Correlation neglect in asset pricing*

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Abstract

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 pattern arises from a model in which investors do not fully recognize that earnings announced in the second month of a quarter are inherently similar to those announced in the first month, thereby overreacting to such predictably repetitive earnings. The same pattern exists in the cross-section and time series of industry returns. Evidence from survey data lends support to the mechanism of correlation neglect.

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

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1 Introduction

Predicting stock market returns with past returns is famously difficult. Kendall and Hill (1953) and Fama (1965) documented decades ago that serial correlations in stock returns are close to zero. In his seminal work, Fama (1970) defines the weakest form of the efficient market hypothesis as that prices reflect all information in past prices. This hypothesis appears to work especially well for the U.S. aggregate market. Poterba and Summers (1988) show, for example, that monthly market returns in the United States have a small, insignificantly positive autocorrelation over a horizon of 12 months. The lack of correlation between past and future market returns in the United States is not only a widely accepted statistical phenomenon, but also an emblem of market efficiency.[1]

We document that the U.S. 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 special and important to investors because they contain fresh earnings news about the aggregate economy. This is owing to the nature of the earnings cycle in the United States. Take January as an example. At the end of the December, firms close their books for Q4, and they announce Q4 earnings in January, February, and March. January therefore contains the early earnings announcements and is the first time that investors learn about the economy's performance in Q4. 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" earnings months, as they produce fresh news about aggregate earnings.

The second month of each quarter contains about equally many earnings announcements as does a newsy month. The aggregate earnings announced in the second month are, however, predictably repetitive of those announced in the preceding newsy month because the

[1] At longer horizons of multiple years, Poterba and Summers (1988) show a negative autocorrelation on the U.S. market. Focusing on weekly returns, Lo and MacKinlay (1988) document a positive autocorrelation on an index of small U.S. stocks (or an equally weighted market index). The low month-to-month autocorrelation of the U.S. market returns is nevertheless an important, frequently cited piece of evidence supporting the notion of market efficiency.

announced earnings are of the same fiscal quarter (Q4 in our example above). We call these second months "repetitive" earnings months, as they contain earnings announcements that produce repetitive aggregate earnings "news." The third month of a quarter contains substantially fewer earnings announcements and produce muted earnings news. The terminology allows us to compactly describe our return pattern in one sentence: a newsy month's return positively predicts the next repetitive month's return, which then negatively predicts the next newsy month's return.

One way to test our mechanism is to examine earnings expectations themselves. Specifically, our hypothesis states that 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 act of correlation neglect leads to overreaction in the repetitive months that are predictably in the same direction as the news in the preceding newsy month, giving rise to the newsy-to-repetitive return continuation. As the next newsy month comes, these overreactions are correctly, leading to the repetitive-to-newsy return reversal. If this is accurate, we would see it not only in the return data, but also in the expectations data.

We evaluate this prediction using survey data from IBES. We first show that sell-side analysts indeed exhibit correlation neglect, leading to different types of predictability in earnings growth revisions in the newsy and repetitive months. This evidence is uniquely useful because survey data are direct measures of market expectations, albeit imperfect. Moreover, we show that the predictable reversals in market returns do not occur until the earnings seasons begin. This alignment in timing suggests that it is indeed the earnings seasons that drive the return predictability, as opposed to other quarterly fluctuations unrelated to earnings announcements.

In addition to predictions confirmed in the aggregate setting, our theory also makes predictions about segments of the market, and about the cross-section. In particular, the correlation neglect mechanism that we propose should additionally apply to industry returns. It should also apply in the cross-section, in the sense that the industries for which there is

the strongest signals should be the most predictable, after controlling for the market return. Both patterns of predictability are statistically and economically significant.

We formalize the correlation neglect mechanism with a model in which there is variability in the second month regarding whether the information from the first is brought to investors' attention or not. A fully rational investor would not react to this "news," understanding that the new information was correlated with the old. An investor who believes he or she is seeing a genuinely new observation reacts; this reaction is predictable because the information is in fact the same as in the first quarter, and it also causes stock prices to rise or fall by more than is warranted.

These findings have broader implications. First, we provide evidence of return predictability that is robust, and economically and statistically significant, with monthly out-of-sample R^2 statistics of 4% , thus contributing to the debate on whether return predictability actually exists (Goyal and Welch 2008, Campbell and Thompson 2008,Goyal et al. 2024).[2] Second, we show that three important and commonly made assumptions about stock market returns are not innocuous: i) the expected stock market return is persistent, ii) the expected stock market return almost always exceeds the risk-free rate, and iii) the stock market return is covariance-stationary. Finally, we provide asset pricing and survey evidence for correlation neglect: investors seem to treat repeated information as new independent observations, even if they have substantial incentive to do otherwise.

Besides the very substantial literature on continuation and reversal, several recent papers make points that are related to ours. First, the "tug-of-war" pattern between continuation and reversal we document for monthly stock market returns is mirrored in intraday market returns: Lou et al. (2022) show that open-to-close stock market returns positively predict future close-to-open stock market returns, which then negatively predict future open-to-close returns.[3] The authors attribute their findings to clientele effects: the overreaction arises from news being repeatedly consumed by a second clientele (households). In our paper, the

[2]In contrast, Goyal et al. (2024) find out-of-sample R^2 statistics, should they be positive, tend to be in the tens of basis points, a finding that we replicate using our methodology.

[3]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.

overreaction aries from news itself being repeated in the second month of a quarter. Second, Fedyk and Hodson (2023) document that repetitive "news" on Bloomberg terminals generates overreactions in returns of related stocks, and that such overreaction is stronger when the repetition is more subtle, a result that, like ours, suggests correlation neglect. Finally, Enke and Zimmermann (2019) find that human subjects do not fully discount correlated news in experiments even when they are given a simple setup and clear instructions. We contribute to this literature by showing that the correlation neglect mechanism further exists in aggregate stock market returns and the cross section of industry returns.

