Aggregate Sales Growth and Stock Market Returns

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Abstract

We examine the predictive content of aggregate sales growth (*ASG*) for stock market performance. *ASG* negatively predicts future stock market excess returns. In-sample tests show a one-standard-deviation increase in *ASG* leads to a decline of more than 6% in future annualized market excess returns. This negative relation is incremental to aggregate earnings growth and macroeconomic return predictors. In addition, the return-predicting power of *ASG* persists in out-of-sample tests, and mean-variance investors can construct a viable trading strategy via the forecasts based on *ASG* in real time. We explore potential channels. *ASG* negatively predicts various measures of aggregate earnings surprises, while being unrelated to subsequent discount rate proxies. Our findings suggest that the predictive ability of aggregate sales growth stems predominantly from a cash flow channel.

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1 Introduction

The earnings-return relation is one of the bedrocks of the extant financial accounting literature. Ever since Ball and Brown (1968), cross-sectional firm-level studies have repeatedly documented a positive relation between earnings changes and subsequent stock returns. This broadly suggests that future stock prices are predictable based on earnings information. However, this cross-sectional return predictability does not appear to "aggregate to" time-series return predictability: prior research (e.g., Kothari et al. 2006; Ball et al. 2009) finds that *aggregate* earnings growth is unrelated to future market excess returns.[1] This lack of cross-sectional aggregation to (the) time-series remains a puzzle.

In this paper, we examine whether sales growth, a key source of earnings growth, contains return-predicting information at the aggregate level. Sales, as the top line of the income statement, directly drives earnings growth, making it a primary and immediate determinant of corporate profitability. While earnings are shaped by a variety of cost management decisions, one-time items, and accrued expenses, sales growth provides more direct measure of business activity (e.g., Lev 2018). This suggests that aggregate sales growth could offer a different signal about future market returns than aggregate earnings.

Our examination of aggregate sales growth is further motivated by the literature on aggregate investment. Multiple theories predict a negative association between aggregate investment and future market returns (e.g. Cochrane 1991; Lamont 2000), a finding which is confirmed empirically by Arif and Lee (2014). But while investment reflects managers' forward-looking beliefs about the economy and their willingness to commit resources to

[1] On the other hand, aggregate earnings growth is negatively associated with *contemporaneous* stock market returns (Kothari et al. 2006; Sadka 2007; Sadka and Sadka 2009; Cready and Gurun 2010; Ball and Sadka 2015).

future growth, sales growth captures real-time sentiment in economic activity, as it reflects the purchasing behavior of consumers and businesses. Thus, aggregate sales growth offers a complementary perspective, one that encompasses demand-side forces. Examining how aggregate sales relates to future returns therefore both builds on the foundation laid by research on aggregate investment, while revisiting the idea that aggregate earnings is not associated with time-series return predictability. Thus we provide new insights into aggregate financial statement information and the dynamics of stock return predictability.

We begin by constructing a simple monthly time series of aggregate sales growth - hereafter *ASG* - between January 1985 and December 2023. In each month, *ASG* is computed as the value-weighted average of one-year sales growth across all U.S. public firms. We then run a simple time-series regression of future excess market returns on *ASG* to establish whether sales growth in the aggregate can help predict future stock market performance. We find that *ASG* significantly and negatively predicts future market excess returns. A one-standard deviation increase in *ASG* corresponds to a 6.72% decrease in the future annualized market excess returns.

Our explanatory power is good. *ASG* yields R^2 statistics of 1.47%, 4.59%, 9.27%, and 17.10%, at the monthly, quarterly, semi-annual, and annual horizons, respectively. The IVX-Wald statistics of Kostakis et al. (2015) are also significant at all forecast horizons, indicating that the aggregate return predictability of *ASG* does not stem from *ASG*'s degree of persistence.

With our primary result in hand, we next turn to assessing incremental explanatory power. We compare how well *ASG* performs relative to aggregate earnings growth (*AEG*), as well as popular economic return predictors, and whether it contains incremental information beyond these variables when any (or even all, in our internet appendix) are included in our regression simultaneously. For *AEG* we compute six measures (value-weighted and equal-weighted average versions of one-year earnings growth across all U.S. public firms, using three different scaling measures: absolute value of one-year-lagged earnings; one-year-lagged book value of equity; or one-year-lagged market value of equity). For the comparison economic predictors, we obtain the 14 economic variables used by Goyal and Welch (2008). These include dividend yield (Fama and French 1988; Kothari and Shanken 1997; Ang and Bekaert 2007), dividend-payout ratio (Lamont 1998), earnings-price ratio (Campbell and Shiller 1988), stock variance (French et al. 1987; Guo 2006), book-to-market ratio (Kothari and Shanken 1997; Pontiff and Schall 1998), net equity expansion (Baker and Wurgler 2000), Treasury bill rate (Fama and Schwert 1977; Breen et al. 1989; Ang and Bekaert 2007), term spread (Campbell 1987; Fama and French 1988), and inflation (Fama and Schwert 1977; Campbell and Vuolteenaho 2004). At each of our four forecast horizons, we find that *ASG* outperforms all the above variables in predicting future aggregate returns,[2] and that its predictive power remains largely unchanged after controlling for them.

We proceed to examine whether *ASG*'s ability to predict future market excess returns persists in *out-of-sample* tests. Goyal and Welch (2008) show that popular predictors with significant in-sample aggregate return predictability often fail to outperform the simple historical average benchmark forecast, in out-of-sample tests. We employ the two common evaluation metrics in the literature, the out-of-sample R^2_{OS} statistics of Campbell and Thompson (2008) and the mean squared forecasting error

[2]Consistent with the findings in prior literature, all 6 measures of AEG are insignificantly related to future stock market returns.

(MSFE)-adjusted statistic of Clark and West (2007). We find that *ASG* produces positive out-of-sample R_{OS}^2 of 1.82%, 5.29%, 9.51%, and 13.68%, at the monthly, quarterly, semi-annual, and annual horizons, respectively. Crucially, these out-of-sample R_{OS}^2 are statistically significant and larger than those for the 6 *AEG* measures and 14 economic variables.

For a different perspective, we examine the economic significance of *ASG*'s predictive ability via an asset allocation analysis. Following Kandel and Stambaugh (1996) and Campbell and Thompson (2008), we use the out-of-sample forecasts to compute the certainty equivalent return (CER) gain, and the Sharpe ratio for a mean-variance investor who optimally allocates her wealth between equities and the risk-free asset. Under the (reasonable-by-literature) assumption of an investor with a relative risk aversion of three, they would be willing to pay an annual portfolio management fee of 4.41% to have access to the predictive regression forecasts based on *ASG*, instead of using the historical average return forecast. By contrast, the same investor would prefer the historical average return forecast or pay much less to gain access to the predictive regression forecasts based on any one of the 6 *AEG* measures or any one of the 14 economic variables. In addition, the annualized Sharpe ratio of *ASG* is 0.71, which is much higher than those of the 6 *AEG* measures, the 14 economic variables, or the market portfolio over the same out-of-sample evaluation period. Overall, *ASG*'s aggregate return predictive ability for the stock market surpasses that of *AEG* as well as typical macroeconomic variables, in both in-sample and out-of-sample tests.

We explore the economic channel of such ability, or why *ASG* negatively predicts future market excess returns? Our first pass begins with Campbell (1991)'s return decomposition analysis. It bifurcates unexpected returns into two components: cash flow news (change in expected cash flows) and discount rate news (change in expected returns). If the cash flow channel is primarily driving *ASG*'s ability to predict lower future returns, then *ASG* should negatively predict future aggregate cash flow news. If, on the other hand, the discount rate channel plays the major role in *ASG*'s negative return predictability, *ASG* should be positively related to future discount rate innovations. Since *ASG*'s negative return-predicting ability persists from one month to one year, we examine how *ASG* is related to measures of cash flow news and discount rate news in the next one to four quarters.

We examine the cash flow channel by studying the relationship between *ASG* and future aggregate earnings surprises, as earnings is a standard proxy for cash flows (Sadka 2007; Sadka and Sadka 2009). We (again) construct six measures similar to *AEG*, but this time for aggregate earnings surprises. The surprises are based on a seasonal random walk model.[3] We find that *ASG* negatively predicts all six measures in the next one to four quarters, controlling for autocorrelation in aggregate earnings surprises. In other words, high *ASG* is followed by more pessimistic cash flow news in the future, providing preliminary evidence that *ASG*'s predictive ability operates via a cash flow channel.

We also link ASG with earnings surprises calculated using analysts' consensus EPS forecasts. We exploit different forecast period end dates from I/B/E/S to form investors' time-varying earnings expectations, and construct 6 measures of aggregate "analyst-based" earnings surprises accordingly.[4] We find that *ASG* is negatively related to all six aggregate

[3] The 6 measures are computed as the cross-sectional value-weighted or equal-weighted average of seasonally differenced earnings, scaled by either the absolute value of earnings, book value of equity, or market equity four quarters prior.

[4] Again, the 6 measures are computed as the cross-sectional value-weighted or equal-weighted average of

"analyst-based" earnings surprise measures in the next one to four quarters. This finding provides a sharper "errors-in-expectations" story of the cash flow channel: during periods of high *ASG*, investors form overly optimistic beliefs about future aggregate earnings. Hence, the negative return predictability of *ASG* stems from the correction of investors' initial cash flow expectation error.

To investigate the discount rate channel, we examine the relationship between *ASG* and unexpected future inflation. Following the literature (e.g., Shivakumar 2007; Shivakumar and Urcan 2017), we use two measures: percentage change in seasonally-adjusted Producers Price Index (PPI), and percentage change in seasonally-adjusted Consumer Price Index (CPI). We find that *ASG* is unrelated to future inflation in the next one to four quarters, strongly suggesting that time-varying discount rate is not the primary channel through which *ASG* predicts future stock market returns.

We conduct a battery of additional analyses as robustness checks. First, we document that *ASG* still exhibits incremental return-predicting power when controlling for aggregate investment growth measures. Moreover, it performs better than these measures in out-of-sample tests. Second, we find that *ASG* defined via an equal-weighting method also negatively predicts future market excess returns. Third, we employ alternative econometric methods (Hodrick 1992; Rapach et al. 2016) to account for serial correlation in residuals caused by overlapping data (e.g., Nelson and Kim 1993; Goetzmann and Jorion 1993), and still find that the negative relation between *ASG* and future market excess returns is statistically significant. Fourth, *ASG*'s return-predictive power, as well as its economic value from an asset allocation perspective, persist in alternative out-of-sample

firm-level reported earnings, but this time minus *analysts'* expected earnings, scaled by either the absolute value of earnings, book value of equity, or market equity four quarters prior.

periods.

Our study makes two main contributions. First, we contribute to a vast literature studying the relation between aggregate earnings changes and stock market returns (e.g., Kothari et al. 2006; Sadka 2007; Shivakumar 2007; Sadka and Sadka 2009; Cready and Gurun 2010; Ball and Sadka 2015). Since prior studies do not find evidence of stock market return predictability based on aggregate earnings changes, our study is contributory by showing that a key determinant (i.e. sales) is value-relevant in the aggregate. Moreover, we find that *ASG* contains incremental price-relevant information beyond aggregate earnings growth, as well as well-known economic return predictors. In this sense, our paper also contributes to the equity premium literature in finance and economics (e.g., Goyal and Welch 2008; Cooper and Priestley 2009; Kelly and Pruitt 2013; Rapach et al. 2016; Atanasov et al. 2020; Goyal et al. 2024) from an accounting perspective (e.g., Anilowski et al. 2007; Howe et al. 2009; Bradshaw 2011; Ball and Sadka 2015; Kothari et al. 2016).

Second, we contribute to a literature studying whether aggregate earnings growth has predictive ability for economic variables and aggregate earnings news (e.g., Shivakumar 2007; Konchitchki and Patatoukas 2014a; Konchitchki and Patatoukas 2014b; Gallo et al. 2016; Shivakumar and Urcan 2017).[5] In particular, our results imply that *ASG* and aggregate earnings growth contain different information content. First, future aggregate earnings growth is increasing in current aggregate earnings growth (Kothari et al. 2006; Kalay et al. 2014) while decreasing in *ASG*. Second, future inflation is increasing in aggregate earnings growth (Shivakumar 2007; Shivakumar and Urcan 2017), while

[5]As Shivakumar (2007, p65) states: "...it is important to discern these relationships (aggregate corporate earnings, aggregate stock market returns, and the macroeconomy) in order to improve our understanding of capital markets and economies".

insignificantly related to *ASG*. The above findings provide strong evidence that the economic source of *ASG*'s return predictability primarily operates via a cash flow channel, and help distinguish between the information content of aggregate earnings growth and that of *ASG*.

The rest of the paper is structured as follows. Section 2 discusses related literature. Section 3 describes the sample and variables. Section 4 examines the return-predicting power of *ASG* in both in-sample and out-of-sample tests. Section 5 investigate the economic channels of *ASG*'s return predictability. Section 6 performs additional tests of the main results as robustness checks. Finally, Section 7 concludes the paper.

2 Related Literature

A positive relation between earnings and subsequent stock returns at the firm-level is well documented in the post-earnings announcement drift literature (e.g., Ball and Brown 1968; Beaver 1968; Foster et al. 1984; Bernard and Thomas 1989). Further, Ball et al. (2009) find that common earnings factors explain a substantial portion of firm-level earnings variation. In addition, Sadka et al. (2024) find that while the cross-sectional firm-level earnings-returns relation has declined, the firm-level time-series relation (Teets and Wasley 1996) has marginally increased. None of these papers studies aggregate sales growth.

Kothari et al. (2006) extend the firm-level analysis of the earnings-return relation to the aggregate level and document a negative relation between aggregate earnings changes and contemporaneous stock market returns. In contrast, Choi et al. (2016) show that aggregate earnings news based on revisions in analyst forecasts is positively related to contemporaneous stock returns. Cready and Gurun (2010) document a negative relation between three-day announcement period earnings announcement surprises and stock market returns. On the other hand, Sadka and Sadka (2009) find that earnings changes are significantly more predictable at the aggregate level than at the firm level, and the negative relation between expected earnings and expected returns may determine the contemporaneous earnings-return relation. However, the sign of the aggregate earnings-return relation appears to vary over time (Sadka and Sadka 2009; Zolotoy et al. 2017; Kim et al. 2020). Again, there is little consensus across studies on the influence of earnings growth, and there is no exploration of the role of sales growth.

