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Predicting Analysts' S&P 500 Earnings Forecast Errors and Stock Market Returns using Macroeconomic Data and Nowcasts*

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Abstract

This study scrutinizes the quality of "bottom-up" forecasts of near-term S&P 500 Composite earnings, derived by aggregating analysts' forecasts for individual firm-level earnings. We examine whether forecasts are broadly consistent with current macroeconomic conditions reflected in economists' near-term outlook and other available data. To the contrary, we find that a simple macroeconomic model of aggregate S&P 500 earnings, coupled with GDP forecasts from the Blue Chip Survey and recent dollar exchange rate movements, can predict large and statistically significant errors in equity analysts' bottom-up forecasts for S&P 500 earnings in the current quarter and the quarter ahead. This finding is robust to the requirement that our econometric model is calibrated using only data available at the time of forecast. Moreover, the discrepancy between the macro-model-based earnings forecasts and analysts' forecasts has predictive power for 3-month-ahead stock returns.

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I. Introduction

The informational efficiency of Wall Street analysts' quarterly earnings forecasts has been analyzed extensively, though largely in the context of earnings forecasts for individual firms' earnings and implications for firm-level stock returns. Comparatively little has been said regarding the role of analyst earnings forecast inefficiencies as a driver of aggregate market stock returns. Even where research is geared toward gauging the efficiency of analyst earnings forecasts with respect to macroeconomic data, the metrics of inference are largely based on firm-level earnings and returns. Our analysis fills an important gap by gauging the extent to which macroeconomic information is incorporated into analysts' outlook for aggregate earnings. We examine the extent to which the aggregated, or "bottom-up," forecasts of S&P 500 constituents' near-term earnings fails to incorporate available information about the macroeconomy. Our results also contribute to the asset-pricing literature with new evidence on the importance of cash flow news for explaining aggregate stock market returns.

We begin by first examining the extent to which news on near-term earnings, as measured by revisions to analysts' forecasts, affects stock market returns from 1994-2023. We find a very strong positive relationship. Even after excluding the handful of outlier quarters associated with financial crises, the positive effect of near-term earnings news accounts for more than 10 percent of the variation in 3-month and 6-month Composite Index returns. This result appears to contradict the *negative* aggregate earnings-returns relationship documented in earlier research. However, this discrepancy is likely attributable, in part, to our more recent sample period; out sample begins in 1994, toward the end of a monetary policy regime largely focused on reducing inflation (Zolotoy, Frederickson, & Lyon, 2017).

The crux of our analysis involves testing whether analysts' forecast errors, at the aggregate level, could have been predicted by available macroeconomic data. Specifically, we propose and estimate a simple model of growth in aggregate S&P 500 quarterly earnings as a function of GDP growth, inflation, and dollar exchange rate appreciation. We then gauge the extent to which analysts' current-quarter and quarter-ahead forecasts for S&P 500 earnings are consistent with the trajectory implied by the model and available macroeconomic data. We then examine how well analysts' forecast errors can be predicted based on the gap between their forecasts and earnings growth implied by macroeconomic conditions and, finally, test the extent to which the predictability of analysts' forecast errors predicts equity market returns.

Unpacking our methods and findings in greater detail, we build a parsimonious and interpretable model of corporate profits growth within the context of the national income and product accounts. The resulting model provides predictions for the signs and plausible ranges of magnitudes for coefficients on key macroeconomic variables and is estimated on quarterly growth in S&P 500 profits from 1993-2023. Ultimately, the econometric model contains only a few explanatory variables: growth in real GDP, measures of output and wage inflation, and appreciation in the dollar exchange rate. In part, parsimony is driven in part by the public availability of macroeconomic forecasts, which is largely limited to GDP and its components.[1] The dollar exchange rate is hypothesized to be a key determinant because many S&P 500 companies produce exports or generate sales at foreign subsidiaries: all else the same, dollar depreciation tends to boost the dollar value of U.S. corporations' earnings through a few channels. Overall, our macroeconomic variables explain between 25 to 45 percent of the variation in S&P 500 earnings growth, or up to 75 percent when controlling for asset-write-downs by commercial banks.

A true test of whether analysts or sophisticated investors incorporate known macroeconomic information into their forecasts requires that the parameters of the macro model used for predicting earnings be based only on information available when analysts recorded their forecasts. Therefore, to reduce look-ahead bias, we use the early part of our sample, 1993-1998, to estimate an initial set of model coefficients. Those parameters are used in conjunction with macroeconomic forecasts from the Blue Chip survey and other incoming data observed midway through the first quarter of 1999 to produce a forecast for S&P 500 earnings growth over the first two quarters of 1999. That is, we produce a "nowcast" for first-quarter growth and a forecast for the second quarter. New historical data is then added, quarter by quarter, to iteratively update model parameters over the rest of the sample.

When we compare the accuracy of both the macro-model-based forecasts and analyst forecasts using simple correlation analysis, we find that (i) analyst forecasts for the current quarter are somewhat more accurate than the macro-based forecasts, whereas (ii) the reverse is true for the cumulative growth over the current and subsequent quarters. Amazingly, the bottom-up analyst growth forecasts are largely uncorrelated with the macro-based growth forecasts, which suggests that analysts' forecasts do not incorporate recent macroeconomic information. Simple regressions are then used to examine the extent to which the gap between macro-based forecasts and analysts' forecasts helps predict analyst forecast errors in the current (nowcast) quarter and the quarter ahead. We find that the gap between our macro model growth forecasts and analyst growth forecasts can predict about 50 percent of analysts' forecast errors for the current quarter and about 40 percent of their forecast errors for quarter-ahead earnings.

The final stage of our analysis involves testing whether those predicted forecast errors would have, in turn, predicted S&P 500 returns. We examine returns over both a three-month and six-month horizon, with the latter horizon roughly marking the point in time when the actual results for quarter-ahead earnings have largely been released to the public. By themselves, the model-predicted forecast errors predict about 8 percent of the variation in both 3-month stock returns, with the expected sign, but only about 4 to 5 percent of 6-month return variation. Moreover, when we include a control for equity market valuation using the S&P 500 dividend yield, or similar so-called "return factors", we find that the incremental explanatory power of our predicted forecast errors is little changed.

[1] In particular, the main public surveys of economic forecasts do not contain forecasts of the key determinants of labor costs (private sector payrolls and the wages) which tend to grow roughly in line with real GDP and prices, though frequently not in tandem.

Our findings contribute both to (i) asset pricing research on how much cash flow news accounts for the variation in aggregate stock market returns and valuations as well as to (ii) accounting research on the efficiency of analyst earnings forecasts. In particular, our analysis sheds new light on the effect of *contemporaneous* earnings news on aggregate stock returns. Several previous studies found that current earnings growth had a counterintuitive negative effect on aggregate stock prices (e.g., Kothari, Lewellen, and Warner (2006) and Cready and Gurun (2010)), which was interpreted as suggesting that favorable cash flows news tends to be more than offset by correlated discount rate news. More recently, however, Zolotoy, Frederickson, and Lyon (2017) found the earnings-returns relationship to be regime-dependent, negative when market concerns are dominated by anti-inflationary monetary policy but positive when the markets are instead focused on other risks. Our post-1992 sample period overlaps mostly with the regime when inflationary risks were not dominant.

Our analysis also has bearing on the role of news of future cash flows in explaining variation in returns. Beginning with Campbell & Shiller (1988) and amplified by Cochrane (2008), among others, researchers found little evidence that *future* divided growth could explain much of the variation in equity valuations. That inference is overturned by more recent studies that do not impose the assumption of rational expectations but instead employ "subjective" (survey-based) measures of expected cash flow growth. Chen, Da, and Zhao (2013) and De La O and Myers (2021, 2024), both using Wall Street analysts' forecasts compiled by I/B/E/S but different modeling frameworks, show that much of variation in equity valuations and returns is explained by changes in earnings growth forecasts, particularly forecasts of earnings only one or two years ahead. Our analysis shows that forecasts for earnings just one quarter ahead (together with the current quarter) can explain a substantial portion of three-month and six-month returns.

Among the accounting studies focused on the transmission of macroeconomic news into analysts' firm-level earnings forecasts, a couple of the more recent and salient studies are Hugon, Kumar, and Lin (2016) and Carabias (2018). The former focuses on GDP news, gauged using consensus forecasts of GDP growth, and finds that GDP forecasts predict analyst forecast errors for current-quarter firm-level earnings. The latter study constructs a composite real-time index of macroeconomic growth news based on a broad swath of economic data releases and then uses this real-time macro indicator for nowcasting quarterly firm-level earnings. Those nowcasts are found to have significant power for predicting analysts' firm-level earnings forecast errors, and, in turn, their stock returns. Another related study is Chordia and Shivakumar (2005), which shows that earnings forecasts do not fully incorporate aggregate inflation news; that is, inflation data predicts subsequent firm-level earnings surprises and excess returns.

Further insight on such findings of forecast inefficiency is provided by Hugon, Kumar, and Lin (2016), which compares the performance of earnings forecasts from analysts working at firms with active in-house macroeconomists to that from analysts at firms lacking such a department. They show that forecasts by analysts in the former group appear to be better at incorporating the GDP news and suggest that those analysts lacking the exposure to colleagues who closely follow macroeconomic news tend to focus too much on firm-level information.

