What can we learn about the equity premium from professional forecasts? [†]

Yizhe Deng[a] Yunqi Wang[b] Ti Zhou[*]

December 2022

[†]We would like especially thank Jonas Eriksen and Jun Tu, whose comments greatly improved the paper. We also thank Jian Chen, Dashan Huang, Difang Huang, Gang Li, Kai Li, Weikai Li, Wolfgang Schadner, Guohao Tang, Yang You, Chu Zhang, Ran Zhang, Shen Zhao, Guofu Zhou, Hao Zhou, and participants at Tianjin University, Xiamen University, the 2020 China International Risk Forum, the 18th International Symposium on Financial System Engineering and Risk Management, the Fourth China Finance Scholar Forum, the 2021 NFA Conference, the 2021 FMA Annual Meeting, the 2021 CUHK-Shenzhen Five-Star Workshop, the 2022 Asian Meeting of the Econometric Society in China, and the 2022 AsianFA Annual Meeting for their helpful comments and suggestions. All remaining errors are ours.

[a]China Investment Corporation Research Institute, Beijing, China. E-mail address: dengyz@china-inv.cn.

[b]School of Business, Southern University of Science and Technology, Shenzhen, China. E-mail address: wangyq2019@mail.sustech.edu.cn.

[*]Corresponding author: School of Business, Southern University of Science and Technology, No. 1088 Xueyuan Rd., Shenzhen 518055, China. Tel.: +86-755-88018610. E-mail address: zhout@sustech.edu.cn.

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Abstract

Using macroeconomic forecasts by professional economists, we construct a comprehensive macro condition index that summarizes subjective expectations of output, inflation, labor and housing market conditions. The index varies strongly over business cycles and significantly predicts stock returns both in and out of sample. Through the comparison with realized macroeconomic variables, we demonstrate that our index primarily reflects the true yet unobserved macroeconomic condition that matters for the equity premium. Further analysis shows that the predictability is not driven by survey forecast biases and is mainly from a discount rate channel. Consequently, the predictive power of the index comes from investor's rational response to the changing macroeconomic condition. Overall, our findings portray a tight relation between the equity premium and broad aspects of the macroeconomy, suggesting that multiple state variables, especially those related to labor and housing market conditions, are at work empirically.

***JEL classification*: C53; G11; G12; G17**

***Keywords*: Macroeconomic forecasts, professional forecaster, return predictability, term structure, discount rate**

1 Introduction

Expectations are key to asset pricing in that investors price assets based on their beliefs. This in turn suggests that we are expected to learn about the future return from present beliefs. Nonetheless, the literature has indicated a notable discrepancy between subjective expectations and objective expectations (Bordalo, Gennaioli, Ma, and Shleifer, 2020; Koijen, Schmeling, and Vrugt, 2015; Nagel and Xu, 2022). Perhaps the most puzzling finding is that survey expectations of stock returns do not correlate strongly (or even positively) with objective expectations (Amromin and Sharpe, 2014; Greenwood and Shleifer, 2014). Indeed, investors' return expectations are found to vary procyclically, which contradicts the countercyclical equity premium variation implied by a host of equilibrium asset pricing models (Bansal and Yaron, 2004; Campbell and Cochrane, 1999; Piazzesi, Schneider, and Tuzel, 2007). So, is it true that survey forecasts barely tell anything about the equity premium that accords with theoretical expectations?

Not really. In this paper, instead of aiming to reconcile the disconnect between survey expectations of returns and objective expectations, we explore the information content of survey forecasts on macroeconomic conditions for the equity premium. We show that professional forecasts on several aspects of the macroeconomy collectively provide a certain amount of information about the equity premium and the uncovered return predictability is congruous with the common implication of equilibrium models. Specifically, we use the macroeconomic forecast from the Survey of Professional Forecasters (SPF), which has a long history stretching back to 1968 and a broad coverage on macroeconomic fundamentals. We collect the consensus current-quarter forecasts (i.e., "nowcasts") of seven key macro variables with the longest records since the initiation of the SPF, including forecasts on the real gross domestic product (GDP), industrial production, recession probability, unemployment rate, corporate profits, housing starts, and inflation. We apply the partial least squares (PLS) approach (Kelly and Pruitt, 2013, 2015; Wold, 1966) to condense these forecasts into a single factor that tracks the equity premium, which we refer to as the *macro condition index* (M^{PLS}). The index loads positively on unemployment and housing starts forecasts, and negatively on output-related variables forecasts, such as the GDP and industrial production growth forecasts. Empirically, M^{PLS} features a countercyclical pattern, implying that an increase in M^{PLS} represents a deterioration in expected macroeconomic conditions.

We show that M^{PLS} positively and significantly predicts the quarterly market excess return from 1969 to 2019. Specifically, a one-standard-deviation increase in M^{PLS} signals a 8.3% increase in the next-quarter annualized return, which is economically sizable. The regression R^2 of M^{PLS} is 5.75%. By contrast, most of the individual SPF forecasts evince insignificant predictive power with R^2 values below 3%. The strong predictability of M^{PLS} thus highlights the efficacy of PLS in dimension reduction. In addition, M^{PLS} subsumes the predictability of popular predictors and time-varying risk premium proxies, such as the consumption–wealth ratio (Lettau and Ludvigson, 2001). The positive predictive power of M^{PLS} is consistent with a multitude of equilibrium models in which the equity premium varies countercyclically. Our results also imply that expected returns are high when the aggregate output growth is expected to be low or when the unemployment rate or housing starts growth is expected to be high. In the out-of-sample (OOS) test, M^{PLS} substantially outperforms the historical mean forecast (Welch and Goyal, 2008) with a significant OOS R^2 value (Campbell and Thompson, 2008) of 3.12% from 1984 to 2019. This reveals that the relation between M^{PLS} and expected returns is stable.

We also study the return predictability over long horizons and show that $\mathrm{M}^{\mathrm{PLS}}$ significantly predicts market excess returns up to three years ahead both in- and OOS, suggesting that the expected current macroeconomic condition has a persistent impact on the equity premium. Besides, in a similar manner as $\mathrm{M}^{\mathrm{PLS}}$, we construct a *long-term macro condition index* LT-$\mathrm{M}^{\mathrm{PLS}}$ based on the term structure of SPF forecasts covering one to three quarters ahead. In comparison with $\mathrm{M}^{\mathrm{PLS}}$, LT-$\mathrm{M}^{\mathrm{PLS}}$ underperforms at the quarterly forecast horizon, while it exhibits more prominent forecasting ability and provides a significant amount of incremental information to $\mathrm{M}^{\mathrm{PLS}}$ at longer horizons. By construction, LT-$\mathrm{M}^{\mathrm{PLS}}$ contains information about the expected long-term macroeconomic condition and business cycle duration, which is largely absent from $\mathrm{M}^{\mathrm{PLS}}$. We note that LT-$\mathrm{M}^{\mathrm{PLS}}$ loads more on unemployment and output-related variables forecasts while less on housing starts forecasts relative to $\mathrm{M}^{\mathrm{PLS}}$. Therefore, our finding reveals that expectations about long-term macroeconomic conditions, especially those related to the output growth and the labor market condition, are of particular importance in explaining the long-term equity premium variation. Furthermore, we note that LT-$\mathrm{M}^{\mathrm{PLS}}$ is more persistent than $\mathrm{M}^{\mathrm{PLS}}$ with an autocorrelation coefficient of 0.91, implying that the long-term equity premium has significant low-frequency movement.

What is the economic driving force underlying the predictive power of $\mathrm{M}^{\mathrm{PLS}}$? A number of studies document that the subjective belief from survey data contain biases (Bordalo et al., 2020; Coibion and Gorodnichenko, 2015), while belief biases could generate return predictability (Alti and Tetlock, 2014; De La O and Myers, 2021). In particular, using survey forecasts of dividend growth and returns of the S&P 500 index, De La O and Myers (2021) argue for the importance of misspecified beliefs about future cash flows as a key driver of the aggregate expected return. Therefore, we first address an essential question that whether the subjective expectation errors in the SPF projections drive the predictive power of $\mathrm{M}^{\mathrm{PLS}}$.

We demonstrate that the predictability of $\mathrm{M}^{\mathrm{PLS}}$ remains intact after controlling for the ex-post SPF forecast error that proxies for the unobserved belief bias. This suggests that the forecaster bias is unlikely to be the primary driver of the predictive power of $\mathrm{M}^{\mathrm{PLS}}$.

To glean further insight into the predictive power of $\mathrm{M}^{\mathrm{PLS}}$, we construct a macro condition index using the realized values of the current-quarter macroeconomic variables, which serves as the objective counterpart to $\mathrm{M}^{\mathrm{PLS}}$. We find that the objective macro condition index and $\mathrm{M}^{\mathrm{PLS}}$ exhibit comparably predictive ability and their information content is almost identical. Nevertheless, due to publication lags in macroeconomic data, this objective index is unattainable in real time. Alternatively, we construct an attainable objective macro condition index using the one-quarter-lagged macroeconomic data. This time the predictability of the lagged objective index is subsumed by $\mathrm{M}^{\mathrm{PLS}}$. These pieces of evidence point to the notion that $\mathrm{M}^{\mathrm{PLS}}$ fundamentally reflects the "true yet unobserved" macroeconomic condition that matters for the equity premium. Thus, our finding suggests that the SPF consensus forecasts are forward-looking and $\mathrm{M}^{\mathrm{PLS}}$ predicts the market return through the natural link between economic conditions and the equity premium (Cochrane, 2008; Fama and French, 1989).

As we mentioned, the macro condition index $\mathrm{M}^{\mathrm{PLS}}$ exhibits countercyclical dynamics. Consistent with this feature, we find that $\mathrm{M}^{\mathrm{PLS}}$ produces countercyclical equity premium forecasts and its forecasting performance is inversely related to business cycles: the forecasting gain relative to the historical mean is particularly large during economic downturns. Besides, we show that $\mathrm{M}^{\mathrm{PLS}}$ displays stronger predictive power for small firms and cyclical industries, whose risk premia are known to exhibit greater cyclicality (Gomes, Kogan, and Yogo, 2009; Perez-Quiros and Timmermann, 2000), than for large firms and defensive industries. These results indicate that M^{PLS} tracks the variation in the equity premium related to business cycle frequency fluctuations. Moreover, we find that M^{PLS} significantly predicts the market reaction to unexpected changes in the Federal funds rate. Since this reaction is largely attributed to changes in the risk premium (Bernanke and Kuttner, 2005), M^{PLS} conveys important information about discount rates. Additional evidence from a return decomposition analysis illustrates that the incremental predictive power of M^{PLS} relative to conventional economic predictors stems from the discount rate channel.

We stress that our macro condition index primarily reflects the labor and housing market conditions that are closely tied to the equity premium variation according to asset pricing theory. First, Q-theory–based production models with adjustment costs posit that the time variation of the aggregate risk premium affects current and future labor hiring and investment decisions (Chen and Zhang, 2011; Cochrane, 1991; Hall, 2017; Lettau and Ludvigson, 2002; Møller and Priestley, 2021); the expected labor and housing market conditions, in turn, should provide information about the equity premium today. Second, consumption-based models with time-varying composition risks predict that the equity premium varies with labor and housing market conditions even in the absence of changing cash flow risks.[1] All the above models suggest that the stock market and labor and housing markets are linked through time-varying discount rates, and hence provide rationale that M^{PLS} predicts the return primarily from the discount rate channel rather than the cash flow channel.

We also compare M^{PLS} to other economically motivated macroeconomic variables, such

[1]For instance, Santos and Veronesi (2006) predict the equity premium rises when the share of labor income to consumption falls because equities are riskier in the sense that their payoffs are more correlated with aggregate consumption. In the housing consumption model of Piazzesi et al. (2007) with nonseparable utility over housing and nonhousing consumption, the marginal utility of investors increases and becomes more volatile in severe recessions when the expenditure share of housing drops, giving rise to a higher equity premium. The incomplete market model of Lustig and Van Nieuwerburgh (2005) with housing collateral posits that a decrease in house prices reduces the collateral value of housing and increases the equity premium.

as the price–output ratio (Rangvid, 2006), the ratio of labor income to consumption (Santos and Veronesi, 2006), the ratio of non-housing consumption to total consumption (Piazzesi et al., 2007), the output gap (Cooper and Priestley, 2009), payroll growth (Chen and Zhang, 2011), and cyclical consumption (Atanasov, Møller, and Priestley, 2020). The index $\mathrm{M}^{\mathrm{PLS}}$ retains predictive power after conditioning on these macro variables and even subsumes their predictability. Cochrane (2017) emphasizes the importance of exploring multiple state variables beyond a single one in standard macro-finance models in explaining the time variation of the expected market return. Since our macro condition index incorporates output-related information as well as information about the labor and housing markets, it appears a more comprehensive macroeconomic condition measure that better tracks the equity premium than those standalone indicators which reflect a specific aspect of the macroeconomy. Furthermore, we document insignificant relations between $\mathrm{M}^{\mathrm{PLS}}$ and measures of investor sentiment and disagreement proposed by the literature (Baker and Wurgler, 2006; Huang, Jiang, Tu, and Zhou, 2015; Huang, Li, and Wang, 2021), and the information embodied in $\mathrm{M}^{\mathrm{PLS}}$ is essentially orthogonal to that in the sentiment and disagreement measures. Thus, it is unlikely that $\mathrm{M}^{\mathrm{PLS}}$ predicts returns through the sentiment or disagreement channel, further reinforcing our risk-based explanation.

We conduct a series of tests to verify the robustness of our findings. The standard inferences for predictive regression coefficients are subject to small-sample bias when regressors are persistent and endogenous (Stambaugh, 1999). Besides, the ordinary least squares (OLS) t-statistic is inflated when return observations are overlapping. To address these issues, we employ a wild bootstrap procedure, the Hodrick-corrected t-statistic (Hodrick, 1992), and the IVX methodology of Kostakis, Magdalinos, and Stamatogiannis (2015) to verify our statistical inference for $\mathrm{M}^{\mathrm{PLS}}$. Moreover, we show that the strong predictive power of $\mathrm{M}^{\mathrm{PLS}}$ is not confined to a particular sample period, is robust to the logarithmic excess return, extends to characteristic equity portfolios, and can be generalized to European equity markets using the SPF data from the European Central Bank. These results greatly alleviate the concern of data snooping biases. Through a commonly used asset allocation framework (Campbell and Thompson, 2008; Cooper and Priestley, 2009), we show that the OOS predictability of M^{PLS} can generate sizable economic gains for investors in real time.

Our paper contributes to the debate about the information content of survey data. Particularly, we show that subjective expectations of the underlying macroeconomic condition are informative about the equity premium. Different from existing studies showing that belief biases in survey forecasts generate return predictability, we demonstrate that the SPF consensus forecasts predict the market through investor's rational response to the changing macroeconomic condition. The forecasted expected return by M^{PLS} is countercyclical in- and OOS, consistent with most asset pricing theory and making a contrast to the finding of Nagel and Xu (2022) and Greenwood and Shleifer (2014), among others. Thus, our results imply that professional forecasters are generally more sophisticated and well-trained than other sources of survey respondent and their forecasts convey important information that helps to understand the equity premium variation.

Our paper also complements the literature studying return predictability based on macroeconomic variables. We take a novel perspective by using survey forecasts on macroeconomic variables, which allows us to bypass the publication lag and data revision issues associated with standard macroeconomic data.[2] Importantly, our macro condition index essentially reflects the underlying macroeconomic condition which is not yet observed in the realized

[2] Ghysels, Horan, and Moench (2018) find that the out-of-sample predictive power of macroeconomic variables on Treasury bond returns is substantially weakened when vintage macroeconomic data rather than final revised data are used.

data. Accordingly, our approach examines the relation between economic conditions and the equity premium in a more timely manner than using conventional macroeconomic variables.

We are not the first paper to explore the stock return predictability using survey-based forecasts of macroeconomic fundamentals (e.g., Campbell and Diebold, 2009; Colacito, Ghysels, Meng, and Siwasarit, 2016).[3] We are, however, the first paper to reveal a tight link between the expected return and broad aspects of the macroeconomy using survey data. More importantly, our finding is not contaminated by the potentially existed belief biases in survey forecasts, and suggests that multiple state variable risks, especially those related to labor and housing market conditions, are at work empirically. Additionally, we illustrate the unique information contained in the term structure of SPF forecasts and highlight the significance of expected long-term macroeconomic condition in explaining the long-term equity premium variation. All these findings have important implications for future asset pricing research.

The remainder of the paper proceeds as follows. Section 2 describes the data and the construction of the macro condition index. Section 3 reports the equity premium forecasting results. Section 4 explores the sources of the predictability. Section 5 provides some extension results and robustness checks. Section 6 concludes the paper.

2 Data and the Macro Condition Index

In this section, we introduce the SPF macroeconomic forecast data and describe the econometric methods for constructing the macro condition index.

[3] In addition, Eriksen (2017) finds a strong relation between expected economic conditions and bond risk premia using SPF survey data.

2.1 SPF Macro Variables Forecasts

The macro forecast data used to construct the macro condition index are obtained from the SPF, one of the oldest macroeconomic surveys in the United States. The data are quarterly, spanning from the fourth quarter of 1968 (1968Q4) to the fourth quarter of 2019 (2019Q4), and are available from the Federal Reserve Bank of Philadelphia (`https://www.philadelphiafed.org/surveys-and-data`). Unlike the realized macroeconomic data that are published with lags, the SPF forecasts are publicly available in real time. Moreover, they are proven to be forward-looking and informative. For instance, the SPF inflation forecasts lead the consumers' forecasts of the University of Michigan Surveys of Consumers (Carroll, 2003) and well forecast realized inflations (Ang, Bekaert, and Wei, 2007). We collect the forecasts on the following seven macro variables, which have the longest records since the initiation of the SPF:

- The growth rate for the chain-weighted real GDP (hereafter GDP_e)
- The growth rate for the industrial production index (Indprod_e)
- The probability of the chain-weighted real GDP level falling below the level of the preceding quarter (Recess_e)
- The civilian unemployment rate (Unemp_e)
- The growth rate for quarterly nominal corporate profits after tax (Cprof_e)
- The growth rate for housing starts (Housing_e)
- The growth rate for the chain-weighted GDP price index (Infl_e)[4]

[4]According to the SPF, professional forecasters are able to access the Bureau of Economic Analysis's advance estimates about historical quarters when they receive the questionnaires. The forecasts are typically released at the end of the middle month of each quarter. Nonetheless, due to a few exceptions with delayed releases, we carefully treat all surveys as available only at the end of each quarter, following Huang et al. (2021). Besides the seven variables we use, the SPF covers a few other macro variables, such as nonfarm

For each macro variable, the survey provides a so-called *nowcast* for the current quarter and *forecasts* over horizons ranging from one to four quarters ahead. We denote the dataset comprising only nowcasts on the seven macro variables as SPF7. In addition, we denote the dataset comprising the term structure of forecasts on the seven macro variables from one quarter up to three quarters ahead as SPF7TS.[5]

The SPF forecasts for the real GDP, industrial production, corporate profits, housing starts, and the GDP price index (i.e., inflation) appear in the form of annualized *quarter-over-quarter* growth rate forecasts, defined as

$$\tilde{y}_{i,t+j|t} = 100 \times \left[\left(\frac{\tilde{Y}_{i,t+j|t}}{\tilde{Y}_{i,t+j-1|t}} \right)^4 - 1 \right], \quad j = 0, 1, ..., 3, \tag{1}$$

where $i = \{\text{GDP, Indprod, Cprof, Housing, Infl}\}$, and $\tilde{Y}_{i,t+j|t}$ denotes the quarter t consensus forecast (the mean of projections made by individual forecasters) at the level of macro variable i for quarter $t + j$. For the unemployment rate and the probability of a decline in the real GDP (recession probability hereafter), we directly use the level forecasts.

[**Insert Table I and Figure 1 here**]

Panel A of Table I reports the descriptive statistics of the SPF data. Starting with nowcasts, we note that many of them are persistent. In particular, Unemp_e and Infl_e have the highest autocorrelation coefficient of 0.96. Consistent with the fact that the growth of industrial production and corporate profit tends to be more volatile than the GDP growth, Indprod_e and Cprof_e have higher means and volatility than GDP_e does. As shown in column (8), the relatively strong correlations of Unemp_e and Housing_e with the future market return

payroll employment and real fixed investment. However, all these forecasts start in 1981 or later; therefore, we exclude them from our analysis.

[5] We remove four-quarter-ahead SPF forecasts for missing observations in early years.

(0.16 and 0.19, respectively) imply that they likely contain useful information about the equity premium. The pairwise correlations in Table IA.1 of the Internet Appendix reveal that Unemp_e, Infl_e, and Recess_e are positively correlated with each other and are negatively correlated with the other forecasts. The correlation coefficients range from -0.88 to 0.93, suggesting that the nowcasts collectively capture a common aspect about macroeconomic conditions. Turning to longer horizons forecasts in Panel A, we find that the term structures of GDP_e, Indprod_e, Cprof_e, and Housing_e are upward sloping, while that of Recess_e is slightly downward sloping. The term structures of Unemp_e and Infl_e are nearly flat.

To provide additional perspectives on the dynamics of the SPF forecasts, we plot their term structures in Figure 1. The shaded area denotes National Bureau of Economic Research (NBER) recessions. The forecasts for the real GDP, industrial production, and corporate profits vary procyclically, while those for the unemployment rate and recession probability vary countercyclically. Notably, we observe that six of the seven recessions, except for the 2001 recession, were preceded by substantial declines in Housing_e, consistent with the leading role of housing in business cycles (Leamer, 2015). The unemployment rate forecasts are relatively smooth and they usually surge during recessions while gradually decline thereafter. Interestingly, though the 2008 global financial crisis is the most prolonged recession in our sample, the growth forecasts for the real GDP, industrial production, housing starts, and corporate profits are the lowest in the mid-1970s (oil shock recession) and early 1980 recessions.

