Correlation neglect in asset prices*

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Abstract

The U.S. stock market return during the first month of a quarter positively predicts the second month's return, which in turn negatively predicts the first month's return of the next quarter. This pattern arises because investors fail to fully recognize that earnings announced in the second month of a quarter are inherently similar to those announced in the first month, leading them to overreact to predictably repetitive earnings news. A model formalizing this form of correlation neglect yields additional predictions for survey data and for both the time-series and cross-section of returns, all of which are borne out in the data. These results provide evidence of correlation neglect even among sophisticated, financially incentivized decision-makers, underscoring its importance as a behavioral phenomenon.

Keywords: behavioral finance, correlation neglect, earnings announcements, efficient market hypothesis, stock return autocorrelation

JEL codes: G12, G14, G40

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1 Introduction

Predicting stock market returns based on past returns has posed a decades-long challenge. Early research by Kendall and Hill (1953) and Fama (1965) revealed minimal serial correlation in stock returns. Fama (1970) introduced the efficient market hypothesis, which, in its weak form, postulates that prices already incorporate all available information from past prices. Poterba and Summers (1988) applied this hypothesis to the US aggregate stock market, finding that monthly returns exhibit a small, statistically insignificant positive autocorrelation over a 12-month period.[1] The lack of correlation between past and future market returns is not only a well-recognized statistical phenomenon but also an emblem of market efficiency.

We document that the US market return during the first month of a quarter positively predicts the second month's return, which then negatively predicts the first month's return of the next quarter. These first months of a quarter are important because, owing to the US corporate earnings cycle, they contain fresh earnings news about the aggregate economy. For example, at the end of December, firms close their books for Q4. 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. The first months of the quarters are famously known as the "earnings seasons" among practitioners and receive heightened attention. Throughout this paper, we refer to them as "newsy" months, as they produce fresh news about aggregate earnings.

The second month of each quarter contains roughly the same number of earnings announcements as does a newsy month. However, the aggregate earnings announced in the second month are to some degree repetitive of those announced in the preceding newsy month because the announced earnings are of the same fiscal quarter (Q4 in our example above). We call these second months "repetitive" months, as they contain earnings announcements

[1] Furthermore, Poterba and Summers (1988) noted a negative autocorrelation over longer time horizons, while Lo and MacKinlay (1988) identified a positive autocorrelation in weekly returns for small stocks. Despite these variations, the consistently low month-to-month autocorrelation in the aggregate market returns remains a crucial piece of evidence supporting the concept of market efficiency.

that produce repetitive aggregate earnings "news." Such repetition is not verbatim—different firms announce in the first and the second months of a quarter—but subtle in that the announcements pertain to earnings that share an aggregate component. In contrast, the third month of a quarter contains substantially fewer earnings announcements. This month produces little in the way of "news," repetitive or otherwise. Our empirical findings, restated in this terminology, are that a newsy month's return positively predicts the next repetitive month's return, which then negatively predicts the next newsy month's return. We show that this pattern is economically and statistically significant, produces high out-of-sample R^2 coefficients, and forms a profitable trading strategy.

Embedded in our decision to look at this pattern of predictability is a hypothesis: imperfectly rational investors use announced earnings to forecast future earnings but fail to fully account for the repetitive nature of the earnings in the second month of a quarter. This hypothesis generates the prediction above: because the "news" is the same in the second month, investors react to it in the same direction as in the first month. Investors, however, now have priced in too much information, and thus, when more about the true state is revealed, there is a correction. Enke and Zimmermann (2019) previously identified this mechanism, correlation neglect, in experimental data. We formalize this mechanism using a model and show that it has the implication stated above. We also show how this mechanism arises naturally from basic memory processes, as in Wachter and Kahana (2024).[2]

Our theory of correlation neglect generates additional predictions. First, according to the theory, the eventual reversal occurs because of the initial over-reaction. We show that indeed, these two legs of the strategy are significantly correlated. Second, our model invokes fundamental aspects of behavior rather than specific aspects of the aggregate market. Thus, it should also exist for industry returns relative to the market, which we also verify: excess returns in a repetitive month are positively correlated with the previous month's excess re-

[2]A sophisticated theoretical literature develops models of correlation neglect in settings where agents learn from one another and from various contemporaneous signals (DeMarzo et al., 2003; Eyster and Rabin, 2010; Golub and Jackson, 2010; Bohren, 2016). Unlike previous settings, our agents learn over time and the information becomes embedded into asset prices, requiring, as we show, a somewhat different approach in the specification of the signals and the fundamentals. Nonetheless, a basic similarity is that agents keep a "running tally" (DeMarzo et al., 2003), rather than unraveling the correlations with each new observation.

turns and negatively predict the following newsy month's excess returns. Third, because the mechanism is based on expectations, we should see it in expectations data. Controlling for average latency in revisions, earnings revisions in repetitive months are positively correlated with the previous month's revisions, whereas earnings revisions in the next quarter's newsy months are negatively correlated with the previous repetitive month's revisions. In addition, we show that continuation and reversal are stronger when the announcements in the repetitive month more closely resemble those in the newsy month, and that the cross-sectional results are stronger in industries that are larger and also in those in which firms are more tightly connected. In both of these cases, investors are more likely to receive a signal in the second month that they interpret as additive to that of the first month. Each of these findings are predicted by the correlation neglect model.

These findings have broader implications. Correlation neglect represents a fundamental departure from rational expectations. Prior work links correlation neglect to failures of democratic institutions (Ortoleva and Snowberg, 2015) and places it among the constellation of factors leading to the 2008 financial crisis (Akerlof and Shiller, 2009).[3] At the same time, an empirical literature provides direct evidence of correlation neglect in an experimental setting (Enke and Zimmermann, 2019), in the pricing of individual securities (Fedyk and Hodson, 2023; Tetlock, 2011), and in announcement day returns (Gilbert et al., 2012). Our study shows that correlation neglect is large enough to affect aggregate stock returns at a monthly horizon. For this to be the case, correlation neglect needs to be present among a broad set of sophisticated and financially incentivized agents. Our findings therefore support the view that correlation neglect is both pervasive and significant, with potential consequences for our most important institutions.

Within the literature on financial markets, our paper relates to the work on continuation and reversal, too vast to cite in its entirety. Specifically, our work relates to that of Lou et al. (2022), who show a continuation and reversal pattern at the intra-day level. Open-

[3]The repetition of narratives can create the illusion of independent signals, linking correlation neglect to broader processes of belief formation; see also Goetzmann et al. (2024). Levy and Razin (2015) develop a model in which correlation neglect can improve voting outcomes.

to-close stock market returns positively predict future close-to-open stock market returns, which then negatively predict future open-to-close returns. [4] The authors attribute their findings to clientele effects: the overreaction arises from news being repeatedly consumed by a new set of investors, while in our paper, the overreaction arises from news itself being repeated in the second month of a quarter. As mentioned above, Fedyk and Hodson (2023) report experimental findings in which finance professionals treat old information as news when combined with new content. They then find the same pattern in weekly firm-level returns using a sample of Bloomberg news articles that they classify as novel, a reprint (in which case the correlation is easy to detect and ignored), and a recombination. In addition to formalizing the mechanism of correlation neglect in a model that also accounts for their results, we show that it exists in the aggregate market at a monthly level, in industry returns, and in survey data. Charles (2025) shows how firms that announce together become associated in the memory of investors. Like our work, this work also links announcements to memory phenomenon, but exploits the role of associations to identify the role of memory, as opposed to the role of repetition to reinforce (incorrectly) a set of beliefs. Guo (2025) shows that, in the newsy months, investors under-extrapolate when forecasting earnings in non-newsy months and over-extrapolate when forecasting those in newsy months, assuming that earnings shocks decay at a linear rate, when in fact they decline with a step function. The cognitive error is parameter compression (two different decay rates are averaged together) rather than correlation neglect. In what follows, we show that both effects are significant in the data in the presence of the other.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 describes our return predictability regressions, both in and out-of-sample. Section 4 describes the model and its additional predictions, which Section 5 tests. Section 6 evaluates several alternative explanations. Section 7 concludes.

[4] Relatedly, Lou et al. (2019) find that close-to-open (open-to-close) stock returns positively predict future close-to-open (open-to-close) returns, and negatively predict future open-to-close (close-to-open) returns.

2 Data

Our return data come from CRSP and Ken French's website, accounting data come from Compustat North America, and LTG 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 United States: Compustat and IBES. Both data sources have been used individually in major studies. These announcement days often disagree, though the disagreements are usually small and mostly concentrated before December 1994 (Dellavigna and Pollet 2009). We implement the algorithm in Dellavigna and Pollet (2009), which combines the Compustat and IBES announcement dates to form the best estimate of the actual announcement dates.[5] If the adjusted announcement date is the same as the IBES announcement date, we also shift the date to the next trading date if the IBES announcement time is after the market closure, following Johnson and So (2018a).

In terms of specific variables, we use the market factor from Fama and French (1993) to represent aggregate market excess returns and the SIC code to represent industries. We 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.

3 Predicting aggregate stock market returns

3.1 The earnings cycle

We first characterize the US earnings cycle, which originates from i) aligned fiscal quarters and ii) heterogeneous announcement lags. Panel A of Table 1 shows that the vast majority of US firms close their books for a given fiscal quarter on the last day of a calendar quarter.

[5] The algorithm is effectively as follows: 1) when the two sources differ, use the earlier date, and 2) when they agree and the date is before January 1, 1990, shift the day to the previous trading date.

Therefore, the fiscal quarters over which the earnings are recorded are effectively the calendar quarters. Although fiscal quarters are aligned, firms do not announce their quarterly earnings together. Almost all firms announce within three months of the fiscal quarter end date, but there is much variation in their announcement lags. Panel B shows that among the on-cycle announcements, about 45% occur in the first month of a quarter, about 48% in the second month, and about 8% in the last month.

The quarterly cycles of earnings announcements imply that each of the three months of the quarter has a different status. The first month is the first time that investors learn about the *aggregate* economy's performance in the previous quarter. This economy-level learning is possible because corporate earnings have a common time component: the aggregate economic condition in fiscal quarter 4 (FQ4) of 2023 influences all firms,[6] and consequently, if early announcers' FQ4 earnings are good, then FQ4 is more likely than not a good quarter for everyone. Earnings announced in the first month of a quarter therefore provide new information about aggregate earnings earned in the previous quarter. We refer to these first months of quarters as newsy earnings months, or newsy months for convenience.

The second months, in contrast, see earnings that are predictably repetitive of those announced in the first months. This is again owing to the shared aggregate component of corporate earnings: earnings announced in February, like those announced in January, are earned in Q4 of the previous year and therefore inherently similar. We refer to the second months of the quarters as the repetitive earnings months, or simply repetitive months. The third months of the quarters also contain announcements of predictably repetitive earnings. However, since they contain substantially fewer on-cycle earnings announcements, the repetition is muted.

[6]Appendix C empirically analyzes this common time component and demonstrates its economic significance.

3.2 Forecasting regressions

We demonstrate our baseline predictability pattern in the US stock market returns with the following monthly time series regression:

$$mkt_t = \alpha + \beta mkt_{nr(t)} + \epsilon_t. \tag{1}$$

Here, mkt_t is the return of the US stock market in excess of the risk-free rate in month t, and $nr(t)$ is the most recent month before t that is newsy or repetitive. For example, if t is February, then $nr(t)$ is January, and if t is March or April, $nr(t)$ is February.

Panel A, Column 1 of Table 2 performs regression 1 on the sub-sample in which the dependent variable month t is repetitive. The positive coefficient of 0.279 implies that a newsy month's return positively predicts the return in the subsequent repetitive month. Column 2 is on the subsample in which t is newsy. The negative coefficient of -0.279 shows that a repetitive month's return negatively predicts the return in the next newsy month. These values are economically sizable, given they are bounded by -1 and 1 in a stationary time series.

Column 3 extracts the difference of the coefficients in columns 1 and 2 by performing the following regression on the combined sample in which t is either newsy or repetitive:

$$mkt_t = \alpha + \beta_1 mkt_{nr(t)} + \beta_2 mkt_{nr(t)} \times I_t^n + \gamma I_t^n + \epsilon_t. \tag{2}$$

Here, I_t^n is a dummy variable that indicates whether the month t is newsy. The most important number in Table 2 is the coefficient on the interaction term, β_2. Its value of -0.557 captures the difference in columns 1 and 2 and emblematizes the table. Economically, it demonstrates that the monthly autocorrelation of stock market returns varies strongly and predictably. Without the third months of quarters that contain muted earnings news, the first-order autocorrelation of the monthly stock market returns alternates between strongly positive (newsy predicting repetitive) and strongly negative (repetitive predicting newsy).