2 Predicting aggregate stock market returns

We first characterize the U.S. 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 the US firms close their books for a given fiscal quarter on the last day of a calendar quarter. Therefore, the fiscal quarters over which the earnings are recorded are effectively the calendar quarters. While the fiscal quarters are aligned, firms do not announce their quarterly earnings together. Almost all firms announce within the three months after 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 implies that each of the three months in 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, 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 the 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 quarters as the repetitive earnings months, or simply repetitive months. The third months of quarters also contain announcements of predictably repetitive earnings. However, as they contain substantially fewer on-cycle earnings announcements, the repetition is muted.

2.1 Baseline return pattern

We demonstrate our baseline predictability pattern in the U.S. 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 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. 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 conducts regression 1 on the subsample 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, as they are bounded by -1 and 1 in stationary time series.

Column 3 extracts the difference of the coefficients in Column 1 and 2 by conducting 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 indicating whether 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 the U.S. stock market returns varies strongly across subsamples and lags. The associated t-statistic of -4.35 implies that the observed relation is unlikely to arise from noise.[4] While this statistic is an useful diagnostic, the time-series return forecasting literature (e.g., Goyal and Welch (2008)) has critiqued and moved away from it. We examine more standard performance metrics such as out-of-sample R^2 and trading strategy behavior in the next subsection.

Panel B, C, and D of Table 2 report results of the same regressions as in Panel A, except that they are on the first half, second half, and the post-WWII portion of the full 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.

2.2 Further evaluation

We now evaluate the baseline pattern from three additional aspects: i) out-of-sample forecasting performance, ii) trading strategy performance, and iii) and contribution to the existing literature.

Forecasting performance Goyal and Welch (2008) made an important critique on the literature studying stock market return predictability, which is that in a linear regression

[4]It further implies that an in-sample, market-neutral trading strategy that bets on both the continuation in Column 1 and the reversal in Column 2 approximately yields an annualized Sharpe ratio of $4.35/\sqrt{98} = 0.44$, where the number 98 is the number of years in the sample. This back-of-envelope calculation approximates the market excess returns with the regression residuals (which works in low-R^2 settings) and is merely a convenient heuristic. We formally construct a trading strategy in the next subsection.

model, any proposed signals to forecast returns can only be used with estimated coefficients, and if such estimation is done on data available in real time, the signals often generate negative "out-of-sample" (OOS) R^2. This means that such signals, when employed to predict the stock market returns in real time, often fail to outperform the returns' historical average.

Table 3 presents the out-of-sample R^2 generated by our signal. Following Campbell and Thompson (2008), we extend the CRSP aggregate market return series to 1872 using GFD data, 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 signal s_{t-1}, which forecasts mkt_t, 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.

Table 3 estimates the expanding-window OLS coefficients for our signal and compute the real-time forecasts for mkt_t in multiple ways. These methods are kept simple, with no constraint or shrinkage applied. Column 1 shows that even the most naive method—combining the signal values and the regression coefficients of historical returns on historical signals and a freely estimated constant—generates an R^2 of 4.20%. This number appears an order of magnitude higher than what are generated by other time-series signals for monthly US stock market returns surveyed in the comprehensive study of Goyal and Welch (2008), Rapach and Zhou (2022), and Goyal et al. (2024). This high R^2, along with those generated with methods 2 and 3, mitigates the concern that the signal implied by the time-series results in this paper could not have been successfully used to forecast stock market excess returns in real time.

Trading strategy Good forecasting performance does not necessarily translate into successful trading strategies.[5] We now use our signal 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.

Overall, the strategy implements two rules with data available in real time. First, it

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

places proportional weights on the market to the signal value, with a mean of zero. Second, the portfolio weight is scaled so that the strategy has a historical volatility of 5% per month. Specifically, for month t, the unscaled portfolio weight is simply s_{t-1}. The unscaled strategy volatility $\bar{\sigma}^s_{t-1}$ is the unscaled strategy's historical volatility up to $t-1$. The scaled portfolio weight is then $s_{t-1}\frac{0.05}{\bar{\sigma}^s_{t-1}}$. We further truncate the weight on the market at -3 and 3 to limit the impact of extreme observations.[6] The strategy's construction involves no look-ahead bias, 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 on individual stocks.

Relation to the existing literature Goyal et al. (2024) recently surveyed the literature on aggregate stock market return predictability and examined the signals' out-of-sample forecasting performance. Table 3 of their paper shows that among an expanded set of 34 predictors, the monthly in-sample R^2s are on average 0.32%, OOS R^2 are on average -0.44% after applying the regression constraints in Campbell and Thompson (2008). These results reaffirm the conclusion of Goyal and Welch (2008) that existing signals "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."

We replicate and extend their results in Table A1. The vast majority of OOS R^2s in this table are negative, with the maximum being 0.60% even as multiple implementations of the regressions are attempted. This reaffirms the conclusion of Goyal and Welch (2008). By documenting a predictor that generates an OOS R^2 that is an order of magnitude larger than the numbers in Table A1, we shift the literature's prior on an important question: How

[6]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.

predictable is the U.S. monthly stock market returns?

Our paper also relates to Guo (2025), which also which also focuses on earnings seasons (newsy months in our language). Guo also shows evidence for subtle expectational errors around earnings data that lead to return predictability patterns. In this case, the error relates to parameter compression: investors assume that earnings announcements equally close in time are equally close in information content. However, earnings announcements in any given quarter are closer than those in separate quarters. More generally, the true relevance of a newsy month's return follows a step pattern, where as the hypothesis in the paper is that it follows a straight line.

The mechanisms are distinguishable in the data. Table 5 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 $\sum_{j=1}^{4} mkt_{nm(t,j)}$, which 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.

Overall, our proposed signal featuring the tug-of-war between market return continuation and reversal appears to i) generate positive OOS R^2, ii) produce a profitable trading strategy, and iii) add value to the existing literature. It is therefore worthwhile to consider possible explanations for the pattern.