2.2 Macro Condition Index

We assume a linear relation between the expected market excess return and the macroeconomic condition M:

$$\mathbb{E}_t(R_{t+1}) = \alpha + \beta M_t, \tag{2}$$

where M_t summarizes the macroeconomic condition that matters for the equity premium but is unobservable at time t. Eq. (2) is consistent with a host of equilibrium models that the equity premium varies over economic conditions. Importantly, Eq. (2) implies that information about M_t can be used to predict the future market return since the realized market excess return equals its conditional expectation plus a zero-mean shock that is unrelated to M_t (i.e., $R_{t+1} = \mathbb{E}_t(R_{t+1}) + \epsilon_{t+1}$).

In this paper, we consider that the SPF survey forecasts contain certain information about M_t. Let $\tilde{y}_t = (\tilde{y}_{1,t}, \tilde{y}_{2,t}, ..., \tilde{y}_{N,t})'$ denote the vector of SPF forecasts on the N macro variables. We assume a linear factor model for $\tilde{y}_{i,t}$ that follows

$$\tilde{y}_{i,t} = \delta_{i,0} + \delta_{i,1} M_t + \delta_{i,2} E_t + \eta_{i,t}, \quad i = 1, ..., N, \tag{3}$$

where E_t is the common measurement (or learning) error of all forecasts but is irrelevant to the equity premium according to Eq. (2) and $\eta_{i,t}$ is the idiosyncratic shock to $\tilde{y}_{i,t}$ exclusively. A naive way to predict the market return is to run a multivariate regression using all SPF forecasts. However, this approach is unable to separate M_t from return-irrelevant components in the SPF forecasts, and is also subject to the overfitting problem (Welch and Goyal, 2008). We therefore consider the PLS approach (Kelly and Pruitt, 2015; Wold, 1966) to efficiently consolidate information in the SPF forecasts into a single factor. Following the literature (Huang et al., 2015), we use the one-period-ahead market excess return (R_{t+1}) as the PLS proxy variable.[6] According to Kelly and Pruitt (2013, 2015) and Huang et al. (2015), by employing the information contained in the proxy variable to discipline the dimension reduction, the extracted PLS factor contains information that is most relevant for forecasting (M_t in our case) while filtering out irrelevant common and idiosyncratic noises in predictors (E_t and $\eta_{i,t}$ in our case). This helps us to better recover the relation between the macroeconomic condition and the equity premium.

We refer to the common factor extracted by PLS from the seven SPF nowcasts as the macro condition index $\mathrm{M}^{\mathrm{PLS}}$. Essentially, $\mathrm{M}^{\mathrm{PLS}}$ is a linear combination of the seven SPF nowcasts where the weight on each nowcast is based on its covariance with the future market excess return. The index $\mathrm{M}^{\mathrm{PLS}}$ estimated using the full-sample data is given by,

$$\begin{aligned}\mathrm{M}^{\mathrm{PLS}} = & -0.35\mathrm{GDP}_e - 0.44\mathrm{Indprod}_e + 0.01\mathrm{Recess}_e + 0.66\mathrm{Unemp}_e \\ & - 0.22\mathrm{Cprof}_e + 0.80\mathrm{Housing}_e - 0.47\mathrm{Infl}_e,\end{aligned} \tag{4}$$

where each underlying survey forecast is standardized to have unit variance. Observe that $\mathrm{M}^{\mathrm{PLS}}$ positively loads on the unemployment forecast while negatively on the GDP, industrial production, and corporate profits growth rates forecasts. Accordingly, an increase in $\mathrm{M}^{\mathrm{PLS}}$ foreshadows a deterioration in expected macroeconomic conditions.

[**Insert Figure 2 here**]

Figure 2 plots $\mathrm{M}^{\mathrm{PLS}}$ along with the Chicago Fed National Activity Index (CFNAI), which measures the overall economic activity and related inflationary pressure. First observe that

[6]The PLS method is implemented via a two-stage regression. In the first stage, we run a time-series regression for each SPF forecast $\tilde{y}_{i,t}$ on R_{t+1}. In the second stage, we run a cross-sectional regression of the union of SPF forecasts on the slope estimates obtained in the first stage. As a result, the slope estimate for the cross-sectional regression is the estimated PLS factor.

an increase in $\mathrm{M}^{\mathrm{PLS}}$ (solid line) usually coincides with a decrease in the CFNAI (dash-dotted line). Because a positive (negative) value of the CFNAI indicates that the aggregate economic activity is above (below) the long-term trend, the inverse relation between $\mathrm{M}^{\mathrm{PLS}}$ and the CFNAI suggests that $\mathrm{M}^{\mathrm{PLS}}$ is negatively related to economic conditions. In addition, $\mathrm{M}^{\mathrm{PLS}}$ tracks the switching of the NBER-dated business cycle phases between recessions and expansions. It declines to relatively lower levels near the peaks preceding several recessions, whereas it often spikes in recessions and takes seven of its local maximum values very close to the troughs of these recessions. Also note that $\mathrm{M}^{\mathrm{PLS}}$ features a gradual decline after 2009. This is mainly due to its relatively large loading on Unemp_e such that $\mathrm{M}^{\mathrm{PLS}}$ reflects the slow decline in the unemployment rate after the 2008 recession.

2.3 Market Return Data and Other Predictors

We proxy for the market return with the monthly return on the Center for Research in Security Prices (CRSP) value-weighted index and the risk-free rate by the one-month T-bill rate. The monthly returns are compounded into quarterly returns to match the frequency of the SPF data. We subtract the risk-free return from the market to measure the realized premium. According to Panel B in Table I, the quarterly market risk premium has a mean of 1.65% and a standard deviation of 8.64, producing a Sharpe ratio of 0.19 (not tabulated). In addition to the SPF survey variables, we consider 16 popular predictors studied by Welch and Goyal (2008), including the commonly used ones such as dividend–price ratio (DP), the earnings–price ratio (EP), net equity expansion (NTIS), the three-month Treasury bill rate (TBL), the long-term government bond yield (LTY),the term spread (TMS), the default yield spread (DFY), inflation rate (INFL), the consumption–wealth ratio (CAY), and the investment–capital ratio (IK).[7]

3 Equity Premium Prediction

3.1 In-Sample Analysis

We estimate the one-step-ahead predictive regression model using the full-sample return data from 1969Q1 to 2019Q4,

$$R_{t+1} = a + \beta X_t + \epsilon_{t+1}, \tag{5}$$

where R_{t+1} is the quarterly market excess return in annualized terms and X_t is the predictor of interest. Each predictor is standardized to have a zero mean and unit variance to ease interpretation, and t-statistics are Newey and West (1987) corrected.

Panel A of Table II reports the results. The index $\mathrm{M}^{\mathrm{PLS}}$ positively predicts the market excess return with a slope estimate of 0.083 (t-stat $=$ 3.65) and a sizable R^2 of 5.75%. Recall that $\mathrm{M}^{\mathrm{PLS}}$ is inversely related to expected economic conditions. Thus, the equity premium is high when the macro condition index is high during bad economic times, and low when the index is low during good times. Our result is consistent with the countercyclical equity premium implied by rational equilibrium models. The value of the slope estimate is economically large. A one-standard-deviation increase in $\mathrm{M}^{\mathrm{PLS}}$ leads to a rise in the equity premium of 8.3% at an annual rate. The magnitude compares favorably to alternative macroeconomic predictors in the literature. For instance, the corresponding impacts on the

[7] The CRSP return data are obtained from Kenneth French's website (`http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/`). The data of economic predictors are obtained from Amit Goyal's website (`http://www.hec.unil.ch/agoyal`). More detailed variable definitions can be found in the Internet Appendix.

equity premium of the consumption–wealth ratio (Lettau and Ludvigson, 2001) and the output gap (Cooper and Priestley, 2009) are 4.1% and 7.7%, respectively.

[**Insert Table II here**]

We next analyze the predictability of the seven individual SPF variables. From the middle block of Panel A of Table II, we observe that the slope estimates of GDP_e, Indprod_e, and Cprof_e are negative, while that of Recess_e is positive. These findings are consistent with the inverse relation between expected economic conditions and the equity premium documented by Campbell and Diebold (2009) using survey data. The negative coefficient of Infl_e is in line with Fama and Schwert (1977). The positive coefficient of Unemp_e corroborates the implication of the search and matching model of Hall (2017) that high unemployment reflects a high aggregate discount rate and hence expected unemployment should positively forecast market returns.[8] Notably, the significant predictability of Housing_e supports the notion that the housing market's fluctuation is important in explaining the variation of the equity premium (Lustig and Van Nieuwerburgh, 2005; Piazzesi et al., 2007). In addition, the production model of Cochrane (1991) ties stock returns to investment returns in a complete market and implies that expected returns are high when expected investment growth is high. Since Housing_e proxies for the expected residential investment growth, it should positively forecast stock returns according to the model.[9] Nevertheless, only Unemp_e and Housing_e are significant. We also evaluate the kitchen sink model using all the SPF forecasts. The model achieves an R^2 of 6.85%, which roughly equals the summation of the R^2

[8]The production-based model with search frictions by Chen and Zhang (2011) implies a negative relation between the aggregate discount rate and the short-run employment growth. To the extent that unemployment is negatively correlated with payroll growth, our result is consistent with their model.

[9]The fixed investment data used by Cochrane (1991) to construct investment growth include both nonresidential investment and residential investment. Cochrane (1996) finds that residential investment growth helps to price the cross-section of stock returns. Lamont (2000) points out that residential investment leads nonresidential investment.

values produced by the seven SPF variables, suggesting that each survey forecast contains unique information about the equity premium. The kitchen sink model sets a ceiling on the in-sample predictability of the seven SPF forecasts, while $\mathrm{M}^{\mathrm{PLS}}$ alone displays comparable predictive ability.

In the interest of comparison, we report the forecasting results for the 16 predictive variables from Welch and Goyal in the remaining rows of Panel A of Table II. Only four variables (LTR, TMS, CAY, and IK) are significant at the 10% level or better, and none produces an R^2 higher than 2% (except for IK). These results echo the evidence of Welch and Goyal (2008), that numerous predictors lose their in-sample predictability after the oil shock in the mid-1970s. Similarly, we construct $\mathrm{Econ}^{\mathrm{PLS}}$, that is, the PLS factor extracted from the 16 economic variables. The term $\mathrm{Econ}^{\mathrm{PLS}}$ significantly predicts the market return, with an R^2 of 6.04% that is slightly higher than the R^2 of $\mathrm{M}^{\mathrm{PLS}}$. Kelly and Pruitt (2013) point out that the in-sample estimation of a PLS factor introduces a finite-sample look-ahead bias, since it is estimated by using the information of future market returns. Following Huang et al. (2015), we construct the look-ahead bias-free PLS factors recursively and report their predictive regression estimates in Table IA.3 in the Internet Appendix. The relation between $\mathrm{M}^{\mathrm{PLS}}_{\text{Bias-free}}$ and the market return remains robust, with a slope of 0.070 that is significant at the 1% level. By contrast, the sign of the slope of $\mathrm{Econ}^{\mathrm{PLS}}_{\text{Bias-free}}$ reverses, albeit it is significant.

Controlling for Common Predictive Variables

Table IA.2 in the Internet Appendix shows that $\mathrm{M}^{\mathrm{PLS}}$ is related to the predictive variables that track business cycle fluctuations, such as TMS ($\rho = 0.46$) and IK ($\rho = -0.54$), and is weakly related to market-based valuation ratios such as DY ($\rho = 0.08$). To ascertain whether the macro condition index contributes incremental information to existing predictors, we estimate a bivariate regression,

$$R_{t+1} = \alpha + \beta\, \mathrm{M}_t^{\mathrm{PLS}} + \psi Ctrl_t + \epsilon_{t+1}, \tag{6}$$

where $Ctrl$ is one of the variables listed in the first column of Table II other than $\mathrm{M}^{\mathrm{PLS}}$.

Panel B of Table II shows that all the β estimates of $\mathrm{M}^{\mathrm{PLS}}$ remain sizable and positively significant, whereas individual macro forecasts become insignificant. Moreover, adding the individual forecasts merely increases R^2 by less than 1% relative to using $\mathrm{M}^{\mathrm{PLS}}$ alone, suggesting that the macro condition index summarizes almost all the predictive information in individual macro condition proxies. The results are virtually the same when the control variable is replaced by any of the 16 economic and financial variables. The only exception is when we control for $\mathrm{Econ}^{\mathrm{PLS}}$. In that case, the regression slope of $\mathrm{M}^{\mathrm{PLS}}$ drops to 0.052, significant at the 10% level, whereas $\mathrm{Econ}^{\mathrm{PLS}}$ becomes insignificant.

In summary, the macro condition index constructed from the seven SPF nowcast variables positively and significantly predicts the quarterly market excess return over the sample from 1969 to 2019. The index retains predictive power after controlling for a variety of popular predictors and provides incremental information to these variables.

3.2 Out-of-sample Analysis

Welch and Goyal (2008), among others, underline the necessity of using the OOS test to ascertain the predictability in real time, since the OOS test is immune from the look-ahead bias and over-fitting problems of the in-sample analysis. We thus examine the OOS forecasting performance of $\mathrm{M}^{\mathrm{PLS}}$ in this subsection.

To generate OOS forecasts, we recursively construct the OOS macro condition index and estimate the regression coefficients of Eq. (5) using only the information available at the time the forecasts are made. We assess how well a predictive model forecasts the market return OOS based on several statistical criteria. First, we calculate the OOS R^2 of Campbell and Thompson (2008), defined as one minus the ratio of the mean squared forecast error (MSFE) of predictive model i over the benchmark model's MSFE,

$$R^2_{OS} = 1 - \frac{\text{MSFE}_{Model\ i}}{\text{MSFE}_{Bench}} = 1 - \frac{\sum_{t=q+1}^{T}(R_t - \hat{R}_{i,t})^2}{\sum_{t=q+1}^{T}(R_t - \bar{R}_t)^2}, \tag{7}$$

where the OOS forecasting starts at time $q+1$ and q denotes the length of the initial training period; $\bar{R}_t = \frac{1}{t}\sum_{s=1}^{t} R_s$ is the historical mean benchmark forecast, that is, the best forecast under the constant expected return model; $\hat{R}_{i,t}$ is the return forecast by predictive model i. Evidently, a lower $\text{MSFE}_{Model\ i}$ relative to MSFE_{Bench} leads to a positive R^2_{OS}, implying that the predictive model outperforms the historical mean benchmark in terms of OOS predictive accuracy. We rely on the MSFE-adjusted statistic of Clark and West (2007) to test the null hypothesis $R^2_{OS} \leq 0$ against the one-sided alternative hypothesis $R^2_{OS} > 0$.

The second measure is the difference in the cumulative squared forecast errors (DCSFEs), defined as the difference between the CSFE for the historical mean benchmark forecast and that for predictive model i.[10] Welch and Goyal (2008) advocate using the time series plot of $\{\text{DCSFE}_{i,t}\}$ as a visual tool to diagnose the stability of a predictive model relative to the historical mean benchmark.

[10]Specifically, DCSFE for predictive model i is calculated as

$$\text{DCSFE}_{i,t+1} = \text{CSFE}_{Bench,t+1} - \text{CSFE}_{Model\ i,t+1},$$

where

$$\text{CSFE}_{Bench,t+1} = \sum_{s=q+1}^{t+1}(R_s - \bar{R}_s)^2 \quad \text{and} \quad \text{CSFE}_{Model\ i,t+1} = \sum_{s=q+1}^{t+1}(R_s - \hat{R}_{i,s})^2.$$

The third metric is the forecast-encompassing test that helps to rank two competing predictive models according to their information content. Specifically, we form an optimal convex combination forecast using the forecasts generated by models i and j,

$$\tilde{R}_{t+1} = (1-\lambda)\hat{R}_{i,t+1} + \lambda\hat{R}_{j,t+1}, \qquad 0 \leq \lambda \leq 1. \tag{8}$$

A positive λ indicates that model j provides incremental forecasting information to model i, while a trivial λ implies that model j fails to contribute any additional information in forming the optimal forecast, thereby being "encompassed" by model i. We gauge the significance of λ based on the statistic of Harvey, Leybourne, and Newbold (1998) (hereafter, HLN statistic), which tests the null hypothesis $\lambda = 0$ against the one-sided alternative $\lambda > 0$.

Out-of-sample Forecasting Performance

Table III reports the R^2_{OS} statistics of predicting the quarterly market excess return. We use the first 60 quarters as the initial estimation period, such that the OOS period spans 1984Q1 to 2019Q4 and contains 144 observations in total.[11] Panel A shows that $\mathrm{M}^{\mathrm{PLS}}$ produces an R^2_{OS} of 3.12% with a MSFE-adjusted statistic of 2.15, implying that it delivers a significantly lower MSFE than the historical mean forecast at the 5% level or better. The economic magnitude is also sizable. According to Campbell and Thompson (2008), given a quarterly market Sharpe ratio of 0.19, mean–variance investors could increase their expected portfolio returns by a proportional factor of 0.86 if they switched from using the historical mean forecast to the forecast made by $\mathrm{M}^{\mathrm{PLS}}$. For comparison, we examine the

[11] According to Welch and Goyal (2008), our choice of the initial training window balances between an adequate number of start-up observations to estimate parameters reliably and a sufficiently long OOS period for evaluating the predictive performance.

forecasting performance of the individual survey variables. Only Housing$_e$ has a significant R^2_{OS} of 1.64%, while Unemp$_e$ fails to extend its significant in-sample predictability to the OOS forecasting.

[**Insert Table III and Figure 3 here**]

We further use the DCSFE to examine OOS forecasting performance stability of each variable. The top Panel of Figure 3 depicts the series of DCSFEs for the univariate models based on the individual SPF variables. Only Housing$_e$ exhibits a relatively stable predictive ability in that its DCSFE series progressively increase over time and remain positive in the latest decade. Notably, the frequent ups and downs in the DCSFE series of Unemp$_e$ indicate the instability risk of using a single predictive variable: Unemp$_e$ underperforms the historical mean forecast during the dot-com boom (1995–2000) but performs well during and after the Great Recession when the unemployment rate was relatively high.The bottom Panel of Figure 3 shows that M$^{\text{PLS}}$ ends up with lower CSFEs relative to the historical mean forecast, consistent with its positive R^2_{OS} value. Importantly, the slope of its DCSFE series is mostly positive over the OOS period. Thus, in contrast to individual SPF variables, the OOS forecasting gain of M$^{\text{PLS}}$ relative to the historical mean benchmark is not confined to specific episodes. By integrating the predictive information in individual macro condition proxies, M$^{\text{PLS}}$ reduces the negative impacts of false signals in the proxies, thereby generating more stable performance. Interestingly, the forecasting performance of M$^{\text{PLS}}$ appears to be stronger during recessions and displays a countercyclical pattern. We will conduct a thorough analysis of this pattern in Section 4.3.

Moreover, we employ an OOS forecast-encompassing test to compare the information content of M$^{\text{PLS}}$ with that of individual survey variables. According to the HLN statistics

(λ) reported in Column (3) of Table III, all individual survey variables (except for Housing$_e$) fail to encompass M$^{\text{PLS}}$ and the λ values of M$^{\text{PLS}}$ are close to one. Though we cannot reject the null hypothesis that Housing$_e$ encompasses M$^{\text{PLS}}$ at conventional significant levels, the large encompassing coefficient λ (0.88) shows that M$^{\text{PLS}}$ dominates Housing$_e$ in forming the optimal composite forecast. The dominant role played by M$^{\text{PLS}}$ in the encompassing tests implies that M$^{\text{PLS}}$ has incorporated most of the predictive information in the seven SPF variables.

Panel B of Table III presents the OOS forecasting results of the traditional predictive variables. Most of these predictors fail to beat the historical mean benchmark forecast in terms of the MSFE, resulting in negative R^2_{OS} statistics. Neither Econ$^{\text{PLS}}$ outperforms the historical mean forecast. Among the 16 economic predictors, only inflation delivers a positive R^2_{OS} of 1.13% that is significant at the 10% level. From the encompassing test results presented in column (6), we confirm that M$^{\text{PLS}}$ provides incremental predictive information to the conventional predictors.[12]

To summarize, the results of OOS tests reaffirm that M$^{\text{PLS}}$ is a strong predictor for the market return. As stressed by Rapach, Strauss, and Zhou (2010) and Dangl and Halling (2012), among others, model uncertainty and parameter instability render the intertemporal relations between conventional predictors and future returns unstable. Nonetheless, M$^{\text{PLS}}$ appears to suffer less from the instability risk and outstrips many popular forecasting variables by generating more reliable OOS return forecasts.

[12]The only exception is SVAR. Its negative R^2_{OS} of -59.72% signals great variation in its OOS forecasts, rendering the encompassing test result insignificant due to the huge standard error of the weight estimate.

3.3 Long-Horizon Prediction

Economic conditions tend to persist in the short run, and thus their impact on the equity premium is expected to persist as well (Campbell and Diebold, 2009).[13] The SPF forecasts reflect the persistence of economic conditions, as indicated by their strong autocorrelation in Table I. We therefore expect $\mathrm{M}^{\mathrm{PLS}}$ to predict long-term market returns as well. To verify this conjecture, we run the long-horizon overlapping regression (Fama and French, 1989):

$$R_{t+1:t+h} = a + \beta\,\mathrm{M}_t^{\mathrm{PLS}} + \epsilon_{t+1:t+h}, \quad h = 2, 4, 8, 12 \text{ quarters}, \tag{9}$$

where $R_{t+1:t+h}$ is the market excess return from quarter $t+1$ to $t+h$ in annualized terms and the forecast horizons $h = 2, 4, 8, 12$ quarters correspond to the next half, one, two, and three years, respectively. The Newey–West-corrected t-statistics with $2(h-1)$ lags is used to account for the serial correlation in the error term.