Another strand of literature examines the relation between aggregate earnings growth and macroeconomic variables. Shivakumar (2007) documents that aggregate earnings growth is positively related to future nominal GDP growth and growth in seasonally adjusted consumer price index.[6] Konchitchki and Patatoukas (2014a) document that aggregate earnings growth positively predicts future nominal GDP growth, and Konchitchki and Patatoukas (2014b) document that accounting profitability aggregated across the 100 largest firms is a leading indicator of real GDP growth. On the other hand, Gaertner et al. (2020) show that only negative aggregate earnings growth predicts future GDP growth, and Abdalla and Carabias (2022) document that aggregate special items conveys more information about future real GDP growth than aggregate earnings before special items.

Cready and Gurun (2010) document a positive relation between earnings news and inflation changes reflected in Treasury inflation-protected securities (TIPS). In addition, Gallo et al. (2016) provide evidence that aggregate earnings changes predict federal funds

[6] We do not find a statistically significant relation between aggregate sales growth (*ASG*) and future real or nominal GDP growth.

rate changes. Shivakumar and Urcan (2017) show the positive relation between aggregate earnings growth and future inflation stems from higher investment demand of production goods, and Hann et al. (2021) find that aggregate earnings contain useful information about future labor market conditions. Our conclusions must therefore reflect results that control for macroeconomic variables' influence on the aggregate returns-sales relation.

3 Data and Variables

We obtain firm-level data from the Center for Research in Security Prices (CRSP) monthly and Compustat database for the period of January 1985 to December 2023.[7] To guard against look-ahead bias, we assume that all accounting items except for earnings are available four months after the fiscal period end (Jensen et al. 2023), and earnings data is available on the earnings announcement date.

We begin by constructing individual stocks' one-year sales growth in each month. We focus on one-year sales growth to mitigate the seasonality issue in sales revenue.[8] First, we define one-year sales revenue for firm *i* in month *t*, $SALES_{i,t}$, as the sum of firm *i*'s quarterly sales revenue (Compustat item SALEQ) over the most recent four quarters as of month *t*. If SALEQ is unavailable, we use the Compustat revenue item REVTQ. Next, we compute aggregate sales growth (*ASG*), as the cross-sectional value-weighted average of individual firm's one-year sales growth:

$$ASG_t = \frac{\sum_i SALES\_GROWTH_{i,t} \times MCAP_{i,t}}{\sum_i MCAP_{i,t}}, \tag{1}$$

[7]Since analyst EPS forecasts are important in our analysis in Section 5 and are available for most firms after 1984, we choose 1985 to 2023 as our sample period.
[8]In Table IA1 of the Internet Appendix we show that the main results are robust to the use of one-quarter or three-year sales growth.

where $SALES\_GROWTH_{i,t} = (SALES_{i,t} - SALES_{i,t-12})/SALES_{i,t-12}$ is the one-year sales growth of firm i as of month t and $MCAP_{i,t}$ is the market capitalization of firm i in month t. The value-weighting approach places more emphasis on sales growth of firms with large capitalization, which is consistent with our goal of predicting the excess return on the value-weighted market portfolio.[9] To mitigate the effect of outliers, we winsorize sales growth at the 1% and 99% levels in each month. In Figure 1, we plot the time-series of *ASG* during our sample period. We find that *ASG* exhibits substantial variation, reaching its maximum around the 2000 dot-com bubble crash and its minimum after the 2008 financial crisis.

Following similar procedures, we define 6 measures of aggregate earnings growth (*AEG*). First, we define the one-year earnings for firm i in month t, $EARNINGS_{i,t}$, as the sum of firm i's quarterly income before extraordinary items (Compustat item IBQ) over the most recent four quarters as of month t. Next, we compute 6 measures of aggregate earnings growth (*AEG1, AEG2, AEG3, AEG4, AEG5,* and *AEG6*) in month t as the cross-sectional value-weighted or equal-weighted average of individual firm's one-year earnings growth across all U.S. public firms, scaled by three different metrics. The one-year earnings growth is annual earnings change ($EARNINGS_{i,t} - EARNINGS_{i,t-12}$), and the scaling variables are absolute value of one-year-lagged earnings ($|EARNINGS_{i,t-12}|$), book value of equity at the end of month t-12, or market value of equity at the end of month t-12.

In addition, we obtain 14 economic variables that have been shown to predict aggregate stock market returns in Goyal and Welch (2008), including the log dividend-

[9] In Section 6, we show that the main results are robust to defining aggregate sales growth via the equal-weighting approach.

price ratio (*DP*), log dividend yield (*DY*), log earnings-price ratio (*EP*), log dividend payout ratio (*DE*), stock variance (*SVAR*), book-to-market ratio (*BM*), net equity expansion (*NTIS*), Treasury bill rate (*TBL*), long-term bond yield (*LTY*), long-term bond return (*LTR*), term spread (*TMS*), default yield spread (*DFY*), default return spread (*DFR*), and inflation rate (*INFL*).[10] See the Appendix for the definitions of *ASG*, 6 measures of *AEG*, and these 14 economic variables.

Table 1 reports summary statistics for the above variables over our sample period. In particular, *ASG* has a time-series mean, median, minimum, and maximum of 14.33%, 13.35%, -6.37% (in January 2010), and 47.74% (in August 2000), respectively. The statistics of the economic variables are generally within norms from other studies (e.g., Rapach et al. 2016). Table 2 presents the pairwise correlation coefficients between *ASG*, the 6 *AEG* measures, and the 14 economic variables. We find that *ASG* is positively correlated with the first three AEG measures (*AEG1*, *AEG2*, and *AEG3*), but is mostly unrelated to the remaining three AEG measures (*AEG4*, *AEG5*, and *AEG6*). In addition, *ASG* is negatively correlated with the log dividend-price ratio (-0.45), log dividend yield (-0.45), log dividend payout ratio (-0.32), book-to-market ratio (-0.45), term spread (-0.44), and positive correlated with Treasury bill rate (0.38) and inflation rate (0.27).

4 Empirical Results

In this section, we examine whether *ASG* is significantly related to future market excess returns. We then compare *ASG*'s return predictability with that of the 6 *AEG* measures and the 14 economic variables in Goyal and Welch (2008), and test whether the predictive ability of *ASG* is incremental to those variables.

[10]The data are obtained from Amit Goyal's webpage at https://sites.google.com/view/agoyal145.

4.1 In-sample tests

4.1.1 Baseline predictive regression

We start with single variable regressions. The dependent variable is log market excess return in month t, denoted by r_t. It is the log return on the CRSP value-weighted index of U.S. stocks listed on the NYSE, AMEX, and NASDAQ, minus the log return on a one-month Treasury bill. The standard predictive regression model for analyzing aggregate stock return predictability is:

$$r_{t,t+h} = \alpha + \beta ASG_t + \varepsilon_{t,t+h}, \tag{2}$$

where $r_{t,t+h} = (1/h)(r_{t+1} + \cdots + r_{t+h})$ represents the h-month-ahead average log excess return on the CRSP value-weighted index.[11] We standardize *ASG* to have mean zero and unit variance to facilitate comparisons with other variables.

We focus on predicting future market excess returns at the monthly (h = 1), quarterly (h = 3), semi-annual (h = 6), and annual horizons (h = 12). When h > 1, there are overlapping monthly observations in our regressions, which implies that the regression residuals will be serially correlated. Hence, to test the statistical significance of β in Equation (2), we use the Newey and West (1987) heteroskedasticity- and autocorrelation-robust t-statistic truncated at lag h (our results are robust using other truncation lags) to account for overlap-introduced serial correlation among residuals (e.g., Nelson and Kim 1993; Goetzmann and Jorion 1993). In Section 6, we show that the results are robust to using alternative econometric methods (Hodrick 1992; Rapach et al. 2016) to compute statistical significance.

Table 3 reports the OLS estimates of β and the corresponding t-statistics, and R^2s

[11]Our results are robust to using the return on the S&P500 index as the market return.

from predictive regressions in Equation (2). We find that the estimated coefficient on *ASG* is significantly negative and that *ASG* has an economically sizable predictive effect on future market excess returns. For example, the estimate of β is -0.56% at the monthly horizon, which implies that a one-standard-deviation increase in *ASG* leads to a decrease of 6.72% (=|-0.56% × 12|) in future annualized excess return. In addition, the remaining columns show that the negative return predictability of *ASG* extends to longer horizons of one quarter to one year. In particular, a one-standard-deviation increase in *ASG* leads to a decrease of 6.84%, 6.84%, and 6.60% in future annualized excess return at the quarterly, semi-annual, and annual horizons, respectively. We also find that consistent with previous studies (e.g., Fama and French 1988), the R^2 statistic increases with the forecast horizon. Specifically, the regression R^2 increases from 1.47% at the monthly horizon to 17.10% at the annual horizon.

There are econometric concerns (e.g., Cavanagh et al. 1995; Torous et al. 2004) when regressors are highly persistent in long-horizon predictive regressions. To alleviate these concerns, Kostakis et al. (2015) develops a Wald test that is robust to the regressor's degree of persistence (unit root, local-to-unit-root, near-stationary, or stationary persistence classes). Since *ASG*, like many return predictors in the literature, is highly persistent by construction, we employ their IVX-Wald test statistics to test the null hypothesis H_0: $\beta = 0$ against the alternative hypothesis H_A: $\beta \neq 0$ for *ASG* in Equation (2). The last row of Table 3 reports the IVX-Wald statistics, and we find that the null hypothesis of $\beta = 0$ can be rejected at the 5% level at the monthly horizon and at the 1% level at the quarterly, semi-annual, and annual horizons, suggesting that the return predicting power of *ASG* is not a statistical artifact of its persistence.

In Table IA1 of the Internet Appendix, we define aggregate sales growth as the cross-sectional value-weighted average of individual firms' one-quarter or three-year sales growth, and perform the baseline predictive regression in Equation (2). We find that the estimated coefficients *ASG* are smaller in magnitude but remain significantly negative, and the IVX-Wald statistics are significant across all forecast horizons. The results indicate that *ASG*'s return predictability is robust to alternative formation periods of sales growth. Overall, we provide solid evidence that *ASG* negatively predicts future market excess returns at various forecast horizons.

4.1.2 Controlling for aggregate earnings growth and economic variables

Next we compare the relative explanatory power of *ASG* for future stock market performance, with that of variables typically found in the extant literature. We first show the explanatory power of the controls, examine the forecasting power of the 6 *AEG* measures and the 14 economic variables in Goyal and Welch (2008), by running the predictive regressions of the following form:

$$r_{t,t+h} = \alpha + \phi Z_t + \varepsilon_{t,t+h}, \tag{3}$$

where Z_t is one of the 6 *AEG* measures or one of the 14 economic variables and h = 1, 3, 6, or 12. All independent variables are standardized to have zero mean and unit variance. Equations (2) and (3) allow us to compare the return predictability of the above variables with that of *ASG* across various forecast horizons.

Table 4 reports the OLS estimates of ϕ, the corresponding Newey and West (1987) t-statistics (h lags), and R^2 statistics from predictive regressions in Equation (3). First, consistent with the findings in prior literature, we show that none of the 6 *AEG* measures exhibit aggregate return-predicting power. This is in direct contrast to the predictive ability of *ASG*. Next we find that most economic variables fail to exhibit significant return predictability, and none of the economic variables is able to significantly predict aggregate market returns at the 5% level across all four horizons in our sample period. In particular, the log dividend-price ratio (*DP*), log dividend yield (*DY*), and book-to-market ratio (*BM*) are the top three return predictors, with a one-standard-deviation increase resulting in 4.68% to 5.05% change in future annualized excess returns. However, none of the variables is able to predict future excess returns at the 5% level at the monthly forecast horizon. Overall, *ASG*'s predictive ability outperforms that of the 20 variables (in terms of both the size of the estimated coefficient and the R^2 statistics).

To examine whether the negative forecasting power of *ASG* on future market excess returns is subsumed by any of the 6 *AEG* measures or the 14 economic variables, we run the following bivariate regression, each time using a different control variable:

$$r_{t,t+h} = \alpha + \beta ASG_t + \phi Z_t + \varepsilon_{t,t+h}, \tag{4}$$

where each independent variable is standardized to have zero mean and unit variance.

Table 5 reports the OLS estimates of β and ϕ, the corresponding *t*-statistics, and R^2*s* from the bivariate predictive regressions in Equation (4). We find that controlling for any of the 6 *AEG* measures or any of the 14 economic variables does not reduce the forecasting power of *ASG* at all forecast horizons. Specifically, the estimates of β remain negative and are similar to the estimates in Table 3 after inclusion of an additional predictor variable. In contrast, the estimates of ϕ are mostly statistically insignificant, suggesting that the return-predicting power of the 20 variables disappears after controlling for *ASG*.

We also attempt to control for 6 *AEG* measures and 14 economic variables in Goyal and Welch (2008) simultaneously when testing the return-predicting power of *ASG*. Since some of the variables are highly correlated as reported in Table 2, including all variables in one regression may result in a multicollinearity issue. Hence, in order to test the predictive power of *ASG* while controlling for the return-predicting content of the above 20 variables in a parsimonious manner, we run a regression of $r_{t,t+h}$ on *ASG* and the first principal component extracted from the 20 variables for h = 1, 3, 6, and 12.[12] We report the results in Table IA2 of the Internet Appendix, and find that including the first principal component of the 20 variables in the predictive regression has very little effect on the negative return predictability of *ASG*.

Overall, Table 5 shows that the forecasting power of the *ASG* remains quantitatively the same as in the case of using the *ASG* alone. Hence, the return predicting power of *ASG* is not subsumed by aggregate earnings growth or well-known macroeconomic return predictors, indicating that *ASG* contains market-level information that is incremental to that contained in these variables.

4.2 Out-of-sample tests

In this section, we investigate whether the return-predicting power of *ASG* holds in out-of-sample tests as well. Goyal and Welch (2008) show that the simple trailing sample average of past market returns often beats an out-of-sample predictive regression forecast as a predictor of future market returns. In other words, in-sample high return predictability does not necessarily correspond to high out-of-sample return predictability. In addition, out-of-sample tests are more relevant for investors to evaluate return predictability in real time. As a result, we first study the out-of-sample forecasting power for the aggregate

[12] Principal component analysis is often used in the accounting and finance literature to extract the systematic factors from a large set of variables (e.g., Connor and Korajczyk 1988; Ball et al. 2009).

market of *ASG*, and then examine the economic value of the return predictability of *ASG* from an asset allocation perspective.

