Macro Risk Premia and the Business Cycle*

Abstract

This study finds that macro risk premia are predictably negative after the ex-ante identified onset of recessions, 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 the return spreads between cyclical and countercyclical firms. A long-short strategy exploiting this time variation yields 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 flatter macro beta-expected return relation and delayed macro risk premia responses to recessions.

JEL Classification: E70, E71, G12, G41

Keywords: Beta, Business cycle, Macro risk, Subjective expectations

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 hard to reconcile with rational expectations, which suggest that prices should decline promptly 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 flatter 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

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[1] The stickiness in consensus macro beliefs can be triggered by 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, ex-ante signals indicating the onset of a recession are gradually incorporated into asset prices, resulting in the observed delayed drift in macro risk premia during these times. As we show, analyst expectations about cyclical (high macro beta) firms' earnings are overly optimistic at the onset of recessions, and downward revisions are exceptionally high following the onset of recessions. Moreover, cyclical firms experience more reductions in investments and downgrades in credit ratings following the onset of recessions. The findings align with investors' slow recognition of recessions and the resulting larger delayed response of cyclical firms, which are more sensitive to macroeconomic changes. Further, we collect 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 the 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 form a new measure of the expectation wedge using the difference between machine learning and survey-based output expectations. A general premise of our approach is that machine learning algorithms can approximate rational forecasts in real time (Kahneman, 2011; Bianchi, Ludvigson, and Ma, 2022). We predict that when the deviation between machine forecasts and survey forecasts is large, 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 quarterly real GDP growth expectations of the machine learning and real-time forecasters predicts the returns of long-short portfolios based on macro betas. A one standard deviation increase in the expectation wedge leads to 1.13% higher long-short portfolio returns in the next quarter, with a t-statistic of 4.06. The effect is robust to various empirical specifications. For instance, we obtain similar results after controlling for various competing economic forces such as investor sentiment, disagreement, and leverage constraints, as well as various known risk factors.

Leveraging the expectation wedge available in real time, we analyze the economic relevance of our findings through a trading strategy that tilts toward cyclical (countercyclical) stocks when investors are overly pessimistic (optimistic). Specifically, we increase (decrease) exposure to macro variables following a high (low) expectation wedge. This timing strategy generates a positive unconditional alpha, earning a capital asset pricing model (CAPM) alpha of 5.45% per annum by reducing risk-taking when investors overestimate output growth. The results cannot be explained by conventional factor models. The annualized alpha is 4.77% using the Fama and French (2015) five-factor model augmented with the time-series momentum factor of Moskowitz, Ooi, and Pedersen (2012) and volatility-managed factor of Moreira and Muir (2017) as the benchmark. 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, coupling the expectation wedge with investor sentiment—another variable related to investor misperception—to form a long-short portfolio based on macro betas 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 future improvements in real output growth. The sticky belief hypothesis may not be the sole explanation for these findings, as 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 featuring a cross-section of assets for 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 are determined by a rational risk premia component and near-term forecastable changes in cash flows that are not yet incorporated into prices. 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 premia component to induce a negative risk-return relation when the economy is transitioning to a recession. Hence, overestimating the future cash flows of cyclical firms at the onset of recessions in subjective expectations offsets the positive increase in macro risk premia. This can potentially lead to underperformance of cyclical stocks relative to countercyclical stocks following the onset of recessions, 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 the 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 the role of expectations 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) indicate 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 with 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 high- and low-market beta stocks is significantly lower than theoretical predictions and has garnered significant scholarly attention (Black, 1972; Chen, Roll, and Ross, 1986; Frazzini and Pedersen, 2014). This finding is extended by Shen, Yu, and Zhao (2017) and Herskovic, Moreira, and Muir (2019), who demonstrate 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 exist. Shen, Yu, and Zhao (2017) find empirically that aggregate investor sentiment attenuates the relation between macro beta and expected returns. In contrast, investor sentiment, proxied by investor misperceptions, endogenously arises within our framework. The various pieces of our evidence together suggest 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 source 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), company fundamentals from Compustat, corporate bond returns from Lehman Brothers Fixed Income Database, TRACE, and Mergent FISD/NAIC, Standard & Poor's (S&P) Long-Term Domestic Issuer Credit Rating from S&P Credit Ratings, and security analyst forecasts from Thomson Reuters I/B/E/S. Additionally, we gather macro variables from the Federal Reserve Economic Data and Amit Goyal's webpage, enabling us to construct macro beta-sorted portfolios. The series for the market returns, risk-free rate, and Fama and French (2015) five factors come from Kenneth R. French's data library. We collect investor sentiment indices from three major sources: the Baker and Wurgler (2006) sentiment index orthogonalized to economic conditions from Jeffrey Wurgler's webpage, and the survey-based sentiment indices from the American Association of Individual Investors (AA) and Investors Intelligence (II). 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) managed by the Federal Reserve Bank of Philadelphia, which is the oldest quarterly survey of macro forecasts in the U.S. The SPF summarizes forecasts on various aspects of the macroeconomy from leading financial institutions, professional forecasting firms, and academic institutions since the fourth quarter of 1968. Following Bordalo et al. (2020), we compute consensus SPF forecasts as means from the individual-level forecasts available at 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.[2]

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);

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[2] 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`.

6. UI, the unexpected inflation (Chen, Roll, and Ross, 1986);
7. DEI, the changes in expected inflation (Fama and Gibbons, 1984);
8. VOL, the change in monthly market volatility (French, Schwert, and Stambaugh, 1987);
9. MKT, the excess returns of the stock market (Chen, Roll, and Ross, 1986); and
10. LAB, the growth rate in nominal labor income per capita (Jagannathan and Wang, 1996).

Details of these macro variables are described in Appendix A.1.[3] 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 the two series by negative 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 exhibit significantly positive excess returns, despite generally having large and statistically significant post-formation betas (Panel B). For example, consumption growth (CON), a macro variable with a

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[3] 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 unanticipated inflation series, UI.

strong theoretical grounding in the consumption-based asset pricing models, shows a negative annual premium of -0.95% (t-statistic = -0.49). Noise in the macro beta estimation may introduce 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 -0.53%.

[**Place Table 1 about here**]

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 rate, consumption growth, labor income growth, and initial claims growth. According to standard asset pricing models, the cyclicality of these factor returns imposes higher risk for risk-averse investors, who therefore demand an overall positive risk premium for holding them. However, Panel A shows that cyclical firms do not earn a higher return than countercyclical firms on average. This is consistent with studies finding that the estimated prices of risk for the 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 introduces the study's new empirical findings, which serve as motivation for 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 estimate 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%.[4] Figure 1 depicts the one-year returns of long-short macro beta-sorted portfolios around recessions, revealing two main findings. First, the 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 as 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 slowly increase afterward. 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.

[Place Figure 1 about here]

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. The recession probability of Chauvet and Piger (2008) is derived from a real-time dataset of coincident monthly variables, highlighted by the NBER in identifying business cycle turning points, using a parametric Markov-switching dynamic factor model. 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. Recession dates are determined based on the following mechanical rules implying that a recession occurs when:

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[4] 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.

(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 a similar conclusion. 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 if 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. Value-weighted bond portfolios are formed by value-weighting firm-level bond returns using their lagged market capitalization. Panel A of Figure 2 shows that the results continue to hold in corporate bond returns. Measured using corporate bond returns, the macro risk premia remain negative for several months at the onset of recessions and then gradually rise above zero. An investor who invests in 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 -1.0% across all 10 macro variables, or -1.7% when excluding the inflation-related variables, which are sizable in magnitude.

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, it appears to be more consistent with an 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 forecast made for the next fiscal year (i.e., Forecast Period Indicator (FPI) variable equal to 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 the changes in the mean EPS forecasts. Finally, these differences are then 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 gradually make downward earnings expectation revisions relatively strongly for cyclical firms. Results here 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' slow reactions to recessions, which more significantly affect 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 around 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. Following the release of new information around 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 realize the relative overpricing of cyclical firms. Consequently, they require a higher return on equity and corporate bonds for these firms, causing a contraction in corporate real activities such as investment. To illustrate this, Panel E shows that at the start of recessions, the cost of capital increases, accompanied by a relative slowdown in the investment growth of cyclical firms. Thus, cyclical firms appear to overinvest before the onset of recessions. However, the subsequent relative reduction in investments by cyclical firms may also be attributable to mean reversion in the quantity of investments. To investigate this further, we examine the credit ratings (forward-looking opinions of credit risk) aggregated at the portfolio level, as presented in Panel F.[5] 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 and credibility.[6] Together, the relevant errors and real activities are consistent with the distorted beliefs of investors and their responses to surprises.[7]

[Place Figure 2 about here]

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

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

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

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 determine whether the strategy's profits are due to rational variation in expected returns or to behavioral 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 characteristic-based factors—including value, momentum, and profitability—that are commonly used in leading multifactor models. To see this, we follow Chen et al. (2025) in using 13 characteristic-based factors from leading multifactor models and repeat the analysis for the average long-short factor beta-sorted portfolio.[8] We use factor data provided directly by the original authors. As Figure 3 shows, the same phenomenon is not observed in characteristic-based factors. At the onset of recessions, stocks with higher exposures to characteristic-based factors earn relatively higher returns. The return spread between stocks with high and low characteristics-based factor betas gradually decays to zero, in contrast to the pattern observed for macro variables. We verify that firms with high characteristics-based factor betas have consumption and market betas similar to those of firms with low characteristics-based factor betas; that is, they are not more cyclical. This suggests that firms with different characteristics-based factor exposures do not underreact to recession information differently, unlike macro variable exposures. Taken together, these findings serve as a placebo test and underscore the unique role of sticky macro expectations in the macro beta-return relation.

[Place Figure 3 about here]

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[8] 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 behavior (PEAD) factors from Daniel, Hirshleifer, and Sun (2020) behavioral factor model.

In the Appendix, we report results using an alternative proxy for 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 goes long in high-volatility stocks and short 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, the evidence further supports the view that cyclical risk is priced with a delay at the onset of recessions.

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 (i.e., one-month T-bill return) during bad economic times and market downturns, while staying 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 the 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 goes 100% into cash; otherwise, the strategy goes 100% into the long-short portfolio.[9]

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 earned an annualized mean excess return of 0.97% with an annualized standard deviation of 8.56% by 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 amount of time—a mix of 80% in the long-short portfolio and 20% in T-bills—generates an annualized mean excess return of -0.43% and volatility of 7.92%, as shown in column (5). These numbers imply that the simple strategy produces an overall Sharpe ratio increase of 0.17 over 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 consider factor-adjusted returns using a benchmark of the five-factor model from Fama and French (2015), augmented with the

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[9] Table A1 in the Appendix explores robustness with respect to the choice of the six-month moving average.

time-series momentum factor from Moskowitz, Ooi, and Pedersen (2012) and the volatility-managed factor from Moreira and Muir (2017). As shown in the bottom rows of Panel A, the simple strategy generates an annualized alpha of 1.77% (*t*-statistic = 1.82). Alternatively, we construct another timing strategy based on U.S. industrial production growth. As shown in column (2), this strategy invests in factors 72% of the time and is profitable, yielding a Sharpe ratio increase of 0.11 and an annualized alpha of 1.85% (*t*-statistic = 1.83). The increases in Sharpe ratios and alphas from these strategies suggest that following macro trends can improve the performance of the long-short portfolio. Column (3) reports another timing strategy based on the yield spread, 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 2.01% (*t*-statistic = 2.05). Conversely, columns (4) and (5) show that, without timing, the fixed-allocation strategies of 100% and 80/20 in the long-short portfolio yield small and statistically insignificant alphas.