[**Insert Tables IV here**]

Panel A of Table IV reports the in- and OOS forecasting results of $\mathrm{M}^{\mathrm{PLS}}$ over long horizons. We observe that $\mathrm{M}^{\mathrm{PLS}}$ significantly predicts the long-run market excess returns up to 12 quarters and produces significantly positive R^2_{OS} values at all horizons considered. This implies that the expected current economic conditions have a persistent impact on the future equity premium. Nonetheless, since $\mathrm{M}^{\mathrm{PLS}}$ is built on SPF nowcasts only, it has limited information about the future long-term macroeconomic conditions that matter for the long-term equity premium. To see why, we first apply Eq. (2) to the expected market

[13] For instance, the one-period transitional probability of the economy staying in the expansion (contraction) regime is estimated to be 0.90 (0.75) in the Markov regime-switching model of Hamilton (1989).

excess return at time $t+h$ ($h \geq 1$),

$$\mathbb{E}_t(R_{t+1}) = \alpha + \beta M_t, \tag{10}$$

$$\mathbb{E}_{t+1}(R_{t+2}) = \alpha + \beta M_{t+1}, \tag{11}$$

$$\vdots$$

$$\mathbb{E}_{t+j}(R_{t+h+1}) = \alpha + \beta M_{t+h}. \tag{12}$$

Then, we add up the above equations and take the time-t expectation,

$$\frac{1}{h}\mathbb{E}_t(R_{t+1:t+h}) = \alpha + \frac{1}{h}\beta[M_t + \mathbb{E}_t(M_{t+1}) + \cdots + \mathbb{E}_t(M_{t+h-1})]. \tag{13}$$

Importantly, Eq. (13) indicates that the expected long-term macroeconomic condition helps to track the long-term equity premium variation. Since the duration of business cycles is time varying (Diebold and Rudebusch, 1990; Filardo and Gordon, 1998), solely using $\mathrm{M}^{\mathrm{PLS}}$ could be insufficient to track the expected long-term market return. We are thus motivated to explore the information content of SPF7TS which is consist of multi-step ahead SPF forecasts and likely conveys information about the long-term equity premium. Analogous to the construction of $\mathrm{M}^{\mathrm{PLS}}$, we apply the PLS method to extract the common factor from SPF7TS using one-period-ahead market excess returns as the PLS proxy variable, to which we refer as the *long-term macro condition index* (LT-$\mathrm{M}^{\mathrm{PLS}}$).

[**Insert Figure 4 here**]

Before digging into the forecasting performance of LT-$\mathrm{M}^{\mathrm{PLS}}$, we compare the full-sample estimated PLS weights of LT-$\mathrm{M}^{\mathrm{PLS}}$ with $\mathrm{M}^{\mathrm{PLS}}$ in Figure 4. Two important observations follow the figure. First, LT-$\mathrm{M}^{\mathrm{PLS}}$ has a PLS weight structure similar to $\mathrm{M}^{\mathrm{PLS}}$: it positively loads on the SPF forecasts of unemployment and recession probability while negatively on the GDP, industrial production, and corporate profits forecasts. Thus, an increase in LT-$\mathrm{M}^{\mathrm{PLS}}$ anticipates a deteriorating macroeconomic condition in the long run. Second, we observe a homogeneity in the sign of PLS weights but a heterogeneity in the size of weights within each group of SPF forecasts. For example, the (absolute) weights for the forecasts on GDP, industrial production, recession probability, unemployment, and corporate profits increase from the forecasting horizon of one quarter to three quarters, suggesting that the relatively long-term forecasts on these macro variables are more related to the equity premium variation. By contrast, the next-quarter forecasts for housing starts and inflation are assigned with higher weights relative to the corresponding three-quarter-ahead forecasts. In short, the PLS weight of LT-$\mathrm{M}^{\mathrm{PLS}}$ displays a salient term structure feature. Meanwhile, compared with $\mathrm{M}^{\mathrm{PLS}}$, LT-$\mathrm{M}^{\mathrm{PLS}}$ loads more on the unemployment forecasts while less on the housing starts forecasts, leading to a higher autocorrelation of LT-$\mathrm{M}^{\mathrm{PLS}}$ of 0.91 (untabulated) than that of $\mathrm{M}^{\mathrm{PLS}}$ (0.69).

Panel B of Table IV presents the forecasting results of LT-$\mathrm{M}^{\mathrm{PLS}}$. We find that LT-$\mathrm{M}^{\mathrm{PLS}}$ positively and significantly predicts market excess returns up to 12 quarters. Though LT-$\mathrm{M}^{\mathrm{PLS}}$ underperforms $\mathrm{M}^{\mathrm{PLS}}$ at the quarterly forecast horizon, the former generally exhibits stronger predictive power than the latter at longer forecast horizons. In particular, the OOS R^2 values of LT-$\mathrm{M}^{\mathrm{PLS}}$ are uniformly larger than the $\mathrm{M}^{\mathrm{PLS}}$ counterparts for horizons longer than one quarter. Intuitively, by incorporating the rich information in the term structure of SPF forecasts, LT-$\mathrm{M}^{\mathrm{PLS}}$ reflects the future long-term macro condition that governs the long-term equity premium variation. Besides, the greater persistence allows LT-$\mathrm{M}^{\mathrm{PLS}}$ to better track the low-frequency movement in the long-term equity premium than $\mathrm{M}^{\mathrm{PLS}}$ does.

To formally examine whether LT-M^{PLS} provides incremental information about the long-term equity premium to M^{PLS}, we include LT-M^{PLS} into regression (9). Panel C shows that the slope estimate associated with LT-M^{PLS} becomes statistically significant for horizons longer than one year (four quarters), suggesting that LT-M^{PLS} provides a substantial amount of incremental information about the long-term equity premium to M^{PLS}. This is consistent with the Q-theory–based production model that the discount rate has impacts on long-term investment growth and employment growth (Chen and Zhang, 2011; Lettau and Ludvigson, 2002). Consequently, forecasts for the long-term labor and housing market conditions should provide information about the equity premium today. Moreover, the slope estimate of LT-M^{PLS} dominates that of M^{PLS} at the two-year and three-year horizons. Recall that LT-M^{PLS} places a larger weight on forecasts for the output-related variables (such as, GDP and corporate profits) and unemployment relative to M^{PLS}. This implies that information about the output growth and the labor market condition plays a more important role in explaining the long-term equity premium variation.

In summary, empirical results in this section demonstrate that our macro condition indices significantly predict market returns at the horizons from one quarter to three years ahead both in- and OOS. Our study implies that the forecasts of macroeconomic conditions predict stock market returns, which complements the finding of Fama (1990) that stock market returns predict future real economic activities. Importantly, the information content of SPF macro forecasts and the return predictability generally agree in term of the forecast horizon. Our results also supplement the findings of Campbell and Diebold (2009) by portraying a tight relation between the equity premium and broad aspects of the expected macroeconomic condition related to output, inflation, and labor and housing markets.

4 Sources of Predictability

The preceding analysis documents the strong predictability of macro condition indices built on the SPF forecasts. In this section, we explore the sources of their predictive power.

4.1 Impact of Belief Biases

Whereas we construct our macro condition index using the SPF consensus forecasts, there is a debate on the quality of professional forecasts. Some argue that due to information frictions, the forecasts are deviated from full-information rational expectations but are consistent with rational learning (Coibion and Gorodnichenko, 2015), while others question the rationality of forecasters (Bordalo et al., 2020). Recently, using survey data of dividend growth and returns on the S&P 500 index, De La O and Myers (2021) argue that misspecified beliefs about future cash flows play a dominant role in explaining the market price movements. This raises a concern whereby the predictive ability of $\mathrm{M}^{\mathrm{PLS}}$ is correlated with forecaster biases. If so, controlling for the belief biases in SPF projections would undermine the power of $\mathrm{M}^{\mathrm{PLS}}$. Since the belief bias is unobservable, we use the *ex-post* forecast error of SPF projection as a proxy of it. This is because the *ex-post* SPF forecast error can be decomposed as,

$$\mathrm{FE}_{i,t+j|t} \equiv \underbrace{(y_{i,t+j} - \tilde{y}_{i,t+j|t})}_{\text{forecast errors}} = \underbrace{(y_{i,t+j} - \mathbb{E}_t[y_{i,t+j}])}_{\text{innovation}} + \underbrace{(\mathbb{E}_t[y_{i,t+j}] - \tilde{y}_{i,t+j|t})}_{\text{belief bias}}, \tag{14}$$

where $y_{i,t+j}$ denotes macro variable i (e.g., the GDP growth) at $t+j$-th quarter, $\tilde{y}_{i,t+j|t}$ is the associated SPF forecast made at quarter t, and $\mathbb{E}_t[y_{i,t+j}]$ is the mathematical expectation of $y_{i,t+j}$ conditioning on all available information up to quarter t. That is, the forecast error comprises both the unpredictable innovation and belief biases.[14]

At the quarterly horizon, the baseline predictive regression (5) augmented with SPF forecast errors is,

$$R_{t+1} = \alpha + \beta\, \mathrm{M}_t^{\mathrm{PLS}} + \gamma \mathrm{FE}_{i,t|t} + \epsilon_{t+1}, \tag{15}$$

where $\mathrm{FE}_{i,t|t}$ denotes the forecast error of SPF nowcast for variable i.[15] According to the decomposition (14), since $\mathrm{M}^{\mathrm{PLS}}$ is uncorrelated with the innovation, controlling for SPF forecast errors would weaken the power of $\mathrm{M}^{\mathrm{PLS}}$ if and only if the predictive ability of $\mathrm{M}^{\mathrm{PLS}}$ stems from the belief bias component; otherwise, the β estimate in regression (15) should be identical to that in regression (5). Panel A of Table V reports the regression estimates. Controlling for SPF forecast errors, either individually or jointly, does not attenuate the forecasting power of $\mathrm{M}^{\mathrm{PLS}}$. For instance, as shown in column (6), $\mathrm{M}^{\mathrm{PLS}}$ continues to predict market returns after controlling for the forecast errors of all SPF nowcasts, and its slope estimate (0.077) is barely different from that (0.083) in the baseline regression (5).

[**Insert Table V here**]

Next, we run a predictive regression similar to (15) for the one-year-ahead return, in which we control for the forecast errors of SPF projections for variable i at all different horizons, i.e., $\{\mathrm{FE}_{i,t+j|t}\}_{j=0}^{3} = \{y_{i,t} - \tilde{y}_{i,t|t}, y_{i,t+1} - \tilde{y}_{i,t+1|t}, y_{i,t+2} - \tilde{y}_{i,t+2|t}, y_{i,t+3} - \tilde{y}_{i,t+3|t}\}$. To reduce dimension, we control for the first principal component (PC) of $\{\mathrm{FE}_{i,t+j|t}\}_{j=0}^{3}$ for each macro variable i. The results are reported in Panel B of Table V. As shown in column (6), the coefficient of $\mathrm{M}^{\mathrm{PLS}}$ (0.067) is almost the same as the value (0.068) reported in Table IV after the inclusion of all the first PCs of the forecast errors. Conditioning on *ex-post* forecast

[14] The forecast error is defined as the difference between the first-release value of macro variables and the SPF forecast/nowcast, as in Bordalo et al. (2020). We calculate forecast errors for all the SPF variables that we consider except for Recess_e.

[15] Due to publication lags of macroeconomic variables, $y_{i,t}$ is not available until $t+1$.

errors has negligible impact on the predictability of $\mathrm{M}^{\mathrm{PLS}}$. It is thus implausible that the predictive power of $\mathrm{M}^{\mathrm{PLS}}$ originates from the forecaster biases about future macroeconomic conditions.

4.2 Compare with Realized Macro Variables

To further investigate the economic underpinnings of the predictive power of $\mathrm{M}^{\mathrm{PLS}}$, we ask the question that whether $\mathrm{M}^{\mathrm{PLS}}$ aggregates information about the "true yet unobserved" macroeconomic condition as we stated in the theoretical framework outlined in Section 2.2. We answer this question from two folds. First, we construct an objective counterpart to $\mathrm{M}^{\mathrm{PLS}}$ via the PLS method but using the realized values of SPF7 (not available until time $t+1$), to which we refer as $\mathrm{M}^{\mathrm{PLS}}_{\mathrm{obj}}$. If $\mathrm{M}^{\mathrm{PLS}}$ predicts the market only through the "true" information about macroeconomic conditions, then $\mathrm{M}^{\mathrm{PLS}}$ hardly can improve return predictability over $\mathrm{M}^{\mathrm{PLS}}_{\mathrm{obj}}$ and vice versa. Second, we test whether the information about the macroeconomic condition incorporated by $\mathrm{M}^{\mathrm{PLS}}$ is actually unobserved. In a similar fashion, we construct a lagged objective counterpart to $\mathrm{M}^{\mathrm{PLS}}$ using the lagged realized values of SPF7 (already available at time t), to which we refer as $\mathrm{M}^{\mathrm{PLS}}_{\text{lag-obj}}$. If $\mathrm{M}^{\mathrm{PLS}}$ improves predictability over $\mathrm{M}^{\mathrm{PLS}}_{\text{lag-obj}}$, then the former likely contains the "unobserved" information about macroeconomic condition relative to the latter.

We use the most recent vintage data (by the time of December 2019) of GDP, industrial production, unemployment rate, corporate profits after tax, housing starts, and inflation rate to calculate the realized counterparts of SPF7, where the data are available from Federal Reserve Bank of St. Louis.[16] To compare the information content of $\mathrm{M}^{\mathrm{PLS}}$ against that

[16]The realized counterparts are only attainable for GDP_e, $\mathrm{Indprod}_e$, Unemp_e, Cprof_e, $\mathrm{Housing}_e$, and Infl_e but not for Recess_e. However, since $\mathrm{M}^{\mathrm{PLS}}$ merely places a weight of 0.01 on Recess_e, comparisons among $\mathrm{M}^{\mathrm{PLS}}$, $\mathrm{M}^{\mathrm{PLS}}_{\mathrm{obj}}$, and $\mathrm{M}^{\mathrm{PLS}}_{\text{lag-obj}}$ are still of great meaning.

of $\mathrm{M}_{\mathrm{obj}}^{\mathrm{PLS}}$, we run the predictive regression comprising $\mathrm{M}_{\mathrm{obj}}^{\mathrm{PLS}}$ ($\mathrm{M}^{\mathrm{PLS}}$) and the orthogonalized $\mathrm{M}^{\mathrm{PLS}}$ ($\mathrm{M}_{\mathrm{obj}}^{\mathrm{PLS}}$) with respect to $\mathrm{M}_{\mathrm{obj}}^{\mathrm{PLS}}$ ($\mathrm{M}^{\mathrm{PLS}}$) which is denoted as $\mathrm{M}^{\mathrm{PLS},\perp}$ ($\mathrm{M}_{\mathrm{obj}}^{\mathrm{PLS},\perp}$). By doing so, we could pin down whether $\mathrm{M}^{\mathrm{PLS}}$ can improve return predictability over $\mathrm{M}_{\mathrm{obj}}^{\mathrm{PLS}}$ or the other way around.

[**Insert Table VI here**]

The first two regressions in Table VI compare indices $\mathrm{M}^{\mathrm{PLS}}$ and $\mathrm{M}_{\mathrm{obj}}^{\mathrm{PLS}}$. Note that $\mathrm{M}_{\mathrm{obj}}^{\mathrm{PLS}}$ evinces substantial ability in explaining the market excess return variation, with a slope estimate of 0.080 that is significant at the 1% level. This is not surprising since the construction of $\mathrm{M}_{\mathrm{obj}}^{\mathrm{PLS}}$ introduces a look-forward bias in that it uses future information. Meanwhile, the orthogonalized $\mathrm{M}^{\mathrm{PLS}}$ barely provides additional information to $\mathrm{M}_{\mathrm{obj}}^{\mathrm{PLS}}$, and neither does $\mathrm{M}_{\mathrm{obj}}^{\mathrm{PLS},\perp}$ to $\mathrm{M}^{\mathrm{PLS}}$. This reveals that the information aggregated by $\mathrm{M}^{\mathrm{PLS}}$ is primarily relevant to the "true" macroeconomic condition, and hence, $\mathrm{M}^{\mathrm{PLS}}$ predicts return only through the link between economic conditions and the equity premium (Cochrane, 2008; Fama and French, 1989). The rest two regressions in Table VI compare the content of $\mathrm{M}^{\mathrm{PLS}}$ against that of $\mathrm{M}_{\text{lag-obj}}^{\mathrm{PLS}}$. From the third regression, we find that the slope estimate of $\mathrm{M}^{\mathrm{PLS},\perp}$ is about the same size as that of $\mathrm{M}_{\text{lag-obj}}^{\mathrm{PLS}}$ and is significant at the 5% level, suggesting that $\mathrm{M}^{\mathrm{PLS}}$ contains incremental forecasting information to $\mathrm{M}_{\text{lag-obj}}^{\mathrm{PLS}}$. By contrast, as indicated by the fourth regression, $\mathrm{M}_{\text{lag-obj}}^{\mathrm{PLS}}$ barely improves return predictability over $\mathrm{M}^{\mathrm{PLS}}$. It is thus conceivable that $\mathrm{M}^{\mathrm{PLS}}$ reflects the macroeconomic condition relevant for the equity premium but yet unobserved at the time of forecasts. Therefore, our findings strongly support the notion that $\mathrm{M}^{\mathrm{PLS}}$ aggregates the information about the "true yet unobserved" macroeconomic condition. This in turn suggests that the predictive ability of $\mathrm{M}^{\mathrm{PLS}}$ derives from investor's rational response to changing expected economic conditions.

4.3 Links to the Macroeconomy

The preceding analyses demonstrate that M^{PLS} mainly reflects the unobserved macroeconomic condition that matters for the equity premium. In this subsection, we take a closer look at the forecasting performance of M^{PLS} to further investigate the source of its predictive power.

Forecasting Performance over Different Economic Conditions

Recent studies document that the degree of equity premium predictability is time varying. Specifically, the forecasting performance of conventional predictors, such as the dividend–price ratio, is stronger during recessions than expansions (Dangl and Halling, 2012; Henkel, Martin, and Nardari, 2011; Rapach et al., 2010). It is thus of interest to investigate how the predictive power of M^{PLS} is related to economic states. We follow Eriksen (2017) to use the difference in squared forecast error (DSFE) at each observation point to measure the predictive performance relative to the historical mean benchmark. A positive DSFE signals an OOS forecasting gain relative to the historical mean. We employ several variables to measure economic conditions, including the real GDP growth, real consumption growth, real labor income growth, the CFNAI, and the macro uncertainty index of Jurado, Ludvigson, and Ng (2015). Panel A of Table VII presents the contemporaneous correlations between the predictive performance and the macro variables. We find that the forecasting accuracy and economic gains of M^{PLS} are negatively correlated with economy growth and positively correlated with macro uncertainty.

[**Insert Table VII here**]

Another commonly used approach to gauge the forecasting performance over different time periods is to compute the subsample R^2_{OS}. Following Rapach et al. (2010), we calculate the R^2_{OS} values during good and bad economic times as

$$R^2_{OS,c} = 1 - \frac{\sum_{t=q+1}^{T} I_t^c (R_t - \hat{R}_t)^2}{\sum_{t=q+1}^{T} I_t^c (R_t - \bar{R}_t)^2}, \quad c = \text{Good, Bad}, \tag{16}$$

where I_t^{Good} (I_t^{Bad}) equals one whenever the economy is in an NBER-dated expansion (recession) in quarter t, and zero otherwise. Panel B of Table VII demonstrates that $\mathrm{M}^{\mathrm{PLS}}$ exhibits more substantial predictive power during NBER-dated recessions than during expansions, with an R^2_{OS} of 7.29% that is three times larger than its expansion counterpart. In sum, the forecasting gains of $\mathrm{M}^{\mathrm{PLS}}$ relative to the historical mean tend to be larger in bad times during which economic activities are weak and macro uncertainty is high, revealing a tight relation between the predictability of $\mathrm{M}^{\mathrm{PLS}}$ and business cycle variations.

Countercyclical Macro Condition Index and Equity Premia

Although there is no consensus on the reason for the time-varying market return predictability, the cyclicality of the equity premium provides a plausible explanation (Henkel et al., 2011). A common implication of the equilibrium asset pricing model is that the decreased risk-bearing capacity in economic bad times, such as recessions, produces countercyclical equity premia (Cochrane, 2017). Accordingly, the equity premium is higher and more variable during recessions, leading to the countercyclical predictability.

In light of the countercyclical predictive power of $\mathrm{M}^{\mathrm{PLS}}$, we investigate how $\mathrm{M}^{\mathrm{PLS}}$ and its return forecasts are related to the business cycles. We first examine the intertemporal relation between $\mathrm{M}^{\mathrm{PLS}}$ and the economic condition by plotting the correlations of $\mathrm{M}^{\mathrm{PLS}}$ with leads and lags of the CFNAI in Figure 5. Consistent with the countercyclical dynamic exhibited by $\mathrm{M}^{\mathrm{PLS}}$ in Figure 2, Figure 5 indicates a negative contemporaneous correlation (-0.40) between $\mathrm{M}^{\mathrm{PLS}}$ and the CFNAI. Meanwhile, the CFNAI and $\mathrm{M}^{\mathrm{PLS}}$ are negatively correlated in the very short term, but are positively correlated from three quarters up to two years into the future, suggesting that $\mathrm{M}^{\mathrm{PLS}}$ slightly leads the CFNAI. That is, high levels of $\mathrm{M}^{\mathrm{PLS}}$ signal a forthcoming business cycle trough followed by a resurgence in economic activities.