4.2.1 Out-of-sample R^2

The key requirement for the out-of-sample analysis is that in order to forecast $r_{t,t+h}$, we can only use information available up to month *t*. Specifically, we recursively compute the out-of-sample forecast of the *h*-month-ahead average log excess return as

$$\hat{r}_{t,t+h} = \hat{\alpha}_t + \hat{\beta}_t ASG_t, \quad (5)$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates of α and β, respectively, in Equation (2) based on data from the beginning of the sample through month *t*.

We evaluate the out-of-sample forecasting performance based on the widely used Campbell and Thompson (2008) R^2_{OS} statistic, which measures the proportional reduction in mean squared forecast error (MSFE) for the out-of-sample predictive regression forecast relative to the historical mean return benchmark. In particular, the sample R^2_{OS} statistic when the forecast horizon is *h* months is defined as:

$$R^2_{OS} = 1 - \frac{\sum_{t=p}^{T-h}\left(r_{t,t+h} - \hat{r}_{t,t+h}\right)^2}{\sum_{t=p}^{T-h}\left(r_{t,t+h} - \bar{r}_t\right)^2}, \quad (6)$$

where *p* is a fixed number chosen for the initial sample training and the benchmark forecast $\bar{r}_t$ is the monthly average log excess return from the beginning of the sample through month *t*,

$$\bar{r}_t = \frac{1}{t}\sum_{s=1}^{t} r_s . \quad (7)$$

If *ASG*'s out-of-sample return predictability is inferior (superior) to that of the historical return mean, its mean squared forecast error, MSFE, should be lower (higher) than that of $\bar{r}$, and thus the R^2_{OS} statistic should be negative (positive). In particular, Clark and West (2007) develop a MSFE-adjusted statistic to test the null hypothesis $H_0: R^2_{OS} \leq 0$ against the alternative hypothesis $H_A: R^2_{OS} > 0$.

We follow the suggestion in Goyal and Welch (2008) and Goyal et al. (2024) to have the out-of-sample period start 20 years after the in-sample estimation period, i.e., p = 240 in Equation (6). In particular, we use the data over January 1985 through December 2004 as the initial estimation period, so the out-of-sample evaluation period spans over January 2005 through December 2023. In addition, for comparison we perform the out-of-sample analysis for each of the 6 *AEG* measures as well as the 14 economic variables in Goyal and Welch (2008) following the same procedure.

Table 6 presents the out-of-sample R^2_{OS} statistics as well as the statistical significance based on the Clark and West (2007) statistics for *ASG*, the 6 *AEG* measures, and the 14 economic variables. The first row shows that the out-of-sample R^2_{OS} statistics of *ASG* are all positive and statistically significant across all four forecast horizons, suggesting that out-of-sample forecasts based on *ASG* deliver a lower average forecasting error than the historical average return forecast. In particular, R^2_{OS} is 1.82%, 5.29%, 9.51%, and 13.68% at the monthly, quarterly, semi-annual, and annual horizons, respectively. By contrast, we find that none but one of the other 20 variables consistently outperform the historical average return benchmark in terms of MSFE at all forecast horizons. The only exception is the book-to-market ratio (*BM*), which produces significant R^2_{OS} statistics of 0.79%, 2.64%, 4.57%, and 7.49% at the monthly, quarterly, semi-annual, and annual horizons. However, these statistics are still below those of *ASG*.

In sum, Table 6 shows that *ASG* exhibits significant out-of-sample return predictability across all four forecast horizons, suggesting that its in-sample forecasting power for the aggregate market does not stem from a statistical fluke.

4.2.2 Asset allocation

We now turn to implementable investor allocation decisions which rely on *ASG*. In particular, we examine whether investors can construct a viable trading strategy via the out-of-sample forecasts based on *ASG* in real time. Suppose a risk-averse investor with quadratic mean-variance utility function invests her wealth in the stock market and the one-month T-bill. At the end of month t, she allocates a portion of w_t to the stock market (and thus $1 - w_t$ to the T-bill) to maximize her expected utility in month t+1

$$U = E(R_{p,t+1}) - \frac{\gamma}{2} Var(R_{p,t+1}), \tag{8}$$

where R_p is the return of the investor's portfolio and γ is investor's coefficient of relative risk aversion.[13] The optimal portfolio weight of this maximization problem is

$$w_t^* = \frac{1}{r} \frac{\hat{R}_{t,+1}}{\hat{\sigma}_{t+1}^2}, \tag{9}$$

where $\hat{R}_{t,+1}$ and $\hat{\sigma}_{t+1}^2$ are the investor's estimates of the mean and variance of market excess returns based on information up to month t.[14]

We assume that the investor always uses a ten-year rolling window of past monthly market excess returns to estimate $\hat{\sigma}_{t+1}^2$, so w_t^* differs only because of the different $\hat{R}_{t+1}$ forecasts in month t. Specifically, at the end of month t, the investor can estimate $\hat{R}_{t+1}$ either via the prevailing mean excess return (the historical average market excess return from the beginning of the sample through month t), or via the out-of-sample forecast

[13]The investor's portfolio return in month t+1 is $w_t R_{t+1}$+$R_{f,t+1}$, where R and R_f are the market excess return and risk-free rate, and $R_{f,t+1}$ is known at t.

[14]Here we forecast the simple excess return instead log excess return for the asset allocation analysis.

$\hat{R}_{t,+1} = \hat{\alpha}_t + \hat{\beta}_t X_t$ based on a predictor *X*, where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates of α and β estimated recursively from a regression of R_{t+1} on X_t based on data from the beginning of the sample through month *t*.

Then we consider *X* to be either *ASG*, one of the 6 *AEG* measures, or one of the 14 economic variables in Goyal and Welch (2008). Following the setup in the previous section, we use the data over January 1985 through December 2004 as the initial estimation period, and the data over January 2005 through December 2023 as the out-of-sample forecast evaluation period.

The certainty equivalent return (CER) of the investor's portfolio is

$$CER = \hat{\mu}_p - \frac{\gamma}{2}\hat{\sigma}_p^2, \tag{10}$$

where $\hat{\mu}_p$ and $\hat{\sigma}_p^2$ are the mean and variance of the investor's portfolio return over the forecast evaluation period. The CER can be interpreted as the risk-free compensation to the investor for holding the risky market portfolio. Next, we compute the CER gain as the difference between the CER for the investor when she uses the predictive regression forecast based on a predictor (*ASG*, or *AEG*, or economic variable) in asset allocation, and the CER when she uses the prevailing average excess return forecast. We multiply the CER gain by 12 so that we can interpret it as the annual portfolio management fee that an investor would be willing to pay to access the predictive regression forecasts in place of the prevailing mean excess return forecasts.

Table 7 reports the CER gain (in %) and annualized Sharpe ratio of the investor's portfolio when she utilizes *ASG*, one of the 6 *AEG* measures, one of the 14 economic variables, or a buy-and-hold portfolio[15] that passively holds the market portfolio in asset allocation for the forecast evaluation period, respectively. The Sharpe ratio of the portfolio is defined as the mean portfolio return in excess of the risk-free rate divided by the standard deviation of the excess portfolio return. We consider two coefficients of relative risk aversion (γ = 3 or 5), and restrict w_t to be positive (shorting is not allowed) and to not exceed 150%.

We find that *ASG* provides an annualized CER gain of 4.41% when $\gamma = 3$, indicating that an investor with a relative risk aversion of three would be willing to pay an annual portfolio management fee of 4.41% to have access to the predictive regression forecasts based on *ASG*, instead of using the historical average return forecast. In contrast, while buy-and-hold strategy and some of the 20 variables deliver positive CER gains, those gains are much smaller compared to that of *ASG*. In addition, *ASG* produces the highest annualized Sharpe ratio (= 0.71). These findings persist when we assume a more risk-averse investor ($\gamma = 5$).

Overall, the results in Table 7 indicate that from an asset allocation perspective, the forecasting power of *ASG* has considerable economic value for a risk-averse investor. The performance of *ASG* stands out as its CER gains and Sharpe ratios perform the best among all the alternatives we consider.

5 Economic channels

Having documented the strong return predictive power of *ASG* in both in-sample and out-of-sample tests, we proceed to explore the economic source of *ASG*'s return predictability. To begin with, we follow Campbell (1991)'s approach to decompose future

[15] Löffler (2022) and Goyal et al. (2024) show that a buy-and-hold strategy is a stringent benchmark to beat.

market return into three components:

$$R_{t+1} = E_t[R_{t+1}] + (E_{t+1} - E_t)\left[\sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}\right] - (E_{t+1} - E_t)\left[\sum_{j=0}^{\infty} \rho^j \Delta R_{t+1+j}\right]$$

$$= E_t[R_{t+1}] + N_{CF,t+1} - N_{R,t+1}, \tag{11}$$

where R_{t+1} denotes log market return in month $t + 1$, Δd_t denotes log dividend growth in month t, ρ is a log linearization constant (the inverse of 1 plus the mean dividend yield), and $E[\cdot]$ is the expectation operator. The three components of future market return are: expected return ($E_t[R_{t+1}]$), future cash flow news ($N_{CF,t+1}$) that captures changes in expected cash flows, and future discount rate news ($N_{R,t+1}$) that captures changes in expected returns.

Based on this framework, the relation between *ASG* and future market returns can be expressed as follows:

$$cov(R_{t+1}, ASG_t) = cov(E_t[R_{t+1}], ASG_t) + cov(N_{CF,t+1}, ASG_t) - cov(N_{R,t+1}, ASG_t). \tag{12}$$

From above we see that the relation between *ASG* and future market returns is driven by the association between *ASG* and contemporaneous expected returns (the expected return channel), the association between *ASG* and future cash flow news (the cash flow channel), and the association between *ASG* and future discount rate news (the discount rate channel).

If the expected return channel is the main driver for the negative relation between *ASG* and future market returns, then *ASG* should be negatively related to contemporaneous expected returns according to Equation (12). In addition, controlling for contemporaneous expected returns should largely subsume *ASG*'s return predictive power. In Table 2, we indeed find a negative correlation coefficient between *ASG* and the log dividend-price ratio, a standard expected return measure in the literature (e.g., Campbell and Shiller 1988;

Cochrane 1992; Greenwood and Shleifer 2014). However, the bivariate predictive regression in Table 5 shows that when controlling for the log dividend-price ratio, the estimated slopes on ASG remain significantly negative. Hence, we dismiss the expected return channel as the primary channel through which ASG negatively predicts future market returns.

Next, we explore the cash flow channel and the discount rate channel. For the cash flow channel to contribute to the negative relation between ASG and future market return, the association between ASG and future cash flow news should be negative; i.e., $cov(N_{CF,t+1}, ASG_t) < 0$. For the discount rate channel to contribute to the negative relation between ASG and future market return, the association between ASG and future discount rate news should be positive $(cov(N_{R,t+1}, ASG_t) > 0)$.

Our empirical design for testing the cash flow and discount rate channels is as follows. We begin by defining for each month t, the next one, two, three, and four quarters as the periods [t + 1, t + 3], [t + 4, t + 6], [t + 7, t + 9], and [t + 10, t + 12], respectively. Then, we examine whether ASG in month t negatively predicts measures of cash flow, and/or positively predicts discount rate news in the next one to four quarters. In particular, we run the following predictive regression for h = 3, 6, 9, and 12:

$$CF/DR\ news_{t+h-2,t+h} = \alpha + \beta ASG_t + \sum_i \beta_i Control\ Variables_i + \varepsilon_{t+h}. \quad (13)$$

To control for potential serial correlation (e.g., Gallo et al. 2016; Shivakumar and Urcan 2017), we include four lags of the dependent variable in the prior four quarters as control variables (i.e., $CF/DR\ news_{t-2,t}$, $CF/DR\ news_{t-5,t-3}$, $CF/DR\ news_{t-8,t-6}$, and $CF/DR\ news_{t-11,t-9}$). If the cash flow channel contributes to ASG's negative return predictability, β should be significantly negative. If the discount rate channel contributes to *ASG*'s negative return predictability, β should be significantly positive.

5.1 The cash flow channel

That channel argues investors tend to form overly optimistic expectations about future aggregate earnings prospects during periods of high *ASG*, which leads to negative aggregate earnings surprises.[16] The cash flow channel would be supported if *ASG* is associated with lower future cash flow innovations. We therefore examine whether *ASG* negatively predicts aggregate earnings surprises based on two proxies: a seasonal random walk model (e.g., Sadka 2007; Sadka and Sadka 2009); and aggregate analyst-based earnings surprises in the next one to four quarters.

5.1.1 Aggregate earnings surprise based on a seasonal random walk model

We compute aggregate earnings surprise based on a seasonal random walk model in months [t + h - 2, t + h], where h takes one of four possible values: 3, 6, 9, 12. First, we locate all firms in our sample issuing quarterly earnings announcements during months [t + h - 2, t + h] with non-missing earnings, book value of equity, and market capitalization in the four quarters prior.[17] Next, we compute firm-level earnings surprise as the seasonally differenced earnings (earnings minus earnings four quarters prior), and scale by either the absolute value of earnings, book value of equity, or market value of equity four quarters prior. We then compute aggregate earnings surprise as the cross-sectional value-weighted or its equal-weighted average counterpart.[18] We denote the aggregate earnings

[16]The "errors-in-expectations" hypothesis is related to prior research (e.g., Lakonishok et al. 1994; La Porta et al. 1997; Doukas et al. 2002) studying the value premium in the cross-section of stocks. These papers argue that investors are too optimistic (pessimistic) about future earnings prospects of glamour (value) stocks, and the future return difference is driven by the correction of expectation errors. Our paper differs from those studies by studying how *aggregate* expectation errors for future *aggregate* earnings prospects contribute to the negative relation between *ASG* and future market excess returns.

[17]We use Compustat item RDQ to locate the earnings announcement date.

[18]Value weights are calculated as the market capitalization in month t + h - 3. We use the beginning-of-

surprise: $AES_{t+h-2,t+h}$,

To explore the relation between *ASG* and aggregate earnings surprises, we estimate the following time- series regressions using observations from January 1985 to December 2023:

$$AES_{t+h-2,t+h} = \alpha + \beta ASG_t + \sum_i \beta_i Control\ Variables_i + \varepsilon_{t+h}, \quad (14)$$

where the control variables are the aggregate earnings surprises in the past four quarters ($AES_{t-2,t}$, $AES_{t-5,t-3}$, $AES_{t-8,t-6}$, and $AES_{t-11,t-9}$). We run the regression separately for all four horizons h, equal to 3, 6, 9, or 12. All independent variables are standardized to have mean zero and unit variance. If *ASG* predicts lower aggregate cash flow news as represented by lower aggregate earnings surprises based on a seasonal random walk model, the slope β should be negative.