[**Place Table 2 about here**]

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 benefits by significantly reducing the maximum drawdowns. Notably, during recessions, the average maximum drawdown is 27.35% for the strategy that times the recession probability, which is significantly lower than the corresponding figure of 35.35% for the 80/20 strategy. Hence, the long-short macro beta-sorted portfolio returns seem slow to update 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 potential mechanisms, we directly evaluate the sticky belief conjecture using data on recession likelihood expectations from the SPF. The SPF surveys professional respondents about recession probabilities, which are defined as the probabilities of a decline in the level of real GDP in a given quarter (the current and 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} is 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 check 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 expected future probability of a recession tends to be revised upward later. More precisely, 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), analysts' forecast revisions should be unpredictable from past data. Table 3 reports the results for an econometric test of predictability. Columns (1) to (3) present results for the regression of the forecast revisions in recession probabilities on the past forecast revisions. The results of Table 3 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% confidence 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 consistent sluggish responses in expectations.

[**Place Table 3 about here**]

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.[10] The nowcast—a prediction of the current-quarter recession probability—is expected to be more accurate as more information has been released at that time. Specifically, we define the forecast error for recession probabilities as the difference between the nowcast and prior forecast. Columns (4)-(6) of Table 3 report the results for the forecast error (nowcast minus forecast) regressed on the forecast revisions. In column (4), the higher the revisions in recession probability forecasts, the higher the realization relative to the forecast. We again find an underreaction

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[10] Gómez-Cram's (2022) definition of the rational recession probability differs from that of the SPF, as the former estimates the probability of a recession state within a state-space model.

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 previous studies (Coibion and Gorodnichenko, 2015; Bordalo et al., 2020).[11]

Since we observe more pronounced underreaction in the returns of macro beta-sorted portfolios at the onset of recessions than during expansions, it is appealing to verify whether the underreaction effect in forecasts is asymmetric. To test this hypothesis, we modify the regressions by including both upward and downward forecast revisions, allowing us to capture the asymmetric impact by separating forecast revisions into upward and downward components. As shown in Table 4, the underreaction to bad news (upward revisions in recession probability) appears to be more pronounced than the underreaction to good news (downward revisions in recession probability). At the one-quarter-ahead horizon, the underreaction to good news is not even statistically significant. Thus, this asymmetry explains why underreaction is stronger at the onset of recessions than at the onset of expansions.

[**Place Table 4 about here**]

In summary, recession probability expectations from surveys exhibit predictable forecast errors, as the expectations display an underreaction 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.[12]

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

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

[12] 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 levels of macro beta, particularly at the onset of recessions.

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 by averaging the predictions of multiple decision trees (Breiman, 2001).[13] Random forest regression models are an ensemble of decision trees that bootstrap the predictions of different decision trees. Each tree is trained on a random sample, usually drawn with replacement. Instead of considering all predictors, the decision trees are modified so that they use a strict random subset of features at each node to render the individual decision trees' predictions to be less correlated. The final prediction of the random forest model is obtained by averaging each decision tree's predictions. Specifically, we predict the next-quarter real GDP growth using a random forest model:

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

where the 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., unemployment rate and initial jobless claims), investment (e.g., private residential/nonresidential fixed investment), inflation (e.g., the GDP deflator), and valuation (e.g., the S&P 500 index), and g is a nonlinear function. While we cannot exhaustively capture every real-time variable, the comprehensive coverage of our inputs provides a reasonable proxy for the full information environment. To ensure that our forecasting avoids look-ahead bias, we construct features using realizations from the previous two quarters, based on initially realized values (released at the end of the first month of the following quarter) from the Philadelphia Fed. Real-time data simulate the actual information set available to investors and account for the fact that macro variables are sometimes released with a delay or receive revisions by statistical agencies following publication. Appendix A.2 details the methodology and features used in the machine learning forecasts.

To trace out the difference between the machine learning and survey output expectations,

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[13] Cassella et al. (2023) and Zhang, Zhu, and Linnainmaa (2025) characterize the time-varying systematic expectation errors of earnings expectations using the random forest.

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 forecast real GDP growth realized next quarter using machine learning 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 only differ by an unpredictable noise component. However, the graph indicates that machine and survey forecasts can differ significantly. As the bottom panel shows, the wedge in output forecasts tends to be low before the onset of recessions and gradually increases afterward. Hence, this wedge should reflect the gap between the information set of the econometrician (who relies on algorithms) and survey forecaster (who is subject to belief distortions).

[Place Figure 5 about here]

To statistically compare the in-sample forecast precision of the machine learning forecasts with 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 fitted from 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: an increase of 1 percentage point in the machine learning forecast translates into an increase of 83 basis points (bps) 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 the same 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 the bivariate regression results, which include both machine learning and survey forecasts. Notably, the loading on machine learning is 0.60 (t-statistic = 2.42), whereas the loading on the survey forecast is 0.41 (t-statistic = 1.33). This indicates that the machine learning forecast subsumes the predictive ability of the survey forecast. The p-values test whether $\beta_P = 1, \beta_S = 0$ or $\beta_P = 0, \beta_S = 1$. We fail to reject the null hypothesis that machine learning forecasts subsume survey forecasts ($\beta_P = 1, \beta_S = 0$). Conversely, we reject the null hypothesis that survey forecasts subsume machine learning forecasts ($\beta_P = 0, \beta_S = 1$) at the 10% level.

Panel A continues to examine the out-of-sample forecasting ability. We consider the average predictive accuracy of the machine learning versus the 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 17% 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.

[**Place Table 5 about here**]

Finally, Panel B examines the ability of the wedge variable to predict the 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 relationship between the wedge and survey forecast errors remains consistent (t-statistic = 3.46). Further, column (3) examines the relationship between survey forecast errors and machine learning and survey forecasts, revealing a similar conclusion: when included together in the regression, the machine learning forecast is more positively associated with future survey forecast errors relative to the survey forecast.

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 the machine learning and survey-based output expectations, we now turn to linking it to the predictability in returns of long-short portfolios based on macro betas. To test the predictive ability of the wedge in expectations, 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 fitted from 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 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 (leverage) of He, Kelly, and Manela (2017), the Baker and Wurgler (2006) sentiment index, and real GDP growth forecast dispersion.

[Place Table 6 about here]

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 the comparison 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 forecasts 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% confidence level, with a *t*-statistic of 4.06. In terms of economic significance, a one-standard-deviation increase in the wedge variable predicts long-short portfolio returns that are 1.13% larger over the next quarter.

The economic magnitude of the coefficient is sizable, given that the realized returns average -0.53% 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 1.38% (t-statistic = 4.12) larger 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 predictability of macro risk premia by the expectation wedge.

Next, we confirm the robustness of this analysis through a battery of additional tests. As an alternative to our machine learning method, 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). In this analysis, the wedge between machine learning and survey forecasts still significantly predicts long-short portfolio returns (Table A3). Returning to our baseline specifications, Figure A5 plots the coefficient estimates for the 10 individual macro variables, which exhibit remarkable consistency at the individual factor level. The wedge variable positively predicts the returns for the majority of the 10 individual macro variables. Meanwhile, 7 out of the 10 macro variables yield statistically significant estimates at the 10% level. For some inflation-related variables, such as UI and DEI, we observe weaker effects. This result 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. We have thus far estimated long-short portfolio returns from stock returns, and the results should also apply 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 when measured with corporate bond returns, the predictive power of the expectation wedge persists.

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) larger over the next quarter. This estimate is slightly smaller in magnitude compared to that 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 predictive ability remains similar (columns (3) and (4)). Overall, the predictive ability of the wedge variable remains intact when using factor alphas.

[Place Table 7 about here]

3.5 Performance Gains from Timing Expectation Wedges

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 this strategy. Specifically, at the end of each quarter, we increase risk-taking when the estimate of expected returns is high and decrease 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 for 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 the strategy performance and report the results in Table 8. Panel A of Table 8 indicates that this trading strategy earns large excess returns and alphas. The estimated market α is both economically and statistically significant, with a 5.45% annualized alpha (t-statistic = 3.67). Clearly, this is because the wedge variable effectively predicts the returns on macro beta-sorted long-short portfolios. In contrast, if there were no timing, the buy-and-hold long-short strategy would generate negative excess returns and market alphas. Notably, the buy-and-hold long-short strategy has a market alpha estimate of -3.84, with a t-statistic of -2.03. Thus, timing the wedge variable can increase the alpha by 9%. 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 4.62% (t-statistic = 2.66). However, is the alpha of our strategy a repackaging of existing factors, such as volatility management, which also incur less risk during bad times? 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 the time-series momentum and volatility-managed market factors as controls, with an alpha estimate of 4.77% (t-statistic = 2.70). Hence, by directly capturing belief biases, we can achieve higher strategy performance compared to the results in Table 2.

[**Place Table 8 about here**]

Crucially, the timing strategy not only increases average returns but also avoids 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 less severe maximum drawdowns than the buy-and-hold long-short strategy. Similarly, during recessions, the timing strategy records an average maximum drawdown of 15.05%, which is much smaller than the buy-and-hold long-short strategy (43.11%).

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 thus our expectation wedge, we construct a composite signal: the equal-weighted average of the standardized signals of the expectation wedge and the (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 6.98% (t-statistic = 2.90) and a market α of 8.02% (t-statistic = 2.61). Such a strategy also reports lower maximum drawdowns, as reported in Panel B of Table 8. Taken together, this evidence suggests that investors can yield 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 to shed light on the underlying economic mechanism. To understand the sources of these strategy alphas, 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 in 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 the estimates for real GDP growth forecast errors and recession probability forecast changes from the SPF.

[**Place Figure 6 about here**]

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 panels further show that the strategy achieves this performance by increasing (decreasing) the conditional market beta when the expectation wedge is high (low). 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.

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. Now, we consider the reverse case: 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 we observe an underreaction in macro beliefs, the long-short portfolio returns should also predict news about future macro conditions, as they are both 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 the results of predictive regressions of the 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 the linear probability model.[14] 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 credit spread signals deteriorations in macroeconomic conditions (Gilchrist and Zakrajšek, 2012). Column (2) shows that controlling for other variables, such as the term spread and credit spread, does not materially alter the predictive power of the macro risk premia. Thus, the long-short portfolio returns contain additional information about recession states beyond common controlling predictors. Moreover, columns (3) through (6) show that the long-short portfolio returns positively predict the next quarter's real GDP growth and industrial production growth, as indicated by the coefficient estimates on the lagged long-short portfolio returns, which are highly statistically significant at conventional levels. In Panel B, we report the results of 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 slightly diminishes compared to that observed in Panel A.

