharpe ratio of the portfolio is always meaningful though.

[31] One may argue that this scaling, even though it does not change the portfolio's Sharpe ratio, still has look-ahead bias in it, because the number 5.34% is not known in advance. This can similarly

aggregate stock market.

It is worth noting that the forecasting system that I use can be applied to a generic signal. The system also extends to a multivariate setting without having to worry about the difference in sample span for different signals—for missing signals one can just fill in a neutral value of 0. Here I delegate the constant term in the regression to the expanding window mean of past returns. This is to keep the forecasting system simple so that I observe my signal's effect in isolation. Campbell and Thompson (2008) put forth better options for the purpose of optimal forecasting.

Table C1 regresses the said time-series portfolio returns on a constant and contemporaneous factors, including the market, value, size, and momentum. The coefficients on the constant are of interest. In column 1, the coefficient of 0.823 means that the portfolio has an average return of 0.823% per month, which is about 10% per annum. This corresponds to an annualized Sharpe ratio of 0.44, which is about the same as that on the aggregate market. It is worth noticing that explaining the sheer scale of this Sharpe ratio is non-trivial when the underlying instrument is just the aggregate market: the equity premium puzzle (Mehra and Prescott (1985)) inspired sophisticated models developed by generations of scholars (e.g. Abel (1990)), Constantinides (1990), Campbell and Cochrane (1999), Bansal and Yaron (2004), Rietz (1988), Barro (2006), Gabaix (2012), Wachter (2013)). Therefore the predictability I document is worth thinking carefully about.

In column 2, we see that the strategy is indeed roughly market neutral, as designed. It leads to a CAPM alpha of about 0.75% per month. In column 3 and 4 we see that the 3-factor and 4-factor alphas of this strategy are 0.64% and 0.74% per month. It is worth noting that even though my trading strategy involves substantial rebalancing, the underlying instrument is the aggregate market, and the incurred trading cost is likely lower than strategies that require stock level rebalancing, such as the value, size, and the momentum factors.

C.2 Cross sectional

Having discussed the time series strategy I now move to the cross sectional strategy trading on US industries. For each industry i and month t, I compute i's total excess return of the past four newsy months, and then cross sectionally demean with market cap weight at the end of month t. I then flip the sign of this total excess return if month

be dealt with using an expanding window approach, and it leads to similar results.

$t+1$ is newsy to arrive at the signal $x_{i,t}$. I then compute a expanding window standard deviation σ_t of the signal x across all industry-month up to month t, weighting by market cap divided by the total market cap of the cross section. The portfolio weight is $x_{i,t}/\sigma_t$ winsorize at [-2, 2] to make sure no extreme position is taken. Lastly, the portfolio is then scaled so that it has the same volatility as the aggregate market excess return, which is 5.34% per month. Notice this strategy is market neutral in each cross section.

Table C2 regresses this cross sectional portfolio returns on the market, value, size, and momentum factors. Column 1 shows that the average return of this portfolio is about 0.62% per month, and the annualized Sharpe ratio is about 0.33. Across the rows we see that the multi-factor alphas of this strategy is strongly positive, even though it declines as factors are added in, because it has small positive loadings on the size and the momentum factors. It is worth noting that the factor's loading on the momentum factor is not very strong. This is because it bets against continuation one third of the times, and it is at the industry level and uses only newsy month returns as the predictors. Overall, this shows that the cross sectional return predictability I document can also be translated into a trading strategy.

Table C1

Time series strategies and alphas

	(1)	(2)	(3)	(4)
	ts_pf_t	ts_pf_t	ts_pf_t	ts_pf_t
$MKT_t - Rf_{t-1}$		0.110	-0.021	-0.046
		[0.88]	[-0.25]	[-0.57]
HML_t			0.361**	0.309*
			[2.14]	[1.88]
SMB_t			0.391	0.386
			[1.29]	[1.25]
MOM_t				-0.112
				[-1.07]
$const$	0.823***	0.748***	0.635***	0.743***
	[4.29]	[4.34]	[3.83]	[3.90]
N	1,136	1,136	1,136	1,134
R-sq	0.000	0.008	0.082	0.087

Column 1 shows results from the following monthly time-series regression: $ts\_pf_t = \alpha + \epsilon_t$. Here ts_pf_t is our time-series portfolio return in month t. This portfolio longs or shorts the aggregate market for a given month, and the weight is proportional to the previous-month-end forecasted market return subtracting the expanding window mean of aggregate market returns and scaled to have the same volatility as the aggregate market excess return, which is 5.34% per month. The said forecasted market return is constructed with the following steps: 1) demean the total return of the past four newsy months (January, April, July, and October) with the expanding window mean; 2) flip sign if the next month is newsy to arrive at our signal; 3) regress the aggregate market return on lag one month signal and the expanding window mean aggregate market return based on data available in real time at each month, and with the coefficient on the expanding window mean aggregate market return constrained to 1; 4) compute the forecast as the coefficient estimated at a given month times the signal plus the expanding window mean aggregate market return. Notice the forecast is designed to use only data available in real time. Column 2-4 add in the market, value, size, and momentum factor returns on the right hand side. In column 1, the coefficient of the constant represents the average return of time-series portfolio. In column 2-4 it represents its alphas with different factor models. Data are monthly from 1926 to 2021. Returns are all in percentage unit. T-stats computed with White standard errors are reported in the square brackets.

Table C2
Cross sectional strategies and alphas

	(1)	(2)	(3)	(4)
	cs_pf_t	cs_pf_t	cs_pf_t	cs_pf_t
$MKT_t - Rf_{t-1}$		-0.026	-0.067	-0.054
		[-0.73]	[-1.46]	[-1.14]
HML_t			0.001	0.028
			[0.01]	[0.29]
SMB_t			0.211*	0.214*
			[1.79]	[1.81]
MOM_t				0.057
				[0.69]
$const$	0.619***	0.638***	0.621***	0.566***
	[3.89]	[3.98]	[3.90]	[3.27]
N	1,136	1,136	1,136	1,134
R-sq	0.000	0.001	0.015	0.017

Column 1 shows results from the following monthly time-series regression: $cs\_pf_t = \alpha + \epsilon_t$. Here cs_pf_t is our cross-sectional portfolio return in month t. This portfolio takes long and short positions on industries in a given month, and the weight is constructed with the following steps: 1) for each industry-month, compute the total excess return of the past four newsy months (January, April, July, and October), and cross sectionally demean with market cap weight; 2) flip sign if the next month is newsy; 3) scale by expanding window standard deviation of the signal, and winsorize at [-2, 2] to make sure no extreme position is taken. The portfolio is then scaled so that it has the same volatility as the aggregate market excess return, which is 5.34% per month. Column 2-4 add in the market, value, size, and momentum factor returns on the right hand side. In column 1, the coefficient of the constant represents the average return of time-series portfolio. In column 2-4 it represents its alphas with different factor models. Data are monthly from 1926 to 2021. Returns are all in percentage unit. T-stats computed with White standard errors are reported in the square brackets.