Internet Appendix

Macroeconomic Expectations and Expected Returns

IA.1 Variable Definition

This section presents the definition of the 16 financial and economic variables of Welch and Goyal (2008) used in the paper.

- 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): Ratio of book equity value to market equity value for the Dow Jones Industrial Average.
- Net Equity Expansion (NTIS): 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 three-month Treasury bill (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 three-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).

The data of the 16 predictors are obtained from Amit Goyal's website (`http://www.hec.unil.ch/agoyal`).

IA.2 Return Decomposition

This section provides a detailed description on the return decomposition methodology developed by Campbell (1991). 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

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

where

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

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

$\bar{x}$ is the mean of x_t, and $\Delta d_{t+1} = d_{t+1} - d_t$. Iterating Eq. (IA.1) forward recursively, we have

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

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. (IA.4) yields the dividend-price ratio decomposition of Campbell (1991),

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

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

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

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

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

where $\eta^r_{t+1} = r_{t+1} - \mathbb{E}_t(r_{t+1})$, $\eta^{\mathrm{CF}}_{t+1} = (\mathbb{E}_{t+1} - \mathbb{E}_t)\left(\sum_{j=0}^{\infty}\rho^j\Delta d_{t+j+1}\right)$, and $\eta^{\mathrm{DR}}_{t+1} = (\mathbb{E}_{t+1} - \mathbb{E}_t)\left(\sum_{j=1}^{\infty}\rho^j r_{t+j+1}\right)$ 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:

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

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.[1] Let $e_1' = [1, 0, ..., 0]'$ be an $(n+2)$-vector, the stock return innovation and discount rate news are given by

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

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

and

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

respectively. Accordingly, the cash flow news is obtained as

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

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

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

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

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

Empirically, we use OLS to estimate A and $\{u_{t+1}\}_{t=1}^{T-1}$ in Eq. (IA.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. (IA.9)–(IA.12) to obtain the estimated return decomposition components, $\hat{\mathbb{E}}_t(r_{t+1})$, $\hat{\eta}_{t+1}^{r}$, $\hat{\eta}_{t+1}^{\text{DR}}$, and $\hat{\eta}_{t+1}^{\text{CF}}$ for $t = 1, ..., T-1$.

IA.3 Supplementary Results

This section presents supplementary results for the paper, including the pairwise correlations of predictor variables used in the paper, the performance of look-ahead bias-free PLS factors $M_{\text{Bias-free}}^{\text{PLS}}$, and the results of robustness analysis (Section IA.3.1), predictions of characteristic-sorted equity portfolios (Section IA.3.2), comparisons with additional predictor variables (Section IA.3.3), other macroeconomic survey data (Section IA.3.4), and the SPF 10-year equity premium forecasts (Section IA.3.5).

IA.3.1 Robustness Analysis

We conduct several robustness tests for the predictive ability of M^{PLS}. First, we investigate the subsample predictability of M^{PLS} by splitting the whole sample into two subsamples, namely, 1969Q1 to 1994Q2 (the first-half sample) and 1994Q3 to 2019Q4 (the second-half sample). Panels A and B of Table IA.4 show that the in-sample forecasting results for the first- and second-half samples are comparable to the full-sample results shown in Tables II and IX in the paper. For instance, the quarterly regression slope estimates of M^{PLS} are 0.087 and 0.090 in the first- and second-half samples, respectively, close to the full-sample estimate of 0.083. Next, we evaluate the OOS forecasting performance of M^{PLS} over alternative evaluation periods: 1980Q1 to 2019Q4, 1990Q1 to 2019Q4, and 2000Q1 to 2019Q4. As shown in Panel C, M^{PLS} consistently outperforms the historical mean benchmark and generates significant R^2_{OS} statistics, at whatever point the OOS forecasting starts. Therefore, in contrast with the results of Welch and Goyal (2008) who argue that numerous existing predictors evince weak in-sample significance and unstable OOS performance over 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 recent decades.