[Place Table 9 about here]

To further uncover the source of the predictive ability of the long-short portfolio returns, we examine its relation to survey forecast revisions and errors.[15] Table 10 confirms that long-short portfolio returns predict revisions and errors in the SPF forecasts. Across specifications, we consider forecasts of different horizons. While the SPF respondents are professional forecasters, they do not seem to fully incorporate the information embedded in long-short portfolio returns. Panel A shows that long-short portfolio returns negatively predict

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

[15] 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.

revisions and errors in recession probability forecasts with a sizable magnitude. 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 the revisions and errors in the forecasts of growth in real GDP and industrial production, respectively. The ability of the long-short portfolio returns to predict revisions and errors in survey forecasts indicates that information does not seem to be fully incorporated into the investors' forecasts. 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.

[Place Table 10 about here]

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.

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, motivating and reconciling our empirical findings. We allow the representative agent to have biased beliefs about the dynamics of the macro variable. Our model offers 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

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

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.

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 and η as follows:

$$\begin{aligned} \lambda_u &\equiv -\frac{\mathrm{Cov}_t^S(m_{t+1}, u_{t+1})}{\mathrm{Var}_t^S(u_{t+1})} \\ &= \rho_c \sigma_z \left(\gamma + (1-\lambda)\kappa_1 \rho_z \frac{\gamma - 1/\psi}{1-\kappa_1 \rho_z}\right), \end{aligned} \tag{13}$$

$$\lambda_\eta \equiv -\frac{\mathrm{Cov}_t^S(m_{t+1}, \eta_{t+1})}{\mathrm{Var}_t^S(\eta_{t+1})} = \gamma \sigma_c. \tag{14}$$

All proofs are included in Appendix B. The price of macro risk, denoted as 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 λ_u is priced because shocks of u 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 conveys favorable news about future consumption growth, implying a positive 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.

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

$$r_{i,t+1} = \kappa_{i,0} + \kappa_{i,1} pd_{i,t+1} - pd_{i,t} + \Delta d_{i,t+1}, \tag{15}$$

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

$$\beta_{u,i} \equiv \frac{\mathrm{Cov}_t^S\left(u_{t+1}, r_{i,t+1}\right)}{\mathrm{Var}_t^S\left(u_{t+1}\right)} = \sigma_z \left(\rho_i + (1-\lambda)\kappa_{i,1}\rho_z \frac{\rho_i - \rho_c/\psi}{1-\kappa_{i,1}\rho_z}\right), \tag{16}$$

$$\beta_{\eta,i} \equiv \frac{\mathrm{Cov}_t^S\left(\eta_{t+1}, r_{i,t+1}\right)}{\mathrm{Var}_t^S\left(\eta_{t+1}\right)} = \sigma_i. \tag{17}$$

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

$$E_t^S[r_{i,t+1} - r_{f,t}] = \lambda_u \beta_{u,i} + \lambda_\eta \beta_{\eta,i} - \frac{1}{2}\beta_{u,i}^2 - \frac{1}{2}\beta_{\eta,i}^2. \tag{18}$$

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. 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. 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:

$$E^P[r_{H,t} - r_{L,t}] = E^S[r_{H,t} - r_{L,t}] = \lambda_u \beta_{u,HL} - \frac{1}{2}\beta_{u,H}^2 + \frac{1}{2}\beta_{u,L}^2, \tag{19}$$

where the superscripts P and S denote objective and subjective expectations, respectively. The first equality in equation (19) relies on the fact that, on average, misperceptions of the macro variable z cancel out when computing the unconditional macro risk premium. This equation reconciles the weakened macro risk premium in the cross-section of assets observed in the data. Note that the representative investor with sticky beliefs underestimates the impact of macro shocks u on the wealth-consumption ratio (i.e., the expected path of consumption growth) and hence on marginal utility.[16] For instance, following adverse macro shocks, the wealth-consumption ratio should decrease more than subjective expectations suggest, while marginal utility should increase more than subjective expectations suggest. 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 a negative but weaker covariance between future macro shocks and marginal utility, reducing the required compensation for bearing macro risk and hence the price of macro risk under subjective expectations than under 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. Consequently, the model also implies a reduced compensation for bearing macro risk and hence a lower price of macro risk under objective expectations than under FIRE. As shown in equation (13), the price of macro risk λ_u decreases with the expectation stickiness parameter λ when $\gamma, \psi > 1$. 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 also explicitly derive the conditional expectations of the macro risk premia. Specifically, we can write the relation between objective and subjective macro risk premia

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[16] As shown in equation (A1) in the Appendix, when $\gamma, \psi > 1$, the log wealth-consumption ratio wc_t is a linearly increasing function of both the state variable x_t and the macro variable z_t. Under this condition, upward revisions in expected future macro variable increase wealth value while decreasing marginal utility, as shown in equation (A22) in the Appendix (see also Campbell (2017)).

as follows:

$$\begin{aligned} E_t^P[r_{H,t+1} - r_{L,t+1}] &= E_t^S[r_{H,t+1} - r_{L,t+1}] + \frac{\beta_{u,HL}}{\sigma_z}\left(E_t^P[z_{t+1}] - E_t^S[z_{t+1}]\right) \\ &= E_t^S[r_{H,t+1} - r_{L,t+1}] + \frac{\beta_{u,HL}}{\sigma_z}\left(\rho_z(z_t - \mu_z) - \rho_z x_t\right), \end{aligned} \tag{20}$$

where the superscripts P and S denote objective and subjective expectations, respectively. Equation (20) 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 (20), 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 like the start of recessions ($E_t^P[z_{t+1}] < E_t^S[z_{t+1}]$). Negative and predictable future returns (to the econometrician) arise from the cash-flow news in the second term in equation (20), offsetting the risk premium component ($E_t^S[r_{H,t+1} - r_{L,t+1}]$), the first term in equation (20).

The return dynamics suggest that the late recognition of poor cash flows at the onset of recessions, under subjective beliefs, can lead to predictability of macro risk premia from the econometrician's perspective. To illustrate this, we simulate a negative macro shock in our model to see 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 macro risk premia to a one-standard-deviation surprise decrease in the macro shock u. In these simulations, we fix the degree of 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. At time -1, a negative shock to the macro variable results in an immediate decrease in macro risk premia.[17] 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, which leads the subsequent macro risk premia to be negative or near zero. In addition, the subsequent macro risk premia tend to increase over time as more and more information is incorporated (see the solid blue line in Figure 7). After several months, the macro shock is almost fully integrated into prices, and the macro risk premium reverts to the level of the unconditional macro risk premium, which is smaller in magnitude than the rational case

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[17] 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.

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 after the onset of recessions, slowly rising thereafter as investors gradually correct their expectations.

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. The negative macro risk premia at the start of recessions are puzzling, as cyclical stocks are riskier and should earn a positive risk premium that is likely to be countercyclical, as suggested by leading asset pricing models with rational expectations and empirical evidence. 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 the sticky macro beliefs by examining professional and analyst forecasts and corporate 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 real output forecasts, capturing the predictable errors in subjective real output forecasts. This expectation wedge positively predicts macro beta-sorted long-short portfolio returns, and a trading strategy based on it generates substantial alphas. Third, sticky macro beliefs produce a smaller price of macro risk in both subjective and objective expectations, explaining the unconditionally flatter relationship between macro betas and returns, and the slow response of macro risk premia to recessions.

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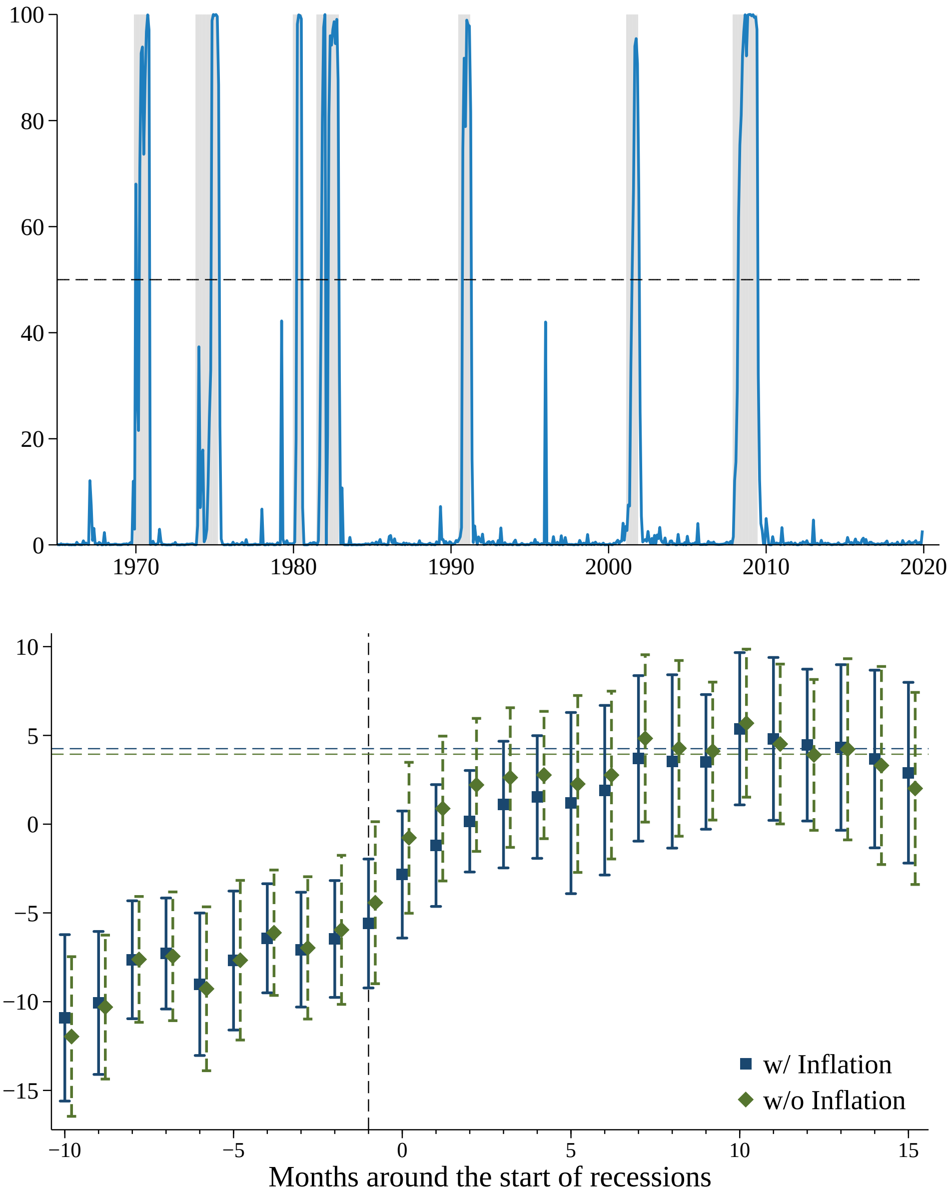
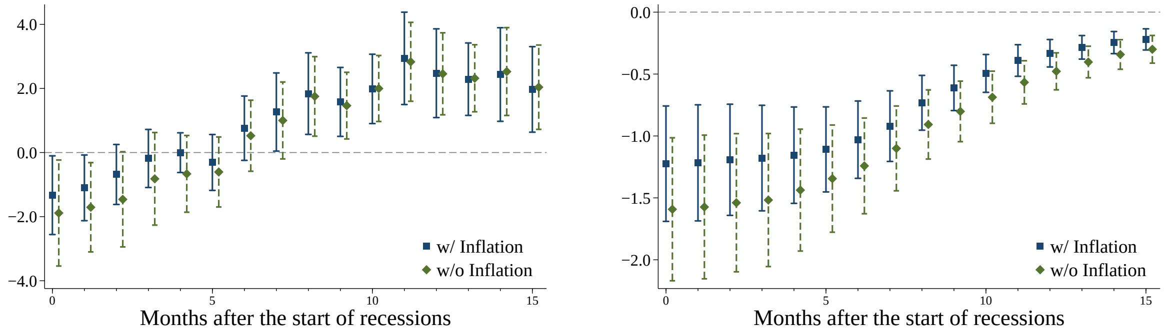
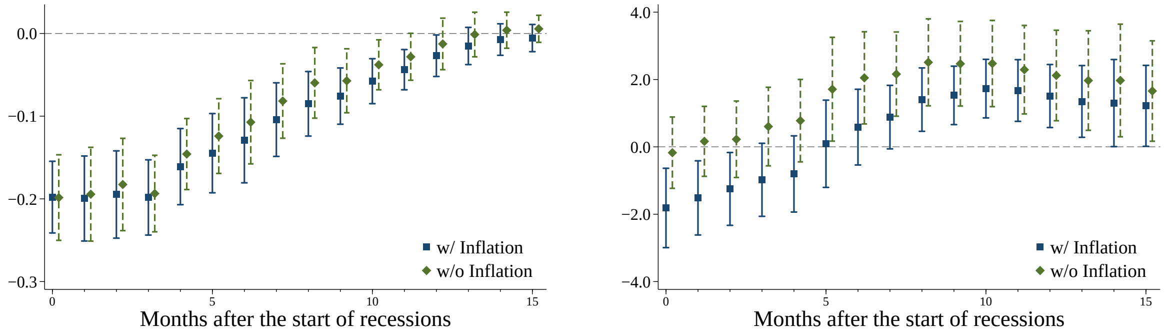