Table 8 reports the OLS estimates of β, the corresponding Newey and West (1987) *t*-statistics, and R^2 statistics from predictive regressions in Equation (14). We find that *ASG* is negatively and significantly related to aggregate earnings surprises based on a seasonal random walk model in the next one to four quarters across different scaling or aggregating methods. In addition, the negative relation persists after the inclusion of control variables. In other words, *ASG* has a negative impact on aggregate earnings surprises, and this effect is incremental to the well-documented autocorrelation in aggregate earnings surprises (e.g., Kothari et al. 2006; Kalay et al. 2014).

Overall, the results in Table 8 provide preliminary evidence for the cash flow channel. The ability of *ASG* to negatively predict market returns in the next one to twelve months is strongly related to AGS's ability to forecast unpleasant cash flow news in the

period market capitalization as value weights following Sadka and Sadka (2009).

next one to four quarters.

5.1.2 Aggregating earnings surprise based on analysts' earnings forecasts

We offer an alternative measure of earnings surprise based on investor expectations formed from analysts' forecasts. Since analysts' earnings forecasts are dynamic in nature we can examine a sharper "errors-in-expectations" hypothesis to buttress the cash flow channel.

For each month *t* we define the *h*-month-ahead aggregate analyst-based earnings surprise ($AAES_{t+h-2,t+h}|_t$) as follows. We locate all firms in our sample issuing quarterly earnings announcements during months [t + h - 2, t + h] with non-missing earnings, book value of equity, and market capitalization four quarters prior. For each firm we obtain analysts' mean consensus quarterly earnings per share (EPS) forecasts in month *t* from (I/B/E/S) where available.[19] For a given firm in month *t*, we have at most four mean consensus EPS forecasts, reflecting analysts' average EPS expectations for the firm's next one to four quarters.

Next, we compute firm-level earnings surprise as the difference between quarterly reported earnings and analyst's expected earnings, scaled by one of three variables, each four quarters prior: the absolute of earnings, or book value of equity, or market value of equity. Finally, we compute aggregate analyst-based earnings surprise as the cross-sectional value-weighted or equal-weighted average of firm-level earnings surprise. For the value-weighted version, weights are calculated as the market capitalization in month t + h – 3.

To investigate the relation between *ASG* and aggregate analyst-based earnings

[19]The results are robust to the use of the median consensus EPS forecasts.

surprises in the next one to four quarters, we estimate the following time-series regressions for h = 3, 6, 9, and 12 using observations from January 1985 to December 2023:

$$AAES_{t+h-2,t+h}|_t = \alpha + \beta ASG_t + \sum_i \beta_i Control\ Variables_i + \varepsilon_{t+h}\,, \qquad (15)$$

where the control variables are the aggregate analyst-based earnings surprises in the past four quarters.[20] All independent variables are standardized to have mean zero and unit variance. If *ASG* negatively predicts future stock returns because it reflects correction of mispricing due to cash flow expectation error, β should be negative.

Table 9 reports the OLS estimates of β, the corresponding Newey and West (1987) *t*-statistics, and R^2 statistics from predictive regressions in Equation (15). We find that the slope estimates of β are mostly negative and statistically significant in the next one to four quarters across different scaling and aggregating methods, with or without the inclusion of control variables. The findings mostly indicate that *ASG* reflects overly optimistic expectation errors for future cash flows, and these expectation errors are a driver for the predictive power of *ASG* for future stock returns.

5.2 The discount rate channel

In this section, we investigate whether the discount rate channel plays a role in *ASG*'s negative return predictability. To do so we examine the relation between *ASG* and future discount rate innovations. We define two measures of discount rate news following Shivakumar and Urcan (2017): one based on Consumer Price Index (CPI) that reflects price changes of consumer goods; the other based on Producer Price Index (PPI) that reflects price changes of production goods. Both series are obtained from FRED system of St.

[20] We use aggregate analyst-based earnings of the same forecast horizon as control variables, i.e., $AAES_{t-2,t}|_{t-h}, AAES_{t-5,t-3}|_{t-3-h}, AAES_{t-8,t-6}|_{t-6-h}, and\ AAES_{t-11,t-9}|_{t-9-h}$.

Louis Fed. Specifically, CPI inflation is the percentage change in the seasonally adjusted CPI for All Urban Consumers, and PPI inflation is the percentage change in the seasonally adjusted PPI for final demand for finished goods. We compute for each month t the h-month ahead growth in CPI (PPI) inflation as the cumulative CPI (PPI) inflation during month $[t + h - 2, t + h]$.

To study the relation between *ASG* and CPI inflation (PPI inflation) in the next four quarters, we estimate the following time series regressions (separately) for $h = 3$, 6, 9, and 12, using observations from January 1985 to December 2023:

$$\Delta CPI_{t+h-2,t+h} = \alpha + \beta ASG_t + \sum_i \beta_i Control\ Variables_i + \varepsilon_{t+h}, \tag{18}$$

and

$$\Delta PPI_{t+h-2,t+h} = \alpha + \beta ASG_t + \sum_i \beta_i Control\ Variables_i + \varepsilon_{t+h}, \tag{19}$$

where $\Delta CPI_{t+h-2,t+h}$ is the h-month ahead CPI inflation and $\Delta PPI_{t+h-2,t+h}$ is the h-month ahead PPI inflation. The control variables are CPI inflation in the past four quarters (i.e., $\Delta CPI_{t-2,t}$, $\Delta CPI_{t-5,t-3}$, $\Delta CPI_{t-8,t-6}$, and $\Delta CPI_{t-11,t-9}$) in Equation (18), and PPI inflation in the past four quarters (i.e., $\Delta PPI_{t-2,t}$, $\Delta PPI_{t-5,t-3}$, $\Delta PPI_{t-8,t-6}$, and $\Delta PPI_{t-11,t-9}$) in Equation (19). We standardize all independent variables to have mean zero and unit variance.

Table 10 reports the OLS estimates of β, the corresponding Newey and West (1987) t-statistics, and R^2 statistics from predictive regressions in Equations (18) and (19). First, *ASG* is positively related to CPI inflation in the next quarter, providing some support of the discount rate channel. However, *ASG* is unrelated to CPI inflation in the next two to four quarters or PPI inflation in the next one to three quarters. Since the relation between *ASG* and the two inflation measures is mostly weak, we conclude that the discount rate channel contributes very little to *ASG*'s negative return predictability.

6 Robustness tests

6.1 Aggregate sales growth and aggregate investment

We examine whether *ASG*'s return predictability resembles that of aggregate investment growth's effect. To make this comparison we consider two investment measures based on prior work: total asset growth (Cooper et al. 2008), and net operating assets growth (Arif and Lee 2014). Both papers conclude that the predictive power of investment growth reflects behavioral bias, and specifically that larger asset growth leads investors to over-optimism (and subsequent disappointment). This behavioral bias interpretation is also potentially applicable to our *ASG* results, and so we control for both measures. But there are important caveats to be made.

Investment growth need not always result in sales growth. Sufficient demand conditions must be present, and there is obvious uncertainty about the lag between investment and sales with important variation across industries and firms. These potential contaminants motivate our direct approach that uses *ASG*. Moreover, investment by one firm may imply sales by another firm (B2B) which raises further contamination questions. Finally, our documented evidence of a cash flow channel is more consistent with use of sales growth to predict stock returns.

We compute aggregate total assets growth (*ATAG*) and aggregate net operating assets growth (*ANOAG*) as the cross-sectional value-weighted average of individual firms' one-year total assets growth and one-year net operating assets growth, respectively. Next, we perform the analogous analyses of Table 5 (in-sample bivariate predictive regressions), Table 6 (out-of-sample R_{OS}^2), and Table 7 (out-of-sample CER gain and Sharpe ratio) using

ATAG and *ANOAG* as return predictors. We report results in Panel A, Panel B, and Panel C of Table 11, respectively.

In Panel A when *ASG* and *ATAG* are both included in the predictive regression, the coefficients on *ASG* (β) are significantly negative at the 10% level at the quarterly, semi-annual, and annual forecast horizons, while the coefficient on *ATAG* (ϕ) is significantly negative at the 1% level only at the annual forecast horizon. When *ASG* and *ANOAG* are both included in the predictive regression, the coefficients on *ASG* are significantly negative at the 10% level at the quarterly and semi-annual forecast horizons, while the coefficient on *ANOAG* is significantly negative at the 10% level at the annual forecast horizon. The results indicate that *ASG* retains incremental explanatory power for future market excess returns when aggregate investment measures are included in the predictive regressions.

More importantly, *ASG* dominates aggregate investment growth in out-of-sample tests. In Panels B and C, we find that the out-of-sample R^2_{OS}, CER gain, and Sharpe ratio of *ATAG* and *ANOAG* are lower than that of *ASG* across all forecast horizons. Given the requirement of no look-ahead bias in OOS tests, these results give us confidence in the strength of the *predictive* power of *ASG* relative to investment measures.

6.2 Aggregate sales growth via the equal-weighting method

We use the equal-weighting method to aggregate firm-level one-year sales growth to the market level, which alleviates the domination of large-cap stocks in shaping aggregate sales growth. Then we examine whether the equal-weighted aggregate sales growth (*ASG_EW*) continues to negatively predict future market excess returns by running the regressions in Equation (2). Table 12 reports the results. We find that the estimated coefficient on *ASG_EW* remains negative and statistically significant. In particular, a one-standard-deviation increase in *ASG* leads to a decrease of 6.12%, 6.24%, 6.00%, and 5.28% in future annualized excess return at the quarterly, semi-annual, and annual horizons, respectively. In addition, the IVX-Wald statistics are all significant at the 5% level. Hence, we show that the negative return-predicting power of aggregate sales growth is not driven solely by large firms.

6.3 Alternative methods to compute standard errors

We employ alternative methods to account for serial correlation in regression residuals caused by overlapping data. In particular, we compute p-value based on Hodrick (1992) standard errors which uses the moving-average structure of the aggregated error as well as fixed-regressor wild bootstrapped p-value (1,000 simulations) following the approach in Rapach et al. (2016). We again test the null hypothesis $H_0: \beta = 0$ against the alternative hypothesis $H_A: \beta < 0$ for *ASG* in Equation (2). Table 13 reports the results, and we find that the negative relation between value-weighted (and equal-weighted) *ASG* and future market excess returns continues to be statistically significant across all forecast horizons.

6.4 Different out-of-sample periods

Since out-of-sample tests are sensitive to sample split dates and different papers make their own choices, we consider two alternative out-of-sample periods (January 2010 to December 2023 and January 2015 to December 2023). Re-running the tests in Table 6 (out-of-sample R^2_{OS} statistics) and Table 7 (CER gains and Sharpe ratios), we offer new results with new out-of-sample periods in Table 14 and Table 15, respectively.[21]

[21]The two out-of-sample periods correspond to p=300 (25 years) and p=360 (30 years) in Equation (6). We

In Table 14 we find that *ASG* continues to produce significant out-of-sample R_{OS}^2 statistics of 1.95% (1.99%), 8.30% (8.59%), 18.21% (18.76%), 26.83% (23.52%) at the monthly, quarterly, semi-annual, and annual forecast horizons during the out-of-sample period of January 2010 to December 2023 (January 2015 to December 2023). By contrast, none of the 22 variables (6 *AEG* measures, 14 economic variables, *ATAG*, and *ANOAG*) produces significantly positive R_{OS}^2 in the two out-of-sample periods. In Table 15 we find that *ASG* also continues to outperform from an asset allocation perspective, since its CER gains and Sharpe ratios are larger than those of the 22 variables in the two out-of-sample periods. Hence, we conclude that the out-of-sample return-predicting ability of *ASG* is robust to alternative out-of-sample forecast evaluation periods.

7 Conclusion

This paper examines the price-relevant information contained in aggregate sales growth (*ASG*). We find that *ASG* is a statistically and economically significant stock market return predictor. Specifically, *ASG* negatively predicts future market excess returns at the monthly, quarterly, semi-annual, and annual horizons. In addition, the predictive power of *ASG* is greater than that of aggregate earnings growth as well as the macroeconomic predictors in Goyal and Welch (2008), and remains largely unchanged after controlling for them. In out-of-sample tests, *ASG*'s return forecasting power continues to stand out: it produces significant out-of-sample R-squared and sizeable economic gains for a mean-variance investor from asset allocation at the monthly to annual forecast horizons.

Campbell (1991)'s return decomposition suggests that the negative return

also include aggregate total assets growth (*ATAG*) and aggregate net operating assets growth (*ANOAG*) as predictors.

predictability of *ASG* arises from a cash flow (discount rate) channel if *ASG* negatively (positively) predicts future aggregate cash flow (discount rate) innovations. We find that high *ASG* is negatively related to aggregate earnings surprises, either based on a seasonal random walk model or based on analysts' earnings forecasts. In contrast, the relation between *ASG* and future inflation measures is weak. These findings suggest that *ASG*'s ability to predict lower market returns stems predominantly from the cash flow channel.

Overall, this paper studies the predictive content of *ASG* and thus adds to the growing literature studying the information content of accounting variables at the aggregate level in capital markets. Some questions remain unresolved in this paper. For example, why do aggregate earnings growth and *ASG* have different information content? Do other items on the income statement also exhibit return predictability at the aggregate level? We leave these interesting questions for future research.