Perhaps most closely related to our analysis is a recent study by Park, Peterson, and Weisbrod (2024), which examines the efficiency of earnings forecasts at the aggregate level, similarly measured by the bottom-up forecasts for S&P 500 earnings from LSEG I/B/E/S. They compare the analysts' bottom-up consensus forecast for 12-month-ahead earnings with an analogous "top-down" consensus forecast produced by strategists at a similar set of investment firms. Consistent with the hypothesis that strategists are more attentive to the big-picture macroeconomic environment, they show that the gap between the top-down and bottom-up forecasts positively predicts a weighted sum of earnings surprises over the subsequent three months as well as stock returns from 1 to 5 months ahead. Moreover, they find that gap between forecasts is correlated with macroeconomic indicators such as recent readings on the unemployment rate and investor sentiment.

Our study provides a sharper picture of the forecast inefficiencies in bottom-up forecasts beyond the Park, Peterson, and Weisbrod (2024) study in several ways. First, our sample covers a 30-year history of independent quarterly forecasts, rather than a 20-year history of substantially overlapping forecasts for year-ahead earnings. Moreover, our focus on analysts' quarterly forecasts, rather than a less finely delineated 12-months-ahead period, allows us to account for, in a structural model, how macroeconomic data translates into S&P 500 earnings and earnings forecasts. This allows us to gauge the extent to which analyst forecasts reflect, or fail to reflect, macroeconomic news, rather than simply test for the statistical significance of forecast error predictability.

The paper proceeds as follows. The next section introduces our measure of aggregate earnings news, describes the sample period, and highlights the positive effect of earnings news on stock returns. Section III develops the macroeconomic accounting model proposed for S&P 500 earnings growth. Section IV estimates variations on our macro model of earnings growth, including real-time parameter estimates. In Section V we compare bottom-up analyst forecasts for current-quarter and quarter-ahead earnings, the comparable forecasts from our macro models, and actual earnings growth; we then estimate a simple model for predicting analyst forecast errors. Section VI examines the extent to which analyst forecast errors predicted by the macro model can also predict three-month and six-month stock returns. Section VII concludes.

II. Composite S&P 500 Earnings, Forecast Revisions and Index Returns

This section begins by reviewing the data used to measure historical quarterly aggregate earnings for the S&P 500 Composite as well as the closely related data on analysts' bottom-up forecasts of S&P 500 quarterly earnings. We then examine and broadly characterize earnings growth over the 30-year sample period under our study, highlighting the potential outsized influence on our statistical inference from extreme growth outliers. Finally, we examine the value-relevance of the analysts' aggregated forecasts for current-quarter and quarter-ahead S&P 500 earnings. This is accomplished by estimating regressions of 3-month and 6-month returns on contemporaneous revisions to these earnings forecasts.

S&P 500 Composite Historical Earnings and Earnings Forecast Data

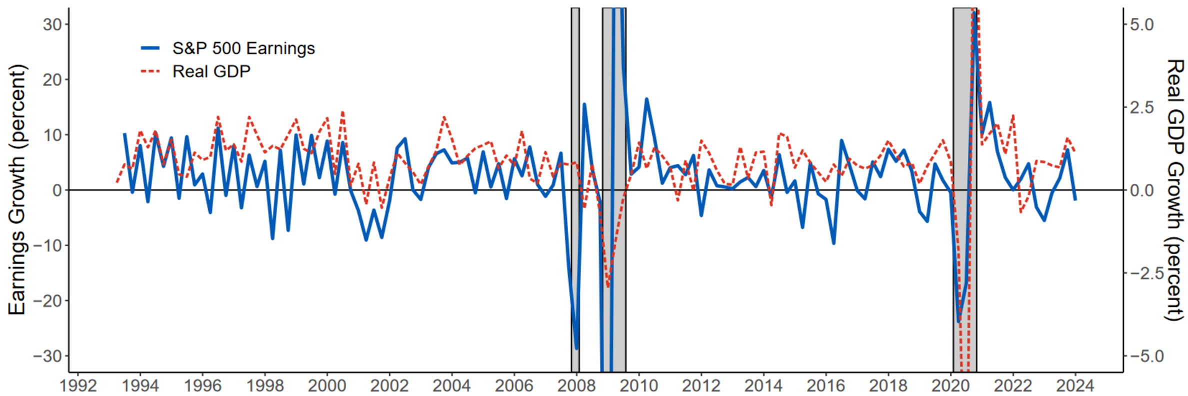
Various measures of historical aggregate S&P 500 quarterly earnings have been employed in academic studies and by financial market participants. The measure of historical earnings we use, constructed and published by LSEG I/B/E/S, is based on the operating earnings per share of each of the index constituents as judged by the consensus of equity analysts polled by I/B/E/S. Thus, by definition, this measure should be the most comparable measure to that reflected in those same analysts' earnings forecasts. Aggregated up to produce a value for the S&P 500 Composite, this has also been among the closely tracked measures of earnings by other market participants. Even today, the methodology is largely consistent with the legacy data on aggregate S&P 500 earnings per share originally produced by I/B/E/S.

Aggregated ("bottom-up") forecasts for the S&P 500 earnings are similarly constructed from analysts' consensus firm-level forecasts of quarterly and annual earnings, aggregated to the index level using S&P's official index constituents and weightings. Those forecasts have been published (now by LSEG I/B/E/S) weekly since 1994 in the *Weekly Aggregates Report*. From those weekly reports, we extract snapshots of their forecasts for S&P 500 earnings per share for the current quarter and for the quarter ahead. In addition, we extract the estimates of earnings per share for the recently ended quarter, calculated as a blend of actual operating earnings of firms that have already reported with the forecasts for those yet to report. Our dataset is constructed by extracting a snapshot of these data items from one specific week's report during each quarter, namely, from the first week of the third month of each quarter.

The historical quarterly values for (realized) S&P 500 earnings per share are also cobbled together from the *Weekly Aggregates Report*. Specifically, the measure we use for quarterly S&P 500 historical operating earnings per share (EPS) are the estimates for previous-quarter earnings per share that were published in the Weekly Aggregates Report 12 to 13 weeks after that quarter ended. The resulting historical earnings series runs from 1993-2023. We convert the values of forecasts and realized earnings from earnings per share to total earnings by multiplying by the quarterly S&P 500 Composite Divisor published by S&P Global.

Figure 1 provides some perspective on the volatility and cyclicality of profits over our 30-year sample. Growth in S&P 500 operating earnings, measured as the quarterly change in the log of earnings, is plotted by the solid blue line. The dashed red line plots quarterly growth in real GDP (gauged by the more compressed righthand scale). While quarterly earnings growth has largely fluctuated within a range of plus or minus 10 percentage points, a few sizable exceptions stand out and are highlighted by the gray shading. In particular, over the entire sample three dramatic quarter-over-quarter drops in earnings occurred, all in excess of 25 percent (2007:Q4, 2008:Q4, and 2020:Q1), in two instances followed two quarters hence by similarly dramatic rebounds. In all three cases, the outsized declines largely reflected huge asset write-offs by financial institutions, two of them around the onset of the Great Financial Crises, and one at the onset of the pandemic.[2]

Figure 1
Growth in S&P 500 earnings versus Real GDP, quarterly rate



Note: Shaded regions highlight outsized drops (and rebounds) in earnings reflecting huge asset write−offs by financial institutions during the onset of the Great Financial Crises and the pandemic.
Source: LSEG I/B/E/S Weekly Aggregates, FDIC Quarterly Banking Profile.

The positive covariation between earnings and GDP growth is visually apparent, though with some glaring exceptions around the onset of the 2008-2009 financial crises.[3] When we turn to the analysis of the central question of this paper, on whether analyst forecasts reflect observed macroeconomic conditions, we will focus on the subsample that excludes these seven quarters. Not only are these outlier observations bound to have an outsized influence on statistical inferences, but they are also periods where profit dynamics are largely driven by the timing asset write-offs by financial institutions, rather than current-quarter economic activity. Such losses (and rebounds) undoubtedly would result in outsized prediction errors both by analysts and macroeconomic models. Even so, we show that the inclusion of these outlier observations only boosts the baseline estimates of earnings news effects on stock returns, to which we now turn.

Analyst Forecast Revisions and S&P 500 Returns

To match the frequency and timing of our quarterly snapshots of S&P 500 earnings forecasts with S&P 500 returns, we extract the daily close values of the S&P 500 Total Return Index for the first Thursday of the third month of each quarter, the same day that bottom-up earnings forecasts are assembled.[4] Consider, for example, the 3-month return equal to the

[2] For instance, in the wake of the collapse of Fannie Mae and AIG in September of 2008 and the associated collateral damage, it would be folly to apply a simple macro model to predict earnings or analyst forecast errors in the quarter or two ahead.

[3] Over the full sample, the correlation between GDP and profit growth on a quarter-over-quarter basis is 32 percent, compared to 27 percent for the subsample that excludes the 7 highlighted observations. On a four-quarter growth basis, the correlations for the full sample and subsample excluding these outliers are 55 and 59 percent, respectively.

[4] We use the S&P 500 Total Return Index because this measures daily returns on the S&P 500 including any dividends received.

change in the log of the total return index from the first week of March to the first week of June. That return, earned over the period from late in the first quarter to late in the second quarter, is paired with the revisions to (the log level of) the bottom-up forecasts of first quarter ("current-quarter") and second quarter ("quarter-ahead") earnings. Six-month returns and forecast revisions are constructed analogously.[5] Returns are converted to excess returns by subtracting the beginning-of-period value of the 3-month or 6-month Treasury Bill yield.