Second, to address the concerns surrounding econometric inferences for predictive regressions with persistent and endogenous regressors and overlapping observations (Hodrick, 1992; Stambaugh, 1999), we follow Huang, Jiang, Tu, and Zhou (2015) to apply a wild bootstrap procedure to compute empirical p-values for the slope estimates in Eqs. (5) and (15) of the paper. The simulation procedure accounts for the persistence of the predictors, the conditional correlation between the predictors and market returns, and the general forms of the return distribution. The results in Table IA.5 corroborate the robustness of our econometric inference for M^{PLS}. It is worth mentioning that the correlation between the return innovations and the innovations in M^{PLS} is nearly zero, however. Thereby, the finite-sample bias problem is unlikely to drive our findings.

Third, we consider the logarithms of market returns instead of the simple return. We utilize the Hodrick (1992) standard error and the extended instrumental variable–Wald statistic of Kostakis, Magdalinos, and Stamatogiannis (2015) to assess the significance of the short- and long-horizon predictability for logarithm excess returns. Panel B of Table IA.5 shows that M^{PLS} predicts the logarithm market excess return from one quarter to three years.

Finally, we experiment with several alternative ways to construct the consensus macroeconomic forecasts upon which we build the subjective macro condition indices, and we document quantitatively similar results.[2] Overall, the predictive power of M^{PLS} is not confined to a particular period, is not affected by the finite-sample bias problem, and is robust to the types of compounding returns and the way the consensus forecasts are constructed.

IA.3.2 Characteristic-Sorted Equity Portfolios

We assess the forecasting ability of M^{PLS} for stock portfolios sorted on size and Standard Industrial Classification codes. The portfolio return data are obtained from Kenneth French's data library. Panel A of Table IA.6 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 the variation of M^{PLS} and exhibit a higher degree of predictability relative to large firms. Panel B 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 meaningful manner. The β estimates of M^{PLS} for 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. This result highlights the substantial cross sectional differences in the sensitivities. In addition, 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. Overall, the predictive ability of M^{PLS} extends strongly to the cross section of stock returns.

Perez-Quiros and Timmermann (2000) posit that small firms are more vulnerable than large firms to changes in economic states due to the weak ability of small firms to raise external funds during recessions. Consequently, the former's risk premia are more sensitive to business cycle fluctuations. Gomes, Kogan, and Yogo (2009) find that the stronger cyclical

[2]For instance, we use the cross-sectional median of the forecasts made by individual forecasters as the consensus forecast in Eq.(1) of the paper 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 that prior to the current quarter when calculating growth rate forecasts for different horizons. These results are available upon request.

demand for durable goods than that for nondurable goods makes the risk premia of firms producing durable goods higher and vary more countercyclically. Both studies imply cross sectional differences in the sensitivity of firms' risk premia to macroeconomic conditions. The results in Table IA.6 support this theoretical prediction and reinforce our conclusion that M^{PLS} tracks the variation in the equity premium related to business cycle frequency fluctuations.

IA.3.3 Further Predictor Variables Considered

The more recent literature has proposed a number of predictors that are motivated by asset pricing theory and are constructed based on realized macroeconomic data. 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 (NHOUS) of Piazzesi, Schneider, and Tuzel (2007), payroll growth (PAYROLL) of Chen and Zhang (2011), and the ratio of new orders to shipments of durable goods (NO/S) of Jones and Tuzel (2013), as well as OG and CC. We closely follow the instructions of the original papers and construct these variables using final revised macroeconomic data.[3] In addition, 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 Index of Consumer Sentiment from the MSC (S^{MSC}); the investor sentiment indices of Baker and Wurgler (2006) and Huang et al. (2015), denoted by S^{BW} and S^{HJTZ}, respectively; and the disagreement index (D^{HLW}) of Huang, Li, and Wang (2021). In this subsection, we analyze how M^{PLS} is related to these (objective) macroeconomic predictor variables and measures of investment sentiment and disagreement.

Panel A of Table IA.7 reports the in-sample estimation results for the univariate predictive regression of the quarterly excess market return on one of the above predictors considered. Of the eight macro variables listed above, OG, CC, and NO/S significantly predict the market return in our sample, with sizable R^2 values of 4.92%, 3.98%, and 1.94%, respectively.

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

For the sentiment and disagreement indices, S^{HJTZ} exhibits the greatest predictive ability, with an R^2 of 6.49%, followed by the disagreement index D^{HLW}, with an R^2 of 4.8%.