The associated t-statistic of -4.35 implies that the observed relation is unlikely to arise from noise or data mining.

Panels B, C, and D of Table 2 report results of the same regressions in the first half, second half, and post-WWII portion of the sample, respectively. The pattern operates in each of these episodes and is not the sole result of a small number of observations, warranting further evaluation of its reliability.

3.3 Out of sample performance

In an influential critique of the return predictability literature, Goyal and Welch (2008) note that when data available in real time are used to forecast returns, predictors often generate negative out-of-sample (OOS) R^2. This means that equity premium estimates generated using these predictors often fail to outperform the historical average.

Table 3 presents out-of-sample R^2 coefficients. Following Campbell and Thompson (2008), we extend the CRSP aggregate market return series to 1872 using data from Global Financial, and evaluate the R^2 from 1926. The benchmark underlying these R^2s is the expanding-window mean excess return $\overline{mkt_t}$, the average stock market return in excess of the risk free rate up to month t. Our predictor for mkt_t is $z_{t-1} \equiv mkt_{nr(t)} - \overline{mkt_{t-1}}$ for a repetitive t, $z_{t-1} \equiv -(mkt_{nr(t)} - \overline{mkt_{t-1}})$ for a newsy t, and 0 otherwise.

Table 3 reports the expanding-window OLS coefficients for our predictor and the real-time forecasts for mkt_t in multiple ways. Column 1 shows that the simplest method —- combining the predictor values and the regression coefficients of historical returns on historical predictors and a freely estimated constant — generates an R^2 of 4.20%, an order of magnitude higher than what is generated by other time series predictors for monthly stock market returns surveyed by Goyal and Welch (2008), Rapach and Zhou (2022), and Goyal et al. (2024). More sophisticated methods for estimating the average return in the constant term slightly improve this performance, as columns 2 and 3 show.[7] Our predictor variable

[7]Goyal et al. (2024) recently surveyed the literature on aggregate stock market return predictability and examined the predictors' out-of-sample forecasting performance. Table 3 of their paper shows that among an expanded set of 34 monthly predictors, the monthly in-sample R^2s are on average 0.32%, OOS R^2 are

can thus be used in real time to forecast aggregate returns.

The ability to forecast returns does not necessarily imply a profitable trading strategy.[8] We now use our predictor to construct a beta-neutral market timing strategy that rebalances positions in i) the stock market and ii) the risk-free bond and examine its performance.

The strategy implements two rules with data available in real time. First, it places a weight on the market that is proportional to the predictor value, with a mean of zero. Second, it scales this portfolio weight so that the strategy has a historical volatility of 5% per month. Specifically, for month t, the unscaled portfolio weight is simply z_{t-1}. The unscaled strategy volatility $\bar{\sigma}^z_{t-1}$ is the unscaled strategy's historical volatility up to $t-1$. The scaled portfolio weight is then $z_{t-1}\frac{0.05}{\bar{\sigma}^z_{t-1}}$. We further truncate the weight on the market at -3 and 3 to limit the impact of extreme observations.[9] The strategy's construction involves no look-ahead bias,[10] and the scaling can be adjusted according to an investor's risk appetite.

Column 1 of Table 4 shows that this trading strategy yields a monthly return of 0.668% (i.e., 8.02% per annum). Columns 2-4 show that the CAPM alpha, Fama-French 3-factor alpha, and FF3 + Momentum alpha are 0.554%, 0.402%, and 0.715% per month, respectively. Our time-series strategy adds value to these factors. Moreover, as it involves only positions on aggregate stock market and the risk-free bond, it is likely much cheaper to implement than the controlled cross-sectional factors, which involve positions in individual stocks.

Overall, our proposed predictor appears to i) generate positive OOS R^2, ii) produce a profitable trading strategy. We now consider a possible explanation.

on average -0.44% after applying the sign constraints in Campbell and Thompson (2008). These results reaffirm the conclusion of Goyal and Welch (2008) that existing predictors "predicted poorly both in-sample (IS) and out-of-sample (OOS)... seem unstable... and would not have helped an investor with access only to available information to profitably time the market."

[8] The converse of the statement is not true either.

[9] Our results do not appreciably change if this step is dropped, although in practice, implausibly high leverage cannot be implemented and a similar constraint would exist explicitly or implicitly.

[10] Historical investors, however, could not read our current paper.

4 Model

A parsimonious mechanism that jointly explains the continuation and reversal arms of the return pattern is correlation neglect: investors do not fully discount the inherently repetitive earnings announced in the second month of a quarter and thus overreact to them, creating the return continuation that gets corrected in the next newsy month. Below, we build a model of correlation neglect, which we show, in Appendix A, emerges from basic principles of human memory. While our model shares a basic mechanism with that of Enke and Zimmermann (2019), it differs from this paper in several respects. In Appendix B, we explain why it is necessary to depart from the Enke and Zimmermann model to apply their intuition to asset prices.

Assume that the economy is either in a high or low-productivity state. If the economy is in the high-productivity state, the aggregate market is worth 1, whereas it is worth 0 if it is in a low-productivity state. The high-productivity state occurs with probability p, which is unknown to investors. We assume that investors have a prior distribution over p, and specifically that this is a Beta distribution such that they would ex-ante estimate a probability p^* with a sample size of τ.[11] To fix ideas and eliminate unnecessary notation, we set $\tau = 1$. We also assume that investors are, on average, rational, in that the true unconditional distribution of p is drawn from the prior distribution.

This model has three periods. Period 1 corresponds to the first month of a quarter, namely a newsy month. Period 2 is the repetitive month that follows. Period 3 is the first month of the following quarter. In period 1, investors receive a signal $\hat{s}_1 = s_1$, with $s_1 \sim \text{Bernoulli}(p)$. In period 2, this signal is potentially repeated (as opposed to an independent signal being drawn from Bernoulli(p)). Whether or not the signal is repeated is independent of the original signal. We let p_x denote the probability that a signal is repeated, and let $x \sim \text{Bernoulli}(p_x)$ determine if it is repeated or not. If $x = 1$, then s_1 is brought again to investors' attention, namely $\hat{s}_2 = s_1 = \hat{s}_1$. If $x = 0$, investors see an independent draw from Bernoulli(p), $\hat{s}_2 = s_2$.

[11] The distribution is fully characterized by p^* and τ.

To focus on the mechanism of correlation neglect, we assume investors are risk-neutral and the riskfree rate is equal to zero.[12] Under these conditions, the value of the market is equal to the posterior mean of p. If, out of T observations, N indicate that the economy is in a high-productivity state, this posterior mean equals

$$E[p|N \text{ out of } T] = \frac{N + p^*\tau + 1}{T + \tau + 2}. \quad (3)$$

The investors' prior implies that the price prior to observing the signal in the first period is $P_0 = E[p] = (p^* + 1)/3$. After observing signal s_1 in the first period, the mean shifts so that the price equals

$$P_1 = E[p|s_1] = \frac{s_1 + p^* + 1}{4}.$$

For simplicity, we define returns as differences in prices rather than percent changes. The return $R_1 = P_1 - P_0$. Note that $E[R_1] = 0$.

Equilibrium with rational investors

The rational investor computes the period-2 price P_2 given observed $\hat{s}_2$. The investors do not see the outcome of x , but incorporate the possibility that $x = 1$, and therefore, that $\hat{s}_2$ is a repeat of an earlier signal. In expectation, given s_1,

$$E[P_2|s_1 = 1] = E[P_2|x = 1, s_1 = 1]P(x = 1|s_1 = 1) + E[P_2|x = 0, s_1 = 1]P(x = 0|s_1) \quad (4)$$

Because x is independent of s_1, (4) reduces to

$$E[P_2|s_1 = 1] = E[P_2|x = 1, s_1 = 1]p_x + E[P_2|x = 0, s_1 = 1](1 - p_x).$$

[12]We assume that the agent is using signals extracted from individual firms to estimate the true state of the market, which will be revealed in the subsequent quarter. The "real world" can therefore be viewed as a sequence of independent but overlapping three-period models, in which we abstract from autocorrelation in the true state of the economy.

If rational investors were to know $x = 1$, they would not update based on s_2. Therefore $E[P_2|x = 1, s_1 = 1] = P_1$. Moreover, if investors were to know $x = 0$, they would update based on the outcome of s_2 as an independent draw. Because (3) follows a martingale as observations accumulate, we again have $E[P_2|x = 0, s_1 = 1] = P_1$.[13] It follows that $E[R_2] = E[E[R_2|s_1]] = E[E[P_2 - P_1|s_1]] = 0$ and that

$$E[R_2R_1] = E[E[R_2R_1|P_1]] = E[E[(P_2 - P_1)R_1|P_1]] = E[E[P_2 - P_1|s_1]R_1] = 0.$$

The second-to-last equality follows because P_1 reveals s_1 and because R_1 is known given s_1. The last equality follows because $E[P_2 - P_1|s_1] = 0$ for all values of s_1. Therefore $\text{Cov}(R_1, R_2) = 0$, and there is no continuation in the case of a rational investor. Similar reasoning establishes $E[R_3R_2] = 0$ and thus that there is no reversal in the case of a rational investor.

Equilibrium with correlation neglect

The investor with correlation neglect calculates

$$P_2 = \frac{\hat{s}_1 + \hat{s}_2 + p^* + 1}{5}$$

[13]Note that

$$\begin{aligned} E[P_2|s_1 = 1, x = 0] &= \frac{s_1 + p^* + 1}{5}(1 - P_1) + \frac{s_1 + p^* + 2}{5}P_1 \\ &= \left(\frac{s_1 + p^* + 2}{5} - \frac{s_1 + p^* + 1}{5}\right)P_1 + \frac{s_1 + p^* + 1}{5} \\ &= \frac{1}{5}P_1 + \frac{4}{5}P_1 = P_1. \end{aligned}$$

Using an argument similar to (4),

$$\begin{aligned}
E[P_2|s_1] &= E\left[p_x \frac{2s_1 + p^* + 1}{5} + (1 - p_x)\frac{s_1 + s_2 + p^* + 1}{5}\right] \\
&= E\left[p_x\left(\frac{2s_1 + p^* + 1}{5} - P_1\right) + p_x P_1 + (1 - p_x)E\left[\frac{s_1 + s_2 + p^* + 1}{5}\middle| s_1\right]\right] \\
&= E\left[p_x\left(\frac{2s_1 + p^* + 1}{5} - P_1\right) + p_x P_1 + (1 - p_x)P_1\right],
\end{aligned}$$

where the last line follows from the aforementioned martingale property. Therefore

$$E[P_2] = p_x E\left[\frac{2s_1 + p^* + 1}{5} - P_1\right] + E[P_1] = E[P_1],$$

establishing that $E[R_2] = 0$. We have used the fact that

$$E\left[\frac{2s_1 + p^* + 1}{5} - P_1\right] = E\left[\frac{3s_1 - p^* - 1}{20}\right] = 0,$$

because $E[s_1] = E[p] = (p^* + 1)/3$.[14]

Similarly, if we let $P_2^{\mathcal{R}}$ denote the period-2 price for the rational investor,

$$E[R_3] = E[P_3 - P_2^{\mathcal{R}} + P_2^{\mathcal{R}} - P_2] = E[P_2^{\mathcal{R}} - P_2] = E[P_1 - P_2] = 0,$$

where we twice use the martingale property. The last line follows from $E[R_2 = 0]$ as mentioned previously. The investor with correlation neglect is not directionally right or wrong.

However, unlike in the case with the rational agent, R_2 is positively correlated with R_1 and R_3 negatively correlated with R_2. Intuitively, the agent double-counts s_1 in the second period, not adjusting for the fact that it may be the same signal as before. Because R_2 has mean zero, it suffices to show that $E[R_2 R_1] > 0$. Again applying the argument from (4),

$$E[R_2 R_1] = E[E[R_2 R_1|s_1]|x = 1]p_x + E[E[R_2 R_1|s_1]|x = 0](1 - p_x).$$

[14]We can make a stronger statement: because s_1 is a binary variable, it must have a Bernoulli distribution. Because $E[s_1] = E[E[s_1|p]] = (p^* + 1)/3$ the properties of the Bernoulli distribution, indicate that the unconditional probability of $s_1 = 1$ is $(p^* + 1)/3$.