The regression results are reported in Table 1, where each specification is run on the full sample of 118 observation, running from March 1994 through September 2023, and the trimmed subsample, which excludes the three episodes with outsized earnings declines associated with extraordinary asset write-downs.[6] In particular, to help with identification of the effects from the two quarters' forecast revisions, we construct the *excess revision to quarter-ahead earnings*, equal to the difference between the revisions to quarter-ahead and current-quarter earnings. This is included as a regressor along with the revision to current-quarter earnings. This specification is chosen due to the high correlation between revisions to the two quarters' earnings forecasts, which is 63 (47) percent for 3-month (6-month) revisions in the full sample, and even higher in the trimmed sample. The results from regressing 3-month excess returns on the revision to current-quarter earnings and the excess revision to quarter-ahead earnings are shown in the columns (1) and (2) for the full sample and the trimmed subsample, respectively. In both cases, the revision to the current-quarter earnings has a positive and highly significant coefficient. In each case, a one percentage point positive revision results in around one half percent higher return in each case. The excess revision to quarter-ahead earnings has a coefficient of half the size in both cases, but it is only statistically significant in the full sample. Finally, the regression R-squared is 11 percent for the trimmed sample and about double that for the full sample.

The third and fourth columns shows the results after adding the log(dividend yield), which gets a significant coefficient exceeding 0.1 in both cases and boosts the regression R-squared in each case by about 10 percentage points. The strong predictive power of the log dividend yield is not without precedent and can be understood as largely the result of our sample period.[7] Another noteworthy observation is that adding the log dividend yield as a return predictor does not dampen the estimated effect of earnings revisions on returns; indeed, the coefficients on revisions are of similar magnitude to the respective regressions that do not include the dividend yield regressor, and they also remain highly statistically significant. The takeaway from these regressions we wish to emphasize is that earnings revisions have strong

[5] The 6-month return on the S&P 500 from first Thursday of March to first Thursday of September is matched with the 6-month revision to first-quarter (current-quarter) and second-quarter (quarter-ahead) earnings forecasts. To be precise, the six-month revision to the current-quarter forecast could alternatively be called a (6-month) forecast error because it is equal to (the log of) the *realized* value of first-quarter earnings (observed around the last week of June) minus (the log of) the forecast from the first week of March.

[6] While that criterion excluded 7 quarters, for the 3-month return regressions, which include the revision to the quarter ahead, we also exclude the observation that precedes each episode; for 6-month return specifications, we lose an additional 3 observations.

[7] In particular, Lettau and Nieuwerburgh (2008) demonstrate structural breaks in predictive regressions using the dividend yield, which owe to breaks in the time series of the dividend yield, one of which is around 1994, when our sample begins. Accommodating those breaks boosts the predictive power or the dividend yield considerably.

explanatory power regardless of whether we exclude, or do not exclude, the extreme earnings growth observations.[8]

The last four columns show the analogous set of regressions for six-month excess returns, on six-month revisions. The results from columns (5) and (6) are similar to those in (1) and (2), only here we find that the (excess) revision to the quarter ahead forecast is a very strong predictor, with effects that are on par with the current-quarter revision. This makes perfect sense because, over the latter half of the six-month horizon, information about quarter-ahead earnings becomes relatively more abundant and salient. The R-squared for the full sample doubles in the six-month regression, but only increases slightly in the trimmed sample. Finally, when we add the log dividend yield in columns (7) and (8), the regression R-squared jumps considerably in both samples, and the dividend yield has a coefficient that is about 50 percent larger than in the 3-month regressions. The main conclusion, though, is that adding the dividend yield does not alter the estimated effects of earnings news on returns. Having documented the positive effects of revisions to analysts bottom-up S&P 500 quarterly forecasts on contemporaneous returns, we can now turn to the central focus of our analysis.

III. A Macroeconomic Accounting Model of Profit Growth

In this section, we develop the macroeconomic model to be used for explaining and predicting S&P 500 earnings growth. We begin with a closed-economy macroeconomic framework useful for motivating a simple log-linear empirical model of profit growth based on a small number of macroeconomic factors. The most notable abstraction from reality in this framework is that it models all domestic product as being produced by S&P 500 firms. Since we are ultimately modeling the *growth* in profits, this abstraction largely amounts to assuming that the growth rates in output, prices and labor costs of S&P 500 firms move in parallel with growth rates for the overall U.S. economy.

In this world, we can write down and expand upon the following accounting framework:

$$Profits \ = \ (1 - labor\ share) * (Net\ Domestic\ Product)$$

where *Net Domestic Product = GDP – Capital Consumption*, and *labor share* is total labor compensation as a fraction of Net Domestic Product.

Taking logs and first differences yields:

$$dlog\ Profits \ = \ dlog(Net\ Domestic\ Product) + \ dlog(1 - labor\ share)$$

Assuming that capital consumption (or depreciation) grows at the same pace as nominal GDP and, thus, Net Domestic Product, we can write profits as a function of GDP growth:

$$dlog\ Profits \ \approx \ dlog(rGDP) \ + \ dlog(pGDP) \ + \ dlog(1 - labor\ share)$$

[8] As noted in the introduction, our finding of unambiguously positive effects of current-quarter earnings news on stock returns, while contradicting many previous findings, likely reflects, at least in part, our later sample period.

where nominal GDP growth is decomposed into the growth in real GDP (*rGDP)* and the GDP deflator (*pGDP*).

The key approximation for deriving our log linear model of profit growth is based on the presumption that, over time, the ratio of the labor income to corporate profits fluctuates around, and not too far from, some central tendency, say, the value m. In that case, it can be shown that:

$$dlog(1 - Laborshare) \approx -m * dlog(laborShare)$$

For the U.S. nonfinancial corporate sector, the ratio of total labor compensation to (pretax) corporate profits, m, has generally averaged in the neighborhood of 5 over the past few decades. In that case, this approximation implies that a 1 percent decline in labor's share of income would generally be counterbalanced by an increase in capital income share of around 5 percent.

Finally, we can decompose the growth in labor share into the growth of four key macroeconomic variables,

$$-dlog(labor\ share) = dlog(rGDP) + dlog(pGDP) - dlog\left(\frac{comp}{hr}\right) - dlog(hrs)$$

and plug this expression (multiplied by m) into profit growth equation and combine terms:

$$dlog\ Profits = (m+1)[dlog(rGDP) + dlog(pGDP)] + m\left[-dlog\left(\frac{comp}{hr}\right) - dlog(hrs)\right]$$

This simple model, built off a national accounting framework, provides some perspective on plausible coefficients of our econometric model of S&P 500 profits growth. For instance, it suggests that a 1 percentage point increase in real GDP growth (holding other growth rates constant), might be expected to boost profits by around 5 to 7 percent, provided that the average ratio of labor compensation to profits (m) falls in the neighborhood 5.

Among the many simplifying abstractions behind this framework, arguably the most important is assumption that profits are generated in the US, since, in reality, a substantial proportion of the profits generated by S&P 500 companies are earned by their subsidiaries located outside of the US. Another potentially problematic assumption is that our framework models corporate profits as simply the residual of revenues minus the costs of production, and therefore abstracts from accounting losses (or gains) companies book as a result of asset write-downs. Most notably, it ignores losses from debt write-offs that have occasionally huge effects on the profits of financial corporations, companies that account for roughly 20 percent of S&P 500 profits on average. In the next section, we introduce control variables to address these two important real-world departures from the baseline model. [9]

IV. Estimating Macroeconomic Drivers of S&P 500 Earnings Growth

[9] Another notable assumption of our model is that U.S. corporations are largely equity financed, so that the growth rate in corporate profits parallels the growth in total capital income, or profits plus net interest expense. Because in the aggregate, net interest expense is relatively small and slow-moving relative to corporate output, there is no straightforward and useful way to control for this component of capital income, so our empirical model implicitly relegates its dynamics to the error term.

This section implements the estimation of macroeconomic models for explaining and then ultimately predicting growth in quarterly S&P 500 operating earnings. We first describe the data used for model estimation. We then explore a handful of variations on the empirical specifications, considering their relative explanatory power and precision and plausibility of coefficient estimates. In order to reduce the look-ahead bias inherent in such analysis, we construct and compare real-time coefficient estimates for predicting earnings and analyst forecast errors.

Macroeconomic Variables

As shown in the previous section, our core macro model posits that aggregate S&P 500 earnings growth can be written as a linear function of real GDP growth, price inflation, and the growth in labor input and labor compensation rates. Among these items, the macroeconomic variable that has received the most attention in related previous empirical research is real GDP growth. Taken literally, our model prescribes using the **GDP deflator** together with real GDP, as the two topline factors driving corporate revenues and profits. Instead, we gauge topline inflation using the more closely followed **PCE deflator.** The rationale for this is that items priced by the PCE deflator more closely correspond to business sector goods and services. On the contrary, a large fraction (roughly two-thirds) of goods and services priced by the GDP deflator, but not by the PCE deflator, are government services, the prices of which should have no direct (positive) effect on corporate revenue and profits.[10]

We model the quarterly growth in labor expenses with two macroeconomic indicators, the quarterly growth in the **Employment Compensation Index** (ECI), which gauges average hourly labor cost, and the growth in nonfarm private payrolls, which gauges the growth in labor input. The ECI is based on a survey filled out during the last month of the quarter. We calculate current-quarter growth in the ECI, our measure of growth in labor compensation rate, by taking the log change in the quarterly index value. Private nonfarm payrolls are published monthly; for this variable, we measure quarterly labor input as the average level of payrolls over the three months of the quarter and its quarterly growth as the log change in this average level.