In Panel B of Table IA.7, we estimate bivariate regressions to compare the information content of M^{PLS} with alternative predictors considered. We find that M^{PLS} remains positively significant after controlling for one of the macro variables constructed from realized macroeconomic data or their first principal component (MACRO$^{\text{PC}}$). Turning to the results of conditioning on investor sentiment and disagreement indices, the slope estimate of M^{PLS} hardly changes compared to its univariate regression estimate, and neither do the estimates of S^{BW}, S^{HJTZ}, and D^{HLW}. This finding reflects that the information content of M^{PLS} is orthogonal to that of S^{BW}, S^{HJTZ}, and D^{HLW}. Column (7) of Table IA.7 reports the contemporaneous correlations between M^{PLS}. The strong correlation ($\rho = -0.55$) between M^{PLS} and MACRO$^{\text{PC}}$ reveals that M^{PLS} co-moves with the common variation of macro predictors built on realized macroeconomic data. By contrast, M^{PLS} has much lower correlations with S^{HJTZ} (-0.13) and D^{HLW} (-0.21). The predictability of M^{PLS} is thus unlikely to stem from the sentiment or disagreement channels, consistent with our explanation based on time-varying risk premia.

IA.3.4 Other Macroeconomic Survey Data

Our main result shows that the macroeconomic forecasts made by professional forecasters are informative about the countercyclical objective U.S. equity premium. In this subsection, we investigate whether our main finding holds for other markets and whether the finding is affected by the type of survey respondents. We consider macroeconomic expectations data obtained from two additional sources: the European Central Bank (ECB) SPF and the Michigan Surveys of Consumers (MSC). Analogous to the U.S. SPF, the ECB SPF elicits professional forecasters' expectations of aggregate macroeconomic conditions in the whole euro area on a quarterly basis since 1999. Specifically, we collect the current- and next-year ECB SPF forecasts of inflation, real GDP growth, and unemployment.[4] We construct a subjective macro condition index for the whole euro area based on the ECB SPF forecasts via the PLS method, using the one-period-ahead return on the Europe STOXX index as the

[4]The ECB SPF data are publicly available at `https://www.ecb.europa.eu/stats/ecb_surveys/survey_of_professional_forecasters/`. We choose the three macro variables that have the longest time span since the initiation of the ECB SPF.

PLS proxy, to which we refer as ECB-M$^{\text{PLS}}$. We examine whether ECB-M$^{\text{PLS}}$ can predict European stock markets returns, including those of France, Germany, Italy, the Netherlands, Sweden, Switzerland, and the UK, as well as the Europe STOXX index. The choices of European countries in our analysis and their corresponding market indices follow Rapach, Strauss, and Zhou (2013).

Table IA.8 shows that ECB-M$^{\text{PLS}}$ significantly predicts the European stock markets returns, with sizable R^2 values ranging from 9.08% (Germany) to 13.85% (the Netherlands), over the sample period from 1999Q1 to 2019Q4. Untabulated results show that ECB-M$^{\text{PLS}}$ loads negatively on the GDP growth and inflation forecasts and positively and heavily on the unemployment forecast. As a result, ECB-M$^{\text{PLS}}$ varies countercyclically over business cycles. The positive and substantial predictability generated by ECB-M$^{\text{PLS}}$ is in accord with our main results based on the U.S. SPF data and provides international evidence that labor market conditions are key to the equity premium variation. Moreover, our finding that the professional forecasts of future macroeconomic conditions are informative about the expected return is not peculiar to the U.S. market. The predictability uncovered using the ECB SPF data thereby serves as an OOS test of our baseline results and further alleviates the data snooping concern.