Appendix: Definitions of ASG, 6 Measures of AEG, and 14 Economic Variables in Goyal and Welch (2008)

Variables	Descriptions
ASG	Aggregate sales growth, defined as the cross-sectional value-weighted average of individual firm's one-year sales revenue growth.
AEG1	The cross-sectional value-weighted average of individual firm's one-year earnings growth, where one-year earnings growth is annual earnings change scaled by the absolute value of one-year-lagged earnings.
AEG2	The cross-sectional equal-weighted average of individual firm's one-year earnings growth, where one-year earnings growth is annual earnings change scaled by the absolute value of one-year-lagged earnings.
AEG3	The cross-sectional value-weighted average of individual firm's one-year earnings growth, where one-year earnings growth is annual earnings change scaled by one-year-lagged book value of equity.
AEG4	The cross-sectional equal-weighted average of individual firm's one-year earnings growth, where one-year earnings growth is annual earnings change scaled by one-year-lagged book value of equity.
AEG5	The cross-sectional value-weighted average of individual firm's one-year earnings growth, where one-year earnings growth is annual earnings change scaled by one-year-lagged market value of equity.
AEG6	The cross-sectional equal-weighted average of individual firm's one-year earnings growth, where one-year earnings growth is annual earnings change scaled by one-year-lagged market value of equity.
DP	Log dividend-price ratio, calculated as the log of a 12-month moving sum of dividends paid on the S&P 500 index minus the log of prices on the S&P 500 index.
DY	Log dividend yield, calculated as the log of a 12-month moving sum of dividends paid on the S&P 500 index minus the log of lagged prices on the S&P 500 index.
EP	Log earnings-price ratio, calculated as the log of a 12-month moving sum of earnings on the S&P 500 index minus the log of prices on the S&P 500 index.
DE	Log dividend-payout ratio, calculated as the log of a 12-month moving sum of dividends paid on the S&P 500 index minus the log of a 12-month moving sum of earnings on the S&P 500 index.
SVAR	Stock variance, calculated as the sum of squared daily returns on the S&P 500 index.
BM	The book-to-market value ratio for the Dow Jones Industrial Average.
NTIS	Net equity expansion, calculated as the ratio of a 12-month moving sum of net equity issues by NYSE-listed stocks to the total end-of-year market capitalization of NYSE stocks.
TBL	Treasury bill rate, calculated as the interest rate on a three-month Treasury bill (secondary market).
LTY	The long-term government bond yield.
LTR	The return on long-term government bonds.
TMS	Term spread, calculated as the long-term yield on government bonds minus the Treasury bill rate.
DFY	Default yield spread, calculated as the difference between Moody's BAA- and AAA-rated corporate bond yields.
DFR	Default return spread, calculated as the long-term corporate bond return minus the long-term government bond return.
INFL	Inflation rate, calculated as the growth rate in CPI for all urban consumers. We use lagged 2-month inflation in the regression to account for the delay in CPI releases.
ATAG	Aggregate total assets growth, defined as the cross-sectional value-weighted average of individual firm's one-year total assets growth.
ANOAG	Aggregate net operating assets growth, defined as the cross-sectional value-weighted average of individual firm's one-year net operating assets growth.

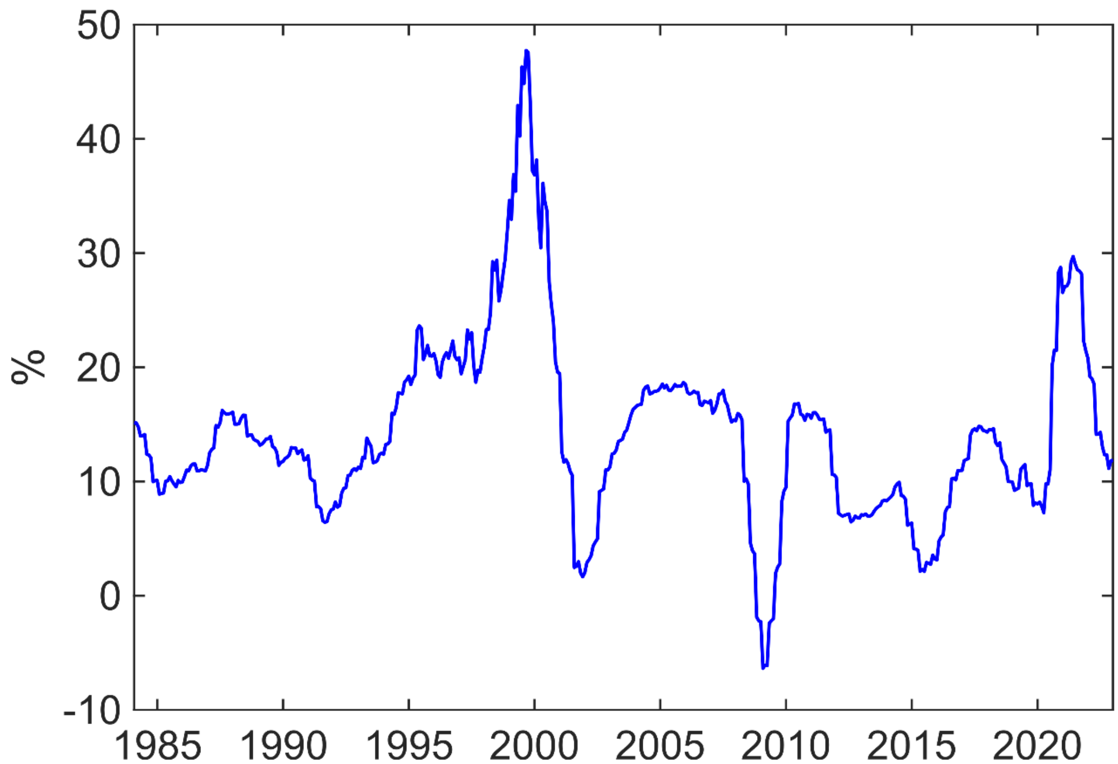

Figure 1. Aggregate Sales Growth. This figure plots the time series of aggregate sales growth (*ASG*) from January 1985 to December 2022. *ASG* is defined as the cross-sectional value-weighted average of individual firm's one-years sales revenue growth. See Section 3 for a detailed definition of *ASG*.

Table 1. Summary Statistics

Variable	Mean	Median	Min	Max	Std
ASG (%)	14.33	13.35	-6.37	47.74	8.05
AEG1 (%)	33.09	31.93	-71.14	136.91	32.53
AEG2 (%)	-17.97	-14.36	-271.24	104.29	50.91
AEG3 (%)	3.40	3.40	-5.29	18.54	3.32
AEG4 (%)	1.97	1.70	-11.03	23.60	4.66
AEG5 (%)	0.78	0.72	-6.68	6.81	1.51
AEG6 (%)	0.42	0.21	-13.61	16.15	3.72
DP	-3.87	-3.93	-4.52	-3.15	0.32
DY	-3.86	-3.93	-4.53	-3.09	0.32
EP	-3.07	-3.05	-4.84	-2.38	0.35
DE	-0.80	-0.88	-1.24	1.38	0.36
SVAR ($\times 10^2$)	0.28	0.14	0.02	7.32	0.61
BM	0.31	0.30	0.12	0.73	0.11
NTIS	0.05	0.05	0.01	0.12	0.02
TBL (%, ann.)	3.14	3.03	0.01	8.82	2.53
LTY (%, ann.)	5.25	4.98	0.62	12.09	2.44
LTR (%)	0.67	0.65	-11.24	14.43	2.96
TMS (%, ann.)	2.11	2.10	-1.57	4.55	1.38
DFY (%, ann.)	0.98	0.92	0.55	3.38	0.36
DFR (%)	0.01	0.04	-9.76	7.37	1.63
INFL (%)	0.23	0.23	-1.92	1.37	0.33

The table reports summary statistics for aggregate sales growth (*ASG*), 6 measures of aggregate earnings growth (*AEG*), and 14 economic variables from Goyal and Welch (2008). *ASG* is defined as the cross-sectional value-weighted average of individual firm's one-year sales revenue growth. *AEG* is defined as the cross-sectional value-weighted/equal-weighted average of individual firms' one-year earnings growth, where one-year earnings growth is annual earnings change scaled by the absolute value of one-year-lagged earnings, one-year-lagged book value of equity, or one-year-lagged market value of equity. The 14 economic variables are the log dividend-price ratio (*DP*), log earnings-price ratio (*EP*), log dividend-payout ratio (*DE*), stock variance (*SVAR*), book-to-market value ratio (*BM*), net equity expansion (*NTIS*), three-month treasury bill rate (*TBL*), long-term yield (*LTY*), long-term return (*LTR*), term spread (*TMS*), default yield spread (*DFY*), default return spread (*DFR*), and inflation (*INFL*). See Section 3 and Appendix for more details on the sample and variable constructions. The sample period is 1985:01-2023:12.

Table 2. Pairwise Correlation

	ASG	*AEG1*	*AEG2*	*AEG3*	*AEG4*	*AEG5*	*AEG6*	*DP*	*DY*	*EP*	*DE*	*SVAR*	*BM*	*NTIS*	*TBL*	*LTY*	*LTR*	*TMS*	*DFY*	*DFR*	*INFL*
ASG	1.00																				
AEG1	0.26	1.00																			
AEG2	0.22	0.85	1.00																		
AEG3	0.28	0.90	0.77	1.00																	
AEG4	-0.13	0.69	0.70	0.75	1.00																
AEG5	0.12	0.76	0.74	0.77	0.80	1.00															
AEG6	-0.03	0.70	0.74	0.70	0.88	0.87	1.00														
DP	-0.45	-0.24	-0.23	-0.23	0.00	-0.11	-0.20	1.00													
DY	-0.45	-0.24	-0.24	-0.23	0.00	-0.11	-0.20	0.99	1.00												
EP	-0.07	0.39	0.55	0.31	0.40	0.46	0.32	0.41	0.41	1.00											
DE	-0.32	-0.59	-0.74	-0.50	-0.39	-0.54	-0.48	0.46	0.46	-0.61	1.00										
SVAR	0.03	-0.06	-0.12	-0.06	-0.09	-0.08	-0.07	0.06	0.00	-0.16	0.20	1.00									
BM	-0.45	-0.20	-0.14	-0.18	0.10	-0.02	-0.07	0.88	0.88	0.48	0.30	0.02	1.00								
NTIS	0.04	0.17	0.12	0.19	0.30	0.22	0.27	-0.15	-0.15	-0.06	-0.07	-0.14	-0.20	1.00							
TBL	0.38	-0.06	-0.07	-0.08	-0.10	0.00	-0.17	0.40	0.40	0.40	-0.04	-0.09	0.31	0.01	1.00						
LTY	0.14	-0.15	-0.16	-0.14	0.03	0.02	-0.09	0.59	0.59	0.36	0.16	-0.07	0.53	0.22	0.85	1.00					
LTR	-0.02	0.03	0.03	-0.01	0.02	0.05	0.03	0.11	0.11	0.09	0.00	0.17	0.12	0.00	0.09	0.05	1.00				
TMS	-0.44	-0.16	-0.16	-0.11	0.25	0.03	0.16	0.32	0.31	-0.09	0.36	0.05	0.37	0.36	-0.34	0.21	-0.08	1.00			
DFY	-0.21	-0.39	-0.43	-0.32	-0.22	-0.32	-0.26	0.36	0.34	-0.30	0.60	0.39	0.39	-0.50	-0.14	-0.02	0.05	0.22	1.00		
DFR	-0.07	-0.11	-0.16	-0.09	-0.06	-0.09	-0.06	-0.03	0.02	-0.16	0.13	-0.29	-0.02	0.00	-0.06	-0.02	-0.49	0.06	0.09	1.00	
INFL	0.15	0.15	0.13	0.18	0.09	0.10	0.08	-0.01	-0.01	0.14	-0.15	-0.06	0.02	0.03	0.15	0.11	0.05	-0.07	-0.20	-0.11	1.00

The table displays Pearson correlation coefficients for aggregate sales growth (*ASG*), 6 measures of aggregate earnings growth (*AEG*), and the14 economic variables from Goyal and Welch (2008). *ASG* is defined as the cross-sectional value-weighted average of individual firm's one-year sales revenue growth. *AEG* is defined as the cross-sectional value-weighted/equal-weighted average of individual firms' one-year earnings growth, where one-year earnings growth is annual earnings change scaled by the absolute value of one-year-lagged earnings, one-year-lagged book value of equity, or one-year-lagged market value of equity. The economic variables are the log dividend-price ratio (*DP*), log earnings-price ratio (*EP*), log dividend-payout ratio (*DE*), stock variance (*SVAR*), book-to-market value ratio (*BM*), net equity expansion (*NTIS*), three-month treasury bill rate (*TBL*), long-term yield (*LTY*), long-term return (*LTR*), term spread (*TMS*), default yield spread (*DFY*), default return spread (*DFR*), and inflation (*INFL*). See Section 3 and Appendix for more details on the sample and variable constructions. The sample period is 1985:01-2023:12.

Table 3. Benchmark Predictive Regressions: Aggregate Sales Growth

	$h = 1$	$h = 3$	$h = 6$	$h = 12$
Intercept	0.59***	0.58***	0.59***	0.58***
	(2.77)	(3.20)	(3.46)	(3.72)
ASG	-0.56**	-0.57***	-0.57***	-0.55***
	(-2.57)	(-3.71)	(-4.32)	(-4.98)
R^2	1.47	4.59	9.27	17.10
IVX-Wald	6.24**	6.80***	7.05***	7.08***

The table presents the estimation results for the following predictive regression model:

$$r_{t,t+h} = \alpha + \beta ASG_t + \epsilon_{t,t+h}$$

where ASG_t is aggregate sales growth in month t and $r_{t,t+h} = (1/\text{h})(r_{t+h} + \cdot \cdot + r_{t+h})$ is the h-month-ahead average log excess return (in %) on the CRSP value-weighted index in month t. ASG is standardized to have zero mean and unit variance. See Section 3 for more details on the sample and variable constructions. For each regression, the table reports the regression coefficients, Newey and West (1987) heteroskedasticity- and autocorrelation-robust t-statistics in parentheses (h lags), R^2s (in %), and the IVX-Wald statistics of Kostakis et al. (2015). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1985:01-2023:12.