As noted earlier, our core macro model abstracts from the role of earnings generated abroad and losses from asset write-downs. We use recent **dollar appreciation** as a proxy for the relative strength of S&P 500 companies' foreign-source earnings. The dollar exchange rate affects or signals the growth of foreign-source earnings via three distinct channels. The first is the "translation effect": when the dollar declines in value, earnings generated in foreign currencies translate into more dollars. Second, a weaker dollar tends to boost the (dollar) prices at which US firms can sell their exports. Third, a weaker dollar tends to signal the relative strength of foreign economies and, thus foreign earnings. We control for the exchange rate effect on current-quarter earnings using the percent change in the trade-weighted dollar exchange rate (Nominal Broad Dollar US Index published by the Federal Reserve Board), between the beginning of the previous quarter and the beginning of the current quarter.

[10] By the same token, one could argue for using the growth in real PCE instead of real GDP, but doing so would omit real capital expenditures from our model, a relatively volatile component of real corporate production and sales.

The second ad hoc factor we control for are losses associated with defaults. Our baseline macro model gauges only profits earned from production and sales by nonfinancial companies, which will not directly reflect the impact from financial losses incurred due to defaults. Such losses are mostly incurred by financial firms (in the S&P 500) and occasionally have a very large effect on aggregate profits. Our rough proxy for identifying the effect of financial losses is the total quarterly provisions for loan losses reported by all FDIC-insured institutions, compiled and published in the FDIC Quarterly Banking Profile.[11] Specifically, our control variable is equal to the current-quarter change in total U.S. domestic loan loss provisions, normalized by previous-quarter S&P 500 profits, which facilitates a structural interpretation of its regression coefficient.

Estimating the Full Macro Model over 1993-2023

We begin by estimating the empirical macro model of profit growth on the historical sample. Specifically, we estimate growth in S&P 500 profits on the four variables indicated by the nonfinancial domestic profits model as well as dollar appreciation. In specifications which estimate quarter-over-quarter growth (rather than four-quarter growth), we also include a first order moving-average error term to control for unmodeled idiosyncratic factors, including measurement errors that might be prone to reversal in the subsequent quarter.

Column 1 of Table 2 shows estimates with all four variables from the macro model as well as the control for profits from foreign operations, dollar appreciation. Although at the low end of the range of values predicted by our closed-economy framework, the coefficient of 4.1 on Real GDP is broadly consistent with the model. In addition, PCE deflator growth has a positive and significant effect on earnings, though the coefficient's magnitude (2.72) is smaller than implied by our macro model. As expected, the negative coefficient on growth in employee compensation indicates that increased compensation reduces earnings growth, all else the same. The main contradiction to our model is the payrolls coefficient, which qualitatively has the wrong sign though is close to zero and statistically insignificant.

Lagged dollar appreciation has the predicted negative effect on profit growth and is highly statistically significant. Appreciation of the dollar by 1 percent reduces profit growth by about ¾ of a percent. Finally, the MA(1) error term is negative and significant. One might reasonably expect a negative MA(1) coefficient when estimating a model in changes when there is an underlying fundamental relationship between levels, particularly if there is measurement error in the (level of the) dependent variable. In the case at hand, one plausible explanation for this result is that some firms' quarterly earnings do not always align with calendar quarters, because fiscal quarters for some firms overlap with calendar quarters.[12] All told, the regression R-squared of 24 indicates our model explains only about a quarter of the variance in profit growth.

[11] I/B/E/S bottom-up estimates reflect after-tax S&P 500 earnings. Accordingly, we adjust loan loss provisions to gauge them on an after-tax basis. Loan loss provisions are taxed at approximately 30% from 1993 to 2017 and 20% thereafter.

[12] For instance, Walmart's third quarter runs from August-October. If the economy was very strong in October, this would boost fourth-quarter GDP growth; however, Walmart will report results from the strong October as part of their third-quarter earnings. Our empirical model in this case would find offsetting errors in the third and fourth quarters.

Column (2) shows largely identical results when we drop the insignificant payrolls variable, which appeared ineffective at controlling for growth in the quantity of labor input. The employment compensation coefficient, equal to -3.0, is a bit larger in magnitude than the coefficient on output price inflation. Taken at face value, this would imply that a simultaneous 1 percentage point increase in the growth rate of both PCE inflation and the ECI would have a small negative net effect on earnings, in contrast to the predictions of our baseline macro model. An identical increase in output prices and wage rates should leave the profit share of nominal output (the markup) unchanged, while boosting nominal output by 1 percent and corporate earnings by the same.

Column (3) shows results when we re-estimate the model in column (2), but with the imposition of a linear coefficient constraint on the wage and price coefficients implied by the macro model. Specifically, this constraint requires that the coefficient on price inflation and wage inflation add up to 1.0, allowing for a more parsimonious statistical model.[13] As shown, imposing this constraint has little effect on the estimated coefficients on real GDP or the dollar, compared to column (2), but it results in a smaller magnitude coefficient on wage growth (-2.07) and a somewhat larger price inflation coefficient. The measures of specification fit indicate this restriction is not rejected by the data; in particular, the lower Akaike Information Criteria (AIC) value slightly favors the more parsimonious model.

In column (4) we take the previous specification with the cross-coefficient constraint and add our proxy for capital losses. Its coefficient is highly significant, and the magnitude suggests that a one percentage point increase in FDIC-reported bank loan loss provisions, as a fraction of (lagged) S&P 500 earnings, coincides with a one a one percentage point decline in earnings. Relative to the results in column (3), adding loan loss provisions results in modest attenuation of the GDP coefficient, while the regression R-squared bumps up to 31 percent. While this loan loss variable cannot be used for forecasting earnings growth, it is helpful to see that adding it does not have a major impact on the coefficients of other regressors.

In Column (5), we show the results from regressing the four-quarter change in log earnings on the four-quarter change in the right-hand side variables, again something of a robustness check on estimates in column (3). Expanding to a four-quarter growth frame should remove the effects of higher frequency noise, including any seasonal effects driving quarterly earnings fluctuations. Also, if our quarter-over-quarter growth model abstracts significantly from more drawn out dynamics, then the magnitude of the coefficients would presumably differ (perhaps become larger) in the four-quarter specification. On the contrary, while the four-quarter regression does exhibit a stronger fit – an adjusted R-squared of 44 percent, compared to 33 percent in column (3), coefficient estimates are quite similar. Finally, in column (6) we add the Loan Loss variable to the four-quarter growth specification. Its inclusion results in some attenuation in the other coefficients, while boosting the R-squared to a 74 percent, which is notable given that these

[13] To be precise, this is a less restrictive constraint than what is implied by the model, which holds that the coefficients on price growth and wage growth are positive and negative, respectively, and that they add up to 1.0.

regressions exclude observations with the most dramatic changes in loan losses. All told, we conclude that model estimates in column (3) are reasonably robust.

A Simplified Model based on GDP and the Dollar Exchange Rate

Before moving on to examining the robustness of our model to partial-sample estimates required for our real-time forecasting exercise, we consider a simplified model of earnings growth that focuses on the explanatory power of real GDP and the dollar exchange rate. These are the two macroeconomic variables that appear most important statistically in Table 1 and seem to be among the most salient in previous research that focuses on macroeconomic influences on firm-level earnings. The first two columns in Table 2 show results from regressing quarterly earnings growth on real GDP growth and dollar appreciation. The second column again allows us to examine whether controlling for loan losses has substantial effects on coefficient estimates.

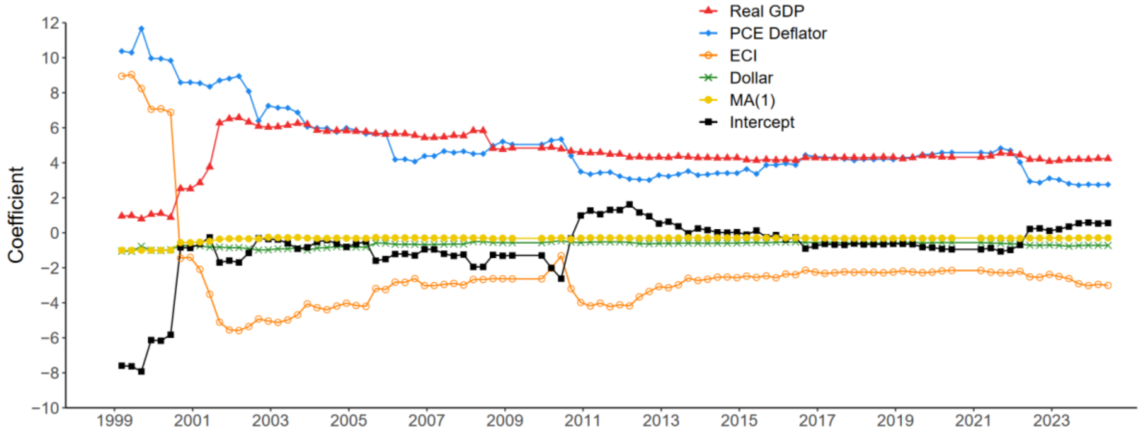
Focusing first on column (1) in Table 2, real GDP growth continues to have a sizable effect on earnings growth, albeit a bit smaller compared to the full model estimates in columns (2) and (3) of Table 1. Second, the estimated dollar effect also remains highly significant and sizable, with the expected sign. Finally, the adjusted R-squared, at 21 percent, is not dramatically smaller than that for the more complete model. Columns (2), (3), and (4) examine the robustness of these results, in the first case by adding our control for loan losses, and in the second and third case by running four-quarter growth specifications. Here, as in the full model specifications in Table 2, we find such modifications boost the R-squared but produce similar coefficients on GDP growth.