[**Insert Figures 5 and 6 here**]

Figure 6 plots the return forecasted by $\mathrm{M}^{\mathrm{PLS}}$, the historical mean forecast, and the realized market excess return smoothed by a four-quarter moving average over the OOS period. Analogous to $\mathrm{M}^{\mathrm{PLS}}$, forecasts produced by $\mathrm{M}^{\mathrm{PLS}}$ also behave countercyclically: they tend to fall during expansions and rise rapidly near the troughs of recessions, thereby capturing market rebounds around business cycle troughs. By contrast, the historical mean forecasts display a much weaker connection to business cycle phases and appear to be overly smooth, as they completely ignore any information related to business cycles. The forecasts based on $\mathrm{M}^{\mathrm{PLS}}$ are also more volatile than the historical mean forecasts. Because the realized returns display even stronger volatility, intuitively, $\mathrm{M}^{\mathrm{PLS}}$ is more likely to explain the great variation of returns. In addition, since $\mathrm{M}^{\mathrm{PLS}}$ has a large loading on Unemp_e, $\mathrm{M}^{\mathrm{PLS}}$ reflects the slow recovery of the labor market after the 2008 Great Recession. Consequently, the return forecasts by $\mathrm{M}^{\mathrm{PLS}}$ successfully track the gradually declined realized equity premium over the prolonged period following 2008.

In conclusion, $\mathrm{M}^{\mathrm{PLS}}$ exhibits countercyclical dynamics, giving rise to countercyclical equity premium forecasts. Its success in predicting the market is largely due to the ability to capture the time variation in the equity premium related to business cycle frequency fluctuations.

4.4 Forecasting Channel and Return Decomposition

By construction, M^{PLS} summarizes information about inflation, unemployment, and the GDP growth, which are key inputs for decisions made by the Federal Open Market Committee (FOMC) to adjust the Federal funds rate. In addition, unexpected increases (decreases) in the Federal funds rate can cause negative (positive) market reactions (Bernanke and Kuttner, 2005), and this reaction is largely attributed to changes in the risk premium. To shed light on the predictive power of M^{PLS}, we investigate the intertemporal relation of M^{PLS} with the Federal funds rate surprise and the resultant market reaction. We define the quarter-t Federal funds rate surprise (FOMC surprise$_t$) and resultant market return (FOMC R_t) as the sum of the unexpected one-day change in the Federal funds rate and the sum of the CRSP value-weighted return, respectively, on each FOMC announcement day in quarter t. Due to the availability of Federal funds futures data, our analysis begins in June 1989 and ends in December 2007, as in Bernanke and Kuttner (2005) and Gallo, Hann, and Li (2016).[17]

Panel A of Table VIII reports the forecasting results for FOMC surprise$_t$ and FOMC R_t over the sample period from 1989Q2 to 2007Q4. Two important observations follow the table. First, M^{PLS} significantly and negatively predicts surprises in the Federal funds rate on the FOMC announcement day. In particular, a one-standard-deviation increase in M^{PLS} foreshadows a 3.142 bps unexpected decrease in the Federal funds rate. Since FOMC is likely to decrease the Federal funds rate when the overall economy is weaker than expected, the negative association between M^{PLS} and Federal funds rate surprises supports the notion

[17] We thank Kenneth Kuttner for making the Federal funds rate surprise data available at `https://econ.williams.edu/faculty-pages/research/`.

that an increase in $\mathrm{M}^{\mathrm{PLS}}$ anticipates a deteriorating macroeconomic condition. Second, $\mathrm{M}^{\mathrm{PLS}}$ significantly and positively predicts market returns on the FOMC announcement day. This accords with the finding that the stock market reacts positively to unexpected decreases in the Federal funds rate (Bernanke and Kuttner, 2005). Taken together, the above findings suggest that $\mathrm{M}^{\mathrm{PLS}}$ is predictive of the Federal funds rate adjustment and provide preliminary evidence that $\mathrm{M}^{\mathrm{PLS}}$ conveys important information about the discount rate.

[**Insert Table VIII here**]

To further elucidate the forecasting channel of $\mathrm{M}^{\mathrm{PLS}}$, we conduct a return decomposition analysis. According to Campbell (1991), the logarithm market return (r_{t+1}) can be decomposed into the expected return and two news components, the cash flow news (η_t^{CF}) and the discount rate news (η_t^{DR}):

$$r_{t+1} = \mathbb{E}_t(r_{t+1}) + \underbrace{(\mathbb{E}_{t+1} - \mathbb{E}_t)\left(\sum_{j=0}^{\infty} \rho^j \Delta d_{t+j+1}\right)}_{\text{cash flow news}} - \underbrace{(\mathbb{E}_{t+1} - \mathbb{E}_t)\left(\sum_{j=1}^{\infty} \rho^j r_{t+j+1}\right)}_{\text{discount rate news}}, \tag{17}$$

where Δd_{t+j+1} is the log dividend growth at time $t+j+1$ and ρ is a log-linearization constant between zero and one. The two news components, η_t^{CF} and η_t^{DR}, are unexpected returns caused by revisions in expectations of current and future cash flows and future discount rates, respectively. For a detailed description, see Section B of the Internet Appendix. We then run the following regression to examine the predictability of $\mathrm{M}^{\mathrm{PLS}}$ for individual return components:

$$w_{t+1} = \alpha_w + \beta_w \, \mathrm{M}_t^{\mathrm{PLS}} + \epsilon_{t+1}, \tag{18}$$

where w_{t+1} is one of the three estimated return components for quarter $t+1$. We set α_w equal to zero when $w = \hat{\eta}^{\mathrm{CF}}$ or $\hat{\eta}^{\mathrm{DR}}$. By comparing the slope estimates of the three return components, we can gain a deeper understanding of the economic channel through which $\mathrm{M}^{\mathrm{PLS}}$ forecasts the stock market return.

Panel B of Table VIII reports the slope estimates $\hat{\beta}_y$ of the above regression over the sample period from 1969Q1 to 2019Q4. The expected return, the cash flow news, and the discount rate news are estimated based on the vector autoregression (VAR) model (Campbell, 1991) comprising the variables presented in column (1). Following Engsted, Pedersen, and Tanggaard (2012), we always include DP in the VAR to properly estimate the cash flow news and discount rate news. The $\hat{\beta}_{\hat{E}}$ estimates in column (2) are mostly significant, revealing that $\mathrm{M}^{\mathrm{PLS}}$ is strongly correlated with the expected returns conditioning on the variables in column (1). Most of the $\hat{\beta}_{\mathrm{CF}}$ estimates are insignificant. In sharp contrast, all the $\hat{\beta}_{\mathrm{DR}}$ estimates are significant and are usually two to three times larger than the corresponding $\hat{\beta}_{\hat{E}}$ and $\hat{\beta}_{\mathrm{CF}}$. We observe similar results in the last row of Table VIII where we include the first three PCs of the 16 predictors in the VAR to enrich the conditional information set.

The above finding that $\mathrm{M}^{\mathrm{PLS}}$ predicts the market discount rate news rather than the cash flow news is generally congruous with the mechanism behind equilibrium models with time-varying composition risks. As shown by Santos and Veronesi (2006) and Piazzesi et al. (2007), the changing composition risks—arising from the change in the fraction of total consumption funded by labor income or the change in the expenditure share on housing services—generate the equity premium predictability even in absence of time-varying cash flow risks. Since the conventional business cycle variables and market condition proxies that we use in the VAR model say less about the labor and housing markets conditions, the unique information about unemployment and housing starts incorporated by $\mathrm{M}^{\mathrm{PLS}}$ helps it to better anticipates changes in the discount rate induced by fluctuations in labor income and housing expenditure. Therefore, the predictability of $\mathrm{M}^{\mathrm{PLS}}$ mainly comes from the discount rate channel in the sense of Campbell (1991).

4.5 Further Predictive Variables Considered

The predictability literature over the recent two decades has identified a number of theoretically motivated macro variables that measure economic conditions and predict market returns. How does the information content of our macro condition index compare to these macro variables? We conduct in-sample tests to understand their information content. Specifically, we consider the consumption volatility measure (σ_c) of Bansal, Khatchatrian, and Yaron (2005), the price–output ratio (py) of Rangvid (2006), the share of labor income to consumption (s^w) of Santos and Veronesi (2006), the ratio of non-housing consumption to total consumption (house) of Piazzesi et al. (2007), the output gap (OG) of Cooper and Priestley (2009), payroll growth (payroll) studied by Chen and Zhang (2011), the ratio of new orders to shipments of durable goods (NO/S) of Jones and Tuzel (2013), and the cyclical consumption (CC) of Atanasov et al. (2020). We closely follow the instruction of the original paper and construct these macro variables using revised macroeconomic data.[18] Besides, the SPF forecasts upon which our index is built are potentially related to investor sentiment and disagreement. We therefore consider several investor sentiment and disagreement indices that are found to be correlated with business cycles and/or future stock returns, including the University of Michigan Consumer Sentiment Index (S^{MC}), the investor sentiment indices of Baker and Wurgler (2006) and Huang et al. (2015), denoted by S^{BW} and $\mathrm{S}^{\mathrm{HJTZ}}$, respec-

[18]We follow Piazzesi et al. (2007) to construct a quarterly variable that measures the expenditure share on non-housing consumption, while their variable is available annually. Similarly, we construct a quarterly price–output ratio following Rangvid (2006).

tively, and the disagreement index ($\mathrm{D}^{\mathrm{HLW}}$) of Huang et al. (2021).[19] Finally, we compare with the disaggregated BM ratio PLS factor developed by Kelly and Pruitt (2013) based on 100 BM ratios ($\mathrm{BM}^{\mathrm{KP}}$).

[**Insert Table IX here**]

Panel A of Table IX reports the univariate predictive regression results. Among the eight macro variables listed above, OG, CC, and NO/S, significantly predict the quarterly market excess return in our sample, with R^2 values of 4.92%, 3.98%, and 1.94%, respectively. Nonetheless, our macro condition index $\mathrm{M}^{\mathrm{PLS}}$ appears to be the strongest among all the macro variables. For the sentiment and disagreement indices, $\mathrm{S}^{\mathrm{HJTZ}}$ exhibits the greatest predictive ability with an R^2 of 6.49%, followed by the disagreement index $\mathrm{D}^{\mathrm{HLW}}$ with an R^2 of 4.8%. It is worth noting that $\mathrm{BM}^{\mathrm{KP}}$ is a powerful predictor with a hefty R^2 of 15.97%.

To disentangle the information content of $\mathrm{M}^{\mathrm{PLS}}$, we run bivariate predictive regressions in Panel B. We find that $\mathrm{M}^{\mathrm{PLS}}$ remains positively significant conditioning on the other macro variables or their first PC ($\mathrm{Macro}^{\mathrm{PC}}$) and even subsumes their predictability. Turning to the results of controlling for investor sentiment and disagreement indices, the slope of $\mathrm{M}^{\mathrm{PLS}}$ hardly changes compared to the counterpart of the univariate regression. So do the slopes of S^{BW}, $\mathrm{S}^{\mathrm{HJTZ}}$, and $\mathrm{D}^{\mathrm{HLW}}$. This reflects that the information content of $\mathrm{M}^{\mathrm{PLS}}$ is orthogonal to that of S^{BW}, $\mathrm{S}^{\mathrm{HJTZ}}$, and $\mathrm{D}^{\mathrm{HLW}}$. Similar result is observed when we control for $\mathrm{BM}^{\mathrm{KP}}$.

Column (7) of Table IX looks into the contemporaneous correlations between $\mathrm{M}^{\mathrm{PLS}}$ and other variables. First, the strong correlation ($\rho = -0.54$) between $\mathrm{M}^{\mathrm{PLS}}$ and $\mathrm{Macro}^{\mathrm{PC}}$ shows that $\mathrm{M}^{\mathrm{PLS}}$ co-moves with the common variation of macro predictors built on realized macroeconomic data. In contrast, $\mathrm{M}^{\mathrm{PLS}}$ has much lower correlations with $\mathrm{S}^{\mathrm{HJTZ}}$ (-0.13)

[19]We thank Guofu Zhou and Dashan Huang for making the data available in their webpages.

and $\mathrm{D}^{\mathrm{HLW}}$ (-0.21), reaffirming the distinctness in their information sources. Second, the relatively high correlations (in absolute value) between $\mathrm{M}^{\mathrm{PLS}}$ and OG (-0.58), CC (-0.52) are very plausible since they all reflect business cycle fluctuations in certain manners.[20] Since CC measures the inverse of effective risk aversion (Atanasov et al., 2020), the negative correlation with CC indicates that $\mathrm{M}^{\mathrm{PLS}}$ likely captures the rising equity premium induced by heightened risk aversion during recessions.

Notwithstanding the similarity between $\mathrm{M}^{\mathrm{PLS}}$ and OG and CC, $\mathrm{M}^{\mathrm{PLS}}$ also comprises of expectations about labor and housing market conditions. Because human capital and house constitute a dominant fraction of the total wealth portfolio, which plays a central role in asset pricing, their risks are important drivers of investors' marginal utility and hence the equity premium (Lustig and Van Nieuwerburgh, 2005; Piazzesi et al., 2007; Santos and Veronesi, 2006). From the perspective of production-based models, expectations about future labor and housing market conditions contain information about the current equity premium (Chen and Zhang, 2011; Cochrane, 1991; Hall, 2017; Lettau and Ludvigson, 2002). For instance, Hall (2017) shows that under the search-and-matching paradigm, a higher discount rate diminishes the marginal value of new hirings and raises unemployment. All these models tie the stock market with labor and housing markets through time-varying discount rates. By exploiting a richer information set, $\mathrm{M}^{\mathrm{PLS}}$ subsumes the predictability of those standalone variables that capture only a particular sector of the macroeconomy, thereby contributing to the largest R^2 among all macro variables. To conclude, $\mathrm{M}^{\mathrm{PLS}}$ is a more comprehensive measure of economic conditions, and its predictive power originates from an economic fundamentals channel rather than the sentiment or disagreement channels.

[20]The relatively high correlation between $\mathrm{M}^{\mathrm{PLS}}$ and payroll growth (-0.51) is consistent with the notion that $\mathrm{M}^{\mathrm{PLS}}$ loads on the unemployment forecast and hence inversely reflects labor market conditions.

5 Extensions and Robustness Tests

In this section, we first investigate the extent to which M^{PLS} can forecast returns on characteristic-sorted portfolios. Second, we perform several robustness checks for our findings. Third, we provide international evidence on using SPF forecasts to predict market returns. Finally, we assess the economic significance of the predictability.

5.1 Characteristic-sorted Equity Portfolios

We assess the forecasting ability of M^{PLS} for stock portfolios sorted on size and industry SIC codes. The portfolio return data are obtained from Kenneth French's data library. Panel A of Table X shows that M^{PLS} significantly and positively predicts all of the 10 size-sorted portfolios over the sample period from 1969Q1 to 2019Q4. The R^2_{OS} statistics (column (4)) over the OOS period (1984Q1–2019Q4) are also significant and well above 2%. More importantly, the β estimates in column (2) increase monotonically from large to small firms. That is, the risk premia on smaller firms are more exposed to M^{PLS} and exhibit a higher degree of predictability. Besides the size-sorted portfolios, Panel B in Table X shows that the predictability of M^{PLS} is pervasive across all industry portfolios. Similar to Panel A, the regression slopes and R^2 statistics vary across industries in a sensible manner. The β estimates and in-sample R^2 values for the returns on cyclical industries, such as durable goods and high-tech equipment, are usually two to three times larger than those for defensive industries, including healthcare equipment and utilities. In particular, we uncover the highest level of predictability for the durable goods industry, with the largest in-sample and OOS R^2 values of 8.94% and 6.13%, respectively, whereas these values for nondurable goods are comparably small. Therefore, the predictive ability of M^{PLS} strongly extends to the cross-section of stock returns.

[**Insert Table X here**]

Perez-Quiros and Timmermann (2000) posit that small firms are more vulnerable than large firms to changes in economic states. Consequently, the former's risk premia are more sensitive to business cycle fluctuations. Gomes et al. (2009) derive that the stronger cyclical demand for durable goods than that for nondurable goods makes the risk premia of firms producing durable goods higher and vary more countercyclically. The more significant predictive power of $\mathrm{M}^{\mathrm{PLS}}$ for small firms and the durable goods industry is in line with these theories and reinforces our previous argument that the predictability of the macro condition index comes from its ability to capture business cycle–related risk premia.

5.2 Robustness Analysis

In this subsection, we explore the robustness of the predictive ability of $\mathrm{M}^{\mathrm{PLS}}$. First, we consider two subsamples, namely, 1969Q1 to 1994Q2 (the first-half sample) and 1994Q3 to 2019Q4 (the second-half sample). As presented in Panels A and B of Table XI, the in-sample forecasting results for the first- and second-half sample periods are comparable to the full-sample results shown in Tables II and IV. In particular, the quarterly regression slope estimates of $\mathrm{M}^{\mathrm{PLS}}$ are 0.087 and 0.090 in the first- and second-half samples, slightly larger than the full-sample value of 0.083. Besides the OOS period from 1984Q1 to 2019Q4 used in our baseline analysis, we consider three alternative OOS evaluation periods: 1980Q1 to 2019Q4, 1990Q1 to 2019Q4, and 2000Q1 to 2019Q4. As shown by Panel C, $\mathrm{M}^{\mathrm{PLS}}$ consistently outperforms the historical mean benchmark and generates significant R^2_{OS} statistics, whatever the point at which OOS forecasting starts. Therefore, in contrast with Welch and

Goyal (2008) and Goyal, Welch, and Zafirov (2021) who argue that a lion's share of existing predictors evince weak in-sample significance and unstable OOS performance over the recent decades, we show that the predictive power of M^{PLS} is not sensitive to the choice of sample period and remains strong and reliable during the recent decades.

[**Insert Table XI here**]

Second, to address the concerns surrounding econometric inferences for predictive regressions with persistent and endogenous regressors and overlapping observations, we follow Huang et al. (2015) to apply a wild bootstrap procedure to compute empirical p-values for the slope estimates in Eqs. (5) and (9).[21] The simulation procedure accounts for the persistence of predictors, the conditional correlation between the predictors and excess market returns, and general forms of return distribution. The results in Panel A of Table IA.5 in the Internet Appendix corroborate the robustness of our econometric inference for M^{PLS}.

Third, we consider logarithm market returns instead of simple returns. We utilize the Hodrick (1992) standard error and the IVX–Wald statistic of Kostakis et al. (2015) to test the significance of the short- and long-horizon predictability for logarithm excess returns. Panel B of Table IA.5 shows that M^{PLS} continues to predict the logarithm market excess return over the five forecast horizons. Finally, we experiment with several alternative ways to construct the consensus forecasts upon which we build the macro condition indices, and we document quantitatively similar results.[22] Overall, the predictive power of M^{PLS} is not confined to a particular period and is robust to the type of compounding returns and the

[21] For all that, since M^{PLS} does not include asset prices and has a much lower autocorrelation (0.69) than those of valuation ratios (e.g., DP) that are typically over 0.95, the finite-sample bias problem should less be a concern.

[22] For instance, we use the median of the forecasts by individual forecasters as the consensus forecast in Eq.(1) instead of the mean; we compute the growth rate forecasts by individual forecasters first and then take the mean or median; we fix the base quarter to be the one prior to the current quarter when calculating growth rate forecasts for different horizons. These results are available upon request.

way the consensus forecasts are constructed.

5.3 International Evidence

The European Central Bank (ECB) also conducts a survey among professional forecasters similar to the SPF on expected economic conditions for the whole euro area on a quarterly basis since 1999. It is of interest to examine whether the predictability of the macro condition index found in our main results generalizes to the European markets. We use the ECB SPF current- and next-year forecasts on inflation, real GDP growth, and unemployment to construct PLS macro condition indices for the aggregate European stock market and for individual countries, including France, Germany, Italy, the Netherlands, Sweden, Switzerland, and the United Kingdom.[23] Though Sweden, Switzerland, and the United Kingdom are not member states of the euro zone, they are important industrialized European countries with developed markets. We follow Rapach, Strauss, and Zhou (2013) to obtain the country-level market indices and use the STOXX Europe 600 index as a proxy for the aggregate European market.[24] Then, we estimate the following predictive regression:

$$R_{i,t+1} = \alpha + \beta \, \mathrm{EM}_{i,t}^{\mathrm{PLS}} + \epsilon_{i,t+1}, \tag{19}$$

where $R_{i,t+1}$ is the excess return of country i or the STOXX Europe 600 Index, and $\mathrm{EM}_{i,t}^{\mathrm{PLS}}$ denotes the PLS macro condition index based on the ECB SPF data.

[**Insert Table XII here**]

[23]The data are publicly available (`https://www.ecb.europa.eu/stats/ecb_surveys/survey_of_professional_forecasters/`).

[24]Excess returns are computed relative to the domestic three-month Treasury bill rates and are denominated in national currency.

Table XII shows that the macro condition indices significantly predict quarterly returns on their corresponding market indices over the sample period from 1999Q1 to 2019Q4. All slope estimates are sizable and significant at the 1% level, associated with hefty in-sample R^2 values ranging from 9.11% (Germany) to 13.93% (Netherlands). These results suggest that the predictive ability of the macro condition index formed based on survey forecasts of future economic conditions is not peculiar to the U.S. market. This analysis of international predictability serves as an OOS test of the in-sample evidence of the U.S. stock market and further alleviates the concern of data snooping biases.