Figure 1: Ex-ante recession probability and one-year macro risk premia. The top panel plots the real-time recession probability (in percentages) from Gómez-Cram (2022). The bottom panel plots the one-year return spreads between cyclical and countercyclical firms around the onset of recessions. It shows the percentage return for an investor who buys the average long-short portfolio based on macro betas m months relative to expecting to be in a recession and holds it for one year. Recessions are identified ex-ante using the Gómez-Cram (2022) recession probability, which assumes that investors expect to be in a recession whenever the recession probability first 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.



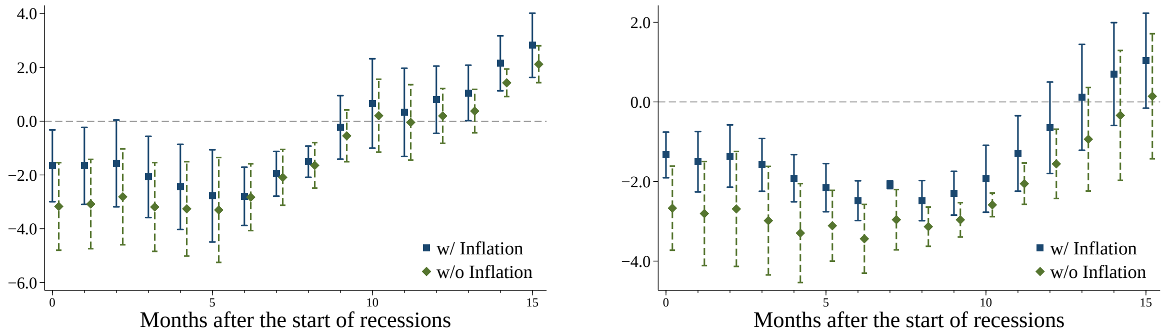
(A) Corporate bond returns

(B) Forecast errors



(C) Forecast revisions

(D) Earnings announcement returns



(E) ΔInvestment

(F) ΔRatings (downgrades)

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. This figure shows average portfolio-level values (multiplied by 100) for long-short portfolios that are purchased m months after a recession is expected and held for one year. Recessions are identified ex-ante using the Gómez-Cram (2022) recession probability, which assumes that investors expect to be in a recession whenever the recession probability first 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.

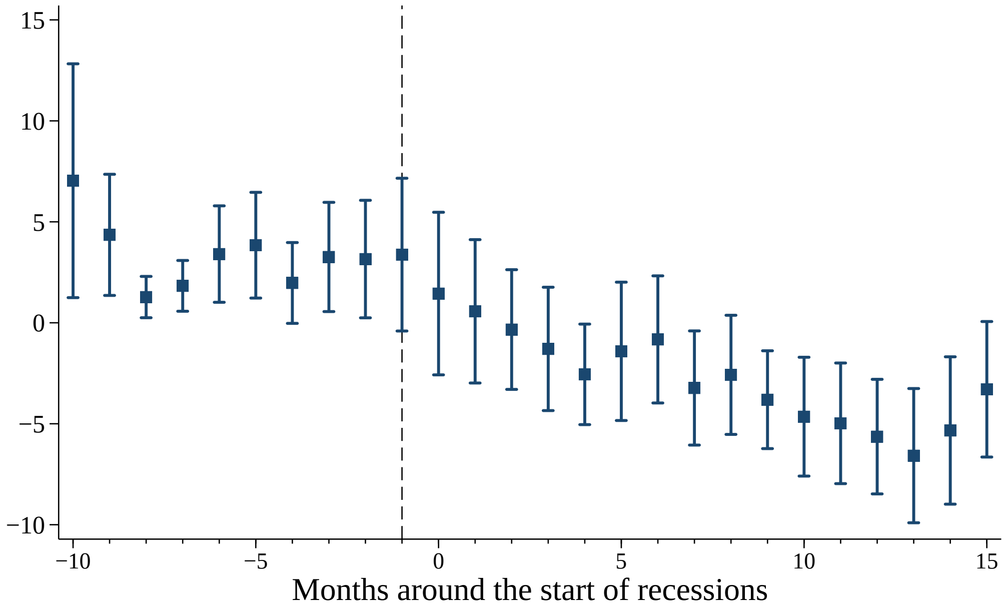


Figure 3: Recessions and returns to characteristics-based factor betas. This figure plots the one-year realized characteristics-based factor beta strategy returns around the onset of recessions. It shows the return for an investor who buys the average characteristics-based factor beta strategy m months relative to expecting to be in a recession and holds it for one year. 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. Recessions are identified ex-ante using the Gómez-Cram (2022) recession probability, which assumes that investors expect to be in a recession whenever the recession probability first 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.

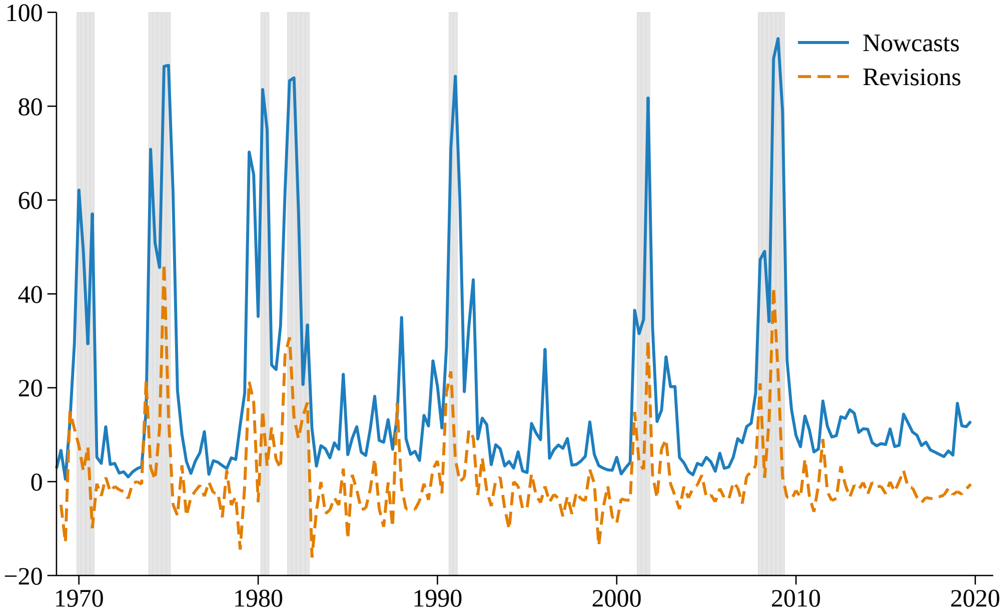


Figure 4: SPF recession probabilities. This figure plots the nowcasts for current-quarter recession probability ("Nowcasts") and revisions in one-quarter-ahead forecasts ("Revisions"). The recession probability forecast represents the expected probability (in percent) of a decline in the level of real 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. Survey expectations are also for the one-quarter-ahead horizon, taken from the SPF. 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).

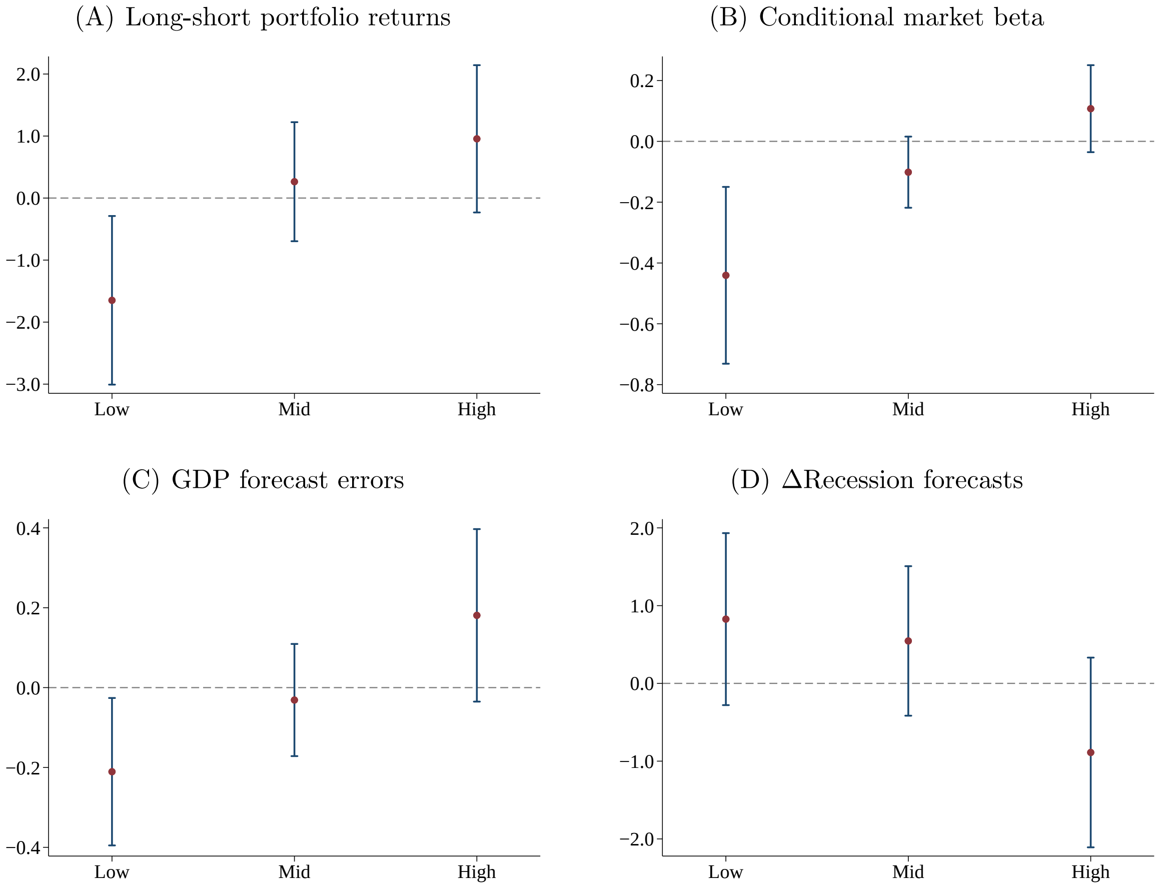


Figure 6: Sorts on expectation wedges. This figure sorts the wedges in machine learning and survey expectations of real GDP growth for quarter t (available in quarter $t-1$) into three buckets based on the wedge's 30th and 70th percentiles for the entire sample. For each bucket, the figure displays the 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.

