

Aggregate Earnings and Recession Predictability

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Abstract: We examine whether aggregate earnings contain macroeconomic information content about U.S. recessions. We find that a one-standard-deviation decline in aggregate earnings growth raises the probability of a recession in the subsequent quarter by up to 8.3%. This predictive ability is incremental to conventional recession predictors and is primarily driven by negative earnings growth, consistent with accounting conservatism. The predictive signal is concentrated in cyclically sensitive sectors, whereas earnings from noncyclical sectors exhibit little predictive content. Although aggregate special items growth displays modest short-term predictive power, their contribution diminishes over longer horizons. Overall, our findings suggest that aggregate earnings provide timely signals of macroeconomic tail risk and offer a novel accounting-based perspective on recession forecasting.

Keywords: macro-accounting, aggregate earnings, special items, recessions

JEL Classification: E01, G01, M41.

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1 Introduction

Historically, limited attention has been paid to aggregate accounting information in the context of forecasting economic recessions. Traditional forecasting models have largely relied on financial market indicators, and have typically ignored accounting information, implicitly assuming that markets already incorporate the relevant information embedded in accounting data. Konchitchki and Patatoukas (2014b) challenge this view, showing that accounting aggregates contain macroeconomic information content not fully reflected in stock prices. Subsequent studies further document that aggregate earnings predict a range of macroeconomic outcomes, including gross domestic product (GDP), employment, inflation, and policy variables.¹ If aggregate earnings predict many business-cycle-related variables, they may also contain information about the business cycle itself, particularly economic recessions—the most critical phase of the cycle for economic decision-making.²

Whether aggregate earnings predict recessions has distinct economic implications that remain largely unexplored in the macro-accounting literature. Prior research primarily examines whether aggregate earnings forecast the conditional *mean* of GDP growth and other macroeconomic variables.³ In contrast, predicting recessions focuses on *left-tail events* in economic activity and the downside comovement among macroeconomic variables.⁴ Accordingly, if aggregate earnings help predict recessions, it suggests that their macroeconomic information content extends beyond forecasting average economic activity to capturing macroeconomic tail risk.

Conceptually, several economic mechanisms suggest why aggregate earnings may predict future recessions. Two mechanisms operate primarily through *information channels*, whereby aggregate earnings reflect underlying macroeconomic conditions. First, aggregate earnings

¹See, for example, studies on GDP (Abdalla and Carabias, 2022; Collins and Nguyen, 2022; Datar et al., 2020; Kausar and Park, 2024; Konchitchki and Patatoukas, 2014a,b; Nallareddy and Ogneva, 2017), labor market outcomes (Hann et al., 2021), inflation (Kottimukkalur et al., 2025; Shivakumar, 2007; Shivakumar and Urcan, 2017), monetary policy (Gallo et al., 2016), and fiscal policy (Welsch et al., 2025).

²For example, when a recession is anticipated, policymakers may adjust monetary policy to stabilize the macroeconomy, investors may strategically alter asset allocations to time the market, and corporate managers may reallocate resources and adjust hiring or hedging decisions accordingly.

³These studies typically employ OLS frameworks, which estimate the conditional mean of the dependent variable given the predictors.

⁴That is, forecasting recessions involves predicting not only the first moment of economic activity but also higher-moment features of its distribution (Delle Monache et al., 2024). Moreover, modeling recessions is econometrically advantageous when the economy evolves across discrete states: it mitigates spurious accuracy in point forecasts of continuous macroeconomic variables (Estrella, 1998).

are closely related to corporate profits, an important component of GDP in national income accounting, and prior research shows that they contain information about future output dynamics (e.g., Abdalla and Carabias, 2022; Abdalla et al., 2021). Second, accounting conservatism requires firms to recognize losses more promptly than gains, causing earnings to incorporate adverse economic information relatively quickly (e.g., Basu, 1997; Crawley, 2015).

A third mechanism operates through a *propagation channel*, whereby declines in corporate earnings affect real investment and thus overall economic activity. Corporate investment depends on internally generated funds and access to external finance, both of which are closely tied to firms' earnings (e.g., Fazzari et al., 1988; Lian and Ma, 2020). Declines in earnings reduce internally generated funds available for investment. At the same time, given that modern debt contracts rely extensively on accounting-based performance measures such as EBITDA, deteriorating earnings can also tighten borrowing capacity and restrict access to external finance (Beatty et al., 2008; Nikolaev, 2010; Roberts and Sufi, 2009). Together, weaker internal funds and tighter financing conditions reinforce reductions in firms' investment expenditures. When these responses operate broadly across firms, they can propagate to the macroeconomy through declines in aggregate investment, output, and employment, contributing to the broad-based contractions that characterize recessions. Taken together, these informational and propagation mechanisms motivate our empirical investigation.

We begin our empirical analysis by examining whether aggregate earnings predict future recessions using probit models, the canonical framework widely adopted in recession forecasting literature (e.g., Beneish et al., 2023; Estrella, 1998; Estrella and Mishkin, 1998; Kauppi and Saikkonen, 2008; Nyberg, 2010). Using quarterly U.S. data from 1971:Q1 to 2021:Q4, our analysis shows that declines in aggregate earnings growth possess significant in-sample predictive power for future recessions across forecasting horizons of one to four quarters. Importantly, this predictive ability is incremental to the benchmark model that includes well-established leading indicators, such as term spreads, credit spreads, stock returns, inflation, and the macroeconomic uncertainty index. Based on average marginal effects (AMEs) derived from probit models, we find that a one-standard-deviation decline in aggregate earnings growth raises the predicted probability of entering a recession by up to 8.3% in the

subsequent quarter.

We next examine whether the predictive content of aggregate earnings is driven by special items. Although Abdalla and Carabias (2022) suggest that special items may embed useful macroeconomic information, our results show that their predictive power is short-lived, dissipating rapidly over time. This pattern is consistent with the transitory nature of special items, which makes them less likely to capture the persistent and broad-based dynamics that characterize recessions. Importantly, aggregate earnings growth continues to predict recessions after controlling for special items, indicating that earnings contain macroeconomic information content beyond that reflected in special items.

Estrella and Mishkin (1998) raise the concern that many recession predictors perform well in-sample but fail to maintain out-of-sample reliability. We therefore assess the out-of-sample predictive performance of aggregate earnings. It is evident that a parsimonious model using only two accounting predictors, namely aggregate earnings and special items growth, delivers reasonably good out-of-sample performance at short horizons. Beyond individual forecasting models, we employ a forecast combination strategy to address model uncertainty and potential misspecification (e.g., Bates and Granger, 1969; Berge, 2015; Faust et al., 2013; Rapach et al., 2010; Stock and Watson, 2004). Combining forecasts from conventional recession predictors and those from two accounting-based predictors substantially improves short-horizon out-of-sample forecast performance.

We further examine the asymmetric predictive content of aggregate earnings growth for U.S. recessions by decomposing earnings growth into positive and negative components. Our results show that negative changes in aggregate earnings significantly increase the predicted probability of recession, whereas positive changes do not meaningfully reduce recession risk. This asymmetry is consistent with Gaertner et al. (2020), who argue that aggregate accounting earnings respond more quickly to adverse economic developments than to favorable ones because of accounting conservatism. The sign asymmetry is also consistent with earnings-based debt contracting, under which deteriorating earnings move firms closer to violating covenants and may tighten borrowing capacity, whereas comparable earnings improvements need not generate proportionate improvements in financing conditions. Accordingly, negative aggregate

earnings growth is particularly informative because it not only signals downside risks in the economy but may also coincide with tighter financing conditions that reinforce those risks.

We also examine the sectoral heterogeneity in the predictive content of aggregate earnings. We construct two measures of aggregate earnings growth based on cyclically sensitive and noncyclical sectors. Our empirical results show that earnings growth from cyclically sensitive industries exhibits stronger predictive power for recessions than earnings growth from noncyclical sectors. This pattern is consistent with a propagation mechanism: cyclically sensitive industries experience larger earnings declines following adverse shocks, prompting firms to reduce investment and production, thereby amplifying economic contractions. As a result, earnings from these industries provide more informative signals about future downturns.

Finally, we decompose aggregate earnings growth into expected and surprise components and find that both components predict recessions. This finding suggests that the predictive content of aggregate earnings reflects multiple underlying mechanisms. Consistent with the informational mechanisms, earnings surprises capture unexpected news about future cash flows that is not fully reflected in other macroeconomic or financial variables. In contrast, the expected earnings component reflects persistent operating performance that is closely related to financing conditions and investment decisions, making it more consistent with financial propagation mechanisms than with a purely informational explanation. Although this decomposition cannot fully distinguish between these mechanisms, it provides suggestive evidence that both informational and propagation channels contribute to the predictive content of aggregate earnings.

Our study makes two contributions. First, we broaden the macroeconomic role of aggregate earnings in the macro-accounting literature. Prior studies primarily focus on GDP predictability, attributing the predictive ability of aggregate earnings to their timely incorporation of information about aggregate corporate profitability. We find that aggregate earnings also predict recessions, extending their predictive content beyond average economic activity to macroeconomic tail events. In the macroeconomic tail-risk literature, such events are widely viewed as arising from, and being amplified by, deteriorating financial conditions (e.g., Adrian et al., 2019; Loria et al., 2025). Building on this strand of literature, our findings suggest that the pre-

dictive content of aggregate earnings is also consistent with propagation mechanisms associated with deteriorating financial conditions that amplify adverse macroeconomic shocks, extending the traditional informational view that aggregate earnings primarily convey information about underlying macroeconomic conditions.

Second, we contribute to the recession forecasting literature by demonstrating that accounting information complements conventional market-based recession predictors. While the existing literature primarily relies on macroeconomic and financial market indicators, it pays little attention to accounting information. Our findings suggest that accounting information not only summarizes firms' past operating performance but also influences their future investment and financing decisions, thereby providing a link between firm-level accounting performance and macroeconomic fluctuations. Accordingly, we highlight the value of accounting information in recession forecasting and the broader macroeconomic tail-risk literature.

Our paper is closely related to that of Beneish et al. (2023), which is the only other study that investigates whether aggregate accounting information can predict economic recessions. Beneish et al. (2023) focus on aggregate financial misreporting, arguing that distorted financial information accumulates over time and typically unravels before a recession, making misreporting a potential early signal. In contrast, we show that aggregate earnings growth predicts recessions because it captures firms' underlying operating performance rather than distortions in financial reporting. Together, the two studies suggest that aggregate accounting signals—whether arising from distorted financial reporting or from underlying fundamental information—can provide early warnings of macroeconomic turning points.

The remainder of the paper proceeds as follows. Section 2 develops the hypotheses and underlying mechanisms. Sections 3 and 4 describe the empirical framework and data. Section 5 presents the baseline results, and Section 6 investigates the sources of the predictive content of aggregate earnings. Section 7 reports robustness analyses. Section 8 concludes.

2 Hypothesis Development and Related Literature

In the U.S., the Business Cycle Dating Committee of the National Bureau of Economic Research (NBER) maintains the official chronology of business cycles. It defines a recession as “a significant decline in economic activity that is spread across the economy and lasts more than a few months.”⁵ Unlike simple rules based solely on GDP growth,⁶ the NBER determines recession dates using a broad set of real economic indicators, placing particular emphasis on measures of employment and real personal income, together with indicators of production, sales, and aggregate output.⁷ This definition implies that a plausible recession predictor should capture broad-based changes in economic activity, rather than merely predict a single macroeconomic outcome such as GDP growth.

We argue that aggregate earnings growth can serve as a leading recession indicator through several economic mechanisms. First, aggregate earnings may reflect underlying macroeconomic conditions. A growing body of accounting research documents that aggregate earnings growth predicts GDP growth, suggesting that accounting aggregates contain useful information about future output dynamics (e.g., Abdalla and Carabias, 2022; Collins and Nguyen, 2022; Kausar and Park, 2024; Konchitchki and Patatoukas, 2014a,b; Nallareddy and Ogneva, 2017). Some studies attribute this predictive power to the “corporate profit link” hypothesis, which is based on the income approach to measuring aggregate output using gross domestic income (GDI) (e.g., Abdalla and Carabias, 2022; Abdalla et al., 2021; Konchitchki and Patatoukas, 2014a).⁸ Given that aggregate earnings are considered a timely proxy for corporate profits, which are a key component of GDI, they directly signal shifts in aggregate output and, by extension, economic recessions.

Second, aggregate earnings may be particularly informative about downside risks in the macroeconomy due to accounting conservatism (e.g., Crawley, 2015; Kausar and Park, 2024;

⁵See how NBER defines recessions: <https://www.nber.org/research/business-cycle-dating>.

⁶The link between GDP and recessions dates back to 1974, when U.S. economist Julius Shiskin informally defined a recession as “negative GDP growth for two consecutive quarters,” a rule of thumb he later acknowledged was overly simplistic but remains widely cited today. See the *New York Times*, <https://www.nytimes.com/1974/12/01/archives/the-changing-business-cycle-points-op-view.html>.

⁷See <https://www.nber.org/research/business-cycle-dating>.

⁸GDP = gross domestic income (GDI) = operating surplus + employee compensation + interests + taxes + depreciation, where operating surplus = corporate profit + proprietor income + rental income.

Laurion and Patatoukas, 2016). Gaertner et al. (2020) document an asymmetric “sign effect,” showing that negative changes in aggregate earnings consistently predict subsequent GDP growth, whereas positive changes do not. Abdalla and Carabias (2022) corroborate this finding using aggregate special items. Both studies attribute this asymmetry to conditional conservatism, which requires the timelier recognition of economic losses than gains (Basu, 1997; Watts, 2003). As a result, negative earnings shocks incorporate adverse economic news more promptly, making declines in aggregate earnings particularly informative about the risk of transitions into recessionary states. More broadly, this mechanism highlights that accounting institutions shape how macroeconomic conditions are reflected in aggregate accounting information (e.g., Crawley, 2015).

The first two mechanisms explain why aggregate earnings may predict recessions through their informational role. Specifically, aggregate earnings summarize underlying macroeconomic conditions and recognize adverse economic news in a timely manner.⁹ Accordingly, these mechanisms imply a *lead-lag* relationship between aggregate earnings and future recessions, but do not necessarily require earnings to *influence* subsequent economic activity. We next discuss complementary propagation mechanisms through which deteriorating earnings may propagate macroeconomic downturns by influencing firms’ investment and financing decisions.