The recent literature on subjective return expectations reveals substantial heterogeneity in beliefs across professionals and individual investors. We are interested in a comparison between professionals' macroeconomic expectations and individual investors'. Specifically, we collect the quarterly households' macroeconomic expectations from the MSC on the following three aspects: 1) business conditions: including the forecasts of current business conditions compared with a year ago (MSC_{cur}), expected changes in business conditions in a year ($\text{MSC}_{\text{1yrChg}}$), and business conditions expected during the next year (MSC_{1yr}) and during the next five years (MSC_{5yr}); 2) employment, including expected changes in aggregate employment during the next year (MSC_{Emp}); 3) housing market, including the expectation about the current buying conditions for houses ($\text{MSC}_{\text{Housing}}$).[5] In addition to the expectations of the overall business conditions, we collect households' expectations about labor and housing market conditions since we have elucidated their importance in explaining

[5]The Survey Research Center at the University of Michigan has been conducting surveys on consumers in the U.S. since 1946. The questionnaire asks respondents regarding their beliefs about the economy and stock market performance. Amromin and Sharpe (2014), Greenwood and Shleifer (2014), and Nagel and Xu (2022) analyze the return expectations from the MSC.

the equity premium variation. It is worth mentioning that the MSC summarizes households' views of economic conditions based on the spread in their answers. For example, the survey question underlying MSC_{cur} is:

> *Would you say that at the present time business conditions are better or worse than they were a year ago?*

The responses are classified into three categories: i) better now, ii) about the same, iii) worse now, and MSC_{cur} is a diffusion index computed as the percentage of households that respond "better" minus the percentage that respond "worse".

Panel A of Table IA.9 presents the forecasting results for the quarterly excess market return using the MSC survey forecasts. We note that all the MSC business conditions forecasts negatively predict the market return. In addition, MSC_{Emp} and $\text{MSC}_{\text{Housing}}$ predict the market with negative and positive signs, respectively. The signs of these regression coefficients conform to our main results in Table II based on the SPF data and the theoretical prediction that expected returns are high when economic conditions are expected to deteriorate.[6] Nonetheless, none of the individual MSC variables evinces significant predictive power.

We then use the PLS method to consolidate the six MSC variables into a single factor, to which we refer as the households' macro condition index (MSC^{PLS}). The index loads negatively on households' expected business conditions and positively on the buying condition of houses. Notably, MSC^{PLS} is negatively correlated to the CFNAI index, OG, and CC, and significantly predicts the market with a positive sign. This result suggests that households' macroeconomic expectations also provide information about the objective countercyclical equity premium, and lends additional support to our conclusion that survey-based macroeconomic expectations are useful for learning the equity premium. Greenwood and Shleifer (2014) find that the return expectations of households have insignificant relations with various measures of macroeconomic conditions. Our finding and their evidence together imply that households might neglect the macroeconomic information that they possess when forming their return expectations. This argument helps to reconcile the difference in the cyclicality between professionals' return expectations and households'.

The MSC macroeconomic forecasts, however, appear to be less informative and noisier

[6] An increase in MSC_{Emp} indicates that the MSC respondents believe that there will be less unemployment than now during the coming 12 months.

than the SPF forecasts. As shown in Panel B of Table IA.9, MSC^{PLS} loses its significance after controlling for M^{PLS}, suggesting that their predictability stems from the same channel but the predictive power of MSC^{PLS} is weaker than that of M^{PLS}. One possibility for this finding is that professional forecasters are well trained and possess superior information-processing ability. By contrast, individual investors are typically lack of professional knowledge and it would be costly for them to make reasonably rational forecasts for economic conditions (Carroll, 2003). Consequently, professional macroeconomic expectations are more accurate than households' expectations. Furthermore, since the MSC asks participants to give a brief outlook of economic conditions rather than eliciting the level of the macroeconomic variable, this could introduce additional biases and measurement errors into the resultant forecasts.

IA.3.5 SPF 10-year Equity Premium Forecasts

In addition to macroeconomic forecasts, the SPF also elicits forecasters' expectations of the (annualized) average return on the three-month Treasury bill and that on the S&P 500 index over the next 10 years. These forecasts are made on an annual basis since 1992. By subtracting the forecasted S&P 500 return from the forecasted bill rate, we can obtain a rough estimate of the expected equity premium over the next 10 years made by SPF forecasters. How does this direct long-horizon equity premium forecast compare with the 10-year equity premium forecast produced by M^{PLS}?[7]