Real-time Model Estimates

A realistic test for the historical predictive performance should require the macro-model to be calibrated using only historical data, that is, data available when its earnings forecasts would have been produced. Here, we use the early data on actual earnings growth, from the years 1993-1998, to estimate a set of initial model parameters, i.e. regression coefficients. We then proceed to construct a time series of real-time macro model coefficients by iteratively adding one quarter of historical data and re-estimating the model. As in the full sample estimates, we exclude the seven extreme growth observations from the estimation of parameters. The resulting time series of real-time coefficient estimates can then be used, in conjunction with historical Blue Chip forecasts and other data, to construct a series of real-time model-based earnings forecasts.

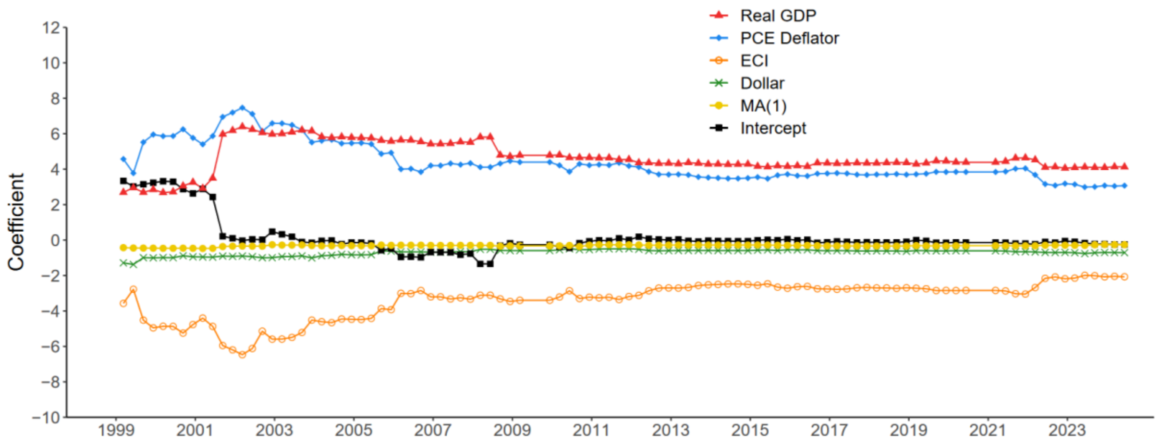
We begin the estimation of real-time coefficients using the full-model specification in column 2 of Table 2. The resulting time series of coefficient estimates are plotted in Figure 2.A, beginning with the coefficients used to forecast earnings in the first quarter of 1999, estimated over 1993-1998. Given the small start-up sample and the relatively high identification demands (6 parameters), it is perhaps not surprising that coefficients in the early years are quite unstable. Moreover, in those early observations the sign of the wage inflation coefficient contradicts the predictions (and intuition) of our baseline theoretical model, while the price coefficient is much larger than suggested by the model. Coefficient estimates eventually stabilize, again, around 2002; thereon, they fall within a range broadly consistent with the theoretical framework.

Figure 2.A. Iterated coefficient estimates: Full macro model



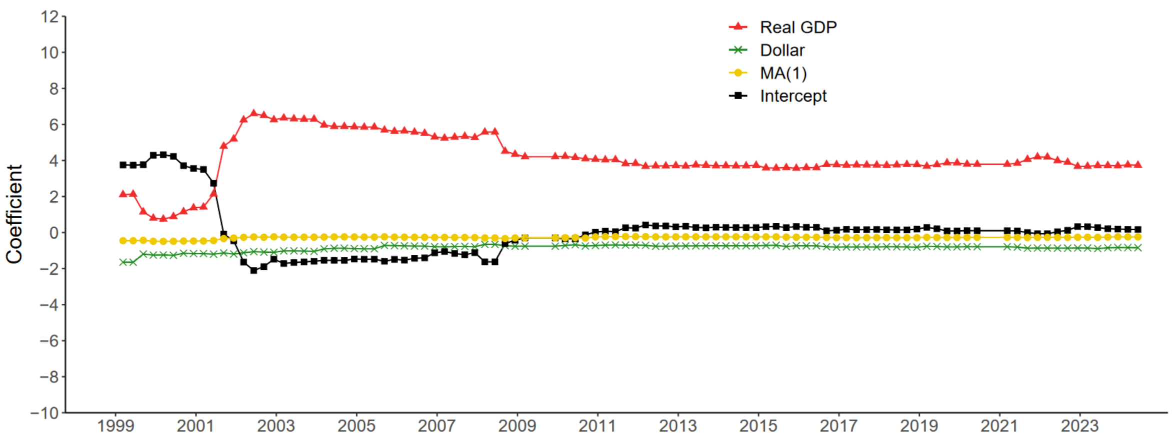
Source: Authors' calculations.

Figure 2.B. Iterated coefficient estimates: Full model with constraint



Source: Authors' calculations.

Figure 2.C. Iterated coefficient estimates: Simple Model



Source: Authors' calculations.

To reduce identification difficulties, we apply the single cross-coefficient constraint used in the full sample regression in column (3) of Table 2, which requires that the coefficients on price inflation and wage inflation add up to 1.0. (This will also constrain the wage coefficient to be negative if the price inflation coefficient is greater than 1.0.) Figure 2.B shows the results when that constraint is applied. Although adding the constraint does not eliminate entirely the instability of early small-sample estimates, all coefficients fall within plausible ranges. In any case, given the more stable coefficients from the constrained model, we employ the associated set of coefficient estimates for our subsequent tests of the full macro model's ability to predict earnings and analyst forecast errors. For most of our analysis, rather than discard the observations in the 1994-1998 start-up sample, we use the in-sample coefficient estimates (the first set of coefficients in time series plots) to construct the earnings forecasts for these years.[14]

Figure 2.C shows the resulting time series of coefficient estimates for the simple macro model, specification reported in the first column of table 3. The early-sample coefficient estimates are again somewhat unstable and differ notably from their full-sample (final) values. In particular, the GDP coefficient ranges between 1 and 7 over the first few years, while the intercept also fluctuates, bumping higher to compensate for low GDP coefficients. By the early 2000s, all the coefficients appear to stabilize and then fluctuate within a relatively narrow range that persists through the end our sample.

V. Predicting Analyst Forecast Errors with Macro-Model Forecasts

This section describes the main thrust of our analysis, where we examine the extent to which macro model forecasts can predict equity analysts' bottom-up forecasts for aggregate S&P 500 earnings. We begin by detailing the data structure and the timing of our various forecast-related variables. We then examine correlations among realized earnings growth, analysts' forecasts, and macro-model forecasts. After that, we examine the extent to which the discrepancy between macro model and analysts aggregate forecasts can predict analysts' aggregate forecast errors.

Macroeconomic Forecast Inputs

Given the time series array of model parameter estimates (shown in 2.B or 2.C), forecasting S&P 500 earnings for the current quarter (or quarter ahead) requires plugging into the model the current-quarter (or quarter-ahead) values for the macro model variables. Consensus economic forecasts of our two macroeconomic indicators of topline growth, real GDP and PCE Deflator, are obtained from the Blue Chip Economic Indicators (BCEI), based on its monthly survey of over 50 leading business economists. Until very recently the survey did not include forecasts of the PCE deflator, so we instead use GDP deflator forecasts.[15] The survey is conducted the first week each month. To match the timing of our quarterly snapshot of analysts' S&P 500 earnings forecasts,

[14] Dropping the pre-1999 sample period model-implied earnings forecasts from subsequent analysis has little effect on our inferences, and, if anything, tends to strengthen our findings (despite the loss of observations).

