Macro Risk Premia and the Business Cycle*

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Abstract

This study finds that macro risk premia are predictably negative after the ex-ante identified onset of recessions and then slowly recover. Survey forecasts indicate that these findings reflect investors' slow reaction to recessions. At recession onsets, investors are overly optimistic about cyclical firms, inflating their prices and lowering subsequent returns. The wedge between machine-learning and survey-based output forecasts positively predicts return spreads between cyclical and countercyclical firms. A long-short strategy exploiting this time variation yields an 8% annual alpha. Reversely, the return spreads between cyclical and countercyclical firms predict real economic activity and survey forecast errors. A model with sticky beliefs reconciles the unconditionally flat macro beta-expected return relation and delayed response of macro risk premia to recessions.

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1 Introduction

Leading asset pricing theories imply that assets with high exposure to macro risks (e.g., cyclical stocks) are riskier and should command higher risk premia. In addition, existing empirical evidence suggests that these premia are countercyclical, consistent with leading asset pricing models such as Campbell and Cochrane (1999). However, recent empirical work documents that the returns of long-short portfolios based on macro betas—that is, the return spreads between cyclical and countercyclical stocks—are small and weak (Shen, Yu, and Zhao, 2017; Herskovic, Moreira, and Muir, 2019). This paper presents new evidence that the conditional variation in macro risk premia at the onset of recessions deepens this puzzle. Specifically, using the ex-ante recession probability identified by the state-space model of Gómez-Cram (2022), we find that macro risk premia are predictably negative for several months following the onset of recessions but gradually increase thereafter. The return spreads between cyclical and countercyclical stocks do not reach their maximum until 10 months after the start of recessions. This conditional variation is difficult to reconcile with rational expectations, under which prices should decline instantly in response to unfavorable macro news and subsequently earn high and positive risk premia following the ex-ante identified onset of recessions, highlighting the need for a behavioral approach.

In this paper, we investigate whether sticky macro expectations can account for the unconditionally flat relation between macro betas and expected returns, as well as the conditional variation in macro risk premia across business cycles. A growing literature documents sticky or slow-moving macro expectations among households, firm managers, financial analysts, and professional forecasters (Mankiw and Reis, 2002; Coibion and Gorodnichenko, 2015; Malmendier and Nagel, 2016; Ma et al., 2024). The stickiness embedded in consensus macro beliefs can have significant dynamic effects on the aggregate economy and market returns (Carroll et al., 2020; Gómez-Cram, 2022; Lochstoer and Muir, 2022).[1] However, the effects of such belief distortions on cross-sectional macro risk premia remain unclear. Specifically, can the same sticky bias in macro expectations provide new insights into the behavior of cross-sectional macro risk premia?

We begin by presenting evidence suggesting that sticky expectations of macro variables account for the delayed response of macro risk premia to recessions. Under sticky macro

[1]The stickiness in consensus macro beliefs may arise from conservatism (Barberis, Shleifer, and Vishny, 1998), inattention (Mankiw and Reis, 2002), or noisy information (Coibion and Gorodnichenko, 2015). We remain agnostic about the exact cause and instead focus on its asset pricing implications.

expectations, signals of recession onset are incorporated only gradually into asset prices, producing the observed drift in macro risk premia. As we show, analyst expectations for cyclical (high macro beta) firms' earnings are overly optimistic at the onset of recessions, and downward revisions are exceptionally large thereafter. Moreover, cyclical firms experience greater reductions in investment and more credit-rating downgrades once recessions begin. These findings align with investors' slow recognition of recessions and the larger, delayed response of cyclical firms, which are more sensitive to macroeconomic changes. We also examine survey evidence from professional forecasters. Using the test of full-information rational expectations (FIRE) by Coibion and Gorodnichenko (2015), we find direct evidence of underreaction in the Survey of Professional Forecasters' (SPF) recession probability forecasts. Survey forecasts of recession probabilities are overly optimistic following negative news, and both errors and revisions in forecasts are predictable. These findings are consistent with recent research that emphasizes underreaction to macro news at short horizons (Coibion and Gorodnichenko, 2015; Bordalo et al., 2020; Gómez-Cram, 2022).

To further gauge the presence of macro belief biases, we construct a new expectation-wedge measure defined as the difference between machine-learning and survey-based output forecasts. A key premise of our approach is that machine-learning algorithms can approximate rational forecasts in real time (Bianchi, Ludvigson, and Ma, 2022). We predict that when machine forecasts substantially exceed survey forecasts, investors tend to be overly pessimistic, resulting in higher subsequent returns of cyclical stocks relative to countercyclical stocks. This is precisely what we find: the wedge between machine-learning forecasts and survey forecasts of quarterly real GDP growth predicts the returns of long-short portfolios based on macro betas. A one-standard-deviation increase in the expectation wedge predicts 1.13% higher long-short portfolio returns in the next quarter, with a t-statistic of 4.01. The effect is robust to various empirical specifications. For instance, we obtain similar results after controlling for competing explanations, including investor sentiment, disagreement, leverage constraints, and standard risk factors.

Leveraging the real-time expectation wedge, we assess the economic relevance of our findings with a trading strategy that tilts toward cyclical (countercyclical) stocks when investors are overly pessimistic (optimistic). Specifically, we increase (decrease) exposure to macro risk following a high (low) expectation wedge. This timing strategy generates a positive unconditional alpha, earning a capital asset pricing model (CAPM) alpha of 5.43% per annum by reducing risk-taking when investors overestimate output growth. The results cannot be explained by conventional factor models. The annualized alpha is 4.79% relative

to a benchmark comprising the Fama and French (2015) five-factor model, the time-series momentum factor of Moskowitz, Ooi, and Pedersen (2012), and the volatility-managed factor of Moreira and Muir (2017). The strategy's substantial gains may be surprising, given the consensus in the literature that the unconditional long-short portfolios based on macro betas are unprofitable, with return spreads close to zero (Shen, Yu, and Zhao, 2017; Herskovic, Moreira, and Muir, 2019). Moreover, a strategy that combines the expectation wedge with investor sentiment to time the macro-beta long-short portfolio yields an annual alpha of 8%.

If investors hold sticky macro expectations, news about future macro conditions is incorporated slowly into the cross-section of stock returns. Consequently, return spreads between cyclical and countercyclical firms can also predict future macro conditions because both are correlated with past macro news. Indeed, we find that such long-short portfolio returns are significant predictors of higher future real output growth. The sticky-belief hypothesis may not be the sole explanation for these findings: they are also consistent with rational expectations, since asset prices are forward-looking (Stock and Watson, 2003). However, the sticky belief hypothesis does provide a key auxiliary prediction that we can test with data—namely, that long-short portfolio returns should predict errors and revisions in investors' macro expectations. To explore this channel, we show that long-short portfolio returns predict errors and revisions in survey forecasts of recession probability and real output growth. Thus, the predictive power of long-short portfolio returns for real economic activity can be partially attributed to slow information updating, echoing the literature showing that underreaction induces predictability in certain stock returns and inflation rates (Hong, Torous, and Valkanov, 2007; Hong et al., 2025).

Lastly, to provide a formal theoretical foundation for our empirical findings, we develop a dynamic model of a cross-section of assets in which investors discount future cash flows based on subjective expectations. If subjective beliefs about future cash flows react to new information with a lag, macro risk premia consist of a rational risk-premium component and predictable near-term cash-flow changes that have not yet been incorporated into prices.[2] Cyclical firms are more sensitive to belief biases about the macroeconomy, as their higher macro beta magnifies the impact of subjective cash-flow expectations. In this model, the subjective cash-flow component of expected returns can offset the rational risk premium component, inducing a negative risk-return relation when the economy is transitioning to a recession. Hence, investors' subjective overestimation of cyclical firms' future cash flows

[2]With a slight abuse of terminology, we refer to the econometrician's expected returns on long-short portfolios sorted on macro betas as macro risk premia, although they include a correction for belief bias.

at recession onsets offsets the increase in the rational macro risk premium. This offset can lead cyclical stocks to underperform countercyclical stocks following recession onsets, as observed in the data. Importantly, consistent with the data, the model also implies a flatter unconditional relation between macro betas and expected returns. The intuition for this result is as follows. When investors have sticky macro beliefs and a preference for early resolution of uncertainty, they underestimate the impact of macro shocks on the expected path of consumption growth and hence marginal utility. This effect makes macro shocks appear less risky to investors, leading to a lower price of macro risk under subjective expectations than under FIRE. In addition, since positive and negative belief biases induced by sticky expectations cancel each other out, the average macro risk premium is equal under subjective and objective expectations. As a result, the model also produces a flatter unconditional macro beta-expected return relation under objective expectations than under FIRE.

Our research contributes to the growing literature in finance and macroeconomics that emphasizes expectation formation by relaxing the FIRE assumption. Gómez-Cram (2022) and Anarkulova, Cederburg, and Zhou (2025) document that investors' slow reaction to recessions explains the negative aggregate stock market returns at the beginning of economic recessions. Lochstoer and Muir (2022) show that investors have slow-moving beliefs about stock market volatility, thereby weakening the risk-return relation in the aggregate time series. We differ from these earlier aggregate time-series studies by examining rich cross-sectional risk premia across a broad set of macro variables, emphasizing the heterogeneous impact of distorted macro beliefs on individual firms. In addition to generating conditional variation in the cross-sectional risk-return relation, we show that sticky expectations can also yield an unconditionally flat relation between macro betas and expected returns.

More broadly, we contribute to the ongoing debate on what drives equity price variations: discount rate news or cash-flow news. In particular, Delao and Myers (2021) show that the connection between cash-flow expectations and asset prices is stronger than that between expected returns and asset prices. Delao and Myers (2024) further show that short-term earnings growth expectation errors are critical in explaining stock market returns. We complement this literature by emphasizing the role of near-term subjective output beliefs in driving macro risk premia.

Moreover, our work closely connects to the literature on the pricing of macroeconomic and market risks. One of the most persistent anomalous findings in financial economics is that the return difference between stocks with high and low market betas is significantly smaller than

theory predicts and has garnered significant scholarly attention (Black, 1972; Chen, Roll, and Ross, 1986; Frazzini and Pedersen, 2014). Shen, Yu, and Zhao (2017) and Herskovic, Moreira, and Muir (2019) extend this finding by showing that most common macro risks are not priced in the cross section of stocks. Several explanations have been proposed in the literature to account for the muted relationship between betas and expected returns. Frazzini and Pedersen (2014) show that leverage-constrained investors bid up the prices of high-beta assets due to their high expected returns, producing negative CAPM alphas for these stocks. Hong and Sraer (2016) suggest that high-beta assets are more sensitive to investor disagreement and are overpriced when short-sale constraints bind. Shen, Yu, and Zhao (2017) find empirically that aggregate investor sentiment attenuates the relation between macro beta and expected returns. In contrast, investor sentiment arises endogenously from investor misperceptions in our framework. Together, the evidence suggests that predictable macro misperceptions transmit to macro risk premia, distorting the macro beta-expected return relation.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 presents our main empirical results. Section 4 presents the model. Finally, Section 5 concludes.

2 Data Description and Methodology

2.1 Data and Variables

We obtain returns on U.S. common stocks (share codes 10 and 11) traded on the NYSE, Amex, and Nasdaq from the Center for Research in Security Prices (CRSP) and company fundamentals from Compustat. Corporate bond returns come from the Lehman Brothers Fixed Income Database, TRACE, and Mergent FISD/NAIC; long-term domestic issuer credit ratings come from Standard & Poor's (S&P) Credit Ratings; and analyst forecasts come from Thomson Reuters I/B/E/S. Additionally, we gather macro variables from the Federal Reserve Economic Data (FRED) and Amit Goyal's webpage, enabling us to construct macro beta-sorted portfolios. The series for market returns, the risk-free rate, and the Fama and French (2015) five factors come from Kenneth R. French's data library. We collect three investor-sentiment indices: the Baker and Wurgler (2006) index orthogonalized to economic conditions, obtained from Jeffrey Wurgler's webpage; the American Association of Individual Investors (AA) survey index; and the Investors Intelligence (II) survey index. Lastly, we

obtain the intermediary capital ratio of He, Kelly, and Manela (2017) from Zhiguo He's webpage. The full sample runs from 1965 to 2019.

Macro forecasts are from the Survey of Professional Forecasters (SPF), the oldest quarterly survey of macro forecasts in the U.S., managed by the Federal Reserve Bank of Philadelphia. Since the fourth quarter of 1968, the SPF has collected forecasts on various aspects of the macroeconomy from financial institutions, professional forecasting firms, and academic institutions. Following Bordalo et al. (2020), we compute consensus SPF forecasts as the mean of the individual-level forecasts available in each quarter. We calculate forecasts, forecast errors, and forecast revisions at the individual level and average them across forecasters to compute the consensus. To calculate forecast errors, we match forecasts with real-time actual outcomes, which come from the initial releases of the Philadelphia Fed's Real-Time Data Set.[3]

2.2 Macro Variables

To study the pricing of theoretically grounded macro variables, we investigate long-short portfolios sorted on macro betas following the literature (Chen, Roll, and Ross, 1986; Shen, Yu, and Zhao, 2017; Herskovic, Moreira, and Muir, 2019). Specifically, following the literature, we consider a set of 10 macro variables that capture different aspects of the economy, such as output, consumption, employment, and interest rates:

1. CON, the growth of real personal consumption expenditures on nondurable goods and services per capita (Chen, Roll, and Ross, 1986);
2. TFP, the growth rate of aggregate total factor productivity (Jermann, 1998);
3. IPG, the monthly growth rate of industrial production (Chen, Roll, and Ross, 1986);
4. TERM, the yield spread between 10-year and 1-year Treasury bonds (Harvey, 1988);
5. DEF, the default premium, measured as the monthly change in the yield spread between BAA-rated and AAA-rated corporate bonds (Keim and Stambaugh, 1986);
6. UI, the unexpected inflation (Chen, Roll, and Ross, 1986);

[3]The vintage data are taken from the Philadelphia Fed's website: `https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/real-time-data-set-full-time-series-history`.

7. DEI, the change in expected inflation (Fama and Gibbons, 1984);

8. VOL, the change in monthly market volatility (French, Schwert, and Stambaugh, 1987);

9. MKT, the stock-market excess return (Chen, Roll, and Ross, 1986); and

10. LAB, the growth rate of nominal labor income per capita (Jagannathan and Wang, 1996).

Appendix A.1 describes the construction of these macro variables.[4] Our goal is to form portfolios by sorting individual stocks based on their sensitivity to macro variables. We estimate each stock's macro beta by regressing excess stock returns on macro variables using a five-year rolling window with a minimum of 24 observations, using lagged macro variables when necessary to account for publication delays, following convention. Firms with the largest and smallest exposures to a particular macro variable are assigned to the fifth and first quintile portfolios, respectively. The long-short portfolio consists of a long position in firms in the fifth quintile (typically cyclical firms) and a short position in firms in the first quintile (typically countercyclical firms). In this paper, we use "high macro beta" and "cyclical" firms interchangeably, and "low macro beta" and "countercyclical" firms interchangeably.

Among the 10 macro variables, most have a clear theoretical foundation for the sign of the price of risk. In particular, prior studies (French, Schwert, and Stambaugh, 1987; Keim and Stambaugh, 1986) indicate that DEF and VOL carry negative prices of risk, so we multiply these two series by minus one before forming portfolios. However, because our prior on the price of risk for the two inflation-related variables (UI and DEI) is not as strong as for the other eight variables (e.g., Boons et al., 2020), we present the main empirical results based on two sets of averages for the combination strategy: one including and one excluding the inflation-related variables.

In Panel A of Table 1, we demonstrate the failure of macro risk pricing in the cross-section of stocks by presenting a flat relation between macro betas and portfolio expected returns. Across all 10 macro variables, none of the high-minus-low portfolios has a statistically significant positive excess return, despite generally having large and statistically significant post-formation betas (Panel B). For example, consumption growth (CON), a macro variable with strong theoretical grounding in consumption-based asset pricing models, has an annual premium of -0.95% (t-statistic = -0.49). Noise in macro beta estimation may introduce

[4]Following Shen, Yu, and Zhao (2017), we do not include the change in the real interest rate in our study, as it is perfectly negatively correlated with the unexpected inflation series UI.

measurement error, making it challenging to estimate macro risk premia from beta-sorted portfolios and potentially weakening the predictability we document. Nevertheless, even the average portfolio across all 10 macro variables, which may have less noise, exhibits an economically and statistically insignificant premium of -0.50%.

The remaining panels of Table 1 show how these macro beta-sorted long-short portfolios load onto business cycle risks. Specifically, Panel C shows that all long-short portfolios have positive exposure to the market factor. Panel D further shows that all long-short portfolios exhibit positive exposure to common growth—the first principal component of real GDP growth, TFP growth, consumption growth, labor income growth, and initial claims growth. According to standard asset pricing models, the cyclicality of these portfolio returns makes them risky to risk-averse investors, who therefore demand an overall positive risk premium for holding them. However, Panel A shows that cyclical firms do not earn higher returns than countercyclical firms on average. This is consistent with studies finding that the estimated prices of risk for macro variables using hedged portfolios are near zero (Shen, Yu, and Zhao, 2017; Herskovic, Moreira, and Muir, 2019).

3 Main Empirical Analysis

3.1 Macro Risk Premia over Business Cycles

This subsection presents the new empirical findings that motivate the subsequent analysis. Specifically, we investigate how macro risk premia vary over the business cycle. Without committing to a specific dynamic asset pricing model, we analyze long-short macro beta-sorted portfolios conditional on real-time business cycle dates. Our findings indicate that the state of the business cycle provides valuable insights into macro risk premia, though these insights diverge from the predictions of leading rational models.

To establish business cycle turning points, we use the real-time recession probabilities of Gómez-Cram (2022), who estimates them with a state-space model based on real-time macroeconomic data. We assume that investors anticipate a recession whenever the real-time recession probability first exceeds 50%.[5] Figure 1 depicts the one-year returns of long-short macro beta-sorted portfolios around recessions, revealing two main findings. First, the

[5]This 50% threshold rule follows Gómez-Cram (2022). Our conclusions remain robust to alternative thresholds near 50% and to other real-time measures of recession probability.

macro risk premium is weak and even negative at the onset of recessions. Specifically, an investor who buys cyclical stocks and shorts countercyclical stocks in the first three months of a recession and holds for 12 months earns an average return of -1.3%. Excluding the inflation-related variables (UI and DEI), for which the sign of the risk premium is debatable, yields a similar conclusion. Second, the figure reveals that the one-year returns of long-short portfolios increase slowly after entering a recession. The return spreads between cyclical and countercyclical stocks do not reach their maximum until 10 months after the start of recessions, which is relatively late given that the average length of a National Bureau of Economic Research (NBER) recession during our sample period is 12 months. As a result, macro risk premia are predictably weak for several months after the ex-ante identified onset of recessions and increase slowly thereafter. The results echo the empirical findings of Gómez-Cram (2022), who shows that stock market returns are initially negative at the start of recessions. This evidence is difficult to reconcile with rational expectations, under which prices should decline promptly in response to adverse macro shocks and risk premia should subsequently be positive. Moreover, if risk premia are fully rational and countercyclical, possibly due to countercyclical risk aversion (Lustig and Verdelhan, 2012; Campbell and Cochrane, 1999), then risk premia should be exceptionally high following recession onsets, contradicting our empirical evidence.

Furthermore, to ensure the robustness of our empirical specification, we consider two alternative mechanical recession dates with ex-ante information following Lustig and Verdelhan (2012): the Chauvet and Piger (2008) recession probability and the Chicago Fed National Activity Index (CFNAI). Both indices are publicly available at a monthly frequency starting from 1967. Chauvet and Piger (2008) estimate recession probabilities with a parametric Markov-switching dynamic factor model using a real-time dataset of coincident monthly indicators that the NBER emphasizes when identifying business-cycle turning points. The Chicago Fed index is a weighted average of 85 monthly indicators of national economic activity. The vintage CFNAI series, available on the Chicago Fed's website, is used in this paper to align as closely as possible with real-time estimates. We determine recession onsets using the following mechanical rules: (1) the Chauvet and Piger (2008) recession probability exceeds 50% and (2) the Chicago Fed index falls below -0.72 (Berge and Jordà, 2011). Figure A1 in the Appendix presents the results of the two alternative approaches, which lead to similar conclusions. In both cases, investment strategies based on 10 macro variables yield weak or negative returns at the onset of recessions and gradually improve thereafter.

Firms finance their assets using a mixture of debt and equity claims, and the equity and corporate bond markets are potentially integrated (Ghaderi et al., 2025). Therefore, one may wonder whether the patterns observed in stock returns might also manifest in corporate bond returns. To examine this possibility, we sort stocks into quintiles based on stock macro beta and reconstruct long-short portfolios using firm-level excess corporate bond returns. We form value-weighted bond portfolios using firms' lagged market capitalizations as weights. Panel A of Figure 2 shows that the results continue to hold for corporate bond returns. When measured using corporate bond returns, macro risk premia remain negative for several months at the onset of recessions and then gradually rise above zero. An investor who buys a hedged portfolio of corporate bonds during the first three months of a recession and holds it for 12 months earns an average return of -1.1% across all 10 macro variables and -1.6% when the inflation-related variables are excluded. Both estimates are economically sizable.

Reconciling this evidence with leading rational asset pricing models is challenging, as these models typically posit an immediate drop in prices of cyclical stocks followed by a quick reversion to a positive risk premium. Instead, the evidence appears more consistent with underreaction in investor expectations. We present further evidence favoring this explanation. To calculate forecast errors and revisions, we construct subjective cash-flow expectations using consensus analyst earnings per share (EPS) forecasts from the Thomson Reuters unadjusted I/B/E/S History File. Specifically, we focus on the forecasts made for the next fiscal year (i.e., FPI = 1). Forecast errors are defined as the difference between actual EPS values from the I/B/E/S unadjusted actuals database and the mean EPS forecasts. Forecast revisions are defined as changes in the mean EPS forecasts. Finally, these differences are normalized by the stock price. Panel B shows that following the onset of recessions, analysts' expectation errors are more negative for cyclical firms, suggesting that analysts are overly optimistic about these firms. As Panel C further shows, analysts make larger downward earnings forecast revisions for cyclical firms. Results are reported for long-short portfolios for brevity. Figure A2 confirms that both cyclical and countercyclical firms experience negative forecast errors and downward forecast revisions, but the effect is stronger for cyclical firms. These findings are consistent with investors' gradual recognition of recessions, whose effects are stronger for cyclical firms.

Engelberg, McLean, and Pontiff (2018) suggest that abnormal returns are higher on earnings announcement days because investors' biased expectations tend to be corrected upon the arrival of news. If this is the case, abnormal stock price movements should

be observed around subsequent earnings announcements as investors correct their belief errors. To assess this possibility, we calculate the (-1, +1) three-day window announcement returns during the next quarter after portfolio formation for each stock and aggregate at the portfolio level. Panel D shows that, consistent with the biased belief explanation, earnings announcement returns are initially negative following the onset of recessions. This suggests that investors are too optimistic about cyclical firms relative to countercyclical firms at the onset of recessions. As new information arrives at earnings announcements, investors gradually update their beliefs, reducing the stock prices of cyclical firms relative to countercyclical firms.