The second term equals zero. Therefore

$$E[R_2R_1] = E[E[R_2R_1|s_1]|x=1]p_x = E\left[\left(\frac{3s_1-p^*-1}{20}\right)\left(\frac{3s_1-p^*-1}{12}\right)\right]p_x > 0, \qquad (5)$$

where the second line follows because R_1 is a constant in s_1.

Finally, we show reversal: $E[R_3R_2] < 0$. We follow the same line of argument as above for $E[R_2R_1] > 0$, breaking up the unconditional expectation into a terms that condition on the outcome of x:

$$E[R_3R_2] = E[E[R_3R_2|\hat{s}_1,\hat{s}_2]|x=1]p_x + E[E[R_2R_1|\hat{s}_1,\hat{s}_2]|x=0](1-p_x).$$

The second term equals zero. To evaluate the first term, note that $E[P_3|x=1,\hat{s}_1,\hat{s}_2] = P_1$ because there is no information in period 2. By definition, $P_3 - P_1 = P_3 - P_2 + P_2 - P_1$. Therefore $E[R_3 + R_2|x=1,\hat{s}_1,\hat{s}_2] = 0$. It follows that any reaction to "news" in the second period will be an over-reaction that will, on average, be corrected in the third and final period:

$$\begin{aligned} E[R_3R_2] &= E[E[R_3R_2|x=1,\hat{s}_1,\hat{s}_2]]p_x \\ &= E[E[R_3|x=1,\hat{s}_1,\hat{s}_2]R_2]p_x, \\ &= -E[R_2^2]p_x < 0, \end{aligned} \qquad (6)$$

where the second line follows because R_2 is a constant in $\hat{s}_1,\hat{s}_2$.

Clearly, both continuation and reversal are increasing in p_x, which leads to testable predictions that we explore in the next section. Moreover, if the signal in period 2 is similar to that of period 1, continuation and reversal will be greater than otherwise. In our stylized set-up, we compare continuation and reversal under $\hat{s}_1 = \hat{s}_2$ to $\hat{s}_1 \neq \hat{s}_2$. The probabilistic environment is designed to capture the main feature of the analysis in Section 5.2 below, in which samples are divided based on the similarity of the signals in period 2. This is an ex-post conditioning that affects measurement of the population moments. For example,

$E[R_1|\hat{s}_2 \neq \hat{s}_1] \neq 0$ and $E[R_2|\hat{s}_2 \neq \hat{s}_1] \neq 0$ because $\hat{s}_2 \neq \hat{s}_1$ conveys information about the unknown p that is not realized until the second period (similarly, $E[R_1|\hat{s}_2 = \hat{s}_1] \neq 0$ and $E[R_2|\hat{s}_2 = \hat{s}_1] \neq 0$). However, $E[R_3|\hat{s}_2 \neq \hat{s}_1] = E[R_3|\hat{s}_2 = \hat{s}_1] = 0$ because the information is already embedded in P_2 and because $E[R_3] = 0$.

Our model is simplistic in that signals are zero or 1, and thus they can either be equal or diametrically opposite. In this extreme case, when $\hat{s}_1 \neq \hat{s}_2$, we no longer see continuation:

$$E\left[(R_2 - E[R_2|\hat{s}_1 \neq \hat{s}_2])(R_1 - E[R_1|\hat{s}_1 \neq \hat{s}_2]) \mid \hat{s}_1 \neq \hat{s}_2\right] = -E\left[(P_1 - E[P_1|\hat{s}_1 \neq \hat{s}_2])^2\right] < 0, \tag{7}$$

noting that P_2 is a constant under the conditioning set. Moreover, because $P_2 = P_2^{\mathcal{R}}$, the rational forecast in period 2 under this condition, there is no reversal.[15]

We now show that there is continuation in the case of correlation neglect and $\hat{s}_1 = \hat{s}_2$.[16] When $\hat{s}_1 = \hat{s}_2$, in the economy with correlation neglect, $P_2 = (2s_1 + p^* + 1)/5$, so that $R_2 = (3s_1 - p^* - 1)/20$ Recall that $R_1 = (3s_1 - p^* - 1)/12$. Finally,

$$\begin{aligned} E\left[(R_2 - E[R_2|\hat{s}_1 = \hat{s}_2])(R_1 - E[R_1|\hat{s}_1 = \hat{s}_2])|\hat{s}_1 = \hat{s}_2\right] &= \frac{3}{80}E[(s_1 - E[s_1|\hat{s}_1 = \hat{s}_2])^2|\hat{s}_1 = \hat{s}_2] \\ &> 0 \end{aligned} \tag{8}$$

where the equality follows because all constant terms cancel out with their expectations. This establishes continuation in the case of $\hat{s}_1 = \hat{s}_2$. Finally, because $E[R_3R_2]$ is a weighted average of its value under the conditions $\hat{s}_1 = \hat{s}_2$ and $\hat{s}_1 \neq \hat{s}_2$, and because it is equal to zero under the latter condition (when $P_2 = P_2^{\mathcal{R}}$), it must be negative when $\hat{s}_1 = \hat{s}_2$. The argument suffices because $E[R_3|\hat{s}_2 \neq \hat{s}_1] = E[R_3|\hat{s}_2 = \hat{s}_1] = 0$ as mentioned earlier. Therefore, the continuation and reversal pattern is stronger when signals are more similar than otherwise, an implication of the model which we test below.

[15] P_3 is a draw from a Bernoulli distribution with mean $P_2^{\mathcal{R}}$, and $P_3 - P_2^{\mathcal{R}}$ is independent of anything in the information set as of Period 2.

[16] One might think that this step would be unnecessary, since we know that there is continuation in population and also that there will be no continuation in samples with $\hat{s}_1 \neq \hat{s}_2$. However, while $E[R_1R_2]$ is a weighted average of $E[R_1R_2|\hat{s}_1 = \hat{s}_2]$ and $E[R_1R_2|\hat{s}_1 \neq \hat{s}_2]$, the same cannot be said for $\mathrm{Cov}(R_1, R_2)$ because the means under the two conditioning sets are not the same.

5 Evaluating the model's predictions

The model in Section 4 explains why returns in the first month of each quarter predict those of the second month with a positive sign and those of the second month predict those of the subsequent first month of the quarter with a negative sign. We now derive several additional predictions.

The first prediction is straightforward. Given that the driving force is investors' beliefs, we should see analogous results in survey data.

Prediction 1 (Survey data)**.** *Revisions in beliefs in a repetitive month are likely to be in the same direction as those in the previous newsy month, and revisions in a newsy month are likely in the opposite direction to revisions in the previous repetitive month.*

Note that the expectation revision in a newsy month is $E^{\mathrm{CN}}[p|s] - p^*$, where $E^{\mathrm{CN}}[\cdot]$ denotes the subjective expectation of the investors exhibiting correlation neglect. It equals R_1. The revision in the repetitive month is $E^{\mathrm{CN}}[p|s,x] - E^{\mathrm{CN}}[p|s]$, which equals R_2. These are positively correlated, as we show above. In the following newsy month, the expectation revision, if there is a positive outcome, is $1 - E^{\mathrm{CN}}[p|s,x]$ and $-E^{\mathrm{CN}}[p|s,x]$ otherwise. For the reasons described above, this is negatively correlated with the revision in the repetitive month. Section 5.1 discusses tests of this hypothesis.

Equations 7–8 and the surrounding discussion show that samples in which the second signal is relatively similar to the first are those in which continuation and reversal will be enhanced:

Prediction 2 (Similarity of announcements)**.** *Return predictability will be stronger when the announcement in the repetitive month is more similar to the previous newsy month.*

Section 5.2 discusses tests of this hypothesis.

Equations 5 and 6 show that when p_x increases, so do both continuation and reversal. The parameter p_x itself is unobservable. Nonetheless, there are several tests of the model that emerge from these equations. Section 3.3 shows how a trading strategy can earn abnormal profits based on trading on this anomaly. Suppose that p_x is a persistent state variable that varies over time. We would observe periods of time in which continuation is strong, to also be those times in which reversal is strong.

Prediction 3. *Continuation and reversal share an underlying mechanism. Therefore when continuation is particularly strong in the data, so is reversal.*

Section 5.3 discusses tests of this hypothesis.

To connect the theoretical results from the model to the empirical results, we identify $\hat{s}_1$ and $\hat{s}_2$ with company-level announcements that are informative regarding the underlying state of the economy p. The mistake that investors make lies in assuming that they are independent draws. We could, however, have equally well viewed $\hat{s}_1$ and $\hat{s}_2$ as company-level announcements that are informative of a particular industry, which is a smaller but more tightly connected economy. This prediction is especially interesting, as investors appear keen to learn industry-level information in the newsy months (e.g., Foster (1981), Brochet et al. (2018), Thomas and Zhang (2008), Hilary and Shen (2013), Hann et al. (2019)). We should then observe that industry returns in excess of the market should also exhibit a similar continuation and reversal pattern.

Prediction 4. *Industry excess returns should also exhibit continuation and reversal.*

Section 5.4.1 discusses tests of this hypothesis. An extension to the global stock market returns is done in Appendix D.

Just as the time-series trading strategies opened up additional avenues for testing the model, so too does the cross-sectional trading strategy in Section 5.4.1. Industries differ by their size and their degree of connectivity. In the model, this could be interpreted as differences in p_x between industries. Specifically, p_x increases with size, as idiosyncratic components of earnings are increasingly diversified. It should also increase with the degree of connectivity, as the industry component of earnings is likely stronger in more connected industries.

Prediction 5. *Excess returns on larger industries are more likely to exhibit continuation and reversal, as are excess returns on industries that are more highly connected.*

Section 5.4.2 tests this hypothesis.

5.1 Survey data

An influential branch of the behavioral finance literature uses survey data from IBES to measure investors' expectations of aggregate cash flow growth (Nagel and Xu, 2022; De La O and Myers, 2021; Bordalo et al., 2024). As Prediction 1 states, our model traces the continuation and reversal effects to beliefs. Following Bordalo et al., we extract beliefs using the long-term growth (LTG) measure from the IBES Adjusted Details file.[17] Following Bordalo et al. (2024), we use medians across analysts to represent firm-level consensus, and then aggregate firm-level LTG revisions in each month using the market capitalization weight within the S&P 500 universe to obtain revisions in aggregate cash flow growth expectations. Our model predicts that investors overreact in the repetitive months in the sense that i) revisions in a repetitive month are likely in the same direction as those in the preceding newsy month and ii) revisions in a repetitive month are likely followed by correction in the opposite direction in the subsequent newsy month. These lead to two predictions on the time series of aggregate LTG revisions. First, revisions in a repetitive month are positively correlated with revisions in the previous newsy month. Second, revisions in a newsy month are negatively correlated with revisions in the previous repetitive month.

Column 1 of Table 5 tests prediction i) by running the following regression on the sample in which t is repetitive:

$$Rev_t = \alpha + \beta Rev_{t-1} + \epsilon_t.$$

Here, Rev_t is the aggregate LTG revisions in month t, and as t is repetitive, $t-1$ is newsy. The positive and significant coefficient of 0.543 indicates that revisions in a repetitive month indeed tend to be in the same direction as those in the previous newsy month. However, this

[17] We do not use the Summary files, which contain middle-of-the-month consensuses struck on the Thursday after the 3rd Friday of the month, because we need revisions month-end to month-end.

number is not in itself convincing. Survey data naturally incorporate latency,[18] resulting in a positive unconditional autocorrelation in revisions. Column 2 controls for this unconditional latency and extracts the extra effect using an interaction term between Rev_{t-1} and a dummy variable indicating whether t is repetitive. The resulting coefficient of 0.323 is again highly significant, indicating that the positive relation between the revisions in a repetitive month and the previous newsy month goes above and beyond what is implied by the data latency alone.