As shown by Figure IA.2, the 10-year equity premium forecasts by the SPF share similarities with those by M^{PLS}: both of them tend to rise during NBER recessions (e.g., the 2008 Great Recession) and decline during expansions (e.g., the post-2008 Great Recession period). Therefore, the more direct SPF equity premium forecast also displays countercyclical dynamics, consistent with the result of M^{PLS}. The correlations of the median and mean SPF equity premium forecasts with the M^{PLS} forecast are 0.40 and 0.29, respectively. Nonetheless, we note that the forecasted risk premia over the next 10 years by M^{PLS} appear

[7] More specifically, we run the long-horizon overlapping regression using M^{PLS}, as indicated by equation (15) in the paper, for the 10-year annualized S&P 500 logarithmic excess return ($h = 40$). We use the logarithmic excess return to mitigate the impact of volatility on long-term returns (Jensen's inequality's effect). Note that the SPF stock and bill return forecasts are for the current and next nine years (e.g., the return forecast made in 1992Q1 is for the period from 1992Q1 to 2001Q4). Therefore, in each year-end quarter t since 1991, we calculated the 10-year equity premium forecast as $\hat{\alpha} + \hat{\beta}\, M_t^{\text{PLS}}$ where $\hat{\alpha}$ and $\hat{\beta}$ are the OLS estimates of the predictive regression.

to be higher than the direct SPF forecasts.

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

This table presents the pairwise correlations between the current-quarter SPF forecasts(nowcasts) for the seven aspects of the macroeconomy. The seven SPF nowcasts include 1) gross domestic product growth (GDP_e), 2) the industrial production index growth (IP_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 (HOUS_e), and 7) GDP price index growth (INFL_e). The sample period is from 1968Q4 to 2019Q3.

(1) Variable	(2) GDP_e	(3) IP_e	(4) RECESS_e	(5) UNEMP_e	(6) CPROF_e	(7) HOUS_e
GDP_e	1.00					
IP_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	
HOUS_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 between 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 index): 1984Q1-2019Q4**

This table presents the OLS estimates, Newey–West t-statistics with one lag, 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,

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

where R_{t+1} is the annualized excess return on the CRSP NYSE/AMEX/NASDAQ value-weighted index in quarter $t+1$, X refers to one of the variable sets $\{M, \text{ECON}\}$, and $X^{\text{PLS}}_{\text{Bias-free}}$ denotes the look-ahead bias-free factor extracted via PLS. Panel B reports the results of the bivariate predictive regression model,

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

where CTRL denotes one of the control variables taken from the first column other than $M^{\text{PLS}}_{\text{Bias-free}}$. 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 (%)	
$\text{ECON}^{\text{PLS}}_{\text{Bias-free}}$		−0.072	−2.82***	4.81	
$M^{\text{PLS}}_{\text{Bias-free}}$		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
$\text{ECON}^{\text{PLS}}_{\text{Bias-free}}$	0.048	1.75*	−0.051	−1.80*	6.57
GDP_e	0.070	2.39**	−0.001	−0.04	4.58
IP_e	0.065	2.45**	−0.021	−0.70	4.97
RECESS_e	0.075	2.56**	−0.015	−0.40	4.76
UNEMP_e	0.092	2.61***	−0.029	−0.79	4.89
CPROF_e	0.067	2.58***	−0.022	−0.91	5.03
HOUS_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: **Return Predictability for Subsamples**

This table presents the forecasting results of the predictive regression

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

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 OLS slope estimate, Newey–West t-statistic (computed using a lag length of $max[1, 2^*(h-1)]$), 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) with a lag length of $max[1, 2^*(h-1)]$). *, **, 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-stat	2.59***	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-stat	2.77***	2.06**	1.62	2.13**	1.93*
R^2(%)	7.43	8.02	6.04	11.14	12.53
Panel C: alternative OOS 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 IA.5: **Robustness Checks for the Statistical Inference**

This table presents the results of additional statistical inference procedure for the significance of the β estimate of the following predictive regression,

$$R_{t+1:t+h} = \alpha + \beta\, M_t^{\text{PLS}} + e_{t+1:t+h},$$

where h denotes the forecast horizon. The forecasting target $R_{t+1:t+h}$ in Panels A (B) is the h-quarter-ahead annualized simple (log) excess return on the CRSP NYSE/AMEX/NASDAQ value-weighted index. For predictive regressions in Panel A, we report the OLS slope estimate and the Newey–West t-statistic with a lag length of $max[1, 2^*(h-1)]$ (t-NW) where the statistical significance is judged based on one-sided wild bootstrapped p-values as in Huang et al. (2015). In Panel B, we report the OLS slope estimate, the Hodrick (1992) 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	3.80***	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**