The third mechanism proposes a propagation mechanism in which declines in aggregate earnings reduce firms’ investment, thereby affecting broader macroeconomic activity (Kottimukkalur et al., 2025; Shivakumar and Urcan, 2014, 2017). A large literature documents that corporate investment is positively associated with internally generated funds, often proxied by earnings (e.g., Fazzari et al., 1988). While subsequent studies debate whether such investment–cash flow sensitivity reflects financing constraints or investment opportunities (e.g., Abel, 2018; Erickson and Whited, 2000; Kaplan and Zingales, 1997), both interpretations imply that declines in corporate earnings are associated with reductions in investment

⁹Beyond reflecting existing macroeconomic conditions, accounting information may also influence macroeconomic outcomes through expectation formation and monetary policy transmission. Li et al. (2023) show that the Federal Reserve systematically uses firm-level accounting reports to assess macroeconomic conditions. By entering policymakers’ information sets, accounting information may shape expectations about future economic conditions and, in turn, influence monetary policy decisions and broader macroeconomic outcomes. In addition, Armstrong et al. (2019) show that accounting information can strengthen the transmission of monetary policy, providing another channel through which accounting information may affect macroeconomic outcomes.

activity. If such effects operate broadly across firms, declines in aggregate earnings may reduce aggregate investment and thereby propagate contractions in output, employment, and other macroeconomic outcomes.¹⁰ Consistent with this view, recent studies show that aggregate earnings predict labor market outcomes such as job creation (Hann et al., 2021) and personal income (Welsch et al., 2025). Given that the NBER places particular weight on employment and income indicators when dating recessions¹¹, the ability of aggregate earnings to predict these variables further suggests that earnings are linked to the broad-based downside comovement in economic activity characteristic of recessionary episodes.

In addition to the direct investment channel, aggregate earnings may affect the macroeconomy through firms' access to external finance. Modern debt contracts rely extensively on accounting-based performance measures. Lian and Ma (2020) show that a substantial portion of corporate borrowing capacity is determined by operating earnings.¹² Because financial covenants are commonly based on accounting performance measures such as EBITDA and interest coverage ratios, declines in earnings increase the likelihood of covenant violations, transferring control rights to lenders, tightening borrowing constraints, and ultimately reducing firms' investment and credit availability (Beatty et al., 2008; Nikolaev, 2010; Roberts and Sufi, 2009).¹³

Consequently, aggregate earnings provide information not only about current profitability but also about the economy's aggregate distance to covenant violations and the associated tightening of credit conditions.¹⁴ Reduced access to external finance further depresses firms'

¹⁰In both neoclassical and New Keynesian frameworks, shocks that reduce investment—whether originating from the supply or demand side—can lead to declines in output and labor demand. Specifically, when lower earnings reduce capital accumulation, the marginal productivity of labor will also decrease, making it less profitable for firms to hire labor and expand output. We illustrate it with a simple model. Assume that investment decisions are a function of firm profitability, such that $I_t = \phi_0 + \phi_1 \Pi_t$, with $\phi_1 > 0$. Under a standard production framework, output is given by $Y_t = A_t K_t^\alpha L_t^{1-\alpha}$, with capital evolving as $K_{t+1} = (1 - \delta)K_t + I_t$. Wages are determined by the marginal product of labor: $w_t = MPL_t = (1 - \alpha)A_t K_t^\alpha L_t^{-\alpha}$, which implies that the derived labor demand is $L_t^d = [(1 - \alpha)A_t K_t^\alpha w_t^{-1}]^{1/\alpha}$. Assuming that labor supply is sticky in the short run, it follows that $\frac{\partial L_{t+1}^d}{\partial \Pi_t} > 0$ and $\frac{\partial Y_{t+1}^d}{\partial \Pi_t} > 0$. In other words, higher (lower) firm profitability, measured by Π_t , leads to higher (lower) investment, which increases (decreases) next-period capital stock, driving up (down) labor demand and output.

¹¹The NBER dates recessions based on a wide range of indicators, but state that they place particular weight on two measures, “real personal income less transfers and nonfarm payroll employment” (<https://www.nber.org/research/business-cycle-dating>).

¹²Armstrong et al. (2019) show that financing constraints are more sensitive to earnings fluctuations when accounting quality is lower, that is, when information asymmetry is greater.

¹³Corporate loan agreements commonly contain financial covenants based on accounting performance measures, including EBITDA, leverage ratios (e.g., Debt-to-EBITDA), and interest coverage ratios (ICR). These covenants typically require firms to maintain specified financial thresholds. Failure to satisfy these requirements transfers control rights to lenders, who may renegotiate loan terms, accelerate repayment, restrict additional borrowing, or impose limits on corporate investment (Chodorow-Reich and Falato, 2022; Roberts and Sufi, 2009).

¹⁴Unlike the distance-to-default measure commonly used in the credit risk literature, distance to covenant violation is based on accounting performance measures embedded in debt contracts. Because covenant violations typically occur before default, this concept captures an earlier deterioration in firms' borrowing capacity and financing conditions.

investment, reinforcing the direct investment channel discussed above. This mechanism resembles the financial accelerator emphasized in the macroeconomic literature, whereby tighter borrowing constraints amplify aggregate downturns (Bernanke et al., 1999; Kiyotaki and Moore, 1997).

Taken together, these mechanisms are complementary rather than mutually exclusive. Informational mechanisms suggest why aggregate earnings may provide early signals of future recessions, whereas propagation mechanisms explain how deteriorating earnings may contribute to broader economic contractions. Accordingly, we develop the following hypotheses.

- **H1: Changes in aggregate earnings contain incremental predictive content for economic recessions.**
- **H2: Negative changes in earnings are more informative for forecasting recessions than positive changes.**

3 Empirical Framework

When the economy evolves across distinct discrete states, using a binary dependent variable, such as recession indicators, helps mitigate the problem of spurious accuracy often present in continuous macroeconomic forecasts (Estrella, 1998). In addition, binary recession indicators are more robust to model instability and real-time data revisions than real-time GDP forecasts (Rudebusch and Williams, 2009). Accordingly, we model recession as a binary variable equal to one if the economy enters a recession and zero otherwise.

3.1 Probit Models

We estimate the probability of a future recession using a probit model, a standard framework in the recession forecasting literature (Estrella, 1998; Estrella and Mishkin, 1998;

Kauppi and Saikkonen, 2008; Nyberg, 2010).^{15 16} The model is specified as

$$P(D_{t+k} = 1 | \pi_t) = \Phi(\pi_t),$$

where D_{t+k} equals one if the economy is in recession at quarter $t+k$ and zero otherwise, $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution, and π_t is a latent index constructed from recession predictors.

We estimate the following specifications for the latent index π_t^i ($i = 1, \dots, 4$):

$$\pi_t^1 \equiv \alpha + \beta^{AE} \Delta_4 AE_t, \quad (1)$$

$$\pi_t^2 \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t, \quad (2)$$

$$\pi_t^3 \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t + \gamma' X_t, \quad (3)$$

$$\pi_t^4 \equiv \alpha + \gamma' X_t, \quad (4)$$

where $\Delta_4 AE_t$ denotes the annual change in aggregate earnings and $\Delta_4 SPI_t$ the annual change in aggregate special items. $X_t = [TERM_t, CRED_t, INFL_t, \Delta SP500_t, MacroU_t]'$ includes five common recession predictors: the term spread, credit spread, consumer price inflation, S&P 500 returns, and the macroeconomic uncertainty index of Jurado et al. (2015). Equations (1)–(4) are estimated using maximum likelihood with Newey–West standard errors.¹⁷

We expect β^{AE} to be significantly negative in Equations (1)–(3), indicating that aggregate earnings growth adds incremental predictive power for recessions beyond conventional predictors in Equation (4).

3.2 Out-of-Sample Evaluation Metrics

As many predictors perform well in-sample but poorly out-of-sample (Estrella and Mishkin, 1998), we evaluate the out-of-sample performance of accounting-based predictors using pseudo- R^2 , the quadratic probability score (QPS), and the area under the receiver operating characteristic curve (ROC/AUC) (Berge and Jorda, 2011; Borio et al., 2020; Liu and Moench,

¹⁵We estimate static probit models because the NBER identifies recessions with substantial delays rather than in real time, with lags ranging from several months to more than one year. In the Appendix, we show that dynamic probit specifications yield similar conclusions.

¹⁶We adopt the probit specification rather than logit because prior studies show that probit models exhibit superior predictive performance for business cycle turning points (Chin et al., 2000; Del Negro, 2001).

¹⁷We follow Kauppi and Saikkonen (2008) in using the Parzen kernel with the bandwidth suggested by Andrews (1993) for the Newey–West estimator.

2016). The pseudo- R^2 measures the improvement in model likelihood relative to a benchmark specification. The QPS evaluates the accuracy of predicted recession probabilities using a proper scoring rule that penalizes larger probabilistic forecast errors. The ROC/AUC measures the model’s ability to rank recession risk across business cycle states. Appendix A1 provides detailed definitions of these metrics. Together, these metrics provide a comprehensive assessment of model fit, probabilistic forecast accuracy, and classification performance.

4 Data

The dataset used in this study spans the period from the first quarter of 1971 to the fourth quarter of 2021. Quarterly firm-level accounting data are sourced from Compustat. Following the methodologies of Kothari et al. (2006) and Shivakumar (2007), we use earnings before extraordinary items (Compustat item *ibq*) to construct aggregate earnings, denoted as AE_t . Aggregate special items, denoted as SPI_t , are measured using Compustat item *spiq*. We calculate year-over-year changes in the value-weighted aggregate earnings and special items, denoted as $wdibq_t$ and $wrdspiq_t$, respectively. As control variables, we include term spreads ($TERM_t$), credit spreads ($CRED_t$), annual consumer price index (CPI) inflation ($INFL_t$), stock market returns ($\Delta SP500_t$), and a U.S. macroeconomic uncertainty index ($MacroU_t$). Details on the construction and data sources for these variables are provided in Appendix A2.¹⁸ To verify stationarity, we conduct the Dickey–Fuller generalized least squares (DF-GLS) unit root tests. As reported in Appendix A4, we find that all variables are stationary.

Table 1 reports summary statistics for all key variables, measured quarterly. On average, the U.S. economy is in recession 16% of the time. Aggregate earnings grow by 1.10%, special items decline by 0.12%, term spreads average 1.52%, credit spreads 1.08%, inflation 3.92%, and S&P 500 returns 1.93%, and the macroeconomic uncertainty index is 0.66.

Table 2 reports correlation coefficients between aggregate earnings growth and future recessions, measured at one quarter ahead ($t + 1$) in Panel A and four quarters ahead ($t + 4$) in

¹⁸In Appendix A3, we demonstrate that our constructed measures, i.e., changes in aggregate earnings and special items, have predictive power for GDP growth, consistent with the findings of Konchitchki and Patatoukas (2014a), Gaertner et al. (2020), and Abdalla and Carabias (2022). This provides reassurance that our variables are appropriately constructed and align with established empirical patterns.

Panel B. The results indicate that changes in aggregate earnings are significantly and negatively correlated with future recessions for both horizons. In contrast, changes in special items exhibit a significant negative correlation only in the short term ($t + 1$), with no statistically significant relationship at the longer horizon ($t + 4$).

5 Baseline Results

This section examines the in-sample and out-of-sample performance of aggregate earnings in predicting U.S. recessions.

5.1 In-Sample Analysis

Table 3 reports the in-sample estimation results for Equations (1)–(4). The first column presents the estimates from Equation (1), which focus exclusively on the predictive ability of aggregate earnings growth. The coefficient on $\Delta_4 AE_t$ is negative and statistically significant at both the one-quarter ($k = 1$) and four-quarter ($k = 4$) horizons, indicating that declines in aggregate earnings growth are associated with a higher probability of future recessions. This evidence is consistent with prior studies showing that increases in aggregate earnings predict stronger future economic activity, including real GDP growth and employment growth (Abdalla and Carabias, 2022; Hann et al., 2021; Konchitchki and Patatoukas, 2014a). In this sense, increases (decreases) in aggregate earnings signal stronger (weaker) future macroeconomic conditions.

The second column of Table 3 reports estimates from Equation (2), which jointly includes changes in aggregate earnings and changes in special items. Consistent with the results from Equation (1), the coefficient on $\Delta_4 AE_t$ remains negative and statistically significant at both the one-quarter ($k = 1$) and four-quarter ($k = 4$) horizons, indicating that aggregate earnings growth contains predictive information beyond that captured by changes in special items. In contrast, the coefficient on $\Delta_4 SPI_t$ is significantly negative at the one-quarter horizon but becomes insignificant at the four-quarter horizon.

The third column of Table 3 reports the estimates from Equation (3), the most compre-

hensive “kitchen sink” specification that includes both accounting-based variables and the conventional recession predictors X_t , namely the term spread, credit spread, CPI inflation, stock market returns, and the U.S. macroeconomic uncertainty index. The estimated coefficients of the conventional predictors are broadly consistent with economic intuition. The negative coefficients on $TERM_t$ and $\Delta SP500_t$ indicate that a flatter yield curve and lower stock market returns are associated with a higher probability of recession. In contrast, the positive coefficients on $CRED_t$ and $MacroU_t$ suggest that wider corporate credit spreads and higher macroeconomic uncertainty are linked to an increased likelihood of recession.

Importantly, the coefficient on the variable of primary interest, $\Delta_4 AE_t$, remains negative and statistically significant, indicating that aggregate earnings growth contains predictive information about future recessions beyond that captured by the conventional predictors in X_t . The evaluation metrics also show clear improvements relative to Equations (1)–(2), with higher pseudo- R^2 and AUC values and a lower QPS . The model exhibits strong classification performance, with the AUC reaching 0.943 at the one-quarter horizon ($k = 1$).

For comparison, the fourth column of Table 3 reports estimates from Equation (4), which serves as a benchmark by including only the conventional predictors X_t and excluding accounting-based variables. The results show that Equation (3) consistently outperforms this benchmark across all evaluation metrics. Specifically, the model incorporating aggregate accounting predictors exhibits higher pseudo- R^2 , AUC , and log-likelihood values, as well as a lower QPS . These findings indicate that accounting information provides incremental predictive power and enhances the performance of conventional recession forecasting models.

Figure 1 plots the ROC curves at the one-quarter horizon for our predictive models, corroborating the results reported in Table 3. The red ROC curve for Equation (3) lies above the blue curve for Equation (4) over most of the range, particularly when the false positive rate is relatively small, between 0.05 and 0.2. As the ROC curve summarizes the tradeoff between the false positive rate (the probability of a Type I error, i.e., the size of the test) and the true positive rate (one minus the probability of a Type II error, i.e., the power of the test), this pattern indicates that incorporating accounting variables increases the model’s ability to correctly identify recessions while preserving low Type I error rates.

We further quantify the effect of aggregate earnings on recession probabilities by computing the average marginal effect (AME) of $\Delta_4 AE_t$ for Equations (1)–(3) reported in Table 3. The estimated AMEs imply that a one-standard-deviation decline in aggregate earnings growth increases the probability of a recession by 3.0%–8.3% at the one-quarter horizon and by 4.8%–7.3% at the four-quarter horizon, depending on the specifications.

Finally, Figure 2 plots the in-sample predicted recession probabilities from Equation (3). The predicted probabilities closely track NBER-designated recession periods and generate forecasts with relatively few false signals.

In summary, our in-sample predictive tests support **Hypothesis H1**: changes in aggregate earnings contain incremental predictive content for economic recessions. We show that changes in aggregate earnings demonstrate stable and persistent predictive power for future recession probabilities. In contrast, the predictive significance of special items is more nuanced and relatively short-lived.