As investors correct their belief errors, they recognize the relative overpricing of cyclical firms. Consequently, they require higher returns on equity and corporate bonds for these firms, and real activity, such as investment, contracts. Consistent with this channel, Panel E shows a relative slowdown in cyclical firms' investment growth at the start of recessions. We caution, however, that investment dynamics alone cannot identify belief distortions, since models with investment adjustment costs (Christiano, Eichenbaum, and Evans, 2005) can generate gradual investment declines under FIRE. To investigate this further, we examine the credit ratings (forward-looking opinions of credit risk) aggregated at the portfolio level in Panel F.[6] We observe more downgrades in the credit ratings of cyclical firms, as indicated by the three-month changes in S&P issuer credit ratings, suggesting a deterioration in issuer quality.[7] Together, the patterns in forecast errors and real activity are most parsimoniously explained by distorted investor beliefs and their gradual correction.[8]

One might naturally wonder how macro risk premia behave during expansions. Figure A3 plots the returns of the long-short macro beta-sorted portfolio around the onset of expansions. As the Gómez-Cram (2022) recession probability is derived from a regime-switching model with two economic states—expansion and recession—we define expansions as periods when the recession probability first falls below 50%. As can be seen, the performance of the long-short portfolio based on macro betas remains relatively stable at the onset of expansions, showing no discernible trend. Hence, during expansions, we cannot clearly distinguish whether observed return variation reflects rational expected return dynamics or behavioral

[6]The S&P long-term issuer credit rating is converted to a numerical scale, with AAA=22 and D=1, such that positive (negative) changes indicate upgrades (downgrades).

[7]Figure A2 confirms that both cyclical and countercyclical firms experience credit rating downgrades after recession onsets, with a stronger effect for cyclical firms.

[8]This mechanism differs from the disagreement-based explanation proposed by Hong and Sraer (2016), since disagreement about aggregate output typically rises after recession onsets (Patton and Timmermann, 2010), which implies inflated prices and initially higher returns for high-beta stocks.

biases. This asymmetry is consistent with the view that bad news propagates more slowly than good news (Hong, Torous, and Valkanov, 2007), inducing a more pronounced underreaction to macro news at the onset of recessions than expansions. We empirically confirm this view in the next subsection.

Another interesting question is whether the same pattern of underreaction applies to other factors, such as characteristics-based factors—including value, momentum, and profitability—that are commonly used in leading multifactor models. Stambaugh and Yuan (2017) and Chen et al. (2025) suggest that these factors likely reflect mispricing and are therefore not expected to be procyclical or to exhibit the same behavior around recessions. To examine this, we follow Chen et al. (2025) in using 13 characteristics-based factors from leading multifactor models and repeat the analysis for the average long-short factor beta-sorted portfolio.[9] Figure 3 shows that characteristics-based factors exhibit a distinct pattern. At the onset of recessions, stocks with higher characteristics-based factor betas earn relatively higher returns, and the return spread between high- and low-beta stocks gradually decays to zero, in contrast to the pattern observed for macro factors. This contrasting pattern likely reflects differences in business cycle exposure: unlike stocks sorted on macro betas, stocks with high characteristics-based factor betas tend to be *less* cyclical than their low-beta counterparts, generating negative exposures to both the market and common growth factors in long-short portfolios (Panels C and D of Table A1 in the Appendix). Taken together, these findings suggest that not all factors are created equal; a factor's exposure to the business cycle may help explain its return dynamics around recessions.

In the Appendix, we report results using an alternative proxy for cyclical risk: stock-level total volatility. Stocks with high total volatility tend to be more cyclical and riskier than those with low total volatility. Figure A4 presents the returns of a strategy that takes a long position in high-volatility stocks and a short position in low-volatility stocks around the onset of recessions. As before, the risk premium is weak at the start of recessions but gradually increases thereafter. Overall, this evidence further supports the view that cyclical risk is priced with a delay at the onset of recessions.

[9]These factors include size (SMB), value (HML), operating profitability (RMW), and investment (CMA) factors from Fama and French (2015) five-factor model, investment (IA) and profitability (ROE) factors from Hou, Xue, and Zhang (2015) q-factor model, the profitable-minus-unprofitable (PMU) factor from Novy-Marx (2013), the quality-minus-junk (QMJ) factor from Asness, Frazzini, and Pedersen (2019), the momentum (MOM) factor from Carhart (1997) four-factor model, the management- (MGMT) and performance-related mispricing (PERF) factors from Stambaugh and Yuan (2017) mispricing factor model, and the long- (FIN) and short-run (PEAD) factors from Daniel, Hirshleifer, and Sun (2020) behavioral factor model. Factor data come from the original authors, except PMU, which is from Chen and Zimmermann (2022).

In the next set of tests, we illustrate the economic significance of the stylized fact through a simple strategy that capitalizes on this pattern. From a market participant's perspective, this pattern implies that an investor can profit by reducing exposure to macro risks at the start of economic and market downturns and then increasing risk-taking later. As long-short portfolios based on macro betas are inherently exposed to economic states, we follow Gómez-Cram (2022) and form trading strategies that switch to cash (the one-month T-bill) during bad economic times and market downturns, while remaining fully invested in the average long-short portfolio based on macro betas (the long-short portfolio) during other times. Specifically, suppose that at the end of a given month, the Gómez-Cram (2022) recession probability exceeds its six-month moving average, while the realized market return falls below its six-month moving average, indicating a contractionary period and a market downturn, respectively. In this case, the strategy allocates 100% to cash; otherwise, it allocates 100% to the long-short portfolio.[10]

Column (1) of Panel A in Table 2 reports various performance measures for this simple trading strategy. From June 1965 to December 2019, the strategy earns an annualized mean excess return of 1.01% with an annualized standard deviation of 8.55% while being fully invested in the long-short portfolio 80% of the time. For comparison, a fixed-allocation strategy invested in the long-short portfolio the same unconditional fraction of time—a mix of 80% in the long-short portfolio and 20% in T-bills—generates an annualized mean excess return of -0.41% and volatility of 7.91%, as shown in column (5). These numbers imply that the simple strategy raises the Sharpe ratio by 0.17 relative to the 80/20 strategy.

As this strategy takes less risk following bad times, it potentially overlaps with the volatility-managed portfolios of Moreira and Muir (2017) and time-series momentum of Moskowitz, Ooi, and Pedersen (2012). Hence, we evaluate factor-adjusted returns relative to a benchmark comprising the five-factor model of Fama and French (2015) augmented with the time-series momentum factor of Moskowitz, Ooi, and Pedersen (2012) and the volatility-managed factor of Moreira and Muir (2017). As shown in the bottom rows of Panel A, the simple strategy generates an annualized alpha of 1.81% (t-statistic = 1.86). Alternatively, we construct a timing strategy based on U.S. industrial production growth. Column (2) shows that this strategy invests in the long-short portfolio 72% of the time and is profitable, yielding a Sharpe ratio increase of 0.11 and an annualized alpha of 1.86% (t-statistic = 1.84). The higher Sharpe ratios and alphas of these strategies suggest that following macro trends

[10]Table A2 in the Appendix explores robustness with respect to the choice of the six-month moving average.

can improve the performance of the long-short portfolio. Column (3) reports another timing strategy based on the term premium, which the literature identifies as a positive indicator of real economic activity (Estrella and Hardouvelis, 1991; Boons, 2016). Under this alternative definition, the strategy is fully invested in the long-short portfolio 74% of the time and delivers an annualized alpha of 2.03% (t-statistic = 2.07). Conversely, columns (4) and (5) show that, without timing, the fixed-allocation strategies yield small and statistically insignificant alphas.

Additionally, Panel B of Table 2 reports average maximum drawdowns during expansions and recessions, helping us assess the strategy's performance across business cycles. Expansions and recessions are defined as periods when the Gómez-Cram (2022) recession probability is below or above 50%, respectively. We find that the strategy significantly reduces maximum drawdowns. Notably, during recessions, the average maximum drawdown is 27.19% for the strategy that times the recession probability, which is substantially lower than the corresponding figure of 35.08% for the 80/20 strategy. Hence, the long-short macro beta-sorted portfolio returns appear slow to incorporate information about recent variations in macro conditions, which can be used to improve strategy performance. In Section 3.5, we further discuss refined portfolio strategies that condition on variables related to biases in macro beliefs. Our results indicate that such strategies can generate alphas as high as 8% per annum.

3.2 Properties of Survey Expectations

To further support our proposed mechanism, we directly evaluate the sticky belief conjecture using data on recession-probability expectations from the SPF. The SPF asks professional forecasters to report the probability that the level of real GDP will decline in the current quarter and in each of the subsequent four quarters. Formally, a quarter-t probability forecast of a recession in quarter $t+h$ is defined as $Pr_t(GDP_{t+h} < 0)$, where GDP_{t+h} denotes the real GDP growth in quarter $t+h$.

The literature provides ample evidence of underreaction in consensus forecasts of macro variables from professional forecasters (Coibion and Gorodnichenko, 2015; Bordalo et al., 2020). We confirm that underreaction also occurs in consensus recession probability forecasts. Before discussing formal regressions, we graphically examine subjective recession probabilities. Figure 4 depicts the current-quarter recession probability forecasts ("nowcasts"), along with revisions in one-quarter-ahead forecasts. As shown, the onset

of NBER recessions appears to be associated with excessive optimism, as the forecasts of future recession probabilities tend to be revised upward later. Specifically, when the current recession probability is high, the expected future probability is revised upward.

Under the assumption of rational expectations (and knowledge of the data-generating process), forecast revisions should be unpredictable from past data. Table 3 reports the results of an econometric test of predictability. Columns (1) to (3) present results for the regression of recession-probability forecast revisions on lagged forecast revisions. The results support the main message presented in Figure 4. The estimated coefficient on the forecast revision is positive for all three specifications and statistically significant at the 1% level. Across the three columns, higher revisions in recession probability forecasts are associated with higher revisions in the future, suggesting a rejection of FIRE and indicating sluggish responses in expectations.

We next examine forecast errors, which should also be unpredictable under rational expectations. As we do not observe the realized probability of negative GDP growth, we use the nowcast as a proxy for the realized probability.[11] The nowcast—a prediction of the current-quarter recession probability—should be more accurate because more information is available by that time. Specifically, we define the forecast error for recession probabilities as the difference between the nowcast and the prior forecast. Columns (4)-(6) of Table 3 report the results of regressing the forecast error (nowcast minus forecast) on forecast revisions. In column (4), higher revisions in recession probability forecasts are associated with higher realizations relative to the forecast. We again find underreaction in survey expectations of recession probabilities. The FIRE test results for the SPF recession probability series have not been examined in the literature; however, the estimates of the slope parameters fall within a range similar to those found in prior studies (Coibion and Gorodnichenko, 2015; Bordalo et al., 2020).[12]

Since we observe more pronounced underreaction in the returns of macro beta-sorted portfolios at the onset of recessions than during expansions, we next test whether underreaction in forecasts is also asymmetric. To test this hypothesis, we modify the regressions by including both upward and downward forecast revisions, allowing us to capture any asymmetric impact by separating forecast revisions into upward and downward

[11] Gómez-Cram's (2022) definition of rational recession probability differs from that of the SPF: the former estimates the probability of a recession state within a state-space model, whereas the latter defines it as the probability of a decline in real GDP.

[12] In untabulated results, we also observe underreaction in real GDP growth forecasts, which has already been documented in the literature (see, for example, Bordalo et al., 2020).

components. As shown in Table 4, the underreaction to bad news (upward revisions in recession probability) appears more pronounced than underreaction to good news (downward revisions in recession probability). At the one-quarter-ahead horizon, the underreaction to good news is statistically insignificant. This asymmetry thus explains why underreaction is stronger at the onset of recessions than at the onset of expansions.

In summary, survey-based recession-probability forecasts exhibit predictable errors because they underreact to recent news. Motivated by evidence of sticky expectations, we investigate in the following analyses how predictable errors in macro survey forecasts induce predictability in macro risk premia.[13]

3.3 Wedge between Machine Learning and Survey Expectations

In the previous subsection, we confirm stickiness in subjective expectations of economic states, as surveys exhibit predictable forecast errors. However, such realized forecast errors cannot be fully attributed to belief biases—even if subjective expectations are fully rational ex-ante, unanticipated shocks could still induce a gap between forecasts and realizations. We therefore require a real-time proxy for the objective ex-ante economic state to characterize how subjective expectations predictably deviate from objective expectations. Since actual economic states such as NBER recessions are identified with considerable delay, we instead focus on assessing biases in subjective real GDP growth forecasts.

Following Bianchi, Ludvigson, and Ma (2022), we construct such a statistical benchmark using machine-learning-based real-time forecasts of real GDP growth. We use the random forest algorithm for its ability to capture complex relationships and mitigate overfitting (Breiman, 2001).[14] Random forest regression models are ensembles of decision trees, each trained on a bootstrap sample of the data. At each node, a tree considers a randomly selected subset of predictors, which reduces the correlation among the individual trees' predictions. The final prediction of the random forest model is obtained by averaging the predictions of the individual trees. Specifically, we predict next-quarter real GDP growth using a random

[13]Our findings do not contradict the work on overreaction in macro beliefs, which tends to be more prevalent (i) for long-term forecasts and for macro variables with low persistence (Bordalo et al., 2020); (ii) for individual-level forecasts (Bordalo et al., 2020); and (iii) when interacting with financial constraints and following favorable news (He, Su, and Yu, 2024). We differ by examining how stickiness in short-term consensus beliefs about persistent macro variables influences the cross-section of stocks with different macro beta exposures, particularly at the onset of recessions.

[14]Cassella et al. (2023) and Zhang, Zhu, and Linnainmaa (2025) characterize time-varying systematic errors in earnings expectations using random forests.

forest model:

$$E_t^P[GDP_{t+1}] = g(x_{t-1}, x_{t-2}), \tag{1}$$

where next-quarter real GDP growth serves as the target variable; the vector of input features, x, includes variables related to real output (e.g., GDP and industrial production), employment (e.g., the unemployment rate and initial jobless claims), investment (e.g., private residential and nonresidential fixed investment), inflation (e.g., the GDP deflator), and financial markets (e.g., the S&P 500 index); and g is a nonlinear function. While we cannot exhaustively capture every real-time variable, the broad coverage of our inputs provides a reasonable proxy for the full information environment.[15] To avoid look-ahead bias, we construct features using first-release values for the previous two quarters from the Philadelphia Fed; these values are available by the end of the first month of the following quarter. These real-time data capture the information set actually available to investors, accounting for the fact that macro variables are often released with a delay and subsequently revised by statistical agencies. Finally, using only pre-sample data, we select the hyperparameters from a grid of commonly used values covering a representative range of specifications and hold them fixed thereafter. Appendix A.2 details the methodology and features used in the machine learning forecasts.

To trace out the difference between machine learning and survey output forecasts, we define the "wedge" variable as follows:

$$\Delta_t \equiv E_t^P[GDP_{t+1}] - E_t^S[GDP_{t+1}]. \tag{2}$$

This wedge variable is constructed using a rolling window of 40 quarters. Hence, each quarter, we use machine learning to forecast next-quarter real GDP growth and compare it with survey forecasts.

The top panel of Figure 5 depicts the time variation in the machine-learning forecast, survey forecast, and actual values. Absent expectational and statistical biases, both machine and survey forecasts should differ only by an unpredictable noise component. However, the graph indicates that machine and survey forecasts can differ substantially. As the bottom panel shows, the wedge in output forecasts tends to be low before the onset of recessions and gradually increases afterward. This systematic variation over the business cycle is difficult to reconcile with unpredictable noise and instead suggests that the wedge reflects belief

[15] We include financial variables because they are part of forecasters' information sets, following Bianchi, Ludvigson, and Ma (2022). Untabulated results show that our findings remain qualitatively similar, though slightly weaker, when these variables are excluded from the machine-learning features.

distortions in survey expectations.

To statistically compare the in-sample accuracy of the machine learning forecasts with that of professional forecasts, we estimate the following regression:

$$GDP_{t+1} = \alpha + \beta_P E_t^P[GDP_{t+1}] + \beta_S E_t^S[GDP_{t+1}] + \epsilon_{t+1}, \tag{3}$$

where $E_t^P[GDP_{t+1}]$ is the expected real GDP growth produced by rolling random forests and $E_t^S[GDP_{t+1}]$ is the survey expectation. This equation regresses realized GDP growth on machine learning and survey forecasts.

Panel A of Table 5 reports the results. Column (1) shows that the loading on the machine learning forecast is 0.83: a one-percentage-point increase in the machine-learning forecast is associated with a 0.83-percentage-point increase in realized real GDP growth. Following Romer and Romer (2000), we assess the unconditional unbiasedness of the forecast by jointly testing the null hypothesis that the intercept α equals zero (i.e., no level shift) and the slope β equals one (i.e., a change in the forecast reflects a change in the realized value of equal magnitude). The null hypothesis of unconditional unbiasedness is not rejected at conventional significance levels (p-value = 0.47). In comparison, column (2) shows that the loading on the survey forecast is slightly smaller at 0.78. The machine learning forecast yields higher forecast accuracy in terms of in-sample R^2.

Column (3) reports bivariate regression results that include both machine learning and survey forecasts. The loading on the machine learning forecast is 0.60 (t-statistic = 2.42), whereas the loading on the survey forecast is 0.41 (t-statistic = 1.33). Under the interpretation that realized GDP growth can be viewed as a linear combination of the two forecasts, the ratio of the coefficients implies a relative weight of roughly 60% on the machine learning forecast and 40% on the survey forecast. The results indicate that realized GDP growth aligns more closely with the machine learning forecast, which subsumes the predictive power of the survey forecast. Joint hypothesis tests provide a sharper assessment and we fail to reject the null that the machine learning forecast subsumes the survey forecast ($\beta_P = 1, \beta_S = 0$; p-value = 0.26), while rejecting the converse null ($\beta_P = 0, \beta_S = 1$) at the 10% level (p-value = 0.05). Taken together, these results are consistent with greater informational content in the machine learning forecast.

Panel A also examines out-of-sample forecasting ability. We compare the predictive accuracy of machine-learning and survey forecasts using out-of-sample R^2 (R^2_{oos}), which

compares the mean squared errors obtained from these forecasts (MSE_μ) with those from the historical average (MSE_H): $R^2_{\text{oos}} = 1 - MSE_\mu/MSE_H$, where $\mu = P$ for the machine learning forecast model and $\mu = S$ for survey forecasts. As shown in the last row, the out-of-sample R^2 for machine learning forecasts is 18% larger than that for survey forecasts. Overall, the machine learning model outperforms the survey forecasts, subsuming the predictive power of survey forecasts in horse-race regressions.

Finally, Panel B examines the ability of the wedge variable to predict errors in survey forecasts. Column (1) shows that the wedge positively predicts survey forecast errors (t-statistic = 2.41), as the machine learning approach incorporates public information more efficiently than survey forecasters do. When controlling for survey forecast revisions in column (2), the coefficient on the wedge remains positive and statistically significant (t-statistic = 3.46). Further, column (3) examines how survey forecast errors relate to the machine-learning and survey forecasts, revealing a similar conclusion: when both are included in the regression, the machine learning forecast is more positively associated with future survey forecast errors than the survey forecast is.

Taking stock, these results indicate that the difference between machine learning and survey forecasts effectively captures predictable biases in survey forecasts.

3.4 Implications for Macro Risk Premia Predictability

After constructing a real-time wedge between machine-learning and survey-based output expectations, we now test whether it predicts returns on long-short portfolios based on macro betas. To test the predictive ability of the wedge, we perform the following regression:

$$f_{t+1} = \alpha + \beta\Delta_t + \delta' z_t + \epsilon_{t+1}, \tag{4}$$

where $\Delta_t \equiv E_t^P[GDP_{t+1}] - E_t^S[GDP_{t+1}]$ is the wedge between the machine learning and survey forecasts of one-quarter-ahead real GDP growth. The machine learning forecast $E_t^P[GDP_{t+1}]$ is produced by rolling random forests using the past 10 years of quarterly data, and the survey forecast $E_t^S[GDP_{t+1}]$ is from the SPF. f_{t+1} is the average return in quarter $t+1$ on the ten long-short portfolios sorted on macro betas.

We consider several control variables, denoted by z_t, based on extant research. Recent studies explore the time variation in macro risk premia, showing that these premia are influenced by economic forces such as money illusion (Cohen, Polk, and Vuolteenaho, 2005),

leverage constraints (Frazzini and Pedersen, 2014), aggregate disagreement (Hong and Sraer, 2016), and investor sentiment (Shen, Yu, and Zhao, 2017). In addition, macro risk premia may also be influenced by risk aversion and other macro conditions. Therefore, we control for the surplus consumption ratio of Campbell and Cochrane (1999), the term spread, the default premium, the inflation rate, the intermediary capital ratio of He, Kelly, and Manela (2017) (the inverse of intermediary leverage), the Baker and Wurgler (2006) sentiment index, and real GDP growth forecast dispersion.

Table 6 reports the regression results using both machine learning and survey expectations of real GDP growth as predictors, as well as constrained regressions using their difference, the wedge variable. For comparability of coefficients, the dependent variable is expressed in quarterly percentages, while the explanatory variables are standardized to have a mean of zero and standard deviation of one. The wedge variable positively predicts the long-short portfolio return over the next quarter. Specifically, in column (1), the coefficient on the wedge variable is statistically significant at the 1% level, with a t-statistic of 4.01. In terms of economic significance, a one-standard-deviation increase in the wedge variable predicts long-short portfolio returns that are 1.13% higher over the next quarter. The economic magnitude of the coefficient is sizable given that the realized returns average -0.50% per year. For the unconstrained specification in column (2), the long-short portfolio returns load positively on machine learning forecasts and negatively on survey forecasts of real GDP growth, with coefficients of roughly the same magnitude. As the literature identifies several variables that influence the pricing of macro risk, we control for them in the predictive regressions in columns (3) and (4). Column (3) shows that a one-standard-deviation increase in the wedge variable predicts long-short portfolio returns that are 1.37% (t-statistic = 4.07) higher over the next quarter. Additionally, inflation and sentiment have negative coefficients—higher inflation or sentiment is associated with a flatter macro beta-return relation. A similar result is observed in column (4). This evidence confirms the expectation wedge's predictive power for macro risk premia.

Next, we confirm the robustness of this analysis through a battery of additional tests. As an alternative to our machine learning approach, we also construct a real GDP growth forecast using a composite benchmark that averages the forecasts from ridge regression, elastic net, random forest, extra trees, and gradient boosted regression trees (Gu, Kelly, and Xiu, 2020). With this approach, the wedge between machine learning and survey forecasts still significantly predicts long-short portfolio returns (Table A4). Returning to our baseline specifications, Figure A5 plots the coefficient estimates for the 10 individual

macro variables, which exhibit remarkable consistency at the individual macro-variable level. The wedge variable positively predicts returns for the majority of the 10 individual macro variables, with 7 out of 10 yielding statistically significant estimates at the 10% level. For some inflation-related variables, such as UI and DEI, we observe weaker effects. This is to be expected because the correlation between inflation and consumption could be time-varying and occasionally weak (Boons et al., 2020). In Figure A5, we verify that our findings are robust even after excluding UI and DEI. Nevertheless, we include them in our main analysis to maintain consistency with the literature. Thus far, we have constructed the long-short portfolios using equity returns. We next test whether the results extend to corporate bond returns. We repeat the analysis by sorting firms into quintiles based on their stock macro betas and measuring portfolio returns using firm-level excess corporate bond returns. Figure A5 shows that the predictive power of the expectation wedge persists when measured with corporate bond returns.