3 Explaining the return pattern

Before proposing an explanation, we note two telltale features of the data that inform us about the type of explanations that are likely to drive our return pattern.

First, the continuation and reversal arms appear tightly linked. We separate the return of trading strategy (as constructed in subsection 2.2) in each year into the component earned in the newsy months and that earned in the repetitive months. Table 6 regresses the two

components on each other, both in the raw return unit and ranked to limit the influence of outliers. The strong positive coefficients imply that, a year in which the continuation effect is strong is also likely to see 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.

Second, our signal implies expected market excess returns that are frequently negative. 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 means 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.

Given these two features, a parsimonious mechanism that jointly explain 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. To formalize this intuition, we apply the model of Enke and Zimmermann (2019) to asset pricing.

Assume that the economy is either in a high-productivity state (h) or a low-productivity state (l). 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. Investors have a prior distribution over p. The distribution is beta, such that they would estimate a probability p^* with a sample size of τ. To fix ideas and eliminate unnecessary notation, we set $\tau = 1$.

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 s, with $s \sim \text{Bernoulli}(p)$.

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 determined by a Bernoulli random variable x. If $x = 1$, then s is brought again to investors' attention. If $x = 0$, then $\tilde{s}$ is drawn from Bernoulli($(p^* + 1)/3$). Note that $\tilde{s}$ is not informative about p.

Investors are risk-neutral and the riskfree rate is equal to zero. The value of the market is equal to the posterior mean of p. The posterior mean is determined by the following formula:

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

After observing signal s, and substituting $\tau = 1$:

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

and

$$R_1 = P_1 - P_0 = \frac{s + p^* + 1}{4} - \frac{p^* + 1}{3}$$

which is positive of $s = 1$ and negative if $s = 0$. For future reference, note that from the econometrician and investor's perspective, $E[R_1] = E[E[R_1|p]] = E[\frac{p+p^*+1}{4} - \frac{p^*+1}{3}] = 0$.

Equilibrium with rational investors

There is no information and hence no change in the second period, $P_2 = P_1$ and $R_2 = 0$. In the third and final period, conditional on p, the return is again Bernoulli with outcomes $1 - P_1$ with probability p and $-P_1$ with probability $1 - p$. From the agent's point of view, $E[R_3|s] = 0$, and moreover R_3 is independent of s. Moreover, unconditionally, $E[R_3] = 0$.[7]

Conditional on s, p has a beta distribution, and then conditional on p, the return is

[7]Note that

$$\begin{aligned} E[R_3] &= E[E[R_3|p]] \\ &= E[p(1 - P_1) + (1 - p)(-P_1)] \\ &= E[E[p(1 - P_1) + (1 - p)(-P_1) + s]] = 0 \end{aligned}$$

because $P_1 = E[p|s_1]$.

again Bernoulli with outcomes $1 - E[P_1]$ or $-E[P_1]$, and is independent of R_1 (and of course the constant R_2).. We are interested in unconditional distributions, because that is what the econometrician observes. It suffices to compute $E[R_1 R_3]$. However, $E[R_1 R_3] = E[E[R_1 R_3|p,s]] = E[E[R_1|p,s]E[R_3|p,s]] = 0$ showing that these are indeed independent.

Equilibrium with correlation neglect

Investors form

$$P_2 = E^{\text{CN}}[p] = \frac{s + sx + \tilde{s}(1-x) + p^* + 1}{5}$$

Thus

$$R_2 = P_2 - P_1 = \frac{sx + \tilde{s}(1-x) + s + p^* + 1}{5} - \frac{s + p^* + 1}{4}$$

Note that under our assumption regarding $\tilde{s}$, p_x is irrelevant and the investor is neither optimistic nor pessimistic on average:

$$\begin{aligned}
E[R_2] &= E[E[R_2|s,\tilde{s}]] \\
&= E\left[\frac{sp_x + \tilde{s}(1-p_x) + s + p^* + 1}{5} - \frac{s + p^* + 1}{4}\right] \\
&= E[E\left[\frac{sp_x + \tilde{s}(1-p_x) + s + p^* + 1}{5} - \frac{s + p^* + 1}{4}|p\right]] \\
&= \frac{pp_x + (1 + p*/3)(1-p_x) + p + p^* + 1}{5} - \frac{p + p^* + 1}{4} = 0
\end{aligned}$$

However, unlike in the case with the rational agent, R_2 is positively correlated with R_1, provided that the probability of seeing the signal is sufficiently high. Intuitively, the agent double-counts s in the second period, not realizing that it is the same signal as before. It

suffices to show that $E[R_1 R_2] < 0$. First note that

$$\begin{aligned} E[R_1 R_2] &= E[R_1 R_2 | s, \tilde{s}] \\ &= E[(\frac{p_x s + (1-p_x)\tilde{s} + s + p^* + 1}{5} - \frac{s + p* + 1}{4}) R_1 | s] \\ &= E[(\frac{p_x s + (1-p_x)(p^*+1)/3 + s + p^* + 1}{5} - \frac{s + p^* + 1}{4}) R_1] \\ &= \end{aligned}$$

Note that R_2 has mean zero. It suffices to show that

$$E[(\frac{p_x s + (1-p_x)(p^*+1)/3 + s + p^* + 1}{5} - \frac{s + p^* + 1}{4}) s] > 0$$

where we have eliminated constant terms in R_2. This is positive assuming that there is sufficiently high probability that the signal is brought to the investor's attention as can be seen by substituting in $s = 0$. Namely, $p_x + (1-p_x)(p^*+1)/3 > (p^*+2)/4$. If, for example $p^* = 1/2$, then $p_x > 1/4$ suffices. Note that if $p_x = 0$, for example, the investor increments based on noise in the second period that is uncorrelated with s_1.