5.2 Out-of-Sample Analysis

To assess whether the predictive performance observed in-sample carries over to an out-of-sample setting, we conduct out-of-sample forecasting exercises following Estrella and Mishkin (1998), which replicate the information available to policymakers when evaluating recession risks *ex ante*. Our data period commences in 1971:Q1. We set the out-of-sample evaluation period from 2000:Q1 to 2021:Q4, which covers three major recessionary episodes in U.S. history: the burst of the dot-com bubble, the global financial crisis, and the COVID-19 pandemic. The initial in-sample estimation window runs from 1971:Q1 to 1999:Q4 inclusive. Subsequently, we recursively reestimate the probit model by expanding the estimation window one quarter at a time, incorporating newly available information each time, and compute the corresponding k -quarter-ahead recession probability forecasts.

Table 4 reports the out-of-sample forecasts generated from Equations (2) and (4). We benchmark our two accounting predictors, namely aggregate earnings growth and special items growth, against a widely adopted five-indicator predictive model that includes the term spread,

credit spread, inflation, S&P 500 returns, and macroeconomic uncertainty. Column 1 presents the results for the five-predictor benchmark model. Although it performs reasonably well in the long term (pseudo- $R^2 = 0.159$ at $k = 4$), its pseudo- R^2 is poor for the shorter horizon ($k = 1$). In contrast, the parsimonious two-predictor accounting-based model (see Column 2) maintains a positive pseudo- R^2 at $k = 1$ (0.065), highlighting its superior short-term predictive power. It is evident that a parsimonious model using only accounting predictors, including aggregate earnings growth and special items growth, delivers reasonably good out-of-sample performance at short horizons.

Beyond individual forecasting models, we employ a forecast combination strategy to address model uncertainty and potential misspecification (e.g., Bates and Granger, 1969; Berge, 2015; Faust et al., 2013; Rapach et al., 2010; Stock and Watson, 2004). Specifically, we construct the combined out-of-sample forecasts using an equally weighted averaging method.¹⁹ Suppose that the out-of-sample predicted recession probabilities are denoted by $\hat{\Phi}(\pi_t^2 | \Delta_4 AE_t, \Delta_4 SPI_t)$ from Equation (2), and $\hat{\Phi}(\pi_t^4 | X_t)$ from Equation (4). We propose out-of-sample combined forecasts that weight each model equally, as follows:

$$\hat{\Phi}_{FC} = \frac{\hat{\Phi}(\pi_t^2 | \Delta_4 AE_t, \Delta_4 SPI_t) + \hat{\Phi}(\pi_t^4 | X_t)}{2}, \quad (5)$$

where $\hat{\Phi}_{FC}$ denotes the equally weighted combined forecasts derived by averaging the out-of-sample predictions generated by the accounting-based predictive model in Equation (2) and the classical predictive model in Equation (4).²⁰ If the out-of-sample evaluation metrics from the combined forecasts, $\hat{\Phi}_{FC}$, outperform those from the classical recession predictors (i.e., $\hat{\Phi}(\pi_t^4 | X_t)$), then the aggregate accounting predictors, namely $\Delta_4 AE_t$ and $\Delta_4 SPI_t$, must contain incremental information that improves forecasts of future recessions.

Combining the forecasts from the classical five-predictor model and the two-predictor accounting-based model (Column 3, $\hat{\Phi}_{FC}$) achieves the highest pseudo- R^2 (0.319) and the lowest QPS (0.168) at $k = 1$, with a slightly better AUC, thereby outperforming both standalone

¹⁹We avoid estimating a single model that includes all candidate predictors, as in Equation (3), based on the concerns raised by Rapach et al. (2010) and Welch and Goyal (2007), who refer to this as the “kitchen sink” approach. Pooling all predictors in one regression increases the risk of overfitting: although it may achieve a good in-sample fit, it often captures noise rather than true predictive signals, thereby degrading out-of-sample performance. Moreover, when predictors are highly correlated, including them all in a single regression can exacerbate multicollinearity, which increases estimation uncertainty. Both overfitting and inflated estimation error can weaken the robustness of forecasts beyond the estimation sample.

²⁰After comparing five weighting schemes, Rapach et al. (2010) find that the equally weighted forecasts have robust performance.

models. At the longer horizon of $k = 4$, the combined model continues to improve predictive accuracy, with a lower QPS (0.275) than either of the standalone specifications. These findings underscore the incremental value of accounting-based indicators for policymakers and practitioners: they not only exhibit strong standalone predictive performance but also enhance the forecasting accuracy of conventional predictive models when used in combination.

Figure 3 illustrates the one-quarter-ahead predictions of recession probabilities using the combined forecasts from Equations (2) and (4), specifically $\hat{\Phi}_{FC}$. It clearly captures the three recession episodes during the out-of-sample period, including the dot-com crisis, the global financial crisis, and the COVID-19 pandemic.

In summary, our out-of-sample predictive test results align with our in-sample results, supporting **Hypothesis H1** that changes in aggregate earnings contain incremental predictive content for economic recessions. We show that in addition to their in-sample predictive ability, changes in aggregate earnings and special items provide complementary and incremental information in out-of-sample settings, beyond that contained in traditional recession predictors.

6 Source of Predictive Content

This section investigates the sources of the predictive content in aggregate earnings. While the baseline results establish that aggregate earnings predict future recessions, they do not reveal which features of earnings drive this predictive ability or through which economic mechanisms it arises. We therefore conduct three complementary analyses. First, we examine whether the predictive content differs between positive and negative earnings changes, motivated by the asymmetric recognition of gains and losses under conditional conservatism. Second, we investigate whether the predictive content is concentrated in cyclically sensitive industries, where macroeconomic shocks are more likely to propagate through real economic activity. Finally, we decompose aggregate earnings into expected and surprise components to assess whether recession predictability primarily reflects unexpected information or also extends to the more persistent component of aggregate earnings. Together, these analyses provide complementary evidence on both the informational sources and the economic mechanisms underlying aggre-

gate earnings' predictive ability.

6.1 Sign Asymmetry

In this section, we follow Gaertner et al. (2020) and decompose changes in aggregate earnings and special items into positive and negative components to examine whether the predictive content for future recessions is asymmetric and differs by sign. As Gaertner et al. (2020) argue, the sign of earnings changes is informative about relative timeliness: losses tend to be recognized in financial statements more promptly than gains. This asymmetric timeliness is consistent with conditional conservatism (Basu, 1997), under which the verification threshold for recognizing good news is higher than for bad news. Earlier recognition of bad news not only accelerates the incorporation of adverse economic information into reported earnings, but may also move firms closer to violating earnings-based debt covenants, thereby tightening borrowing capacity and reinforcing the transmission of adverse shocks.

In contrast, the earnings smoothing literature suggests that managers may reduce volatility in reported performance by spreading unusually high gains and unusually large losses across reporting periods. Prior to recessions, such smoothing behavior may mask emerging economic weakness, as managers spread losses over multiple periods to avoid sharp declines in reported earnings. This practice can dampen the immediacy of negative signals and may delay the reflection of downturn-related losses in aggregate earnings. Whereas conditional conservatism predicts earlier recognition of bad news, earnings smoothing implies a more gradual incorporation of both good and bad news, which may attenuate the timeliness and magnitude of earnings-based recession signals.

Reconciling these perspectives, timely loss recognition under conservatism can sometimes be noisy at the firm level, raising the possibility that some negative news is less accurate. However, aggregation can mitigate idiosyncratic noise: to the extent that firm-specific errors are largely uncorrelated, they diversify away, and systematic downturn-related losses are more likely to comove, preserving the informational content of aggregate signals. Thus, even in the presence of earnings smoothing, promptly recognized losses may still carry earlier information

about macroeconomic deterioration at the aggregate level, consistent with our findings in this section that negative components exhibit stronger predictive content.

Following Gaertner et al. (2020), we specify the following probit models to capture the possible asymmetric predictive power of $\Delta_4 AE_t$ and $\Delta_4 SPI_t$:

$$\pi_t^{ASY1} \equiv \alpha + \beta^{AE+} \Delta_4 AE_t^+ + \beta^{AE-} \Delta_4 AE_t^-, \quad (6)$$

$$\pi_t^{ASY2} \equiv \alpha + \beta^{AE+} \Delta_4 AE_t^+ + \beta^{AE-} \Delta_4 AE_t^- + \beta^{SPI+} \Delta_4 SPI_t^+ + \beta^{SPI-} \Delta_4 SPI_t^-, \quad (7)$$

$$\pi_t^{ASY3} \equiv \alpha + \beta^{AE+} \Delta_4 AE_t^+ + \beta^{AE-} \Delta_4 AE_t^- + \beta^{SPI+} \Delta_4 SPI_t^+ + \beta^{SPI-} \Delta_4 SPI_t^- + \gamma' X_t, \quad (8)$$

where

$$\Delta_4 AE_t^+ = \Delta_4 AE_t \times I(\Delta_4 AE_t > 0)$$

$$\Delta_4 AE_t^- = \Delta_4 AE_t \times I(\Delta_4 AE_t \leq 0)$$

$$\Delta_4 SPI_t^+ = \Delta_4 SPI_t \times I(\Delta_4 SPI_t > 0)$$

$$\Delta_4 SPI_t^- = \Delta_4 SPI_t \times I(\Delta_4 SPI_t \leq 0)$$

$I(\Delta_4 AE_t > 0)$ and $I(\Delta_4 SPI_t > 0)$ are indicators that take a value of one when $\Delta_4 AE_t$ and $\Delta_4 SPI_t$ are positive, and zero otherwise. Similarly, $I(\Delta_4 AE_t \leq 0)$ and $I(\Delta_4 SPI_t \leq 0)$ are indicators that assume a value of one when $\Delta_4 AE_t$ and $\Delta_4 SPI_t$ are zero or negative. Equation (6) investigates the possible asymmetric predictive content of changes in aggregate earnings. Equation (7) incorporates the asymmetric responses of both $\Delta_4 AE_t$ and $\Delta_4 SPI_t$. Finally, Equation (8) includes X_t as additional predictors.

Table 5 presents the in-sample predictive results of Equations (6)–(8) for $k = 1$ and $k = 4$. Across all models, β^{AE+} is statistically insignificant at all horizons. In contrast, β^{AE-} is negative and statistically significant, indicating that only negative changes in aggregate earnings predict future recessions. Furthermore, when comparing Table 5 with Table 3, we find that $|\beta^{AE-}| > |\beta^{AE}|$ at $k = 4$ for all models. This suggests that negative changes in aggregate earnings possess stronger predictive power for recessions over a longer horizon. We do not find predictive asymmetry between β^{SPI+} and β^{SPI-} . We observe that β^{SPI-} is insignificant across models and horizons. In contrast, β^{SPI+} is significant at $k = 1$, but this significance disappears

when the control vector X_t is included. Overall, negative changes in special items do not provide earlier signals of adverse macroeconomic conditions than positive changes, possibly due to earnings smoothing through SPI_t , which eliminates asymmetric effects.

Furthermore, a comparison of the evaluation metrics with those reported for Equations (1)–(3) in Table 3 reveals that accounting for asymmetric responses to earnings changes and special items enhances in-sample predictive performance. This is evidenced by higher pseudo- R^2 and AUC values, alongside a lower QPS .

In summary, our results confirm **Hypothesis H2** that negative changes in aggregate earnings are more informative than positive ones in forecasting recessions. We conclude that the predictive power of $\Delta_4 AE_t$ for future recessions is primarily influenced by negative changes in aggregate earnings ($\Delta_4 AE_t^-$). Conversely, changes in aggregate special items do not demonstrate asymmetric predictive effects in regard to the probability of recession, and their predictive power is both short-lived and transitory. Although Gaertner et al. (2020) find that the predictive power of negative changes in aggregate earnings for future GDP growth diminishes after controlling for negative changes in special items,²¹ we demonstrate that negative changes in aggregate earnings continue to indicate future recessions. This suggests that forecasting NBER recessions using negative changes in aggregate earnings may be more effective than predicting real GDP growth.

6.2 Sectoral Heterogeneity

In this section, we examine whether the predictive content of aggregate earnings growth varies across sectors. Both New Keynesian and neoclassical frameworks imply that industries more closely linked to durable goods production and investment activity exhibit stronger cyclical responses to macroeconomic shocks (Berman and Pfleeger, 1997; Konovalova and Maksimov, 2017).²² Following an adverse macroeconomic shock, these cyclically sensitive industries tend

²¹Gaertner et al. (2020) attribute this finding to the fact that the Bureau of Economic Analysis excludes many conditionally conservative accounting accruals in its measure of corporate profits (Laurion and Patatoukas, 2016), which would otherwise accelerate the recognition of adverse news in accounting earnings.

²²New Keynesian and neoclassical frameworks offer different perspectives on the sources of business cycle fluctuations. New Keynesian models emphasize aggregate demand shocks, often reflected in fluctuations in durable consumption, whereas neoclassical frameworks highlight real (supply-side) shocks, such as productivity shocks, that operate through investment and capital accumulation.

to experience larger and more pronounced declines in earnings. Firms in these sectors may respond by adjusting investment and production, thereby reducing capital accumulation and output. Through propagation in output and labor markets, these responses can amplify the adverse macroeconomic shock, making earnings from these industries more informative about future downturns.

Motivated by this theoretical intuition, we examine whether aggregate earnings from more cyclically sensitive industries contain stronger signals of future recessions than those from non-cyclical industries. We classify industries as cyclically sensitive based on economic characteristics commonly associated with higher exposure to business cycle fluctuations. Specifically, we consider whether industries rely heavily on discretionary income (e.g., automotive, leisure, durables), exhibit high capital intensity or leverage (e.g., construction and real estate), face strong product-market competition and volatile demand (e.g., retail and raw materials), or operate with high fixed cost structures that create substantial operating leverage (e.g., manufacturing and transportation).²³ Using four-digit standard industrial classification codes, we classify the following as cyclically sensitive industries: construction (1500–1799), durable goods (2000–2599), printing (2700–2799), chemicals (2800–2899), machinery (3400–3599), auto (3710, 3711, 3714), transport (4000–4799), retail (5000–5999), fire (6000–6799), and leisure (7000–7999). Although this classification is necessarily approximate, it provides a transparent and economically motivated means of examining differences across industries.

Tables 6 and 7 report the in-sample predictive results for cyclically sensitive and noncyclical industries, respectively. Consistent with our hypothesis, aggregate earnings from cyclically sensitive industries exhibit significant in-sample predictive ability across models and horizons, whereas those from noncyclical industries are generally insignificant. The AMEs in our probit models echo these patterns. For example, in Equation (1), the absolute AME of aggregate earnings $|\text{AME}(\beta^{AE})|$ from cyclically sensitive industries equals 0.083, which is almost identical to the baseline AME using all industries (3), whereas the AME for noncyclical industries is smaller. These comparisons suggest that aggregate earnings in cyclically sensitive sectors may

²³Operating leverage refers to the sensitivity of profits to changes in revenue when a firm relies heavily on fixed costs. For instance, in the airline industry, an increase in the passenger load factor from 60% to 80% can substantially raise profitability by lowering the average fixed cost per passenger.

contribute disproportionately to the predictive content of our baseline model.