One remaining question is whether the predictive ability of the expectation wedge is absorbed by risk factors. To investigate this, we control for conventional risk factors in the regression and present the results in Table 7. As before, the factor model includes the five-factor model of Fama and French (2015), augmented with the time-series momentum factor and volatility-managed factor. In column (1), we see that a one-standard-deviation increase in the wedge variable predicts long-short portfolio returns that are 0.70% (t-statistic = 2.82) higher over the next quarter. This estimate is slightly smaller than the estimate in Table 6. For the unconstrained specification in column (2), we observe opposite signs for the coefficient estimates on the machine learning and survey forecasts. Likewise, when we include various control variables in the regression, the coefficient estimates remain similar (columns (3) and (4)). Overall, the predictive ability of the wedge variable remains intact when using factor alphas.

3.5 Performance Gains from Timing the Expectation Wedge

To illustrate the economic relevance of our empirical findings, we construct a trading strategy that times the expectation wedge, Δ_t, and demonstrate that investors can reap significant profits from it. Specifically, at the end of each quarter, we increase risk exposure when Δ_t is high and reduce it when Δ_t is low,

$$f_{t+1}^{\Delta} = c\Delta_t f_{t+1}, \tag{5}$$

where f_{t+1} is the average return on the long-short portfolios based on macro betas, and the constant c controls the strategy's average risk exposure. To facilitate interpretation, we follow Moreira and Muir (2017) and choose c such that the managed return, f_{t+1}^{Δ}, has the same unconditional volatility as the average long-short macro beta-sorted portfolio. Intuitively, this proposed trading strategy tilts toward cyclical stocks when investors are overly pessimistic and shifts toward countercyclical stocks when investors are overly optimistic.

We perform a series of tests on strategy performance and report the results in Table 8. Panel A indicates that this trading strategy earns large excess returns and alphas. The estimated annual market alpha is 5.43% and is both economically and statistically significant (t-statistic = 3.64), consistent with the wedge's predictive power for returns on long-short portfolios sorted on macro betas. In contrast, without timing, the buy-and-hold long-short strategy generates negative excess returns and market alphas. Thus, timing the wedge raises alpha by roughly 9 percentage points relative to the buy-and-hold benchmark. Additionally, when we use the Fama and French (2015) five-factor model as the benchmark, this trading strategy produces a significant annual five-factor alpha of 4.64% (t-statistic = 2.65). A potential concern is that the strategy merely repackages existing approaches, such as volatility management, that reduce risk in adverse periods. Our strategy takes less risk when subjective expectations are overly optimistic. Relatedly, Moreira and Muir (2017) show that taking less risk when volatility is high produces large portfolio alphas. To mitigate this concern, we further add the time-series momentum factor of Moskowitz, Ooi, and Pedersen (2012) and the volatility-managed market factor of Moreira and Muir (2017). The final rows of Panel A show that the alpha remains intact after adding these factors as controls, with an estimate of 4.79% (t-statistic = 2.70). Hence, by directly capturing belief biases, this strategy achieves higher performance than the strategies reported in Table 2.

Crucially, the timing strategy not only increases average returns but also reduces drawdowns. Panel B of Table 8 reports the average maximum drawdowns in expansions and recessions. As can be seen, during expansions, the timing strategy experiences smaller maximum drawdowns than the buy-and-hold long-short strategy. Similarly, during recessions, the timing strategy records an average maximum drawdown of 15.20%, which is much smaller than that of the buy-and-hold long-short strategy (42.67%).

In related work, Shen, Yu, and Zhao (2017) show that returns to cyclical firms tend to be higher following periods of low investor sentiment. Since investor sentiment is conceptually linked to investor misperception and therefore to our expectation wedge, we

construct a composite signal: the equal-weighted average of the standardized expectation wedge and the standardized inverse sentiment index, where the latter is measured as the recursively constructed first principal component of the Baker and Wurgler (2006) sentiment index together with the AA and II survey sentiment indices. We use principal component analysis to isolate the common component in investor sentiment. Repeating the analysis in equation (5) by conditioning on this composite signal, we obtain an excess return of 6.99% (t-statistic = 2.92) and a market α of 8.00% (t-statistic = 2.61). This strategy also exhibits lower maximum drawdowns, as shown in Panel B of Table 8. Taken together, this evidence suggests that investors can earn significant gains from macro beta-sorted long-short portfolios by timing the wedge between objective and subjective output expectations.

3.6 Unveiling the Unconditional Alpha

Here, we further investigate the origins of the alpha in our trading strategy that times the expectation wedge, shedding light on the underlying economic mechanism. To investigate this mechanism, Figure 6 shows the results of the conditional sorts based on the expectation wedge. For each bucket, the figure displays the corresponding average values and 90% confidence intervals for four measures over the next quarter. The top panels show the estimates for macro beta-sorted long-short portfolio returns and conditional market risk exposure, while the bottom panels depict estimates for real GDP growth forecast errors and changes in recession-probability forecasts from the SPF.

Figure 6 indicates that when the expectation wedge is in the lowest bucket, the long-short portfolio produces negative returns over the next quarter. In contrast, when the expectation wedge is in the highest bucket, the long-short portfolio generates positive returns. The top-right panel shows that the conditional market beta rises with the expectation wedge, so the strategy takes more market risk in high-wedge periods and less in low-wedge periods. Specifically, as shown in the bottom panels, this strategy seeks to avoid predictable disappointments in survey forecasts of macro conditions (real GDP growth and recession probabilities) and the associated negative long-short portfolio returns, while increasing risk-taking otherwise. Overall, the proposed trading strategy's alpha likely derives from efficiently timing output and business cycles.

In essence, our findings suggest that market participants systematically underestimate transitions across economic states, particularly before economic downturns. While these results may resemble the documented effects of investor sentiment on the cross-section

of stock returns (Baker and Wurgler, 2006; Shen, Yu, and Zhao, 2017), our expectation wedge measure differs from existing sentiment indices in concept, mechanism, and empirical implications. First, whereas standard sentiment proxies (Baker and Wurgler, 2006) are aggregate, reduced-form measures capturing a broad spectrum of investor misperceptions, our wedge is a structural estimate of a specific belief distortion: the divergence between objective statistical forecasts of output growth and forecasters' subjective beliefs. Second, the wedge predicts not only macro risk premia but also future survey forecast errors, suggesting that it operates through predictable biases in macro expectations. Third, the wedge's predictive ability is largely orthogonal to extant sentiment indices, as it remains significant after controlling for sentiment.

3.7 Implications for Recession Predictions

Thus far, we have focused on how the wedge in expectations predicts the return spread between cyclical and countercyclical firms. We now consider the reverse direction: how such long-short portfolio returns predict real economic activity. Forecasting macro variables using financial indicators has long attracted interest from academics and practitioners, as it offers valuable insights for portfolio formation and economic policy design. If there is underreaction in macro beliefs, long-short portfolio returns should also predict future macro conditions, as both are correlated with past macro news. Hence, we adopt this reverse approach and examine whether the long-short portfolio returns can predict real economic activity, as well as errors and revisions in survey forecasts.

Table 9 shows that long-short portfolio returns positively predict future real activities. In Panel A, we report results from predictive regressions of one-quarter-ahead real activities. Specifically, we regress the NBER recession dummy, real GDP growth, and industrial production growth on long-short portfolio returns and other control variables. In particular, column (1) indicates that the long-short portfolio returns negatively predict the recession dummy in a linear probability model.[16] The economic significance of the coefficient is notable: a one-standard-deviation increase in the long-short portfolio returns translates into a reduction of approximately 6 percentage points in the probability of a recession. In the literature, the yield spread forecasts improvements in real economic activity (Harvey, 1988; Estrella and Hardouvelis, 1991), whereas the default spread signals deterioration in macroeconomic conditions (Gilchrist and Zakrajšek, 2012). Column (2) shows that

[16]The results are similar when using either a probit or logit model to predict the likelihood of a recession.

controlling for other variables, such as the term spread and default spread, does not materially alter the predictive power of macro risk premia. Thus, the long-short portfolio returns contain additional information about recession states beyond common predictors. Moreover, columns (3) through (6) show that the long-short portfolio returns positively predict next-quarter real GDP growth and industrial production growth, as indicated by the statistically significant coefficient estimates on the lagged long-short portfolio returns. In Panel B, we report the results from predictive regressions of the one-year-ahead real activities, averaged over the next four quarters. Interestingly, the long-short portfolio returns' predictive power persists, as the coefficient estimates on the lagged long-short portfolio returns remain statistically significant. However, the economic magnitude is slightly smaller than in Panel A.

To further uncover the source of the predictive ability of the long-short portfolio returns, we examine their relation to survey forecast revisions and errors.[17] Table 10 confirms that long-short portfolio returns predict revisions and errors in the SPF forecasts. We report results for one-, two-, and three-quarter-ahead forecasts. While the SPF respondents are professional forecasters, they do not appear to fully incorporate the information embedded in long-short portfolio returns. Panel A shows that long-short portfolio returns predict economically sizable negative revisions and errors in recession-probability forecasts. A one-standard-deviation increase in the long-short portfolio returns is associated with a downward revision of approximately 3 percentage points in the one-quarter-ahead recession probability. Additionally, Panels B and C indicate that the long-short portfolio returns positively predict revisions and errors in forecasts of real GDP growth and industrial production growth, respectively. The ability of long-short portfolio returns to predict revisions and errors in survey forecasts suggests that information is incorporated into investors' forecasts only gradually. These results parallel those of Hong et al. (2025), who examine the inflation beta and show that the return on a long-short inflation beta portfolio can predict future inflation and inflation forecast errors.

To summarize, our results suggest that the long-short portfolio returns are a useful indicator of future economic states and real activities, possibly due to the slow diffusion of information into expectations.

[17] In the sticky expectations model of Section 4, the macro forecast error is positively autocorrelated, producing a positive relation between the macro forecast error and the previous period's returns of long-short portfolios based on macro betas.

4 Theoretical Framework

In this section, based on the literature (Boons et al., 2020; Lochstoer and Muir, 2022), we develop a consumption-based asset pricing model with a representative agent to motivate and reconcile our empirical findings. We allow the representative agent to have biased beliefs about the dynamics of the macro variable. Our model admits tractable solutions and reveals how belief errors influence the macro risk premium in the stock market.

4.1 Preferences and Transition Dynamics

The representative agent has preferences given by the recursive utility function of Epstein and Zin (1989),

$$U_t = \left[(1-\delta)C_t^{\frac{1-\gamma}{\theta}} + \delta\left[E_t^S\left(U_{t+1}^{1-\gamma}\right)\right]^{\frac{1}{\theta}}\right]^{\frac{\theta}{1-\gamma}}. \tag{6}$$

In this parameterization, E_t^S denotes conditional expectations under the agent's subjective beliefs, C_t is aggregate consumption, δ is the time discount factor, γ is the coefficient of relative risk aversion, and $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$, where ψ is the elasticity of intertemporal substitution (EIS). The parameters satisfy $\gamma, \psi > 1$, which is the standard preference parameter configuration for asset pricing models with Epstein-Zin preferences (e.g., Bansal and Yaron, 2004). The first-order condition for the representative agent's problem implies that the gross return $R_{i,t+1}$ on any tradable asset i satisfies the Euler equation:

$$1 = E_t^S[M_{t+1}R_{i,t+1}], \tag{7}$$

with a stochastic discount factor M_{t+1} given by

$$m_{t+1} \equiv \ln M_{t+1} = \theta \ln \delta - \theta\frac{1}{\psi}\Delta c_{t+1} + (\theta-1)r_{c,t+1}, \tag{8}$$

where $r_{c,t+1}$ is the log return on the wealth portfolio, that is, the aggregate consumption claim. The wealth portfolio is defined as an asset that pays out aggregate consumption as dividends (Campbell, 2017).

Here, lowercase letters denote logarithms; hence, $\Delta c_t = \ln C_t - \ln C_{t-1}$ and $r_{c,t} = \ln(R_{c,t})$. The processes for consumption growth, Δc_t, macro variable, z_t, and dividend growth for

asset i, $\Delta d_{i,t}$, are exogenous and given by the following:

$$z_{t+1} = \mu_z + \rho_z(z_t - \mu_z) + \sigma_z u_{t+1}, \tag{9}$$

$$\Delta c_t = \mu_c + \rho_c(z_t - \mu_z) + \sigma_c \eta_t, \tag{10}$$

$$\Delta d_{i,t} = \mu_i + \rho_i(z_t - \mu_z) + \sigma_i \eta_t, \tag{11}$$

where u_t and η_t are independent and identically distributed standard normal. The macro variable z drives aggregate consumption growth; through the representative agent's pricing, the model generates quantities of macro risk for the cross-section of assets and a market price of macro risk in equilibrium. To connect with our empirical analysis, we will simulate a negative shock to the macro variable z_t that roughly corresponds to the ex-ante identified onset of recessions.

4.2 Subjective Expectations

We model aggregate beliefs about macro variables following evidence from the survey data. Specifically, the representative agent's subjective expectations of the macro variable z_{t+1} are given by

$$\begin{aligned} E_t^S[z_{t+1}] &= (1-\lambda)E_t^P[z_{t+1}] + \lambda E_{t-1}^S[z_{t+1}] \\ &= \mu_z + \rho_z x_t, \\ x_t &= (1-\lambda)\sum_{j=0}^{\infty}(\lambda\rho_z)^j (z_{t-j} - \mu_z). \end{aligned} \tag{12}$$

The superscripts P and S on the expectation denote that it is taken under objective and subjective beliefs, respectively. The parameter λ captures the degree of expectation rigidity. When λ is zero, the agent has rational expectations about the macro dynamics. A positive λ indicates that the agent has sticky expectations, possibly due to inattention or noisy information (Coibion and Gorodnichenko, 2015).

Under the representative agent's beliefs, the shock to the macro variable is

$$\begin{aligned} \sigma_z u_{t+1}^S &\equiv z_{t+1} - E_t^S[z_{t+1}] \\ &= \rho_z(z_t - \mu_z) - \rho_z x_t + \sigma_z u_{t+1}, \end{aligned} \tag{13}$$

where $\rho_z(z_t - \mu_z) - \rho_z x_t = E_t^P[z_{t+1}] - E_t^S[z_{t+1}]$ is the bias in the subjective expectation of the macro variable. The dynamics of x_t under the representative agent's subjective beliefs

can thus be written as

$$x_{t+1} = \rho_z x_t + (1-\lambda)\sigma_z u^S_{t+1}. \tag{14}$$

Because beliefs are sticky, the perceived shock is attenuated by a factor of $1-\lambda$.

4.3 The Price and Quantity of Macro Risk

To understand the asset pricing implications, we study the price and quantity of macro risk under subjective expectations.

We can identify the prices of risk for u^S and η as follows:

$$\begin{aligned}\lambda_u &\equiv -\frac{\mathrm{Cov}^S_t(m_{t+1}, u^S_{t+1})}{\mathrm{Var}^S_t(u^S_{t+1})} \\ &= \rho_c\sigma_z\left(\gamma + (1-\lambda)\kappa_1\rho_z\frac{\gamma - 1/\psi}{1-\kappa_1\rho_z}\right), \qquad (15)\end{aligned}$$

$$\lambda_\eta \equiv -\frac{\mathrm{Cov}^S_t(m_{t+1}, \eta_{t+1})}{\mathrm{Var}^S_t(\eta_{t+1})} = \gamma\sigma_c. \tag{16}$$

All proofs are included in Appendix B. The price of macro risk, denoted by λ_u, is defined as the compensation that investors require to hold one unit of macro risk (innovations in z). In our model, the macro risk is priced because innovations u^S provide information about the expected future path of consumption growth, and changes in this path affect the representative agent's marginal utility. The model offers an intuitive explanation for the sign of the macro risk premium. When ρ_c is positive, the representative agent demands positive compensation for bearing macro risk because a positive shock to u^S conveys favorable news about future consumption growth, implying a negative covariance between z and marginal utility. However, for macro variables with negative ρ_c, such as the default spread, the representative agent is willing to accept a lower expected return for holding credit risk, since shocks to the default spread coincide with unfavorable news about future consumption growth, making it a hedge for consumption and marginal utility. For simplicity, we assume $\rho_c > 0$ in the remaining discussion.

To derive the quantity of risk, we use a Campbell-Shiller approximation, which gives returns on any asset i, $r_{i,t+1}$,

$$r_{i,t+1} = \kappa_{i,0} + \kappa_{i,1} pd_{i,t+1} - pd_{i,t} + \Delta d_{i,t+1}, \tag{17}$$

where $\kappa_{i,0}$ and $\kappa_{i,1}$ are approximation constants. Hence, the quantities of risk for u^S and η are given by the following betas:

$$\beta_{u,i} \equiv \frac{\text{Cov}_t^S\left(u_{t+1}^S, r_{i,t+1}\right)}{\text{Var}_t^S\left(u_{t+1}^S\right)} = \sigma_z\left(\rho_i + (1-\lambda)\kappa_{i,1}\rho_z\frac{\rho_i - \rho_c/\psi}{1-\kappa_{i,1}\rho_z}\right), \tag{18}$$

$$\beta_{\eta,i} \equiv \frac{\text{Cov}_t^S\left(\eta_{t+1}, r_{i,t+1}\right)}{\text{Var}_t^S\left(\eta_{t+1}\right)} = \sigma_i. \tag{19}$$

Thus, the expected excess returns for asset i under subjective expectations can be written as follows:

$$E_t^S[r_{i,t+1} - r_{f,t}] = \lambda_u\beta_{u,i} + \lambda_\eta\beta_{\eta,i} - \frac{1}{2}\beta_{u,i}^2 - \frac{1}{2}\beta_{\eta,i}^2. \tag{20}$$

The last two terms represent Jensen's inequality correction terms in the derivation of expected log excess returns. This equation implies that the conditional expected excess returns for any risky asset are positive and constant, as in similar models with constant consumption growth volatility (see also Bansal and Yaron, 2004).

4.4 Macro Risk Premium Dynamics

To derive the model-implied macro risk premium from the cross-section of stock returns, we model two assets that represent the high (H) and low (L) macro beta portfolios for macro variable innovations u^S. Without loss of generality, we assume that the two assets have the same consumption growth beta (i.e., $\beta_{\eta,H} = \beta_{\eta,L}$). Hence, the return spread between these two assets purely reflects their differential exposure to the macro risk of u^S. We use $\beta_{u,HL}$ to denote the High-minus-Low macro beta, defined as the spread between the two assets' betas, $\beta_{u,H} - \beta_{u,L}$.

Given the subjective expectation dynamics, we can derive the unconditional macro risk premium:

$$E^P[r_{H,t} - r_{L,t}] = E^S[r_{H,t} - r_{L,t}] = \lambda_u\beta_{u,HL} - \frac{1}{2}\beta_{u,H}^2 + \frac{1}{2}\beta_{u,L}^2, \tag{21}$$

where the superscripts P and S denote objective and subjective expectations, respectively. The first equality in equation (21) relies on the fact that, on average, misperceptions of the macro variable z cancel out when computing the unconditional macro risk premium.

This equation helps explain the weak cross-sectional macro risk premium observed in the data. Note that the representative investor with sticky beliefs underestimates the impact of macro shocks u^S on the wealth-consumption ratio (i.e., the expected path of consumption growth) and hence on marginal utility.[18] For instance, following adverse macro shocks, the wealth-consumption ratio should fall, and marginal utility should rise, by more than investors subjectively expect. This is because marginal utility is inversely related to the return on the wealth portfolio when investors prefer early resolution of uncertainty ($\gamma > 1/\psi$), as evident from equation (8). In equilibrium, the representative investor perceives the covariance between future macro shocks and marginal utility as negative but smaller in magnitude, lowering the required compensation for bearing macro risk and thus the subjective price of macro risk relative to FIRE. Since the positive and negative belief biases due to sticky expectations cancel out, the average macro risk premium is equal under subjective and objective expectations. When investors prefer early resolution of uncertainty, sticky expectations lower the objective price of macro risk relative to FIRE. Therefore, sticky expectations weaken the cross-sectional risk-return trade-off, leading to a flatter relation between macro betas and expected returns relative to FIRE.

More important, our study focuses on the time variation in macro risk premia. In our model, we can derive the conditional macro risk premium explicitly. Specifically, we can write the relation between objective and subjective macro risk premia as follows:

$$\begin{aligned} E_t^P[r_{H,t+1} - r_{L,t+1}] &= E_t^S[r_{H,t+1} - r_{L,t+1}] + \frac{\beta_{u,HL}}{\sigma_z}\left(E_t^P[z_{t+1}] - E_t^S[z_{t+1}]\right) \\ &= E_t^S[r_{H,t+1} - r_{L,t+1}] + \frac{\beta_{u,HL}}{\sigma_z}\left(\rho_z(z_t - \mu_z) - \rho_z x_t\right), \end{aligned} \tag{22}$$

where the superscripts P and S denote objective and subjective expectations, respectively. Equation (22) implies that the wedge between objective and subjective macro expectations is positively related to future returns of long-short portfolios based on macro betas, consistent with our earlier empirical evidence. To further interpret the formula in equation (22), note that under fully rational expectations (i.e., $\lambda = 0$), the conditional macro risk premium is identical under objective and subjective expectations. With $\lambda > 0$, expectations are sticky, and the conditional risk premium is low when investors' beliefs are overly optimistic, that is, when they underreact to recent bad news, such as the onset of recessions ($E_t^P[z_{t+1}] <$

[18] Equation (A1) in the Appendix shows that the log wealth-consumption ratio wc_t is an increasing function of both the state variable x_t and the macro variable z_t. Under a preference for early resolution of uncertainty, upward revisions in the expected future macro variable then raise the wealth-consumption ratio while lowering marginal utility, as shown in Equation (A21) in the Appendix (see also Campbell (2017)).

$E_t^S[z_{t+1}]$). Negative and predictable future returns (to the econometrician) arise from the cash-flow news in the second term in equation (22), offsetting the risk premium component ($E_t^S[r_{H,t+1} - r_{L,t+1}]$), the first term in equation (22).

The return dynamics suggest that investors' delayed recognition of weak cash flows at recession onsets generates predictability in macro risk premia from the econometrician's perspective. To illustrate, we simulate a negative macro shock in our model and qualitatively examine how macro risk premia behave during recessions. Figure 7 plots the impulse response $\frac{\partial(r_{H,t+h} - r_{L,t+h})}{\partial u_t}$ of the one-period return on the long-short macro beta-sorted portfolio to a one-standard-deviation negative innovation u. In these simulations, we calibrate the expectation rigidity parameter using the estimates from Coibion and Gorodnichenko (2015), such that $\lambda = 0.3^{1/12} \approx 0.90$ at a monthly frequency.

In the model with FIRE (the dashed yellow line), a negative shock to the macro variable at time -1 results in an immediate decline in macro risk premia.[19] However, when investors have sticky beliefs (the solid blue line), the price reaction is slow and imperfect. Since subjective beliefs about future cash flows react to this shock with a delay, the prices of cyclical stocks remain too high relative to the rational case at the onset of recessions. Over time, investors gradually update their macro forecasts downward to align with rational expectations, causing macro risk premia to be negative or near zero in the immediate aftermath. They then rise over time as more information is incorporated into prices. After several months, the macro shock is nearly fully incorporated into prices, and the macro risk premium reverts to its steady-state level, which is smaller in magnitude than under FIRE because sticky beliefs reduce the unconditional macro risk premium, as discussed earlier. This is consistent with the empirical findings in Figures 1 and 2, which collectively show that macro risk premia are negative following the onset of recessions and rise slowly thereafter as investors gradually correct their expectations.