Finally, we show that $E[R_3 R_2] < 0$, namely that returns in the second and third period are negatively correlated. This is intuitive: the price in the first period is the optimal forecast, and thus any reaction to "news" in the second period will be an over-reaction that will on average be corrected in the final period. To be precise:

$$\begin{aligned} E[R_3 R_2] &= E[E[R_3 R_2 | s]] \\ &= E[E[R_3 | s] R_2] \\ &= -E[R_2^2] < 0. \end{aligned}$$

The last equality follows from $E[P_3 | s] = P_1$, and therefore that $E[P_3 - P_2 | s_1] = -(P_2 - P_1)$.

4 Testing the hypothesis

Having stated our hypothesis of correlation neglect, we further test it from four additional angles.

4.1 The pre-season periods

Our previous analysis primarily focused on monthly stock returns and utilized the concept of newsy months. However, the period with a significant number of earnings announcements does not immediately begin on the first day of these newsy months. Even the quickest announcers require some time to prepare their statements. Specifically, among companies with fiscal periods aligned with calendar quarters, only 0.27% of earnings announcements occur within the initial week (or the first five trading days) 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 2.93% of the announcements, which aligns more closely with the average weekly rate. Therefore, any market return reversals, if stemming from these earnings announcements, are not expected to occur in the first week of newsy months. Table 7 confirms this prediction. Columns 2 and 3 show a weak reversal in the first week of newsy months and a strong reversal in remaining periods, with the coefficients disproportionate to the length of the predicted returns (about one to three). This analysis suggests that our observed return pattern is indeed tied to the early earnings announcements. This piece of evidence speaks in favor of stories involving these earnings announcements and against those built upon other unrelated quarterly fluctuations.

4.2 Survey data

An influential branch of the behavioral finance literature uses survey data from IBES to measure investors' expectations of aggregate cash flow growth. In particular, Nagel and Xu (2022) and Bordalo et al. (2024) argue that the long-term growth (LTG) measure in

IBES is what matters from aggregate asset prices. We respond to this literature by testing our hypothesis of correlation neglect on the LTG measure from the IBES Adjusted Details file.[8] 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) reactions in a repetitive month are likely in the same direction as those in the preceding newsy month and ii) reactions 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 predicted by revisions in the previous newsy month. Second, revisions in a newsy month are negatively predicted by revisions in the previous repetitive month.

Column 1 of Table 11 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 strongly positive coefficient of 0.543 indicates that revisions in a repetitive month indeed tends to be in the same direction as those in the previous newsy month. However, this number is not in itself convincing. Survey data naturally incorporate latency,[9] resulting in a positive unconditional autocorrelation in revisions. Column 2 controls for this unconditional latency and extracts the overreaction 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.

[8] 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.

[9] One reason why such latency exists in survey data is that analysts often need to issue elaborate analyst reports (i.e., those studied in Barth et al. (2024) and Li et al. (2024)) along with their estimates. This makes issuing estimates more costly, delaying them overall.

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 said above. Column 4 controls for this effect and extract 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.

4.3 Earnings similarity and the strength of the return pattern

A key feature of our mechanism of correlation neglect is that, when the two signals are more similar, the overreaction to the second, repetitive signal amplifies. We now test this prediction. Table 10 shows that, when the earnings announced in the repetitive month more closely resemble those in the preceding newsy month, the return of this repetitive month's return reverses more strongly. This suggests that investors overreact more to a repetitive month's information when it is more similar to that in the previous month.

4.4 The cross section of industries

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. Two stocks randomly drawn from an industry are more connected with each other than two random stocks drawn from an economy. An industry is a smaller economy except more tightly connected. Investors clearly 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:

$$exret_{i,t} = \alpha + \beta exret_{i,nr(t)} + \epsilon_{i,t}. \tag{3}$$

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 less than 20 constituents to ensure a sufficient number of announcers. Table 8 shows that the same tug-of-war pattern between continuation and reversal exists in industry excess returns in addition to 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 Alternative explanations

Predictability reflecting predictable resolution of risks. 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. We have argued that this type of explanations 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. We now ignore this aspect of scale and discuss potential stories that can explain the pattern in direction.

The type of variation in risks that is necessary to explain my 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 6, 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 my predictability pattern.

Another candidate is the risk resolution associated with earnings announcements. Empirically, 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.

Savor and Wilson (2013) document that the equity premium on macroeconomic announcement days is especially large and argue that this is because it resolves important

macroeconomic risks. If this contributes to our pattern of return predictability, the return predictability would be realized on macroeconomic announcement days. A straightforward empirical investigation reveals that the predictability in fact works about equally well on the top five macroeconomic announcement dates on Bloomberg (i.e., FOMC, employment condition, GDP, PPI, and Institute for Supply Management manufacturing). The data suggest that the return predictability documented in this paper does not obviously relate to macroeconomic announcements.

Firms endogenously changing their announcing latency. 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 2018; 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.

6 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 did 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 – Group 3	
	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 signal is $mkt_{nr(t)} - \bar{mkt}_{t-1}$ for a repetitive t, $-(mkt_{nr(t)} - \bar{mkt}_{t-1})$ for a newsy t, and 0 otherwise. For each month t, 2 coefficients—one for the signal and one for the constant term—are extracted from a simple expanding-window OLS regression of historical market excess returns on historical signal values and a constant. For method 1, the forecast in a given month is the estimated coefficient on the signal multiplied with the signal value plus the estimated constant. Method 2 replaces the estimated constant coefficient with $\overline{r_t}$. Method 3 replaces the estimated constant with the average signal (of the dividend/price, earnings/price, and book-to-market based numbers) proposed by Campbell and Thompson (2008) in the valuation constraint + growth specification with fixed coefficients. 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: 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 there 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 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. Data are monthly from 1926 to 2023. T-statistics computed with White standard errors are reported in square brackets.

Table 6: 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 7: The first weeks of the newsy months

	(1) Newsy	(2) Week 1	(3) Ex week 1
$mkt_{nr(t)}$	-0.279***	-0.021	-0.256***
	[-3.02]	[-0.53]	[-2.76]
N	386	386	386

Column 1 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 first month of a quarter (newsy). Column 2 replaces the dependent variable with mkt_t^{FW}, the market excess return during the first five trading days of month t. Column 3 replaces the dependent variable with mkt_t^{ExclFW}, the excess market return during t excluding the first five trading days. Data are monthly from 1926 to 2023. T-statistics computed with White standard errors are reported in square brackets.