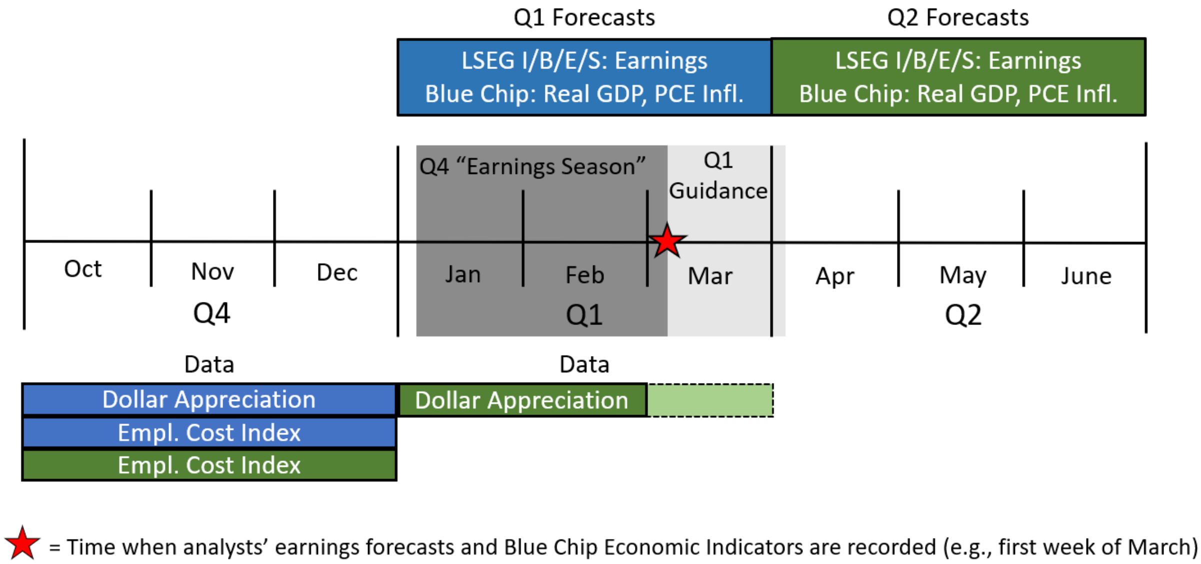
[15] Despite the absence of PCE deflator forecasts, it is still sensible to use the PCE deflator to estimate the effects of prices on actual profits, and then plug in forecasts of the GDP deflator. That is because the forecasts of the GDP deflator (for the quarter ahead) function just as well as forecasts for PCE deflator, that is, they have a correlation with the realized PCE deflator that is similar toits correlation with the GDP deflator.

we use the Blue Chip survey conducted during the first week of the third month of each quarter. We extract the forecasts of GDP growth and price inflation for the current quarter and the quarter ahead, the same two quarters referenced by the bottom-up earnings forecasts.

Neither the Blue Chip survey nor any other readily accessible public source provides economists' forecasts for labor compensation rates or labor input. For simplicity, we use the published estimates of previous-quarter growth as our forecasts of current-quarter and quarter-ahead growth in the employment compensation index (ECI). As indicated earlier, our control for the strength of foreign profits in the current quarter is the dollar's appreciation over the previous quarter (appreciation from the beginning of the previous quarter to the beginning of the current quarter). The analogous input for forecasting quarter-ahead earnings growth is dollar appreciation over the current quarter. We thus use the observed appreciation over the first two months of the current quarter as our estimate of total current-quarter appreciation, thus implicitly assuming zero appreciation over the final month of the quarter.

The timing of information underlying the earnings forecasting exercise is exhibited in the schematic below, using forecasts observed during the first calendar quarter (the first week in March). As reported earlier, we use the forecasts of earnings (from LSEG I/B/E/S) and GDP and inflation (from Blue Chip Economic Indicators), all of which were recorded during the first week of the third month (Mar, Jun, Sept, Dec) of each quarter. While we could have instead picked the first or second months' forecasts for our quarterly snapshots, we chose the third month of the quarter because this is about the time when most S&P 500 constituents' previous-quarter earnings reports have been released. Arguably, this is also when the information flow regarding earnings tends to shift forward to the current quarter and beyond. This is also when many firms tend to begin providing updated guidance on current quarter performance, particularly those desiring to warn of anticipated disappointments.

Finally, the schematic also shows the most recent data available on the macroeconomic variables, items for which forecasts are not readily accessible. The Q4 growth rate in average employee compensation is known after the December index value for the ECI is published at the end of January. This growth rate is used as our forecast of employee compensation growth in Q1 and Q2. At the beginning of March, we can observe dollar appreciation in Q4, used to forecast Q1 earnings. Appreciation over the first two months of Q1 is also observable; that two-month change is the proxy for expected dollar appreciation used in our macro-based forecast of Q2 earnings growth.



Correlations Between Model Forecasts, Analyst Forecasts and Realized Earnings

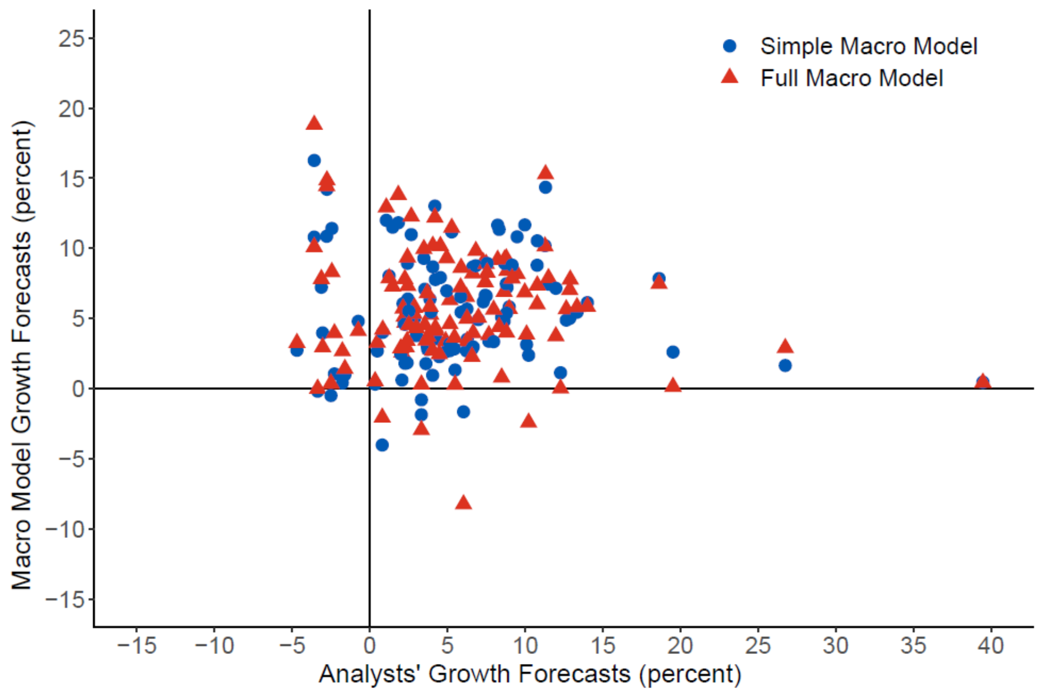
Table 4 displays the correlations between growth forecasts and realized growth, as well as correlations amongst the forecasts, for three forecast horizons: current-quarter, quarter-ahead and cumulative two-quarter growth. For the current quarter, analysts’ growth forecasts have a 61 percent correlation with realized growth, while the two alternative macro models each have a correlation of about 40 percent with realized growth. It is not surprising that the simple and full macro models have similar performance relative to realized growth given the two models produce similar forecasts, with 92 percent correlation. Finally, and perhaps most remarkable, the analyst current-quarter growth forecasts are essentially uncorrelated with the model forecasts, suggesting that analyst and model forecasts both contain independently useful information. Figure 3 shows a scatter plot of model forecasts against analyst forecasts, this lack of correlation is not driven by a couple of wayward observations and is thus endemic to the sample as a whole.

Statistics for the quarter ahead paint a somewhat different picture, as the correlation of analyst quarter-ahead forecasts with realized growth drops considerably, to 0.30, whereas the simple and full macro model quarter-ahead forecast correlations with realized growth remain about the same, at 0.31 and 0.37. Here again, analyst forecasts are entirely uncorrelated with the two model forecasts. Looking to the cumulative two-quarter forecast, the disparity between model and analyst accuracy reverses entirely, with the analyst forecast having a 34 percent correlation, compared with correlations of about 45 percent for the two models. This suggests that model errors from the two consecutive quarters partially offset each other, while analyst errors appear to compound over the two quarters.

Predicting Analyst Forecast Errors

In this section, we examine the extent to which the macro-model-based forecasts can help to predict analyst forecast errors. Specifically, we measure the extent to which the macroeconomic information helps to predict (i) the error in analysts’ forecasts of (the log of) current-quarter earnings, and (ii) the error in analysts' forecasts of (the log of) next quarter's earnings. One can interpret the latter as the error in analysts' forecast of cumulative growth over the two quarters.

Figure 3. Cumulative two-quarter growth forecasts: Analysts vs. Models



Source: LSEG I/B/E/S Weekly Aggregates, authors' calculations.

An intuitive approach for using the macro-model based earnings estimates to predict analysts' forecast errors, which requires relatively little specific *a priori* knowledge about the relationship, is to measure the gap between the model forecast and the analyst forecast. The larger the gap, the larger is the likely underestimate of earnings in the bottom-up analyst forecast. We construct two separate indicators for predicting errors: (i) the gap between the model-implied growth rate and analyst growth forecast for the current quarter, and (ii) the gap between the model-implied growth rate and analyst growth forecast for the quarter ahead. Arguably, the first piece (the current-quarter gap) should be the more informative piece for predicting analysts' current-quarter forecast error, whereas both gaps should be informative for predicting their forecast error for next quarter's earnings.