We follow Gómez-Cram (2022) in assuming symmetric underreaction to simplify the analysis. However, survey evidence in Table 4 shows that forecast revisions are more predictable following unfavorable news than favorable news, suggesting that forecasters underreact more strongly to adverse shocks. We therefore extend the baseline model to allow for asymmetric stickiness in Appendix C. In this specification, the stickiness parameter is higher following bad news ($u_t^S \leq 0$) than following good news ($u_t^S > 0$), with $\lambda^+ > \lambda^-$. The impulse response under this asymmetric specification (the dashed green line) closely

[19] To compare with Figure 1, we simulate a negative macro shock at time -1, enabling a perfect-foresight investor to hold the long-short macro beta-sorted portfolio starting from time 0.

tracks the symmetric sticky-expectations case. In particular, the delayed price reaction and the gradual reversion to a weak steady-state level remain similar. An additional implication of asymmetric stickiness is that investors are on average too optimistic, which attenuates the expected returns of high macro beta firms and lowers the unconditional macro risk premium. Overall, the main mechanisms through which sticky expectations influence macro risk premia, both conditionally and unconditionally, are robust to empirically motivated asymmetry in belief updating.

5 Conclusions

In this paper, we document several new facts about macro risk premia. First, macro risk premia are predictably negative for several months after the ex-ante identified onset of recessions and gradually increase thereafter. These negative premia at recession onsets are puzzling because cyclical stocks are riskier and should earn positive premia. Leading rational-expectations models and existing evidence further suggest that these premia should be countercyclical. Our results indicate that the average investor is slow to act on real-time macro information signaling the onset of recessions. We provide evidence supporting sticky macro beliefs by examining professional and analyst forecasts and real activities. Second, motivated by these findings, we propose a new measure of the expectation wedge based on the difference between machine learning and survey forecasts of real output, capturing the predictable errors in subjective real output forecasts. This expectation wedge positively predicts returns on macro beta-sorted long-short portfolios, and a trading strategy based on it generates substantial alphas. Third, sticky macro beliefs produce a smaller price of macro risk under both subjective and objective expectations, explaining the flatter unconditional relationship between macro betas and returns and the slow response of macro risk premia to recessions.

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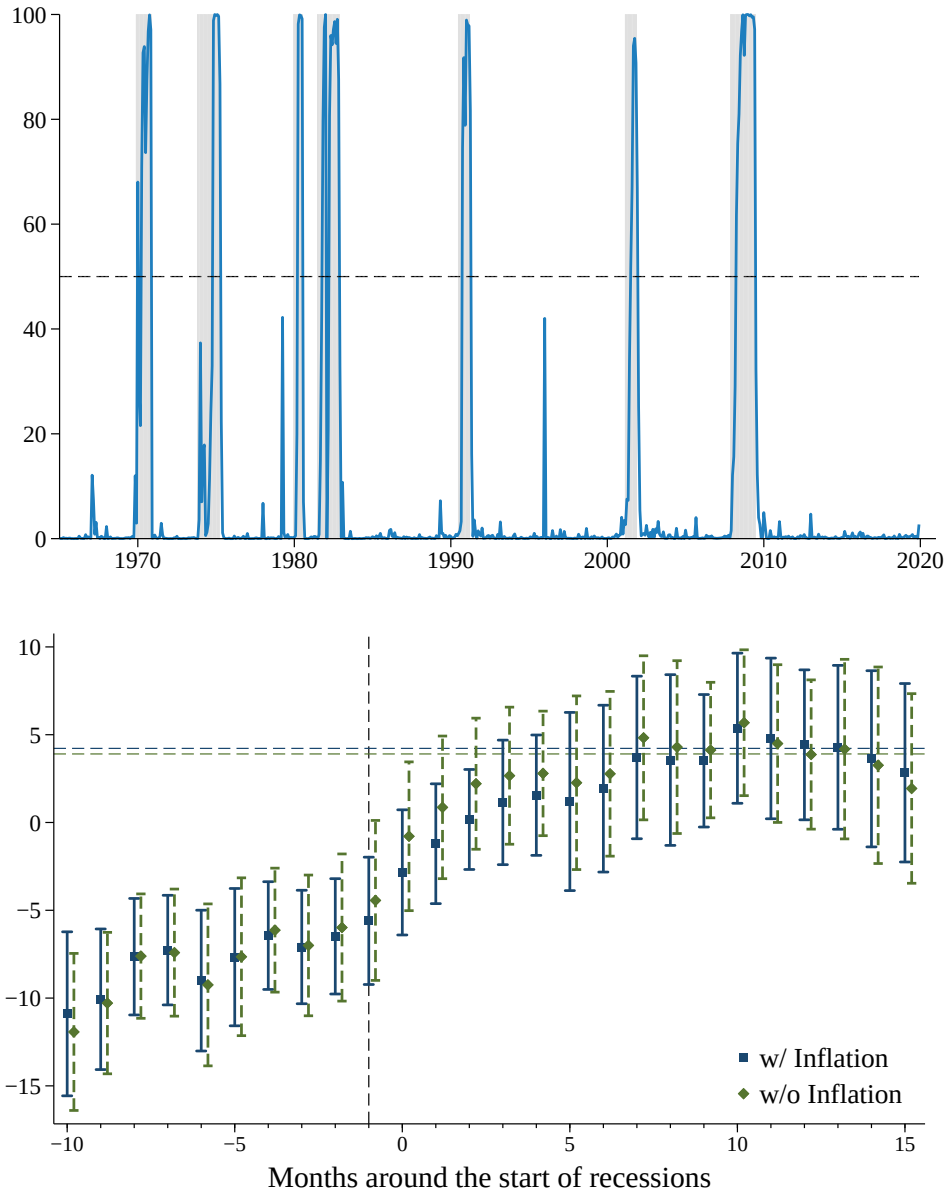


Figure 1: Ex-ante recession probability and one-year macro risk premia. The top panel plots the real-time recession probability (in percentages) from Gómez-Cram (2022). The bottom panel plots the one-year return spreads between cyclical and countercyclical firms around the onset of recessions. It shows the one-year percentage return for an investor who buys the average long-short portfolio based on macro betas at month m relative to the recession onset. Recession onset is identified ex ante as the first month in which the Gómez-Cram (2022) recession probability exceeds 50%. The squares represent the average portfolio return based on all 10 macro variables, and the diamonds represent the average portfolio return based on all macro variables except those related to inflation (UI and DEI). The vertical bars represent a one-standard-deviation error range and account for heteroskedasticity and autocorrelation in the residuals up to six lags. The dashed vertical line indicates the peak month, and the dashed horizontal line indicates the average value for months 10 to 15.

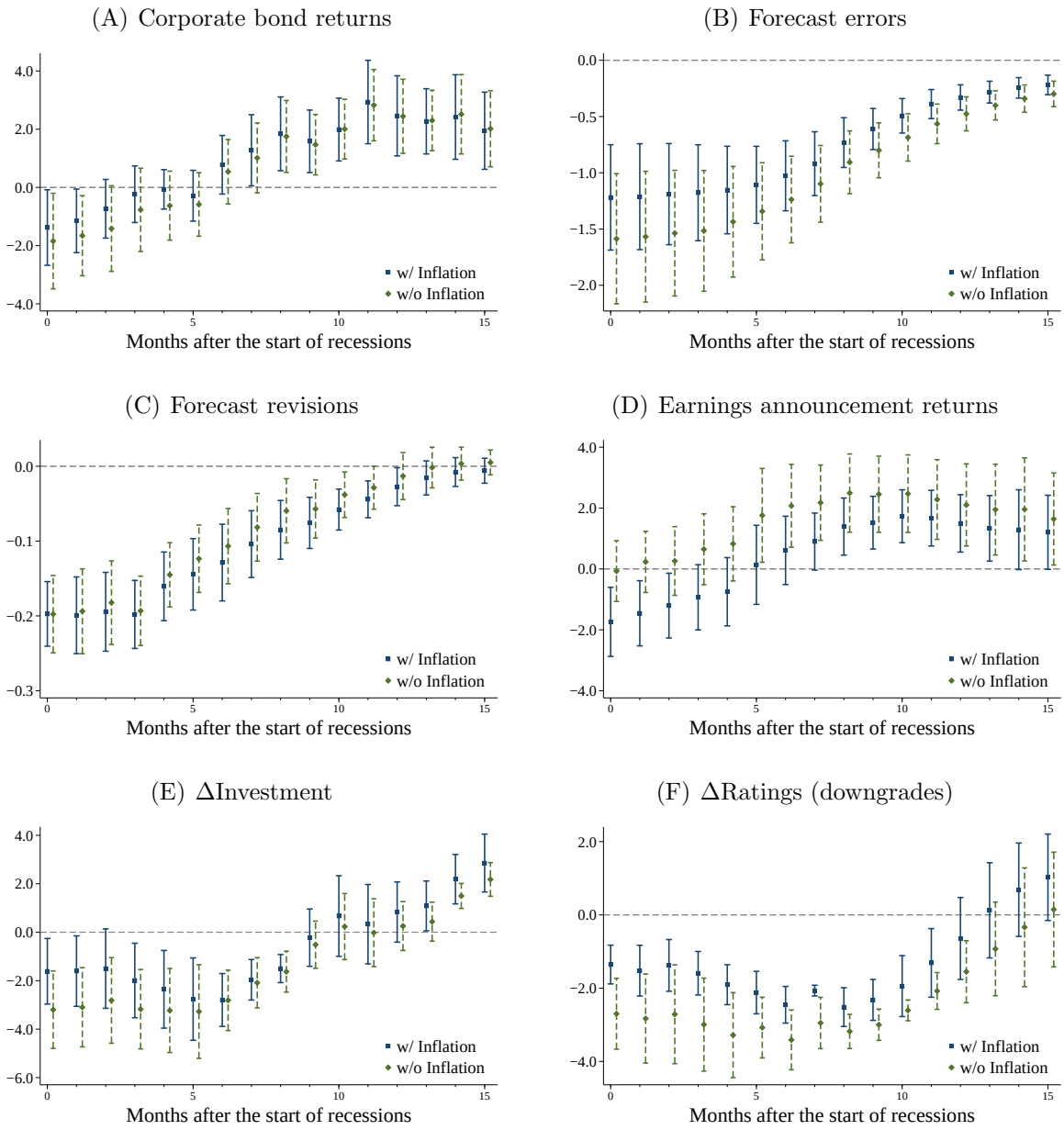


Figure 2: Recessions and belief errors. This figure plots the differences between cyclical and countercyclical firms during recessions across six metrics: corporate bond excess returns, analyst earnings forecast errors, forecast revisions, earnings announcement returns, investment growth rates, and credit rating changes. It shows average portfolio-level values, multiplied by 100, for long-short portfolios purchased m months relative to the recession onset and held for one year. Recession onset is identified ex ante as the first month in which the Gómez-Cram (2022) recession probability exceeds 50%. The squares represent the average based on all 10 macro variables, and the diamonds represent the average based on all macro variables except those related to inflation (UI and DEI). The vertical bars represent a one-standard-deviation error range and account for heteroskedasticity and autocorrelation in the residuals up to six lags.

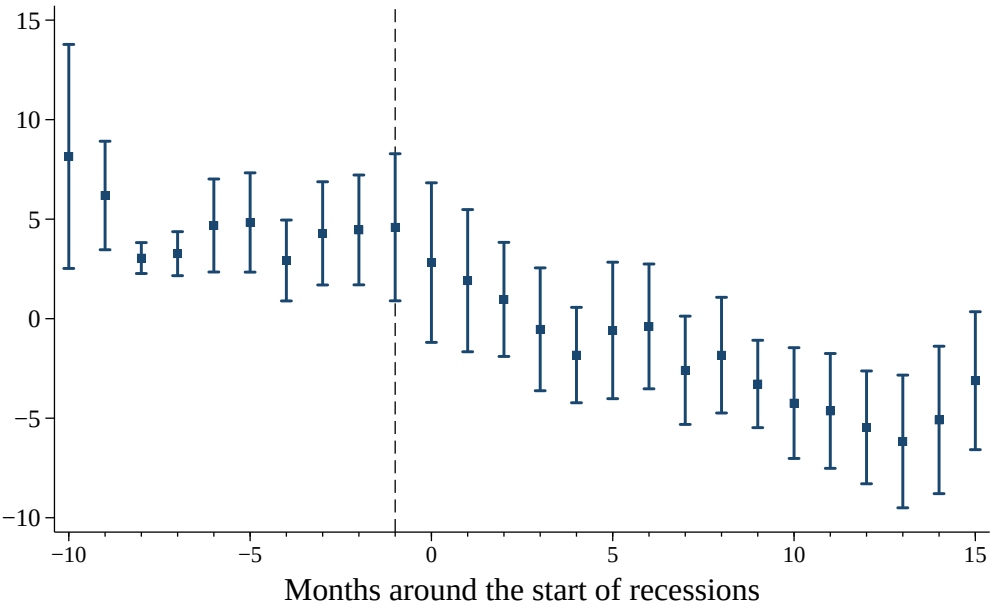


Figure 3: Recessions and returns to characteristics-based factor betas. This figure plots the realized one-year returns to the characteristics-based factor-beta strategy around the onset of recessions. It shows the one-year percentage return for an investor who buys the average characteristics-based factor beta strategy at month m relative to the recession onset. The characteristics-based factor beta strategy takes a long position in high characteristics-based factor beta and a short position in low characteristics-based factor beta stocks. Recession onset is identified ex ante as the first month in which the Gómez-Cram (2022) recession probability exceeds 50%. The vertical bars represent a one-standard-deviation error range and account for heteroskedasticity and autocorrelation in the residuals up to six lags. The dashed vertical line indicates the peak month.

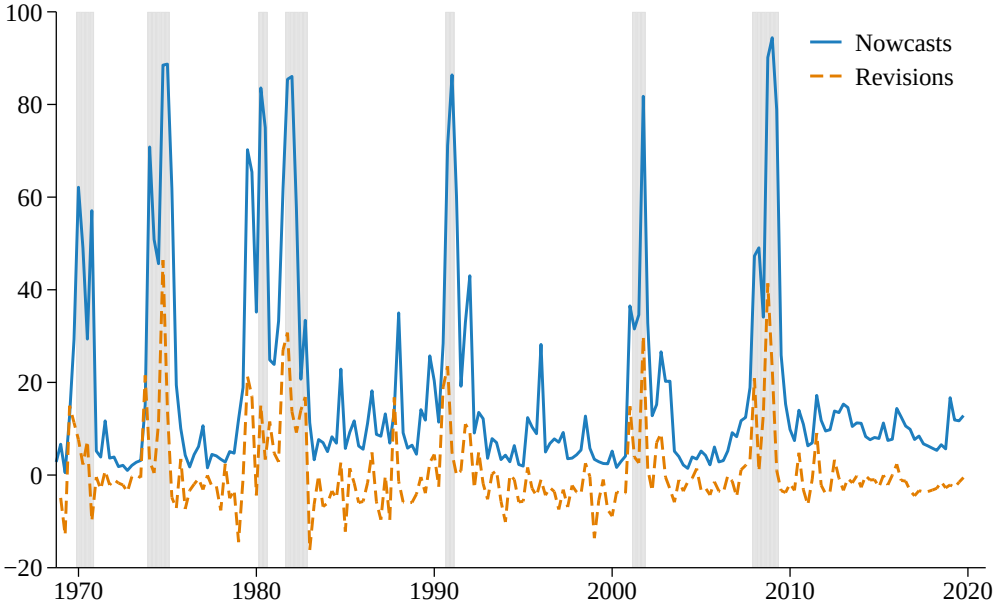


Figure 4: SPF recession probabilities. This figure plots nowcasts for the current-quarter recession probability ("Nowcasts") and revisions in one-quarter-ahead forecasts ("Revisions"). The recession probability forecast represents the expected probability (in percent) of a decline in the level of real GDP. Data on recession expectations are taken from the SPF. The shaded bars indicate NBER recessions.

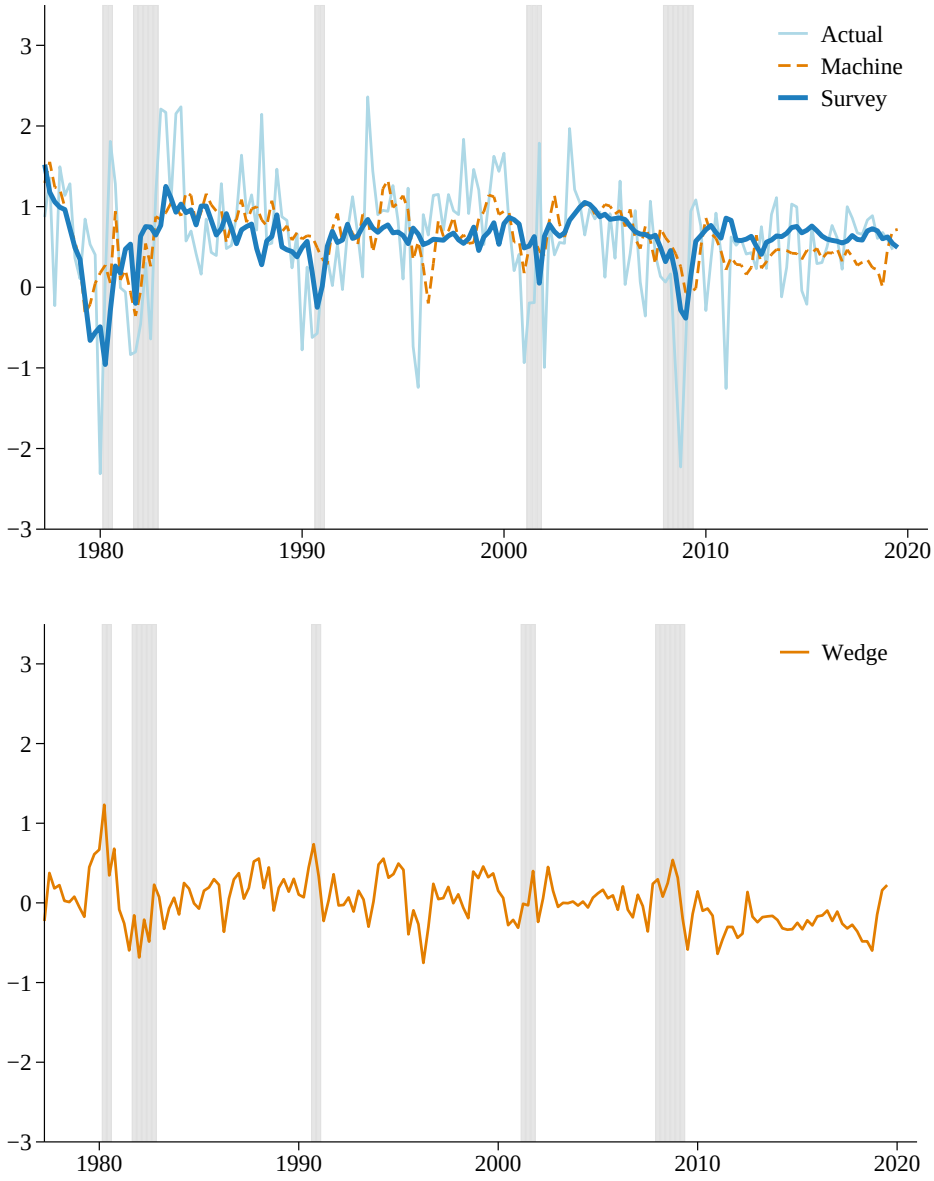


Figure 5: Real output expectations: Machine learning versus survey forecasts. The top panel plots the machine learning forecasts, survey forecasts, and the corresponding actual values of real GDP growth. The machine learning forecast is constructed from rolling random forests that predict real GDP growth one quarter ahead using the past 10 years of quarterly data. The survey forecasts, taken from the SPF, are also for the one-quarter-ahead horizon. The scales are in percent per quarter. The bottom panel shows the difference between the machine learning and survey expectations, as defined in equation (2).

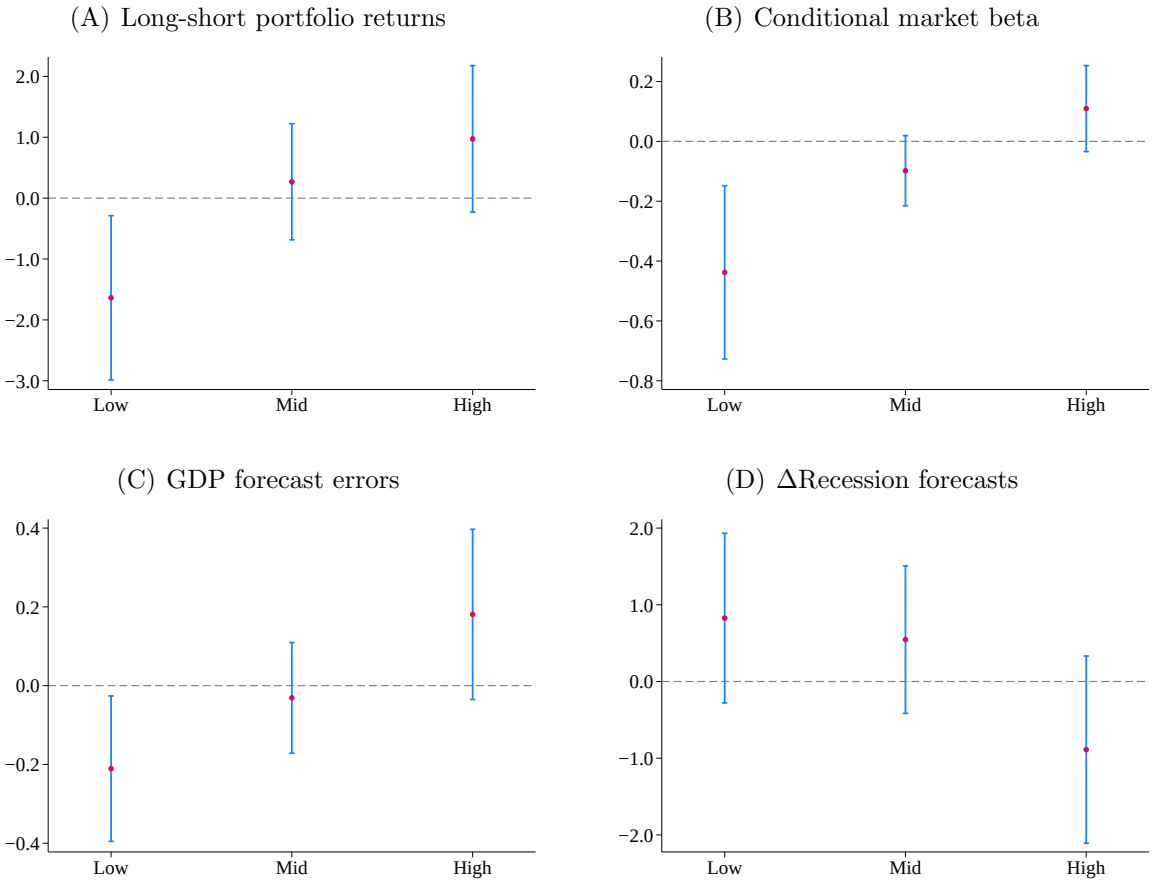


Figure 6: Sorts on the expectation wedge. This figure sorts the wedge in machine-learning and survey expectations of real GDP growth for quarter t (available in quarter $t-1$) into three buckets based on the wedge's 30th and 70th percentiles for the entire sample. For each bucket, the figure displays the corresponding average values and 90% confidence intervals for four measures in the next quarter. Panel A shows results for long-short portfolio returns, which are the average return spreads of 10 macro beta-sorted long-short portfolios. Panel B shows results for conditional market risk exposure, which is the slope coefficient from the regression of the long-short portfolio returns on the market excess returns. Panel C shows results for GDP growth forecast errors, which are measured as the errors in one-quarter-ahead real GDP growth forecasts from the SPF. Panel D shows results for ΔRecession forecasts, which are the average changes in the one-, two-, and three-quarter-ahead SPF recession probability forecasts.