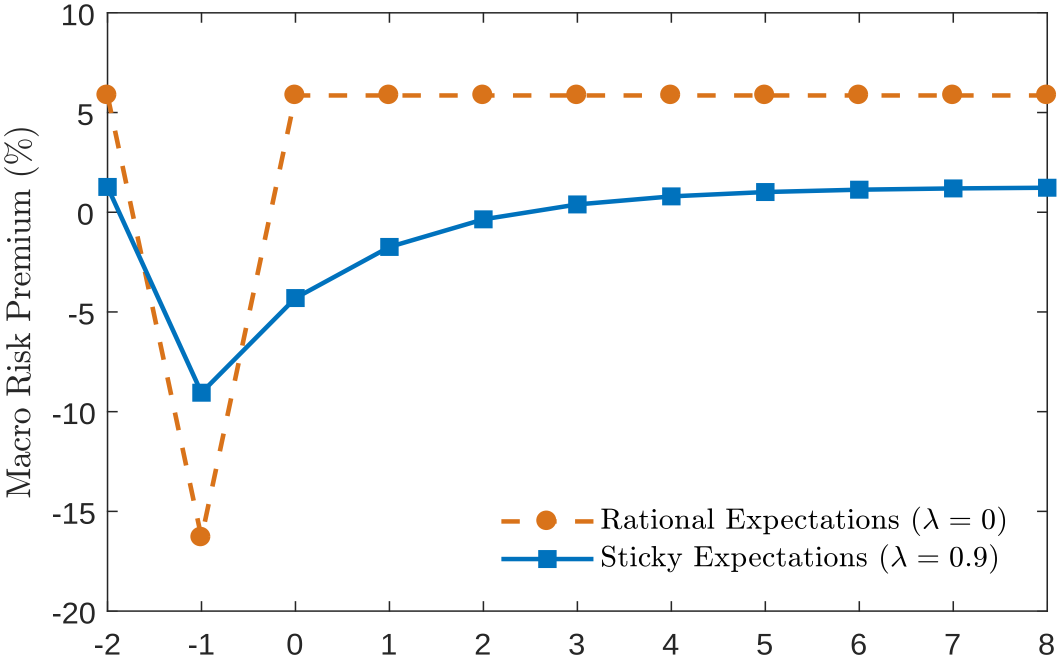


Figure 7: Impulse response to expected macro shocks. This figure plots the impulse response of the one-period log returns of long-short macro beta-sorted portfolios to expected macro variable shocks of one standard deviation ($-1 \times \sigma_z$) at time -1. The model is simulated using monthly decision intervals, and returns are expressed as annualized percentages (by multiplying monthly returns by 1,200). We report results under rational expectations, that is, $\lambda = 0$, and under sticky subjective expectations, $\lambda = 0.9$. We use the parameter values $\delta = 0.99$, $\psi = 2$, $\gamma = 15$, $\rho_z = 0.6$, $\rho_c = 0.5$, $\sigma_z = 0.015$, $\sigma_c = \sigma_H = \sigma_L = 0.002$, $\mu_c = \mu_z = \mu_H = \mu_L = 0.002$, $\rho_H = 0.6$, 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 of long-short macro beta-sorted portfolios to the market and common growth. The common growth is the first principal component of real GDP growth, TFP growth rate, consumption growth, labor income growth, and initial claims growth. The signs of DEF and VOL are inverted so that all 10 macro variables analyzed 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 expressed as annualized percentages by multiplying monthly returns by 1,200. The macro variables are standardized so that exposures represent the annualized return response to a one standard deviation change in the 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 is from January 1965 to December 2019. Newey-West six-lag adjusted *t*-statistics are in parentheses.

Panel A: Mean Excess Returns

CON (1)	TFP (2)	IPG (3)	TERM (4)	DEF (5)	UI (6)	DEI (7)	VOL (8)	MKT (9)	LAB (10)	Ave1 (11)	Ave2 (12)
-0.95	-1.35	1.59	0.47	-1.54	-1.15	-0.97	1.33	0.03	-2.75	-0.53	-0.40
(-0.49)	(-0.61)	(0.87)	(0.22)	(-0.67)	(-0.53)	(-0.50)	(0.52)	(0.01)	(-1.19)	(-0.39)	(-0.26)

Panel B: Post-Formation Beta

CON (1)	TFP (2)	IPG (3)	TERM (4)	DEF (5)	UI (6)	DEI (7)	VOL (8)	MKT (9)	LAB (10)
5.97	3.53	-2.09	4.85	4.73	4.48	7.09	8.76	51.56	1.53
(3.00)	(1.33)	(-1.24)	(2.44)	(1.79)	(1.61)	(2.63)	(1.23)	(12.20)	(0.98)

Panel C: Exposure to Market Factor

CON (1)	TFP (2)	IPG (3)	TERM (4)	DEF (5)	UI (6)	DEI (7)	VOL (8)	MKT (9)	LAB (10)	Ave1 (11)	Ave2 (12)
19.30	15.46	14.14	1.45	24.55	2.91	6.22	29.76	51.56	13.94	17.93	21.27
(6.91)	(5.57)	(4.65)	(0.42)	(6.29)	(0.67)	(1.73)	(6.45)	(12.20)	(2.66)	(6.97)	(8.31)

Panel D: Exposure to Common Growth

CON (1)	TFP (2)	IPG (3)	TERM (4)	DEF (5)	UI (6)	DEI (7)	VOL (8)	MKT (9)	LAB (10)	Ave1 (11)	Ave2 (12)
1.35	1.88	3.28	0.96	5.49	3.91	5.46	8.71	10.46	4.04	4.55	4.52
(0.63)	(0.76)	(1.72)	(0.45)	(2.05)	(1.48)	(2.41)	(2.72)	(2.86)	(1.44)	(2.95)	(2.58)

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 two 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 amount 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	0.97	0.50	0.83	-0.54	-0.43
Std. dev. returns	8.56	8.65	8.25	9.91	7.92
Sharpe ratio increase	0.17	0.11	0.16	–	–
α-FF5-TMom-TVol	1.77	1.85	2.01	0.94	0.75
	(1.82)	(1.83)	(2.05)	(0.91)	(0.91)

Panel B: Average Maximum Drawdown

Economic state	Rec. Prob. (1)	Ind. Prod. (2)	Term Prem. (3)	100% Factors (4)	80/20 Mix (5)
Total	29.09	27.08	24.25	43.73	37.16
Expansions	29.25	27.22	24.46	43.93	37.34
Recessions	27.35	25.63	22.11	41.73	35.35

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		
	$FR^{1}_{t\to t+1}$ (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)
$FR^{1,+}_{t-1\to t}$	0.46			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:

$$GDP_{t+1} = \alpha + \beta_P E_t^P[GDP_{t+1}] + \beta_S E_t^S[GDP_{t+1}] + \epsilon_{t+1},$$
$$FE\_GDP_{t+1} = \alpha + \beta \Delta_t + \delta FR_{t-1\rightarrow t}^1 + \epsilon_{t+1},$$

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, $E_t^P[GDP_{t+1}]$ fitted from 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. $FR_{t-1\rightarrow t}^1$ 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)
$FR_{t-1\rightarrow t}^1$		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 Wedges

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, $E_t^P[GDP_{t+1}]$ fitted from 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 (leverage) of He, Kelly, and Manela (2017), 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		1.38	
	(4.06)		(4.12)	
$E_t^P[GDP_{t+1}]$		1.10		1.37
		(2.85)		(2.76)
$E_t^S[GDP_{t+1}]$		-1.45		-1.69
		(-3.12)		(-4.45)
Surplus ratio$_t$			-0.72	-0.63
			(-1.42)	(-1.21)
Term spread$_t$			0.04	0.18
			(0.07)	(0.28)
Default premium$_t$			0.60	0.51
			(0.89)	(0.84)
Inflation$_t$			-1.11	-1.17
			(-2.37)	(-2.61)
Leverage$_t$			-0.24	-0.19
			(-0.33)	(-0.25)
Sentiment$_t$			-1.92	-1.95
			(-2.86)	(-3.01)
Dispersion$_t$			-0.57	-0.68
			(-1.02)	(-1.20)
Intercept	-0.10	-0.10	-0.09	-0.07
	(-0.23)	(-0.23)	(-0.24)	(-0.18)
Obs	170	170	170	170
R^2	0.04	0.04	0.15	0.15

Table 7: Predictive Power of the Expectation Wedges: 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, $E_t^P[GDP_{t+1}]$ fitted from 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 (leverage) of He, Kelly, and Manela (2017), 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		0.62	
	(2.82)		(2.50)	
$E_t^P[GDP_{t+1}]$		0.70		0.50
		(2.50)		(1.68)
$E_t^S[GDP_{t+1}]$		-0.88		-0.87
		(-2.00)		(-2.50)
Surplus ratio$_t$			0.66	0.74
			(1.67)	(1.92)
Term spread$_t$			0.09	0.23
			(0.32)	(0.69)
Default premium$_t$			0.29	0.20
			(0.67)	(0.53)
Inflation$_t$			-0.89	-0.96
			(-3.57)	(-3.83)
Leverage$_t$			-0.30	-0.26
			(-0.93)	(-0.80)
Sentiment$_t$			-0.49	-0.52
			(-1.22)	(-1.33)
Dispersion$_t$			0.36	0.26
			(0.96)	(0.70)
Intercept	0.28	0.28	0.30	0.32
	(0.70)	(0.69)	(0.96)	(1.04)
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 signals of the expectation wedge and the 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 model, 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 forecast 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	6.98	-0.41
	(3.38)	(2.90)	(-0.23)
α-Mkt	5.45	8.02	-3.84
	(3.67)	(2.61)	(-2.03)
α-FF5	4.62	3.63	0.78
	(2.66)	(2.14)	(0.49)
α-FF5-TMom-TVol	4.77	4.59	1.12
	(2.70)	(2.40)	(0.67)