Table 4. Benchmark Predictive Regressions: Aggregate Earnings Growth and 14 Economic Variables

	$h=1$		$h=3$		$h=6$		$h=12$	
Predictor	ϕ	R^2	ϕ	R^2	ϕ	R^2	ϕ	R^2
AEG1	0.02	0.00	-0.01	0.00	-0.08	0.19	-0.11	0.67
	(0.08)		(-0.03)		(-0.42)		(-0.66)	
AEG2	-0.18	0.15	-0.19	0.51	-0.20	1.17	-0.18	1.83
	(-0.84)		(-0.98)		(-1.14)		(-1.30)	
AEG3	0.04	0.01	0.01	0.00	-0.02	0.01	-0.09	0.45
	(0.17)		(0.05)		(-0.10)		(-0.51)	
AEG4	0.07	0.03	0.11	0.16	0.11	0.31	0.03	0.07
	(0.32)		(0.50)		(0.49)		(0.19)	
AEG5	0.05	0.01	0.00	0.00	0.02	0.01	-0.06	0.19
	(0.22)		(0.00)		(0.09)		(-0.46)	
AEG6	-0.03	0.01	-0.04	0.02	0.02	0.01	-0.02	0.03
	(-0.16)		(-0.19)		(0.11)		(-0.16)	
DP	0.39*	0.73	0.41**	2.34	0.41**	4.63	0.41***	9.35
	(1.77)		(2.28)		(2.51)		(2.66)	
DY	0.42*	0.82	0.41**	2.30	0.40**	4.45	0.41***	9.25
	(1.95)		(2.30)		(2.46)		(2.62)	
EP	0.19	0.17	0.12	0.20	0.08	0.18	0.10	0.61
	(0.66)		(0.45)		(0.31)		(0.50)	
DE	0.15	0.11	0.24	0.78	0.27	2.11	0.25**	3.52
	(0.53)		(1.08)		(1.63)		(2.31)	
SVAR	-0.24	0.27	0.00	0.00	0.12	0.39	0.16**	1.41
	(-0.50)		(0.01)		(0.85)		(2.02)	
BM	0.39*	0.74	0.42**	2.48	0.42***	4.82	0.40***	8.75
	(1.90)		(2.54)		(2.67)		(2.64)	
NTIS	0.12	0.07	0.18	0.47	0.18	0.94	0.14	1.06
	(0.47)		(0.74)		(0.74)		(0.66)	
TBL	-0.11	0.06	-0.10	0.13	-0.11	0.32	-0.14	1.09
	(-0.49)		(-0.52)		(-0.62)		(-0.93)	
LTY	-0.15	0.10	-0.12	0.20	-0.10	0.26	-0.06	0.18
	(-0.65)		(-0.66)		(-0.59)		(-0.37)	

	$h=1$		$h=3$		$h=6$		$h=12$	
Predictor	ϕ	R^2	ϕ	R^2	ϕ	R^2	ϕ	R^2
LTR	0.18	0.15	0.12	0.19	0.17*	0.83	0.09*	0.48
	(0.79)		(0.77)		(1.90)		(1.79)	
TMS	-0.06	0.02	-0.03	0.02	0.03	0.02	0.18	1.59
	(-0.29)		(-0.18)		(0.15)		(1.11)	
DFY	-0.01	0.00	0.06	0.06	0.18	0.90	0.24*	3.15
	(-0.02)		(0.21)		(0.83)		(1.90)	
DFR	0.31	0.47	0.03	0.01	0.08	0.20	0.05	0.12
	(0.84)		(0.13)		(0.59)		(0.60)	
INFL	-0.23	0.25	-0.34**	1.57	-0.39**	4.22	-0.22**	2.62
	(-0.78)		(-2.02)		(-2.53)		(-2.30)	

The table presents the estimation results for the following predictive regression model:

$$r_{t,t+h} = \alpha + \phi Z_t + \epsilon_{t,t+h} \ ,$$

where Z_t is one of the 6 measures of aggregate earnings growth (*AEG)* or one of the Goyal and Welch (2008)'s 14 economic variables in month t, and $r_{t,t+h} = (1/h)(r_{t+h} +\cdot\cdot+ r_{t+h})$ is the h-month-ahead average log excess return (in %) on the CRSP value-weighted index. All predictors are standardized to have zero mean and unit variance. See Section 3 and Appendix for more details on the sample and variable constructions. For each regression, the table reports the regression coefficients, Newey and West (1987) heteroskedasticity- and autocorrelation-robust *t*-statistics in parentheses (h lags), and R^2s (in %). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1985:01-2023:12.

Table 5. Bivariate Predictive Regressions: Controlling for Aggregate Earnings Growth and Economic Variables

	$h=1$			$h=3$			$h=6$			$h=12$		
Predictor	β	ϕ	R^2	β	ϕ	R^2	β	ϕ	R^2	β	ϕ	R^2
AEG1	-0.60***	0.18	1.61	-0.61***	0.16	4.90	-0.59***	0.07	9.42	-0.56***	0.04	17.19
	(-2.63)	(0.80)		(-3.80)	(0.77)		(-4.33)	(0.41)		(-4.51)	(0.30)	
AEG2	-0.54**	-0.06	1.49	-0.56***	-0.07	4.65	-0.56***	-0.08	9.46	-0.53***	-0.06	17.31
	(-2.38)	(-0.27)		(-3.38)	(-0.35)		(-3.99)	(-0.46)		(-4.39)	(-0.49)	
AEG3	-0.61***	0.21	1.66	-0.62***	0.18	5.01	-0.61***	0.15	9.83	-0.57***	0.07	17.36
	(-2.64)	(0.91)		(-3.94)	(0.90)		(-4.93)	(0.76)		(-4.83)	(0.48)	
AEG4	-0.56***	0.00	1.47	-0.57***	0.03	4.60	-0.57***	0.03	9.29	-0.55***	-0.04	17.19
	(-2.62)	(0.00)		(-3.72)	(0.17)		(-4.21)	(0.16)		(-4.99)	(-0.34)	
AEG5	-0.57**	0.11	1.53	-0.58***	0.07	4.65	-0.58***	0.09	9.47	-0.55***	0.01	17.11
	(-2.54)	(0.51)		(-3.57)	(0.33)		(-4.33)	(0.55)		(-4.87)	(0.08)	
AEG6	-0.56***	-0.05	1.49	-0.57***	-0.06	4.63	-0.57***	0.00	9.27	-0.55***	-0.04	17.20
	(-2.59)	(-0.24)		(-3.77)	(-0.30)		(-4.31)	(0.02)		(-5.00)	(-0.38)	
DP	-0.48**	0.18	1.60	-0.49***	0.19	4.99	-0.49***	0.18	10.03	-0.46***	0.20	18.89
	(-1.99)	(0.75)		(-2.73)	(0.96)		(-3.14)	(1.06)		(-4.08)	(1.51)	
DY	-0.46*	0.21	1.63	-0.49***	0.18	4.96	-0.50***	0.17	9.92	-0.46***	0.19	18.78
	(-1.94)	(0.88)		(-2.77)	(0.93)		(-3.17)	(0.98)		(-4.09)	(1.44)	
EP	-0.55**	0.15	1.59	-0.57***	0.08	4.68	-0.57***	0.04	9.32	-0.54***	0.07	17.36
	(-2.52)	(0.55)		(-3.66)	(0.34)		(-4.27)	(0.18)		(-5.03)	(0.40)	
DE	-0.57**	-0.03	1.48	-0.55***	0.06	4.63	-0.54***	0.10	9.51	-0.52***	0.08	17.42
	(-2.29)	(-0.08)		(-3.06)	(0.21)		(-3.52)	(0.44)		(-4.33)	(0.58)	
SVAR	-0.55**	-0.22	1.70	-0.57***	0.02	4.59	-0.58***	0.14	9.80	-0.55***	0.17**	18.84
	(-2.53)	(-0.46)		(-3.72)	(0.05)		(-4.33)	(1.02)		(-4.99)	(2.36)	
BM	-0.48**	0.18	1.60	-0.48***	0.20	5.05	-0.49***	0.19	10.10	-0.47***	0.18	18.57
	(-2.04)	(0.83)		(-2.88)	(1.21)		(-3.30)	(1.24)		(-4.27)	(1.40)	
NTIS	-0.56***	0.14	1.57	-0.58***	0.21	5.17	-0.58***	0.20	10.44	-0.55***	0.16	18.53
	(-2.58)	(0.56)		(-3.72)	(0.83)		(-4.35)	(0.84)		(-5.04)	(0.79)	
TBL	-0.60**	0.12	1.53	-0.63***	0.14	4.83	-0.62***	0.13	9.69	-0.58***	0.08	17.44
	(-2.45)	(0.49)		(-3.48)	(0.68)		(-4.06)	(0.73)		(-4.75)	(0.59)	
LTY	-0.55**	-0.07	1.50	-0.57***	-0.04	4.61	-0.57***	-0.02	9.28	-0.55***	0.02	17.13
	(-2.45)	(-0.30)		(-3.54)	(-0.22)		(-4.16)	(-0.10)		(-4.96)	(0.17)	

Predictor	$h = 1$			$h = 3$			$h = 6$			$h = 12$		
	β	ϕ	R^2	β	ϕ	R^2	β	ϕ	R^2	β	ϕ	R^2
LTR	-0.55**	0.16	1.60	-0.57***	0.11	4.74	-0.57***	0.16*	9.99	-0.55***	0.08*	17.46
	(-2.55)	(0.74)		(-3.67)	(0.72)		(-4.25)	(1.89)		(-4.89)	(1.75)	
TMS	-0.73***	-0.39	2.06	-0.74***	-0.38*	6.11	-0.72***	-0.32*	11.40	-0.61***	-0.14	17.79
	(-2.93)	(-1.56)		(-4.07)	(-1.80)		(-4.51)	(-1.73)		(-4.70)	(-0.91)	
DFY	-0.58**	-0.13	1.55	-0.58***	-0.06	4.63	-0.56***	0.06	9.38	-0.52***	0.13	17.96
	(-2.55)	(-0.36)		(-3.51)	(-0.18)		(-3.94)	(0.26)		(-4.58)	(0.89)	
DFR	-0.54**	0.28	1.84	-0.57***	-0.01	4.59	-0.57***	0.05	9.34	-0.55***	0.01	17.11
	(-2.45)	(0.75)		(-3.74)	(-0.05)		(-4.31)	(0.34)		(-4.98)	(0.14)	
INFL	-0.53**	-0.15	1.58	-0.54***	-0.26	5.49	-0.53***	-0.31**	11.91	-0.53***	-0.14	18.12
	(-2.40)	(-0.53)		(-3.43)	(-1.58)		(-3.97)	(-2.01)		(-4.64)	(-1.31)	

The table presents the estimation results for the following predictive regression model:

$$r_{t,t+h} = \alpha + \beta ASG_t + \phi Z_t + \epsilon_{t,t+h} \ ,$$

where ASG_t is the aggregate sales growth in month *t*, Z_t is one of the 6 measures of aggregate earnings growth (*AEG*) or one of the Goyal and Welch (2008)'s 14 economic variables in month *t*, and $r_{t,t+h} = (1/\mathrm{h})(r_{t+h} + \cdot \cdot + r_{t+h})$ is the h-month-ahead average log excess return (in %) on the CRSP value-weighted index. All independent variables are standardized to have zero mean and unit variance. See Section 3 and Appendix for more details on the sample and variable constructions. For each regression, the table reports the regression coefficients, Newey and West (1987) heteroskedasticity- and autocorrelation-robust *t*-statistics in parentheses (*h* lags), and R^2s (in %). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1985:01-2023:12.

Table 6. Out-Of-Sample R-Squared

Predictor	$h = 1$	$h = 3$	$h = 6$	$h = 12$
ASG	1.82**	5.29***	9.51***	13.68***
AEG1	-1.86	-7.09	-8.66	-7.33
AEG2	-1.92	-8.37	-13.45	-17.29
AEG3	-3.59	-11.55	-19.27	-18.95
AEG4	-1.91	-6.89	-14.53	-24.45
AEG5	-2.07	-8.03	-12.47	-10.56
AEG6	-1.06	-4.78	-9.22	-14.81
DP	0.26	0.96	2.37	6.00*
DY	0.37	1.07	2.35	5.92*
EP	-2.80	-12.79	-24.07	-28.02
DE	-1.55	-6.33	-6.71	4.18
SVAR	-3.76	-5.58	-1.00	0.64
BM	0.79*	2.64**	4.57**	7.49*
NTIS	-0.57	-2.54	-5.83	-7.43
TBL	-0.53	-2.44	-4.54	-3.05
LTY	-0.47	-1.99	-4.68	-10.90
LTR	-0.28	-1.32	-0.28	0.07
TMS	-0.34	-0.96	-1.74	-1.40
DFY	-1.59	-8.57	-14.01	-0.41
DFR	-2.22	-3.77	-2.45	-2.14
INFL	-0.60	1.51**	4.48***	1.91*

The table presents the out-of-sample performance in predicting the h-month-ahead average log excess return on the CRSP value-weighted index using aggregate sales growth (*ASG*), one of the 6 measures of aggregate earnings growth (*AEG*), or one of the 14 economic variables in Goyal and Welch (2008). See Section 3 and Appendix for more details on the sample and variable constructions. We report Campbell and Thompson (2008) R^2_{OS} statistic, which measures the proportional reduction in mean squared forecast error (MSFE) for the out-of-sample predictive regression forecast relative to the historical mean return benchmark. All of the out-of-sample forecasts are estimated recursively using data available at the forecast formation month t. Statistical significance for R^2_{OS} is based on the p-value of the Clark and West (2007) MSFE-adjusted statistic for testing the null hypothesis $H_0: R^2_{OS} \leq 0$ against the alternative hypothesis $H_A: R^2_{OS} > 0$. The out-of-sample evaluation period is 2005:01 to 2023:12.

Table 7. Out-Of-Sample CER gains and Sharpe Ratios

	γ = 3		γ = 5	
Predictor	CER gain	Sharpe ratio	CER gain	Sharpe ratio
ASG	4.41	0.71	2.82	0.69
AEG1	0.67	0.51	-0.29	0.43
AEG2	1.79	0.57	1.20	0.56
AEG3	-0.13	0.46	-0.70	0.41
AEG4	-0.14	0.45	-0.27	0.42
AEG5	0.90	0.52	0.21	0.47
AEG6	-0.02	0.46	0.08	0.45
DP	0.08	0.47	0.24	0.47
DY	0.68	0.51	0.60	0.51
EP	2.08	0.59	1.46	0.59
DE	1.27	0.54	0.88	0.53
SVAR	2.01	0.59	1.06	0.55
BM	1.98	0.60	1.38	0.60
NTIS	-0.31	0.44	-0.04	0.44
TBL	0.27	0.48	-0.04	0.45
LTY	0.29	0.48	-0.41	0.43
LTR	-0.28	0.45	-1.07	0.38
TMS	-0.46	0.44	-0.36	0.42
DFY	-0.22	0.45	-0.10	0.44
DFR	1.82	0.58	0.86	0.53
INFL	-0.05	0.46	-0.03	0.45
Buy-and-hold	1.37	0.55	0.48	0.55

The table reports the annualized certainty equivalent return gain (CER gain, in %) and the annualized Sharpe ratio of a mean-variance investor with relative risk aversion coefficient of three or five (γ = 3 or 5) who allocates her wealth monthly between the stock market and the risk-free asset by applying the out-of-sample forecasts based on *ASG*, one of the 6 measures of aggregate earnings growth (*AEG*), or one of the 14 economic variables in Goyal and Welch (2008). See Section 3 and Appendix for more details on the sample and variable constructions. The CER gain is the difference between the CER for the investor when she uses the predictive regression forecast based on a predictor to form out-of-sample forecasts in asset allocation and the CER when she uses the prevailing average excess return forecasts. Sharpe ratio is the average portfolio excess return divided by its standard deviation. The equity weight is constrained to lie between 0 (no short sales) and 1.5. Buy-and-hold corresponds to the investor passively holding the market portfolio. The out-of-sample evaluation period is 2005:01 to 2023:12.