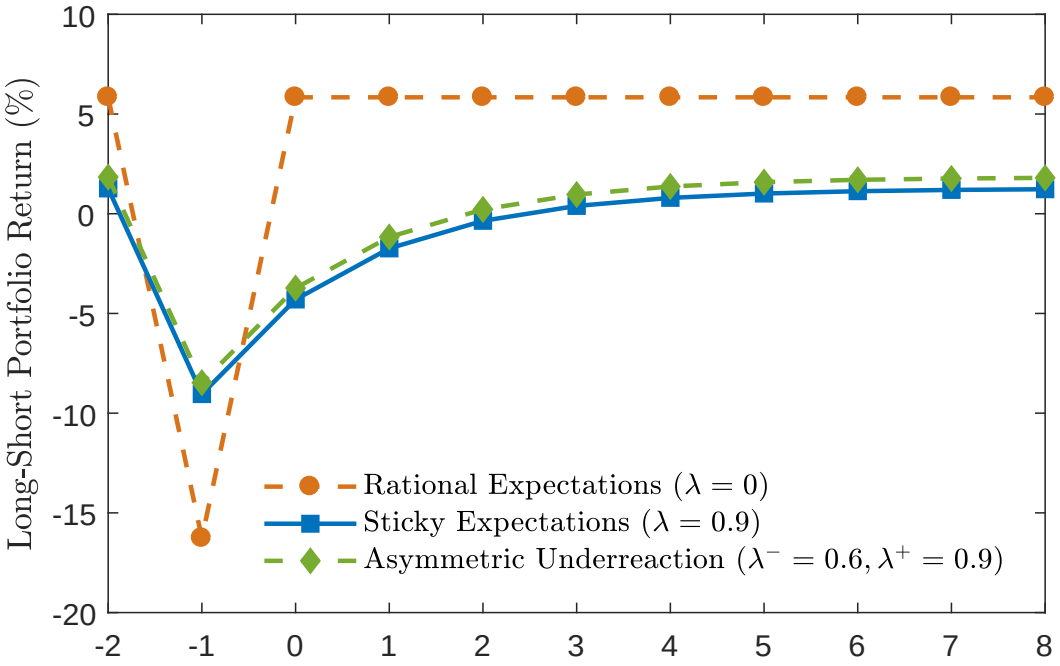


Figure 7: Impulse response to macro-variable shocks. This figure plots the impulse response of the one-period log returns of long-short macro beta-sorted portfolios to a one-standard-deviation adverse macro-variable shock ($-\sigma_z$) at time -1. The model is simulated using monthly decision intervals, and returns are expressed as annualized percentages by multiplying monthly returns by 1,200. We report results under rational expectations ($\lambda = 0$), symmetric sticky subjective expectations ($\lambda = 0.9$), and asymmetric sticky subjective expectations ($\lambda^- = 0.6$, $\lambda^+ = 0.9$), where belief updating is stickier following adverse shocks than favorable shocks. We use the parameter values $\delta = 0.99$, $\psi = 2$, $\gamma = 15$, $\rho_z = 0.6$, $\rho_c = 0.5$, $\sigma_z = 0.015$, $\sigma_c = 0.007$, $\sigma_H = \sigma_L = 0.03$, $\mu_c = \mu_z = \mu_H = \mu_L = 0.002$, $\rho_H = 0.6$, and $\rho_L = 0.1$.

Table 1: Long-Short Portfolio Returns and Exposure to Business Cycles

This table reports the annualized excess returns, post-formation betas, and exposures to the market and common growth for long-short portfolios sorted on macro betas. Common growth is the first principal component of real GDP growth, TFP growth, consumption growth, labor income growth, and initial claims growth. The signs of DEF and VOL are inverted so that all ten macro variables carry positive risk premia. At the end of each month, stocks are sorted into quintiles based on pre-formation macro betas. Long-short portfolios are formed by taking long positions in the highest-beta quintile stocks and short positions in the lowest-beta quintile stocks. Portfolio returns are annualized by multiplying monthly returns by 1,200. All macro variables are standardized so that exposures represent the annualized return response to a one-standard-deviation change in the respective macro variable. The final two columns report *Ave*1, a portfolio that equally combines all long-short portfolios sorted on macro betas, and *Ave*2, a portfolio that equally combines all portfolios except those related to inflation (UI and DEI). The sample period runs from January 1965 to December 2019. Newey-West six-lag adjusted t-statistics are in parentheses.

Panel A: Mean Excess Returns

CON	TFP	IPG	TERM	DEF	UI	DEI	VOL	MKT	LAB	Ave1	Ave2
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
-0.95	-1.35	1.91	0.47	-1.54	-1.16	-0.97	1.33	0.03	-2.75	-0.50	-0.36
(-0.49)	(-0.61)	(1.02)	(0.22)	(-0.67)	(-0.53)	(-0.50)	(0.52)	(0.01)	(-1.19)	(-0.36)	(-0.23)

Panel B: Post-Formation Beta

CON	TFP	IPG	TERM	DEF	UI	DEI	VOL	MKT	LAB
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
5.97	3.53	-1.98	4.85	4.73	4.45	7.08	8.76	51.56	1.53
(3.00)	(1.33)	(-1.14)	(2.44)	(1.79)	(1.60)	(2.63)	(1.23)	(12.20)	(0.98)

Panel C: Exposure to Market Factor

CON	TFP	IPG	TERM	DEF	UI	DEI	VOL	MKT	LAB	Ave1	Ave2
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
19.30	15.46	13.77	1.45	24.55	2.92	6.20	29.76	51.56	13.94	17.89	21.22
(6.91)	(5.57)	(4.58)	(0.42)	(6.29)	(0.67)	(1.72)	(6.45)	(12.20)	(2.66)	(6.97)	(8.31)

Panel D: Exposure to Common Growth

CON	TFP	IPG	TERM	DEF	UI	DEI	VOL	MKT	LAB	Ave1	Ave2
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1.35	1.88	3.44	0.96	5.49	3.92	5.44	8.71	10.46	4.04	4.57	4.54
(0.63)	(0.76)	(1.75)	(0.45)	(2.05)	(1.48)	(2.40)	(2.72)	(2.86)	(1.44)	(2.96)	(2.59)

Table 2: Performance of Trading Strategies

This table reports performance measures for five different strategies. "100% Factors" denotes the buy-and-hold strategy that is fully invested in the average of ten long-short portfolios based on macro betas (the long-short portfolio). "80/20 Mix" denotes the portfolio that allocates 80% to the long-short portfolio and 20% to T-bills. The remaining three strategies switch from the long-short portfolio to cash during bad times and market downturns, and they stay fully invested in the long-short portfolio in the remaining periods. Market downturns are months in which returns are below their six-month moving average. Bad times are periods when any of the following conditions hold: (i) the Gómez-Cram (2022) recession probability (Rec. Prob.) exceeds its six-month moving average; (ii) industrial production growth (Ind. Prod.) falls below its six-month moving average; or (iii) the change in the term premium (Term Prem.) falls below its six-month moving average. Panel A reports the excess returns, alpha, and Sharpe ratio increase relative to the Sharpe ratio obtained from a fixed-allocation strategy that invests in the long-short portfolio for the same unconditional fraction of time. The alpha is based on the Fama and French (2015) five-factor model augmented with the time-series momentum factor of Moskowitz, Ooi, and Pedersen (2012) (TMom) and volatility-managed factor of Moreira and Muir (2017) (TVol). Panel B reports average maximum drawdowns across economic states identified using the recession probability from Gómez-Cram (2022). Newey-West six-lag adjusted t-statistics are in parentheses below the coefficient estimates. We annualize all returns, expressed as a percentage per year, by multiplying monthly returns by 1,200. The evaluation period is from June 1965 to December 2019.

Panel A: Performance Evaluation

Measures	Rec. Prob. (1)	Ind. Prod. (2)	Term Prem. (3)	100% Factors (4)	80/20 Mix (5)
Time invested in factors	80%	72%	74%	100%	80%
Mean excess returns	1.01	0.51	0.85	-0.51	-0.41
Std. dev. returns	8.55	8.63	8.24	9.89	7.91
Sharpe ratio increase	0.17	0.11	0.15	–	–
α-FF5-TMom-TVol	1.81	1.86	2.03	0.97	0.77
	(1.86)	(1.84)	(2.07)	(0.94)	(0.94)

Panel B: Average Maximum Drawdown

Economic state	Rec. Prob. (1)	Ind. Prod. (2)	Term Prem. (3)	100% Factors (4)	80/20 Mix (5)
Total	28.93	27.06	24.07	43.45	36.87
Expansions	29.10	27.20	24.27	43.64	37.05
Recessions	27.19	25.64	21.98	41.47	35.08

Table 3: Survey Expectations of Recessions

The table reports the coefficients in the following regressions ($h = 1, 2, 3$):

$$FR^h_{t\to t+1} = \alpha + \beta FR^h_{t-1\to t} + \epsilon_{t,t+1},$$
$$FE_{t\to t+h} = \alpha + \beta FR^h_{t-1\to t} + \epsilon_{t,t+h},$$

where $F_t(z_{t+h})$ is the forecast of the recession probability for quarter $t+h$ issued in quarter t (nowcast when $h = 0$); $FR^h_{t\to t+1}$ is the forecast revision for the h-quarter-ahead recession probability, defined as the change in the forecast of the quarter $t+h$ recession probability (i.e., $FR^h_{t-1\to t} = F_t(z_{t+h}) - F_{t-1}(z_{t+h})$); and $FE_{t\to t+h}$ is the forecast error for the h-quarter-ahead recession probability, defined as the nowcast minus the forecast of the quarter $t+h$ recession probability (i.e., $FE_{t\to t+h} = F_{t+h}(z_{t+h}) - F_t(z_{t+h})$). Recession probability forecasts are expressed in percent and are taken from the SPF. The full sample runs from 1969Q1 to 2019Q4. Newey-West six-lag adjusted t-statistics are in parentheses.

	Forecast Revisions			Forecast Errors		
	$FR^1_{t\to t+1}$ (1)	$FR^2_{t\to t+1}$ (2)	$FR^3_{t\to t+1}$ (3)	$FE_{t\to t+1}$ (4)	$FE_{t\to t+2}$ (5)	$FE_{t\to t+3}$ (6)
$FR^1_{t-1\to t}$	0.40			0.44		
	(6.19)			(3.39)		
$FR^2_{t-1\to t}$		0.52			0.80	
		(6.56)			(4.32)	
$FR^3_{t-1\to t}$			0.31			1.21
			(3.39)			(4.30)
Intercept	0.44	0.26	-0.19	-0.17	0.75	1.94
	(0.74)	(0.67)	(-0.55)	(-0.24)	(0.51)	(0.88)
Obs	203	203	195	204	204	200
R^2	0.16	0.27	0.10	0.09	0.08	0.06

Table 4: Asymmetry in Underreaction: Good vs. Bad News

The table reports the coefficients in the following regressions ($h = 1, 2, 3$):

$$FR^h_{t\to t+1} = \alpha + \beta^+ FR^{h,+}_{t-1\to t} + \beta^- FR^{h,-}_{t-1\to t} + \epsilon_{t,t+1},$$
$$FE_{t\to t+h} = \alpha + \beta^+ FR^{h,+}_{t-1\to t} + \beta^- FR^{h,-}_{t-1\to t} + \epsilon_{t,t+h},$$

where $F_t(z_{t+h})$ is the forecast of the recession probability for quarter $t+h$ issued in quarter t (nowcast when $h = 0$); $FR^h_{t\to t+1}$ is the forecast revision for the h-quarter-ahead recession probability, defined as the change in the forecast of the quarter $t+h$ recession probability (i.e., $FR^h_{t-1\to t} = F_t(z_{t+h}) - F_{t-1}(z_{t+h})$); $FE_{t\to t+h}$ is the forecast error for the h-quarter-ahead recession probability, defined as the nowcast minus the forecast of the quarter $t+h$ recession probability (i.e., $FE_{t\to t+h} = F_{t+h}(z_{t+h}) - F_t(z_{t+h})$); $FR^{h,+}_{t\to t+1} = \max\{0, FR^h_{t\to t+1}\}$ is the upward forecast revision for the h-quarter-ahead recession probability (bad news); and $FR^{h,-}_{t\to t+1} = \min\{0, FR^h_{t\to t+1}\}$ is the downward forecast revision for the h-quarter-ahead recession probability (good news). Recession probability forecasts are expressed in percent and are taken from the SPF. The full sample runs from 1969Q1 to 2019Q4. Newey-West six-lag adjusted t-statistics are in parentheses.

	Forecast Revisions			Forecast Errors		
	$FR^1_{t\to t+1}$	$FR^2_{t\to t+1}$	$FR^3_{t\to t+1}$	$FE_{t\to t+1}$	$FE_{t\to t+2}$	$FE_{t\to t+3}$
	(1)	(2)	(3)	(4)	(5)	(6)
$FR^{1,+}_{t-1\to t}$	0.46			0.54		
	(5.96)			(3.32)		
$FR^{1,-}_{t-1\to t}$	0.15			0.06		
	(0.78)			(0.30)		
$FR^{2,+}_{t-1\to t}$		0.56			0.75	
		(5.70)			(3.36)	
$FR^{2,-}_{t-1\to t}$		0.37			0.99	
		(1.72)			(1.55)	
$FR^{3,+}_{t-1\to t}$			0.37			1.23
			(2.61)			(2.76)
$FR^{3,-}_{t-1\to t}$			0.21			1.20
			(1.52)			(2.29)
Intercept	-0.39	-0.12	-0.45	-1.44	1.24	1.89
	(-0.37)	(-0.16)	(-0.94)	(-1.23)	(0.46)	(0.62)
Obs	203	203	195	204	204	200
R^2	0.16	0.27	0.10	0.10	0.08	0.06

Table 5: Machine Learning versus Survey Forecasts

The table reports the coefficients in the following regressions:

$$GDP_{t+1} = \alpha + \beta_P E_t^P[GDP_{t+1}] + \beta_S E_t^S[GDP_{t+1}] + \epsilon_{t+1},$$
$$FE_GDP_{t+1} = \alpha + \beta \Delta_t + \delta FR^1_{t-1\to t} + \epsilon_{t+1},$$

where $\Delta_t \equiv E_t^P[GDP_{t+1}] - E_t^S[GDP_{t+1}]$ is the wedge between machine learning and survey expectations of one-quarter-ahead real GDP growth, $E_t^P[GDP_{t+1}]$ is produced by rolling random forests using the past 10 years of quarterly data, and $E_t^S[GDP_{t+1}]$ is the survey real GDP growth expectation. FE_GDP_{t+1} is the error in the one-quarter-ahead GDP survey forecast. $FR^1_{t-1\to t}$ is the survey forecast revision for the one-quarter-ahead real GDP growth rate. Survey forecasts of real GDP growth are from the SPF. The out-of-sample R^2 (R^2_{oos}) is defined as one minus the mean squared error implied by using the machine learning or survey forecast, divided by the mean squared error of using the historical average as a forecast. The sample runs from 1977Q2 to 2019Q4. Newey-West six-lag adjusted t-statistics are in parentheses.

	Panel A: Dependent variable: GDP_{t+1}		
	(1)	(2)	(3)
$E_t^P[GDP_{t+1}]$	0.83		0.60
	(4.88)		(2.42)
$E_t^S[GDP_{t+1}]$		0.78	0.41
		(3.30)	(1.33)
Intercept	0.07	0.11	-0.03
	(0.54)	(0.65)	(-0.20)
p-value ($\alpha = 0, \beta_P$ or $\beta_S = 1$)	0.47	0.58	
p-value ($\beta_P = 1, \beta_S = 0$)			0.26
p-value ($\beta_P = 0, \beta_S = 1$)			0.05
Obs	170	170	170
R^2	0.15	0.12	0.17
R^2_{oos}	0.20	0.17	
	Panel B: Dependent variable: FE_GDP_{t+1}		
	(1)	(2)	(3)
Δ_t	0.60	0.69	
	(2.41)	(3.46)	
$E_t^P[GDP_{t+1}]$			0.60
			(2.42)
$E_t^S[GDP_{t+1}]$			-0.59
			(-1.96)
$FR^1_{t-1\to t}$		0.76	
		(1.84)	
Intercept	-0.03	0.00	-0.03
	(-0.50)	(0.07)	(-0.20)
Obs	170	170	170
R^2	0.07	0.10	0.07

Table 6: Predictive Power of the Expectation Wedge

The table reports the coefficients in the following regressions:

$$f_{t+1} = \alpha + \beta\Delta_t + \delta' z_t + \epsilon_{t+1},$$

where $\Delta_t \equiv E_t^P[GDP_{t+1}] - E_t^S[GDP_{t+1}]$ is the wedge between machine learning and survey expectations of one-quarter-ahead real GDP growth, $E_t^P[GDP_{t+1}]$ is produced by rolling random forests using the past 10 years of quarterly data, and $E_t^S[GDP_{t+1}]$ is the survey real GDP growth expectation. f is the average return spread of the long-short portfolio sorted on macro betas. The control variable z includes the surplus consumption ratio of Campbell and Cochrane (1999), the term spread, the default premium, the inflation rate, the intermediary capital ratio of He, Kelly, and Manela (2017) (the inverse of intermediary leverage), the Baker and Wurgler (2006) sentiment index, and real GDP growth forecast dispersion. The dependent variable is expressed in quarterly percentages, and the explanatory variables are standardized to have a mean of zero and a standard deviation of one. Survey forecasts of real GDP growth are from the SPF. The sample runs from 1977Q2 to 2019Q4. Newey-West six-lag adjusted t-statistics are in parentheses.

	(1)	(2)	(3)	(4)
Δ_t	1.13		1.37	
	(4.01)		(4.07)	
$E_t^P[GDP_{t+1}]$		1.11		1.37
		(2.84)		(2.73)
$E_t^S[GDP_{t+1}]$		-1.45		-1.68
		(-3.09)		(-4.40)
Surplus ratio$_t$			-0.71	-0.63
			(-1.39)	(-1.19)
Term spread$_t$			0.04	0.18
			(0.07)	(0.28)
Default premium$_t$			0.62	0.53
			(0.92)	(0.87)
Inflation$_t$			-1.11	-1.17
			(-2.38)	(-2.63)
Leverage$_t$			-0.21	-0.16
			(-0.27)	(-0.20)
Sentiment$_t$			-1.92	-1.96
			(-2.87)	(-3.01)
Dispersion$_t$			-0.58	-0.69
			(-1.03)	(-1.21)
Intercept	-0.09	-0.09	-0.08	-0.06
	(-0.21)	(-0.21)	(-0.21)	(-0.16)
Obs	170	170	170	170
R^2	0.04	0.04	0.15	0.15

Table 7: Predictive Power of the Expectation Wedge: Alphas

The table reports the coefficients in the following regressions:

$$f_{t+1} = \alpha + \beta\Delta_t + \delta_1' z_t + \delta_2' F_{t+1} + \epsilon_{t+1},$$

where $\Delta_t \equiv E_t^P[GDP_{t+1}] - E_t^S[GDP_{t+1}]$ is the wedge between machine learning and survey expectations of one-quarter-ahead real GDP growth, $E_t^P[GDP_{t+1}]$ is produced by rolling random forests using the past 10 years of quarterly data, and $E_t^S[GDP_{t+1}]$ is the survey real GDP growth expectation. f is the average return spread of the long-short portfolio sorted on macro betas. The control variable z includes the surplus consumption ratio of Campbell and Cochrane (1999), the term spread, the default premium, the inflation rate, the intermediary capital ratio of He, Kelly, and Manela (2017) (the inverse of intermediary leverage), the Baker and Wurgler (2006) sentiment index, and real GDP growth forecast dispersion. The factor model F includes the Fama and French (2015) five-factor model augmented with the time-series momentum factor of Moskowitz, Ooi, and Pedersen (2012) and the volatility-managed factor of Moreira and Muir (2017). The dependent variable is expressed in quarterly percentages, and the explanatory variables are standardized to have a mean of zero and standard deviation of one. Survey forecasts of real GDP growth are from the SPF. The full sample runs from 1977Q2 to 2019Q4. Newey-West six-lag adjusted t-statistics are in parentheses.

	(1)	(2)	(3)	(4)
Δ_t	0.70		0.61	
	(2.82)		(2.47)	
$E_t^P[GDP_{t+1}]$		0.71		0.51
		(2.53)		(1.66)
$E_t^S[GDP_{t+1}]$		-0.87		-0.86
		(-1.98)		(-2.47)
Surplus ratio$_t$			0.68	0.76
			(1.70)	(1.94)
Term spread$_t$			0.10	0.23
			(0.35)	(0.70)
Default premium$_t$			0.31	0.22
			(0.71)	(0.58)
Inflation$_t$			-0.89	-0.95
			(-3.57)	(-3.81)
Leverage$_t$			-0.26	-0.22
			(-0.83)	(-0.70)
Sentiment$_t$			-0.49	-0.52
			(-1.22)	(-1.33)
Dispersion$_t$			0.35	0.25
			(0.94)	(0.68)
Intercept	0.29	0.29	0.33	0.35
	(0.74)	(0.73)	(1.05)	(1.13)
Obs	170	170	170	170
R^2	0.65	0.65	0.67	0.68

Table 8: Performance Evaluation

In Panel A, we run quarterly regressions of trading strategy returns on different factor models. The first timing strategy ("Wedge") adjusts the conditional beta based on an estimate of the wedge between machine learning and the survey output growth forecast. The second timing strategy ("Wedge + Sentiment") adjusts the conditional beta based on a composite signal: the equal-weighted average of the standardized expectation wedge and the standardized inverse of a recursively constructed sentiment index (the first principal component of the Baker and Wurgler (2006) sentiment index, and the AA and II survey sentiment indices). "100% Factors" denotes the buy-and-hold strategy that is fully invested in the average long-short portfolio based on macro betas. We consider three specifications for estimating alphas: (i) the CAPM, with excess market returns (Mkt) being the only factor; (ii) the Fama and French (2015) five-factor model (FF5); and (iii) the Fama and French (2015) five-factor model augmented with the time-series momentum factor of Moskowitz, Ooi, and Pedersen (2012) (TMom) and volatility-managed factor of Moreira and Muir (2017) (TVol). In Panel B, we report the average maximum drawdowns for quarterly returns across economic states identified with the recession probability from Gómez-Cram (2022). Expansions and recessions are defined as periods when the quarterly average Gómez-Cram (2022) recession probability is below or above 50%, respectively. To facilitate interpretation, we annualize all returns, expressed as a percentage per year, by multiplying quarterly returns by 400. The strategy evaluation period spans 1977Q2 to 2019Q4, except for the composite signal strategy, which spans 1987Q4 to 2019Q4. Newey-West six-lag adjusted t-statistics are in parentheses.