5.4 Asset Allocation

In this section, we assess the economic value of the predictability afforded by $\mathrm{M}^{\mathrm{PLS}}$. Following Campbell and Thompson (2008) and Cooper and Priestley (2009), we consider an investor who uses OOS return forecasts to guide asset allocation decisions across the equity market and the risk-free bond in real-time. We assume that the investor has a mean-variance utility function[25] and rebalances her portfolio with a quarterly frequency. At the end of quarter t, the optimal portfolio weight on the market index is

$$w_t = \frac{\hat{R}_{t+1}}{\gamma \hat{\sigma}^2_{t+1}}, \tag{20}$$

where γ is the level of risk aversion, $\hat{R}_{t+1}$ is the OOS forecast of the market excess return by a predictive model, and $\hat{\sigma}^2_{t+1}$ is the market variance forecast. Given a portfolio weight w_t, the

[25] There is debate about the true form of investors' utility function. For instance, the level of investor risk aversion could be time varying because of habit persistence. We use the mean–variance framework to assess economic gains by following the prevailing practice of the predictability literature (Campbell and Thompson, 2008; Cooper and Priestley, 2009; Eriksen, 2017; Rapach et al., 2010). Empirically, this facilitates the comparison of our results to prior studies.

realized portfolio return in quarter $t+1$ is $R_{p,t+1} = w_t R_{t+1} + R_{f,t+1}, t = q, ..., T-1$, where R_{t+1} and $R_{f,t+1}$ denote the realized market excess return and the risk-free rate in quarter $t+1$, respectively. Similar to Campbell and Thompson (2008), we use the sample variance of excess returns over the past 10 years as the market variance forecast, and we impose a short sale constraint and a maximum leverage of 50% on the portfolio weight w_t.

Over the OOS evaluation period, the CER of this asset allocation strategy is

$$\mathrm{CER}_p \equiv \hat{\mu}_p - \frac{1}{2}\gamma\hat{\sigma}_p^2, \tag{21}$$

where $\hat{\mu}_p$ and $\hat{\sigma}_p^2$ are the sample mean and variance of the portfolio returns over the OOS period, respectively. The CER gain of the strategy is then defined as the difference between the strategy's CER and the CER of the benchmark strategy that relies on the historical mean forecast. We test the significance of the CER gain using the method described by DeMiguel, Garlappi, and Uppal (2009). In addition, we compute the annualized Sharpe ratio of a portfolio strategy and employ the statistic of Jobson and Korkie (1981) with the correction of Memmel (2003) to test whether the Sharpe ratio of a strategy is statistically different from that of the strategy based on the historical mean forecast. Finally, we adopt the manipulation-proof performance measure Θ (MPPM; see Goetzmann, Ingersoll, Spiegel, and Welch, 2007) to verify the robustness of the economic value. Similarly, we report the gain in MPPM (annualized and in percent) relative to the historical mean strategy.

[**Insert Table XIII here**]

Table XIII presents the OOS performance of the asset allocation strategies. Panel A shows that, under a risk aversion level of three, $\mathrm{M}^{\mathrm{PLS}}$ generates a CER gain of 3.24% relative to the historical mean forecast and a Sharpe ratio of 0.64 that is significantly higher than that of the historical mean (0.41). In other words, an investor is willing to pay an annual portfolio management fee of 3.24% to switch from the historical mean forecast to the return forecasts based on $\mathrm{M}^{\mathrm{PLS}}$. The index $\mathrm{M}^{\mathrm{PLS}}$ also outweighs all portfolio strategies based on the 16 financial and economic predictors, as well as the buy-and-hold strategy, in terms of the CER gain and Sharpe ratio. The MPPM results in column (3) corroborate the robustness of the economic value delivered by $\mathrm{M}^{\mathrm{PLS}}$. The gain in Θ of $\mathrm{M}^{\mathrm{PLS}}$ (3.17%) is more than twice the amount of the buy-and-hold strategy (1.57%). None of the alternative models generates a higher gain in Θ than the buy-and-hold strategy does, however. The results for $\gamma = 5$ reported in Panel B are broadly in line with those in Panel A. The index $\mathrm{M}^{\mathrm{PLS}}$ continues to outperform all predictive models and the buy-and-hold strategy when the investor becomes more risk averse, irrespective of the performance measure.

In sum, the asset allocation analysis shows that the macro condition index $\mathrm{M}^{\mathrm{PLS}}$ generates sizable real-time economic benefit for a mean–variance investor with reasonable risk aversion levels, consistent with its positive R^2_{OS} in Table III. The performance of $\mathrm{M}^{\mathrm{PLS}}$ clearly stands out and surpasses that of other strategies based on popular predictors in the literature and the buy-and-hold strategy.

6 Conclusion

In this paper, we construct a macro condition index that is aligned with the purpose of tracking the equity premium based on SPF consensus forecasts on output, inflation, unemployment, and housing starts. The index is built without using asset prices, which permits us to directly examine the relation between the equity premium and expected economic conditions. The index displays countercyclical dynamics and positively predicts stock returns in the aggregate and cross section. Its predictability is significant, and remains substantial after controlling for a variety of predictors including macro variables proposed by the recent literature. We also find that a long-term macro condition index constructed from the term structures of the SPF forecasts evinces stronger forecasting ability for long-term market returns. Moreover, we present international evidence confirming the robustness of our findings. Economically, the predictive ability of the index mainly derives from the discount rate channel and unlikely arises from belief biases of the SPF forecasts. Overall, our findings depict a tight inverse relation between the expected stock returns and expected economic conditions, consistent with the common implication of rational asset pricing models.

The macro condition index appears successful for equity premium prediction because it uses the macro forecasts collectively, which enables the index to track the equity premium variation induced by fluctuations in output, inflation, and labor and housing market conditions. Its robust forecasting performance underscores the significance of considering broad aspects of the economy when measuring economic conditions. In particular, our results support the important role of time-varying composition risks arising from the labor and housing markets in explaining the time variation of the equity premium, and are also consistent with Q-theory based production models with adjustment costs. The paper can serve as a guidepost for future research of applied asset pricing models, in that it is of essence to encompass multiple state variables related to labor and housing market conditions in understanding the equity premium variation.

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Table I: **Descriptive Statistics**

This table presents descriptive statistics of the SPF consensus macroeconomic forecasts and the CRSP value-weighted market excess return. The six statistics reported for each variable are the average (Mean), standard deviation (Std), skewness (Skew), kurtosis (Kurt), median (Med), and the first-order autocorrelation coefficient (AR(1)). The heading $\rho(X_t, R_{t+1})$ refers to the Pearson correlation between the time-t survey variable in the first column of Panel A with the excess return on the CRSP index (R) in time $t+1$. The SPF data include survey forecasts for seven macroeconomic variables: 1) the real GDP (GDP_e), 2) industrial production index (Indprod_e), 3) the probability of a decline in real GDP (Recess_e), 4) the unemployment rate (Unemp_e), 5) corporate profits after tax (Cprof_e), 6) housing starts (Housing_e), 7) the GDP price index (Infl_e). The forecasting horizon spans from the current quarter to three-quarter ahead. The consensus forecasts for Unemp_e and Recess_e are in levels, while the other forecasts take the form of quarter-over-quarter growth rates (annualized and in percent). The market risk premium (R) is calculated as the return on the CRSP value-weighted index in excess of the short-term T-bill rate. The sample period is from 1968Q4 to 2019Q4, 205 quarters in total.

(1)	(2) Mean	(3) Std	(4) Skew	(5) Kurt	(6) Med	(7) AR(1)	(8) $\rho(X_t, R_{t+1})$
Panel A: SPF Macroeconomic Forecasts							
I. Current-Quarter Forecast							
GDP_e	2.32	2.11	−1.03	5.32	2.51	0.72	−0.05
Indprod_e	2.44	4.28	−1.00	6.00	3.00	0.62	−0.07
Recess_e	18.31	22.03	1.97	5.96	9.51	0.74	0.02
Unemp_e	6.17	1.63	0.64	2.82	5.87	0.96	0.16
Cprof_e	6.21	11.39	−0.01	5.49	5.86	0.59	−0.02
Housing_e	0.49	21.08	0.35	3.09	−1.55	0.43	0.19
Infl_e	3.48	2.22	1.36	4.09	2.64	0.96	−0.08
II. 1-Quarter Ahead Forecast							
GDP_e	2.59	1.64	−0.70	5.20	2.56	0.79	−0.05
Indprod_e	3.12	3.01	−0.47	5.28	3.18	0.73	−0.01
Recess_e	18.59	15.70	1.86	6.06	12.68	0.79	0.04
Unemp_e	6.19	1.60	0.64	2.81	5.84	0.96	0.16
Cprof_e	6.45	8.91	−0.02	4.65	6.06	0.62	−0.02
Housing_e	5.74	17.87	1.20	5.38	1.90	0.83	0.10
Infl_e	3.46	2.04	1.31	3.90	2.67	0.97	−0.06
III. 2-Quarter Ahead Forecast							
GDP_e	2.80	1.28	−0.54	6.08	2.74	0.81	−0.05
Indprod_e	3.45	2.40	0.03	4.70	3.27	0.79	−0.02
Recess_e	17.78	10.23	1.84	6.57	14.86	0.77	0.05
Unemp_e	6.16	1.56	0.62	2.79	5.85	0.96	0.16
Cprof_e	7.43	7.74	1.20	7.82	6.16	0.57	−0.03
Housing_e	8.08	17.04	1.24	4.75	4.25	0.86	0.08
Infl_e	3.47	1.93	1.22	3.63	2.81	0.98	−0.05
IV. 3-Quarter Ahead Forecast							
GDP_e	2.98	0.96	0.54	3.91	2.86	0.83	−0.10
Indprod_e	3.70	1.98	0.69	4.74	3.32	0.84	−0.04
Recess_e	17.17	6.27	0.89	3.92	16.43	0.77	0.06
Unemp_e	6.12	1.51	0.60	2.77	5.77	0.96	0.16
Cprof_e	8.18	6.92	1.84	10.66	6.65	0.57	−0.05
Housing_e	8.53	15.24	0.98	3.49	4.66	0.89	0.05
Infl_e	3.46	1.85	1.14	3.36	2.80	0.98	−0.04
Panel B: Quarterly Market Risk Premium (%)							
R	1.65	8.64	−0.52	3.68	2.69	0.05	-

Table II: **In-sample Return Predictability: 1969Q1-2019Q4**

This table presents the OLS estimates, Newey-West t-statistics, and R^2 of the in-sample predictive regressions for the quarterly market excess returns. Panel A reports the results of the univariate predictive regression model,

$$R_{t+1} = \alpha + \beta X_t + \epsilon_{t+1},$$

where R_{t+1} is the annualized excess return on the CRSP value-weighted index in quarter $t+1$. The predictive variables X_t include the seven current-quarter survey forecasts (SPF7) as well as a set of 16 financial and economic variables (Econ) from Welch and Goyal (2008). The terms $\mathrm{M}^{\mathrm{PLS}}$ and $\mathrm{Econ}^{\mathrm{PLS}}$ denote the PLS factors extracted from SPF7 and Econ, respectively. The term $\mathrm{SPF7}^{\mathrm{KS}}$ refers to the multivariate linear regression (kitchen sink) using SPF7. Panel B reports the results of the multivariate regression model,

$$R_{t+1} = \alpha + \beta\, \mathrm{M}_t^{\mathrm{PLS}} + \psi Ctrl_t + \epsilon_{t+1}$$

where $Ctrl$ denotes one of the control variables taken from the first column other than $\mathrm{M}^{\mathrm{PLS}}$. The kitchen sink model is omitted for collinearity. Each variable is standardized to have a zero mean and unit variance. The sample period is from 1969Q1 to 2019Q4. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Univariate			**Panel B: Bivariate**				
Variable	β	t-stat	R^2 (%)	β (PLS)	t-stat	ψ (Ctrl)	t-stat	R^2 (%)
SPF variables								
$\mathbf{M}^{\mathbf{PLS}}$	**0.083**	**3.65*** **	**5.75**	-	-	-	-	-
GDP_e	−0.018	−0.56	0.27	0.096	3.45***	0.027	0.72	6.23
$\mathrm{Indprod}_e$	−0.024	−0.82	0.50	0.095	3.34***	0.023	0.64	6.08
Unemp_e	0.055	2.28**	2.53	0.077	3.26***	0.011	0.45	5.82
Recess_e	0.008	0.23	0.05	0.099	3.67***	−0.035	−0.91	6.59
Cprof_e	−0.008	−0.27	0.06	0.088	3.70***	0.018	0.54	5.98
$\mathrm{Housing}_e$	0.065	2.58***	3.54	0.071	2.08**	0.018	0.48	5.90
Infl_e	−0.026	−0.80	0.57	0.081	3.52***	−0.012	−0.39	5.87
$\mathrm{SPF7}^{\mathrm{KS}}$	-	-	6.85	-	-	-	-	-
Economic variables								
DP	0.025	0.94	0.50	0.082	3.77***	0.021	0.83	6.11
DY	0.027	0.99	0.60	0.081	3.77***	0.020	0.79	6.09
EP	0.009	0.28	0.07	0.086	3.66***	0.021	0.69	6.10
DE	0.018	0.61	0.28	0.084	3.62***	−0.002	−0.08	5.75
SVAR	0.017	0.45	0.24	0.082	3.69***	0.007	0.20	5.79
BM	0.006	0.22	0.03	0.083	3.74***	0.009	0.34	5.82
NTIS	−0.023	−0.82	0.46	0.081	3.61***	−0.011	−0.40	5.84
TBL	−0.032	−1.33	0.86	0.080	3.39***	−0.009	−0.36	5.81
LTY	−0.016	−0.68	0.20	0.082	3.71***	−0.008	−0.34	5.80
LTR	0.045	1.65*	1.67	0.080	3.67***	0.039	1.51	7.04
TMS	0.044	1.65*	1.58	0.080	3.10***	0.006	0.21	5.77
DFY	0.033	0.99	0.89	0.082	3.54***	0.003	0.09	5.75
DFR	0.033	1.09	0.92	0.080	3.50***	0.017	0.57	5.97
INFL	−0.041	−1.29	1.39	0.078	3.47***	−0.026	−0.85	6.29
CAY	0.041	1.77*	1.42	0.079	3.55***	0.031	1.37	6.56
IK	−0.059	−2.39**	2.91	0.072	2.70***	−0.020	−0.69	6.00
$\mathrm{Econ}^{\mathrm{PLS}}$	0.085	3.03***	6.04	0.051	1.75*	0.056	1.59	7.48

Table III: **Out-of-sample Return Predictability: 1984Q1-2019Q4**

This table reports the OOS forecasting performance for the quarterly market excess returns. The individual predictive variables include the seven current-quarter survey forecasts (SPF7) as well as a set of 16 financial and economic variables (Econ) from Welch and Goyal (2008). The terms $\mathrm{M}^{\mathrm{Com}}$ and $\mathrm{Econ}^{\mathrm{Com}}$ refer to the equal-weighted forecast combination method based on individual forecasts generated by SPF7 and Econ, respectively. See the notes to Table II for further details on the variable definitions. We use OOS R^2 statistic, whose significance is determined by the MSFE-adjusted statistics by Clark and West (2007) that tests the null hypothesis $R^2_{OS} \leq 0$ against the alternative one $R^2_{OS} > 0$, to assess the predictability of each model. We also report the results of forecast-encompassing tests. The test is conducted by constructing the following optimal composite forecast,

$$\hat{R}_{t+1} = (1-\lambda)\hat{R}^{i}_{t+1} + \lambda \hat{R}^{\mathrm{M}^{\mathrm{PLS}}}_{t+1}, \quad 0 \leq \lambda \leq 1$$

where $\hat{R}^{i}_{t+1}(\hat{R}^{\mathrm{M}^{\mathrm{PLS}}}_{t+1})$ is the market excess return forecast generated by model i in the first and fourth columns ($\mathrm{M}^{\mathrm{PLS}}$). The null hypothesis is $\lambda = 0$, indicating that model i encompasses $\mathrm{M}^{\mathrm{PLS}}$, against the alternative hypothesis $\lambda > 0$ that model i does not encompass $\mathrm{M}^{\mathrm{PLS}}$. The statistical significance of λ is assessed by the upper-tail p-value for the Harvey et al. (1998) statistic. Panel A and B present results for SPF variables and economic variables, respectively. The OOS period is from 1984Q1 to 2019Q4. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: SPF Variables			**Panel B: Economic Variables**	
Variable	R^2_{OS}(%)	Encompassing λ	Variable	R^2_{OS}(%)	Encompassing λ
$\mathbf{M^{PLS}}$	**3.12****	-	DP	−6.63	0.99***
			DY	−8.00	1.00***
GDP_e	−0.05	0.92**	EP	−4.27	0.97***
$\mathrm{Indprod}_e$	0.33	0.86**	DE	−3.16	1.00***
Recess_e	−0.83	1.00**	SVAR	−59.72	0.95
Unemp_e	−0.77	1.00***	BM	−6.91	1.00***
Cprof_e	−0.19	0.90**	NTIS	−2.91	0.79***
$\mathrm{Housing}_e$	1.64**	0.88	TBL	0.05	0.93**
Infl_e	−0.29	0.92**	LTY	−1.19	0.94***
			LTR	0.34	0.70**
			TMS	−2.51	1.00***
			DFY	−4.99	1.00***
			DFR	−7.59	1.00**
			INFL	1.13*	0.75**
			CAY	−2.06	0.77***
			IK	−1.91	1.00***
			$\mathrm{Econ}^{\mathrm{PLS}}$	−12.35	1.00***

Table IV: **Long-horizon Return Predictability**

Panels A and B report the long-horizon forecasting results of $\mathrm{M}^{\mathrm{PLS}}$ and LT-$\mathrm{M}^{\mathrm{PLS}}$, respectively, using the following overlapping regression

$$R_{t+1:t+h} = \alpha + \beta X_t + \epsilon_{t+1:t+h},$$

where h denotes the forecast horizon and $R_{t+1:t+h}$ is the annualized h-quarter-ahead excess return on the CRSP value-weighted index from quarter $t+1$ to quarter $t+h$. The variables $\mathrm{M}^{\mathrm{PLS}}$ and LT-$\mathrm{M}^{\mathrm{PLS}}$ refer to the macro condition index and the long-term macro condition index extracted from the seven SPF nowcasts and the term structures of the seven SPF forecasts, respectively. Panel C reports the estimation results of the following regression

$$R_{t+1:t+h} = \alpha + \beta\,\mathrm{M}^{\mathrm{PLS}} + \psi\,\text{LT-M}^{\mathrm{PLS}} + \epsilon_{t+1:t+h},$$

. For each regression, we present the OLS slope estimate, Newey-West corrected t-statistic with $2(h-1)$ lags, in-sample R^2 statistic, and OOS R^2 statistic (R^2_{OS}) whose significance is assessed by the MSFE-adjusted statistics of Clark and West (2007). Similarly, we use $2(h-1)$ lags for the Newey-West statistics when computing the MSFE-adjusted statistics. The sample period is from 1969Q1 to 2019Q4. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

(1)	(2) $h=1$	(3) $h=2$	(4) $h=4$	(5) $h=8$	(6) $h=12$
Panel A: predictive variable $\mathbf{M^{PLS}}$					
β	0.083	0.070	0.068	0.048	0.047
t-NW	3.65***	3.69***	3.73***	2.97***	3.57***
R^2(%)	5.75	7.24	13.82	13.54	17.13
R^2_{OS}(%)	3.12**	2.51**	1.41*	7.67**	10.98**
Panel B: predictive variable LT-$\mathbf{M^{PLS}}$					
β	0.072	0.069	0.062	0.058	0.058
t-NW	3.05***	3.63***	4.82***	4.31***	5.18***
R^2(%)	4.35	7.11	11.48	19.66	25.98
R^2_{OS}(%)	1.16*	3.78**	7.17**	12.98**	17.52**
Panel C: predictive variables $\mathbf{M^{PLS}}$+LT-$\mathbf{M^{PLS}}$					
β	0.062	0.043	0.048	0.019	0.016
t-NW	2.05**	1.54	1.93**	1.74*	1.67*
ψ	0.034	0.042	0.032	0.046	0.048
t-NW	1.07	1.47	1.70*	4.04***	3.56***
R^2(%)	6.36	8.82	15.62	20.85	27.12
R^2_{OS}(%)	2.16**	3.77**	3.51**	13.85**	17.95**