The first two columns of Table 5 pertain to results using the simple macro model. In particular, the first column shows results from regressing the analyst current-quarter forecast error on the two gap variables, that is, (i) the gap between the simple model growth forecast and the analyst growth forecast for the current quarter and (ii) the analogous gap in predicted growth for the quarter ahead. Here, we find that both the current-quarter and quarter-ahead gap help to predict the analyst current-quarter forecast error. The current-quarter gap is highly significant with a coefficient of 0.52; this implies that, on average, the analyst underestimate of earnings is equal to about half the gap between the competing forecasts, plus 20 percent of the quarter-ahead gap (ignoring the small bias implied by the significant intercept). The R-squared indicates that, all told, the two forecast gaps predict a fairly impressive 48 percent of the variation in the bottom-up forecast error.[16]

The second column shows the result from regressing the bottom-up forecast error for quarter-ahead earnings on the two forecast gaps, again constructed using the simple macro model. As logic would suggest, here we find that the gaps for both the current- quarter and the quarter-ahead forecasts help predict the ultimate error in analysts' forecast for quarter-ahead earnings. Indeed, our finding of roughly the same coefficients (0.68 and 0.65) on the two gaps indicates that the analysts' forecast error on average equals about two-thirds of the cumulative gap over the two quarters. The forecast gaps explain 40 percent of the quarter-ahead forecast error variation. Finally, the third and fourth columns examine the analogous two regressions, where the forecast gaps are based on the earnings forecasts from the full macro model. The results here are almost identical to those based on the simple macro model, suggesting little apparent benefit from using the more complete model.

VI. Predicting Stock Returns using Model-Analyst Forecast Gaps

In this penultimate section, we examine whether market participants understand and anticipate the failure of analysts' forecasts to incorporate information regarding current macroeconomic conditions? If investors efficiently incorporate economic news into their earnings expectations, then the predictability of analysts' errors using available macroeconomic information would not be informative of future returns. Conversely, if investors take analysts' forecasts at face value, then the forecast gaps that predict analyst forecast errors would presumably also predict stock returns. We address this question simply by regressing three-month and six-month S&P 500 index excess returns on the forecast gaps from the previous section.

Table 6 presents the results from regressions of three-month excess returns on the two forecast gaps. The first three columns examine gaps based on the simple macro model (on only GDP growth and dollar appreciation). Column (1) shows that the current-quarter gap predicts excess returns over the subsequent three months at a high level of significance, suggesting that a 10 percentage point gap in current-quarter forecasts predicts an additional 2.5 percent excess return on equities, with an R-squared of 8 percent. In contrast, the forecast gap for quarter-ahead earnings has no marginal predictive power. Column (2) augments the model by controlling for equity valuations with the dividend-price ratio. Consistent with Table 1 results, the dividend yield substantially boosts the regression R-squared. Perhaps more interestingly, its inclusion does not dampen the predictive power of the current-quarter gap. The results in the last three columns, which use the forecast gaps based on the full macro model, yield nearly identical results.

Table 7 extends the return predictability analysis to the six-month horizon. Without conditioning on the dividend-price ratio, the forecast gap variables show only marginal predictive

[16] It should also be noted that the intercept, is statistically significant with a value of nearly 1.35. This suggests that, when the forecast gaps are close to zero, realized earnings tend to exceed the analyst forecast by a small (but statistically significant) margin, a result that seems consistent with a well-known seasonal bias in the current-quarter bottom-up forecasts.

power at the 6-month horizon, as shown in columns (1) and (4). Nonetheless, these two regressions reveal another interesting insight: in both cases the positive coefficient on the quarter-ahead gap are of nearly identical magnitude to that on the current-quarter gap, suggesting that what is relevant for predicting sixth-month returns is the cumulative model-analyst gap in the growth forecasts over the two quarters. In columns (2) and (4), we regress returns on the cumulative gap (defined as the sum of the two gaps), which improves the statistical properties of the regressions (producing a lower AIC and a higher F-statistic in each case) without compromising the model's fit.

When the dividend price-ratio is added in columns (3) and (6), the cumulative gap coefficient increases a bit and is statistically significant for both macro model forecasts. Still, the marginal predictive power of the earnings forecast gap appears to be substantially less important for six-month returns, suggesting that the efficacy of the macro models' information advantage for market timing does not last much beyond three months. This likely reflects, for instance, the growing relative salience of information about the subsequent quarter' earnings as time moves forward.

Our final exercise involves deriving a simple rule for market-timing based on valuations and the gap between the macro-model based forecast and analyst forecasts. In particular, we divide the quarterly observations in our sample into six buckets, first, depending on whether the dividend yield is higher or lower than its median level (1.86 percent) and, second, depending upon whether the current-quarter earnings forecast gap is within the top, middle, or bottom tercile of its historical values (breakpoints at 0.4 percent, 4.50 percent). Table 8 shows the mean return as well as the Sharpe ratio for each bucket. The rightmost column shows the difference in returns between the High and Low Forecast Gap buckets when the dividend yield is either above or below its median.

As suggested by the Table 8 regressions, excess returns for the S&P 500 index are highest in the High-Dividend-Yield, High-Forecast-Gap periods, averaging 6 percent (or 26 percent annual rate). In contrast, the S&P 500 earns negative excess returns, on average, when both the dividend yield and the Forecast Gap are low. As shown by the column to the right, among quarters when the dividend yield is high, we find the difference in average returns between High and Low Forecast-Gap quarters (6.0 versus 1.6) is highly statistically significant. Among quarters with a below-median dividend yield, the analogous difference in average returns (2.8 versus -1.30) is only significant at the 10 percent level. In part, that lower level of significance reflects the very high standard deviation of returns (not shown) in the Low-Low bucket, equal to 8.2 percent, compared to the 4.5 to 5.5 percent range for the other five bins. Also worth noting, the High-High bin performance dominates all others when measured by Sharpe Ratio, which is 1.2 for this bin, but well below 1.0 for four of the other five market-timing bins.

VII. Summary and Conclusion

We began by showing that, when measured carefully, news about near-term S&P 500 Composite earnings has substantial explanatory power for aggregate S&P 500 Index returns from 1994-2023, with positive effects. We then compare analysts' bottom-up forecasts for near-term S&P 500 earnings to model-based forecasts of those earnings derived from macroeconomic data. We find that a simple model based on GDP growth, inflation, and exchange rates can predict a significant portion of the errors in analysts' aggregated forecasts. In turn, the predictable component of the errors in analysts' forecasts can be used to predict short-term stock market returns. The findings suggest that investors can improve their forecasts of S&P 500 earnings and stock market returns by paying more attention to macroeconomic data. They also highlight an important dimension of inefficiency in analysts' forecasts.

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Table 1: Regressions of S&P 500 Excess Returns on Revisions to Bottom-Up Quarterly Forecasts, 1994-2023

	3-Month				6-Month			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Revision to Current Quarter	0.39***	0.51***	0.44***	0.43***	0.33***	0.38**	0.40***	0.40*
	(0.09)	(0.15)	(0.08)	(0.14)	(0.06)	(0.18)	(0.07)	(0.20)
Excess Revision to Quarter-Ahead	0.19*	0.32	0.18*	0.14	0.47***	0.39**	0.47***	0.26*
	(0.11)	(0.22)	(0.10)	(0.21)	(0.04)	(0.18)	(0.05)	(0.13)
log Dividend-Price Ratio			0.13***	0.11***			0.18***	0.17***
			(0.03)	(0.03)			(0.05)	(0.05)
Constant	0.50	0.67	−7.28***	−6.33***	3.83***	3.11***	−7.25**	−7.27**
	(0.82)	(1.07)	(1.89)	(2.04)	(1.01)	(1.17)	(2.92)	(3.20)
N	118	108	118	108	118	105	118	105
R Squared	0.21	0.11	0.33	0.22	0.39	0.12	0.50	0.29
RMSE	7.15	6.03	6.59	5.62	9.26	8.06	8.36	7.24

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Excess returns are the change in the log of S&P 500 Total Return Index over a 3-month (6-month) period starting on the first Thursday of the third month of the quarter, minus the yield on 3-month (6-month) Treasury Bill at beginning of the return period. Revision to Current Quarter is the change in the log of current-quarter earnings forecast over the same roughly 90-day (or 180-day) period that excess returns are measured. Excess Revision to Quarter-Ahead is the difference in revision (over same 90- or 180-day period) to quarter-ahead earnings forecast and current-quarter earnings forecast. Dividend-Price Ratio for S&P 500 is measured at beginning of return period. Newey-West standard errors allowing up to a 1 quarter lag used in 6-month return regressions.
Source: LSEG I/B/E/S, S&P Dow Jones Indices.

Table 2: Regression of S&P 500 Earnings Growth on Macro Model Variables, 1993-2023

	(1) 1Q Growth	(2) 1Q Growth	(3) 1Q Growth	(4) 1Q Growth	(5) 4Q Growth	(6) 4Q Growth
Real GDP	4.15***	4.23***	4.12***	3.77***	4.48***	3.54***
	(0.90)	(0.85)	(0.86)	(0.79)	(0.75)	(0.79)
PCE Deflator	2.63**	2.75**	3.07***	2.75***	2.07**	1.77**
	(1.17)	(1.08)	(1.05)	(0.94)	(0.93)	(0.72)
Employee Comp (lag)	−2.95**	−3.00**	−2.07	−1.75	−1.07	−0.77
	(1.48)	(1.47)				
Private Payrolls (lag)	0.20					
	(0.70)					
Dollar Index (lag)	−0.74***	−0.72***	−0.71***	−0.66***	−0.57*	−0.39**
	(0.17)	(0.17)	(0.17)	(0.15)	(0.30)	(0.17)
Loan Losses				−1.00***		−1.68***
				(0.27)		(0.22)
MA(1)	−0.29***	−0.29***	−0.26**	−0.34***		
	(0.11)	(0.11)	(0.10)	(0.11)		
Constant	0.56	0.56	−0.25	−0.18	−3.77	−2.19
	(1.14)	(1.13)	(0.69)	(0.62)	(3.26)	(2.08)
N	116	116	116	116	113	113
Adj. R Squared	0.24	0.24	0.24	0.31	0.44	0.74
AIC	698.54	696.62	695.37	685.28	834.02	746.45
RMSE	4.58	4.58	4.60	4.36	9.27	6.24

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Dependent variable is actual historical growth of S&P 500 quarterly earnings. Real GDP, PCE Deflator, ECI (Employment Compensation Index), Private Payrolls, and the Dollar Index are measured as one-quarter changes in log levels for columns (1)-(4) and as four-quarter changes in columns (5) and (6). ECI, Private Payrolls, and the Dollar Index use the one-quarter lagged value of growth (or four-quarter growth). The level for Private Payrolls is equal to the average of the 3 months of the quarter. The level for the Dollar Index is the last observation (of the quarter) of a weighted average of the foreign exchange value of the US dollar against the currencies of a broad group of major US trading partners. Loan Losses is defined as total quarterly loan loss provisions for domestic US banks, tabulated by FDIC, normalized by one-quarter lagged actual S&P 500 earnings. In columns 3-6, regressions are estimated with a linear constraint requiring coefficients on PCE Inflation and ECI to add up to 1.0. Columns (5) and (6) use Newey-West standard errors allowing up to a 4 quarter lag.
Source: LSEG I/B/E/S, BEA, US Department of Labor, Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation.