Panel A: Returns and Alphas

Measures	Wedge (1)	Wedge + Sentiment (2)	100% Factors (3)
Mean excess returns	4.65	6.99	-0.37
	(3.36)	(2.92)	(-0.21)
α-Mkt	5.43	8.00	-3.79
	(3.64)	(2.61)	(-2.01)
α-FF5	4.64	3.64	0.84
	(2.65)	(2.14)	(0.53)
α-FF5-TMom-TVol	4.79	4.60	1.19
	(2.70)	(2.40)	(0.71)

Panel B: Average Maximum Drawdown

Economic state	Wedge (1)	Wedge + Sentiment (2)	100% Factors (3)
Total	16.75	9.89	43.69
Expansions	16.89	9.83	43.79
Recessions	15.20	10.65	42.67

Table 9: Long-Short Portfolio Returns and Future Real Activity

The table reports the coefficients in the following quarterly predictive regression:

$$Y_{t\to t+h} = \alpha + \beta f_t + \delta' z_t + \epsilon_{t,t+h},$$

where $h = 1$ or 4. The dependent variable Y is the quarterly NBER recession dummy ("Recess Prob."), real GDP growth ("Real GDP"), and industrial production growth ("Ind. Prod."). The dependent variables are measured over the next quarter (Panel A) and as the average value over the next year (Panel B). f_t is the average return spread of the long-short portfolio sorted on macro betas. The control variable z includes the surplus consumption ratio of Campbell and Cochrane (1999), term spread, and default spread. The dependent variable is expressed in quarterly percentages, and the explanatory variables are standardized to have a mean of zero and standard deviation of one. The sample runs from 1968Q4 to 2019Q4. Newey-West six-lag adjusted t-statistics are in parentheses.

Panel A: One-Quarter-Ahead ($h = 1$)						
	Recess Prob.		Real GDP		Ind. Prod.	
	(1)	(2)	(3)	(4)	(5)	(6)
f_t	-5.87	-5.32	0.18	0.16	0.49	0.45
	(-3.12)	(-2.70)	(3.82)	(3.09)	(3.71)	(3.48)
Surplus ratio$_t$		3.77		0.13		0.20
		(1.48)		(1.70)		(1.53)
Term spread$_t$		-6.86		0.26		0.52
		(-2.12)		(2.98)		(3.28)
Default premium$_t$		11.79		-0.15		-0.30
		(3.39)		(-1.51)		(-1.34)
Intercept	13.20	13.20	0.60	0.60	0.56	0.56
	(3.28)	(4.23)	(6.59)	(7.18)	(3.28)	(3.51)
Obs	204	204	204	204	204	204
R^2	0.03	0.20	0.04	0.13	0.07	0.15
Panel B: One-Year-Ahead ($h = 4$)						
	Recess Prob.		Real GDP		Ind. Prod.	
	(1)	(2)	(3)	(4)	(5)	(6)
f_t	-5.85	-3.92	0.12	0.08	0.35	0.27
	(-2.82)	(-2.47)	(3.49)	(2.74)	(4.69)	(4.70)
Surplus ratio$_t$		2.71		0.12		0.17
		(1.24)		(1.55)		(1.40)
Term spread$_t$		-13.23		0.29		0.54
		(-5.41)		(4.49)		(4.33)
Default premium$_t$		6.03		0.01		0.07
		(2.45)		(0.15)		(0.40)
Intercept	13.40	13.67	0.60	0.59	0.56	0.54
	(3.49)	(4.73)	(6.99)	(7.57)	(3.55)	(3.73)
Obs	201	201	201	201	201	201
R^2	0.05	0.34	0.04	0.22	0.08	0.24

Table 10: Long-Short Portfolio Returns and Survey Expectations

The table reports the coefficients in the following regression:

$$FR^h_{t\to t+1} = \alpha + \beta f_t + \epsilon_{t,t+1},$$
$$FE_{t\to t+h} = \alpha + \beta f_t + \epsilon_{t,t+h},$$

where $h = 1, 2, 3$, $FR^h_{t\to t+1}$ is the forecast revision for the h-quarter-ahead macro variable, and $FE_{t\to t+h}$ is the corresponding forecast error (actual minus forecast). f_t is the average return spread of the long-short portfolio sorted on macro betas. We report results for recession probability (Panel A), real GDP growth (Panel B), and industrial production growth (Panel C). The dependent variable is expressed in quarterly percentages, and the explanatory variables are standardized to have a mean of zero and standard deviation of one. Macroeconomic forecasts are from the SPF. The full sample runs from 1968Q4 to 2019Q4. Newey-West six-lag adjusted t-statistics are in parentheses.

	Forecast Revisions			Forecast Errors		
	$FR^1_{t\to t+1}$	$FR^2_{t\to t+1}$	$FR^3_{t\to t+1}$	$FE_{t\to t+1}$	$FE_{t\to t+2}$	$FE_{t\to t+3}$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Recession Probability						
f_t	-2.82	-1.24	-0.52	-4.49	-3.61	-4.15
	(-5.21)	(-3.83)	(-2.00)	(-4.47)	(-2.66)	(-3.83)
Intercept	0.67	0.56	-0.20	0.06	1.10	1.84
	(0.73)	(0.73)	(-0.43)	(0.06)	(0.59)	(0.75)
Obs	204	204	200	205	205	205
R^2	0.10	0.04	0.01	0.13	0.04	0.04
Panel B: Real GDP Growth						
f_t	0.17	0.19	0.19	0.27	0.33	0.61
	(5.33)	(5.15)	(5.17)	(5.16)	(2.68)	(5.01)
Intercept	-0.12	-0.18	-0.16	-0.01	-0.15	-0.32
	(-2.82)	(-3.15)	(-2.69)	(-0.11)	(-0.82)	(-1.28)
Obs	204	204	199	205	205	205
R^2	0.12	0.11	0.10	0.07	0.04	0.09
Panel C: Industrial Production Growth						
f_t	0.30	0.34	0.33	0.57	0.96	1.34
	(4.32)	(4.35)	(4.14)	(2.83)	(3.09)	(3.59)
Intercept	-0.28	-0.33	-0.32	-0.24	-0.59	-0.99
	(-3.28)	(-3.24)	(-3.00)	(-1.15)	(-1.76)	(-2.15)
Obs	204	204	199	205	205	205
R^2	0.11	0.11	0.10	0.05	0.08	0.10

Appendix for
"Macro Risk Premia and the Business Cycle"

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A Sample Construction and Additional Results

A.1 Macro Variable Construction

We describe the construction of the 10 analyzed macro variables below.

1. **Consumption (CON).** CON is constructed as the monthly log growth of real personal consumption expenditures on nondurable goods and services per capita. Monthly personal consumption data, implicit price deflator data (for real consumption adjustment), and population data are from the Bureau of Economic Analysis (BEA);

2. **Total Factor Productivity (TFP).** The log growth rate of aggregate TFP is used. Quarterly TFP data are from the website of the Federal Reserve Bank of San Francisco;

3. **Industrial Production Growth (IPG).** The monthly log growth rate of industrial production is used, following Chen, Roll, and Ross (1986). Monthly IPG data are from Federal Reserve Economic Data (FRED), maintained by the Federal Reserve Bank of St. Louis;

4. **Term Spread (TERM).** TERM is constructed as the yield spread between 10-year and 1-year Treasury bonds. Monthly 10-year and 1-year Treasury yields are from FRED;

5. **Default Spread (DEF).** DEF is constructed as the default premium measured as the monthly change in the yield spread between BAA-rated and AAA-rated corporate bonds, following Keim and Stambaugh (1986). Monthly BAA and AAA data are from Amit Goyal's website;

6 & 7. **Unexpected Inflation (UI) and Change in Expected Inflation (DEI).** UI is constructed following Chen, Roll, and Ross (1986). Specifically, let $I_t \equiv \log(CPI_t) - \log(CPI_{t-1})$, where CPI_t is the consumer price index in month t. Unexpected inflation is then defined as $UI_t = I_t - E_{t-1}(I_t)$. DEI is estimated by modeling the changes in inflation as an MA(1) process following Fama and Gibbons (1984). The monthly CPI data are from FRED;

8. **Aggregate Market Volatility (VOL).** VOL is constructed following French, Schwert, and Stambaugh (1987) using changes in realized monthly volatility, computed from the daily market returns obtained from Kenneth R. French's website;

9. **Market Excess Return (MKT).** The excess returns on the CRSP value-weighted market are used, following Chen, Roll, and Ross (1986). Monthly market returns are from Kenneth R. French's website; and

10. **Labor Income (LAB).** LAB is constructed as the log growth rate in nominal labor income per capita, following Jagannathan and Wang (1996). Labor income and population data are collected from the BEA.

A.2 Machine Learning Output Forecast Construction

We detail the construction of the machine-learning real GDP growth forecasts below. Our main results use a random forest to generate forecasts of next-quarter real GDP growth. At each node of each tree, the algorithm splits the data by choosing the variable and threshold that minimize the mean squared error (MSE) of the prediction. Following Gu, Kelly, and Xiu (2020), we fit the machine-learning models using a time-series cross-validation approach, in which the hyperparameters (the number of trees, maximum depth, minimum node size, and feature fraction) are chosen on a validation sample. Specifically, the training sample spans 1966Q4 to 1976Q3, and the validation sample consists of a single quarter, 1976Q4, whose forecast error for 1977Q1 real GDP growth becomes known in 1977Q2. We train the model on the training sample under different hyperparameter configurations, evaluate each configuration on the validation sample, and select the one that yields the best performance in terms of MSE. The model is then trained using rolling windows, with the chosen hyperparameters held fixed. Our results are similar across alternative validation periods.

Table A3 details the features used in the machine learning forecasts. The input features include variables related to real output (e.g., GDP and industrial production), employment (e.g., unemployment rate and initial jobless claims), investment (e.g., private residential and nonresidential fixed investment), inflation (e.g., the GDP deflator), and financial markets (e.g., the S&P 500 index). We use the Philadelphia Fed's Real-Time Data Set to obtain vintages of macroeconomic variables, relying on the first releases that become available by the end of the first month of the following quarter. Since the SPF survey deadline typically falls in the middle of the second month of each quarter, the macro variables from the previous two quarters are known at the time of the forecast. We fill early-sample gaps in residential and nonresidential fixed investment and initial jobless claims using vintage data released before the cross-validation period. For financial variables, the actual outcomes are available daily and are permanent (not revised), and we use historical data from Amit Goyal's website. The feature data span 1966Q2 to 2019Q4 (with the first two quarters used for lags). The real GDP forecasts generated by the random forest methodology span 1977Q2 to 2019Q4.

A.3 Additional Results

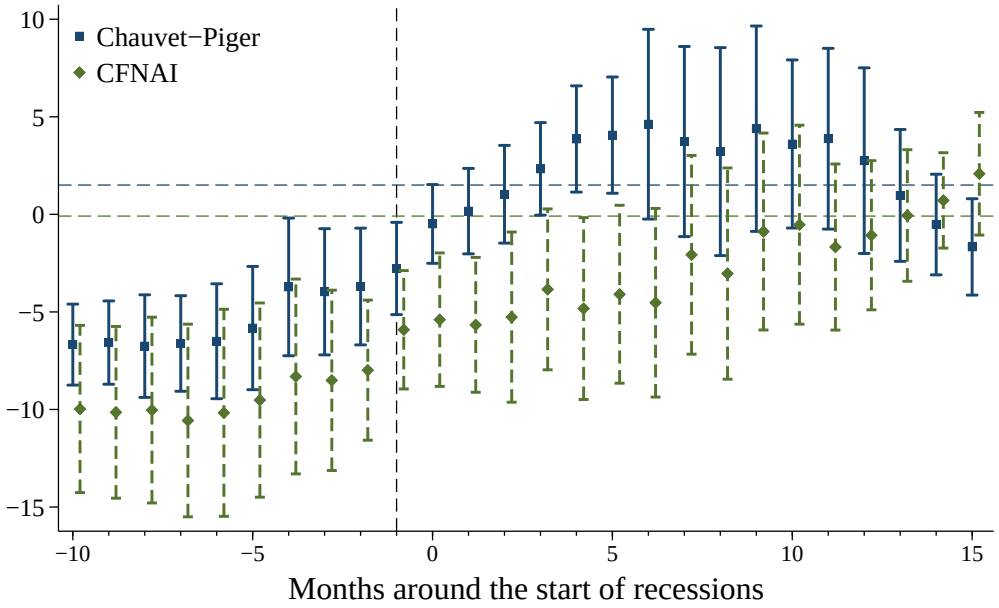


Figure A1: Alternative recession definitions. This figure plots one-year return spreads between cyclical and countercyclical firms around recession onsets under alternative definitions. It shows the one-year percentage return for an investor who buys the average long-short portfolio based on macro betas at month m relative to the recession onset. The squares use recession onsets defined by the Chauvet and Piger (2008) real-time recession probability above 50%; the diamonds use onsets defined by the Chicago Fed index below -0.72. The vertical bars represent a one-standard-deviation error range and account for heteroskedasticity and autocorrelation in the residuals up to six lags. The dashed vertical line indicates the peak month, and the dashed horizontal line indicates the average value for months 10 to 15.

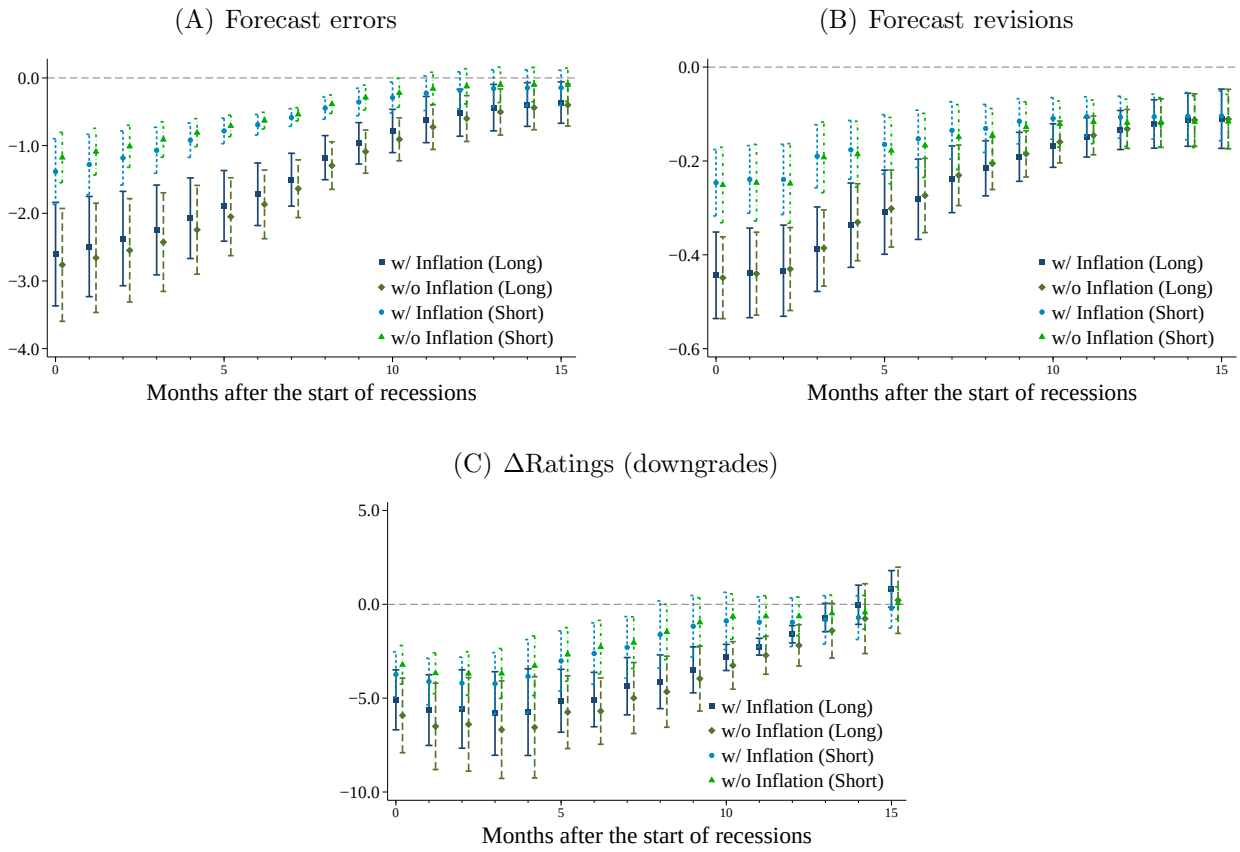


Figure A2: Performance of cyclical and countercyclical firms. This figure plots the analyst earnings forecast errors, forecast revisions, and credit rating changes for the long leg (cyclical firms) and short leg (countercyclical firms) of macro beta-sorted portfolios during recessions. It shows average portfolio-level values, multiplied by 100, for long-short portfolios purchased m months relative to the recession onset and held for one year. Recession onset is identified ex ante as the first month in which the Gómez-Cram (2022) recession probability exceeds 50%. The squares represent the average based on all 10 macro variables, and the diamonds represent the average based on all macro variables except those related to inflation (UI and DEI). The vertical bars represent a one-standard-deviation error range and account for heteroskedasticity and autocorrelation in the residuals up to six lags.

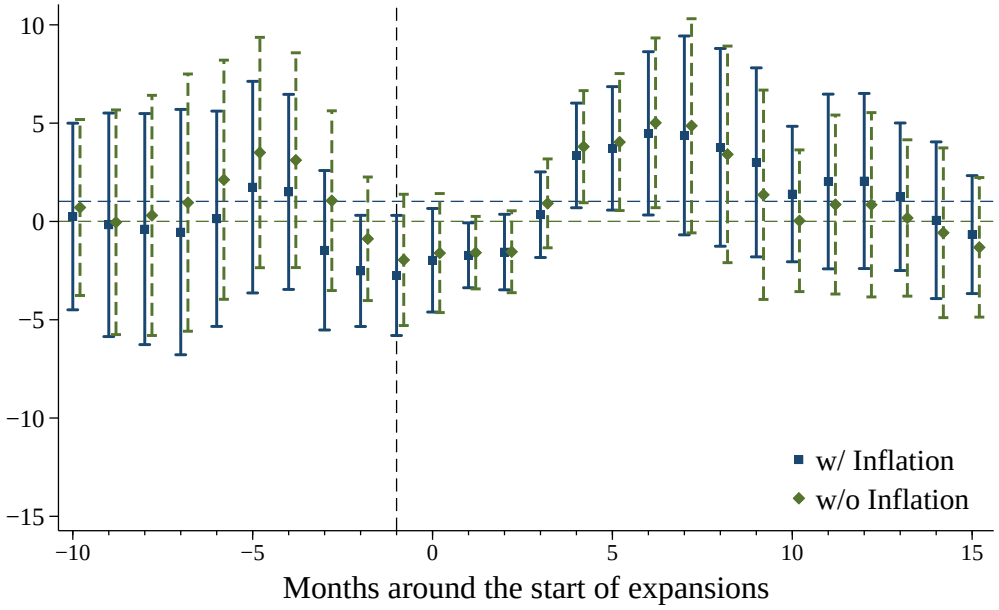


Figure A3: Expansions and one-year macro risk premia. This figure plots the one-year return spreads between cyclical and countercyclical firms around the onset of expansions. It shows the one-year percentage return for an investor who buys the average long-short portfolio based on macro betas at month m relative to the expansion onset. Expansion onset is identified ex ante as the first month in which the Gómez-Cram (2022) recession probability falls below 50%. The squares represent the average portfolio return based on all 10 macro variables, and the diamonds represent the average portfolio return based on all macro variables except those related to inflation (UI and DEI). The vertical bars represent a one-standard-deviation error range and account for heteroskedasticity and autocorrelation in the residuals up to six lags. The dashed vertical line indicates the peak month, and the dashed horizontal line indicates the average value for months 10 to 15.

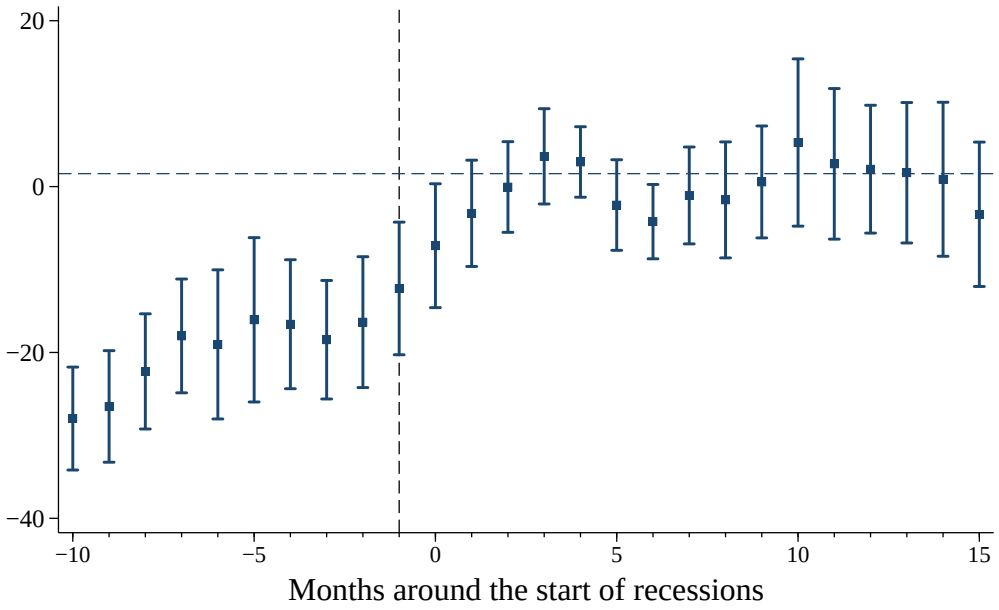


Figure A4: Recessions and volatility-sorted portfolio returns. This figure plots the one-year returns on long-short volatility-sorted portfolios around the onset of recessions. It shows the one-year percentage return for an investor who buys the portfolio at month m relative to the recession onset. The long-short volatility-sorted portfolio takes a long position in high-variance stocks and a short position in low-variance stocks, with variance estimated from 60 days of daily returns. Portfolio returns are obtained from Kenneth French's data library. Recession onset is identified ex ante as the first month in which the Gómez-Cram (2022) recession probability exceeds 50%. The vertical bars represent a one-standard-deviation error range and account for heteroskedasticity and autocorrelation in the residuals up to six lags. The dashed vertical line indicates the peak month, and the dashed horizontal line indicates the average value for months 10 to 15.