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

	(1) Repetitive	(2) Newsy	(3) Difference
	A: Full sample		
$exret_{i,nr(t)}$	0.104***	-0.104**	-0.208***
	[2.65]	[-2.50]	[-3.64]
N	6,594	6,589	13,183
	B: First half		
$exret_{i,nr(t)}$	0.107*	-0.090	-0.197**
	[1.69]	[-1.45]	[-2.22]
N	1,515	1,532	3,047
	C: Second half		
$exret_{i,nr(t)}$	0.102**	-0.112**	-0.214***
	[2.04]	[-2.04]	[-2.89]
N	5,079	5,057	10,136
	D: Post-WWII		
$exret_{i,nr(t)}$	0.090**	-0.091*	-0.180***
	[2.17]	[-1.90]	[-2.86]
N	6,180	6,176	12,356

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 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 there 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 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. 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 20 firms in an industry. 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 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		0.063	0.038	-0.044
		[0.85]	[0.62]	[-0.82]
HML_t			0.207	0.042
			[1.48]	[0.35]
SMB_t			-0.038	-0.057
			[-0.45]	[-0.75]
MOM_t				-0.365***
				[-3.41]
α	0.530***	0.488***	0.439***	0.784***
	[3.38]	[3.05]	[2.82]	[3.99]
N	1,165	1,165	1,165	1,164

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: Aggregate earnings distance and the strength of the reversal arm

	(1)	(2)	(3)	(4)	(5)	(6)
	0-10	10-20	20-50	50-80	80-90	90-100
$mkt_{nr(t)}$	-0.659**	-0.321**	-0.130	-0.236	-0.184	0.262
	[-2.87]	[-2.31]	[-0.79]	[-1.51]	[-0.81]	[1.19]
N	20	20	60	60	20	20

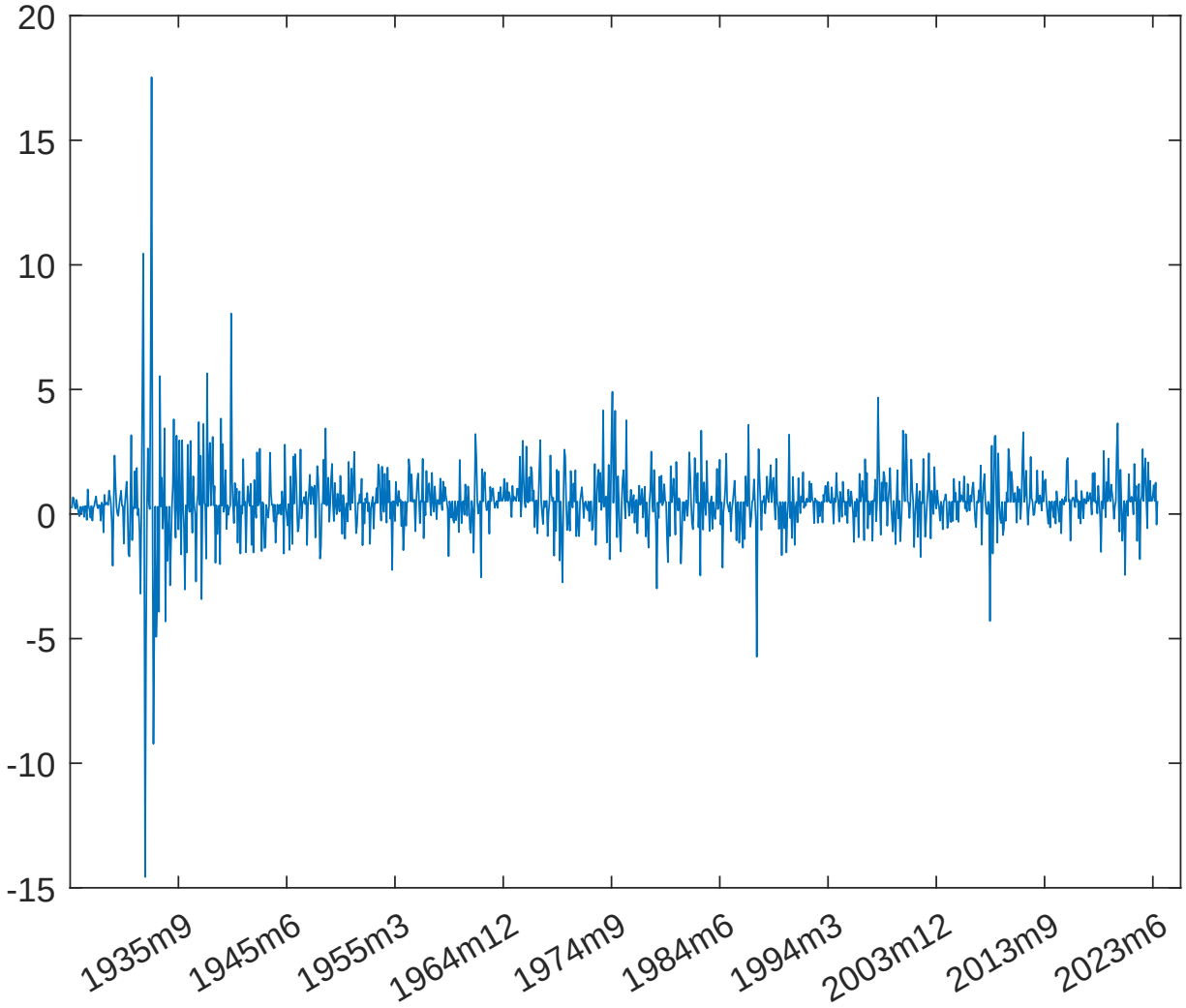
This table presents estimated βs from the monthly time-series regression $mkt_t = \alpha + \beta mkt_{nr(t)} + \epsilon_t$. Here, mkt_t is the U.S. stock market return in excess of the risk free rate in month t, and $nr(t)$ is the most recent month before t that is newsy or repetitive. In this table, t is always the first month of a quarter (i.e., newsy). Across columns, the regression sorts on the distance between the total earnings (scaled by total the book value of equity) announced the most recent repetitive and newsy months before t. The distance increases from column 1 to 6 and are between 0-10th, 10-20th, 20-50th, 50-80th, 80-90th, and 90-100th percentiles of the entire sample, respective. Data are monthly from 1971-2021. T-statistics computed with White standard errors are reported in square brackets.