Column 3 tests prediction ii) by running the following regression on the sample in which t is newsy:

$$Rev_t = \alpha + \beta Rev_{t-2} + \epsilon_t.$$

Here, as t is newsy, $t-2$ is repetitive. We do not observe the negative coefficient predicted by our theory, but rather a near-zero coefficient of 0.038. However, this is simply owing to the confounding latency effect mentioned above. Column 4 controls for this effect and extracts the overreaction coefficient using the interaction term between Rev_{t-2} and a dummy variable indicating whether t is newsy. Here, we can clearly see a significantly negative coefficient of -0.174. This implies that reactions in the repetitive months are indeed overreactions that get corrected in the subsequent newsy month.

5.2 Earnings similarity and the strength of the return pattern

According to our mechanism, investors see a signal in the second month, which they believe is an independent draw from the distribution that produced the signal in the first month. In the data, however, this second signal is comprised of earnings announcements from a different set of firms. These signals have a range of similarities with the first signal, which we capture with differences between aggregate return on equity in the two months. If the signal that investors see is highly dissimilar, then investors are not likely to interpret it as a draw

[18] One factor contributing to the latency in survey data is the requirement for analysts to produce detailed analyst reports (as examined in Barth et al. (2024) and Li et al. (2024)) in addition to their estimates. This increases the cost of generating estimates, thus causing delays in their release.

from the same distribution. Thus, one test of our underlying mechanism (see Prediction 2) is that over-reaction is likely to be especially strong when the earnings in the repetitive month are similar to those announced in the previous newsy month. We now test this prediction. Table 6 reports the key parameter β_2 on the interaction term from regression 2 conducted separately for episodes in which the earnings announced in an repetitive month and the preceding newsy month, as measured by ROE, are unusually similar, moderate, and unusually dissimilar. It shows that, when the earnings announced in the repetitive month more closely resemble those in the preceding newsy month, we indeed observe an amplified pattern of dynamic autocorrelation in the return of this repetitive month and the next newsy month. This confirms our model's prediction that investors overreact more to a repetitive month's earnings when they are more similar to those in the preceding newsy month.

5.3 The association between the continuation and reversal arms

We separate the return of the trading strategy in each year into the component earned in the newsy months and that earned in the repetitive months. Table 7 regresses the two components on each other, both in the raw return unit and ranked to limit the influence of outliers. The significant positive coefficients imply that a year in which the continuation effect is strong is also likely to see a strong reversal. This means that the continuation and reversal arms are likely driven by the same underlying economic force and should therefore be explained by one story rather than two. In our model, the association can naturally be explained by a persistent, time-varying p_x in our model.

5.4 The cross section of industries

5.4.1 Baseline return pattern

The main intuition behind the theory is as follows. If a group of stocks are 1) tightly and obviously connected in fundamentals, so that investors actively infer group-level information from its members' announcements and 2) sizable in number, so that the group as a whole announces progressively along the earnings cycle, then earnings announced in the second month of a quarter will be predictably similar to those announced in the first month. Failure to recognize this inherent similarity leads to predictable overreaction in the second month that later reverses.

This story applies naturally to all stocks in the US economy, but should additionally apply to industry-level returns (see Prediction 4). Two stocks randomly drawn from an industry are more connected with each other than two random stocks drawn from an economy. Investors understand the tight intra-industry connection and actively learn industry-level information from the early earnings announcements (e.g., Foster (1981)). If the story is indeed about the early earnings announcements, the dynamic serial predictive relation in the aggregate market returns should also exist in industry returns in excess of the aggregate market returns.

Table 8 tests this prediction by conducting the following regression:

$$exret_{i,t} = \alpha + \beta exret_{i,nr(t)} + \epsilon_{i,t}. \tag{9}$$

Here $exret_{i,t}$ is the return of industry i in excess of the market return in month t. The returns are weighted by market capitalization, and the regression is weighted by industry-level market capitalization scaled to sum to 1 in each cross-section. Following Lou et al. (2019), we drop stocks with a smaller market capitalization than the 10th percentile on NYSE. We further drop industries with fewer than 10 constituents to ensure a sufficient number of announcers. Table 8 shows that the same pattern of continuation and reversal exists in industry excess returns as in aggregate market returns.

Two points are worth noting. First, this piece of cross-sectional evidence is important in its own right. Table 9 shows that it can also be converted into a profitable trading strategy. Like the regressions in Table 8, this strategy uses market capitalization weights, making it highly implementable. Second, the consistency between aggregate and cross-sectional evidence is not always seen in the return predictability literature. This piece of evidence thus speaks potently in favor of our hypothesis.

5.4.2 Heterogeneity across industries

Rich variation across industries offers further tests of our theory. As mentioned in the previous subsection, our theory works on a group of stocks that are i) tightly connected in fundamentals and ii) sizable in numbers. These two elements are both necessary to set the stage for intra-group learning, generate the newsy and repetitive signals for group-level cash flow in the first and second months of a quarter, and allow for the possibility of correlation neglect. A natural implication of our theory is that the return pattern should be stronger on industries that are more tightly connected and have more constituents. In terms of the theory, connectedness and size should both increase the parameter p_x. The greater is p_x, the more predictable are returns within the group of stocks.

Panel A1 and A2 of Table 10 test Prediction 5. In Panel A1, we measure industry-level earnings connectivity by first computing the covariance of normalized excess ROE for each pair of stocks in the same industry-quarter, and then taking the within-industry average weighted by the average of the market capitalization of the pair of stocks. We then split each cross-section between high connectivity industries and low connectivity ones, and run the regression:

$$exret_{i,t} = \alpha + \beta_1 exret_{i,nr(t)} + \beta_2 exret_{i,nr(t)} \times I_t^n + \gamma I_t^n + \epsilon_{i,t}. \tag{10}$$

We clearly see that the effect of correlation neglect, as measured by the size of the coefficient β_2 on the interaction term, is much larger in the highly connected industries. Panel A2 conducts a similar exercise for the number of firms in each industry and shows that the effect of correlation neglect is larger in the larger industries. Panel A3 conducts an analogous exercise to those in Table 6 and shows that the industry-level effect of correlation neglect is larger when the industry earnings in the repetitive month more closely resemble those in the preceding newsy month. This is consistent with Prediction 2 and the time-series evidence in Table 6.

To further demonstrate that the empirical pattern relates to the economic structure of real industries, we conduct a placebo test in Panel B of Table 10 by randomly generating fake "industries" and conduct regression 10 on the panel of these fake industries. The randomization approaches follow those in Chen et al. (2024). Panel B1 randomly assigns each stock to 1 of the 39 (median number of industries across cross sections) "industries" with uniform probability. This approach generates random industries of roughly equal size (number of constituents). Panel B2 assigns each stock to the industry of a randomly chosen stock in the same cross-section without replacement. This approach preserves the size distribution of the industries in each cross-section. Panel B3 first sorts each cross-section into deciles by $exret_{s,nr(t)}$, where s is a stock, and then assigns each stock to the industry of a randomly chosen stock in the same cross-section-decile. This approach preserves the size distribution of the industries in each cross-section and further controls for $exret_{i,nr(t)}$. The 1st percentiles in Panel B of Table 10 are much less negative than the -0.164 observed in Panel A of Table 10. The results in Panel B3 are especially useful. It tells us that the observed return pattern in Table 10 depends critically on the economic structure of genuine industries and is not the sole result of the regressor $exret_{i,nr(t)}$ itself.

6 Alternative explanations

Known announcement anomalies

Guo (2025) finds that a newsy month's return negatively forecasts future newsy months and positively forecasts other months. Guo' motivating hypothesis is parameter compression. Any given news has exponentially decreasing relevance as time goes on. The decay rate is unknown, however, and investors must estimate it. If investors believe that the decay rate is a fixed parameter, independent of month, then they will overestimate the impact of any given news on newsy months and underestimate it in the others. This hypothesis leads to a different empirical test than in the present paper: one that focuses on the impact of earnings news that occurred multiple lags in the past. Guo (2025) summarizes this news that occurred at multiple lags as $\sum_{j=1}^{4} mkt_{nm(t,j)}$, the average return in the last four newsy months.

The mechanisms are distinguishable in the data. Table 11 shows in monthly stock return regressions that they remain highly significant after controlling for one another. Besides the regressor $mkt_{nr(t)}$, namely the return in the previous month if the second month in the quarter (repetitive) or two months back if the first month in the quarter, the regressions also have the regressor $\sum_{j=1}^{4} mkt_{nm(t,j)}$, the predictor used in Guo (2025) that represents the average return over the last four newsy months. Both coefficients in column 3 are significantly negative, implying that correlation neglect retains its predictive power even when controlling for parameter compression.

A large accounting literature 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 the announcing lag. For instance, deHaan et al. (2015) argue that firms delay earnings announcements with bad results to avoid the early portion of the earnings cycle that 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 our results. Overall, it implies 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 in the newsy month to positively correlate with that in the next repetitive month. 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 the quarter, as bad announcers being moved out of the newsy months makes the newsy months look better, and the subsequent repetitive months look worse than they otherwise would. And even then, it is not clear why a pattern of return reversal would exist between a repetitive month and the upcoming newsy month.

Time-varying risk

The most important set of explanations for return predictability comes 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 our time-series results is that, i) after a good newsy month, the stock market is risky in the subsequent repetitive month, and ii) after a good repetitive month, the subsequent newsy month is safe. Individually, both points are not difficult to accommodate in a risk-based framework. In fact, point ii) naturally arises when a repetitive month resolve risks and take them away from the next newsy month. However, as we show in Table 7, we ideally should have one story that jointly explain both arms of the return pattern. This first requires the risk of the market to vary at a monthly frequency. Standard asset pricing models such as habit, long-run risk, disaster, and intermediary-based asset pricing all involve risks that should be rather persistent at a monthly frequency. So it does not appear hopeful to use standard macro risk factors to explain our predictability pattern.

Furthermore, even if one can identify a non-conventional, high-frequency source of risk, it is unlikely to account for our return pattern in its full scale owing to the frequency at which the expected stock market excess returns are negative. The top panel of Figure 1 plots the expected stock market return implied by Method 2 of Table 3. This time series of expected stock market excess return is negative 24% of the months. This implies that an explanation based on risk alone is unlikely to explain the return pattern in full. In such a risk-based framework, the negative expected returns mean that the stock market is safer than Treasury bills one month out of four. This feature is especially difficult to accommodate, as it is implausible that investors find the stock market to be safer than Treasury bills that often.

Campbell and Thompson (2008) show that the expanding-window regression coefficients used in the out-of-sample expected stock market excess returns incorporate substantial noise, which in turn lead to negative expected stock market excess returns forecasts. Campbell and Thompson (2008) show that, for the stock market predictors they study, these negative forecasts perform poorly, consistent with the notion that they are driven by noise.

In contrast, negative forecasts in our paper do not appear to be driven by noise more than the positive forecasts. The lower panel of Figure 1 plots the in-sample expected stock market returns. These forecasts do not use the expanding-window coefficients, but are still negative 20% of the times. The first two columns of the top panel of Figure 2 decompose the returns of the trading strategy in Table 4 by whether the sign of the out-of-sample excess return forecasts. The next two columns create an analogous in-sample trading strategy and conduct the decomposition based on the in-sample forecasts. The trading strategy does not appear to perform worse when the forecasts are negative. If anything, the performance appears to be better when the out-of-sample forecasts are negative. The negative forecasts in our paper as well as their implications should be taken seriously.

Another candidate is the risk resolution associated with earnings announcements. Savor and Wilson (2016) show that early announcers earn higher excess returns than later announcers (Table IV), which is indeed consistent with the overall importance of the earnings season. This, however, does not explain why the current earnings season being good makes the next repetitive month risky. Neither does it explain why a good repetitive month is followed by a safe newsy month.

Besides the earnings cycle, other macroeconomic fluctuations may also operate on a quarterly frequency. Notably, GDP announcements, although occurring monthly, are quarterly in their nature; FOMC announcements are disproportionately unlikely to occur in the newsy months. Such macroeconomic announcements are shown to have a significant impact on the stock market (see, e.g., Ai et al. (2024) for a survey of the vast literature studying this impact). We investigate whether our return pattern can potentially arise from these announcements. If macroeconomic announcements drive our return pattern, the pattern should be amplified on those macroeconomic announcement days. The fifth and sixth columns of Figure 2 show that, if anything, the return pattern appears weaker on those announcement days.