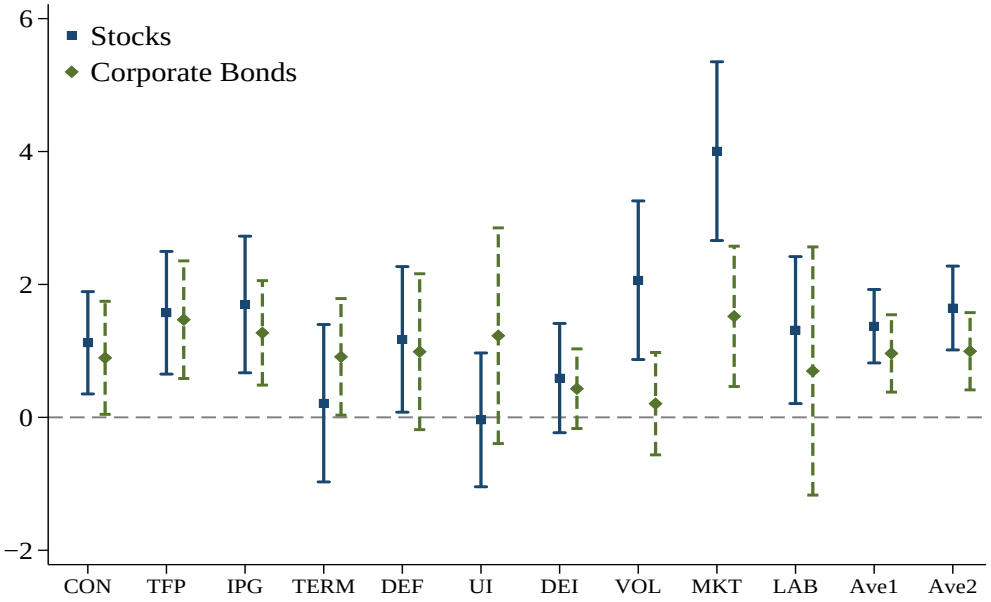


Figure A5: Effects on individual macro beta-sorted portfolios. This figure displays the regression coefficients β and their 90% confidence intervals from the specification in equation (4) for 10 individual long-short portfolios based on macro betas. Estimates are also reported for $Ave1$, a portfolio that equally combines all long-short portfolios based on macro betas, and $Ave2$, a portfolio that equally combines all portfolios except those related to inflation (UI and DEI). The dependent variable is expressed in quarterly percentages, and the explanatory variables are standardized to have a unit standard deviation. The squares represent estimates from long-short portfolios constructed using stock return spreads. The diamonds represent estimates from long-short portfolios constructed using corporate bond return spreads, which are multiplied by 10 for visual comparability. The standard errors account for heteroskedasticity and autocorrelation in the residuals for up to six lags.

Table A1: Characteristics-Based Factor Beta Portfolios and Exposure to Business Cycles

This table reports the annualized excess returns, post-formation betas, and exposures to the market and common growth for long-short portfolios sorted on characteristics-based factor betas. Common growth is the first principal component of real GDP growth, TFP growth, consumption growth, labor income growth, and initial claims growth. At the end of each month, stocks are sorted into quintiles based on their pre-formation betas with respect to each characteristics-based factor. Long-short portfolios are constructed by taking long positions in the highest-beta quintile and short positions in the lowest-beta quintile. Portfolio returns are annualized by multiplying monthly returns by 1,200. All explanatory variables are standardized, so that exposures represent the annualized return response to a one-standard-deviation change in the respective variable. The final column reports *Ave*, a portfolio that equally combines all long-short portfolios sorted on characteristics-based factor betas. The sample period runs from January 1965 to December 2019. Newey-West t-statistics with six lags are in parentheses.

Panel A: Mean Excess Returns

SMB	HML	RMW	CMA	IA	ROE	PMU	QMJ	MOM	MGMT	PERF	FIN	PEAD	Ave
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
0.43	5.00	0.57	0.58	1.52	0.95	2.74	2.63	-3.73	1.92	-2.91	1.29	-3.34	1.18
(0.12)	(1.73)	(0.20)	(0.21)	(0.52)	(0.30)	(1.07)	(0.76)	(-1.35)	(0.57)	(-1.08)	(0.36)	(-1.17)	(0.86)

Panel B: Post-Formation Beta

SMB	HML	RMW	CMA	IA	ROE	PMU	QMJ	MOM	MGMT	PERF	FIN	PEAD	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	
63.18	53.01	52.62	42.42	44.81	51.87	38.43	60.36	22.27	61.22	36.21	63.02	13.73	
(24.26)	(13.27)	(17.14)	(9.17)	(9.36)	(12.23)	(17.36)	(16.96)	(3.37)	(15.38)	(6.18)	(17.95)	(3.13)	

Panel C: Exposure to Market Factor

SMB	HML	RMW	CMA	IA	ROE	PMU	QMJ	MOM	MGMT	PERF	FIN	PEAD	Ave
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
47.07	-19.87	-25.00	-29.75	-29.73	-28.70	1.69	-46.82	-5.15	-41.72	-12.00	-40.88	1.94	-16.49
(10.93)	(-3.23)	(-4.41)	(-6.39)	(-6.04)	(-4.45)	(0.38)	(-8.56)	(-0.91)	(-8.45)	(-2.30)	(-7.21)	(0.31)	(-7.03)

Panel D: Exposure to Common Growth

SMB	HML	RMW	CMA	IA	ROE	PMU	QMJ	MOM	MGMT	PERF	FIN	PEAD	Ave
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
9.29	-5.21	-5.54	-6.38	-6.89	-5.85	-0.78	-10.78	2.14	-9.03	-0.97	-11.37	0.47	-3.63
(2.16)	(-1.41)	(-1.62)	(-2.05)	(-2.01)	(-1.43)	(-0.27)	(-2.57)	(0.69)	(-2.27)	(-0.32)	(-2.64)	(0.14)	(-2.23)

Table A2: Performance of Trading Strategies: Robustness

This table reports performance measures for five different strategies. "100% Factors" denotes the buy-and-hold strategy that is fully invested in the average of ten long-short portfolios based on macro betas (the long-short portfolio). "85/15 Mix" denotes the portfolio that allocates 85% to the long-short portfolio and 15% to T-bills. The remaining three strategies switch from the long-short portfolio to cash during bad times and market downturns, and they stay fully invested in the long-short portfolio in the remaining periods. Market downturns are months in which returns are below their twelve-month moving average. Bad times are periods when any of the following conditions hold: (i) the Gómez-Cram (2022) recession probability (Rec. Prob.) exceeds its twelve-month moving average; (ii) industrial production growth (Ind. Prod.) falls below its twelve-month moving average; or (iii) the change in the term premium (Term Prem.) falls below its twelve-month moving average. Panel A reports the excess returns, alpha, and Sharpe ratio increase relative to the Sharpe ratio obtained from a fixed-allocation strategy that invests in the long-short portfolio for the same unconditional fraction of time. The alpha is based on the Fama and French (2015) five-factor model augmented with the time-series momentum factor of Moskowitz, Ooi, and Pedersen (2012) (TMom) and volatility-managed factor of Moreira and Muir (2017) (TVol). Panel B reports average maximum drawdowns across economic states identified using the recession probability from Gómez-Cram (2022). Newey-West six-lag adjusted t-statistics are in parentheses below the coefficient estimates. We annualize all returns, expressed as a percentage per year, by multiplying monthly returns by 1,200. The evaluation period is from December 1965 to December 2019.

Panel A: Performance Evaluation

Measures	Rec. Prob. (1)	Ind. Prod. (2)	Term Prem. (3)	100% Factors (4)	85/15 Mix (5)
Time invested in factors	85%	74%	75%	100%	85%
Mean excess returns	0.83	0.61	1.06	-0.51	-0.48
Std. dev. returns	8.69	8.72	8.44	9.89	8.43
Sharpe ratio increase	0.15	0.13	0.18	–	–
α-FF5-TMom-TVol	1.40	1.99	2.56	0.97	0.81
	(1.43)	(1.99)	(2.66)	(0.94)	(0.93)

Panel B: Average Maximum Drawdown

Economic state	Rec. Prob. (1)	Ind. Prod. (2)	Term Prem. (3)	100% Factors (4)	85/15 Mix (5)
Total	28.45	26.16	24.79	43.45	38.60
Expansions	28.64	26.29	24.98	43.64	38.78
Recessions	26.47	24.85	22.80	41.47	36.76

Table A3: Features in the Random Forest for Real GDP Growth Forecasts

The first column reports the macroeconomic and financial series used to compute the forecasts of quarterly real GDP growth using random forests. The second column indicates the data source, where 'Philly Fed' denotes the Federal Reserve Bank of Philadelphia and 'Amit Goyal' denotes the Welch and Goyal (2008) data available on Amit Goyal's website. The third column denotes the following data transformation applied to each series x: (1) no transformation; (2) $\Delta x_t = x_t - x_{t-1}$; (3) $x_t/x_{t-1} - 1$. The fourth column indicates the category. The data span from 1966Q2 to 2019Q4.

Data series (1)	Source (2)	Transformation (3)	Category (4)
Real gross domestic product	Philly Fed	3	Output
Industrial production index	Philly Fed	3	Output
Private residential fixed investment	Philly Fed	3	Investment
Private nonresidential fixed investment	Philly Fed	3	Investment
Unemployment rate	Philly Fed	1	Employment
Initial jobless claims	Philly Fed	3	Employment
GDP deflator	Philly Fed	3	Inflation
Real M1 money stock	Philly Fed	3	Money
T-bill rate	Amit Goyal	1	Financial
Term spread	Amit Goyal	1	Financial
Default return spread	Amit Goyal	1	Financial
S&P 500 index	Amit Goyal	1	Financial
Log earnings-price ratio on S&P 500	Amit Goyal	2	Financial

Table A4: Predictive Power of the Expectation Wedge: Robustness

The table reports the coefficients in the following regressions:

$$f_{t+1} = \alpha + \beta\Delta_t + \delta' z_t + \epsilon_{t+1},$$

where $\Delta_t \equiv E_t^P[GDP_{t+1}] - E_t^S[GDP_{t+1}]$ is the wedge between machine learning and survey expectations of one-quarter-ahead real GDP growth, $E_t^P[GDP_{t+1}]$ is produced by a composite benchmark that averages forecasts from ridge regression, elastic net, random forest, extra trees, and gradient boosted regression trees, and $E_t^S[GDP_{t+1}]$ is the survey real GDP growth expectation. f is the average return spread of the long-short portfolio sorted on macro betas. The control variable z includes the surplus consumption ratio of Campbell and Cochrane (1999), the term spread, the default premium, the inflation rate, the intermediary capital ratio of He, Kelly, and Manela (2017) (the inverse of intermediary leverage), the Baker and Wurgler (2006) sentiment index, and real GDP growth forecast dispersion. The dependent variable is expressed in quarterly percentages, and the explanatory variables are standardized to have a mean of zero and a standard deviation of one. Survey forecasts of real GDP growth are from the SPF. The sample runs from 1977Q2 to 2019Q4. Newey-West six-lag adjusted t-statistics are in parentheses.

	(1)	(2)	(3)	(4)
Δ_t	0.82		0.90	
	(3.04)		(2.46)	
$E_t^P[GDP_{t+1}]$		0.72		0.72
		(1.78)		(1.30)
$E_t^S[GDP_{t+1}]$		-1.24		-1.38
		(-2.72)		(-3.39)
Surplus ratio$_t$			-0.31	-0.20
			(-0.60)	(-0.39)
Term spread$_t$			0.04	0.29
			(0.08)	(0.45)
Default premium$_t$			0.52	0.42
			(0.69)	(0.63)
Inflation$_t$			-1.08	-1.19
			(-2.35)	(-2.82)
Leverage$_t$			-0.27	-0.16
			(-0.34)	(-0.20)
Sentiment$_t$			-2.14	-2.15
			(-3.14)	(-3.35)
Dispersion$_t$			-0.50	-0.70
			(-0.88)	(-1.23)
Intercept	-0.09	-0.09	0.04	0.06
	(-0.21)	(-0.21)	(0.11)	(0.16)
Obs	170	170	170	170
R^2	0.02	0.03	0.13	0.13

B Baseline Model Solution

B.1 Coefficients of the Wealth-Consumption Ratio

To price assets, we conjecture (and later verify) that the log wealth-consumption ratio is linear in the state variable x_t and has the following form:

$$wc_t = A_0 + A_1 x_t. \tag{A1}$$

Similarly, we assume that the price-dividend ratio for asset i is

$$pd_{i,t} = D_{i,0} + D_{i,1} x_t. \tag{A2}$$

A Campbell-Shiller approximation gives the return on the aggregate consumption claim (the wealth portfolio), $r_{c,t+1}$, and return on any asset i, $r_{i,t+1}$,

$$r_{c,t+1} = \kappa_0 + \kappa_1 wc_{t+1} - wc_t + \Delta c_{t+1}, \tag{A3}$$

$$r_{i,t+1} = \kappa_{i,0} + \kappa_{i,1} pd_{i,t+1} - pd_{i,t} + \Delta d_{i,t+1}, \tag{A4}$$

with approximation constants

$$\kappa_1 = \frac{e^{\overline{wc}}}{e^{\overline{wc}} + 1}, \qquad \kappa_0 = \ln\left(e^{\overline{wc}} + 1\right) - \frac{e^{\overline{wc}}}{e^{\overline{wc}} + 1}\overline{wc}, \tag{A5}$$

$$\kappa_{i,1} = \frac{e^{\overline{pd}}}{e^{\overline{pd}} + 1}, \qquad \kappa_{i,0} = \ln\left(e^{\overline{pd}} + 1\right) - \frac{e^{\overline{pd}}}{e^{\overline{pd}} + 1}\overline{pd}, \tag{A6}$$

which depend on the unconditional means of the wealth-consumption and price-dividend ratios.

Using equations (8) and (A3), we obtain

$$m_{t+1} + r_{c,t+1} = \theta\left(\ln\delta + \kappa_0\right) + \theta\left(1 - \frac{1}{\psi}\right)\Delta c_{t+1} + \theta\left(\kappa_1 wc_{t+1} - wc_t\right). \tag{A7}$$

The Euler equation for any asset i (including $i = c$) with lognormal returns is

$$0 = E_t^S\left[m_{t+1} + r_{i,t+1}\right] + \frac{1}{2}\operatorname{Var}_t^S\left[m_{t+1} + r_{i,t+1}\right]. \tag{A8}$$

Plugging equation (A7) into (A8) with $i = c$, and evaluating the conditional means and variances, we can express the Euler equation for the consumption claim ($i = c$) as follows:

$$0 = C_0 + C_1 x_t, \tag{A9}$$

where C_0 and C_1 are constants that depend on A_0 and A_1. To satisfy the Euler equation at all times, the coefficients C_0 and C_1 must be identically zero, which yields the following system of equations in A_0 and A_1:

$$(x_t) : 0 = \left(1 - \frac{1}{\psi}\right) \rho_c \rho_z - A_1 \left(1 - \kappa_1 \rho_z\right) \tag{A10}$$

$$\begin{aligned}(const) : 0 =& \frac{\theta^2}{2} \left(1 - \frac{1}{\psi}\right)^2 \sigma_c^2 - \frac{\theta}{\psi} \mu_c + \theta \left(\kappa_1 - 1\right) A_0 + \theta \left(\kappa_0 + \mu_c + \ln \delta\right) \\ &+ \frac{\theta^2}{2} \left((1 - \frac{1}{\psi})\rho_c + \kappa_1 A_1 (1 - \lambda)\right)^2 \sigma_z^2.\end{aligned} \tag{A11}$$

Solving for A_0 and A_1 yields

$$A_1 = \left(1 - \frac{1}{\psi}\right) \frac{\rho_c \rho_z}{1 - \kappa_1 \rho_z} \tag{A12}$$

$$A_0 = \frac{\ln \delta + (1 - \frac{1}{\psi})\mu_c + \kappa_0 + \frac{\theta}{2} \left(1 - \frac{1}{\psi}\right)^2 \sigma_c^2 + \frac{\theta}{2} \left((1 - \frac{1}{\psi})\rho_c + \kappa_1 A_1 (1 - \lambda)\right)^2 \sigma_z^2}{1 - \kappa_1}. \tag{A13}$$

B.2 Coefficients of the Price-Dividend Ratio

To pin down the coefficients of the price-dividend ratio, the calculation is analogous to that for A_0 and A_1. However, instead of using the Euler equation for $r_{c,t}$, we use the one for $r_{i,t}$.

Using equations (8) and (A4), we obtain

$$1 = E_t^S[e^{m_{t+1} + r_{i,t+1}}] = E_t^S[e^{\theta \ln \delta - \frac{\theta}{\psi} \Delta c_{t+1} + (\theta - 1) r_{c,t+1} + r_{i,t+1}}]. \tag{A14}$$

The Euler equation for asset i can then be expressed as follows:

$$0 = F_{i,0} + F_{i,1} x_t. \tag{A15}$$

Collecting the coefficients yields the following:

$$(x_t) : 0 = \rho_i \rho_z - D_{i,1} \left(1 - \kappa_{i,1} \rho_z\right) + \left(\theta - 1\right) \left(\rho_c \rho_z + A_1 \left(\kappa_1 \rho_z - 1\right)\right) - \frac{\theta}{\psi} \rho_c \rho_z \tag{A16}$$

$$\begin{aligned}(const) : 0 =& \theta \ln \delta - \frac{\theta}{\psi} \mu_c + \kappa_{i,0} + (\kappa_{i,1} - 1) D_{i,0} + \mu_i + (\theta - 1)(\kappa_0 + (\kappa_1 - 1) A_0 + \mu_c) \\ &+ \frac{1}{2} \left(\kappa_{i,1} (1 - \lambda) D_{i,1} + \rho_i + \kappa_1 (1 - \lambda)(\theta - 1) A_1 - \gamma \rho_c\right)^2 \sigma_z^2 + \frac{1}{2} (\sigma_i - \gamma \sigma_c)^2,\end{aligned} \tag{A17}$$

which yields

$$D_{i,1} = \frac{\rho_z \rho_i - \rho_z \rho_c / \psi}{1 - \kappa_{i,1} \rho_z} \tag{A18}$$

$$D_{i,0} = \frac{\theta \ln \delta - \gamma \mu_c + \kappa_{i,0} + \mu_i + (\theta - 1)(\kappa_0 + (\kappa_1 - 1) A_0)}{1 - \kappa_{i,1}} + \frac{\frac{1}{2} \left(\kappa_{i,1}(1-\lambda) D_{i,1} + \rho_i + \kappa_1 (1-\lambda)(\theta - 1) A_1 - \gamma \rho_c \right)^2 \sigma_z^2 + \frac{1}{2} (\sigma_i - \gamma \sigma_c)^2}{1 - \kappa_{i,1}}. \tag{A19}$$

B.3 Conditional Pricing

We first investigate the dynamics of the stochastic discount factor (SDF). Under the representative agent's beliefs, the shock to the macro variable is

$$\sigma_z u_{t+1}^S \equiv z_{t+1} - E_t^S [z_{t+1}] = \rho_z (z_t - \mu_z) - \rho_z x_t + \sigma_z u_{t+1}, \tag{A20}$$

where $\rho_z (z_t - \mu_z) - \rho_z x_t = E_t^P [z_{t+1}] - E_t^S [z_{t+1}]$ is the bias in the subjective expectation of the macro variable. Substituting the equilibrium return for $r_{c,t+1}$ from equation (A3) into equation (8), the dynamics of the SDF under the agent's beliefs can be written as

$$m_{t+1} = E_t^S (m_{t+1}) + (\kappa_1 (1-\lambda)(\theta - 1) A_1 - \gamma \rho_c) \sigma_z u_{t+1}^S - \gamma \sigma_c \eta_{t+1}. \tag{A21}$$

This equation provides the economic intuition for why sticky beliefs distort the price of macro risk under subjective expectations. The perceived macro shock u^S enters the SDF. Favorable news about the future macro variable raises the wealth-consumption ratio and lowers marginal utility when investors prefer early resolution of uncertainty ($\gamma > 1/\psi$). Under these preference parameters, a higher λ implies that macro shocks u^S have a weaker effect on the wealth-consumption ratio and hence on marginal utility. As shown below, the representative investor perceives a negative but attenuated covariance between future macro shocks and marginal utility, resulting in a lower price of macro risk under subjective expectations than under full-information rational expectations.

The risk-free rate is given by

$$\begin{aligned} e^{-r_{f,t}} &= E_t^S [M_{t+1}] \\ &= \delta^\theta E_t^S \left[e^{-\gamma \Delta c_{t+1} + (\theta - 1)(\kappa_0 + \kappa_1 w c_{t+1} - w c_t)} \right] \\ &= \delta^\theta e^{-\gamma \mu_c + (\theta - 1)(\kappa_0 + (\kappa_1 - 1) A_0) + \frac{1}{2} (\kappa_1 (\theta - 1)(1 - \lambda) A_1 - \gamma \rho_c)^2 \sigma_z^2 + \frac{1}{2} \gamma^2 \sigma_c^2} \times e^{-\frac{1}{\psi} \rho_z \rho_c x_t}. \end{aligned}$$

Thus, we can derive the risk-free rate:

$$\begin{aligned} r_{f,t} =& -\theta \ln \delta + \gamma \mu_c - (\theta - 1)\left(\kappa_0 + (\kappa_1 - 1)A_0\right) \\ & - \frac{1}{2}\left(\kappa_1(\theta-1)(1-\lambda)A_1 - \gamma\rho_c\right)^2 \sigma_z^2 - \frac{1}{2}\gamma^2\sigma_c^2 + \frac{1}{\psi}\rho_z\rho_c x_t. \end{aligned} \tag{A22}$$

The prices of risk for u^S and η are

$$\begin{aligned} \lambda_u &\equiv -\frac{\mathrm{Cov}_t^S(m_{t+1}, u_{t+1}^S)}{\mathrm{Var}_t^S(u_{t+1}^S)} \\ &= \gamma\rho_c\sigma_z - \kappa_1(\theta-1)(1-\lambda)A_1\sigma_z \\ &= \rho_c\sigma_z\left(\gamma + (1-\lambda)\kappa_1\rho_z\frac{\gamma - 1/\psi}{1-\kappa_1\rho_z}\right), \end{aligned} \tag{A23}$$

$$\lambda_\eta \equiv -\frac{\mathrm{Cov}_t^S(m_{t+1}, \eta_{t+1})}{\mathrm{Var}_t^S(\eta_{t+1})} = \gamma\sigma_c, \tag{A24}$$

and the quantities of risk for u^S and η are given by the betas

$$\begin{aligned} \beta_{u,i} &\equiv \frac{\mathrm{Cov}_t^S\left(u_{t+1}^S, r_{i,t+1}\right)}{\mathrm{Var}_t^S\left(u_{t+1}^S\right)} \\ &= \rho_i\sigma_z + (1-\lambda)\kappa_{i,1}D_{i,1}\sigma_z \\ &= \sigma_z\left(\rho_i + (1-\lambda)\kappa_{i,1}\rho_z\frac{\rho_i - \rho_c/\psi}{1-\kappa_{i,1}\rho_z}\right) \end{aligned} \tag{A25}$$

$$\beta_{\eta,i} \equiv \frac{\mathrm{Cov}_t^S\left(\eta_{t+1}, r_{i,t+1}\right)}{\mathrm{Var}_t^S\left(\eta_{t+1}\right)} = \sigma_i. \tag{A26}$$

The conditional expected log return under subjective expectations for asset i is

$$\begin{aligned} E_t^S[r_{i,t+1}] &= E_t^S[\kappa_{i,0} + \kappa_{i,1}pd_{i,t+1} - pd_{i,t} + \Delta d_{i,t+1}] \\ &= \kappa_{i,0} + \mu_i + D_{i,0}(\kappa_{i,1} - 1) + \frac{1}{\psi}\rho_z\rho_c x_t. \end{aligned} \tag{A27}$$

Using equations (A19), (A22), and (A27), the expected excess returns for asset i can then be written as follows:

$$\begin{aligned} E_t^S[r_{i,t+1} - r_{f,t}] =& \kappa_{i,0} + \mu_i + D_{i,0}(\kappa_{i,1} - 1) + \theta\ln\delta - \gamma\mu_c + (\theta-1)\left(\kappa_0 + (\kappa_1 - 1)A_0\right) \\ & + \frac{1}{2}\left(\kappa_1(\theta-1)(1-\lambda)A_1 - \gamma\rho_c\right)^2\sigma_z^2 + \frac{1}{2}\gamma^2\sigma_c^2 \\ =& \lambda_u\beta_{u,i} + \lambda_\eta\beta_{\eta,i} - \frac{1}{2}\beta_{u,i}^2 - \frac{1}{2}\beta_{\eta,i}^2. \end{aligned} \tag{A28}$$

This equation holds for any individual asset. The last two terms represent Jensen's inequality correction terms in the derivation of expected log excess returns. When we use log expected excess returns instead, these two terms will disappear. This equation implies that the conditional expected excess returns for any risky asset are positive and constant, as in similar models with constant consumption growth volatility (see also Bansal and Yaron, 2004).