We further find that sectoral differences in predictive content are present for aggregate earnings but not for special items. This contrast is consistent with how firms respond to persistent versus transitory shocks. Declines in recurring earnings are more likely to be perceived as persistent and to trigger costly operational adjustments, such as reductions in investment or labor, especially in cyclically sensitive industries where such responses are more pronounced. In contrast, special items typically reflect one-time, unexpected losses that are less likely to signal persistent changes in firm performance. Firms are less likely to adjust investment and employment in response to such transitory shocks. These findings suggest that the predictive ability of aggregate earnings, particularly in cyclically sensitive sectors, is consistent with the propagation of persistent shocks that induce real economic adjustments.

In summary, we find that much of the predictive content in aggregate earnings originates from cyclically sensitive sectors, as the recession predictability based on earnings from these sectors closely matches the predictability obtained when aggregating across all industries.

6.3 Earnings Surprise vs. Expected Earnings Component

To better understand the sources of the predictive ability of aggregate earnings, we decompose aggregate earnings growth into expected and surprise components.²⁴ Rather than serving as a formal identification strategy, this decomposition provides a simple empirical design for assessing whether recession predictability is driven primarily by unexpected earnings news or whether it also extends to the more persistent component of aggregate earnings growth. Under a purely informational interpretation, the predictive content should be concentrated in earnings surprises. If the expected component also predicts recessions, however, this would suggest that unexpected information alone is insufficient to account for the predictive ability of aggregate earnings.

Following Kothari et al. (2006) and Hann et al. (2021), we implement two alternative approaches to decompose aggregate earnings growth into expected and surprise components. In

²⁴Prior studies also argue that removing the predictable component of earnings may reduce the influence of earnings management practices such as income smoothing, thereby producing a cleaner measure of earnings news (Hann et al., 2021; Konchitchki and Patatoukas, 2014a,b).

both approaches, the expected earnings component is estimated based on past earnings and other relevant information available at quarter $t - 1$, while earnings surprises are defined as innovations orthogonal to the expected component. Throughout this section, we interpret the expected component as capturing the more persistent component of aggregate earnings growth because it reflects systematic variation associated with lagged earnings and macroeconomic fundamentals, rather than transitory earnings news. Employing two alternative decomposition methods ensures that a particular specification does not drive our conclusions.

We first follow Kothari et al. (2006) and use discount rate proxies, such as the term spread and the credit spread, together with other recession predictors collected in X_t and one-quarter lagged changes in aggregate earnings to estimate the expected component of earnings changes and the associated earnings surprises. Specifically, we estimate the following linear regression:

$$\Delta_4 AE_t = \alpha + \gamma' X_t + \theta^{AE} \Delta_4 AE_{t-1} + \varepsilon_t^{Surprise}. \quad (9)$$

The estimated residuals, $\hat{\varepsilon}_t^{Surprise}$, are used as a proxy for earnings surprises and are denoted by $\Delta_4 AE_t^{Surprise}$. The expected component of earnings growth is then proxied by $\Delta_4 AE_t - \hat{\varepsilon}_t^{Surprise}$ and denoted as $\Delta_4 AE_t^{Exp}$. By construction, earnings surprises are orthogonal to the expected earnings component, which reflects information related to discount rate proxies, lagged earnings growth, and other macroeconomic predictors.

The second approach is a naïve method that estimates an AR(1) model for $\Delta_4 AE_t$ and uses the resulting innovations to measure earnings news. This approach is adopted by Hann et al. (2021), who show that earnings news extracted in this manner is informative for predicting job creation and destruction in the labor market, highlighting its macroeconomic relevance.

After obtaining the expected earnings components and earnings surprises, we estimate the following probit specification:

$$\pi_t \equiv \alpha + \beta^{AE,Exp} \Delta_4 AE_t^{Exp} + \beta^{AE,Surprise} \Delta_4 AE_t^{Surprise} + \beta^{SPI} \Delta_4 SPI_t + \gamma' X_t, \quad (10)$$

where $\beta^{AE,Exp}$ and $\beta^{AE,Surprises}$ measure the in-sample predictive ability of the expected and surprise components of aggregate earnings, respectively. $\Delta_4 AE_t^{Exp}$ and $\Delta_4 AE_t^{Surprise}$ are generated regressors from a two-stage procedure. In the first stage, we estimate Equation (9) or an

AR(1) model to decompose aggregate earnings. We therefore account for the associated estimation uncertainty in the second-stage probit regression estimation. To address potential biases and inference issues from using generated regressors, we employ a block bootstrap procedure, as described in Appendix A8.

Table 8 reports the estimation results of Equation (10) under the two decomposition methods described above. We find that both $\beta^{AE,Exp}$ and $\beta^{AE,Surprises}$ are statistically significant at horizons $k = 1$ and $k = 4$ across the two methods, indicating that both the expected and surprise components of aggregate earnings contain predictive information for future recessions at both short and longer horizons.²⁵ Moreover, the expected earnings component exhibits a larger economic magnitude than the earnings-surprise component, particularly at longer forecasting horizons.

The stronger predictive ability of the expected component at longer forecasting horizons provides additional insight into the mechanisms underlying recession predictability. Under a purely informational interpretation, unexpected earnings news should account for most of the predictive content and be incorporated into stock prices relatively quickly. Accordingly, its predictive content should diminish over longer forecasting horizons. In contrast, the increasing importance of the expected component over longer horizons is more consistent with financing-related propagation mechanisms that operate gradually rather than contemporaneously. Because firms' borrowing capacity often depends on sustained accounting performance rather than transitory earnings fluctuations (e.g., Beatty et al., 2008; Lian and Ma, 2020), declines in expected earnings may move firms closer to covenant violations, tighten borrowing constraints, reduce investment, and amplify adverse macroeconomic shocks.

Overall, these findings provide suggestive evidence that aggregate earnings reflect multiple underlying mechanisms. On the one hand, earnings surprises capture unexpected cash-flow news that is not fully reflected in other macroeconomic or financial variables, consistent with the informational channel. On the other hand, the expected component captures persistent changes in firms' operating fundamentals that are likely to influence firms' financing condi-

²⁵Based on the pseudo- R^2 , QPS, log-likelihood, and AUC, the two methods appear to be identical at $k = 1$. This similarity arises because the reported results are rounded to the third decimal place; differences between the two cases emerge only at the fourth decimal place.

tions. Our findings therefore broaden the perspective of the macro-accounting literature, which has primarily emphasized the informational role of aggregate earnings through channels such as the corporate profits link and earlier recognition of bad news (e.g., Gaertner et al., 2020; Konchitchki and Patatoukas, 2014a). Our evidence suggests that the predictive content of aggregate earnings reflects not only new information but may also be associated with financing-related propagation mechanisms.

7 Robustness Checks

In this section, we briefly summarize the additional analyses and robustness checks conducted to assess the reliability of our main findings. For brevity, the detailed results are presented in the Appendix.

To begin, we extend our analysis to dynamic probit models by incorporating a lagged recession indicator in Appendix A5. Compared with the baseline models in Table 3, we observe marginal improvements across most evaluation metrics, models, and horizons. However, the coefficient on special items (β^{SPI}) becomes insignificant, suggesting that its predictive content may be absorbed by the lagged recession term. In contrast, the predictive power of aggregate earnings (β^{AE}) remains robust and economically meaningful, with similar magnitude to the static model results. Overall, these findings confirm that our baseline results hold even after controlling for the most recent lagged NBER recession indicator.

Next, in Appendix A6, we examine whether our empirical models exhibit structural instability over the sample period, as structural breaks can significantly impair forecast performance (Rossi, 2013). To test for potential breaks, we employ the sup- LM_T statistic developed by Andrews (1993). The results provide no evidence of structural breaks in any of the models considered, suggesting that the predictive relationships are stable over time.

In Appendix A7, we consider an alternative measure of aggregate earnings. Following Konchitchki and Patatoukas (2014a), we use net income (Compustat item *niq*) in place of earnings before extraordinary items. The corresponding in- and out-of-sample estimates based on

this measure closely resemble our baseline findings reported in Tables 3 and 4.

In Appendix A8, we address potential finite sample biases by implementing a block bootstrap procedure. As established in the literature, bootstrap methods yield more reliable inference in small samples than standard asymptotic t -ratios and help mitigate size distortions. We apply this method to generate empirical p values to assess the statistical significance of our in-sample probit model estimates. In addition, we bootstrap AUC statistics to evaluate out-of-sample forecasting performance. The results confirm that the predictive power of aggregate earnings growth remains robust both in- and out-of-sample, thereby reinforcing the validity of our baseline findings beyond asymptotic inference.

8 Conclusion

In this paper, we examine the role of aggregate earnings growth in forecasting U.S. recessions. Using probit models and various measures of aggregate earnings, we find that aggregate earnings growth consistently predicts recessions one to four quarters ahead. In addition, the predictive content of aggregate earnings exhibits sign asymmetry, sectoral heterogeneity, and the distinct roles for expected and surprise earnings components.

Beyond documenting the predictive ability of aggregate earnings, our findings have broader implications for the recession forecasting literature. Existing literature has primarily relied on macroeconomic and financial indicators, whereas accounting information has received comparatively little attention. Our findings suggest that accounting information contains incremental predictive content that should not be overlooked in recession forecasting.

Our findings also broaden the role of aggregate earnings in the macro-accounting literature. Prior studies have largely interpreted the predictive ability of aggregate earnings through their informational role, emphasizing that accounting earnings incorporate information about future economic conditions in a timely manner. Our evidence suggests a more comprehensive view. While aggregate earnings clearly convey new information about future recessions, the stronger predictive ability of the expected earnings component over longer forecasting horizons can-

not be fully explained by a purely informational interpretation. Instead, we interpret these findings as being more consistent with financing-related propagation mechanisms, whereby persistent deterioration in firms' operating performance may tighten financing conditions and amplify macroeconomic downturns. Taken together, these findings suggest that aggregate earnings should be viewed not only as informative signals of future economic activity but also as indicators that may help illuminate how adverse shocks propagate through the economy.

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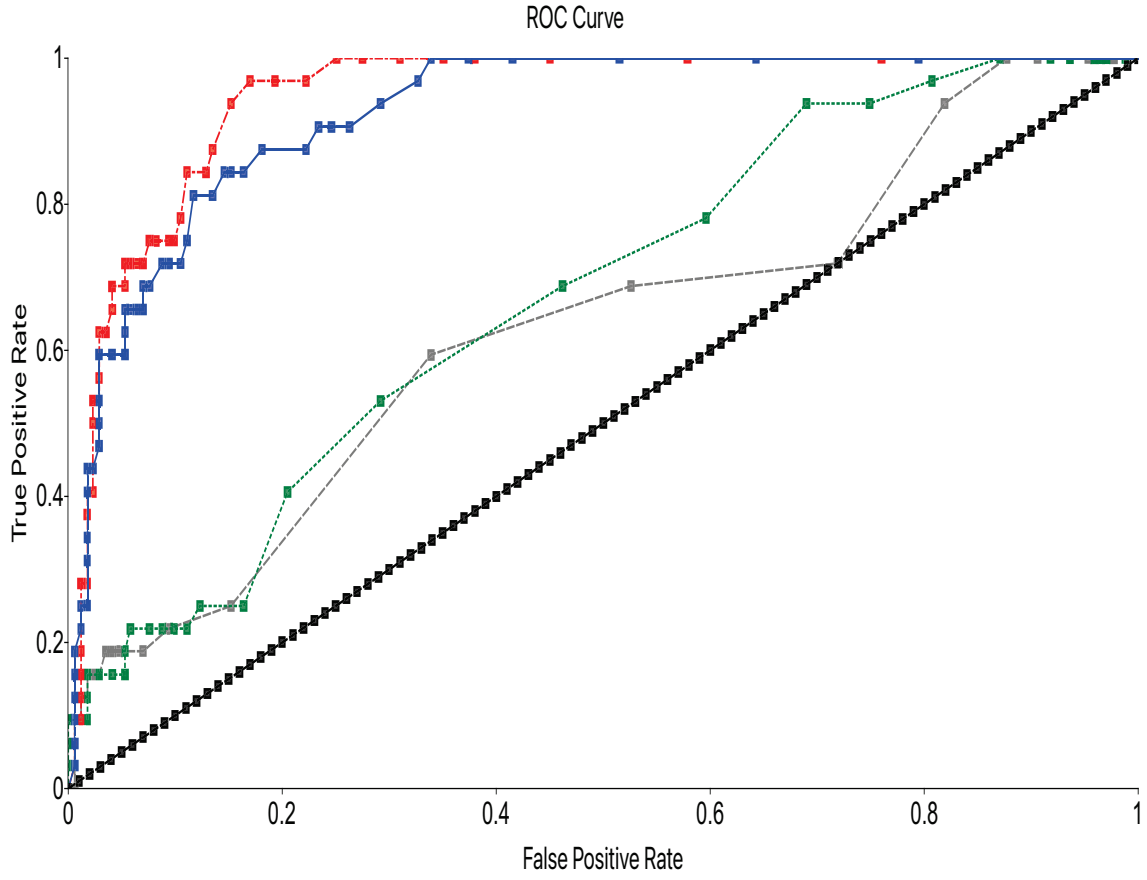
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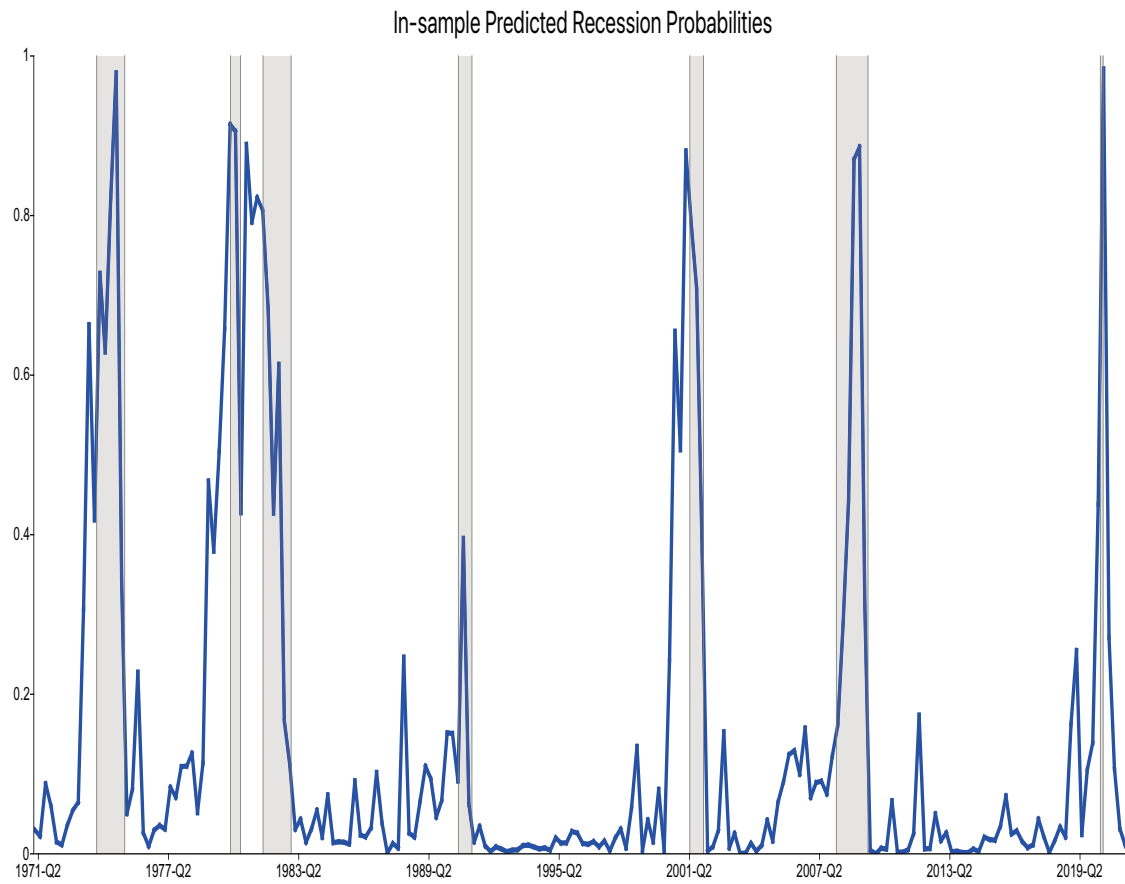
Figures and Tables