Table V: **Impact of Forecast Errors of SPF Projections**

This table presents the estimation results of the following predictive regression,

$$R_{t+1:t+h} = \alpha + \beta\, \mathrm{M}_t^{\mathrm{PLS}} + \gamma \mathrm{FE} + \epsilon_{t+1:t+h},$$

where $R_{t+1:t+h}$ is the annualized excess return on the CRSP value-weighted index from quarter $t+1$ to quarter $t+h$, $\mathrm{M}_t^{\mathrm{PLS}}$ is the PLS macro condition index, and FE is the forecast error of the SPF projection, which is defined as the difference between the first-release value of the macro variable and the SPF forecast/nowcast on that variable. We collect forecast errors for the six macro variables, including the GDP growth (GDP), the industrial production growth (Indprod), the unemployment growth (Unemp), corporate profits growth (Cprof), housing starts growth (Housing), and inflation (Infl). For the quarterly forecast horizon ($h = 1$), we control for the forecast errors of the SPF nowcasts (FE_i), and for the one-year horizon ($h = 4$), we estimate and control for the first PC of the forecast errors across different horizons for each macro variable ($\mathrm{FE}_i^{\mathrm{PC}}$). Newey-West t-statistics are displayed in parentheses. The sample period is from 1969Q1 to 2019Q4. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: return forecast horizon h=1							
$\mathrm{M}^{\mathrm{PLS}}$	0.083	0.076	0.082	0.088	0.082	0.086	0.085
	(3.65)***	(3.40)***	(3.62)***	(3.60)***	(3.58)***	(3.84)***	(3.59)***
$\mathrm{FE}_{\mathrm{GDP}}$	-0.007						0.026
	(-0.28)						(0.82)
$\mathrm{FE}_{\mathrm{Indprod}}$		-0.032					-0.051
		(-1.33)					(-1.63)
$\mathrm{FE}_{\mathrm{Unemp}}$			0.016				0.000
			(0.61)				(0.01)
$\mathrm{FE}_{\mathrm{Cprof}}$				-0.018			-0.025
				(-0.58)			(-0.87)
$\mathrm{FE}_{\mathrm{Housing}}$					0.013		0.006
					(0.69)		(0.32)
$\mathrm{FE}_{\mathrm{Infl}}$						(0.024)	(0.029)
						(0.89)	(1.05)
R^2 (%)	5.79	6.56	5.97	5.99	5.88	6.24	7.87
Panel B: return forecast horizon h=4							
$\mathrm{M}^{\mathrm{PLS}}$	0.064	0.068	0.066	0.070	0.073	0.057	0.069
	(3.53)***	(3.84)***	(3.70)***	(4.06)***	(5.36)***	(3.50)***	(5.31)***
$\mathrm{FE}_{\mathrm{GDP}}^{\mathrm{PC}}$	0.027						0.055
	(1.43)						(1.98)**
$\mathrm{FE}_{\mathrm{Indprod}}^{\mathrm{PC}}$		-0.011					-0.045
		(-0.63)					(-1.53)
$\mathrm{FE}_{\mathrm{Unemp}}^{\mathrm{PC}}$			0.019				-0.003
			(1.08)				(-0.19)
$\mathrm{FE}_{\mathrm{Cprof}}^{\mathrm{PC}}$				0.014			0.024
				(1.08)			(2.07)**
$\mathrm{FE}_{\mathrm{Housing}}^{\mathrm{PC}}$					0.074		0.062
					(6.78)***		(5.19)***
$\mathrm{FE}_{\mathrm{Infl}}^{\mathrm{PC}}$						-0.032	-0.008
						(-1.70)*	(-0.48)
R^2 (%)	15.95	14.20	14.90	14.42	30.26	16.50	35.03

Table VI: **Compare with realized macro variables**

The term R_{t+1} in the four predictive regressions denotes the annualized excess return on the CRSP value-weighted index in quarter $t+1$. The variables $\mathrm{M}^{\mathrm{PLS}}$, $\mathrm{M}^{\mathrm{PLS}}_{\mathrm{obj}}$, and $\mathrm{M}^{\mathrm{PLS}}_{\text{lag-obj}}$ correspond to the macro condition indices constructed by the PLS method using SPF7, the realized counterparts of SPF7 (except for Recess_e), and the lagged realized counterparts of SPF7 (except for Recess_e), respectively. The variable with superscript $\perp$ is orthogonalized to the other predictive variable in the regression. For example, $\mathrm{M}^{\mathrm{PLS},\perp}$ in regression (1) is obtained by orthogonalizing $\mathrm{M}^{\mathrm{PLS}}$ to $\mathrm{M}^{\mathrm{PLS}}_{\mathrm{obj}}$. The sample period is from 1969Q1 to 2019Q4. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

(1)	(2) β	(3) t-stat	(4) ψ	(5) t-stat	(6) R^2 (%)
	Regression: $R_{t+1} = \alpha + \beta\,\mathrm{M}_t^{\mathrm{PLS},\perp} + \psi\,\mathrm{M}^{\mathrm{PLS}}_{\mathrm{obj},t} + \epsilon_{t+1}$				
Model 1	0.055	1.17	0.080	3.64***	6.01
	Regression: $R_{t+1} = \alpha + \beta\,\mathrm{M}_t^{\mathrm{PLS}} + \psi\,\mathrm{M}^{\mathrm{PLS},\perp}_{\mathrm{obj},t} + \epsilon_{t+1}$				
Model 2	0.083	3.91***	0.033	0.68	6.01
	Regression: $R_{t+1} = \alpha + \beta\,\mathrm{M}_t^{\mathrm{PLS},\perp} + \psi\,\mathrm{M}^{\mathrm{PLS}}_{\text{lag-obj},t} + \epsilon_{t+1}$				
Model 3	0.068	2.04**	0.071	3.22***	5.90
	Regression: $R_{t+1} = \alpha + \beta\,\mathrm{M}_t^{\mathrm{PLS}} + \psi\,\mathrm{M}^{\mathrm{PLS},\perp}_{\text{lag-obj},t} + \epsilon_{t+1}$				
Model 4	0.083	3.86***	0.020	0.60	5.90

Table VII: **Relation of Forecasting Performance with Economic Conditions**

Panel A reports the contemporaneous correlations between the OOS performance of market return forecasts and several measures of macroeconomic conditions. The term DSFE_t refers to the difference between the squared forecast error of M^{PLS} and the squared forecast error of the historical mean in quarter t. The macroeconomic condition measures (X_t) include the real GDP growth, real consumption per capita growth, real labor income per capita growth, the Chicago Fed National Activity Index (CFNAI), and the macroeconomic uncertainty index by Jurado et al. (2015). Panel B reports the R^2_{OS} statistics over subsamples. We use the NBER-dated business cycle phase to classify good and bad economic times of the overall economy. We compute the subsample R^2_{OS} statistic as

$$R^2_{OS,c} = 1 - \frac{\sum_{t=1}^{T} I_t^s (R_t - \hat{R}_t)^2}{\sum_{t=1}^{T} I_t^s (R_t - \bar{R}_t)^2}, \quad c = \text{Good, Bad},$$

where I_t^{Good} (I_t^{Bad}) equals one whenever the economy is in NBER expansion (recession) in quarter t, and zero otherwise. $\bar{R}_t$ refers to the historical mean forecast and $\hat{R}_t$ is the market excess return forecast generated by M^{PLS}. The OOS period is from 1984Q1 to 2019Q4. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Correlations with macroeconomic variables (model: M^{PLS})					
	Real GDP	Real Consumption	Real Labor Income	CFNAI	Macro Uncertainty
$\rho(\text{DSFE}_t, X_t)$	−0.14*	−0.17**	−0.19**	−0.18**	0.17**
Panel B: R^2_{OS} (%) over subsamples					
	NBER Recession	NBER Expansion			
M^{PLS}	7.29***	2.12**			

Table VIII: **Predicting FOMC Announcement Returns and Market Return Components**

Panel A reports the forecasting results for Federal funds rate surprise (FOMC surprise$_t$) and market return (FOMC R_t) on the FOMC announcement day in quarter t. FOMC surprise$_t$ is defined as the sum of the unexpected one-day change in the Federal funds rate on each FOMC announcement day in quarter t. FOMC R_t is calculated as the sum of the FOMC announcement-day return of the CRSP value-weighted index in quarter t. Panel B reports the predictive regression estimation results for market return components that are estimated using the Campbell (1991) vector autoregression (VAR) approach. The three estimated components of the CRSP logarithm market return are the expected return, cash flow news, and discount rate news. The in-sample predictive regression model follows

$$w_{t+1} = \alpha_w + \beta_w \, \mathrm{M}_t^{\mathrm{PLS}} + \epsilon_{t+1},$$

where w_{t+1} is one of three estimated return components in quarter $t+1$ and $\mathrm{M}_t^{\mathrm{PLS}}$ denotes the PLS macro condition index extracted from the seven SPF nowcasts. The intercept of the above regression model is set equal to zero when we predict the cash flow news and the discount rate news. We use a VAR approach based on the variables in the first column to calculate the return components, where "r" denotes the CRSP log return. A detailed description to the variables in the first column can be found in the Internet Appendix. The term "PC3" denotes the first three principal components extracted from the 16 financial and economic variables of Welch and Goyal (2008). The sample period is from 1969Q1 to 2019Q4. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: predicting Fed's funds rate surprises and market reactions						
	β	t-stat	R^2			
FOMC Surprise$_t$	−3.142	−2.46**	4.03			
FOMC R_t	0.317	2.20**	3.37			
Panel B: predicting market return components						
	Expected return		Cash flow		Discount rate	
VAR Variables	$\hat{\beta}_{\hat{E}}$	t-stat	$\hat{\beta}_{\mathrm{CF}}$	t-stat	$\hat{\beta}_{\mathrm{DR}}$	t-stat
r, DP, DY	0.108	0.80	0.380	1.61	−1.247	−3.26***
r, DP, DE	0.196	1.67*	0.624	1.57	−0.916	−2.32**
r, DP, SVAR	0.271	2.25**	0.394	1.68*	−1.071	−2.99***
r, DP, BM	0.378	3.02***	0.369	1.55	−0.989	−2.83***
r, DP, NTIS	0.233	1.97**	0.240	0.95	−1.262	−3.15***
r, DP, TBL	0.628	5.02***	0.259	0.91	−0.849	−2.11**
r, DP, TMS	0.525	4.66***	0.298	1.21	−0.913	−2.40**
r, DP, DFY	0.301	2.37**	0.410	1.74*	−1.024	−2.83***
r, DP, CAY	0.315	2.17**	0.199	0.87	−1.222	−2.82***
r, DP, IK	0.628	5.74***	0.463	1.97**	−0.645	−1.66*
r, DP, PC3	0.782	4.64***	0.312	1.29	−0.642	−1.90*

Table IX: **Relation with Other Predictive Variables**

This table presents the forecasting performance for the quarterly market excess return of M^{PLS} and additional predictive variables, including: consumption volatility (σ_c), as in Bansal et al. (2005); the price–output ratio (py), as in Rangvid (2006); the ratio of labor income to consumption (s^w), as in Santos and Veronesi (2006); the quarterly ratio of non-housing consumption to total consumption (house) following the construction of Piazzesi et al. (2007); the output gap (OG), as in Cooper and Priestley (2009); payroll growth (payroll), as in Chen and Zhang (2011); the ratio of new orders to shipments of durable goods (NO/S), as in Jones and Tuzel (2013); the cyclical consumption (CC), as in Atanasov et al. (2020); the Michigan Consumer Sentiment Index (S^{MC}); the Baker–Wurgler investor sentiment index (S^{BW}), as in Baker and Wurgler (2006); the aligned investor sentiment index (S^{HJTZ}), as in Huang et al. (2015); the PLS disagreement index (D^{HLW}), as in Huang et al. (2021); the PLS factor extracted from 100 BM ratios (BM^{KP}), as in Kelly and Pruitt (2013). The term "$Macro^{PC}$ refers to the first PC of the additional eight macro variables considered. Panel A reports the univariate regression results. Panel B reports the results of bivariate regression incorporating the predictors in the first column other than M^{PLS} as control variables. See the notes to Table II for specifications of the regression models. Panel C reports contemporaneous correlations of M^{PLS} with the other predictors in the first column. Each variable is standardized to have a zero mean and unit variance. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The sample period is from 1969Q1 to 2019Q4, except for S^{BW} (1969Q1 to 2018Q4) and D^{HLW} (1970Q1 to 2018Q4).

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Univariate		**Panel B: Bivariate**			**Panel C: Correlation**
Variable	β	R^2 (%)	β (M^{PLS})	ψ (Ctrl)	R^2 (%)	$\rho(M^{PLS}, \text{Ctrl})$
M^{PLS}	0.083***	5.75	-	-	-	-
Other macro variables						
σ_c	−0.034	0.96	0.088***	−0.043*	7.29	0.11
py	−0.037	1.13	0.080***	−0.027	6.33	−0.13
s^w	−0.016	0.22	0.083***	−0.012	5.88	−0.04
house	−0.037	1.14	0.079***	−0.015	5.92	−0.28
OG	−0.077***	4.92	0.058**	−0.043	6.78	−0.58
payroll	−0.047	1.87	0.080***	−0.007	5.78	−0.51
NO/S	−0.048*	1.94	0.076***	−0.020	6.02	−0.38
CC	−0.069***	3.98	0.065***	−0.035	6.51	−0.52
$Macro^{PC}$	−0.062***	3.16	0.070***	−0.023	6.07	−0.54
Variables related to investor's sentiment and disagreement						
S^{MC}	−0.024	0.50	0.087***	0.010	5.82	−0.40
S^{BW}	−0.036	1.07	0.083***	−0.034	6.80	−0.02
S^{HJTZ}	−0.088***	6.49	0.073***	−0.079***	10.79	−0.13
D^{HLW}	−0.077***	4.80	0.068***	−0.062**	8.45	−0.21
Other PLS predictor						
BM^{KP}	0.139***	15.97	0.076***	0.135***	20.82	0.05

Table X: **Predicting Characteristic-sorted Equity Portfolios**

This table presents the forecasting results for the characteristic-sorted equity portfolios with $\mathrm{M}^{\mathrm{PLS}}$. We evaluate the following predictive regression both in- and out-of-sample:

$$R^p_{t+1} = \alpha + \beta\, \mathrm{M}^{\mathrm{PLS}}_t + \epsilon_{t+1},$$

where R^p_{t+1} is the quarterly excess returns on some equity portfolio sorted on a certain characteristic. We report the in-sample slope estimates, in-sample R^2 statistics, and the OOS R^2 statistics. Panels A and B report the results for the 10 size-sorted portfolios and the 10 industry portfolios, receptively. The in-sample period is from 1969Q1 to 2019Q4 and the OOS period is from 1984Q1 to 2019Q4. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Size portfolios				**Panel B: Industry portfolios**		
	β	R^2 (%)	R^2_{OS} (%)		β	R^2 (%)	R^2_{OS} (%)
Small	0.133***	6.41	2.83***	Nondurable	0.080***	5.47	2.47**
Size2	0.115***	5.19	2.17**	Durable	0.146***	8.94	6.13***
Size3	0.109***	5.29	2.70**	Manufacture	0.086***	5.29	4.20**
Size4	0.107***	5.51	2.73**	Energy	0.044	1.33	−1.23
Size5	0.106***	5.69	3.31**	HiTech	0.111***	5.08	1.54**
Size6	0.104***	6.34	4.66***	Telecom	0.054**	2.40	2.18**
Size7	0.096***	5.38	3.18**	Shops	0.111***	7.07	3.43***
Size8	0.093***	5.56	3.96***	Health	0.050**	1.91	0.59
Size9	0.081***	5.04	3.04**	Utility	0.047**	2.41	−0.50
Large	0.073***	5.21	2.51**	Other	0.086***	4.39	2.87**

Table XI: **Return Predictability for Subsamples**

This table presents the forecasting results of the predictive regression

$$R_{t+1:t+h} = \alpha + \beta \, \mathrm{M}_t^{\mathrm{PLS}} + \epsilon_{t+1:t+h},$$

over different subsample periods. Panels A and B present the results for the first-half sample (1969Q1-1994Q2) and second-half sample (1994Q3-2019Q4), respectively. Panel C considers three alternative OOS forecasting evaluation periods: from 1980Q1 to 2019Q4, from 1990Q1 to 2019Q4, and from 2000Q1 to 2019Q4. In Panels A and B, we report the regression slope estimate, Newey-West corrected t-statistic with $2(h-1)$ lags, and in-sample R^2 statistics. In Panel C, we report the OOS R^2 statistics whose significance is assessed by the MSFE-adjusted statistics of Clark and West (2007). *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)
	$h=1$	$h=2$	$h=4$	$h=8$	$h=12$
Panel A: first-half sample (1969Q1-1994Q2)					
β	0.087	0.072	0.079	0.038	0.034
t-NW	2.56***	2.83***	3.11***	1.62	2.31**
$R^2(\%)$	5.75	6.78	18.40	10.50	12.84
Panel B: second-half sample (1994Q3-2019Q4)					
β	0.090	0.067	0.044	0.048	0.047
t-NW	2.88***	2.06**	1.62	2.13**	1.93*
$R^2(\%)$	7.43	8.02	6.04	11.14	12.53
Panel C: alternative out-of-sample evaluation periods					
Forecasting from 1980					
$R^2_{OS}(\%)$	3.38**	3.83**	1.61**	2.56**	15.08***
Forecasting from 1990					
$R^2_{OS}(\%)$	4.29**	4.15**	3.31**	11.04**	14.44**
Forecasting from 2000					
$R^2_{OS}(\%)$	5.69**	7.75**	10.83**	17.48***	29.15***

Table XII: **International Evidence**

This table reports the OLS estimates, Newey-West t-statistics, and R^2 of in-sample predictive regression

$$R_{i,t+1} = \alpha + \beta\,\mathrm{EM}^{\mathrm{PLS}}_{i,t} + \epsilon_{i,t+1},$$

where $R_{i,t+1}$ is the annualized quarterly excess return of one of the seven European countries considered, including France, Germany, Italy, the Netherlands, Sweden, Switzerland, the United Kingdom (UK), or the STOXX Europe 600 Index. We collect survey forecasts on the real GDP growth, unemployment, and inflation for the whole euro area at horizons of the current year and the next year from the ECB Survey of Professional Forecasters, and $\mathrm{EM}^{\mathrm{PLS}}_{i,t}$ is the extracted PLS macro condition index from the ECB survey forecasts using R_i as the target variable. The sample period is from 1999Q1 to 2019Q4. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

(1)	(2) β	(3) t-stat	(4) R^2 (%)	(5)	(6) β	(7) t-stat	(8) R^2 (%)
France	0.135	3.27***	11.33	Sweden	0.143	3.41***	10.67
Germany	0.140	3.00***	9.11	Switzerland	0.095	2.89***	9.62
Italy	0.135	2.89***	11.17	UK	0.103	3.39***	12.42
Netherlands	0.148	3.22***	13.93	STOXX	0.135	3.14***	11.03

Table XIII: **Economic Value of Out-of-sample Return Predictability**

This table reports the results of OOS asset allocation analysis. The investor allocates a portion $\omega_t = \hat{R}_{t+1}/(\gamma\hat{\sigma}^2_{t+1})$ of her wealth to the market index and $1-\omega_t$ to the risk-free asset, where γ is the risk aversion coefficient, $\hat{R}_t$ is the OOS forecast of $t+1$ market index excess return made at time t using the models listed in the first column, and $\hat{\sigma}^2_{t+1}$ is the forecast of $t+1$ market return variance based on calculated as the sample variance of the market excess returns over past ten years. The weight on the market index is constrained to lie between zero and 1.5. HAV corresponds to the strategy using the historical mean forecast. The term Buy&Hold refers to the passive strategy that holds the market index. The certain equivalent return (CER) gain (annualized and in percent) is defined as the difference between the CER delivered by HAV and the CER delivered by any strategy other than HAV in column one, and its statistical significance is determined by the method outlined by DeMiguel et al. (2009). The Sharpe ratio (annualized) is the average portfolio excess return divided by the standard deviation of excess returns. We apply the Jobson and Korkie (1981) statistic corrected by Memmel (2003) to assess whether the difference between the Sharpe ratio of HAV and the Sharpe ratio of any strategy other than HAV in column one is significant. $\triangle\Theta(\%)$ (annualized and in percent) denotes the difference between the manipulation-proof performance measure (MPPM) of HAV and the MPPM of any strategy other than HAV in column one. Panels A and B report the portfolio performance under the constant risk aversion coefficient of three and five, respectively, and we set ρ of MPPM to be the same as γ. Each strategy is quarterly rebalanced. The OOS period is from 1984Q1 to 2019Q4. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: $\gamma = 3$			**Panel B:** $\gamma = 5$		
Variable	CER gain (%)	Sharpe ratio	$\Delta\Theta$ (%)	CER gain (%)	Sharpe ratio	$\Delta\Theta$ (%)
HAV	-	0.41	-	-	0.40	-
Buy & Hold	1.82*	0.52*	1.57	0.24	0.52*	−0.54
M^{PLS}	**3.24****	**0.64****	**3.17**	**1.95****	**0.61***	**1.89**
Economic variables						
DP	−1.40	0.33	−1.36	−0.83	0.33	−0.81
DY	−1.17	0.40	−1.13	−0.69	0.40	−0.67
EP	−0.21	0.48	−0.20	−0.11	0.48	−0.11
DE	−1.08	0.32	−1.17	−0.69	0.32	−0.74
SVAR	−2.91	0.22	−3.29	−2.79	0.20	−3.28
BM	−1.65	0.25	−1.65	−0.97	0.25	−0.98
NTIS	−0.84	0.37	−1.24	−0.95	0.37	−0.92
TBL	0.29	0.43	0.10	0.00	0.41	−0.11
LTY	−0.44	0.37	−0.47	−0.24	0.37	−0.25
LTR	1.03	0.48	1.07	−0.08	0.41	0.04
TMS	−0.17	0.41	−0.81	−1.17	0.34	−2.27
DFY	−1.36	0.29	−1.43	−1.03	0.26	−1.09
DFR	−1.18	0.32	−1.33	−1.07	0.29	−1.21
INFL	0.93	0.47	0.96	0.38	0.45	0.38
CAY	−0.68	0.39	−0.93	−1.41	0.37	−1.99
IK	0.61	0.44	0.07	0.38	0.44	0.00
$Econ^{PLS}$	−1.83	0.34	−2.70	−2.11	0.33	−2.46

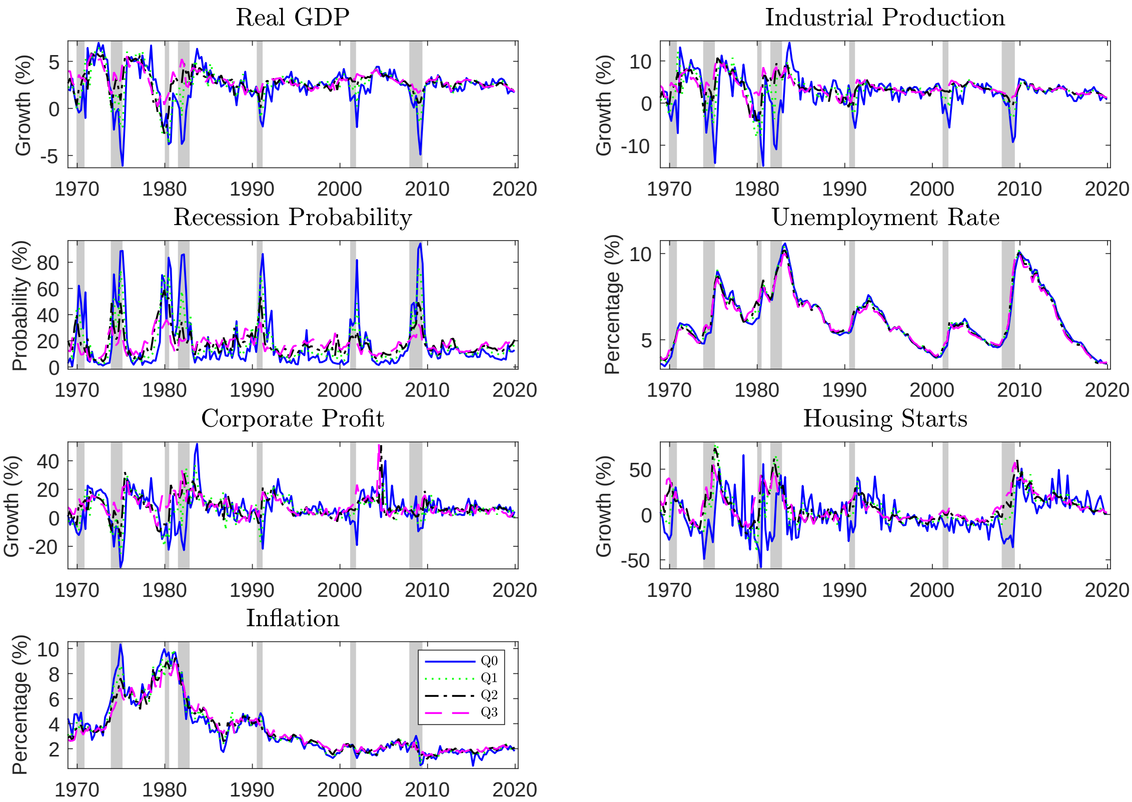

Figure 1: **Consensus Macroeconomic Forecasts from the Survey of Professional Forecasters**

Figure 1 plots the term structure of consensus macroeconomic forecasts for the seven aspects of the macroeconomy, including the Real GDP Growth, Industrial Production Growth, Recession Probability, Unemployment Rate, Corporate Profit Growth, Housing Starts Growth, and Inflation. The term structure of each survey variable is consist of the forecasts of the current quarter and the following three quarters. The solid line depicts the forecast for current quarter. The dotted line depicts one-quarter ahead forecast. The dash-dotted line depicts two-quarter ahead forecast and the dashed line depicts three-quarter ahead forecast. The survey data are from the Survey of Professional Forecasters database. The sample period is from the fourth quarter of 1968 (1968Q4) to the fourth quarter of 2019 (2019Q4). The shaded area corresponds to the NBER recession period.