Finally, using the dynamics of $pd_{i,t}$ in equation (A2), we can derive the process for asset returns as a function of subjective macro risk premia, predictable belief errors, and macro shocks:

$$r_{i,t+1} - r_{f,t} = E_t^S[r_{i,t+1} - r_{f,t}] + \frac{\beta_{u,i}}{\sigma_z}\left(\rho_z(z_t - \mu_z) - \rho_z x_t\right) + \beta_{u,i} u_{t+1} + \beta_{\eta,i}\eta_{t+1}. \tag{A29}$$

B.4 Macro Risk Premium

(i) Conditional Premium

Our study focuses on the conditional variation in the macro risk premium. To derive the macro risk premium implied from the cross-section of stocks, we model two assets representing portfolios with high (H) and low (L) macro betas from our empirical analysis. Without loss of generality, we assume that the two assets have the same consumption growth beta (i.e., $\beta_{\eta,H} = \beta_{\eta,L}$). Hence, the return spread between the two assets purely reflects the macro risk of u^S. The High-minus-Low macro beta, $\beta_{u,HL}$, is simply the difference $\beta_{u,H} - \beta_{u,L}$, as betas are linear in returns:

$$\begin{aligned}\beta_{u,HL} &= \frac{\mathrm{Cov}_t^S\left(u_{t+1}^S, r_{H,t+1}\right)}{\mathrm{Var}_t^S\left(u_{t+1}^S\right)} - \frac{\mathrm{Cov}_t^S\left(u_{t+1}^S, r_{L,t+1}\right)}{\mathrm{Var}_t^S\left(u_{t+1}^S\right)} \\ &= \left((\rho_H - \rho_L) + (1-\lambda)(\kappa_{H,1}D_{H,1} - \kappa_{L,1}D_{L,1})\right)\sigma_z. \end{aligned} \tag{A30}$$

The long-short hedged portfolio, constructed based on macro betas, is expected to capture the macro risk premium. Utilizing the dynamics of asset returns in equation (A29), we can derive the process for macro risk premia as a function of subjective macro risk premia, predictable belief errors, and macro shocks:

$$r_{H,t+1} - r_{L,t+1} = \lambda_u \beta_{u,HL} - \frac{1}{2}\beta_{u,H}^2 + \frac{1}{2}\beta_{u,L}^2 + \frac{\beta_{u,HL}}{\sigma_z}\left(\rho_z(z_t - \mu_z) - \rho_z x_t\right) + \beta_{u,HL} u_{t+1}. \tag{A31}$$

This equation implies that sticky expectations can make macro risk premia predictable from the econometrician's perspective. This is immediately evident by rewriting the macro risk premium

under objective expectations as follows:

$$E_t^P[r_{H,t+1} - r_{L,t+1}] = E_t^S[r_{H,t+1} - r_{L,t+1}] + \frac{\beta_{u,HL}}{\sigma_z}\left(E_t^P[z_{t+1}] - E_t^S[z_{t+1}]\right)$$
$$= E_t^S[r_{H,t+1} - r_{L,t+1}] + \frac{\beta_{u,HL}}{\sigma_z}\left(\rho_z(z_t - \mu_z) - \rho_z x_t\right), \tag{A32}$$

where the superscripts P and S denote objective and subjective expectations, respectively. This equation implies that objective macro risk premia are low when investors' beliefs are overly optimistic, that is, when they underreact to recent bad news ($E_t^P[z_{t+1}] < E_t^S[z_{t+1}]$). In fact, negative and predictable future returns (to the econometrician) may arise from the cash-flow news, offsetting the risk premium component ($E_t^S[r_{H,t+1} - r_{L,t+1}]$).

(ii) Unconditional Premium

Unconditionally, our model can reconcile the weakened macro risk premium in the cross-section of assets as observed in the data. To illustrate this, we first derive the unconditional macro risk premium. Taking unconditional expectations in equation (A32) gives the unconditional macro risk premia:

$$E^P[r_{H,t} - r_{L,t}] = E^S[r_{H,t} - r_{L,t}] = \lambda_u \beta_{u,HL} - \frac{1}{2}\beta_{u,H}^2 + \frac{1}{2}\beta_{u,L}^2, \tag{A33}$$

where the superscripts P and S denote objective and subjective expectations, respectively. The first equality in equation (A33) relies on the fact that, on average, misperceptions of the macro variable z cancel out when computing the unconditional macro risk premium. This equation helps explain the weak cross-sectional macro risk premium observed in the data. Note from equation (A1) that the representative investor with sticky beliefs underestimates the impact of macro shocks u^S on the wealth-consumption ratio (i.e., the expected path of consumption growth) and hence on marginal utility. For instance, following adverse macro shocks, the wealth-consumption ratio should fall, and marginal utility should rise, by more than investors subjectively expect. This is because marginal utility is inversely related to the return on the wealth portfolio when investors prefer early resolution of uncertainty ($\gamma > 1/\psi$), as evident from equation (8). In equilibrium, the representative investor perceives the covariance between future macro shocks and marginal utility as negative but smaller in magnitude, lowering the required compensation for bearing macro risk and thus the subjective price of macro risk relative to FIRE. Since the positive and negative belief biases due to sticky expectations cancel out, the average macro risk premium is equal under subjective and objective expectations. When investors prefer early resolution of uncertainty, sticky expectations lower the objective price of macro risk relative to FIRE. Therefore, sticky expectations weaken the cross-sectional risk-return trade-off, leading to a flatter relation between macro betas and expected returns relative to FIRE.

C Asymmetric Underreaction Extension

This appendix extends the baseline model in Section 4 by allowing the expectation-stickiness parameter to depend on the sign of recent macro news, and presents the model solution.

C.1 Subjective Expectations and Asymmetric Underreaction

The key departure from the symmetric model is that the agent's expectation-stickiness parameter is now time-varying and depends on the sign of the preceding shock:

$$x_{t+1} - \rho_z x_t = (1 - \lambda_t)\,\sigma_z u^S_{t+1}, \qquad \lambda_t = \begin{cases} \lambda^+ \equiv \lambda + \delta_\lambda & u^S_t \le 0, \\ \lambda^- \equiv \lambda & u^S_t > 0, \end{cases} \tag{A34}$$

with $\lambda, \delta_\lambda \ge 0$ and $\lambda^+ < 1$. Because λ_t is known at time t (i.e., $\mathcal{F}_t$-measurable), it is independent of u^S_{t+1} under S. Setting $\delta_\lambda = 0$ recovers the symmetric model. This specification matches the evidence in Table 4: forecast revisions respond less to current macro surprises following unfavorable news because $1 - \lambda^+ \le 1 - \lambda^-$. Indeed,

$$E^S_t[z_{t+1}] - E^S_{t-1}[z_{t+1}] = \rho_z(1 - \lambda_{t-1})(z_t - E^S_{t-1}[z_t]). \tag{A35}$$

We define the expectation wedge $w_t \equiv z_t - \mu_z - x_t$, which evolves according to

$$w_{t+1} = \lambda_t\,\sigma_z u^S_{t+1}. \tag{A36}$$

Since $E^S_t[u^S_{t+1}] = 0$, it follows that $E^S_t[w_{t+1}] = 0$ and $E^S_t[x_{t+1}] = \rho_z x_t$.

To solve the model, we treat the stickiness state $\lambda_t \in \{\lambda^-, \lambda^+\}$ as a two-state regime variable. Under the subjective expectation S, the regime transition matrix is

$$\Pi^S = \begin{pmatrix} \Pi^S_{--} & \Pi^S_{-+} \\ \Pi^S_{+-} & \Pi^S_{++} \end{pmatrix} = \begin{pmatrix} 1/2 & 1/2 \\ 1/2 & 1/2 \end{pmatrix}. \tag{A37}$$

Under the objective expectation P, the transition probabilities depend on the expectation wedge as $u^S_{t+1} \mid \mathcal{F}_t \sim N(\rho_z w_t/\sigma_z, 1)$. The transition matrix under P is therefore

$$\Pi^P = \begin{pmatrix} \Phi(\rho_z w_t/\sigma_z) & \Phi(-\rho_z w_t/\sigma_z) \\ \Phi(\rho_z w_t/\sigma_z) & \Phi(-\rho_z w_t/\sigma_z) \end{pmatrix}, \tag{A38}$$

where $\Phi(\cdot)$ denotes the standard normal CDF. For later use, we define the following quantities,

where the overline denotes the unconditional average across the two stickiness regimes under Π^S:

$$\bar{\lambda} \equiv \tfrac{1}{2}(\lambda^- + \lambda^+) = \lambda + \tfrac{1}{2}\delta_\lambda, \tag{A39}$$

$$\overline{(1-\lambda)^2} \equiv \tfrac{1}{2}(1-\lambda^-)^2 + \tfrac{1}{2}(1-\lambda^+)^2. \tag{A40}$$

C.2 Coefficients of the Wealth-Consumption Ratio

To derive the wealth-consumption ratio, we conjecture that

$$wc_t = A_0(\lambda_t) + A_1(\lambda_t)\, x_t, \tag{A41}$$

allowing both the intercept and the slope to be state-dependent. By the Campbell-Shiller approximation, the return on the aggregate consumption claim is

$$r_{c,t+1} = \kappa_0 + \kappa_1 wc_{t+1} - wc_t + \Delta c_{t+1}. \tag{A42}$$

We solve the Euler equation using iterated expectations and a log-linear approximation, following Schorfheide, Song, and Yaron (2018). Conditional on state $j \in \{-,+\}$, the Euler equation is

$$1 = \sum_{k\in\{-,+\}} \Pi^S_{jk}\, E^S_t\left[e^{m_{t+1}+r_{c,t+1}} \,\middle|\, \lambda_t = \lambda^j,\ \lambda_{t+1} = \lambda^k\right]. \tag{A43}$$

The slope and state-specific intercepts are given by

$$A_1 = \frac{\left(1-\frac{1}{\psi}\right)\rho_c\rho_z}{1-\kappa_1\rho_z}, \tag{A44}$$

$$A_0(\lambda^j) = \ln\delta + \kappa_0 + \left(1-\tfrac{1}{\psi}\right)\mu_c + \kappa_1\bar{A}_0 + \frac{\alpha_j^2+\tau^2}{2\theta} + \frac{\mathcal{M}(d;\alpha_j)}{\theta}, \tag{A45}$$

with $j \in \{-,+\}$ and

$$\begin{aligned}
\Delta_A &\equiv A_0(\lambda^+) - A_0(\lambda^-), \qquad d \equiv \theta\kappa_1\Delta_A,\\
\alpha_j &= \theta\left[\kappa_1 A_1(1-\lambda^j) + \left(1-\tfrac{1}{\psi}\right)\rho_c\right]\sigma_z, \qquad \tau = \theta\left(1-\tfrac{1}{\psi}\right)\sigma_c,\\
\mathcal{M}(d;x) &\equiv \log\left(e^{-d/2}\Phi(x) + e^{d/2}\Phi(-x)\right),\\
\bar{A}_0 &= \frac{1}{1-\kappa_1}\left[\ln\delta + \kappa_0 + \left(1-\tfrac{1}{\psi}\right)\mu_c + \frac{\alpha_-^2+\alpha_+^2}{4\theta} + \frac{\tau^2}{2\theta} + \frac{\mathcal{M}(d;\alpha_-)+\mathcal{M}(d;\alpha_+)}{2\theta}\right].
\end{aligned} \tag{A46}$$

The first-order approximations are[20]

$$\bar{A}_0 \approx \frac{1}{1-\kappa_1}\left[\ln\delta + \kappa_0 + \left(1-\tfrac{1}{\psi}\right)\mu_c + \frac{\alpha_-^2+\alpha_+^2}{4\theta} + \frac{\tau^2}{2\theta}\right], \tag{A47}$$

$$A_0(\lambda^j) \approx \ln\delta + \kappa_0 + \left(1-\tfrac{1}{\psi}\right)\mu_c + \kappa_1\bar{A}_0 + \frac{\alpha_j^2+\tau^2}{2\theta}, \qquad j\in\{-,+\}. \tag{A48}$$

Note that A_1 is independent of the state, whereas A_0 differs across states.

C.3 Coefficients of the Price-Dividend Ratio

To derive the log price-dividend ratio, we conjecture that

$$pd_{i,t} = D_{i,0}(\lambda_t) + D_{i,1}(\lambda_t)\, x_t, \tag{A49}$$

with the Campbell-Shiller approximation

$$r_{i,t+1} = \kappa_{i,0} + \kappa_{i,1} pd_{i,t+1} - pd_{i,t} + \Delta d_{i,t+1}. \tag{A50}$$

For each state $j\in\{-,+\}$, the Euler equation is

$$1 = \sum_{k\in\{-,+\}} \Pi_{jk}^S\, E_t^S\left[e^{m_{t+1}+r_{i,t+1}} \,\middle|\, \lambda_t=\lambda^j,\ \lambda_{t+1}=\lambda^k\right]. \tag{A51}$$

Applying the law of iterated expectations to equation (A51) and log-linearizing yields the slope coefficient and a first-order approximation to the state-specific intercept,

$$D_{i,1} = \frac{\left(\rho_i - \frac{\rho_c}{\psi}\right)\rho_z}{1-\kappa_{i,1}\rho_z}, \tag{A52}$$

$$\begin{aligned} D_{i,0}(\lambda^j) \approx{}& \frac{K_i - (\theta-1)(1-\kappa_1)\bar{A}_0 + \frac{1}{2}\left[G_i(1-\bar{\lambda}) + \rho_i - \gamma\rho_c\right]^2\sigma_z^2 + \frac{1}{2}(\sigma_i-\gamma\sigma_c)^2}{1-\kappa_{i,1}} \\ &- \{G_i\left[G_i(1-\bar{\lambda}) + \rho_i - \gamma\rho_c\right] - \theta(\theta-1)\kappa_1 A_1[\kappa_1 A_1(1-\bar{\lambda}) + (1-\frac{1}{\psi})\rho_c]\}(\lambda^j-\bar{\lambda})\sigma_z^2, \end{aligned} \tag{A53}$$

where

$$\begin{aligned} G_i &\equiv \kappa_{i,1}D_{i,1} + \kappa_1(\theta-1)A_1, \\ K_i &\equiv \theta\ln\delta + (\theta-1)\kappa_0 - \gamma\mu_c + \kappa_{i,0} + \mu_i. \end{aligned} \tag{A54}$$

[20] Here and below, we omit terms of order $O(\delta_\lambda^2)$ and $O(\delta_\lambda\sigma_z^3)$.

Thus $D_{i,1}$ is state-independent, whereas $D_{i,0}$ varies across states. The corresponding first-order approximation to the regime-averaged intercept is

$$\bar{D}_{i,0} \approx \frac{1}{1-\kappa_{i,1}} \left\{ K_i - (\theta-1)(1-\kappa_1)\bar{A}_0 + \frac{1}{2}\left[G_i(1-\bar{\lambda}) + \rho_i - \gamma\rho_c\right]^2 \sigma_z^2 + \frac{1}{2}(\sigma_i - \gamma\sigma_c)^2 \right\}. \quad \text{(A55)}$$

C.4 Conditional Pricing

The prices of risk are given by[21]

$$\lambda_{u,t} = \rho_c\sigma_z \left(\gamma + (1-\lambda_t)\,\kappa_1\rho_z \frac{\gamma - 1/\psi}{1-\kappa_1\rho_z} \right), \quad \lambda_\eta = \gamma\sigma_c. \quad \text{(A56)}$$

Under the conditions $\rho_z > 0$ and $\gamma > 1/\psi$, greater expectation stickiness lowers the price of macro risk when $\rho_c > 0$. Averaging across regimes under the subjective stationary distribution, which assigns probability 1/2 to each regime, yields

$$\bar{\lambda}_u = \rho_c\sigma_z \left(\gamma + (1-\bar{\lambda})\,\kappa_1\rho_z \frac{\gamma - 1/\psi}{1-\kappa_1\rho_z} \right). \quad \text{(A57)}$$

The quantities of risk for asset i are given by

$$\beta_{u,i,t} = \sigma_z \left(\rho_i + (1-\lambda_t)\,\kappa_{i,1}\rho_z \frac{\rho_i - \rho_c/\psi}{1-\kappa_{i,1}\rho_z} \right), \quad \beta_{\eta,i} = \sigma_i, \quad \text{(A58)}$$

and the average of $\beta_{u,i,t}$ across the two states is

$$\bar{\beta}_{u,i} = \sigma_z \left(\rho_i + (1-\bar{\lambda})\,\kappa_{i,1}\rho_z \frac{\rho_i - \rho_c/\psi}{1-\kappa_{i,1}\rho_z} \right). \quad \text{(A59)}$$

C.5 Macro Risk Premium

(i) Conditional Premium

To derive the macro risk premium implied by the cross-section of stocks, we again model two assets representing the High (H) and Low (L) macro beta portfolios from our empirical analysis and assume equal consumption growth betas across the two assets ($\beta_{\eta,H} = \beta_{\eta,L}$). The high-minus-

[21] Strictly speaking, because λ_{t+1} depends on the sign of u^S_{t+1}, the regime-dependent intercept $A_0(\lambda_{t+1})$ is correlated with the macro shock. We use λ and β to denote prices and quantities of risk, respectively; these approximate their covariance-based counterparts when regime differences are small.

low macro beta is state-dependent:

$$\beta_{u,HL,t} \equiv \beta_{u,H,t} - \beta_{u,L,t} = \big[(\rho_H - \rho_L) + (1-\lambda_t)(\kappa_{H,1}D_{H,1} - \kappa_{L,1}D_{L,1})\big]\sigma_z, \tag{A60}$$

with the average macro-beta spread across the two states given by

$$\bar{\beta}_{u,HL} = \big[(\rho_H - \rho_L) + (1-\bar{\lambda})(\kappa_{H,1}D_{H,1} - \kappa_{L,1}D_{L,1})\big]\sigma_z. \tag{A61}$$

Using the return decomposition together with $\beta_{\eta,H} = \beta_{\eta,L}$, the realized return spread is

$$r_{H,t+1} - r_{L,t+1} = E_t^S[r_{H,t+1} - r_{L,t+1}] + \beta_{u,HL,t}u_{t+1}^S + J_{HL,t+1}, \tag{A62}$$

where $J_{HL,t+1} \equiv \kappa_{H,1}\left(D_{H,0}(\lambda_{t+1}) - \bar{D}_{H,0}\right) - \kappa_{L,1}\left(D_{L,0}(\lambda_{t+1}) - \bar{D}_{L,0}\right)$ with $\bar{D}_{i,0} = \frac{1}{2}D_{i,0}(\lambda^-) + \frac{1}{2}D_{i,0}(\lambda^+)$. Taking objective conditional expectations and using $E_t^P[u_{t+1}^S] = \rho_z w_t/\sigma_z$, we obtain

$$E_t^P[r_{H,t+1} - r_{L,t+1}] = E_t^S[r_{H,t+1} - r_{L,t+1}] + \frac{\beta_{u,HL,t}}{\sigma_z}\,\rho_z w_t + E_t^P[J_{HL,t+1}], \tag{A63}$$

where the first two terms imply that objective macro risk premia are low when investors' beliefs are overly optimistic, namely when investors underreact to recent negative news.

(ii) Unconditional Premium

The additional quantity needed for the unconditional macro risk premium under P is the mean expectation wedge. From equation (A36) and $u_{t+1}^S \mid \mathcal{F}_t \sim N(\rho_z w_t/\sigma_z, 1)$ under P, we have

$$E_t^P[w_{t+1}] = \lambda_t\,\rho_z w_t. \tag{A64}$$

Imposing stationarity and decomposing $\lambda_t = \bar{\lambda} + (\lambda_t - \bar{\lambda})$ yields

$$\bar{w} \equiv E^P[w_t] \;\approx\; \frac{-\rho_z\bar{\lambda}\,\delta_\lambda\sigma_z}{\sqrt{2\pi}\,(1-\rho_z\bar{\lambda})\sqrt{1-(\rho_z\bar{\lambda})^2}} \;\leq\; 0. \tag{A65}$$

Hence, stronger underreaction to bad news ($\delta_\lambda > 0$) renders subjective macro forecasts overly optimistic on average.

Equation (A63) shows that the unconditional macro risk premium is approximately

$$E^P[r_{H,t+1} - r_{L,t+1}] \approx E^P[\lambda_{u,t}\beta_{u,HL,t}] - \tfrac{1}{2}E^P[\beta_{u,H,t}^2] + \tfrac{1}{2}E^P[\beta_{u,L,t}^2] + \tfrac{\rho_z}{\sigma_z}E^P[\beta_{u,HL,t}w_t]. \tag{A66}$$

An analogous computation gives

$$E^P[\beta_{u,HL,t} w_t] \approx \bar{\beta}_{u,HL}\, \bar{w} + \frac{(\kappa_{H,1} D_{H,1} - \kappa_{L,1} D_{L,1})\, \bar{\lambda}\, \sigma_z^2\, \delta_\lambda}{\sqrt{2\pi}\sqrt{1-(\rho_z \bar{\lambda})^2}}. \tag{A67}$$

Substituting equation (A67) into equation (A66) yields the unconditional premium

$$\begin{aligned} E^P[r_{H,t+1} - r_{L,t+1}] \approx\ & \overline{\lambda_u \beta_{u,HL}} - \tfrac{1}{2}\,\overline{\beta_{u,H}^2} + \tfrac{1}{2}\,\overline{\beta_{u,L}^2} \\ & - \frac{\bar{\beta}_{u,HL}\, \rho_z^2\, \bar{\lambda}\, \delta_\lambda}{\sqrt{2\pi}\,(1-\rho_z \bar{\lambda})\sqrt{1-(\rho_z \bar{\lambda})^2}} + \frac{(\kappa_{H,1} D_{H,1} - \kappa_{L,1} D_{L,1})\, \bar{\lambda}\, \rho_z\, \sigma_z\, \delta_\lambda}{\sqrt{2\pi}\sqrt{1-(\rho_z \bar{\lambda})^2}}, \end{aligned} \tag{A68}$$

where the overline denotes the unconditional average across stickiness regimes, $\overline{f(\lambda)} \equiv \frac{1}{2} f(\lambda^-) + \frac{1}{2} f(\lambda^+)$. In particular, $\overline{\lambda_u \beta_{u,HL}} = \frac{1}{2}\lambda_u(\lambda^-)\beta_{u,HL}(\lambda^-) + \frac{1}{2}\lambda_u(\lambda^+)\beta_{u,HL}(\lambda^+)$, and $\overline{\beta_{u,i}^2} = \sigma_z^2\big[\rho_i^2 + 2\rho_i(1-\bar{\lambda})\kappa_{i,1} D_{i,1} + \overline{(1-\lambda)^2}(\kappa_{i,1} D_{i,1})^2\big]$. As in the symmetric case, sticky expectations lower the price of macro risk $\bar{\lambda}_u$ relative to the FIRE benchmark. In addition, the first term on the second line reflects the negative mean wedge: asymmetric underreaction generates average optimism and a relative overpricing of high-beta firms, which lowers their objective expected returns. Under asymmetric underreaction, these forces jointly attenuate the objective macro risk premium relative to the FIRE benchmark.