Table IA.6: **Forecasting Characteristic-sorted Equity Portfolios**

This table presents the in-sample and OOS forecasting results for the characteristic-sorted equity portfolios based on the following predictive regression:

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

where R^p_{t+1} is the quarterly excess returns on characteristic-sorted equity portfolios. We report the in-sample OLS slope estimate, in-sample R^2 statistic, and the OOS R^2 statistic for each portfolio. 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 IA.7: **Relation with Other Predictive Variables**

This table presents the in-sample predictive regression estimates of the quarterly market excess return on M^{PLS} and additional predictors variables considered, 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 (NHOUS) 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, Møller, and Priestley (2020); the Index of Consumer Sentiment from the Michigan Surveys of Consumers (MSC) (S^{MSC}); 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 variable MACRO$^{\text{PC}}$ 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 including the predictors in the first column other than M^{PLS} as control variables. Panel C reports contemporaneous correlations of M^{PLS} with the variables listed 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 D^{HLW} (1969Q4 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 (%)	$\rho(M^{\text{PLS}}, \text{CTRL})$
M^{PLS}	0.083***	5.75	-	-	-	-
Other macro variables						
σ_c	−0.034	0.96	0.088***	−0.043*	7.29	0.11
PY	−0.038	1.22	0.079***	−0.027	6.34	−0.14
S^w	−0.016	0.22	0.083***	−0.012	5.88	−0.04
NHOUS	−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$^{\text{PC}}$	−0.062**	3.25	0.070***	−0.024	6.09	−0.55
Variables related to investor's sentiment and disagreement						
S^{MSC}	−0.024	0.50	0.087***	0.010	5.82	−0.40
S^{BW}	−0.036	1.07	0.082***	−0.034	6.73	−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

Table IA.8: **Forecasting European Market Returns with the European Central Bank SPF Data**

This table reports the OLS slope estimate, Newey–West t-statistics with one lag, and R^2 values of the following predictive regression

$$R_{i,t+1} = \alpha + \beta\,\text{ECB-M}_t^{\text{PLS}} + \epsilon_{i,t+1},$$

where $R_{i,t+1}$ is the annualized quarterly excess return on one of the seven European markets considered, including France, Germany, Italy, the Netherlands, Sweden, Switzerland, the United Kingdom (UK), or the excess return on the Europe STOXX Index. Stock market excess returns are computed relative to the domestic three-month Treasury bill rates and are denominated in the national currency. The variable $\text{ECB-M}_t^{\text{PLS}}$ is the PLS factor extracted from the current- and next-year forecasts on the real GDP growth, unemployment, and inflation in the euro area provided by the European Central Bank SPF, using the one-period-ahead excess return on the Europe STOXX Index as the PLS proxy 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	3.29***	11.32	Sweden	0.143	3.35***	10.54
Germany	0.140	2.98***	9.08	Switzerland	0.092	2.69***	9.10
Italy	0.135	2.89***	11.16	UK	0.100	3.24***	11.73
Netherlands	0.148	3.25***	13.85	STOXX	0.135	3.14***	11.03

Table IA.9: **Forecasting U.S. Market Returns with the Michigan Survey of Consumers Data**