Panel B: Average Maximum Drawdown

Economic state	Wedge (1)	Wedge + Sentiment (2)	100% Factors (3)
Total	16.56	9.72	44.13
Expansions	16.69	9.66	44.22
Recessions	15.05	10.46	43.11

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 premium, and the default yield 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	-5.27	0.17	0.15	0.49	0.44
	(-3.12)	(-2.67)	(3.76)	(3.03)	(3.71)	(3.46)
Surplus ratio$_t$		3.89		0.13		0.20
		(1.51)		(1.68)		(1.50)
Term spread$_t$		-6.95		0.26		0.53
		(-2.13)		(2.97)		(3.28)
Default premium$_t$		11.75		-0.15		-0.30
		(3.35)		(-1.50)		(-1.33)
Intercept	13.20	13.26	0.60	0.60	0.56	0.55
	(3.28)	(4.23)	(6.59)	(7.13)	(3.28)	(3.48)
Obs	204	203	204	203	204	203
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	-3.85	0.12	0.08	0.35	0.27
	(-2.82)	(-2.42)	(3.46)	(2.70)	(4.69)	(4.67)
Surplus ratio$_t$		2.91		0.11		0.17
		(1.30)		(1.54)		(1.38)
Term spread$_t$		-13.36		0.29		0.55
		(-5.40)		(4.46)		(4.33)
Default premium$_t$		5.95		0.01		0.07
		(2.39)		(0.15)		(0.40)
Intercept	13.40	13.80	0.60	0.59	0.56	0.54
	(3.49)	(4.72)	(6.98)	(7.52)	(3.54)	(3.70)
Obs	201	200	201	200	201	200
R^2	0.05	0.35	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:

$$FR^h_{t\rightarrow t+1} = \alpha + \beta f_t + \epsilon_{t,t+1},$$
$$FE^h_{t\rightarrow t+1} = \alpha + \beta f_t + \epsilon_{t,t+1},$$

where $h = 1, 2, 3$. $FR^h_{t\rightarrow t+1}$ is the forecast revision for the h-quarter-ahead macro variable, defined as the change in the forecast for quarter $t + h$ macro variable (i.e., $FR^h_{t\rightarrow t+1} = F_{t+1}(z_{t+h}) - F_t(z_{t+h})$). 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		
	$FR^1_{t\rightarrow t+1}$ (1)	$FR^2_{t\rightarrow t+1}$ (2)	$FR^3_{t\rightarrow t+1}$ (3)	$FE^1_{t\rightarrow t+1}$ (4)	$FE^2_{t\rightarrow t+1}$ (5)	$FE^3_{t\rightarrow t+1}$ (6)
Panel A: Recession Probability						
f_t	-2.81	-1.23	-0.51	-4.48	-3.61	-4.14
	(-5.21)	(-3.81)	(-1.96)	(-4.46)	(-2.66)	(-3.81)
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	0.60
	(5.35)	(5.16)	(5.18)	(5.10)	(2.67)	(4.99)
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	0.08
Panel C: Industrial Production Growth						
f_t	0.30	0.34	0.33	0.56	0.96	1.34
	(4.34)	(4.37)	(4.15)	(2.83)	(3.10)	(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”

In this document, we provide data descriptions and additional results not reported in the main text in Appendix A, and model derivations in Appendix B.

A Sample Construction and Additional Results

A.1 Macro Variable Construction

We describe the detailed 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 deflators 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 the Federal Reserve Bank of St. Louis’s (FRED) website;

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 data are from the 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 at month t. Then, the unexpected inflation is 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 the FRED;

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

9. **Market Excess Return (MKT).** The excess returns on the CSRP 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 machine learning real GDP growth forecasts below. We use a random forest methodology to generate forecasts of next-quarter real GDP growth in our main results. The hyperparameters (number of trees, maximum depth, minimum node size, and feature fraction) are chosen using cross-validation. Specifically, the training data include data from 1966Q4 to 1976Q3, and the cross-validation data include a single quarter, 1976Q4, whose forecast error for 1977Q1 becomes known in 1977Q2. The results are similar across other testing periods. We train the model using the training data for different configurations of the hyperparameters. We evaluate the results on the testing data and select the hyperparameters that yield the best performance. The model is then trained using rolling windows, keeping the hyperparameters chosen fixed.

Table A2 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/nonresidential fixed investment), inflation (e.g., the GDP deflator), and valuation (e.g., the S&P 500 index). We use the Philadelphia Fed's Real-Time Data Set to obtain vintages of macro variables, relying on the initially realized values released at 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 prepend missing residential/nonresidential fixed investment and initial jobless claims in the early part of the sample with 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 features data span from 1966Q2 to 2019Q4 (with the first two quarters used for lags). The real GDP forecasts generated from the random forest methodology span from 1977Q2 to 2019Q4.

A.3 Additional Results

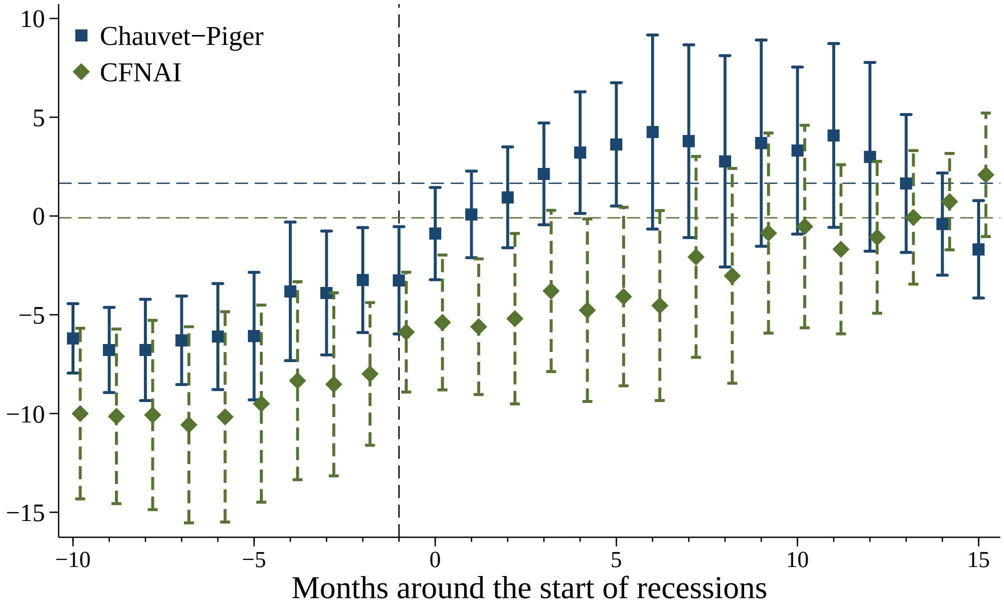
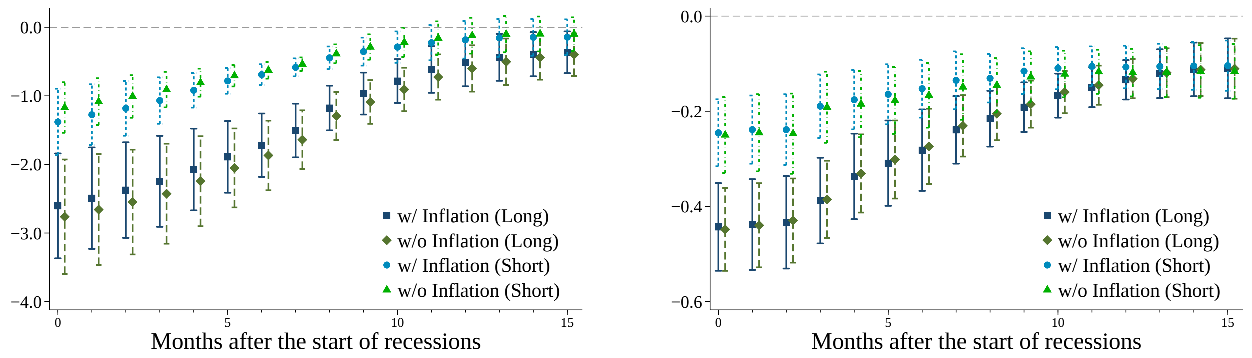
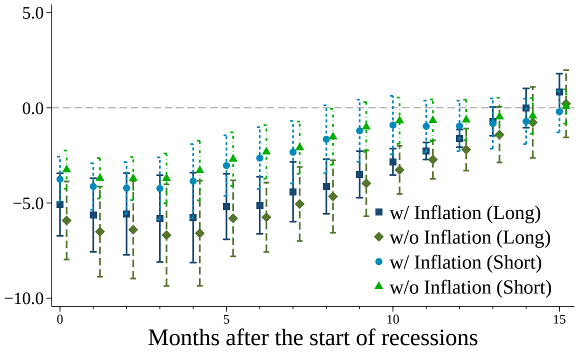


Figure A1: Alternative recession definitions. This figure plots one-year return spreads between cyclical and countercyclical firms around recession onsets under alternative definitions. It shows the percentage return for an investor who buys the average long-short portfolio based on macro betas m months relative to expecting to be in a recession and holds it for one year. The squares correspond to recessions, defined as periods when the Chauvet and Piger (2008) real-time recession probability exceeds 50%. Meanwhile, the diamonds correspond to recessions defined as periods when the Chicago Fed index falls 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.



(A) Forecast errors

(B) Forecast revisions



(C) ΔRatings (downgrades)

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 the average values aggregated at the portfolio level and multiplied by 100 for portfolios that are bought m months after expecting a recession and held for one year. Recessions are identified ex-ante using the Gómez-Cram (2022) recession probability, which assumes that investors expect to be in a recession whenever the recession probability first 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.

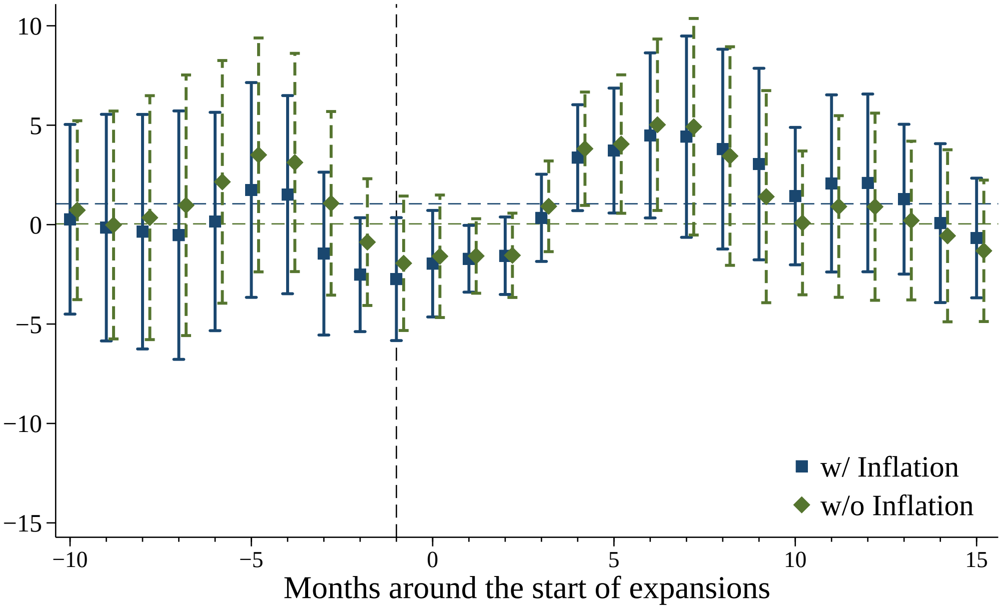


Figure A3: Expansions and one-year macro risk premia. This figure plots the one-year return spreads between cyclical and countercyclical firms around the onset of expansions. It shows the percentage return for an investor who buys the average long-short portfolio based on macro betas m months relative to expecting to be in an expansion and holds it for one year. Expansions are identified ex-ante using the Gómez-Cram (2022) recession probability, assuming that investors expect to be in an expansion whenever the recession probability first 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.