Figure 1: In-sample ROC curves



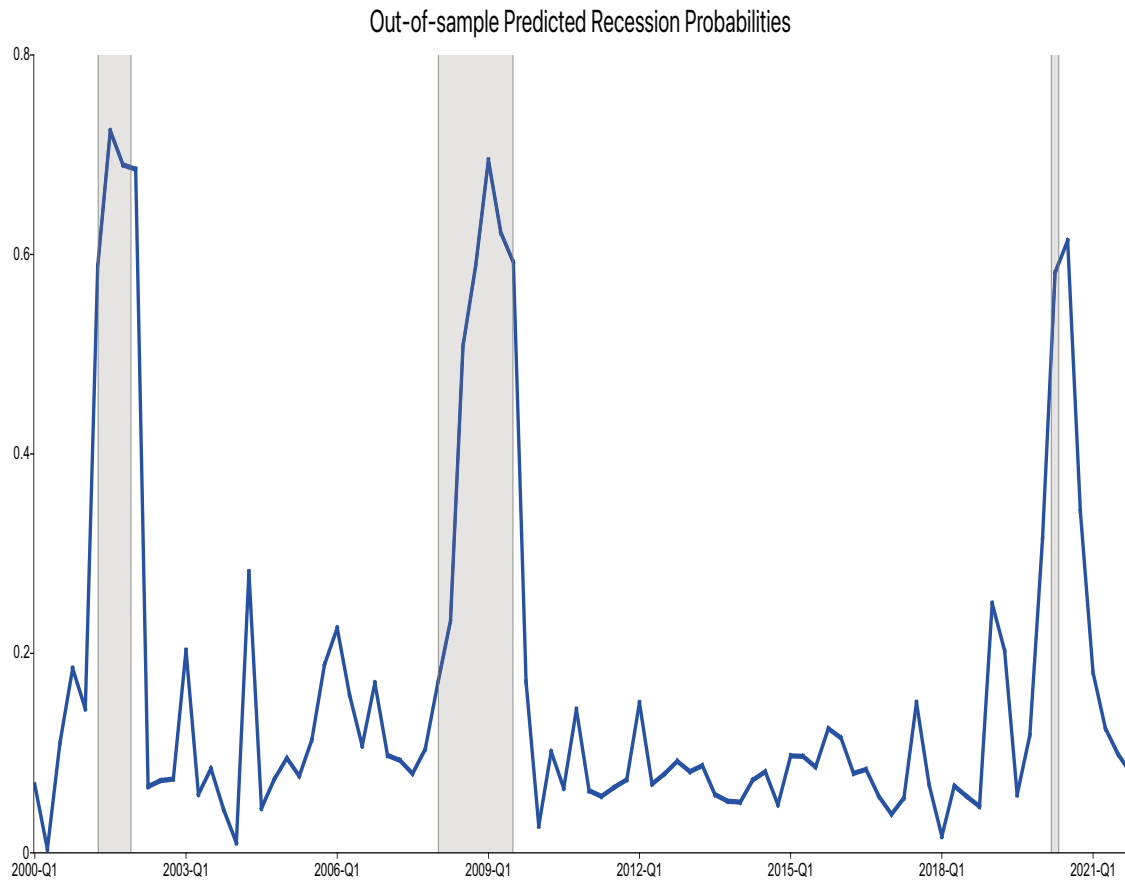
Notes: This figure plots in-sample ROC curves for the probit models. The gray line corresponds to Equation (1), which includes only $\Delta_4 AE_t$. The green line corresponds to Equation (2), which includes $\Delta_4 AE_t$ and $\Delta_4 SPI_t$. The blue line corresponds to Equation (4), which includes only control variables, X_t . Finally, the red line corresponds to Equation (3), which includes $\Delta_4 AE_t$, $\Delta_4 SPI_t$ and X_t . The 45° black solid line represents a coin-toss classifier.

Figure 2: In-sample predicted recessions based on multivariate probit model: one-quarter ahead.



Note: This figure illustrates the in-sample predicted recession probabilities based on Equation (3). The shaded areas represent NBER recession dates.

Figure 3: Out-of-sample predicted recessions based on probit models combination: one-quarter ahead.



Note: This figure illustrates the one-quarter-ahead predictions of recession probabilities using the combined forecasts from Equations (2) and (4), specifically $\hat{\Phi}_{FC}$. The shaded areas represent NBER recession dates.

Table 1: Summary Statistics

Variables	N	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
$Recession_t$	204	0.16	0.36	0.00	0.00	0.00	0.00	1.00
$\Delta_4 AE_t$	204	1.10	6.84	-32.43	0.12	1.20	2.55	32.82
$\Delta_4 SPI_t$	204	-0.12	3.39	-21.36	-0.74	0.01	0.66	17.53
$TERM_t$	204	1.52	1.27	-2.18	0.71	1.63	2.52	3.61
$CRED_t$	204	1.08	0.43	0.56	0.79	0.96	1.27	3.02
$INFL_t$	204	3.92	2.94	-1.62	2.00	3.10	4.64	14.51
$\Delta SP500_t$	204	1.93	8.22	-30.27	-1.32	2.99	7.05	19.55
$MacroU_t$	204	0.66	0.11	0.53	0.59	0.63	0.68	1.20

Note: This table reports descriptive statistics for key variables. The sample includes 204 quaters from 1971Q1 to 2021Q4. Detailed definitions of all variables can be found in [Appendix A2.1](#).

Table 2: Correlations

Panel A: One-quarter ahead recessions								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) $Recession_{t+1}$	1.00							
(2) $\Delta_4 AE_t$	-0.24	1.00						
(3) $\Delta_4 SPI_t$	-0.25	0.38	1.00					
(4) $TERM_t$	-0.36	0.10	0.07	1.00				
(5) $CRED_t$	0.29	-0.11	-0.07	0.11	1.00			
(6) $INFL_t$	0.38	0.01	-0.06	-0.47	0.26	1.00		
(7) $\Delta SP500_t$	-0.34	0.17	0.14	0.04	-0.20	-0.09	1.00	
(8) $MacroU_t$	0.52	-0.01	-0.15	-0.29	0.59	0.37	-0.19	1.00
Panel B: Four-quarter ahead recessions								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) $Recession_{t+4}$	1.00							
(2) $\Delta_4 AE_t$	-0.16	1.00						
(3) $\Delta_4 SPI_t$	0.07	0.47	1.00					
(4) $TERM_t$	-0.54	0.12	0.07	1.00				
(5) $CRED_t$	0.00	-0.07	-0.08	0.11	1.00			
(6) $INFL_t$	0.31	0.01	-0.07	-0.47	0.26	1.00		
(7) $\Delta SP500_t$	-0.03	0.14	0.15	0.04	-0.19	-0.09	1.00	
(8) $MacroU_t$	0.21	-0.12	-0.14	-0.29	0.63	0.38	-0.22	1.00

Note: This table reports correlation coefficients among the key variables. Panel A presents correlations with the one-quarter-ahead NBER recession indicator, based on a sample of 203 quarterly observations from 1971Q2 to 2021Q4. Panel B presents correlations with the four-quarter-ahead NBER recession indicator, using 200 quarterly observations from 1972Q1 to 2021Q4. Correlation coefficients with two-tailed p -values below 0.10 are shown in bold. Detailed definitions of all variables are provided in Appendix A2.1.

Table 3: Result from Probit Models

	Equation (1)		Equation (2)		Equation (3)		Equation (4)	
	<i>k</i> =1	<i>k</i> =4	<i>k</i> =1	<i>k</i> =4	<i>k</i> =1	<i>k</i> =4	<i>k</i> =1	<i>k</i> =4
$\Delta_4 AE_t$	-0.054*** (-3.169)	-0.031* (-1.808)	-0.038** (-2.491)	-0.051** (-2.163)	-0.033** (-2.308)	-0.054*** (-2.589)		
$\Delta_4 SPI_t$			-0.071** (-2.288)	0.068 (1.539)	-0.047 (-1.005)	0.099*** (2.816)		
$TERM_t$					-0.320** (-2.290)	-0.760*** (-3.954)	-0.333*** (-2.933)	-0.778*** (-3.942)
$CRED_t$					0.195 (0.500)	0.273 (0.564)	0.161 (0.375)	0.275 (0.577)
$INFL_t$					0.073* (1.763)	0.006 (0.128)	0.057 (1.373)	-0.011 (-0.210)
$\Delta SP500_t$					-0.049*** (-2.796)	-0.004 (-0.299)	-0.053*** (-3.181)	-0.001 (-0.067)
$MacroU_t$					3.924* (1.941)	0.348 (0.172)	4.261* (1.864)	0.183 (0.099)
AME($\Delta_4 AE_t$)	-0.083*** (-3.287)	-0.048** (-2.277)	-0.055** (-2.562)	-0.073*** (-2.929)	-0.030** (-2.076)	-0.049*** (-3.533)		
AME($\Delta_4 SPI_t$)			-0.060** (-2.423)	0.053 (1.635)	-0.022 (-1.053)	0.050*** (3.447)		
pseudo- R^2	0.055	0.018	0.072	0.038	0.415	0.345	0.372	0.307
QPS	0.248	0.263	0.244	0.250	0.141	0.165	0.153	0.180
AUC	0.618**	0.464	0.669***	0.468	0.943***	0.899***	0.926***	0.894***
p -value	[0.010]	[0.739]	[0.000]	[0.712]	[0.000]	[0.000]	[0.000]	[0.000]
Log-Lik	-82.892	-86.161	-81.218	-84.173	-47.824	-54.303	-51.866	-57.915

Note: The numbers in parentheses and brackets represent t -statistics and p -values, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The dependent variable in this table is the NBER recession indicator. Equation (1): $\pi_t^1 \equiv \alpha + \beta^{AE} \Delta_4 AE_t$; Equation (2): $\pi_t^2 \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t$; Equation (3): $\pi_t^3 \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t + \gamma' X_t$; Equation (4): $\pi_t^4 \equiv \alpha + \gamma' X_t$, where $X_t = [TERM_t, CRED_t, INFL_t, \Delta SP500_t, MacroU_t]'$. Detailed definitions of all variables can be found in Appendix A2.1.

Table 4: Out-of-Sample Predicting Results

Forecasts	$\hat{\Phi}(\pi_t^4 X_t)$		$\hat{\Phi}(\pi_t^2 \Delta_4AE_t, \Delta_4SPI_t)$		$\hat{\Phi}_{FC} = \frac{\hat{\Phi}(\pi_t^4) + \hat{\Phi}(\pi_t^2)}{2}$	
	$k=1$	$k=4$	$k=1$	$k=4$	$k=1$	$k=4$
pseudo- R^2	-0.002	0.159	0.065	-1.082	0.319	0.063
QPS	0.187	0.315	0.227	0.303	0.168	0.275
AUC	0.900***	0.762***	0.756***	0.267	0.904***	0.736***
p -value	[0.000]	[0.000]	[0.000]	[0.998]	[0.000]	[0.000]

Note: The numbers in parentheses and brackets represent t -statistics and p -values, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The dependent variable in this table is the NBER recession indicator. $\pi_t^2 \equiv \alpha + \beta^{AE} \Delta_4AE_t + \beta^{SPI} \Delta_4SPI_t$. $\pi_t^4 \equiv \alpha + \gamma'X_t$, where $X_t = [TERM_t, CRED_t, INFL_t, \Delta SP500_t, MacroUt_t]'$. $\hat{\Phi}_{FC} = \frac{\hat{\Phi}(\pi_t^2) + \hat{\Phi}(\pi_t^4)}{2}$. Detailed definitions of all variables can be found in Appendix A2.1.