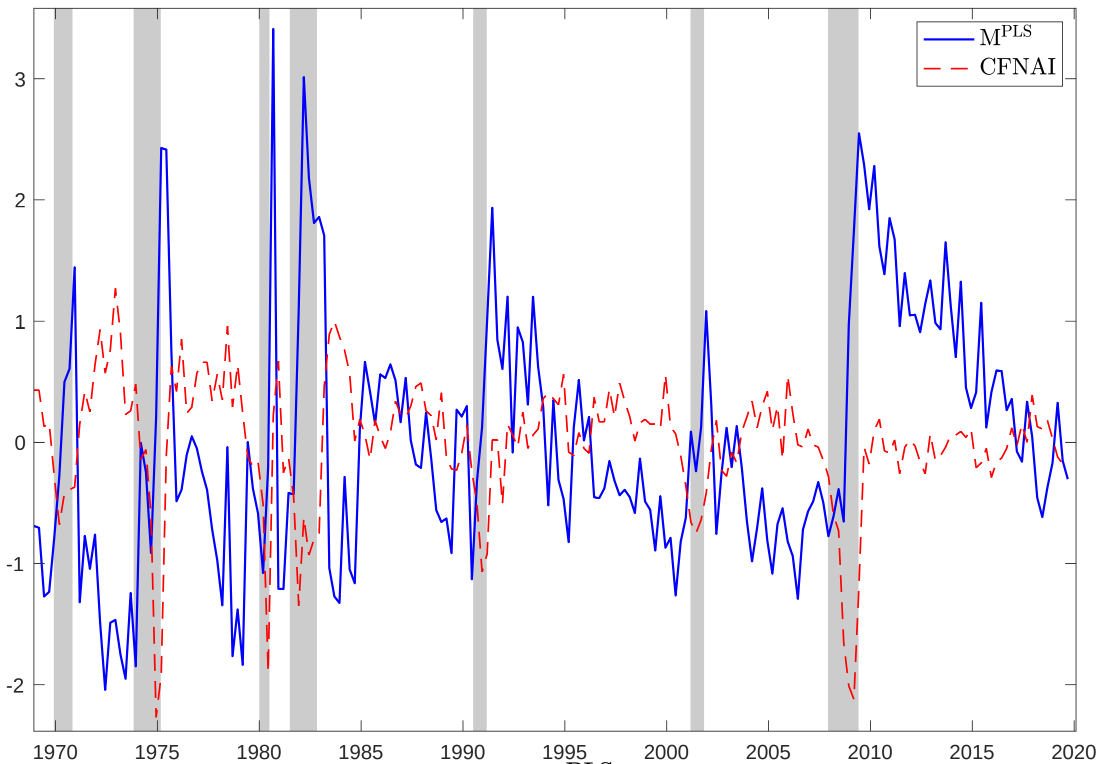

Figure 2: **Time series of $\mathbf{M^{PLS}}$ and the CFNAI**

Figure 2 depicts the time series of the macro condition index constructed by PLS using the seven current-quarter SPF forecasts M^{PLS}, and the Chicago Fed National Activity Index (CFNAI). The sample period is from 1968Q4 to 2019Q3. The shaded area corresponds to the NBER-dated recession period.

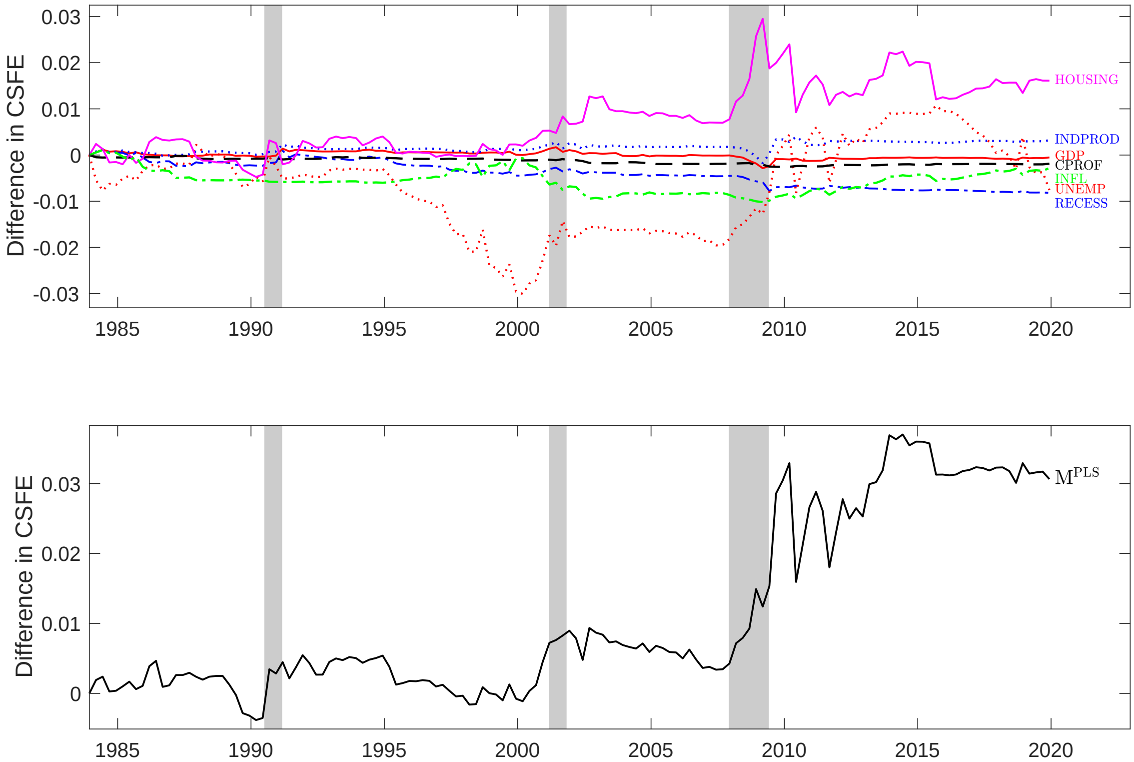

Figure 3: **The differences in cumulative squared forecast errors (CSFE) over quarterly horizon**

Figure 3 depicts the difference between the CSFE for the predictive regression models and the CSFE for the recursive historical mean over the quarterly forecast horizon. The upper panel shows the results for the seven SPF variables. The lower panel shows the results for the macro condition index M^{PLS}. The shaded area corresponds to the NBER recession period. The out-of-sample period is from 1984Q1 to 2019Q4.

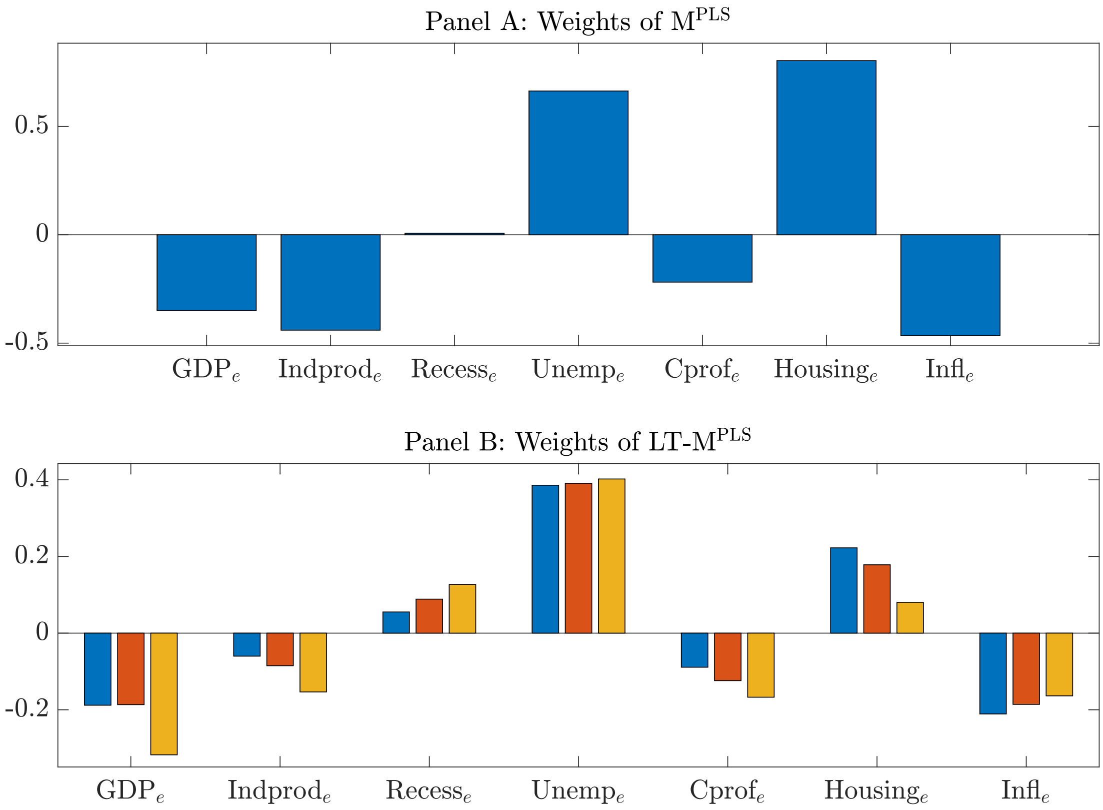

Figure 4: **In-sample PLS weights of $\mathbf{M^{PLS}}$ and LT-$\mathbf{M^{PLS}}$**

Panel A depicts the in-sample estimated PLS weights for the macro condition index M^{PLS} constructed based on the seven current-quarter survey forecasts. Panel B depicts the in-sample estimated PLS weights for the long-term macro condition index M^{PLS} constructed based on the term structure of the seven survey forecasts. The sample period is from 1969Q1 to 2019Q4.

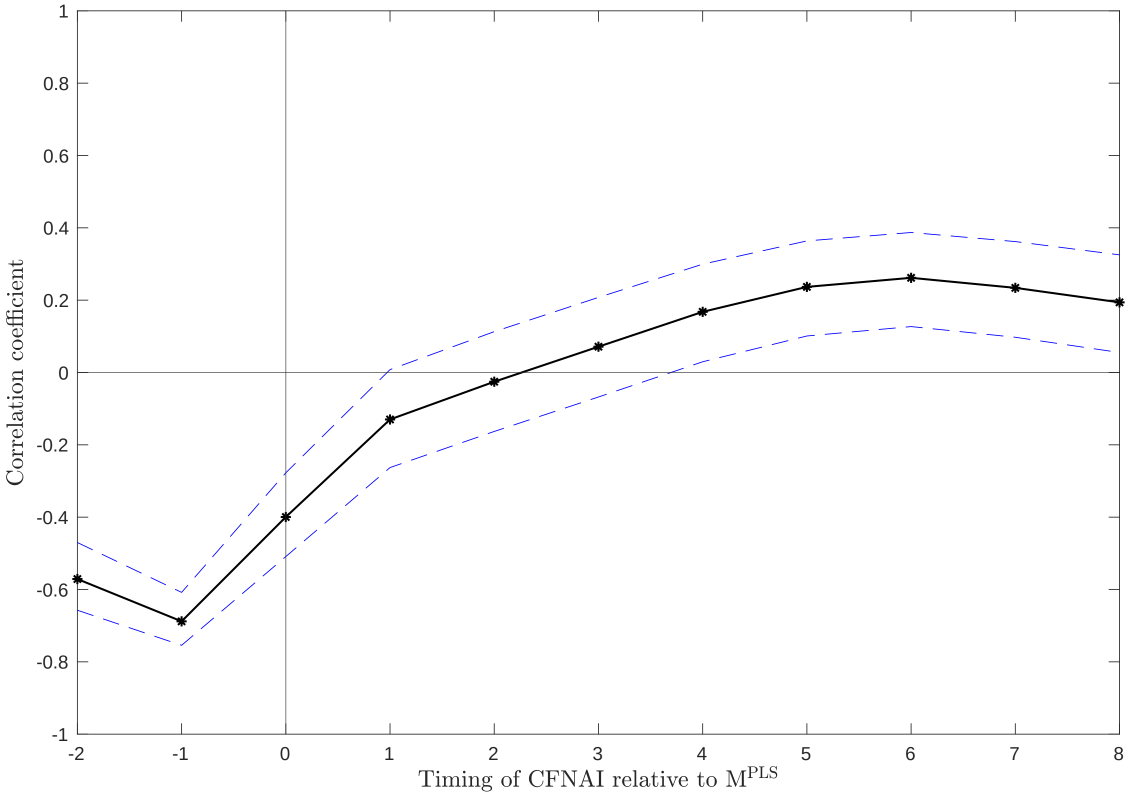

Figure 5: **Correlations between $\mathbf{M^{PLS}}$ and the CFNAI**

Figure 5 shows correlations between M^{PLS} in quarter t and the CFNAI in quarter $t + \tau$, where τ is the value on the x-axis. The dashed lines depict the 95% confidence interval for correlation coefficients. The sample period is from 1968Q4 to 2019Q3. The shaded area corresponds to the NBER-dated recession period.

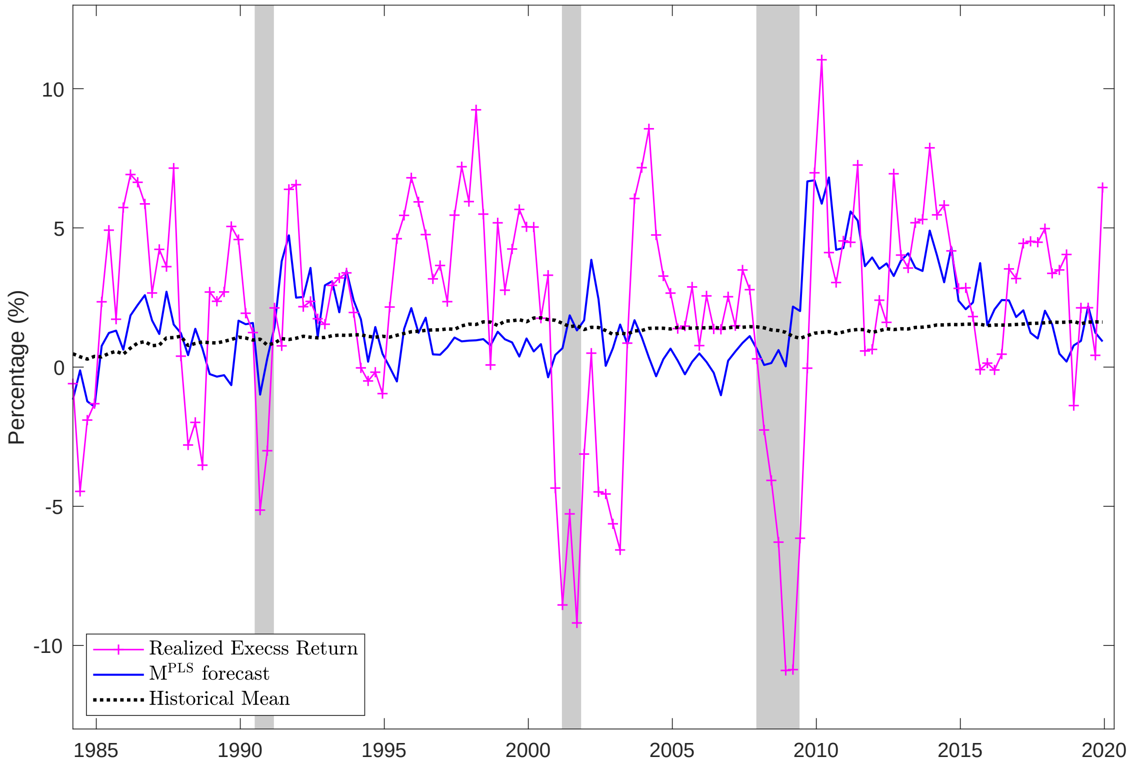

Figure 6: **Out-of-sample Market Risk Premium Forecasts**

Figure 6 depicts the realized market excess return smoothed by a four-quarter moving average (solid line with sign marker), the historical mean return forecast (dotted line), and the return forecast generated by M^{PLS} (solid line). The sample period is from 1984Q1 to 2019Q4. The shaded area corresponds to the NBER recession period.

Internet Appendices

This section presents supplementary results to the paper "Expected Macroeconomic Conditions and Expected Returns", including the definition of the 16 financial and economic variables from Welch and Goyal (2008) used in the paper, a detailed description on the return decomposition methodology, and supplementary tables.

A Variable Definition

- Dividend Price Ratio (DP): Difference between the log of 1-year moving sum of dividends paid on the S&P 500 index and the log of the S&P 500 index level.
- Dividend Yield (DY): Difference between the logarithm of 1-year moving sum of dividends paid on the S&P 500 index and the log of lagged S&P 500 index level.
- Earnings Price Ratio (EP): The log of earnings minus the log of the S&P 500 index level. Earnings are 12-month moving sums of earnings on the S&P 500 index.
- Dividend Payout Ratio (DE): Difference between the log of dividends and the log of the earnings of the S&P 500 index.
- Stock variance (SVAR): Sum of squared daily S&P 500 index returns.
- Book-to-Market Ratio (BM): The ratio of book equity value to market equity value for the Dow Jones Industrial Average.
- Net Equity Expansion (NTIS): The ratio of 12-month moving sums of net issues by NYSE-listed stocks divided by the total end-of-year market capitalization of NYSE stocks.
- Treasury Bill Rate (TBL): Yield on a 3-month Treasury bill traded in the secondary market.
- Long Term Yield (LTY): Long-term government bond yield.
- Long Term Rate of Returns (LTR): Return on long-term government bonds.
- Term Spread (TMS): Difference in yield between the long-term government bonds and the 3-month Treasury bill.

- Default Yield Spread (DFY): Difference between BAA and AAA-rated corporate bond yields.
- Default Return Spread (DFR): Difference in return between the long-term corporate bonds and long-term government bonds.
- Inflation (INFL): Inflation is the growth rate of Consumer Price Index (All Urban Consumers). Since the inflation data is released in the next month, we use the lagged inflation, following Welch and Goyal (2008).
- Consumption to Wealth Ratio (CAY): The residual from a co-integration regression of the aggregate consumption on aggregate wealth and labor income (Lettau and Ludvigson, 2001).
- Investment to Capital Ratio (IK): The ratio of aggregate (private nonresidential fixed) investment to aggregate capital for the whole economy (Cochrane, 1991).