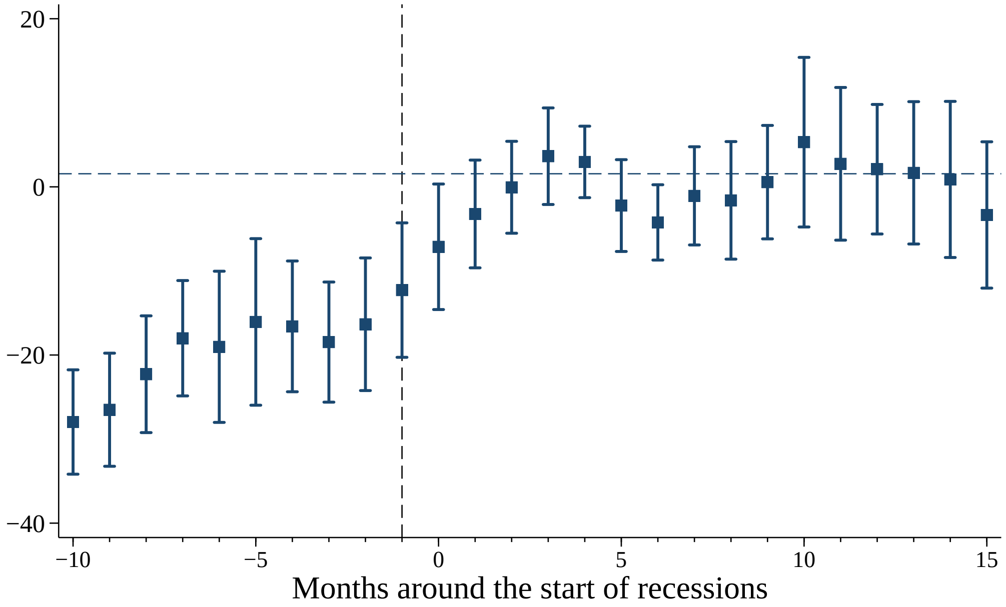


Figure A4: Recessions and volatility-sorted portfolio returns. This figure plots the one-year returns on long-short volatility-sorted portfolios around the onset of recessions. It shows the percentage return for an investor who buys the portfolio m months relative to expecting to be in a recession and holds it for one year. 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 using data from Kenneth R. French's website. Recessions are identified ex-ante using the Gómez-Cram (2022) recession probability, which assumes that investors expect to be in a recession whenever the recession probability first 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.

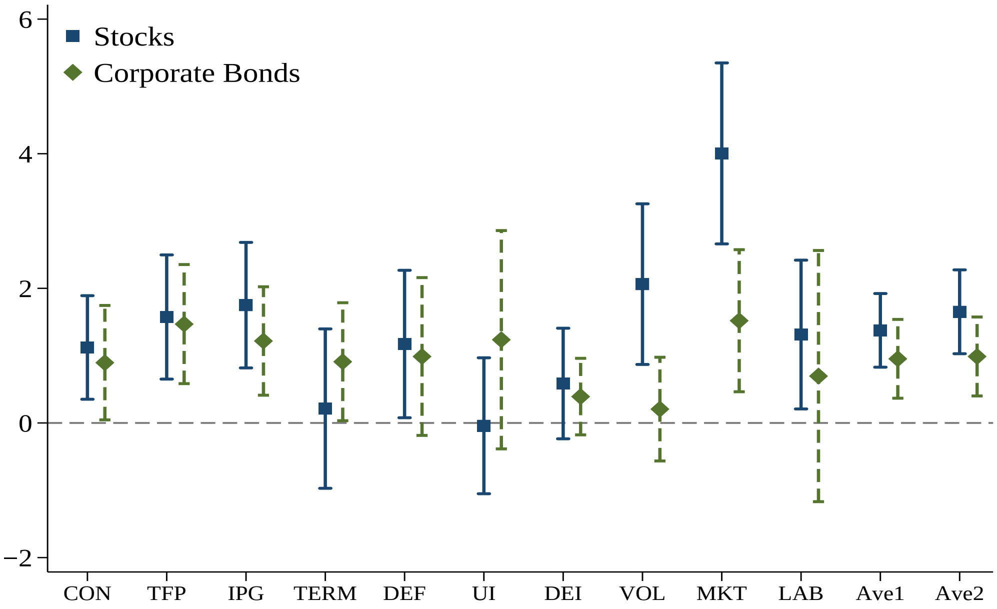


Figure A5: Effects on individual macro beta-sorted portfolios. This figure displays the regression coefficients β and their 90% confidence intervals from the specification in equation (4) for 10 individual long-short portfolios based on macro betas. Estimates are also reported for $Ave1$, a portfolio 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 to facilitate graphical illustration. The standard errors account for heteroskedasticity and autocorrelation in the residuals for up to six lags.

Table A1: 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 two 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 amount 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	0.80	0.43	1.05	-0.54	-0.50
Std. dev. returns	8.70	8.81	8.45	9.91	8.44
Sharpe ratio increase	0.15	0.11	0.18	–	–
α-FF5-TMom-TVol	1.36	1.82	2.55	0.94	0.78
	(1.39)	(1.83)	(2.65)	(0.91)	(0.89)

Panel B: Average Maximum Drawdown

Economic state	Rec. Prob. (1)	Ind. Prod. (2)	Term Prem. (3)	100% Factors (4)	85/15 Mix (5)
Total	28.62	27.98	25.00	43.73	38.89
Expansions	28.81	28.10	25.20	43.93	39.07
Recessions	26.65	26.75	22.98	41.73	37.02

Table A2: 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. The abbreviations are as follows: Philly Fed refers to the Federal Reserve Bank of Philadelphia, and Amit Goyal refers to the data from Welch and Goyal (2008) 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	Amit Goyal	2	Financial

Table A3: Predictive Power of the Expectation Wedges: 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, $E_t^P[GDP_{t+1}]$ fitted from 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 (leverage) of He, Kelly, and Manela (2017), 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		0.91	
	(3.09)		(2.51)	
$E_t^P[GDP_{t+1}]$		0.71		0.72
		(1.78)		(1.33)
$E_t^S[GDP_{t+1}]$		-1.24		-1.39
		(-2.74)		(-3.44)
Surplus ratio$_t$			-0.32	-0.21
			(-0.62)	(-0.42)
Term spread$_t$			0.04	0.29
			(0.07)	(0.45)
Default premium$_t$			0.50	0.39
			(0.66)	(0.60)
Inflation$_t$			-1.08	-1.20
			(-2.34)	(-2.81)
Leverage$_t$			-0.31	-0.20
			(-0.39)	(-0.25)
Sentiment$_t$			-2.13	-2.15
			(-3.14)	(-3.35)
Dispersion$_t$			-0.49	-0.69
			(-0.87)	(-1.22)
Intercept	-0.10	-0.10	0.03	0.05
	(-0.23)	(-0.23)	(0.07)	(0.13)
Obs	170	170	170	170
R^2	0.02	0.03	0.13	0.14

B 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 returns on the aggregate consumption claim (the wealth portfolio), $r_{c,t+1}$, and returns 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

$$\kappa_1 = \frac{e^{\overline{wc}}}{e^{\overline{wc}} + 1}, \tag{A5}$$

$$\kappa_0 = \ln\left(e^{\overline{wc}} + 1\right) - \frac{e^{\overline{wc}}}{e^{\overline{wc}} + 1}\overline{wc}, \tag{A6}$$

$$\kappa_{i,1} = \frac{e^{\overline{pd}}}{e^{\overline{pd}} + 1}, \tag{A7}$$

$$\kappa_{i,0} = \ln\left(e^{\overline{pd}} + 1\right) - \frac{e^{\overline{pd}}}{e^{\overline{pd}} + 1}\overline{pd}, \tag{A8}$$

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

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

$$m_{t+1} + r_{c,t+1} = \theta\left(\ln\delta + \kappa_0\right) + \theta\left(1 - \frac{1}{\psi}\right)\Delta c_{t+1} + \theta\left(\kappa_1 wc_{t+1} - wc_t\right). \tag{A9}$$

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

$$0 = E_t^S\left[m_{t+1} + r_{i,t+1}\right] + \frac{1}{2}\operatorname{Var}_t^S\left[m_{t+1} + r_{i,t+1}\right]. \tag{A10}$$

Plugging equation (A9) into (A10) with $i = c$, and evaluating the conditional means and variances, the Euler equation for the consumption claim ($i = c$) can be expressed as follows:

$$0 = C_0 + C_1 x_t, \tag{A11}$$

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

$$(x_t) : 0 = \left(1 - \frac{1}{\psi}\right) \rho_c \rho_z - A_1 \left(1 - \kappa_1 \rho_z\right) \tag{A12}$$

$$\begin{aligned}(const) : 0 = \frac{\theta^2}{2}\left(1 - \frac{1}{\psi}\right)^2 \sigma_c^2 - \frac{\theta}{\psi}\mu_c + \theta\left(\kappa_1 - 1\right) A_0 + \theta\left(\kappa_0 + \mu_c + \ln\delta\right) \\ + \frac{\theta^2}{2}\left((1 - \frac{1}{\psi})\rho_c + \kappa_1 A_1 (1 - \lambda)\right)^2 \sigma_z^2.\end{aligned} \tag{A13}$$

We solve for A_0 and A_1

$$A_1 = \left(1 - \frac{1}{\psi}\right) \frac{\rho_c \rho_z}{1 - \kappa_1 \rho_z} \tag{A14}$$

$$A_0 = \frac{\ln\delta + (1 - \frac{1}{\psi})\mu_c + \kappa_0 + \frac{\theta}{2}\left(1 - \frac{1}{\psi}\right)^2 \sigma_c^2 + \frac{\theta}{2}\left((1 - \frac{1}{\psi})\rho_c + \kappa_1 A_1 (1 - \lambda)\right)^2 \sigma_z^2}{1 - \kappa_1}. \tag{A15}$$