This table presents the forecasting results for the quarterly excess return on the CRSP NYSE/AMEX/NASDAQ value-weighted index using macroeconomic forecasts from the Michigan Surveys of Consumers (MSC). Denote by "MSC_{Cur}" the MSC forecast of current business conditions compared with a year ago, "MSC_{1yrChg}" the forecast of expected changes in business conditions in a year, "MSC_{1yr}" and "MSC_{5yr}" the forecast of business conditions expected during the next year and next five years, respectively, "$MSC_{Housing}$" the expectation about the current buying conditions for houses, and "MSC_{Emp}" the expected changes in aggregate employment during the next year. The variable "MSC^{PLS}" is the PLS factor extracted from the above six MSC forecasts using the excess market return as the proxy. Panel A reports the estimation results of the univariate regressions based on the variables listed in the first column and panel B reports the estimation results of the bivariate regressions, consisting of M^{PLS} and one of the variables listed in the first column. The OLS slope estimates, Newey–West t-statistics with one lag, and R^2 values are reported for each regression. 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)	(8)	(9)
	Panel A: Univariate			**Panel B: Bivariate**				
Variable	β	t-stat	R^2 (%)	β (M^{PLS})	t-stat	ψ (MSC)	t-stat	R^2 (%)
Business Conditions								
MSC_{Cur}	−0.009	−0.25	0.06	0.094	3.64***	0.028	0.79	6.29
MSC_{1yrChg}	−0.024	−0.84	0.47	0.086	3.95***	−0.031	−1.13	6.52
MSC_{1yr}	−0.034	−1.08	0.98	0.083	3.19***	−0.001	−0.03	5.75
MSC_{5yr}	−0.032	−1.04	0.85	0.081	3.46***	−0.008	−0.26	5.80
Housing								
$MSC_{Housing}$	0.023	0.71	0.45	0.082	3.62***	0.014	0.47	5.92
Employment Conditions								
MSC_{Emp}	−0.005	−0.16	0.02	0.084	3.74***	0.006	0.19	5.77
Households' Macro Condition Index								
MSC^{PLS}	0.058	2.31**	2.80	0.072	2.79***	0.033	1.18	6.53