Table 8. Aggregate Sales Growth and Aggregate Earnings Surprises

Panel A: *AES* (value-weighted, scaled by the absolute of earnings four quarters prior)								
	$AES_{t+1,t+3}$		$AES_{t+4,t+6}$		$AES_{t+7,t+9}$		$AES_{t+10,t+12}$	
ASG_t	-7.21*	-3.06	-11.25***	-6.61**	-13.27***	-8.98**	-13.22***	-10.66**
	(-1.85)	(-1.41)	(-2.75)	(-1.96)	(-3.59)	(-2.26)	(-3.65)	(-2.52)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	2.92	50.50	7.50	30.38	10.55	19.32	10.06	13.56

Panel B: *AES* (equal-weighted, scaled by the absolute of earnings four quarters prior)								
	$AES_{t+1,t+3}$		$AES_{t+4,t+6}$		$AES_{t+7,t+9}$		$AES_{t+10,t+12}$	
ASG_t	-10.56***	-6.37***	-16.69***	-11.57***	-20.68***	-16.32***	-22.43***	-20.03***
	(-2.97)	(-3.21)	(-4.11)	(-3.82)	(-5.32)	(-4.42)	(-6.27)	(-5.34)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	3.42	51.02	8.87	30.40	13.62	20.26	15.38	17.23

Panel C: *AES* (value-weighted, scaled by book value of equity four quarters prior)								
	$AES_{t+1,t+3}$		$AES_{t+4,t+6}$		$AES_{t+7,t+9}$		$AES_{t+10,t+12}$	
ASG_t	-0.29***	-0.14**	-0.40***	-0.28***	-0.46***	-0.40***	-0.45***	-0.46***
	(-2.63)	(-1.98)	(-3.63)	(-2.79)	(-4.34)	(-3.36)	(-4.00)	(-3.53)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	7.29	50.81	14.04	32.24	18.23	24.74	16.63	20.02

Panel D: *AES* (equal-weighted, scaled by book value of equity four quarters prior)								
	$AES_{t+1,t+3}$		$AES_{t+4,t+6}$		$AES_{t+7,t+9}$		$AES_{t+10,t+12}$	
ASG_t	-0.72***	-0.36***	-0.73***	-0.57***	-0.65***	-0.68***	-0.53***	-0.72***
	(-4.99)	(-4.09)	(-5.39)	(-4.23)	(-3.99)	(-5.02)	(-3.54)	(-3.77)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	25.05	51.95	26.01	36.24	20.63	28.17	13.26	24.45

Panel E: *AES* (value-weighted, scaled by market value of equity four quarters prior)								
	$AES_{t+1,t+3}$		$AES_{t+4,t+6}$		$AES_{t+7,t+9}$		$AES_{t+10,t+12}$	
ASG_t	-0.15**	-0.09**	-0.17**	-0.15**	-0.17***	-0.16***	-0.15***	-0.15***
	(-2.03)	(-2.02)	(-2.55)	(-2.49)	(-3.62)	(-3.24)	(-5.01)	(-3.98)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	7.41	34.08	9.52	14.31	9.22	11.86	6.35	11.08

Panel F: *AES* (equal-weighted, scaled by market value of equity four quarters prior)								
	$AES_{t+1,t+3}$		$AES_{t+4,t+6}$		$AES_{t+7,t+9}$		$AES_{t+10,t+12}$	
ASG_t	-0.49***	-0.26***	-0.47***	-0.39**	-0.39***	-0.40***	-0.27***	-0.35**
	(-2.58)	(-3.23)	(-2.77)	(-2.43)	(-3.21)	(-2.70)	(-2.72)	(-2.57)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	12.62	37.96	11.63	17.80	7.70	11.99	3.39	9.18

This table reports the estimation results for the regressions of the h-month ahead (h = 3, 6, 9, and 12) aggregate earnings surprise based on a seasonal random walk model ($AES_{t+h-2,t+h}$, in %) on aggregate sales growth (*ASG*) in month t:

$$AES_{t+h-2,t+h} = \alpha + \beta ASG_t + \sum_i \beta_i \, Control\,Variables_i + \varepsilon_{t+h},$$

where *ASG* is the aggregate sales growth and the control variables are the aggregate earnings surprises in the past four quarters (i.e., $AES_{t-2,t}$, $AES_{t-5,t-3}$, $AES_{t-8,t-6}$, and $AES_{t-11,t-9}$). The aggregate earnings surprises are calculated as the cross-sectional value-weighted/equal-weighted average of firm-level earnings surprises (seasonally differenced earnings scaled by either the absolute value of earnings, book value of equity, or market value of equity four quarters prior). See Section 5.1.1 for more details on variable constructions. All independent variables are standardized to have zero mean and unit variance. For each regression, the table reports the regression coefficients, Newey and West (1987) heteroskedasticity- and autocorrelation-robust t-statistics in parentheses (h lags), and R^2s (in %). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1985:01 to 2023:12.

Table 9. Aggregate Sales Growth and Aggregate Analyst-Based Earnings Surprises

Panel A: *AAES* (value-weighted, scaled by the absolute value of earnings four quarters prior)								
	$AAES_{t+1,t+3}\|_t$		$AAES_{t+4,t+6}\|_t$		$AAES_{t+7,t+9}\|_t$		$AAES_{t+10,t+12}\|_t$	
ASG_t	-5.99**	-6.62***	-10.89***	-8.44***	-17.27***	-10.36***	-19.72***	-10.05***
	(-2.05)	(-3.15)	(-2.92)	(-3.11)	(-3.97)	(-3.70)	(-4.00)	(-2.97)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	5.11	28.43	9.58	31.97	16.90	44.67	16.48	42.67
Panel B: *AAES* (equal-weighted, scaled by the absolute value of earnings four quarters prior)								
	$AAES_{t+1,t+3}\|_t$		$AAES_{t+4,t+6}\|_t$		$AAES_{t+7,t+9}\|_t$		$AAES_{t+10,t+12}\|_t$	
ASG_t	-4.66*	-4.77**	-10.89***	-7.29***	-16.65***	-8.61***	-20.56***	-9.33***
	(-1.70)	(-2.36)	(-3.36)	(-3.32)	(-5.08)	(-3.93)	(-6.20)	(-3.48)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.87	28.45	3.94	36.97	8.07	46.95	8.37	42.55
Panel C: *AAES* (value-weighted, scaled by book value of equity four quarters prior)								
	$AAES_{t+1,t+3}\|_t$		$AAES_{t+4,t+6}\|_t$		$AAES_{t+7,t+9}\|_t$		$AAES_{t+10,t+12}\|_t$	
ASG_t	-0.27***	-0.23***	-0.42***	-0.29***	-0.61***	-0.35***	-0.67***	-0.31***
	(-3.33)	(-3.75)	(-4.32)	(-4.00)	(-5.55)	(-4.72)	(-5.37)	(-3.35)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	14.51	35.92	20.16	38.93	30.03	52.87	30.12	53.28
Panel D: *AAES* (equal-weighted, scaled by book value of equity four quarters prior)								
	$AAES_{t+1,t+3}\|_t$		$AAES_{t+4,t+6}\|_t$		$AAES_{t+7,t+9}\|_t$		$AAES_{t+10,t+12}\|_t$	
ASG_t	-0.30***	-0.21***	-0.46***	-0.28***	-0.62***	-0.31***	-0.68***	-0.26***
	(-3.73)	(-3.58)	(-5.53)	(-4.38)	(-7.48)	(-4.70)	(-7.23)	(-3.43)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	13.82	41.79	21.36	50.08	28.95	59.14	25.94	56.50
Panel E: *AAES* (value-weighted, scaled by market value of equity four quarters prior)								
	$AAES_{t+1,t+3}\|_t$		$AAES_{t+4,t+6}\|_t$		$AAES_{t+7,t+9}\|_t$		$AAES_{t+10,t+12}\|_t$	
ASG_t	-0.01	-0.04***	-0.04*	-0.05***	-0.07***	-0.06***	-0.08***	-0.05***
	(-0.79)	(-2.80)	(-1.74)	(-3.10)	(-3.30)	(-3.81)	(-3.54)	(-3.30)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.12	17.57	1.04	24.70	3.38	36.54	3.08	39.68
Panel F: *AAES* (equal-weighted, scaled by market value of equity four quarters prior)								
	$AAES_{t+1,t+3}\|_t$		$AAES_{t+4,t+6}\|_t$		$AAES_{t+7,t+9}\|_t$		$AAES_{t+10,t+12}\|_t$	
ASG_t	0.00	-0.05**	-0.06	-0.09***	-0.14***	-0.11***	-0.18***	-0.12***
	(0.12)	(-2.22)	(-1.61)	(-3.96)	(-3.39)	(-4.46)	(-4.08)	(-3.83)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.02	26.79	0.87	36.78	4.59	44.85	5.42	44.21

For each month t, we compute the h-month ahead (h = 3, 6, 9, and 12) aggregate analyst-based earnings surprise ($AAES_{t+h-2,t+h}|_t$, in %). The aggregate analyst-based earnings surprises are calculated as the cross-sectional value-weighted/equal-weighted average of firm-level analyst-based earnings surprises (difference between earnings and analysts' expected earnings, scaled by either the absolute value of earnings, book value of equity, or market value of equity four quarters prior). See Section 5.1.2 for more details on variable constructions. Then, we run predictive regressions of $AAES_{t+h-2,t+h}|_t$ on aggregate sales growth (*ASG*) in month t:

$$AAES_{t+h-2,t+h}|_t = \alpha + \beta ASG_t + \sum_i \beta_i \, Control\ Variables_i + \varepsilon_{t+h},$$

where ASG is the aggregate sales growth and the control variables are the aggregate analyst-based earnings surprises of the same forecast horizon in the past four quarters (i.e., $AAES_{t+h-2,t+h}|_{t-h}$, $AAES_{t-5,t-3}|_{t-3-h}$, $AAES_{t-8,t-6}|_{t-6-h}$, and $AAES_{t-11,t-9}|_{t-9-h}$). All independent variables are standardized to have zero mean and unit variance. For each regression, the table reports the regression coefficients, Newey and West (1987) heteroskedasticity- and autocorrelation-robust *t*-statistics in parentheses (*h* lags), and R^2s (in %). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1985:01 to 2023:12.

Table 10. Aggregate Sales Growth and Inflation Measures

Panel A: CPI inflation (ΔCPI)

	$\Delta CPI_{t+1,t+3}$		$\Delta CPI_{t+4,t+6}$		$\Delta CPI_{t+7,t+9}$		$\Delta CPI_{t+10,t+12}$	
ASG_t	0.11***	0.06*	0.06	0.01	0.02	-0.04	-0.04	-0.08*
	(2.62)	(1.83)	(1.34)	(0.15)	(0.41)	(-1.12)	(-0.87)	(-1.94)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	2.85	9.50	0.78	6.06	0.14	5.92	0.09	4.42

Panel B: PPI inflation (ΔPPI)

	$\Delta PPI_{t+1,t+3}$		$\Delta PPI_{t+4,t+6}$		$\Delta PPI_{t+7,t+9}$		$\Delta PPI_{t+10,t+12}$	
ASG_t	0.08	0.06	-0.03	-0.06	-0.14	-0.17	-0.22**	-0.22**
	(0.87)	(0.77)	(-0.26)	(-0.61)	(-1.44)	(-1.62)	(-2.17)	(-2.03)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.14	6.92	-0.18	3.11	0.89	3.31	2.35	2.85

This table reports the estimation results for the regressions of the h-month ahead (h = 3, 6, 9, and 12) CPI inflation ($\Delta CPI_{t+h-2,t+h}$, in %) and PPI inflation ($\Delta PPI_{t+h-2,t+h}$, in %) on aggregate sales growth (*ASG*) in month t:

$$\Delta CPI_{t+h-2,t+h} = \alpha + \beta ASG_t + \sum_i \beta_i \, Control\,Variables_i + \varepsilon_{t+h},$$

and

$$\Delta PPI_{t+h-2,t+h} = \alpha + \beta ASG_t + \sum_i \beta_i \, Control\,Variables_i + \varepsilon_{t+h},$$

Where ASG is the aggregate sales growth and the control variables are the CPI inflation in the past four quarters (i.e., $\Delta CPI_{t-2,t}$, $\Delta CPI_{t-5,t-3}$, $\Delta CPI_{t-8,t-6}$, and $\Delta CPI_{t-11,t-9}$) for the former regression and PPI inflation in the past four quarters (i.e., $\Delta PPI_{t-2,t}$, $\Delta PPI_{t-5,t-3}$, $\Delta PPI_{t-8,t-6}$, and $\Delta PPI_{t-11,t-9}$) for the latter regression. See Section 5.2 for more details on variable constructions. All independent variables are standardized to have zero mean and unit variance. For each regression, the table reports the regression coefficients, Newey and West (1987) heteroskedasticity- and autocorrelation-robust t-statistics in parentheses (h lags), and R^2s (in %). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1985:01–2023:12.

Table 11. Aggregate Sales Growth and Aggregate Investment

Panel A: In-sample bivariate predictive regressions

	$h=1$			$h=3$			$h=6$			$h=12$		
Predictor	β	ϕ	R^2	β	ϕ	R^2	β	ϕ	R^2	β	ϕ	R^2
ATAG	-0.41	-0.18	1.53	-0.46*	-0.14	4.69	-0.39*	-0.23	9.85	-0.27*	-0.35***	19.67
	(-1.22)	(-0.50)		(-1.81)	(-0.60)		(-1.81)	(-1.35)		(-1.73)	(-3.26)	
ANOAG	-0.23	-0.41	1.76	-0.45*	-0.15	4.71	-0.37*	-0.25	9.92	-0.30	-0.32*	19.11
	(-0.65)	(-1.06)		(-1.77)	(-0.65)		(-1.66)	(-1.33)		(-1.59)	(-1.90)	

Panel B: Out-of-sample R^2_{OS}

Predictor	$h=1$	$h=3$	$h=6$	$h=12$
ASG	1.82***	5.29***	9.51***	13.68***
ATAG	0.62	1.44*	3.62**	8.11***
ANOAG	1.32**	1.92**	3.79***	5.22**

Panel C: Out-of-sample CER gain and Sharpe ratio

	γ = 3		γ = 5	
Predictor	CER gain	Sharpe ratio	CER gain	Sharpe ratio
ASG	4.41	0.71	2.82	0.69
ATAG	1.65	0.56	0.92	0.55
ANOAG	2.91	0.62	2.42	0.66

Panel A, Panel B, and Panel C use aggregate total assets growth (*ATAG*) and aggregate net operating assets growth (*ANOAG*) as predictors, and report the analogous results of Table 5 (in-sample bivariate predictive regressions), Table 6 (out-of-sample R^2_{OS}), and Table 7 (out-of-sample CER gain and Sharpe ratio), respectively. See Tables 5 to 7 for more details. *ATAG* and *ANOAG* are computed as the cross-sectional value-weighted average of individual firm's one-year total assets growth and one-year net operating assets growth, respectively. Newey and West (1987) heteroskedasticity- and autocorrelation-robust t-statistics in parentheses (h lags) are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period for Panel A is 1985:01–2023:12, and the out-of-sample evaluation period for Panel B and Panel C is 2005:01 to 2023:12.