Table 11: Evidence from survey data

	(1) Rev_t	(2) Rev_t	(3) Rev_t	(4) 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.

Figure 1: Implied expected stock market excess returns over time



This figure plots the expected stock market return as in Method 2 of Table 3. The unit is percent per month.

Appendix

A Timing-series signals and trading strategies

In the cross sectional return forecasting literature, it is a common practice to form long-short portfolios according to a signal's values across stocks. For example, Fama and French (1993) create the HML factor by longing the 30% of stocks with the highest book-to-market ratios and shorting the 30% of stocks with the lowest book-to-market ratios. This approach has many benefits, among which are the following three. First, it does not require explicit forecasts for stock returns and estimates no parameter. Second, it works with any stock-level signal. Third, it creates a reasonable risk exposure that makes the portfolio returns comparable across signals, as the equity exposures of the long and short arms of the portfolio are the same 100% and -100%.

In the time-series literature, we do not yet have a commonly used approach to create analogous portfolios. Such portfolios are an useful diagnostic tool that complements the standard metric of out-of-sample R^2 put forth by Goyal and Welch (2008). We develop such a tool in this section. Overall, for a generic signal s, we construct a beta-neutral market-timing strategy that rebalances positions in i) aggregate stock market and ii) the risk-free bond. The strategy implements two rules with data available in real time. First, it places proportional weights on the market to the signal value, with a target mean of zero. Second, the portfolio weight is scaled so that the strategy has a target volatility of, say, 5% per month.

Let s_t be the signal value at the end of period t. Then, the unscaled portfolio weight on the market is s_{t-1}, and the unscaled strategy volatility $\bar{\sigma}^s_{t-1}$ is the unscaled strategy's historical volatility up to $t-1$. The scaled portfolio weight is $s_{t-1}\frac{0.05}{\bar{\sigma}^s_{t-1}}$. We further truncate the weight on the market at -3 and 3 to avoid unrealistic strategies.[10] The strategy's construction involves no look-ahead bias, and the scaling can be adjusted according to an investor's risk appetite.

Columns Return5 and Sharpe5 of Table A1 tabulates means and Sharpe ratios of the portfolios for existing signals in the literature forecasting aggregate stock market returns. Four points are worth noting. First, likely owing to a consistent risk appetite targeting i) a historical strategy volatility of 5% and ii) a maximum market weight of 300% and -300%, the returns are Sharpe ratios of the diagnostic portfolios are rarely catastrophic. This sharply contrasts the message conveyed by the OOS R^2s, which can be several or even tens of

[10]Since overly high leverages are unattainable in practice, such truncation is always (though perhaps implicitly) present when trading in real world.

percentage points negative, even with the constraints from Campbell and Thompson (2008).

Second, the returns and Sharpe ratios have positive mean and median across the 23 signals. The average returns have a mean and median of 0.07% per month, and the Sharpe ratios have a mean and median of 0.05 and 0.04 per annum. This relates to the first point, and again contrasts the message in the OOS R^2s, which, with a 5 year burn-in period, have a mean of -4.42% and a median of -1.49%, and a mean of -1.14% and a median of -0.22% with the CT constraints.

Third, the two metrics based on our diagnostic portfolios are (perhaps surprisingly) dissimilar to the OOS R^2s. Table A2 show that with the same burn-in period of 5 years, the returns and Sharpe ratios have a near-zero correlation of 0.03 and 0.12 with the original OOS R^2 in Goyal and Welch (2008), and a negative correlation of -0.50 and -0.32 with the OOS R^2 in Campbell and Thompson (2008). In contrast, the portfolio-based metrics positively correlate with the in-sample R^2, though at 0.5, this correlation is far from perfect.

Fourth, related to the third point, it is entirely possible for a signal to have very low R^2 but high diagnostic portfolio returns and Sharpe ratio. The signal rtz proposed in Rapach et al. (2016) is such an example. It has low OOS R^2s around -10% but the highest diagnostic portfolio average return of 0.87% per month, and the highest Sharpe ratio of 0.43 per annum.

These four differences arise from a key economic difference between the two sets of metrics. The R^2 computation involves explicit return forecasts and therefore the estimation of an regression coefficient on the signal in real time. This coefficient is an representation of the signal's historical performance: A time-series regression of the market excess return mkt_t on the signal s_{t-1} and a constant yield a coefficient of $\beta^s = \sum_t \frac{(s_{t-1}-\bar{s})}{\sum_t (s_{t-1}-\bar{s})^2} mkt_t = \sum_t w_{t-1} mkt_t$ on s. Here, $\bar{s}$ is the in-sample mean of the signal s. Note that β^s is the mean excess return of a portfolio that rebalances between positions in the aggregate stock market (which yields an excess return of mkt_t) and the risk-free bond (which yields an excess return of 0). The month-t portfolio weight on the stock market $w_{t-1} = \frac{(s_{t-1}-\bar{s})}{\sum_t (s_{t-1}-\bar{s})^2}$ is i) linear in the signal's value s_{t-1}, ii) on average 0, so that the portfolio is on average market neutral, and iii) scaled by $\sum_t (s_{t-1}-\bar{s})^2$, so that the portfolio has unit exposure to s (i.e., $\sum_t \frac{(s_{t-1}-\bar{s})}{\sum_t (s_{t-1}-\bar{s})^2} s_{t-1} = 1$).[11]