Table 5: Result from Probit Models with Asymmetric Timeliness in Earnings and Special Items

Model	Equation (6)		Equation (7)		Equation (8)	
	$k=1$	$k=4$	$k=1$	$k=4$	$k=1$	$k=4$
$\Delta_4 AE_t^+$	-0.097 (-1.050)	-0.017 (-0.459)	-0.059 (-0.920)	-0.025 (-0.578)	-0.086 (-0.594)	-0.017 (-0.436)
$\Delta_4 AE_t^-$	-0.047** (-2.351)	-0.038* (-1.855)	-0.034* (-1.931)	-0.071** (-1.983)	-0.026* (-1.700)	-0.074** (-2.273)
$\Delta_4 SPI_t^+$			-0.325** (-2.347)	0.022 (0.534)	-0.119 (-0.552)	0.075** (2.115)
$\Delta_4 SPI_t^-$			-0.046 (-1.036)	0.110 (1.369)	-0.048 (-0.918)	0.132** (2.216)
$TERM_t$					-0.318** (-2.557)	-0.743*** (-4.082)
$CRED_t$					0.092 (0.225)	0.288 (0.565)
$INFL_t$					0.073 (1.149)	0.011 (0.219)
$\Delta SP500_t$					-0.049*** (-2.626)	-0.003 (-0.211)
$MacroU_t$					4.032*** (4.537)	0.421 (0.210)
AME($\Delta_4 AE_t^+$)	-0.097 (-0.911)	-0.012 (-0.572)	-0.056 (-0.911)	-0.017 (-0.572)	-0.048 (-0.586)	-0.007 (-0.421)
AME($\Delta_4 AE_t^-$)	-0.050** (-2.558)	-0.043** (-2.075)	-0.034** (-2.049)	-0.078** (-2.542)	-0.016* (-1.852)	-0.052*** (-3.127)
AME($\Delta_4 SPI_t^+$)			-0.131** (-1.976)	0.009 (0.554)	-0.028 (-0.923)	0.021 (1.063)
AME($\Delta_4 SPI_t^-$)			-0.025 (-1.072)	0.065 (1.534)	-0.016 (-0.923)	0.050 (1.063)
pseudo- R^2	0.057	0.022	0.090	0.046	0.419	0.350
QPS	0.248	0.261	0.240	0.246	0.140	0.163
AUC	0.630***	0.538	0.683***	0.522	0.948***	0.903***
p -value	[0.005]	[0.244]	[0.000]	[0.348]	[0.000]	[0.000]
Log-Lik	-82.660	-85.778	-79.364	-83.383	-47.471	-53.905

Note: The numbers in parentheses and brackets represent t -statistics and p -values, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The dependent variable in this table is the NBER recession indicator. Equation (6): $\pi_t^{ASY1} \equiv \alpha + \beta^{AE+} \Delta_4 AE_t^+ + \beta^{AE-} \Delta_4 AE_t^-$; Equation (7): $\pi_t^{ASY2} \equiv \alpha + \beta^{AE+} \Delta_4 AE_t^+ + \beta^{AE-} \Delta_4 AE_t^- + \beta^{SPI+} \Delta_4 SPI_t^+ + \beta^{SPI-} \Delta_4 SPI_t^-$; Equation (8): $\pi_t^{ASY3} \equiv \alpha + \beta^{AE+} \Delta_4 AE_t^+ + \beta^{AE-} \Delta_4 AE_{t-k}^- + \beta^{SPI+} \Delta_4 SPI_t^+ + \beta^{SPI-} \Delta_4 SPI_t^- + \gamma' X_t$. Detailed definitions of all variables can be found in Appendix A2.1.

Table 6: Result from Probit Models: Cyclically Sensitive Industries

	Equation (1)		Equation (2)		Equation (3)	
	$k=1$	$k=4$	$k=1$	$k=4$	$k=1$	$k=4$
$\Delta_4 AE_t$	-0.046** (-2.381)	-0.032*** (-2.576)	-0.040** (-2.202)	-0.044** (-2.548)	-0.026* (-1.774)	-0.028* (-1.733)
$\Delta_4 SPI_t$			-0.055* (-1.780)	0.044 (1.082)	-0.059*** (-2.780)	0.007 (0.152)
$TERM_t$					-0.344** (-2.013)	-0.768** (-2.330)
$CRED_t$					0.301 (0.331)	0.358 (0.602)
$INFL_t$					0.070 (0.892)	-0.002 (-0.024)
$\Delta SP500_t$					-0.052 (-1.327)	0.002 (0.137)
$MacroU_t$					3.666 (0.536)	-0.146 (-0.054)
AME($\Delta_4 AE_t$)	-0.083** (-2.359)	-0.052*** (-2.897)	-0.071** (-2.141)	-0.071*** (-3.129)	-0.027 (-1.470)	-0.030* (-1.786)
AME($\Delta_4 SPI_t$)			-0.039* (-1.748)	0.032 (1.150)	-0.024** (-2.255)	0.003 (0.152)
pseudo- R^2	0.063	0.028	0.070	0.034	0.419	0.321
QPS	0.245	0.259	0.245	0.254	0.142	0.174
AUC	0.743***	0.608**	0.727***	0.525	0.945***	0.896***
p -value	[0.000]	[0.018]	[0.000]	[0.322]	[0.000]	[0.000]
Log-Lik	-82.083	-85.160	-81.424	-84.508	-47.463	-56.628

Note: The numbers in parentheses and brackets represent t -statistics and p -values, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The dependent variable in this table is the NBER recession indicator. Equations (1): $\pi_t^1 \equiv \alpha + \beta^{AE} \Delta_4 AE_t$; Equation (2): $\pi_t^2 \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t$; Equation (3): $\pi_t^3 \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t + \gamma' X_t$. $X_t = [TERM_t, CRED_t, INFL_t, \Delta SP500_t, MacroU_t]'$. Detailed definitions of all variables can be found in Appendix A2.1.

Table 7: Result from Probit Models: Noncyclical Industries

	Equation (1)		Equation (2)		Equation (3)	
	<i>k</i> =1	<i>k</i> =4	<i>k</i> =1	<i>k</i> =4	<i>k</i> =1	<i>k</i> =4
$\Delta_4 AE_t$	-0.018 (-1.142)	-0.012 (-1.002)	-0.008 (-0.858)	-0.017 (-1.380)	-0.019 (-1.400)	-0.023** (-1.975)
$\Delta_4 SPI_t$			-0.056** (-2.298)	0.034 (1.502)	-0.028 (-0.779)	0.068*** (3.979)
$TERM_t$					-0.310*** (-2.591)	-0.784*** (-4.068)
$CRED_t$					0.079 (0.185)	0.273 (0.582)
$INFL_t$					0.068 (1.604)	-0.000 (-0.002)
$\Delta SP500_t$					-0.050*** (-2.886)	-0.009 (-0.667)
$MacroU_t$					4.377** (1.983)	0.477 (0.240)
AME($\Delta_4 AE_t$)	-0.041 (-1.147)	-0.026 (-1.032)	-0.018 (-0.881)	-0.038 (-1.486)	-0.024 (-1.488)	-0.033** (-2.290)
AME($\Delta_4 SPI_t$)			-0.066** (-2.179)	0.042 (1.562)	-0.019 (-0.780)	0.053*** (5.366)
pseudo- R^2	0.012	0.005	0.037	0.018	0.389	0.345
QPS	0.263	0.267	0.256	0.261	0.149	0.166
AUC	0.541	0.474	0.627***	0.498	0.935***	0.902***
p -value	[0.227]	[0.676]	[0.006]	[0.515]	[0.000]	[0.000]
Log-Lik	-87.245	-87.428	-84.666	-86.140	-50.269	-54.377

Note: The numbers in parentheses and brackets represent t -statistics and p -values, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The dependent variable in this table is the NBER recession indicator. Equations (1): $\pi_t^1 \equiv \alpha + \beta^{AE} \Delta_4 AE_t$; Equation (2): $\pi_t^2 \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t$; Equation (3): $\pi_t^3 \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t + \gamma' X_t$. $X_t = [TERM_t, CRED_t, INFL_t, \Delta SP500_t, MacroU_t]'$. Detailed definitions of all variables can be found in Appendix A2.1.

Table 8: Result from the Probit Model with Predicted Earnings and Earnings Surprises

	Decomposition: Kothari et al. (2006)		Decomposition: AR(1) of $\Delta_4 AE_t$	
	$k=1$	$k=4$	$k=1$	$k=4$
$\Delta_4 AE_t^{Exp}$	-0.035*	-0.083*	-0.035*	-0.082*
Bootstrapped p -value	[0.097]	[0.057]	[0.094]	[0.056]
$\Delta_4 AE_t^{Surprises}$	-0.034*	-0.047**	-0.034**	-0.047**
Bootstrapped p -value	[0.099]	[0.019]	[0.099]	[0.021]
$\Delta_4 SPI_t$	-0.050	0.107**	-0.050	0.107**
Bootstrapped p -value	[0.229]	[0.011]	[0.229]	[0.011]
$TERM_t$	-0.310*	-0.728***	-0.310*	-0.745***
Bootstrapped p -value	[0.056]	[0.003]	[0.055]	[0.003]
$CRED_t$	0.174	0.179	0.176	0.233
Bootstrapped p -value	[0.435]	[0.397]	[0.433]	[0.370]
$INFL_t$	0.075	0.015	0.075	0.015
Bootstrapped p -value	[0.105]	[0.420]	[0.105]	[0.430]
$\Delta SP500_t$	-0.048**	-0.000	-0.048**	-0.001
Bootstrapped p -value	[0.046]	[0.478]	[0.044]	[0.476]
$MacroU_t$	4.010	0.687	4.003	0.460
Bootstrapped p -value	[0.106]	[0.307]	[0.111]	[0.347]
AME($\Delta_4 AE_t^{Exp}$)	-0.020	-0.047**	-0.020*	-0.047**
Bootstrapped p -value	[0.101]	[0.023]	[0.099]	[0.024]
AME($\Delta_4 AE_t^{Surprise}$)	-0.022	-0.034***	-0.022	-0.034***
Bootstrapped p -value	[0.116]	[0.003]	[0.116]	[0.004]
AME($\Delta_4 SPI_t$)	-0.022	0.053***	-0.022	0.053***
Bootstrapped p -value	[0.220]	[0.000]	[0.220]	[0.001]
pseudo- R^2	0.552	0.360	0.552	0.490
QPS	0.141	0.163	0.141	0.163
AUC	0.945***	0.903***	0.945***	0.903***
Bootstrapped p -value	[0.000]	[0.000]	[0.000]	[0.000]
Log-Lik	-47.732	-53.907	-47.732	-53.903

Note: The numbers in brackets represent p -values, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The dependent variable in this table is the NBER recession indicator. The results are tabulated based on equation (10): $\pi_t \equiv \alpha + \beta^{AE,Exp} \Delta_4 AE_t^{Exp} + \beta^{AE,Surprises} \Delta_4 AE_t^{Surprises} + \beta^{SPI} \Delta_4 SPI_t + \gamma' X_t$, where $X_t = [TERM_t, CRED_t, INFL_t, \Delta SP500_t, MacroU_t]'$. Detailed definitions of all variables can be found in Appendix A2.1.

Appendix: Aggregate Earnings and Recession Predictability

A1 Evaluation Metrics

A1.1 Pseudo- R^2

Following Estrella (1998), the pseudo- R^2 statistic measures the improvement in model likelihood relative to a benchmark model that includes only a constant term. It is calculated as follows:

$$\text{pseudo } R^2 = 1 - \left(\frac{\log L_u}{\log L_c} \right)^{-(2/T) \log L_c}, \quad (\text{A1.1})$$

where L_u denotes the value of the maximized probit likelihood of the unrestricted model, and L_c denotes the value of the maximized likelihood under the restriction that all coefficients are zero, except for the constant term.

The pseudo- R^2 provides a summary measure of the model's relative improvement in likelihood over the benchmark. Higher values indicate greater improvement in fit relative to the constant-only model, whereas values close to zero suggest little incremental explanatory power. Importantly, in contrast with the conventional R^2 in linear regressions, the pseudo- R^2 is not bounded below by zero. A negative pseudo- R^2 indicates that the model's likelihood is lower than that of the benchmark and thus that the model performs worse than a naïve forecasting model based solely on the unconditional recession probability.

A1.2 Quadratic Probability Score

Although the pseudo- R^2 provides a convenient summary measure of improvements in model fit relative to a benchmark, it is sensitive to benchmark choice and is not designed to assess predictive classification performance. To complement this metric, we also employ the QPS proposed by Diebold and Rudebusch (1989), which directly evaluates the accuracy of predicted probabilities, penalizing squared deviations between predicted probabilities and realized outcomes.

$$QPS = \frac{1}{T} \sum_{t=1}^T 2[\hat{P}(D_t = 1) - D_t]^2,$$

where $\hat{P}(D_t = 1) = \Phi(\hat{\pi}_t)$ denotes the model-implied probability of a recession in period t , and D_t is the realized recession indicator. The QPS ranges from zero to two, with a value of zero

indicating perfect probabilistic forecasts.

The QPS measures how closely the model's predicted recession probabilities align with realized outcomes over time: forecasts that assign high probabilities to recessions when recessions occur, and low probabilities when expansions prevail, yield lower QPS values. As the loss is quadratic, the QPS penalizes confident but incorrect forecasts more heavily than small probability errors, reflecting the economic cost of overstating or understating recession risk. Accordingly, lower values of the QPS indicate superior forecasting performance in terms of both probability calibration and overall predictive accuracy.

A1.3 Area under the Receiver Operating Characteristic Curve

To evaluate the model's discriminatory power, we employ the ROC curve, which assesses the model's ability to distinguish between recession and nonrecession periods across a continuum of probability thresholds. The ROC curve plots the true positive rate (the fraction of recession periods correctly identified) against the false positive rate (the fraction of expansion periods incorrectly classified as recessions) as the classification threshold varies from zero to one. The ROC curve summarizes the trade-offs between correctly signaling recessions warnings and avoiding false alarms.

To summarize a model's classification performance, we report the AUC, which represents the probability that the model assigns a higher predicted recession probability to a randomly selected recession period than to a randomly selected nonrecession period. An AUC of one indicates perfect discrimination, meaning that recession periods are always ranked above nonrecession periods, whereas an AUC of 0.5 corresponds to no discriminatory power beyond random guessing. From an economic perspective, higher AUC values imply that the model is more effective at ranking periods by recession risk, even without committing to a specific probability threshold. This property is particularly relevant for policymakers and practitioners, who may adjust decision thresholds depending on their tolerance for false alarms versus missed recessions, but require a model that reliably assigns higher risk to true downturns. We will test whether the model exhibits statistically significant classification ability using standard

procedures proposed by Hanley and McNeil (1982).²⁶

A2 Data Source

Table A2.1 contains a description of all variables used in our empirical analyses. The data are sourced from Compustat, Federal Reserve Economic Data, Professor Robert Shiller's website, Professor Sydney Ludvigson's website, and the Bureau of Economic Analysis.

Table A2.1: Variable Definition

Abbreviation	Definition	Source
$\Delta_4 AE_t$	Changes in aggregate earnings. We propose several measures, which are defined as below.	
$wdibq_t$	Annual growth rate of aggregate earnings before extraordinary items. We construct it using the firm level earnings (compustat <i>ibq</i>), adjusted for inflation using sales. The earnings variables at the firm level are adjusted for inflation using sales (Compustat item <i>saleq</i>). The aggregation is performed using market values (<i>common shares outstanding</i> $\times$ <i>price close</i>) of equity (Compustat items <i>cshoq</i> $\times$ <i>prccq</i>) as weights. We then calculate the year-over-year change in the aggregated earnings to obtain the annual changes in the aggregate earnings before extraordinary items, $wdibq_t$: $wdibq_t = \sum_i \frac{(ibq_{i,t} - ibq_{i,t-4}) \times weight_{i,t}}{saleq_{i,t-4}} \times 100$ where $weight_{i,t} = cshoq_{i,t} \times prccq_{i,t} / \sum_i (cshoq_{i,t} \times prccq_{i,t})$.	Compustat
$wdniq_t$	We use net income (Compustat item <i>niq</i>) as an alternative measure of aggregate earnings. We deflate this measure by sales and use market values of equity as weights for aggregation. Subsequently, we calculate the year-over-year change in net income, denoted as $wdniq_t$: $wdniq_t = \sum_i [(niq_{i,t} - niq_{i,t-4}) \times weight_{i,t}] / saleq_{i,t-4} \times 100.$ (A2.1)	Compustat

²⁶For a more detailed discussion regarding inferences related to ROC curves, see Berge and Jorda (2011).