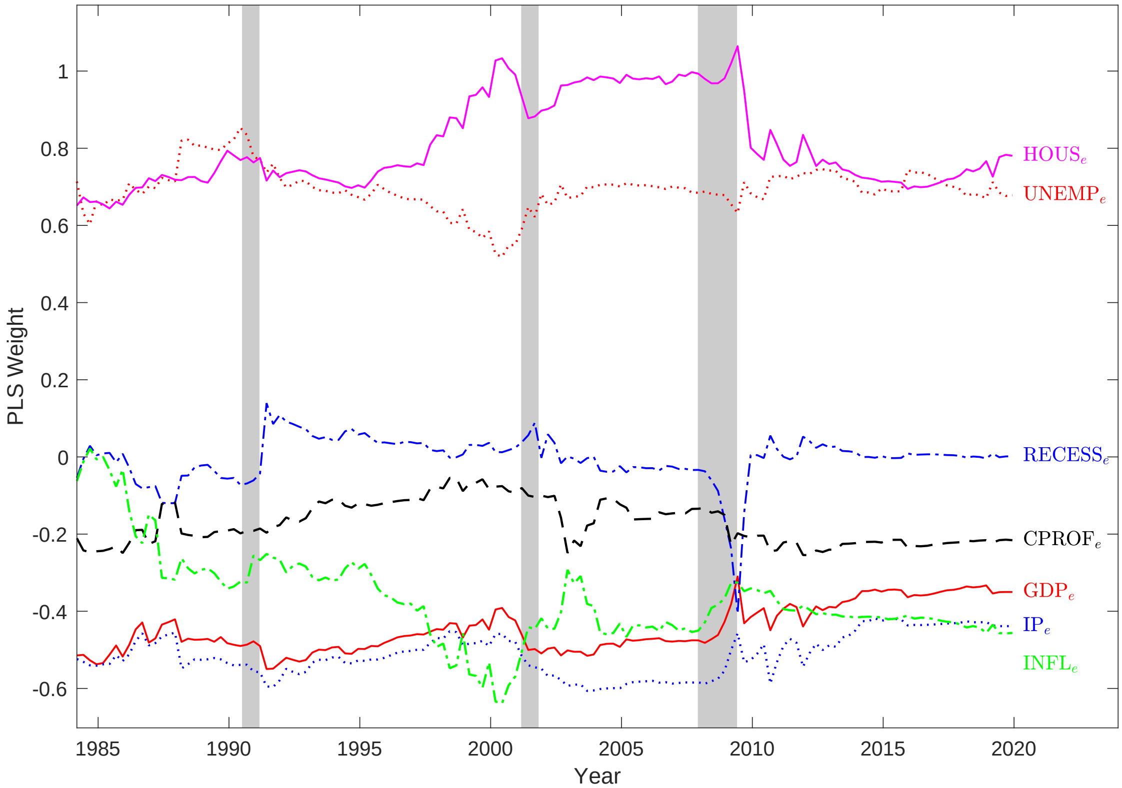

Figure IA.1: **Out-of-sample factor loadings of M^{PLS}**

The plot depicts the recursively estimated PLS weights of the subjective macro condition index M^{PLS} on the SPF nowcasts over the OOS period. The SPF nowcasts cover the following macroeconomic fundamentals: the real GDP growth (GDP), industrial production growth (IP), recession probability (RECESS), unemployment rate (UNEMP), corporate profit growth (CPROF), housing starts growth (HOUS), and inflation (INFL). The sample period is from 1984Q1 to 2019Q4. The shaded area corresponds to the NBER-dated recession period.

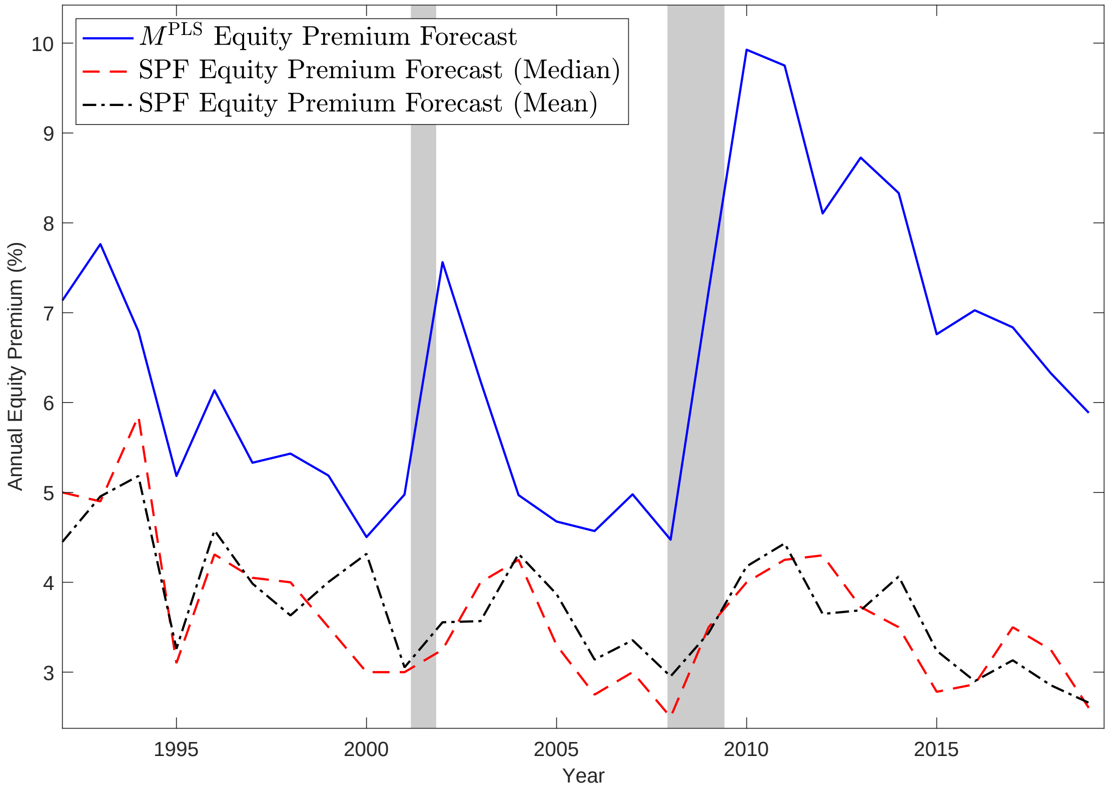

Figure IA.2: **10-year Equity Premium Forecasts**

Figure IA.2 plots the annual-average equity premium forecasts over the next 10 years generated by M^{PLS} (solid line) and the SPF median (dashed line) and mean (dash-dotted line) consensus forecasts of the next 10-year annual-average equity premium. Since the SPF forecasts are only made at the first quarter of each year, the sample spans the period from the first quarter of 1992 to the first quarter of 2019.

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