Using this coefficient to form a quantitative forecast of the market excess return implicitly assumes that performance of the signal's coefficient portfolio is so stable that its past performance reliably predicts its future performance at any point in history. This is a somewhat paradoxical assumption in the first place, as it likely implies too high a T-statistic and a Sharpe ratio—as the coefficient portfolio's return volatility approaches 0, the T-statistic in

[11] If s does not have an economically interpretable scale itself, the scaling in step iii) has no economic interpretation either. Our diagnostic portfolio is designed to mimic this coefficient portfolio, except that we replace the in-sample mean with the expanding mean for implementability, adjust the scaling in iii) for economic interpretability, and impose a position constraint that is inevitable in reality.

the regression and the portfolio's Sharpe ratio both approach infinity. In particular, extreme performance at the beginning of the sample, whether good or bad, tend to lead to forecasts that are overly or insufficiently disperse, degrading the signal's OOS R^2.

Our diagnostic portfolio, on the other hand, requires no quantitative prediction of the signal's performance.[12] The size of the bet on the market is based on a constant risk appetite (5% in our example) and does not change with the past returns of the signal's coefficient portfolio. This is consistent with the construction of cross sectional factors (e.g., HML, SMB, MOM, etc.), in which the stock weights also do not change with the past factor returns. Removing the intermediate step of predicting the signal's performance removes potential errors in that step. Therefore, the diagnostic portfolio-based performance metrics appear better than the OOS R^2s overall. A well-behaved diagnostic portfolio does depend on the stability of the signal's mean and volatility over time, and such stability appears much better supported by the data.

To more directly see why the diagnostic portfolio based metrics can be so different from the OOS R^2, we plot in Figure A1 the univariate expanding window regression coefficients of the aggregate stock market excess return on the signals and a constant. The signals are scaled to have a standard deviation of 1 to make the coefficients comparable. As explained above, degradation in OOS R^2 from in-sample R^2 is in large part owing to these coefficients not being a constant. As the sample size grows over time, the coefficients become increasingly stable, resembling the full sample coefficients which are the last observation in each series. Hence, the largest deviations occur at the beginning of the sample. From this figure, it is immediately obvious that csp, aem, rrz, vrp, gm, and svix are the 6 signals with large and persistent deviations in the coefficients. They are precisely the 6 signals with the lowest OOS R^2.

It is worth emphasizing that we do not imply that the metric of OOS R^2s used in Goyal and Welch (2008) is inappropriate. On the contrary, we believe it is a good, consistent, and general metric. We do want to point out that there are more to this metric. Importantly, poor OOS R^2s do not imply that the corresponding signal cannot be successfully employed in real time trading. The diagnostic portfolio we propose is a simple approach that both complements the OOS R^2s and fills an obvious gap between the practices of two literatures studying the time-series and the cross-sections of stock returns.

[12] If one is evaluating signals *individually*, it is not obvious why such quantitative prediction is necessary in the first place.

Table A1: R^2 in forecasting monthly stock market returns using other signals

	IS	CTOOS10	CTOOS5	OOS10	OOS5	Return5	Sharpe5	Begin	End
dy	0.68%	-0.28%	-0.28%	-0.48%	-0.48%	-0.19%	-0.08	1871m2	2019m12
ep	0.88%	0.27%	0.27%	0.28%	0.28%	0.16%	0.09	1871m1	2019m12
bm	1.04%	0.16%	0.07%	-3.02%	-2.93%	-0.14%	-0.09	1921m3	2019m12
svar	0.25%	0.03%	0.03%	-1.49%	-1.49%	0.06%	0.04	1885m2	2019m12
csp	0.90%	-0.31%	0.24%	-5.81%	-6.12%	-0.16%	-0.10	1937m5	2002m12
ntis	0.75%	-0.18%	0.02%	-0.13%	-0.78%	0.10%**	0.24	1926m12	2019m12
eqis	0.29%	-0.43%	-1.62%	-0.40%	-2.11%	-0.06%	-0.11	1926m10	2008m4
tbl	0.23%	-0.80%	-0.61%	-1.70%	-1.61%	0.08%	0.05	1920m1	2019m12
lty	0.22%	-1.33%	-1.08%	-1.64%	-1.39%	0.14%	0.07	1919m1	2019m12
dfy	0.49%	-0.22%	-0.22%	-2.45%	-2.24%	-0.24%	-0.16	1919m1	2019m12
dfr	0.37%	-0.30%	-1.72%	-0.21%	-1.69%	0.14%	0.12	1926m1	2019m12
infl	0.35%	-0.05%	-0.05%	-0.03%	-0.03%	0.10%	0.10	1913m2	2019m12
ik	1.09%	0.30%	0.30%	-0.03%	-0.01%	0.37%*	0.21	1947m3	2019m12
cay	0.37%	-0.32%	-0.31%	-0.39%	-0.97%	0.25%	0.16	1947m4	2019m12
tms	0.29%	-0.10%	-0.20%	-1.04%	-1.32%	0.14%	0.09	1920m1	2019m12
aem	0.31%	-2.12%	-2.01%	-40.25%	-38.18%	-0.02%	-0.01	1947m4	2009m4
hkm	0.60%	-0.09%	0.00%	-0.28%	-0.30%	-0.03%	-0.02	1970m1	2012m12
rrz	1.45%	-10.18%	-12.30%	-9.83%	-12.00%	0.87**	0.43	1973m1	2014m12
kp	1.05%	0.31%	0.23%	0.36%	0.27%	0.19%***	0.37	1930m1	2019m11
svix	0.21%	-5.04%	-6.21%	-7.26%	-8.67%	-0.27%	-0.12	1996m1	2012m1
gm	0.78%	0.60%	0.36%	-0.52%	-5.20%	0.07%	0.04	1996m1	2012m1
vrp	0.10%	-0.67%	-0.53%	-17.98%	-14.02%	-0.09%	-0.06	1989m12	2019m12
sent	0.39%	-0.10%	-0.64%	-0.01%	-0.67%	0.02%	0.02	1965m7	2019m12