In contrast, our return pattern appears to align with the earnings season, which does not immediately begin on the first day of the newsy months. This is owing to the fact that even the quickest announcers require some time to prepare their statements. Specifically, among companies with fiscal periods aligned with calendar quarters, only 0.13% of the on-cycle earnings announcements occur within the first week of the quarter. This percentage is significantly lower compared to the average weekly announcement rate of about 8%. In contrast, the second week of each quarter sees 1.87% of the announcements, a 15-fold increase from the previous week. Therefore, our pattern of return predictability, if stemming from these earnings announcements, is not expected to occur in the first week of newsy months. The last 2 columns of Figure 2 show that our return predictability pattern is indeed non-existent in the pre-season period.

7 Conclusion

Contrary to prior beliefs, monthly stock market returns in the United States can in fact be predicted with past returns. Specifically, the U.S. stock market's return during the first month of a quarter positively predicts the second month's return, which then negatively predicts the first month's return of the next quarter. The first months of a quarter are "newsy" because they contain fresh earnings news about the aggregate economy, whereas the second months of a quarter contain earnings announcements that produce predictably repetitive "news." We hypothesize that the return predictability pattern arises because investors use announced earnings to predict future earnings, but do not recognize that earnings in the second months of a quarter are inherently repetitive of those in the previous newsy month. Survey data support this hypothesis of correlation neglect, as does out-of-sample evidence across industries. These results challenge the efficient market hypothesis by documenting a strong and pervasive form of return predictability.

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Table 1: When do firms end their fiscal quarters and when do they announce earnings

	A: FQ-end month		B: Earnings announcement month	
	Count	Percent	Count	Percent
Group 1: Jan/Apr/Jul/Oct	82,257	8.6%	358,128	44.7%
Group 2: Feb/May/Aug/Nov	51,169	5.4%	382,162	47.7%
Group 3: Mar/Jun/Sep/Dec	819,534	86.0%	60,649	7.6%
Total	952,960	100.0%	800,939	100.0%

Panel A counts the company-fiscal quarters in Compustat by the months in which they end. The fiscal quarters always end on the last day of a month, and 86.0% means that 86.0% of the fiscal quarters end on the last day of March, June, September, or December. Panel B counts the company-fiscal quarters by the months in which the fiscal quarters' earnings are announced, requiring that i) the fiscal quarter ends in the Group 3 months and ii) the earnings announcement occurs within 92 days of the fiscal quarter end date. Data are quarterly from 1971 to 2023.

Table 2: Continuation and reversal in the U.S. aggregate market returns

	(1) Repetitive	(2) Newsy	(3) Difference
	A: Full sample		
$mkt_{nr(t)}$	0.279***	-0.279***	-0.557***
	[3.13]	[-3.02]	[-4.35]
N	386	386	772
	B: First half		
$mkt_{nr(t)}$	0.358***	-0.327**	-0.685***
	[2.71]	[-2.48]	[-3.67]
N	190	190	380
	C: Second half		
$mkt_{nr(t)}$	0.167***	-0.194**	-0.360***
	[2.77]	[-2.14]	[-3.31]
N	196	196	392
	D: Post-WWII		
$mkt_{nr(t)}$	0.142***	-0.163**	-0.305***
	[2.69]	[-2.31]	[-3.46]
N	304	304	608

This table presents estimated βs from the monthly time-series regression $mkt_t = \alpha + \beta mkt_{nr(t)} + \epsilon_t$. Here, mkt_t is the U.S. stock market return in excess of the risk free rate in month t, and $nr(t)$ is the most recent month before t that is newsy or repetitive. Column 1 is on the sample in which the dependent variable month t is a second month of a quarter (repetitive); column 2 is on the sample in which the dependent variable month t is a first month of a quarter (newsy). Column 3 shows there difference, extracted as β_2 from the regression $mkt_t = \alpha + \beta_1 mkt_{nr(t)} + \beta_2 mkt_{nr(t)} \times I_t^n + \gamma I_t^n + \epsilon_t$ on the combined sample in column 1 and 2, where I_t^n is a dummy variable taking the value of 1 if month t is newsy, and 0 otherwise. In Panel A, B, C, and D, data are monthly from 1926 to 2023, from 1926 to 1973, from 1974 to 2023, and 1947 to 2023, respectively. T-statistics computed with White standard errors are reported in square brackets.

Table 3: Out-of-sample R^2 in forecasting the U.S. stock market returns

Method	1	2	3
OOS R^2	4.20%	4.26%	4.73%

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. The predictor is $mkt_{nr(t)} - m\bar{k}t_{t-1}$ for a repetitive t, $-(mkt_{nr(t)} - m\bar{k}t_{t-1})$ for a newsy t, and 0 otherwise. For each month t, 2 coefficients—one for the predictor and one for the constant term—are extracted from a simple expanding-window OLS regression of historical market excess returns on historical predictor values and a constant. For method 1, the forecast in a given month is the estimated coefficient on the predictor multiplied with the predictor value plus the estimated constant. Method 2 replaces the estimated constant coefficient with $\overline{r_t}$. Method 3 replaces the estimated constant with an average extracted from dividend/price, earnings/price, and book-to-market as Campbell and Thompson (2008) propose. Data are monthly from 1926 to 2023.

Table 4: Time-series strategy performance

	(1) TSP_t	(2) TSP_t	(3) TSP_t	(4) TSP_t
MKT_t		0.169	0.050	-0.024
		[0.96]	[0.39]	[-0.23]
HML_t			0.575**	0.425**
			[2.17]	[2.22]
SMB_t			0.165	0.148
			[0.88]	[0.76]
MOM_t				-0.331**
				[-2.22]
α	0.668***	0.554***	0.402**	0.715***
	[3.51]	[3.24]	[2.32]	[3.73]
N	1,165	1,165	1,165	1,164

Column 1 shows results from the following monthly time-series regression: $TSP_t = \alpha + \epsilon_t$. Here, TSP_t is our time-series portfolio return in month t. This portfolio takes long or short positions in the aggregate market for a given month, and the weight is proportional to the previous-month-end signal value s_{t-1}, which is $mkt_{nr(t)} - \overline{mkt_{t-1}}$ for a repetitive t, $-(mkt_{nr(t)} - \overline{mkt_{t-1}})$ for a newsy t, and 0 otherwise. The market weight is then scaled so that the strategy has a historical volatility of 5% as of $t-1$, and then truncated at 3 and -3. Columns 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 the time-series portfolio. In Columns 2-4, it represents its alphas with different factor models. Data are monthly from 1926 to 2023. Returns are all in percentage units. T-statistics computed with White standard errors are reported in the square brackets.

Table 5: Evidence from survey data

	(1)	(2)	(3)	(4)
	Rev_t	Rev_t	Rev_t	Rev_t
Rev_{t-1}	0.543***	0.220***		
	[4.91]	[2.94]		
I_t^r		0.078		
		[1.15]		
$Rev_{t-1} \times I_t^r$		0.323***		
		[3.42]		
Rev_{t-2}			0.038	0.211***
			[1.02]	[3.92]
I_t^n				-0.052
				[-1.05]
$Rev_{t-2} \times I_t^n$				-0.174***
				[-2.72]
const	-0.032	-0.110**	-0.143***	-0.091*
	[-0.81]	[-2.03]	[-3.04]	[-1.93]
N	170	509	170	509

Column 1 runs the following monthly time-series regression on the sample in which t is repetitive: $Rev_t = \alpha + \beta Rev_{t-1} + \epsilon_t$. Here, Rev_t is the aggregate revision in the IBES long-term growth (LTG) measure for month t within the S&P 500 universe using the market capitalization weight. Column 2 adds in a dummy variable indicating whether t is repetitive and its interaction with Rev_{t-1}, and expands the sample to all months. Columns 3 and 4 conduct analogous regressions to columns 1 and 2, but for newsy months rather than repetitive months. Data are monthly from 1982 to 2024. T-statistics computed with Newey-West standard errors are reported in square brackets.

Table 6: Aggregate earnings distance and the strength of the return pattern

	(1)	(2)	(3)	(4)	(5)
	Lowest 10%	10%-50%	50%-90%	Highest 10%	Low - High
$mkt_{nr(t)} \times I_t^n$	-0.769***	-0.398*	-0.228	-0.084	-0.684**
	[-4.33]	[-1.94]	[-1.51]	[-0.31]	[-2.12]
N	42	170	170	42	84

This table presents estimated β_2s from the monthly time-series regression $mkt_t = \alpha + \beta_1 mkt_{nr(t)} + \beta_2 mkt_{nr(t)} \times I_t^n + \gamma I_t^n + \epsilon_t$.. Here, mkt_t is the U.S. stock market return in excess of the risk free rate in month t, $nr(t)$ is the most recent month before t that is newsy or repetitive, and I_t^n is a dummy variable taking the value of 1 if month t is newsy, and 0 otherwise. Across columns, the regression sorts on the distance between the aggregate ROE announced in the most recent newsy months before t and the subsequent repetitive month. The aggregate ROE in a given month is defined as the total earnings announced in the month divided by the total book value of equity of these announcing firms. The ROE distance is computed as the absolute value of the difference between the newsy and the repetitive months' ROE relative to the median value of the difference across time. The distance increases from column 1 to 6 and is between the 0-10th, 10-50th, 50-90th, and 90-100th percentiles of the sample, respectively. Data are monthly from 1971-2023. T-statistics computed with White standard errors are reported in square brackets.

Table 7: The link between the continuation and reversal effects

	(1) TSP_t^n	(2) TSP_t^r	(3) $Rank(TSP_t^n)$	(4) $Rank(TSP_t^r)$
TSP_t^r	0.957***			
	[15.16]			
TSP_t^n		0.893***		
		[6.87]		
$Rank(TSP_t^r)$			0.361***	
			[3.42]	
$Rank(TSP_t^n)$				0.361***
				[3.40]
N	97	97	97	97

Column 1 shows results from the following annual time-series regression: $TSP_t^n = \alpha + \beta TSP_t^r + \epsilon_t$. Here, TSP_t is our time-series portfolio return in year t. This portfolio takes long or short positions in the aggregate market for a given month, and the weight is proportional to the previous-month-end signal value s_{t-1}, which is $mkt_{nr(t)} - \overline{mkt_{t-1}}$ for a repetitive t, $-(mkt_{nr(t)} - \overline{mkt_{t-1}})$ for a newsy t, and 0 otherwise. The market weight is then scaled so that the strategy has a historical volatility of 5% as of $t-1$, and then truncated at 3 and -3. TSP_t^n is the portfolio's return in the newsy months of year t, and TSP_t^r is the return in the repetitive months of year t. The $Rank(\cdot)$ function ranks the TSP_t^r and TSP_t^n across years, thus transforming them into integers between 1 and 97. T-statistics computed with White standard errors are reported in the square brackets.

Table 8: Continuation and reversal in the U.S. industry excess returns

	(1) Repetitive	(2) Newsy	(3) Difference
	A: Full sample		
$exret_{i,nr(t)}$	0.083***	-0.081**	-0.164***
	[2.68]	[-2.36]	[-3.55]
N	16,214	16,283	32,497
	B: First half		
$exret_{i,nr(t)}$	0.085*	-0.067	-0.152**
	[1.73]	[-1.36]	[-2.19]
	4,049	4,107	8,156
	C: Second half		
$exret_{i,nr(t)}$	0.082**	-0.089*	-0.171***
	[2.06]	[-1.94]	[-2.82]
	12,165	12,176	24,341
	D: Post-WWII		
$exret_{i,nr(t)}$	0.071**	-0.067*	-0.138***
	[2.17]	[-1.72]	[-2.71]
	15,044	15,102	30,146

This table presents estimated βs from the industry-monthly panel regression $exret_{i,t} = \alpha + \beta exret_{i,nr(t)} + \epsilon_{i,t}$. Here, $exret_{i,t}$ is the return of industry i in excess of the market return in month t, and $nr(t)$ is the most recent month before t that is newsy or repetitive. Column 1 is on the sample in which the dependent variable month t is a second month of a quarter (repetitive); column 2 is on the sample in which the dependent variable month t is a first month of a quarter (newsy). Column 3 shows the difference, extracted as β_2 from the regression of $exret_{i,t} = \alpha + \beta_1 exret_{i,nr(t)} + \beta_2 exret_{i,nr(t)} \times I_t^n + \gamma I_t^n + \epsilon_t$on the combined sample in columns 1 and 2, where I_t^n is a dummy variable taking the value of 1 if the month t is newsy, and 0 otherwise. The returns are weighted by market capitalization, and the regression is weighted by industry-level market capitalization scaled to sum to 1 in each cross-section. The regressions require at least 10 firms in an industry. In Panels A, B, C, and D, data are monthly from 1926 to 2023, from 1926 to 1973, from 1974 to 2023, and from 1947 to 2023, respectively. T-statistics computed with standard errors clustered by month are reported in square brackets.