B Return Decomposition

Denote by P_t and D_t the stock price and the dividend at time t, respectively. We define the log dividend-price ratio as $x_t = log(D_t/P_t) = log(D_t) - log(P_t) = d_t - p_t$. According to Campbell (1991), the log-linear approximation of the stock return is given by

$$r_{t+1} = log\left(\frac{P_{t+1} + D_{t+1}}{P_t}\right) \approx k + x_t + \Delta d_{t+1} - \rho x_{t+1}, \tag{OB.1}$$

where

$$\rho = \frac{1}{1 + e^{\bar{x}}} \in (0, 1), \tag{OB.2}$$

$$k = -\rho log(\rho) - (1 - \rho) log(1 - \rho), \tag{OB.3}$$

$\bar{x}$ is the mean of x_t, and $\Delta d_{t+1} = d_{t+1} - d_t$. We can rewrite Eq. (OB.1) as

$$\begin{aligned} x_t &\approx r_{t+1} - k - \Delta d_{t+1} + \rho x_{t+1} \\ &= r_{t+1} - k - \Delta d_{t+1} + \rho(r_{t+2} - k - \Delta d_{t+2} + \rho x_{t+2}) = ... \\ &= -\frac{k}{1-\rho} - \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j} + \sum_{j=1}^{\infty} \rho^{j-1} r_{t+j}, \end{aligned} \tag{OB.4}$$

where in the last step, we impose the no-bubble transversality condition $\lim_{j\to\infty} \rho^j x_{t+j} = 0$. Taking time-$t$ conditional expectation on both sides of Eq. (OB.4) yields the dividend-price ratio decomposition of Campbell (1991),

$$x_t = -\frac{k}{1-\rho} - \mathbb{E}_t\left(\sum_{j=1}^{\infty} \rho^{j-1}\Delta d_{t+j}\right) + \mathbb{E}_t\left(\sum_{j=1}^{\infty} \rho^{j-1} r_{t+j}\right). \tag{OB.5}$$

Using the results from Eqs. (OB.1) and (OB.5), we obtain the following decomposition of the log stock return innovation:

$$r_{t+1} - \mathbb{E}_t(r_{t+1}) = (\mathbb{E}_{t+1} - \mathbb{E}_t)\left(\sum_{j=0}^{\infty} \rho^j \Delta d_{t+j+1}\right) - (\mathbb{E}_{t+1} - \mathbb{E}_t)\left(\sum_{j=1}^{\infty} \rho^j r_{t+j+1}\right). \tag{OB.6}$$

Equation (OB.6) indicates that the unexpected log stock return can be decomposed into cash flow news and discount rate news components:

$$\eta^r_{t+1} = \eta^{\text{CF}}_{t+1} - \eta^{\text{DR}}_{t+1}, \tag{OB.7}$$

where $\eta^r_{t+1} = r_{t+1} - \mathbb{E}_t(r_{t+1})$, $\eta^{\text{CF}}_{t+1} = (\mathbb{E}_{t+1} - \mathbb{E}_t)\left(\sum_{j=0}^{\infty} \rho^j \Delta d_{t+j+1}\right)$, and $\eta^{\text{DR}}_{t+1} = (\mathbb{E}_{t+1} - \mathbb{E}_t)\left(\sum_{j=1}^{\infty} \rho^j r_{t+j+1}\right)$ denote the innovations to the stock return, cash flow, and discount rate, respectively.

Next, we follow Campbell (1991) to use a VAR framework to estimate η^r_{t+1}, η^{CF}_{t+1}, and η^{DR}_{t+1}. Specifically, consider the following VAR(1) model:

$$v_{t+1} = Av_t + u_{t+1}, \tag{OB.8}$$

where $v_t = [r_t, x_t, z_t']'$ is an $(n+2)$-vector, z_t is an n-vector of conditioning variables, A is an $(n+2)$-by-$(n+2)$ matrix of VAR slope coefficients, and u_{t+1} is an $(n+2)$-vector of innovations with zero mean.[26] Let $e_1' = [1, 0, ..., 0]'$ be an $(n+2)$-vector, the stock return innovation and discount rate news are given by

$$\eta^r_{t+1} = e_1' u_{t+1} \tag{OB.9}$$

and

$$\eta^{\text{DR}}_{t+1} = (\mathbb{E}_{t+1} - \mathbb{E}_t)\left(\sum_{j=1}^{\infty} \rho^j e_1' v_{t+1+j}\right) = e_1' \sum_{j=1}^{\infty} \rho^j A^j u_{t+1} = e_1' \rho A (I - \rho A)^{-1} u_{t+1}, \tag{OB.10}$$

[26]The elements in v_t are demeaned before using, while we use the same notation here for convenience.

respectively. Accordingly, the cash flow news is residually defined as

$$\eta_{t+1}^{\mathrm{CF}} = \eta_{t+1}^{r} + \eta_{t+1}^{\mathrm{DR}}. \tag{OB.11}$$

Moreover, Eq. (OB.8) implies that the expected stock return for time $t+1$ made at time t is

$$\mathbb{E}_t(r_{t+1}) = e_1' A v_t. \tag{OB.12}$$

Taken all together, we obtain the decomposition of the log stock return as

$$r_{t+1} = \mathbb{E}_t(r_{t+1}) + \eta_{t+1}^{\mathrm{CF}} - \eta_{t+1}^{\mathrm{DR}}. \tag{OB.13}$$

Empirically, we use OLS to estimate A and $\{u_{t+1}\}_{t=1}^{T-1}$ in Eq. (OB.8) based on sample observations for $\{v_t\}_{t=1}^{T}$. Denote by $\hat{A}$ and $\hat{u_t}$ the OLS estimates, respectively. In addition, we estimate ρ using the sample mean of x_t, and we denote the estimate by $\hat{\rho}$. Finally, we can plug $\hat{A}$, $\hat{u_t}$, and $\hat{\rho}$ into Eqs. (OB.9)–(OB.12) to obtain the estimated return decomposition components, $\hat{\mathbb{E}}_t(r_{t+1})$, $\hat{\eta}_{t+1}^{r}$, $\hat{\eta}_{t+1}^{\mathrm{DR}}$, and $\hat{\eta}_{t+1}^{\mathrm{CF}}$ for $t = 1, ..., T-1$.

C Supplementary Tables and Plots

Table IA.1: **SPF Variable Correlations**

This table presents correlations for the current-quarter forecasts on the seven macroeconomic variables from the Survey of Professional Forecasters (SPF) database. The seven SPF variables includes 1) gross domestic product growth (GDP_e), 2) the industrial production index growth ($\mathrm{Indprod}_e$), 3) the probability of a decline in real GDP (Recess_e), 4) the unemployment rate (Unemp_e), 5) the corporate profits after tax (Cprof_e), 6) housing starts ($\mathrm{Housing}_e$), and 7) GDP price index growth (Infl_e). The sample period is from 1968Q4 to 2019Q3.

(1) Variable	(2) GDP_e	(3) $\mathrm{Indprod}_e$	(4) Recess_e	(5) Unemp_e	(6) Cprof_e	(7) $\mathrm{Housing}_e$
GDP_e	1.00					
$\mathrm{Indprod}_e$	0.93	1.00				
Recess_e	−0.88	−0.83	1.00			
Unemp_e	−0.05	0.03	0.19	1.00		
Cprof_e	0.80	0.79	−0.68	0.16	1.00	
$\mathrm{Housing}_e$	0.19	0.13	−0.17	0.35	0.23	1.00
Infl_e	−0.30	−0.21	0.39	0.19	−0.28	−0.21

Table IA.2: **Predictive Variable Correlations**

This table presents contemporaneous correlations for the 16 economic predictors from Welch and Goyal (2008), as well as the macro condition index (M^{PLS}). The sample period is from 1968Q4 to 2019Q3.

(1) Variable	(2) DP	(3) DY	(4) EP	(5) DE	(6) SVAR	(7) BM	(8) NTIS	(9) TBL	(10) LTY	(11) LTR	(12) TMS	(13) DFY	(14) DFR	(15) INFL	(16) CAY	(17) IK
DP	1.00															
DY	0.98	1.00														
EP	0.73	0.72	1.00													
DE	0.25	0.24	−0.48	1.00												
SVAR	−0.02	−0.11	−0.27	0.36	1.00											
BM	0.91	0.89	0.81	0.02	−0.08	1.00										
NTIS	0.16	0.15	0.15	−0.01	−0.17	0.25	1.00									
TBL	0.68	0.68	0.66	−0.06	−0.13	0.69	0.22	1.00								
LTY	0.74	0.74	0.62	0.07	−0.10	0.69	0.26	0.90	1.00							
LTR	0.04	0.04	0.04	0.00	0.27	0.01	−0.09	−0.06	−0.02	1.00						
TMS	−0.15	−0.13	−0.32	0.27	0.10	−0.26	0.00	−0.55	−0.14	0.09	1.00					
DFY	0.47	0.47	0.13	0.41	0.43	0.45	−0.24	0.25	0.35	0.24	0.10	1.00				
DFR	0.00	0.06	−0.14	0.20	−0.12	−0.01	0.06	−0.07	0.00	−0.42	0.16	0.03	1.00			
INFL	0.48	0.48	0.56	−0.18	−0.10	0.57	0.19	0.51	0.43	0.10	−0.32	0.11	−0.07	1.00		
CAY	−0.13	−0.10	−0.18	0.09	0.08	−0.36	−0.11	0.08	0.27	0.14	0.34	−0.05	−0.06	−0.21	1.00	
IK	−0.14	−0.16	0.13	−0.36	−0.04	0.06	0.09	0.42	0.19	−0.05	−0.59	−0.23	−0.18	0.24	−0.12	1.00
M^{PLS}	0.04	0.08	−0.14	0.25	0.11	−0.04	−0.16	−0.29	−0.10	0.07	0.46	0.36	0.21	−0.19	0.12	−0.54

Table IA.3: **In-sample Return Predictability (look-ahead bias-free PLS forecast): 1984Q1-2019Q4**

This table presents the OLS estimates, Newey-West t-statistics, and R^2 of the in-sample predictive regressions for quarterly market excess return. Panel A reports the results of the univariate predictive regression model,

$$R_{t+1} = \alpha + \beta \mathrm{X}^{\mathrm{PLS}}_{\text{Bias-free},t} + e_{t+1},$$

where R_{t+1} is the excess return on the CRSP value-weighted index (annualized) for quarter $t+1$, X could be one of the variable sets $\{\mathrm{SPF7}, \mathrm{Econ}\}$, and $\mathrm{X}^{\mathrm{PLS}}_{\text{Bias-free}}$ denotes the look-ahead bias-free factor extracted via PLS. Panel B reports the results of the bivariate predictive regression model,

$$R_{t+1} = \alpha + \beta\, \mathrm{M}^{\mathrm{PLS}}_{\text{Bias-free},t} + \psi Ctrl_t + e_{t+1},$$

where $Ctrl$ denotes one of the control variables taken from the first column other than $\mathrm{M}^{\mathrm{PLS}}_{\text{Bias-free}}$. The term $\mathrm{Econ}^{\mathrm{PLS}}_{\text{Bias-free}}$ denotes the look-ahead bias-free factor extracted from a set of 16 financial and economic variables (Econ) from Welch and Goyal (2008) via PLS. Each predictor is standardized to have a zero mean and unit variance. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Since we use the first 15-year data as training period, the in-sample analysis for the look-ahead bias-free PLS forecast is based on the sample period of 1984Q1 through 2019Q4.

(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Univariate		
		β	t-stat	R^2 (%)	
$\mathrm{Econ}^{\mathrm{PLS}}_{\text{Bias-free}}$		−0.072	−2.82***	4.81	
$\mathrm{M}^{\mathrm{PLS}}_{\text{Bias-free}}$		0.070	2.81***	4.58	
			Panel B: Bivariate		
Variable	β (PLS)	t-stat	ψ (Ctrl)	t-stat	R^2 (%)
DP	0.062	2.28**	0.024	0.82	5.05
DY	0.063	2.31**	0.020	0.63	4.88
EP	0.070	2.74***	0.020	0.56	4.96
DE	0.071	2.41**	−0.002	−0.05	4.58
SVAR	0.070	2.81***	−0.002	−0.07	4.58
BM	0.068	2.70***	0.009	0.36	4.64
NTIS	0.070	2.86***	−0.004	−0.12	4.59
TBL	0.073	2.74***	0.009	0.32	4.64
LTY	0.069	2.77***	−0.011	−0.46	4.68
LTR	0.071	2.82***	0.036	1.19	5.79
TMS	0.099	3.12***	−0.054	−1.51	6.52
DFY	0.073	2.72***	−0.013	−0.35	4.72
DFR	0.074	2.84***	−0.012	−0.31	4.69
INFL	0.067	2.73***	−0.034	−1.18	5.65
CAY	0.071	2.83***	0.012	0.62	4.71
IK	0.088	2.57**	0.026	0.66	4.90
$\mathrm{Econ}^{\mathrm{PLS}}_{\text{Bias-free}}$	0.059	2.21**	−0.035	−1.28	5.58
GDP_e	0.070	2.39**	−0.001	−0.04	4.58
$\mathrm{Indprod}_e$	0.065	2.45**	−0.021	−0.70	4.97
Recess_e	0.092	2.61***	−0.029	−0.79	4.89
Unemp_e	0.075	2.56**	−0.015	−0.40	4.76
Cprof_e	0.067	2.58***	−0.022	−0.91	5.03
$\mathrm{Housing}_e$	0.077	2.18**	−0.010	−0.25	4.63
Infl_e	0.068	2.75***	−0.028	−1.02	5.31

Table IA.4: **Long-horizon Return Predictability of Economic Variables and OOS Encompassing Test**

This table reports the OOS forecasting performance of economic variables for multiple forecast horizons ($h = 2,\ 4,\ 8,$ and 12 quarters). See the notes of Table II for details on the variable definitions. Panel A reports the OOS R^2 statistics whose significance is assessed by the MSFE-adjusted statistics of Clark and West (2007) that tests the null hypothesis $R^2_{OS} \leq 0$ against the alternative one $R^2_{OS} > 0$. We account for the serial correlations in overlapping observations by using $2(h-1)$ lags for the Newey-West statistics when computing the MSFE-adjusted statistics. Panel B reports the results of OOS forecast-encompassing tests. The test is conducted by constructing the following optimal composite forecast,

$$\hat{R}_{t+1} = (1-\lambda)\hat{R}^{i}_{t+1} + \lambda \hat{R}^{\text{LT-M}^{\text{PLS}}}_{t+1}, \quad 0 \leq \lambda \leq 1$$

where $\hat{R}^{i}_{t+1}$ ($\hat{R}^{\text{LT-M}^{\text{PLS}}}_{t+1}$) is the market excess return forecast generated by model i in the first column (LT-M$^{\text{PLS}}$). The null hypothesis is $\lambda = 0$, indicating that model i encompasses LT-M$^{\text{PLS}}$, against the alternative hypothesis $\lambda > 0$ that model i does not encompass LT-M$^{\text{PLS}}$. The statistical significance of λ is assessed by the upper-tail p-value for the Harvey et al. (1998) statistic. The OOS period is from 1984Q1 to 2019Q4. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Out-of-sample R^2 (%)				**Panel B: Encompassing λ**			
Variable	$h=2$	$h=4$	$h=8$	$h=12$	$h=2$	$h=4$	$h=8$	$h=12$
DP	−15.44	−31.75	−47.17	−53.48	0.86***	0.93***	1.00**	1.00**
DY	−13.82	−27.05	−36.91	−44.50	0.88***	0.94***	1.00**	1.00**
EP	−11.48	−20.07	−25.88	−30.69	0.82**	0.82**	0.98**	1.00**
DE	−5.77	−4.09	−8.23	−14.07	0.81**	0.71**	0.92*	1.00*
SVAR	−92.81	−52.93	−40.91	−49.98	0.93	0.90	0.90*	0.99*
BM	−16.92	−32.54	−37.30	−46.37	0.91***	0.94***	1.00***	1.00**
NTIS	−9.65	−23.35	−11.33	−11.36	0.76***	0.77***	0.81**	0.92**
TBL	−0.44	−1.33	−6.62	−13.80	0.65**	0.66**	0.91**	1.00*
LTY	−3.12	−8.77	−14.74	−22.36	0.71**	0.74**	0.89*	0.92*
LTR	1.14**	−0.28	1.28***	0.61**	0.55*	0.61**	0.77*	0.87*
TMS	−1.14	4.91***	9.77***	14.63***	0.68**	0.49**	0.60*	0.60*
DFY	−5.91	−5.51	−5.63	−13.05	0.82***	0.75***	0.95**	1.00**
DFR	−2.56	−2.37	−3.03	−0.53	0.72**	0.70**	0.85**	0.91*
INFL	1.16	−1.35	−6.32	−7.59	0.58*	0.66**	0.96**	1.00**
CAY	−2.85	−2.71*	5.99*	−0.96*	0.64**	0.60**	0.58**	0.66*
IK	−0.59	3.91*	4.90	16.28***	0.69**	0.53**	0.80**	0.57*
Econ$^{\text{PLS}}$	−19.25	−21.11	−3.30	−6.10	0.93**	0.94**	0.88**	1.00**

Table IA.5: **Robustness Checks for the Statistical Inference**

This table presents robustness checks concerning β for the predictive regression model,

$$R_{t+1:t+h} = \alpha + \beta\,\mathrm{M}_t^{\mathrm{PLS}} + e_{t+1:t+h},$$

where h denotes the forecast horizon. We use the h-quarter-ahead simple (log) excess return on the CRSP value-weighted index as the forecast target $R_{t+1:t+h}$ in Panels A (B). For predictive regressions in Panel A, we report the OLS estimates and the Newey-West corrected t-statistics with $2(h-1)$ lags (t-NW) where the statistical significance is based on one-sided wild bootstrap p-values following Huang et al. (2015). For predictive regressions in Panel B, we report the OLS estimates, the Hodrick (1992) corrected t-statistics (t-Hodrick), and the Kostakis et al. (2015) Wald statistics (IVX-Wald) that test $H_0 : \beta = 0$ against $H_1 : \beta \neq 0$. The 10%, 5%, and 1% critical values for IVX-Wald are 2.71, 3.84, and 6.64, respectively. The sample period is from 1969Q1 to 2019Q4. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)
	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$
Panel A: *Simple Excess Return*					
β	0.083	0.070	0.068	0.048	0.047
t-NW	3.65***	3.69**	3.73**	2.97	3.57*
Panel B: *Log Excess Return*					
β	0.086	0.071	0.065	0.045	0.042
t-Hodrick	3.64***	3.13***	2.94***	2.24**	2.26**
IVX-Wald	12.27***	9.56***	9.87***	5.77**	6.08**

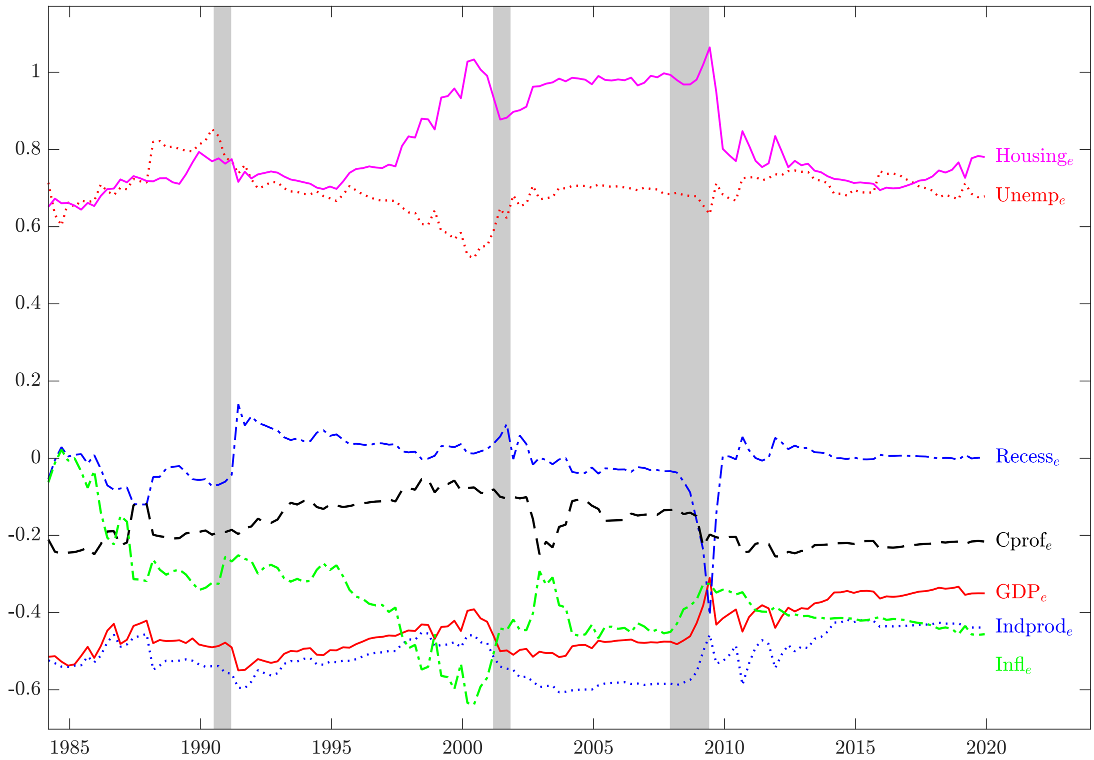

Figure IA.1: **Out-of-sample factor loadings of M^{PLS}**

The plot depicts the PLS weights for the recursively constructed macro condition index M^{PLS} using the seven current-quarter survey forecasts over the out-of-sample period. The seven survey forecasts include current-quarter forecasts on the real GDP growth, industrial production growth, recession probability, unemployment rate, corporate profit growth, housing starts growth, and inflation. The sample period is from 1984Q1 to 2019Q4. The shaded area corresponds to the NBER-dated recession period.