Variable description (*continued*)

Abbreviation	Definition	Source
$\Delta_4 SPI_t$	Annual growth rate of aggregate special items. We construct it using the firm level special items, adjusted for sales. The aggregation is performed using market values of equity as weights, we thus obtain $wrspiq_t$. Finally, we calculate the year-over-year change in the aggregated special items, $wrdspiq_t$, to obtain the annual changes in the special items. Specifically: $wrdspiq_t = \sum_i [(spiq_{i,t} - spiq_{i,t-4}) \times weight_{i,t}] / saleq_{i,t-4} \times 100.$	Compustat
$TERM_t$	The spread between the yield of the ten-year Treasury bond and the rate of the three-month Treasury bill. As noted by Estrella and Trubin (2006), since the constant maturity rates are available only after 1982, we use the secondary market three-month rate (which is calculated on a discount basis) to express it on a bond-equivalent basis. Specifically, $\text{bond-equivalent rate} = \frac{365 \times \text{discount rate}/100}{360 - 91 \times \text{discount rate}/100} \times 100$	FRED
$CRED_t$	Calculated as the difference between the Moody's Baa-rated corporate bond rate and the Aaa-rated corporate bond rate	FRED
$INFL_t$	Annual CPI inflation rate. We use the annual growth rate of the quarterly CPI to measure the quarterly annual inflation. The ticker for quarterly CPI is CPALTT01USQ659N. Specifically, it is calculated as follows: $INFL_t = 100 \times [\log(CPI_t) - \log(CPI_{t-4})].$	FRED
$\Delta SP500_t$	Quarterly changes in stock market index. It is calculated based on the S&P 500 index as $\Delta SP500_t = 100 \times (\log SP500_t - \log SP500_{t-1}).$	Professor Robert Shiller's website
$MacroU_t$	Macroeconomic uncertainty index. We utilize the measure of macroeconomic uncertainty at a three-month forecast horizon, as proposed by Jurado et al. (2015), to proxy US macroeconomic uncertainty. To derive quarterly data for $MacroU_t$, we computed the three-month average of the monthly data.	Professor Sydney Ludvigson's website
$\Delta RGDP_t$	Quarterly Real GDP growth rate. Percent Change from Preceding Period, Seasonally adjusted annual rate from preceding period. Can be downloaded from the FRED (https://fred.stlouisfed.org/series/A191RL1Q225SBEA).	BEA

A3 Predicting Economic Growth

In this section, we examine aggregate accounting earnings and special items as predictors of real GDP growth rather than of NBER recession dates. Prior studies have documented the predictive ability of aggregate earnings and special items for GDP growth (e.g., Abdalla and Carabias, 2022; Konchitchki and Patatoukas, 2014a). To enhance comparability, we repeat their analysis using the same data, sample periods, and control variables as in our recession analysis.

We estimate the following predictive regressions, analogous to Equations (1)–(4):

$$\Delta RGDP_{t+k} = \alpha + \beta^{AE} \Delta_4 AE_t + \varepsilon_{t+k}, \quad (\text{A3.1})$$

$$\Delta RGDP_{t+k} = \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t + \varepsilon_{t+k}, \quad (\text{A3.2})$$

$$\Delta RGDP_{t+k} = \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t + \gamma' X_t + \varepsilon_{t+k}, \quad (\text{A3.3})$$

$$\Delta RGDP_{t+k} = \alpha + \gamma' X_t + \varepsilon_{t+k}, \quad (\text{A3.4})$$

where $\Delta RGDP_{t+k}$ denotes the annualized real GDP growth rate over horizon k and ε_{t+k} denotes the regression errors.

Table A3.1 reports the in-sample estimation results of Equations (A3.1)–(A3.4). We find that changes in aggregate earnings predict the one-quarter-ahead real GDP growth rate when other control variables are excluded. However, they lack predictive power for the four-quarter-ahead real GDP growth.²⁷

In contrast, we find no evidence that special items contain predictive content for real GDP growth. Moreover, the adjusted- R^2 values are generally small and close to zero. Comparing these findings with our baseline probit models suggests that aggregate earnings and special items growth perform better at predicting recessions than at forecasting real GDP growth.

Following Gaertner et al. (2020), we examine the asymmetric timeliness of aggregate earnings and special items in predicting real GDP growth. Specifically, we estimate the following predictive regressions:

²⁷This result is not inconsistent with Abdalla and Carabias (2022), as Abdalla and Carabias (2022) do not examine four-quarter-ahead real GDP predictability.

$$\Delta RGDP_{t+k} = \alpha + \beta^{AE+} \Delta_4 AE_t^+ + \beta^{AE-} \Delta_4 AE_t^- + \varepsilon_{t+k}, \quad (\text{A3.5})$$

$$\Delta RGDP_{t+k} = \alpha + \beta^{AE+} \Delta_4 AE_t^+ + \beta^{AE-} \Delta_4 AE_t^- + \beta^{SPI+} \Delta_4 SPI_t^+ + \beta^{SPI-} \Delta_4 SPI_t^- + \varepsilon_{t+k}, \quad (\text{A3.6})$$

$$\Delta RGDP_{t+k} = \alpha + \beta^{AE+} \Delta_4 AE_t^+ + \beta^{AE-} \Delta_4 AE_t^- + \beta^{SPI+} \Delta_4 SPI_t^+ + \beta^{SPI-} \Delta_4 SPI_t^- + \gamma' X_t + \varepsilon_{t+k}, \quad (\text{A3.7})$$

Table A3.2 presents the results of Equations (A3.5)–(A3.7). We find that negative changes in aggregate earnings predict one-quarter-ahead real GDP growth, whereas positive changes do not. Notably, negative changes in aggregate earnings also predict four-quarter-ahead real GDP growth in Equations (A3.5) and (A3.7), suggesting that these negative changes possess persistent predictive power for future real GDP growth.

In summary, we confirm that aggregate earnings growth predicts future GDP growth, consistent with prior studies. In our empirical results about recession predictability, we further show that aggregate earnings growth appears to contain information about macroeconomic tail risk beyond average output dynamics, highlighting its ability to predict downside economic conditions.

Table A3.1: Result from Predicting Real GDP Growth Models

	Equation (A3.1)		Equation (A3.2)		Equation (A3.3)		Equation (A3.4)	
	<i>k</i> =1	<i>k</i> =4	<i>k</i> =1	<i>k</i> =4	<i>k</i> =1	<i>k</i> =4	<i>k</i> =1	<i>k</i> =4
$\Delta_4 AE_t$	0.055*** (2.662)	-0.001 (-0.016)	0.056** (2.209)	0.008 (0.142)	0.047 (1.426)	-0.007 (-0.158)		
$\Delta_4 SPI_t$			-0.004 (-0.052)	-0.033 (-0.378)	-0.031 (-0.409)	-0.038 (-0.556)		
$TERM_t$					0.422* (1.783)	0.573 (1.556)	0.480** (2.065)	0.565 (1.572)
$CRED_t$					-0.441 (-0.387)	0.969 (0.795)	-0.639 (-0.542)	0.967 (0.808)
$INFL_t$					-0.120 (-0.750)	-0.006 (-0.040)	-0.106 (-0.677)	-0.007 (-0.050)
$\Delta SP500_t$					0.020 (0.267)	0.011 (0.362)	0.025 (0.334)	0.008 (0.274)
$MacroU_t$					-1.355 (-0.170)	-2.106 (-0.409)	-0.642 (-0.079)	-1.933 (-0.383)
adjusted- R^2	0.002	-0.005	-0.003	-0.010	0.014	0.006	0.020	0.015
Log-Lik	-591.0772	-584.433	-591.077	-584.387	-586.756	-580.236	-587.186	-580.354

Note: The numbers in parentheses and brackets represent *t*-statistics and *p*-values, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The dependent variable in this table is the NBER recession indicator. Equations (A3.1): $\Delta RGDP_{t+k} = \alpha + \beta^{AE} \Delta_4 AE_t + \varepsilon_{t+k}$; Equation (A3.2): $\Delta RGDP_{t+k} = \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t + \varepsilon_{t+k}$; Equation (A3.3): $\Delta RGDP_{t+k} = \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t + \gamma' X_t + \varepsilon_{t+k}$; Equation (A3.4): $\Delta RGDP_{t+k} = \alpha + \gamma' X_t + \varepsilon_{t+k}$. where $X_t = [TERM_t, CRED_t, INFL_t, \Delta SP500_t, MacroU_t]'$. Detailed definitions of all variables can be found in Appendix A2.1.

Table A3.2: Result from Real GDP forecasting Models with Asymmetric Timeliness in Earnings and Special Items

Model	Equation (A3.5)		Equation (A3.6)		Equation (A3.7)	
	$k=1$	$k=4$	$k=1$	$k=4$	$k=1$	$k=4$
$\Delta_4 AE_t^+$	0.030 (0.735)	-0.145 (-1.631)	0.016 (0.397)	-0.140 (-1.552)	-0.002 (-0.048)	-0.135 (-1.384)
$\Delta_4 AE_t^-$	0.079*** (2.940)	0.063** (2.021)	0.118** (2.451)	0.086* (1.923)	0.110* (1.685)	0.052 (1.120)
$\Delta_4 SPI_t^+$			0.112 (1.014)	-0.020 (-0.159)	0.028 (0.215)	-0.076 (-0.793)
$\Delta_4 SPI_t^-$			-0.119 (-1.157)	-0.073 (-0.774)	-0.110 (-0.870)	-0.038 (-0.442)
$TERM_t$					0.401 (1.610)	0.580 (1.573)
$CRED_t$					-0.629 (-0.566)	0.642 (0.526)
$INFL_t$					-0.138 (-0.925)	-0.036 (-0.241)
$\Delta SP500_t$					0.019 (0.248)	0.010 (0.338)
$MacroU_t$					-0.538 (-0.073)	-0.975 (-0.206)
adjusted- R^2	-0.002	0.001	-0.007	-0.008	0.008	0.005
Log-Lik	-590.967	-583.305	-590.532	-583.18	-586.333	-579.296

Note: The numbers in parentheses and brackets represent t -statistics and p -values, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The dependent variable in this table is the NBER recession indicator. Equation (A3.5): $\Delta RGDP_{t+k} = \alpha + \beta^{AE+} \Delta_4 AE_t^+ + \beta^{AE-} \Delta_4 AE_t^- + \varepsilon_{t+k}$; Equation (A3.6): $\Delta RGDP_{t+k} = \alpha + \beta^{AE+} \Delta_4 AE_t^+ + \beta^{AE-} \Delta_4 AE_t^- + \beta^{SPI+} \Delta_4 SPI_t^+ + \beta^{SPI-} \Delta_4 SPI_t^- + \varepsilon_{t+k}$; Equation (A3.7): $\Delta RGDP_{t+k} = \alpha + \beta^{AE+} \Delta_4 AE_t^+ + \beta^{AE-} \Delta_4 AE_t^- + \beta^{SPI+} \Delta_4 SPI_t^+ + \beta^{SPI-} \Delta_4 SPI_t^- + \gamma' X_t + \varepsilon_{t+k}$. Detailed definitions of all variables can be found in Appendix A2.1.

A4 Unit Root Test

We examine the stationarity properties of changes in aggregate earnings, special items, and other macroeconomic variables. Table [A4.1](#) reports DF-GLS unit root tests (Elliot et al., 1996). The unit root hypothesis is rejected for all series at the 5% level when the maximum lag length is set to 12, with the optimal lag selected using the Akaike information criterion. All series are therefore stationary, i.e., integrated of order zero, $I(0)$.

Table A4.1: DF-GLS Unit-Root Tests

Variable Names	DF-GLS Statistics	optimal lag length
$wdibq_t$	-4.292***	4
$wdibq_t$ (cyclical sensitive)	-4.881***	0
$wdibq_t$ (cylcal insensitive)	-7.031***	2
$wdibq2_t$	-2.314**	12
$wdniq_t$	-2.435**	12
$wrdspiq_t$	-6.828***	1
$TERM_t$	-1.647*	14
$CRED_t$	-3.517***	14
$INFL_t$	-1.652*	12
$\Delta SP500_t$	-1.760*	13
$MacroU_t$	-3.038***	2

Note: The 1%, 5%, and 10% level of critical values is -2.576, -1.942, and -1.616, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. An intercept is included in the testing equation, and the optimal lag length is chosen by modified Akaike information criterion. Detailed definitions of all variables can be found in Appendix [A2.1](#).

A5 Dynamic Probit Model

As shown by recent research, incorporating a lagged recession indicator can improve model performance. Following Dueker (1997), Kauppi and Saikkonen (2008), and Nyberg (2010), we estimate a dynamic probit model that extends the benchmark specifications (1)–(4) by including a lagged dependent variable, D_{t-1} , as an additional predictor:

$$\pi_t^{D1} \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \omega D_{t-l}, \quad (\text{A5.1})$$

$$\pi_t^{D2} \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 \Delta_4 SPI_t + \omega D_{t-l}, \quad (\text{A5.2})$$

$$\pi_t^{D3} \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t + \omega D_{t-l} + \gamma' X_t, \quad (\text{A5.3})$$

$$\pi_t^{D4} \equiv \alpha + \omega D_{t-l} + \gamma' X_t. \quad (\text{A5.4})$$

where l denotes the lag length of the recession indicator. Following Christiansen et al. (2014), we set $l = 1$, corresponding to a one-quarter (three-month) delay in the availability of the recession indicator.²⁸

Table A5.1 reports the estimation results for Equations (A5.1)–(A5.4). Relative to the baseline models in Table 3, the models show marginal improvements across evaluation metrics. The coefficient on D_{t-1} is significant at $k = 1$ but not at $k = 4$, indicating that the lagged recession indicator improves short-horizon predictive performance. In contrast, β^{SPI} becomes insignificant in Equations (A5.2) and (A5.3), suggesting that the lagged recession indicator absorbs the predictive content of changes in special items. Notably, the predictive ability of aggregate earnings remains unchanged: β^{AE} remains significant across specifications with similar magnitudes to those in Table 3. These results indicate that our baseline findings are robust to controlling for the lagged recession indicator, D_{t-1} .

We combine forecasts from Equations (A5.2) and (A5.4) to improve out-of-sample recession forecasts. Table A5.2 reports the out-of-sample predictive performance of the dynamic probit models. The results are qualitatively similar to the baseline results from the static probit

²⁸As Ng (2012) document, the average publication delay from 1980 to 2008 was approximately nine months (three quarters). Such delays require strong assumptions about the information available at the time of forecasting.

models in Table 4.