Table 9: Cross-sectional strategy performance

	(1) CSP_t	(2) CSP_t	(3) CSP_t	(4) CSP_t
MKT_t		0.062	0.041	-0.044
		[0.92]	[0.68]	[-0.83]
HML_t			0.160	-0.017
			[1.20]	[-0.14]
SMB_t			-0.017	-0.035
			[-0.20]	[-0.44]
MOM_t				-0.381***
				[-3.58]
α	0.533***	0.497***	0.457***	0.827***
	[3.37]	[3.08]	[2.92]	[4.20]
N	1,154	1,153	1,153	1,152

Column 1 shows results from the following monthly time-series regression: $CSP_t = \alpha + \epsilon_t$. Here, CSP_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: i) Compute signal value $s_{i,t-1}$, which is $exret_{i,nr(t-1)}$ for a repetitive t, $-exret_{i,nr(t-1)}$ for a newsy t, and 0 otherwise; ii) cross sectionally demean with market capitalization weight; iii) scale by standard deviation of the signal computed with data up to $t-1$ and Winsorize at [-3, 3] to limit the influence of extreme values; iv) interact with the industry's market capitalization divided by the total market capitalization in $t-1$. Step iv) is a simple way to amply positions in large stocks to lower trading costs. Columns 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 the time-series portfolio. In Columns 2-4, it represents its alphas with respect to different factor models. Data are monthly from 1926 to 2023. Returns are all in percentage units. T-statistics computed with White standard errors are reported in the square brackets.

Table 10: Further analyses across industries

	A: Heterogeneity across industries			B: Random "industries"				
	Low	High	High-Low	1%	5%	50%	95%	99%
	A1: Connectivity			B1: Uniform probability				
$exret_{i,nr(t)} \times I_t^n$	-0.127**	-0.235***	-0.108**	-0.049	-0.035	0.001	0.035	0.049
	[-2.14]	[-3.30]	[-2.00]					
	A2: Size			B2: Preserve industry sizes				
$exret_{i,nr(t)} \times I_t^n$	-0.062**	-0.141***	-0.079**	-0.053	-0.036	-0.001	0.033	0.050
	[-2.31]	[-3.62]	[-2.57]					
	A3: Earnings similarity			B3: Control for $exret_{i,nr(t)}$				
$exret_{i,nr(t)} \times I_t^n$	-0.105	-0.255***	-0.150**	-0.066	-0.050	-0.015	0.021	0.036
	[-1.36]	[-4.14]	[-2.30]					

Panel A of this table presents estimated β_2s from the industry-monthly panel regression: $exret_{i,t} = \alpha + \beta_1 exret_{i,nr(t)} + \beta_2 exret_{i,nr(t)} \times I_t^n + \gamma I_t^n + \epsilon_t$. Here, $exret_{i,t}$ is the return of industry i in excess of market return in month t, $nr(t)$ is the most recent month before t that is newsy or repetitive, and I_t^n is a dummy variable taking the value of 1 if month t is newsy, and 0 otherwise. The returns are weighted by market capitalization, and the regression is weighted by industry-level market capitalization scaled to sum to 1 in each cross-section. The regressions require at least 10 firms in an industry. Panel A1 separates the regression by whether an industry has below- or above-average number of constituents and shows the difference in β_2 in the 3rd column. Panel A2 conducts a similar exercise for within-industry earnings connectivity, measured by first computing the covariance of normalized excess ROE, Winsorized at -4 and 4, for each pair of stocks in the same industry-quarter, and then taking the within-industry average weighted by the average of the market capitalization of the pair of stocks. Panel A3 does so for earnings similarity, computed as the absolute value of the distance between the industry's ROE announced in the newsy month before t and the subsequent repetitive month. Panel B conducts 3 placebo tests on randomly generated, fake "industries," and reports the 1st, 5th, 50th, 95th, and 99th percentiles of the distribution of β_2 generated in 1000 simulations. Data are monthly from 1971-2023. T-statistics computed with standard errors clustered at monthly level are reported in square brackets.

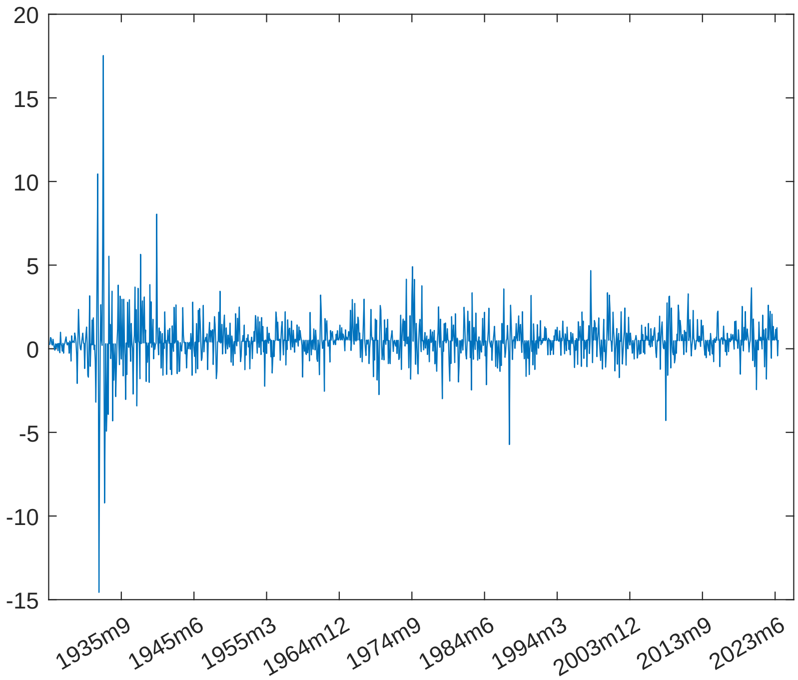
Table 11: Continuation and reversal in the U.S. aggregate market returns, with controls

	(1) Repetitive	(2) Newsy	(3) Difference
$mkt_{nr(t)}$	0.213**	-0.248***	-0.461***
	[2.22]	[-2.70]	[-3.46]
$\sum_{j=1}^{4} mkt_{nm(t,j)}$	0.329**	-0.251*	-0.580***
	[2.46]	[-1.85]	[-3.05]
N	383	383	766

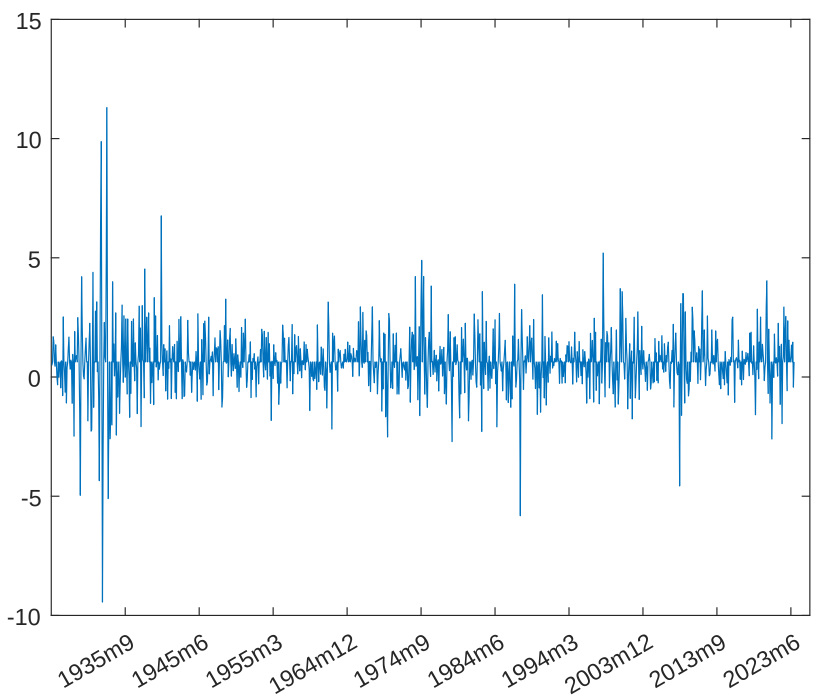
This table presents estimated βs from the monthly time-series regression $mkt_t = \alpha + \beta_1 mkt_{nr(t)} + \beta_2 \sum_{j=1}^{4} mkt_{nm(t,j)} + \epsilon_t$. Here, mkt_t is the U.S. stock market return in excess of the risk-free rate in month t, $nr(t)$ is the most recent month before t that is newsy or repetitive, and $nm(t,j)$ is the jth most recent newsy month before t. Column 1 is on the sample in which the dependent variable month t is a second month of a quarter (repetitive); column 2 is on the sample in which the dependent variable month t is a first month of a quarter (newsy). Column 3 shows their difference, extracted as β_2 from the regression of $mkt_t = \alpha + \beta_1 mkt_{nr(t)} + \beta_2 mkt_{nr(t)} \times I_t^n + \beta_3 \sum_{j=1}^{4} mkt_{nm(t,j)} + \beta_4 \sum_{j=1}^{4} mkt_{nm(t,j)} \times I_t^n + \gamma I_t^n + \epsilon_t$ on the combined sample in columns 1 and 2, where I_t^n is a dummy variable taking the value of 1 if month t is newsy, and 0 otherwise. Data are monthly from 1926 to 2023. T-statistics computed with White standard errors are reported in square brackets.

Figure 1: Implied expected stock market excess returns over time

(a) Out-of-sample



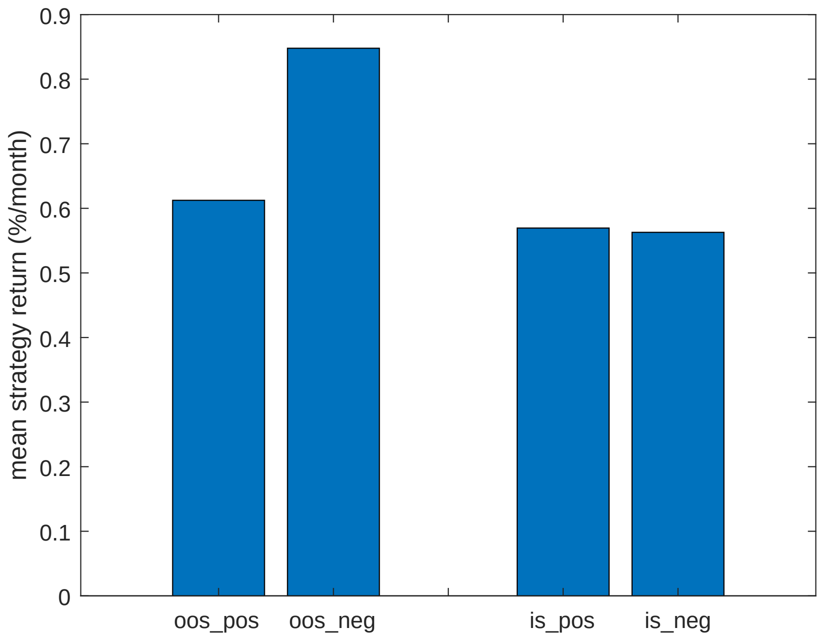
(b) In-sample



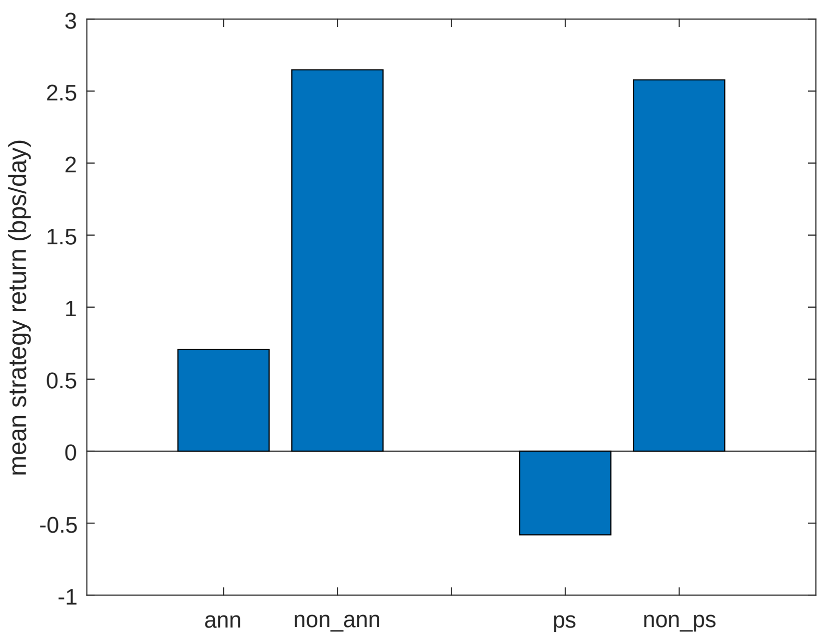
The top panel of this figure plots the expected stock market excess returns as in Method 2 of Table 3. The bottom panel of this figure plots the in-sample expected market excess returns. The unit is percent per month.