Table 12. Benchmark Predictive Regressions: Equal-Weighted Aggregate Sales Growth

	$h = 1$	$h = 3$	$h = 6$	$h = 12$
Intercept	0.59***	0.58***	0.58***	0.57***
	(2.77)	(3.18)	(3.38)	(3.50)
ASG_EW	-0.51**	-0.52***	-0.50***	-0.44***
	(-2.29)	(-3.30)	(-3.48)	(-3.23)
R^2	1.25	3.85	6.97	10.72
IVX-Wald	5.34**	5.82**	5.40**	4.56**

The table presents the estimation results for the following predictive regression model:

$$r_{t,t+h} = \alpha + \beta ASG\_EW_t + \epsilon_{t,t+h}$$

where ASG_EW_t is the cross-sectional equal-weighted average of individual firm's one-year sales revenue growth. in month t and $r_{t,t+h} = (1/\text{h})(r_{t+h} + \cdot \cdot + r_{t+h})$ is the h-month-ahead average log excess return (in %) on the CRSP value-weighted index in month t. ASG_EW is standardized to have zero mean and unit variance. See Section 3 for more details on the sample and variable constructions. For each regression, the table reports the regression coefficients, Newey and West (1987) heteroskedasticity- and autocorrelation-robust t-statistics in parentheses (h lags), R^2s (in %), and the IVX-Wald statistics of Kostakis et al. (2015). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1985:01-2023:12.

Table 13. Alternative Ways to Compute Statistical Significance

Panel A: Value-weighted aggregate sales growth				
	$h = 1$	$h = 3$	$h = 6$	$h = 12$
p(Hodrick)	0.009	0.013	0.001	0.001
p(bootstrapped)	0.008	0.002	0.002	0.002
Panel B: Equal-weighted aggregate sales growth				
	$h = 1$	$h = 3$	$h = 6$	$h = 12$
p(Hodrick)	0.015	0.022	0.007	0.010
p(bootstrapped)	0.008	0.003	0.007	0.010

This table reports the p-values of the regression coefficients on aggregate sales growth in Table 1 and Table 11 based on Hodrick (1992) and a fixed-regressor wild bootstrap approach (1,000 simulations) following Rapach et al. (2016). The sample period is 1985:01-2023:12.

Table 14. Out-Of-Sample R-Squared for Different Out-Of-Sample Periods

	Out-of-sample period: January 2010 to December 2023				Out-of-sample period: January 2015 to December 2023			
Predictor	$h = 1$	$h = 3$	$h = 6$	$h = 12$	$h = 1$	$h = 3$	$h = 6$	$h = 12$
ASG	1.95**	8.30***	18.21***	26.83***	1.99**	8.59**	18.76**	23.52***
AEG1	-0.96	-4.33	-5.46	-5.29	-1.24	-4.96	-6.69	-1.41
AEG2	-0.02	0.63	1.97	-0.76	0.37	2.29**	5.14*	7.80*
AEG3	-2.30	-9.81	-21.72	-21.15	-2.92	-13.59	-32.93	-16.16
AEG4	-1.44	-6.20	-16.57	-34.84	-1.58	-9.43	-26.58	-25.23
AEG5	-0.90	-4.72	-5.86	-5.00	-0.87	-2.20	-7.94	-2.76
AEG6	-0.64	-3.27	-5.50	-13.19	-0.32	-1.21	-10.19	-10.29
DP	0.27	0.59	-0.03	-0.13	0.45	1.59	2.05	7.02
DY	-0.04	-0.09	-0.91	-1.27	0.13	0.69	1.06	5.98
EP	-0.05	-0.56	-1.49	-1.66	-0.51	-2.01	-4.37	-5.09
DE	-0.14	-0.08	-0.76	-3.84	0.31	2.98***	7.53**	10.79**
SVAR	-8.15	-6.42	-0.68	2.37	-12.65	-8.95	-0.35	5.32
BM	0.17	0.77	1.15	0.97	-0.08	-0.23	-2.48	-2.13
NTIS	-0.80	-3.84	-9.95	-20.54	-0.57	-3.25	-10.26	-18.88
TBL	-0.46	-1.78	-2.59	-2.75	-0.09	-0.13	-1.50	-1.35
LTY	-0.58	-2.63	-7.39	-24.74	-0.23	-0.46	-2.88	-6.32
LTR	-0.50	0.22	0.64	-0.99	-0.30	0.70	1.15	1.15
TMS	-0.39	-0.88	-2.90	-12.16	-0.38	-0.74	-3.95	-20.11
DFY	-0.35	-0.25	2.05*	6.55**	-0.22	0.12	2.53*	8.61**
DFR	-1.99	-2.65	-3.21	-3.37	-2.60	-2.70	-2.47	-1.81
INFL	-0.05	3.28**	7.95***	5.24**	0.58	1.37	6.61**	6.57*
ATAG	0.59	1.90**	5.37**	15.81***	0.18	0.24	2.26	8.04*
ANOAG	1.34**	2.03*	3.45**	3.69	1.16*	1.07	0.61	-11.22

The table presents the out-of-sample performance in predicting the h-month-ahead average log excess return on the CRSP value-weighted index using aggregate sales growth (*ASG*), one of the 6 measures of aggregate earnings growth (*AEG*), one of the 14 economic variables in Goyal and Welch (2008), aggregate total assets growth (*ATAG*), or aggregate net operating assets growth (*ANOAG*). See Section 3 and Appendix for more details on the sample and variable constructions. We report Campbell and Thompson (2008) R_{OS}^2 statistic, which measures the proportional reduction in mean squared forecast error (MSFE) for the out-of-sample predictive regression forecast relative to the historical mean return benchmark. All of the out-of-sample forecasts are estimated recursively using data available at the forecast formation month t. Statistical significance for R_{OS}^2 is based on the p-value of the Clark and West (2007) MSFE-adjusted statistic for testing the null hypothesis $H_0: R_{OS}^2 \leq 0$ against the alternative hypothesis $H_A: R_{OS}^2 > 0$. We consider two out-of-sample evaluation periods (2010:01 to 2023:12 and 2015:01 to 2023:12).

Table 15. Out-of-Sample CER Gains and Sharpe Ratios for Different Out-Of-Sample Periods

	Out-of-sample period: January 2010 to December 2023				Out-of-sample period: January 2015 to December 2023			
	γ = 3		γ = 5		γ = 3		γ = 5	
Predictor	CER gain	Sharpe ratio	CER gain	Sharpe ratio	CER gain	Sharpe ratio	CER gain	Sharpe ratio
ASG	5.12	0.92	3.16	0.86	5.71	0.81	3.49	0.76
AEG1	-0.93	0.60	-1.34	0.52	-1.08	0.48	-1.96	0.39
AEG2	0.34	0.68	0.42	0.68	1.44	0.60	1.20	0.59
AEG3	-2.10	0.54	-1.93	0.49	-1.11	0.47	-2.25	0.37
AEG4	-2.04	0.54	-1.46	0.50	-2.18	0.40	-1.72	0.34
AEG5	-1.26	0.59	-1.16	0.53	-1.37	0.46	-1.15	0.41
AEG6	-1.06	0.60	-0.51	0.59	-0.54	0.50	-0.12	0.49
DP	0.83	0.77	0.76	0.77	1.78	0.64	1.47	0.64
DY	0.63	0.80	0.64	0.80	1.61	0.65	1.37	0.65
EP	-0.36	0.64	0.05	0.64	-1.39	0.46	-0.43	0.46
DE	-0.15	0.66	0.07	0.64	1.08	0.58	0.90	0.57
SVAR	0.67	0.70	0.20	0.65	-0.33	0.51	-0.50	0.46
BM	0.99	0.79	0.86	0.79	1.12	0.62	1.08	0.62
NTIS	-1.55	0.57	-0.71	0.57	-1.26	0.46	-0.42	0.45
TBL	-0.37	0.63	-0.50	0.59	0.21	0.55	-0.31	0.50
LTY	-0.26	0.64	-0.95	0.56	0.46	0.56	-0.97	0.49
LTR	-0.57	0.63	-1.58	0.51	0.31	0.54	-1.69	0.42
TMS	-0.60	0.62	-0.48	0.59	-0.61	0.51	-0.55	0.47
DFY	-0.39	0.63	-0.20	0.61	-0.23	0.52	-0.07	0.50
DFR	0.80	0.73	0.66	0.69	2.08	0.64	1.42	0.61
INFL	0.52	0.69	0.43	0.67	1.96	0.62	1.36	0.61
ATAG	1.84	0.73	1.01	0.70	0.92	0.58	0.31	0.55
ANOAG	3.13	0.81	2.64	0.68	3.07	0.68	2.63	0.70
Buy-and-hold	1.20	0.76	1.90	0.76	1.62	0.62	1.20	0.62

The table reports the annualized certainty equivalent return gain (CER gain, in %) and the annualized Sharpe ratio of a mean-variance investor with relative risk aversion coefficient of three or five (γ = 3 or 5) who allocates her wealth monthly between the stock market and the risk-free asset by applying the out-of-sample forecasts based on aggregate sales growth (*ASG*), one of the 6 measures of aggregate earnings growth (*AEG*), one of the 14 economic variables in Goyal and Welch (2008), aggregate total assets growth (*ATAG*), or aggregate net operating assets growth (*ANOAG*). See Section 3 and Appendix for more details on the sample and variable constructions. The CER gain is the difference between the CER for the investor when she uses the predictive regression forecast based on a predictor to form out-of-sample forecasts in asset allocation and the CER when she uses the prevailing average excess return forecasts. Sharpe ratio is the average portfolio excess return divided by its standard deviation. The equity weight is constrained to lie between 0 (no short sales) and 1.5. Buy-and-hold corresponds to the investor passively holding the market portfolio. We consider two out-of-sample evaluation periods (2010:01 to 2023:12 and 2015:01 to 2023:12).

Internet Appendix

Table IA1. Baseline Predictive Regressions: Aggregate 1-quarter/3-year Sales Growth

Panel A: Aggregate 1-quarter sales growth				
	$h=1$	$h=3$	$h=6$	$h=12$
Intercept	0.59***	0.58***	0.58***	0.58***
	(2.75)	(3.12)	(3.37)	(3.67)
ASG_qtr	-0.38*	-0.45***	-0.48***	-0.52***
	(-1.77)	(-2.75)	(-2.99)	(-4.49)
R^2	0.69	2.78	6.33	15.18
IVX-Wald	2.73*	3.98**	4.79**	6.59**
Panel B: Aggregate 3-year sales growth				
	$h=1$	$h=3$	$h=6$	$h=12$
Intercept	0.59***	0.58***	0.58***	0.58***
	(2.76)	(3.16)	(3.38)	(3.68)
ASG_3yr	-0.53**	-0.52***	-0.51***	-0.54***
	(-2.37)	(-2.92)	(-3.15)	(-3.80)
R^2	1.33	3.75	7.35	16.50
IVX-Wald	5.35**	5.19**	5.14**	6.02**

The table presents the estimation results for the following predictive regression model:

$$r_{t,t+h} = \alpha + \beta ASG\_qtr_t + \epsilon_{t,t+h},$$

And

$$r_{t,t+h} = \alpha + \beta ASG\_3yr_t + \epsilon_{t,t+h},$$

where ASG_qtr_t (ASG_3yr_t) is the cross-sectional value-weighted average of individual firm's one-quarter (three-year) sales revenue growth. in month t, and $r_{t,t+h} = (1/\mathrm{h})(r_{t+h} + \cdot\cdot + r_{t+h})$ is the h-month-ahead average log excess return (in %) on the CRSP value-weighted index in month t. ASG_qtr_t (ASG_3yr_t) is standardized to have zero mean and unit variance. For each regression, the table reports the regression coefficients, Newey and West (1987) heteroskedasticity- and autocorrelation-robust t-statistics in parentheses (h lags), R^2s (in %), and the IVX-Wald statistics of Kostakis et al. (2015). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample covers the period from 1985:01 to 2023:12.

Table IA2. Bivariate Predictive Regressions:
Controlling for the First Principal Component of the 20 Variables+

	$h = 1$	$h = 3$	$h = 6$	$h = 12$
Intercept	0.59***	0.58***	0.59***	0.58***
	(2.77)	(3.20)	(3.46)	(3.70)
ASG	-0.57**	-0.58***	-0.57***	-0.53***
	(-2.36)	(-3.23)	(-3.82)	(-4.23)
PC	0.05	0.01	-0.02	-0.06
	(0.18)	(0.05)	(-0.11)	(-0.49)
R^2	1.06	4.18	8.89	16.94

The table presents the estimation results for the following predictive regression model:

$$r_{t,t+h} = \alpha + \beta ASG_t + \delta PC_t + \epsilon_{t,t+h},$$

where ASG_t is aggregate sales growth in month t and $r_{t,t+h} = (1/\mathrm{h})(r_{t+h} + \cdots + r_{t+h})$ is the h-month-ahead average log excess return (in %) on the CRSP value-weighted index in month t. PC is the first principal component extracted from the 6 measures of aggregate earnings growth (AEG) and 14 economic variables in Goyal and Welch (2008). All independent variables are standardized to have mean zero and unit variance. For each regression, the table reports the regression coefficients, Newey and West (1987) heteroskedasticity- and autocorrelation-robust t-statistics in parentheses (h lags), R^2s (in %), and the IVX-Wald statistics of Kostakis et al. (2015). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1985:01-2023:12.

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