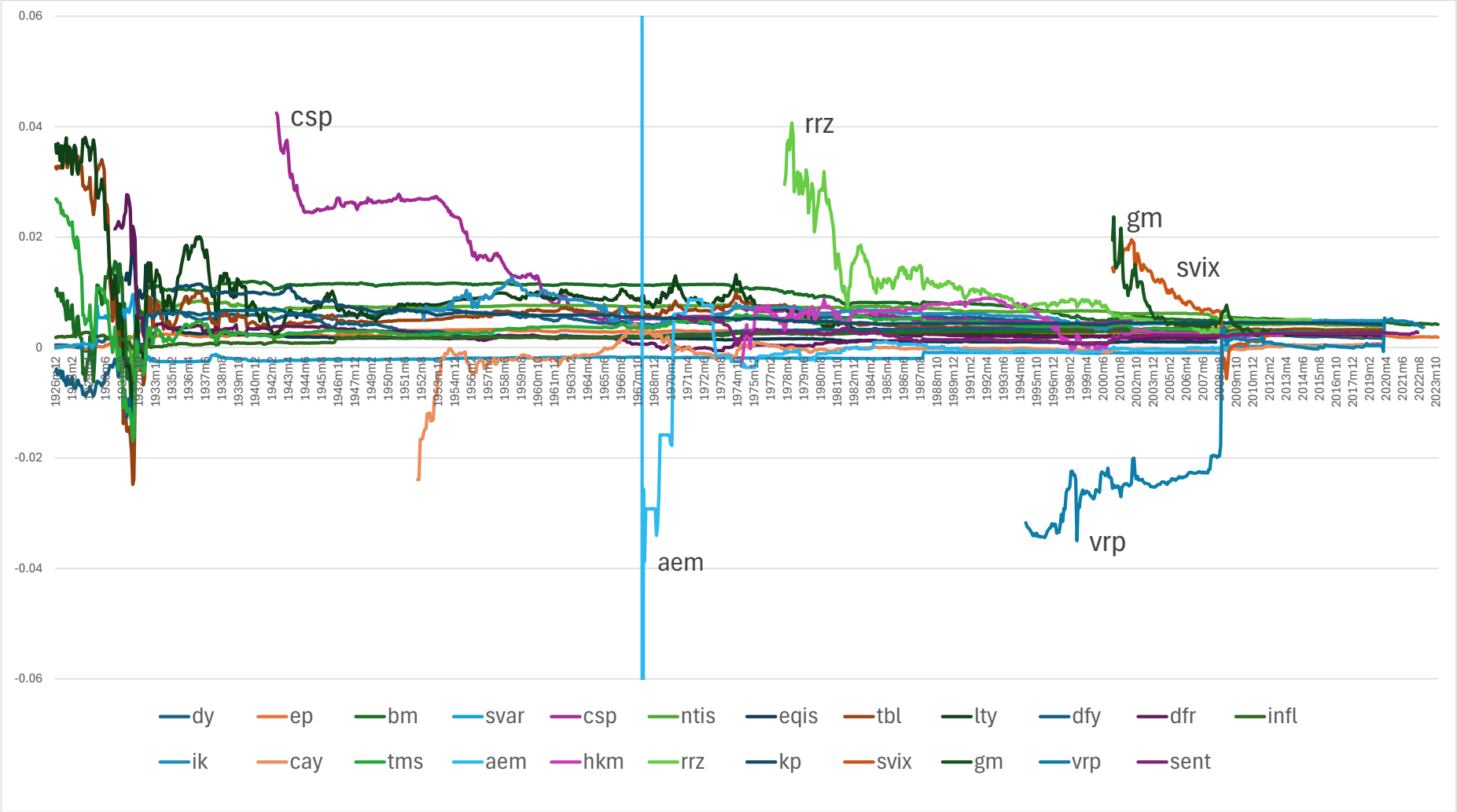
This table displays R^2 and the sample start/end month of various monthly signals that predict monthly stock market returns in the US. The "IS" column shows the in-sample R^2s, the next 4 columns show the out-of-sample R^2s as in Goyal and Welch (2008), and the next 2 columns show the monthly returns and annualized Sharpe ratios of the diagnostic portfolios. Columns with the 5 and 10 suffixes evaluate the R^2s 5 and 10 years after the date's inception (but not after 1926m1). Columns with the "CT" prefix i) truncates the estimated coefficient on the signal at 0 if it has a different sign from that estimated on the full sample and ii) truncates the forecast at the risk-free rate if it exceeds the risk-free rate, as in Campbell and Thompson (2008). All predictors are sourced from Amit Goyal's website (and follow his naming convention) except for the following: eqis is the new equity issuance share from Baker and Wurgler (2000), aem is the financial factor from Adrian et al. (2014), hkm is the leverage factor from He et al. (2017), rrz is the short interest from Rapach et al. (2016), svix is from Martin (2017), gm is the implied cash flow growth from Gao and Martin (2021), sent is the orthogonalized investor sentiment from Baker et al. (2021). I thank Li and Wang (2023) for sharing the data they use, and all the mentioned authors for making their data available online.

Table A2: Correlation among evaluation metrics for aggregate stock market return predictors

	Ret5	Sharpe5	IS	OOS5	CTOOS5
Ret5	1.00				
Sharpe5	0.90	1.00			
IS	0.50	0.51	1.00		
OOS5	0.03	0.12	0.12	1.00	
CTOOS5	-0.50	-0.32	-0.26	0.34	1.00

This table tabulates the correlation among different measures across the 23 signals in Table A1.

Figure A1: The expanding-window averages of the signals' coefficient portfolio returns



This figure plots the expanding window regression coefficients of the aggregate stock market excess returns on the 23 signals in Table A1.