Table 3: Regression of S&P 500 Earnings Growth on Real GDP and Dollar Index, 1993-2023

	(1) 1Q Growth	(2) 1Q Growth	(3) 4Q Growth	(4) 4Q Growth
Real GDP Grw	3.74***	3.41***	4.59***	3.68***
	(0.88)	(0.82)	(0.72)	(0.73)
Dollar Index (Lag)	−0.84***	−0.78***	−0.72**	−0.52***
	(0.17)	(0.16)	(0.32)	(0.18)
Loan Losses		−0.99***		−1.62***
		(0.29)		(0.21)
MA(1)	−0.24**	−0.30***		
	(0.10)	(0.10)		
Constant	0.17	0.29	−2.70	−0.95
	(0.70)	(0.65)	(3.08)	(2.09)
N	116	116	113	113
Adj. R Squared	0.21	0.28	0.44	0.73
AIC	699.77	690.83	831.19	751.44
RMSE	4.73	4.51	9.24	6.44

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Dependent variable is actual historical growth of S&P 500 quarterly earnings. Real GDP and the Dollar Index are measured as one-quarter changes in log levels for columns (1) and (2) and as four-quarter changes in column (3). The Dollar Index uses the one-quarter lagged value of growth (or four-quarter growth). The level for the Dollar Index is the last observation (of the quarter) of a weighted average of the foreign exchange value of the US dollar against the currencies of a broad group of major US trading partners. Loan Losses is defined as total quarterly loan loss provisions for domestic US banks, tabulated by FDIC, normalized by one-quarter lagged actual S&P 500 earnings. Column (3) uses Newey-West standard errors allowing up to a 4 quarter lag.
Source: LSEG I/B/E/S, BEA, Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation.

Table 4: Correlations: Actual Growth, Analysts' Forecasts, and Model Forecasts, 1994-2023

	Current-Quarter Growth			Quarter-Ahead Growth			Cumulative Two-Quarter Growth		
	Analysts	Simple Model	Full Model	Analysts	Simple Model	Full Model	Analysts	Simple Model	Full Model
Realized	0.61	0.38	0.40	0.30	0.31	0.37	0.34	0.46	0.45
Full Model	-0.03	0.92		-0.02	0.89		-0.11	0.86	
Simple Model	0.02			0.00			-0.03		

Note: Model-based forecasts are growth rates implied by real-time macro model coefficient estimates from either Full Model estimation (column (3), Table 2) or Simple Model estimation (column (1), Table 3). Coefficients are applied to the Blue Chip growth forecasts for real GDP and GDP deflator in the current-quarter and quarter-ahead (surveyed during the first week of the third month of current quarter) or to the (observable) previous quarter value of growth in the ECI and the Dollar. Analysts' current-quarter growth forecast is (log of) expected current-quarter earnings minus (log of) near-final bottom-up estimate of previous-quarter earnings. Analysts' quarter-ahead growth is (log of) expected quarter-ahead earnings minus (log of) expected current-quarter earnings. Cumulative two-quarter growth is the sum of current-quarter and quarter-ahead growth forecasts.

Table 5: Regressions Predicting Analyst Forecast Errors Using Model-Analyst Forecast Gaps, 1994-2023

	Simple Macro Model		Full Macro Model	
	Current Quarter	Quarter-Ahead	Current Quarter	Quarter-Ahead
Current Quarter Gap	0.52***	0.68***	0.52***	0.65***
	(0.05)	(0.09)	(0.05)	(0.09)
Quarter-Ahead Gap	0.19**	0.65***	0.19***	0.64***
	(0.07)	(0.12)	(0.07)	(0.12)
Constant	1.35***	−1.02	1.28***	−1.08
	(0.39)	(0.66)	(0.38)	(0.66)
N	108	108	108	108
R Squared	0.48	0.41	0.51	0.43
Adj. R Squared	0.47	0.40	0.50	0.42
F	48.58	37.10	55.23	39.14

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Dependent variable is either analysts' current-quarter forecast error or quarter-ahead forecast error, each equal to the difference between the log of actual earnings and log of forecast earnings. The current-quarter (quarter-ahead) gap is the difference between the growth forecast by the model and that by analysts for the current quarter (quarter ahead).
Source: LSEG I/B/E/S

Table 6: Regressions Predicting S&P 500 3-Month Excess Returns using Model-Analyst Forecast Gaps, 1994-2023

	Simple Macro Model		Full Macro Model	
	(1)	(2)	(3)	(4)
Current Quarter Gap	0.25***	0.30***	0.26***	0.28***
	(0.09)	(0.09)	(0.09)	(0.08)
Quarter-Ahead Gap	−0.04	−0.01	−0.02	−0.05
	(0.12)	(0.12)	(0.12)	(0.12)
log Dividend-Price Ratio		0.10***		0.09***
		(0.03)		(0.03)
Constant	2.06***	−3.86**	2.09***	−3.57**
	(0.67)	(1.66)	(0.67)	(1.69)
N	108	108	108	108
R Squared	0.08	0.19	0.08	0.18
Adj. R Squared	0.06	0.17	0.06	0.16
F	4.29	8.18	4.30	7.59

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Dependent variable is 3-month excess returns, calculated as the change in the (log of) S&P 500 Total Return Index over a 3-month period starting on the first Thursday of the third month of the quarter, minus the yield on 3-month Treasury Bill at beginning of the return period. The current-quarter (quarter-ahead) gap is the difference between the growth forecast by the model and that by analysts for the current quarter (quarter ahead). Dividend-Price Ratio for S&P 500 is measured at beginning of return period.
Source: LSEG I/B/E/S, S&P Dow Jones Indices.

Table 7: Regressions Predicting S&P 500 6-Month Excess Returns using Model-Analyst Forecast Gaps, 1994-2023

	Simple Macro Model			Full Macro Model		
	(1)	(2)	(3)	(4)	(5)	(6)
Current Quarter Gap	0.25			0.25		
	(0.16)			(0.16)		
Quarter-Ahead Gap	0.24			0.32		
	(0.19)			(0.21)		
Cumulative Gap		0.24	0.31**		0.27*	0.27*
		(0.16)	(0.15)		(0.16)	(0.14)
log Dividend-Price Ratio			0.17***			0.16***
			(0.05)			(0.05)
Constant	5.39***	5.41***	−4.84	5.54***	5.37***	−4.02
	(0.97)	(1.04)	(3.36)	(0.93)	(1.03)	(3.23)
N	105	105	105	105	105	105
R Squared	0.04	0.04	0.23	0.06	0.06	0.22
Adj. R Squared	0.02	0.03	0.21	0.04	0.05	0.20
F	2.15	4.35	14.97	3.18	6.32	14.18

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Dependent variable is 6-month excess returns, calculated as the change in the (log of) S&P 500 Total Return Index over a 6-month period starting on the first Thursday of the third month of the quarter, minus the yield on 6-month Treasury Bill at beginning of the return period. The current-quarter (quarter-ahead) gap is the difference between the growth forecast by the model and that by analysts for the current quarter (quarter ahead). The cumulative gap is the sum of the current-quarter and quarter-ahead gaps. Dividend-Price Ratio for S&P 500 is measured at beginning of return period. Newey-West standard errors allowing up to a 1 quarter lag used in all regressions.
Source: LSEG I/B/E/S, S&P Dow Jones Indices.

Table 8: Market-Timing Portfolios, 1994-2023

		Current-Quarter Forecast Gap			
		High	Medium	Low	High-Low Gap
High D/P	Mean	6.0	4.9	1.6	4.4**
	Sharpe Ratio	1.2	1.0	0.3	(0.02)
Low D/P	Mean	2.8	2.8	-1.3	4.1*
	Sharpe Ratio	0.5	0.5	-0.2	(0.08)
High-Low D/P		3.2*	2.1	2.9	
		(0.07)	(0.25)	(0.22)	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports average excess returns and Sharpe ratios for a market timing strategy. The current-quarter forecast gaps, derived from the simple macro model, are segmented into terciles (High, Medium, and Low), while the dividend-price ratio (D/P) is split at the median (High and Low). Additionally, the High-Low column and row present t-test results for mean differences (p-values in parentheses).