Table A5.1: In-Sample Result from Dynamic Probit Models

	Equation (A5.1)		Equation (A5.2)		Equation (A5.3)		Equation (A5.4)	
	$k=1$	$k=4$	$k=1$	$k=4$	$k=1$	$k=4$	$k=1$	$k=4$
$\Delta_4 AE_t$	-0.043** (-2.442)	-0.034* (-1.933)	-0.035** (-2.230)	-0.053** (-2.201)	-0.030* (-1.685)	-0.056** (-2.532)		
$\Delta_4 SPI_t$			-0.036 (-1.178)	0.074* (1.725)	-0.023 (-0.419)	0.107*** (3.101)		
D_{t-1}	1.455*** (5.008)	0.035 (0.115)	1.406*** (4.767)	0.195 (0.767)	1.208*** (3.363)	0.459 (0.656)	1.531*** (3.797)	0.357 (0.541)
$TERM_t$					-0.492*** (-2.949)	-0.815*** (-4.584)	-0.554*** (-3.227)	-0.829*** (-3.225)
$CRED_t$					0.159 (0.431)	0.275 (0.565)	0.123 (0.384)	0.292 (0.407)
$INFL_t$					0.039 (1.003)	-0.002 (-0.037)	0.019 (0.298)	-0.019 (-0.218)
$\Delta SP500_t$					-0.048*** (-2.972)	-0.002 (-0.148)	-0.052** (-2.369)	0.001 (0.069)
$MacroU_t$					1.245 (0.530)	-0.673 (-0.255)	0.782 (0.522)	-0.667 (-0.167)
AME($\Delta_4 AE_t$)	-0.054** (-2.569)	-0.048** (-2.159)	-0.043** (-2.333)	-0.073*** (-2.739)	-0.025 (-1.619)	-0.049*** (-3.501)		
AME($\Delta_4 SPI_t$)			-0.022 (-1.189)	0.058* (1.955)	-0.010 (-0.427)	0.053*** (3.579)		
pseudo- R^2	0.209	0.021	0.213	0.042	0.443	0.351	0.425	0.310
QPS	0.199	0.263	0.198	0.251	0.132	0.167	0.138	0.183
AUC	0.765***	0.505	0.802***	0.526	0.945***	0.901***	0.943***	0.893***
p -value	[0.000]	[0.465]	[0.000]	[0.318]	[0.000]	[0.000]	[0.000]	[0.000]
Log-Lik	-67.523	-85.668	-67.162	-83.599	-45.156	-53.763	-46.878	-57.646

Note: The numbers in parentheses and brackets represent t -statistics and p -values, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The dependent variable in this table is the NBER recession indicator. Equation (A5.1): $\pi_t^{D1} \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \omega D_{t-l}$; Equation (A5.2): $\pi_t^{D2} \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 \Delta_4 SPI_t + \omega D_{t-l}$, Equation (A5.3): $\pi_t^{D3} \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 \Delta_4 SPI_t + \omega D_{t-l} + \gamma' X_t$; Equation (A5.4): $\pi_t^{D4} \equiv \alpha + \omega D_{t-l} + \gamma' X_t$, where $X_t = [TERM_t, CRED_t, INFL_t, \Delta SP500_t, MacroU_t]'$. Detailed definitions of all variables can be found in Appendix A2.1.

Table A5.2: Out-of-Sample Predicting Results: Dynamic Probit Model

Forecasts	$\hat{\Phi}_t^{FC}$	
	$k=1$	$k=4$
pseudo- R^2	0.276	0.038
QPS	0.189	0.274
AUC	0.898***	0.749***
p -value	[0.000]	[0.000]

Note: The numbers in parentheses and brackets represent t -statistics and p -values, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The dependent variable in this table is the NBER recession indicator. $\hat{\Phi}_{FC} = \frac{\hat{\Phi}(\pi_t^{D2}) + \hat{\Phi}(\pi_t^{D4})}{2}$. And $X_t = [TERM_t, CRED_t, INFL_t, \Delta SP500_t, MacroU_t]'$. Detailed definitions of all variables can be found in Appendix [A2.1](#).

A6 Stability

Following Christiansen et al. (2014) and Estrella (2003), we test for instability in our empirical models. The presence of structural breaks can adversely affect the forecast performance of the model (Rossi, 2013).

We apply the $\text{sup-}LM_T$ test of Andrews (1993) to the models in Table 3. The $\text{sup-}LM_T$ statistic is calculated by searching over an interior portion of the sample that excludes 25% of the data at each endpoint. Table A6.1 reports the results. We find no evidence of structural breaks in any specification.

Table A6.1: LM test for Probit Model

	Equation (1)		Equation (2)		Equation (3)		Equation (4)	
	$k=1$	$k=4$	$k=1$	$k=4$	$k=1$	$k=4$	$k=1$	$k=4$
$\text{sup} - LM_T$	7.420	4.810	4.853	4.073	8.571	5.523	13.252	8.809
90% CV	9.230	9.230	9.230	9.230	11.470	11.470	20.510	20.510

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Equations (1): $\pi_t^1 \equiv \alpha + \beta^{AE} \Delta_4 AE_t$; Equation (2): $\pi_t^2 \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t$; Equation (3): $\pi_t^3 \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t + \gamma' X_t$; Equation (4): $\pi_t^4 \equiv \alpha + \gamma' X_t$, where $X_t = [TERM_t, CRED_t, INFL_t, \Delta SP500_t, MacroU_t]'$. Detailed definitions of all variables can be found in Appendix A2.1.

A7 An Alternative Measure of Aggregate Earnings

In this section, we adopt net income (Compustat item *niq*) as an alternative measure of aggregate earnings, following Konchitchki and Patatoukas (2014a). Specifically, we compute the weighted year-over-year growth rate of net income ($wdniq_t$) to capture changes in aggregate earnings, as detailed in Appendix A2.

Table A7.1 reports the in-sample predictive results using Equations (1), (2), and (3), where aggregate earnings growth ($\Delta_4 AE_t$) is proxied by $wdniq_t$, the changes in net income. The results confirm that this alternative measure remains highly significant, with an economic magnitude consistent with the baseline findings in Table 3. Similar patterns emerge in the out-of-sample evaluations presented in Table A7.2.

Table A7.1: In-Sample Predicting Results from Probit Models: Using the Changes in Net Income to Measure Earnings

	Equation (1)		Equation (2)		Equation (3)	
	<i>k</i> =1	<i>k</i> =4	<i>k</i> =1	<i>k</i> =4	<i>k</i> =1	<i>k</i> =4
$\Delta_4 AE_t$	-0.050*** (-3.027)	-0.031* (-1.929)	-0.033** (-2.467)	-0.046** (-2.054)	-0.033** (-2.265)	-0.051** (-2.426)
$\Delta_4 SPI_t$			-0.082*** (-2.946)	0.062 (1.504)	-0.052 (-1.043)	0.097*** (2.789)
$TERM_t$					-0.313** (-2.294)	-0.758*** (-3.837)
$CRED_t$					0.175 (0.437)	0.261 (0.528)
$INFL_t$					0.075* (1.783)	0.007 (0.137)
$\Delta SP500_t$					-0.048*** (-2.741)	-0.004 (-0.282)
$MacroU_t$					3.988** (1.979)	0.392 (0.192)
AME($\Delta_4 AE_t$)	-0.084*** (-3.142)	-0.048** (-2.170)	-0.054** (-2.442)	-0.070** (-2.437)	-0.031** (-2.041)	-0.049*** (-3.062)
AME($\Delta_4 SPI_t$)			-0.061*** (-2.727)	0.049* (1.665)	-0.023 (-1.096)	0.049*** (3.401)
pseudo- R^2	0.052	0.019	0.074	0.035	0.415	0.345
QPS	0.249	0.263	0.243	0.252	0.141	0.166
AUC	0.625***	0.483	0.667***	0.469	0.945***	0.899***
<i>p</i> -value	[0.007]	[0.617]	[0.000]	[0.708]	[0.000]	[0.000]
Log-Lik	-83.174	-86.068	-80.988	-84.452	-47.807	-54.385

Note: The numbers in parentheses and brackets represent *t*-statistics and *p*-values, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The dependent variable in this table is the NBER recession indicator. Equations (1): $\pi_t^1 \equiv \alpha + \beta^{AE} \Delta_4 AE_t$; Equation (2): $\pi_t^2 \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t$; Equation (3): $\pi_t^3 \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t + \gamma' X_t$. Where $X_t = [TERM_t, CRED_t, INFL_t, \Delta SP500_t, MacroU_t]'$. Detailed definitions of all variables can be found in Appendix A2.1.

Table A7.2: Out-of-Sample Predicting Results: Using Net Income to Measure Earnings

Forecasts	$\hat{\Phi}(\pi_t^4 X_t)$		$\hat{\Phi}(\pi_t^2 \Delta_4AE_t, \Delta_4SPI_t)$		$\hat{\Phi}_{FC} = \frac{\hat{\Phi}(\pi_t^4) + \hat{\Phi}(\pi_t^2)}{2}$	
	$k=1$	$k=4$	$k=1$	$k=4$	$k=1$	$k=4$
pseudo- R^2	-0.002	0.159	0.193	-0.505	0.317	0.071
QPS	0.187	0.315	0.229	0.298	0.169	0.212
AUC	0.900***	0.762***	0.759***	0.276	0.904***	0.744***
p -value	[0.000]	[0.000]	[0.000]	[0.997]	[0.000]	[0.000]

Note: The numbers in parentheses and brackets represent t -statistics and p -values, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The dependent variable in this table is the NBER recession indicator. $\hat{\Phi}_{FC} = \frac{\hat{\Phi}(\pi_t^2) + \hat{\Phi}(\pi_t^4)}{2}$; $\pi_t^2 \equiv \alpha + \beta^{AE} \Delta_4AE_t + \beta^{SPI} \Delta_4SPI_t$; $\pi_t^4 \equiv \alpha + \gamma'X_t$, where $X_t = [TERM_t, CRED_t, INFL_t, \Delta SP500_t, MacroU_t]'$. Detailed definitions of all variables can be found in Appendix [A2.1](#).

A8 Bootstrapping P -Values of Probit Model Estimates and AUC Test Statistics

It is well established that the bootstrap method provides more reliable inference in finite samples than asymptotic t -ratios and mitigates size distortion when constructing t -statistics. Accordingly, we implement a block bootstrap procedure that generates empirical p -values to evaluate the statistical significance of the probit model estimates and to verify whether the baseline in-sample results and inferences based on the asymptotic normal distribution remain valid. In addition, we bootstrap the AUC test statistics for both the in-sample and out-of-sample forecasting evaluations.

The block bootstrap is conducted by generating D_t and $[\Delta_4 AE_t, \Delta_4 SPI_t, X_t]$ independently under the null hypothesis that the predictive variables have no explanatory power for recessions. The block length is set to four quarters, and the procedure is repeated 5,000 times. Table A8.1 reports the in-sample predictive test results based on bootstrap p values. Relative to Table 3 in the main text, the statistical significance of the parameter estimates remains largely unchanged. For the $AUC = 0.5$ tests, the statistics are significant at both $k = 1$ and $k = 4$ horizons based on the bootstrap p values, indicating that the proposed models exhibit meaningful classification ability.

Table A8.2 reports the out-of-sample AUC results from the bootstrap procedure. The combined forecast, $\hat{\Phi}_{FC}$, remains statistically significant, supporting the value of forecast combination in improving recession classification performance.

Table A8.1: Results from Probit Models with Bootstrapped p -values

	Equation (1)		Equation (2)		Equation (3)		Equation (4)	
	$k=1$	$k=4$	$k=1$	$k=4$	$k=1$	$k=4$	$k=1$	$k=4$
$\Delta_4 AE_t$	-0.054***	-0.031**	-0.038**	-0.051**	-0.033**	-0.054**		
Bootstrapped p -value	[0.007]	[0.040]	[0.017]	[0.030]	[0.047]	[0.019]		
$\Delta_4 SPI_t$			-0.071**	0.068	-0.047	0.099***		
Bootstrapped p -value			[0.011]	[0.108]	[0.240]	[0.009]		
$TERM_t$					-0.320*	-0.760***	-0.333**	-0.778***
Bootstrapped p -value					[0.057]	[0.003]	[0.012]	[0.003]
$CRED_t$					0.195	0.273	0.161	0.275
Bootstrapped p -value					[0.419]	[0.347]	[0.404]	[0.314]
$INFL_t$					0.073	0.006	0.057	-0.011
Bootstrapped p -value					[0.088]	[0.466]	[0.157]	[0.437]
$\Delta SP500_t$					-0.049**	-0.004	-0.053**	-0.001
Bootstrapped p -value					[0.040]	[0.401]	[0.026]	[0.474]
$MacroU_t$					3.924	0.348	4.261	0.183
Bootstrapped p -value					[0.126]	[0.364]	[0.134]	[0.406]
AME($\Delta_4 AE_t$)	-0.083***	-0.048**	-0.055**	-0.073***	-0.030*	-0.049***		
Bootstrapped p -value	[0.007]	[0.029]	[0.018]	[0.009]	[0.064]	[0.003]		
AME($\Delta_4 SPI_t$)			-0.060**	0.053*	-0.022	0.050***		
Bootstrapped p -value			[0.014]	[0.072]	[0.231]	[0.001]		
AUC	0.618***	0.464***	0.669***	0.468***	0.943***	0.899***	0.926***	0.894***
Bootstrapped p -value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Note: The numbers in parentheses and brackets represent t -statistics and p -values, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The dependent variable in this table is the NBER recession indicator. Equations (1): $\pi_t^1 \equiv \alpha + \beta^{AE} \Delta_4 AE_t$; Equation (2): $\pi_t^2 \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t$; Equation (3): $\pi_t^3 \equiv \alpha + \beta^{AE} \Delta_4 AE_t + \beta^{SPI} \Delta_4 SPI_t + \gamma' X_t$; Equation (4): $\pi_t^4 \equiv \alpha + \gamma' X_t$, where $X_t = [TERM_t, CRED_t, INFL_t, \Delta SP500_t, MacroU_t]'$. Detailed definitions of all variables can be found in Appendix A2.1.

Table A8.2: Out-of-Sample AUC Test Results with Bootstrapped p -values

Forecasts	$\hat{\Phi}(\pi_t^4 X_t)$		$\hat{\Phi}(\pi_t^2 \Delta_4AE_t, \Delta_4SPI_t)$		$\hat{\Phi}_{FC} = \frac{\hat{\Phi}(\pi_t^4) + \hat{\Phi}(\pi_t^2)}{2}$	
	$k=1$	$k=4$	$k=1$	$k=4$	$k=1$	$k=4$
<i>AUC</i>	0.900	0.762	0.756	0.267	0.904***	0.736**
Bootstrapped p -value	[0.324]	[0.471]	[0.152]	[0.255]	[0.009]	[0.014]

Note: The numbers in parentheses and brackets represent t -statistics and p -values, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The dependent variable in this table is the NBER recession indicator. $\hat{\Phi}_{FC} = \frac{\hat{\Phi}(\pi_t^2) + \hat{\Phi}(\pi_t^4)}{2}$; $\pi_t^2 \equiv \alpha + \beta^{AE} \Delta_4AE_t + \beta^{SPI} \Delta_4SPI_t$; $\pi_t^4 \equiv \alpha + \gamma'X_t$, where $X_t = [TERM_t, CRED_t, INFL_t, \Delta SP500_t, MacroU_t]'$. Detailed definitions of all variables can be found in Appendix A2.1.