Figure 2: Trading strategy performance decomposition

(a) Signs of the forecasts



(b) Macro announcement days and the pre-season periods



The top panel of the figure decomposes the average monthly return of the out-of-sample and in-sample trading strategies (as in Table 4 and created based on the in-sample return predictability pattern in Table 2) by the sign of the out-of-sample and in-sample stock market excess return forecasts, respectively. The bottom panel of the figure plots the average daily return of a trading strategy constructed based on the in-sample return predictability pattern in Table 2, normalized to have a volatility of 5% per month. The average returns are computed on macroeconomic announcement days, non-announcement days, the pre-earnings season periods (i.e., the first week of a quarter), and the non-preseason periods.

Appendix

A Memory model

This section shows how the model in Section 4 arises naturally from a cognitive model of contextual encoding and retrieval. As in Wachter and Kahana (2024), agents view features f_t, which are basis vectors in a high-dimensional vector space. These features become embedded in memory together with a temporal context, an internal mental state. Context, through the memory matrix, governs what comes to mind. We assume that contexts decay sufficiently rapidly so that each month's context can be viewed as independent of prior months. However, firms that announce within a month are all aggregated into the same temporal context. The approach of assuming contexts are either independent or the same is also adopted by Charles (2025), and is convenient in that it enables contextual encoding and retrieval without the analytical difficulties of modeling the contextual decay process.

For our purposes, it suffices to consider only part of the features space; that part corresponding to firm-level announcements that the agent interprets as good or bad news for the aggregate market. Thus contexts x_t are a series of independent basis vectors, and features are a series of vectors which, without loss of generality, we can assume to equal $[1, 0]$ for a positive announcement, and $[0, 1]$ for a negative one.[19]

Contexts and features form an outer product, whose sums make up a memory matrix. This is a central assumption of Wachter and Kahana (2024), which builds on Howard and Kahana (2002).[20] The matrix M_0 captures prior information and t_0 is the sum of elements in M_0. Then memory evolves recursively as:

$$M_t = \frac{t_0 + t - 1}{t_0 + 1} M_{t-1} + \frac{1}{t_0 + t} x_t f_t^\top.$$

We set M_0 to match the prior distribution specified in Section 4. Under the assumption that $\{x_t\}$ are independent basis vectors and positive and negative features are as specified below,

[19]More broadly, these features form a subspace of a very high dimensional space on the order of 10^7 or greater, 10^7 being a lower bound on the number of neurons in the brain involved in memory storage. As in Section 4 we consider a series of independent, but overlapping economies of length of three periods. Thus the features that are observed in the subsequent quarter would be independent and equal, for example, to $[0, 0, 1, 0, ...]$ and $[0, 0, 0, 1, ...]$.

[20]Wachter and Kahana (2024, Appendix C) proves the equivalence between the memory matrix evolution below and that of Howard and Kahana (2002).

we find:

$$M_0 = \frac{1}{3}\begin{bmatrix} p^*+1 & 1-p^*+1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

Then, given an observation of either positive or negative news in the first period,

$$M_1 = \frac{1}{4}\begin{bmatrix} p^*+1 & 1-p^*+1 \\ \hat{s}_1 & 1-\hat{s}_1 \\ 0 & 0 \end{bmatrix}$$

and again in the second period

$$M_2 = \frac{1}{5}\begin{bmatrix} p^*+1 & 1-p^*+1 \\ \hat{s}_1 & 1-\hat{s}_1 \\ \hat{s}_2 & 1-\hat{s}_2 \end{bmatrix}$$

Note that what is stored in memory is the observed announcement itself, with no adjustment for the fact that it might be correlated with a previous announcement.

Agents at time t form prices based on their memory and context at time t. They either recognize the state as being good or bad, given current context, which is neutral: $\iota = [1, 1, 1]$. Recognition is based on the inner product of current context with retrieved context, where retrieval is based on the features cues "good," namely $[1, 0]$, or "bad," namely $[0, 1]$. For example, in period 2,

$$\boldsymbol{x}_{good,2} = M_2 \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} p^*+1 \\ \hat{s}_1 \\ \hat{s}_2 \end{bmatrix}$$

Note that $\iota \cdot \boldsymbol{x}_{good,t} = P_t$, the expectation that the agent with correlation neglect forms for the good state in each period.

B Alternative model of correlation neglect

In this section, we consider an alternative model that is based more closely on Enke and Zimmermann (2019). As in the model in Section 4, assume there are three periods, corresponding to the newsy month, the repetitive month, and the first month of the next quarter, when the value of the market portfolio $\tilde{P}$ is drawn from the normal distribution with mean μ. As in Enke and Zimmermann (2019), assume there are latent signals $s_j, j = 1, 2$, jointly normally distributed, independent, and with unknown mean μ. Investors directly observe s_1 in period 1 and $\hat{s}_2 = 1/2(s_1 + s_2)$ in period 2. While Enke and Zimmermann (2019) do not specify a prior distribution, their results are consistent with assuming a normal prior distribution for μ, a known variance for s_j, and then taking the limit as the prior becomes uninformative. We will also make these assumptions, along with specifying μ_0 as the prior mean of μ.

Equilibrium with rational investors

In period 1, $P_1 = s_1$, and $R_1 = P_1 - \mu_0$. In period 2, $P_2 = \hat{s}_2$ and $R_2 = \frac{1}{2}(s_2 - s_1)$. Note that $E[R_1] = E[R_2] = 0$, and therefore $\mathrm{Cov}(R_1, R_2) = E[R_1 R_2] = \frac{1}{2}E[(s_1 - \mu_0)(s_2 - s_1)]$. Returns ex post appear to be predictable: $E[R_2 R_1] < 0$. However, as Lewellen and Shanken (2002) emphasize, the investor cannot profit from this opportunity in real time: $E[R_2|s_1] = 1/2(E[s_2|s_1] - s_1) = 0$. Finally,

$$\begin{aligned} E[R_3 R_2] &= \frac{1}{2}E[(\tilde{P} - \hat{s}_2)(s_2 - s_1)] \\ &= \frac{1}{2}\Big(E[(\tilde{P} - \hat{s}_2)s_2] - E[(\tilde{P} - \hat{s}_2)s_1]\Big) = 0 \end{aligned}$$

where the last equation follows from the symmetry in s_1 and s_2. It may seem surprising that this, too, is not negative. The reason is that the initial "over-reaction" from s_1 is "over-corrected" by s_2. In fact R_3 is negatively correlated with the overall return $R_2 - \mu$.

Equilibrium with correlation neglect

In period 1, again $P_1 = s_1$ and $R_1 = s_1 - \mu_0$. However, in period 2, investors form an inefficient forecast that over-weights s_1, $P_2 = \frac{1}{2}(s_1 + \hat{s}_2) = \frac{3}{4}s_1 + \frac{1}{4}s_2$, because they mistakenly believe that $\hat{s}_2$ is an independent draw. The period 2 return equals $R_2 = P_2 - P_1 = 1/4(s_2 - s_1)$. As before $E[R_1] = E[R_2] = 0$. Again, $\mathrm{Cov}(R_1, R_2) = E[R_1 R_2]$. Though prices in the second period differ in this economy as compared with the one above, the return R_2 differs only by a multiplicative constant. Therefore, by the logic for the rational investor, $\mathrm{Cov}(R_1, R_2) < 0$, which is counterfactual.

Furthermore, $\mathrm{Cov}(R_3, R_2) > 0$. It suffices to show $E[R_3 R_2] > 0$. We have

$$\begin{aligned} E[R_3 R_2] &= \frac{1}{4}E[(\tilde{P} - \frac{3}{4}s_1 - \frac{1}{4}s_2)(s_2 - s_1)] \\ &= \frac{1}{4}E[(\tilde{P} - \hat{s}_2) - \frac{1}{4}s_1 + \frac{1}{4}s_2)))(s_2 - s_1)] \\ &= \frac{1}{4}E[(\tilde{P} - \hat{s}_2)(s_2 - s_1)] + \frac{1}{16}E[(s_2 - s_1)^2] \\ &= \frac{1}{16}E[(s_2 - s_1)^2] > 0 \end{aligned}$$

The fact that the first term is zero follows from the same reasoning as for the rational investor. The intuition for the positive correlation is that P_2 contains "too much" s_1 and "too little" s_2. Thus on average, R_3 moves in the same direction as R_2, which is to say toward s_2 and away from s_1. It might seem surprising that R_2 moves from s_2 and away from s_1 given that the point of correlation neglect is to have P_2 incorporate too much s_1. However, under this form of uncertainty, it is impossible for it to incorporate more than is already in P_1. In effect, the information in s_1 is fully priced in at time 1.

This model differs from the one in the main text in two respects. Most obviously, investors here learn about the mean of a normal distribution, whereas in the main model, investors learn about a probability. When learning about the mean, receiving the same signal twice and incorporating it does not change the investor's estimate of the price (though it does shrink the variance). However, when one is learning about a probability, receiving a signal always causes the mean to update (see Equation 3), though eventually by a vanishingly small amount. In a model with normally distributed risks, over-reaction only occurs in the second moment, not in the first, as in the data. A second difference lies in the unique source of randomness in the second period. In this model, that source of randomness is an extra signal, and creates a negative correlation. In the model in the main text, the source of randomness is whether the first signal is brought to investors' attention or not. Despite these differences, the models have an important source of similarity in that incorrect inference arises from neglecting correlations.

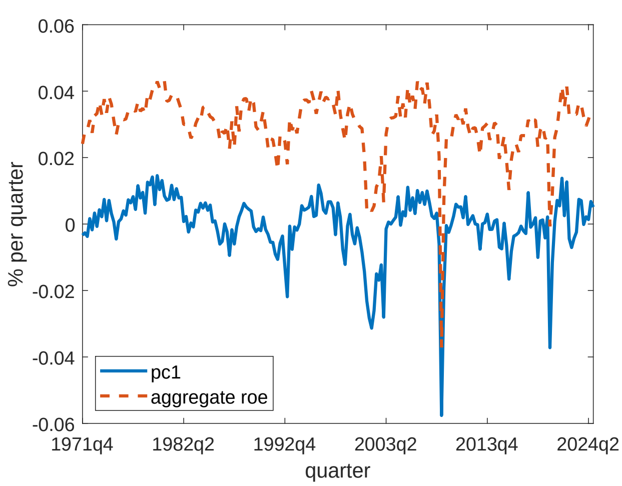
C The common time component in quarterly earnings

In this section, we use four approaches to detect the common time component in quarterly corporate earnings in the United States. We use income before extraordinary items (ibq) from Compustat to measure quarterly firm earnings, and compute return-on-equity (ROE), or earnings divided by book value of equity, as a stationary representation of earnings news. We group each quarterly cross-section of U.S. firms by the first digit of their SIC code, which broadly represents sectors. We then conduct a principal component analysis on the quarterly panel of sector-level return on equity, computed as total quarterly earnings divided by book value of equity within the sector. We then conduct a principal component analysis (PCA) on the panel. Note that using a broad measure of sector rather than a granular measure of industries avoids missing values and enables PCA without any imputation.