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 the A_i. 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

$$\begin{aligned}1 =& E_t^S[e^{m_{t+1} + r_{i,t+1}}] \\ =& E_t^S[e^{\theta \ln\delta - \frac{\theta}{\psi}\Delta c_{t+1} + (\theta - 1) r_{c,t+1} + r_{i,t+1}}].\end{aligned} \tag{A16}$$

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

$$0 = F_{i,0} + F_{i,1} x_t. \tag{A17}$$

Further simplifying, we can derive the following:

$$(x_t): 0 = \rho_i \rho_z - D_{i,1}\left(1-\kappa_{i,1}\rho_z\right) + (\theta-1)\left(\rho_c\rho_z + A_1\left(\kappa_1\rho_z - 1\right)\right) - \frac{\theta}{\psi}\rho_c\rho_z \tag{A18}$$

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

which yields

$$D_{i,1} = \frac{\rho_z\rho_i - \rho_z\rho_c/\psi}{1-\kappa_{i,1}\rho_z} \tag{A20}$$

$$\begin{aligned} D_{i,0} =& \frac{\theta\ln\delta - \gamma\mu_c + \kappa_{i,0} + \mu_i + (\theta-1)(\kappa_0 + (\kappa_1-1)A_0)}{1-\kappa_{i,1}} \\ &+ \frac{\frac{1}{2}\left(\kappa_{i,1}(1-\lambda)D_{i,1} + \rho_i + \kappa_1(1-\lambda)(\theta-1)A_1 - \gamma\rho_c\right)^2\sigma_z^2 + \frac{1}{2}(\sigma_i-\gamma\sigma_c)^2}{1-\kappa_{i,1}}. \end{aligned} \tag{A21}$$

B.3 Conditional Pricing

We first investigate the dynamics of the stochastic discount factor (SDF). Specifically, substituting the equilibrium return for $r_{c,t+1}$ from equation (A3) into equation (8) implies that the innovation to the SDF is as follows:

$$m_{t+1} - E_t^S(m_{t+1}) = (\kappa_1(1-\lambda)(\theta-1)A_1 - \gamma\rho_c)\sigma_z u_{t+1} - \gamma\sigma_c\eta_{t+1}. \tag{A22}$$

This equation provides the economic intuition for why sticky beliefs distort the price of macro risk under subjective expectations. The perceived innovations of the macro variable u enter into the SDF, where favorable news about the expected future macro variable increases the value of wealth and decreases marginal utility when investors prefer early resolution of uncertainty ($\gamma > 1/\psi$). With these preference parameters, a higher λ indicates that macro shocks u have a weaker effect on the wealth-consumption ratio and hence on marginal utility. As we see below, the representative investor perceives a negative but weaker covariance between future macro shocks and marginal utility, producing a lower price of macro risk under subjective expectations than under full-information rational expectations.

The risk-free rate is given by

$$\begin{aligned} e^{-r_{f,t}} =& E_t^S\left[M_{t+1}\right] \\ =& \delta^\theta E_t^S\left[e^{-\gamma\Delta c_{t+1}+(\theta-1)(\kappa_0+\kappa_1 wc_{t+1}-wc_t)}\right] \\ =& \delta^\theta e^{-\gamma\mu_c+(\theta-1)(\kappa_0+(\kappa_1-1)A_0)+\frac{1}{2}(\kappa_1(\theta-1)(1-\lambda)A_1-\gamma\rho_c)^2\sigma_z^2+\frac{1}{2}\gamma^2\sigma_c^2} \\ & \times e^{-\frac{1}{\psi}\rho_z\rho_c x_t}. \end{aligned} \tag{A23}$$

Thus, we can derive the risk-free rate:

$$\begin{aligned} r_{f,t} =& -\theta\ln\delta+\gamma\mu_c-(\theta-1)\left(\kappa_0+(\kappa_1-1)A_0\right) \\ & -\frac{1}{2}\left(\kappa_1(\theta-1)(1-\lambda)A_1-\gamma\rho_c\right)^2\sigma_z^2-\frac{1}{2}\gamma^2\sigma_c^2+\frac{1}{\psi}\rho_z\rho_c x_t. \end{aligned} \tag{A24}$$

The prices of risk for u and η are

$$\begin{aligned} \lambda_u &\equiv -\frac{\mathrm{Cov}_t^S(m_{t+1},u_{t+1})}{\mathrm{Var}_t^S(u_{t+1})} \\ &= \gamma\rho_c\sigma_z-\kappa_1(\theta-1)(1-\lambda)A_1\sigma_z \\ &= \rho_c\sigma_z\left(\gamma+(1-\lambda)\kappa_1\rho_z\frac{\gamma-1/\psi}{1-\kappa_1\rho_z}\right), \end{aligned} \tag{A25}$$

$$\lambda_\eta \equiv -\frac{\mathrm{Cov}_t^S(m_{t+1},\eta_{t+1})}{\mathrm{Var}_t^S(\eta_{t+1})} = \gamma\sigma_c, \tag{A26}$$

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

$$\begin{aligned} \beta_{u,i} &\equiv \frac{\mathrm{Cov}_t^S\left(u_{t+1},r_{i,t+1}\right)}{\mathrm{Var}_t^S\left(u_{t+1}\right)} \\ &= \rho_i\sigma_z+(1-\lambda)\kappa_{i,1}D_{i,1}\sigma_z \\ &= \sigma_z\left(\rho_i+(1-\lambda)\kappa_{i,1}\rho_z\frac{\rho_i-\rho_c/\psi}{1-\kappa_{i,1}\rho_z}\right) \end{aligned} \tag{A27}$$

$$\beta_{\eta,i} \equiv \frac{\mathrm{Cov}_t^S\left(\eta_{t+1},r_{i,t+1}\right)}{\mathrm{Var}_t^S\left(\eta_{t+1}\right)} = \sigma_i. \tag{A28}$$

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

$$\begin{aligned} E_t^S[r_{i,t+1}] &= E_t^S[\kappa_{i,0}+\kappa_{i,1}pd_{i,t+1}-pd_{i,t}+\Delta d_{i,t+1}] \\ &= \kappa_{i,0}+\mu_i+D_{i,0}(\kappa_{i,1}-1)+\frac{1}{\psi}\rho_z\rho_c x_t. \end{aligned} \tag{A29}$$

Using equations (A21), (A24), and (A29), the expected excess returns for asset i can then be written as follows:

$$\begin{aligned}E_t^S[r_{i,t+1} - r_{f,t}] =&\kappa_{i,0} + \mu_i + D_{i,0}(\kappa_{i,1} - 1) + \theta \ln \delta - \gamma \mu_c + (\theta - 1)\left(\kappa_0 + (\kappa_1 - 1)A_0\right) \\ &+ \frac{1}{2}\left(\kappa_1(\theta - 1)(1 - \lambda)A_1 - \gamma\rho_c\right)^2 \sigma_z^2 + \frac{1}{2}\gamma^2\sigma_c^2 \\ =&\lambda_u \beta_{u,i} + \lambda_\eta \beta_{\eta,i} - \frac{1}{2}\beta_{u,i}^2 - \frac{1}{2}\beta_{\eta,i}^2. \end{aligned} \tag{A30}$$

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:

$$r_{i,t+1} - r_{f,t} = E_t^S[r_{i,t+1} - r_{f,t}] + \frac{\beta_{u,i}}{\sigma_z}\left(\rho_z(z_t - \mu_z) - \rho_z x_t\right) + \beta_{u,i} u_{t+1} + \beta_{\eta,i}\eta_{t+1}. \tag{A31}$$

B.4 Macro Risk Premium

(i) Conditional Premium

Our study focuses on the conditional variations in the macro risk premium. To derive the macro risk premium implied from the cross-section of stocks, we model two assets that represent the High (H) and Low (L) macro beta portfolios from our empirical analysis. Without loss of generality, we assume that the two stocks have the same consumption growth beta (i.e., $\beta_{\eta,H} = \beta_{\eta,L}$). Hence, the return spread between the two stocks purely reflects the macro risk of u. 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:

$$\begin{aligned}\beta_{u,HL} &= \frac{\text{Cov}_t^S\left(u_{t+1}, r_{H,t+1}\right)}{\text{Var}_t^S\left(u_{t+1}\right)} - \frac{\text{Cov}_t^S\left(u_{t+1}, r_{L,t+1}\right)}{\text{Var}_t^S\left(u_{t+1}\right)} \\ &= \left((\rho_H - \rho_L) + (1 - \lambda)(\kappa_{H,1}D_{H,1} - \kappa_{L,1}D_{L,1})\right)\sigma_z. \end{aligned} \tag{A32}$$

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 (A31), we can derive the process for macro risk premia as a function of subjective macro risk premia, predictable belief errors, and macro shocks:

$$r_{H,t+1} - r_{L,t+1} = \lambda_u \beta_{u,HL} - \frac{1}{2}\beta_{u,H}^2 + \frac{1}{2}\beta_{u,L}^2 + \frac{\beta_{u,HL}}{\sigma_z}\left(\rho_z(z_t - \mu_z) - \rho_z x_t\right) + \beta_{u,HL} u_{t+1}. \tag{A33}$$

This equation implies that sticky expectations can lead to the predictability of macro risk premia from the econometrician's perspective. This is immediately evident by rewriting the macro risk premium under objective expectations as follows:

$$\begin{aligned} E_t^P[r_{H,t+1} - r_{L,t+1}] &= E_t^S[r_{H,t+1} - r_{L,t+1}] + \frac{\beta_{u,HL}}{\sigma_z}\left(E_t^P[z_{t+1}] - E_t^S[z_{t+1}]\right) \\ &= E_t^S[r_{H,t+1} - r_{L,t+1}] + \frac{\beta_{u,HL}}{\sigma_z}\left(\rho_z(z_t - \mu_z) - \rho_z x_t\right), \end{aligned} \tag{A34}$$

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 (A34) gives the unconditional macro risk premia:

$$E^P[r_{H,t} - r_{L,t}] = E^S[r_{H,t} - r_{L,t}] = \lambda_u \beta_{u,HL} - \frac{1}{2}\beta_{u,H}^2 + \frac{1}{2}\beta_{u,L}^2. \tag{A35}$$

where the superscripts P and S denote objective and subjective expectations, respectively. The first equality in equation (A35) relies on the fact that, on average, misperceptions of the macro variable z cancel out when computing the unconditional macro risk premium. This equation reconciles the weakened macro risk premium in the cross-section of assets observed in the data. Note from equation (A1) that the representative investor with sticky beliefs underestimates the impact of macro shocks u 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 decrease more than subjective expectations suggest, while marginal utility should increase more than subjective expectations suggest. 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 a negative but weaker covariance between future macro shocks and marginal utility, reducing the required compensation for bearing macro risk and hence the price of macro risk than under 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. Consequently, the model also implies a reduced compensation for bearing macro risk and hence a lower price of macro risk under objective expectations than under FIRE. As shown in equation (A25), the price of macro risk λ_u decreases with the expectation stickiness parameter λ under the standard preference parameters $(\gamma, \psi > 1)$. Therefore, sticky expectations weaken the cross-sectional risk-return trade-off, leading to an overall flatter relation between macro betas and expected returns relative to FIRE.