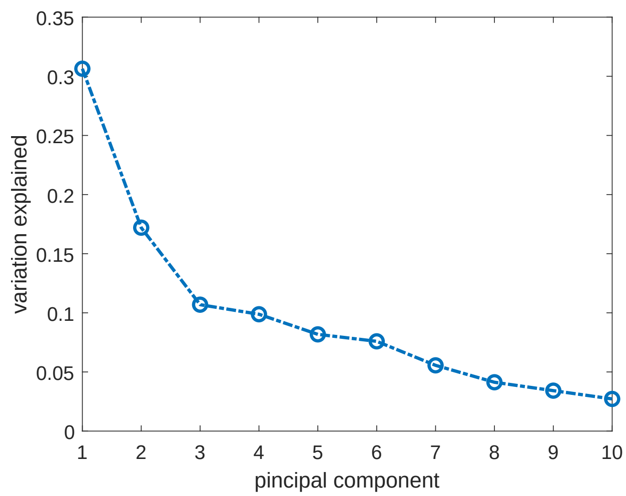
The upper left panel of the Figure C1 shows that the first PC on this panel of earnings is effectively their time component—it has a correlation of 0.93 with aggregate quarterly ROE. The upper right figure shows that the first PC explains about 30% of the total variation on the panel, which is economically significant. The lower left panel is a histogram of the R^2 from firm-level ROE from the aggregate ROE among firms that are ever in the S&P 500 universe. They have a mean of 8.4%. These three panels show that there is clearly a strong common time component in quarterly earnings in the United States.

As a result of this common time component, earnings in a newsy month predict those in the subsequent repetitive month especially strongly. The lower right panel uses three bars to represent predictive coefficients of i) quarter q's newsy month earnings on repetitive month earnings, ii) q's newsy month earnings on $q+1$'s newsy month earnings, and iii) q's repetitive month earnings on $q+1$'s repetitive month earnings. The common time component makes i) significantly larger than ii) and iii), despite of the significant overlap in the firms announcing in two repetitive or newsy months from two adjacent quarters.

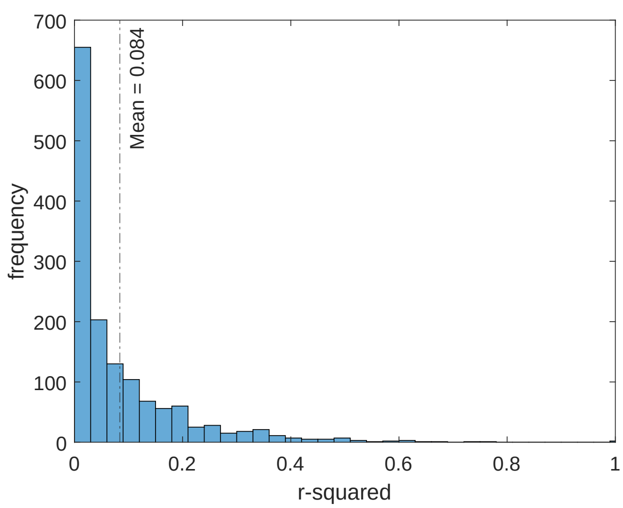
Figure C1: The common component of quarterly earnings



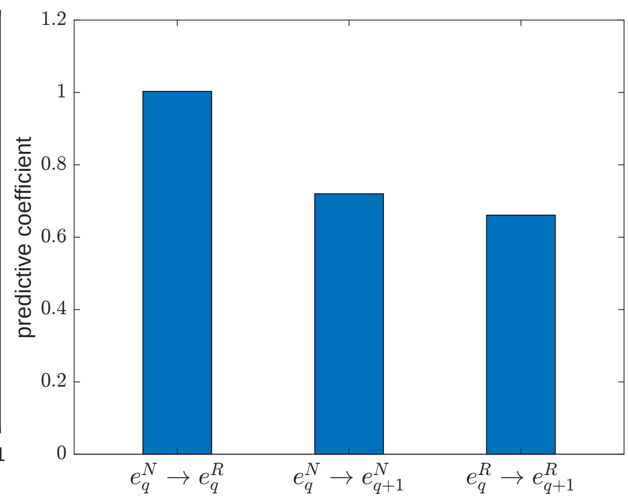
(a) PC1 and aggregate ROE



(b) Variation explained by PCs



(c) Firm level ROE on aggregate ROE



(d) Predicting monthly ROE

Figure (a) conducts a PCA on the quarterly-sector (represented using the first digit of a firm's SIC code) panel of ROE, and plot the first PC against the aggregate quarterly ROE. Figure (b) plots the fraction of total variation explained by each PC on the panel of ROE. Figure (c) conducts regressions of firm level ROE on aggregate ROE among firms that historically have been part of the S&P 500 universe, and plots a histogram of the R^2s. Figure (d) shows predictive coefficients of i) quarter q's newsy month earnings on repetitive month earnings, ii) q's newsy month earnings on $q + 1$'s newsy month earnings, and iii) q's repetitive month earnings on $q + 1$'s repetitive month earnings, from left to right.

D Evidence from global markets

The U.S. stock market serves as the testing ground for financial theories due to its size, liquidity, and high-quality data. As our theory revolves around the earnings seasons, it is applicable to the U.S. market for two additional reasons. First, the earnings announcements in the United States occur much faster than in other major countries. Second, the U.S. market exerts an asymmetric influence on other markets (e.g., Brusa et al. 2020). These two factors make the newsy months in the United States uniquely important, as they take information content away from the newsy months in other countries.

Despite the reduced information content, newsy months in countries other than the U.S. do contain valuable information about these countries' aggregate economies. Earnings seasons are primarily a U.S. feature, but not exclusively so. We therefore find it valuable to carefully investigate the international markets, as they offer another out-of-sample testing ground for our theory. We study the same set of global stock markets as do Moskowitz et al. (2012)—Austria, Australia, Belgium, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, the United Kingdom, Greece, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, Norway, New Zealand, Portugal, Sweden, and Singapore. These are developed markets classified by Morgan Stanley Capital International (MSCI), with high liquidity and accessibility to foreign investors.

We first characterize the global earnings cycle in Table D1. Our data come from Worldscope. Panel A shows that, as in the United States, the fiscal periods of the global markets are aligned with the calendar quarters, with 87.8% of the fiscal periods closing at the end of a calendar quarter. Many countries mandate semi-annual, rather than quarterly, financial reporting, a difference that is not as significant as it seems, given that, in countries requiring semi-annual reporting, comparable numbers of firms have Mar/Sep and Jun/Dec as the end of fiscal periods. Hence, the country as a whole still operates on a quarterly calendar, and the first months of each quarter are still the earliest time for the freshest news to come out. Our theory's prediction therefore directly applies to those countries as well.[21]

Panel B of Table D1 show that the earnings announcements in the global markets are slower than those in the United States. However, about 20% of the announcements occur in the first month of a quarter, and they are more than sufficient for investors to draw lessons about the aggregate cash flow. In other words, the first months of quarters are also newsy in

[21] The only exception is Australia, where Jun/Dec fiscal periods are overwhelmingly more common and the Mar/Sep firms only represent a trivial portion (less than 4%) of the economy. In Australia, the return pattern indeed appears to operate at a semiannual frequency, and adjusting the signal construction accordingly improves its forecasting performance. As this source of variation applies to only one country, we hesitate to read too much into it, and keep the signal construction recipe the same for simplicity.

the global markets. The second months contain about 60% of the earnings announcements, similar to those in the United States. We therefore continue to set the first months of quarters as newsy and the second months as repetitive for the global markets.[22]

As the previous paragraph discusses, we can interpret the same months as newsy, despite the variation in the regulations between the US and other countries. However, our explanation for the return pattern relies not only on the current reporting patterns but also on these reporting patterns remaining stable over the history of the returns that we study. In both the United States and the global sample, the return data start substantially earlier than the accounting data from which the newsy and repetitive months are inferred. However, the history of accounting data is much longer in the United States, and the aggregate earnings cycle remained stable over the course of this longer history. Due to NYSE requirements (Kraft et al. 2017), quarter reporting predates CRSP data from 1926. Such systematic evidence is lacking outside the United States.

Given these contexts, while we still use return data before the 1990s in my global tests, we focus on the financially developed countries, where financial regulation is sounder and has a longer history. Even with this practice, one should place more focus on the post-WWII and post-1974 results for the global sample and interpret the pre-1974 results with more caution. Having said that, we test the predicted return pattern on the global markets in Table D2. The pattern in Table D2 is similar to that in Table 2, affirming our theory with a piece of out-of-sample evidence. The pattern of reversal appears weaker in column 2, although it is likely a result of unconditional return continuation being much stronger outside the United States (Moskowitz et al. (2012)). The key test is again the difference in column 3, which appears statistically significant across the panels.

[22]There is also considerable heterogeneity in reporting lags across countries, although it is rare for the first months of quarters to contain so few earnings announcements that it is impossible for investors to reliably learn anything. Australia is again the most probable exception to it: January and July contain about 1.5% of the on-cycle earnings announcements in Australia, and setting February and August as newsy instead appears to improve our signal's forecasting performance. We, however, choose to keep our signal construction logic uniform across countries for simplicity.

Table D1: **The global earnings cycle: When do firms end their fiscal periods, and when do they announce earnings?**

	A: FP end month		B: Earnings announcement month			
			All announcements		Aligned & timely	
	Count	Percent	Count	Percent	Count	Percent
Group 1: Jan/Apr/Jul/Oct	56,951	5.7%	228,720	23.1%	168,568	19.8%
Group 2: Feb/May/Aug/Nov	64,303	6.5%	559,349	56.4%	534,837	62.7%
Group 3: Mar/Jun/Sep/Dec	870,263	87.8%	203,448	20.5%	149,654	17.5%
Total	991,517	100.0%	991,517	100.0%	853,059	100.0%

Panel A counts the company-fiscal periods in Worldscope by the months in which they ended; 87.8% means that 87.8% of the fiscal periods ended on the last day of March, June, September, or December. Panel B counts the company-fiscal periods by the months in which the fiscal periods' earnings were announced. The "All announcements" columns include all data present in panel A. The "Aligned & timely" columns apply two filters: i) the fiscal quarter ended in the Group 3 months and ii) the earnings announcement occurred within 183 days of the fiscal quarter end date. Data are quarterly and semi-annually from 1998 to 2021.

Table D2: Continuation and reversal in global market returns

	(1) Repetitive	(2) Newsy	(3) Difference
	A: Full sample		
$mkt_{nr(t)}$	0.113***	-0.046	-0.159***
	[3.62]	[-1.15]	[-3.15]
N	6,547	6,549	13,096
	B: First half		
$mkt_{nr(t)}$	0.153***	-0.005	-0.157**
	[3.71]	[-0.10]	[-2.51]
N	2,431	2,432	4,863
	C: Second half		
$mkt_{nr(t)}$	0.094**	-0.068	-0.162**
	[2.15]	[-1.23]	[-2.30]
N	4,116	4,117	8,233
	D: Post-WWII		
$mkt_{nr(t)}$	0.100***	-0.053	-0.154***
	[2.83]	[-1.16]	[-2.64]
N	5,599	5,601	11,200

This table presents estimated βs from the monthly time-series regression $mkt_{c,t} = \alpha + \beta mkt_{c,nr(t)} + \epsilon_{c,t}$. Here, $mkt_{c,t}$ is country c's stock market return in excess of the risk-free rate in month t, and $nr(t)$ is the most recent month before t that is newsy or repetitive. Column 1 is on the sample in which the dependent variable month t is a second month of a quarter (repetitive); column 2 is on the sample in which the dependent variable month t is a first month of a quarter (newsy). Column 3 shows there difference, extracted as β_2 from the regression $mkt_{c,t} = \alpha + \beta_1 mkt_{c,nr(t)} + \beta_2 mkt_{c,nr(t)} \times I_t^n + \gamma I_t^n + \epsilon_{c,t}$ on the combined sample in column 1 and 2, where I_t^n is a dummy variable taking the value of 1 if month t is newsy, and 0 otherwise. In Panels A, B, C, and D, data are monthly from 1926 to 2021, from 1926 to 1973, from 1974 to 2021, and from 1947 to 2021, respectively. T-statistics computed with standard errors clustered by month are reported in square brackets.